

# **ESCUELA POLITÉCNICA NACIONAL**

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**DESARROLLO DE UN MODELO PREDICTIVO CON EL USO DE  
APRENDIZAJE DE MÁQUINA PARA LA DETERMINACIÓN DEL  
COMPORTAMIENTO DE PAGO DE LOS CLIENTES CON LOS DATOS DE UN  
BANCO ECUATORIANO.**

**TRABAJO DE TITULACIÓN PREVIO A LA OBTENCIÓN DEL GRADO DE MAGISTER  
EN SISTEMAS DE INFORMACIÓN**

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## **APROBACIÓN**

Como director del trabajo de titulación **DESARROLLO DE UN MODELO PREDICTIVO PARA LA DETERMINACIÓN DEL COMPORTAMIENTO DE PAGO DE LOS CLIENTES CON LOS DATOS DE UN BANCO ECUATORIANO.**

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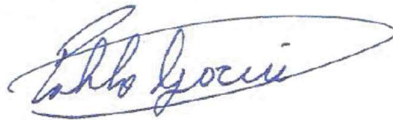
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**Pablo Sebastián García Guevara**

## DEDICATORIA

El presente trabajo investigativo lo dedico principalmente a Dios, por ser el inspirador y darme fuerza para continuar en este proceso de obtener uno de los anhelos más deseados.

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## RESUMEN

Esta tesis de Maestría Tiene como objetivo desarrollar un modelo predictivo con el uso de aprendizaje de máquina para la determinación del comportamiento de pago de los clientes con los datos de un Banco Ecuatoriano. Este modelo predictivo puede ayudar al Banco a anticipar el comportamiento de clientes que posiblemente entraran en mora o dejaran de pagar un préstamo, de manera que se puedan tomar medidas adecuadas como vender cartera o presionar en la cobranza. El análisis del comportamiento de pago del cliente se lo realizo utilizando series de tiempo y se utilizaron 4 modelos de aprendizaje de máquina Modelo de Redes Neuronales Recurrentes, Modelo Redes Temporales Convolucionales, Modelo TRANSFORMER y Modelo N-BEATS mediante el uso de la librería DARTS de PYTHON. Estos modelos se los comparo con el modelo clásico de cadenas de Markov y se utilizaron 3 métricas para compararlos i) El error, ii) F-Score, iv) Matriz de Confusión, y se analizó su comportamiento aumentando el número de predicciones que se realiza. En la parte final se analiza las razones para que los modelos no sean tan robustos y se propone como se podrían aplicar de mejor manera los modelos de aprendizaje de máquina para este tipo de predicciones.

**Palabras clave:** Aprendizaje de Máquina, Markov, Series de Tiempo, Banca.

## ***ABSTRACT***

This Master's thesis aims to develop a predictive model with the use of machine learning to determine the payment behavior of customers with data from an Ecuadorian bank. This predictive model can help the Bank to anticipate the behavior of clients who may be in default or stop paying a loan, so that appropriate measures can be taken such as selling the portfolio or pressuring collections. The analysis of the customer's payment behavior was carried out using time series and 4 machine learning models Recurrent Neural Networks, Temporal Convolutional Networks, TRANSFORMER and NBEATS were used through the use of the DARTS library of PYTHON. These models were compared with the classic Markov chain model and 3 metrics were used to compare them i) The error, ii) F-Score, iii) Confusion Matrix, its behavior was analyzed by increasing the number of predictions that were made. In the last part, the reasons for the models not being robust are analyzed and how machine learning models could be applied in for this type of predictions is proposed.

**Keywords:** Machine Learning, Markov, Time Series, Banking.

## 1. INTRODUCCIÓN

Las entidades Bancarias se dedican a obtener ganancias mediante el movimiento de dinero, uno de los que mayor ganancia les genera es el prestar dinero tanto a personas naturales como a pequeñas y grandes empresas. En el país los bancos prestan millones de dólares al año, ya que mientras más dinero presten más dinero generan gracias al pago de intereses.

Para mantener su estabilidad los Bancos Ecuatorianos deben tener una buena solvencia, la cual se mide a través de la relación entre los fondos con los que cuenta para hacer frente a imprevistos en relación con los riesgos que asume. Es decir, debe mantener un equilibrio entre el dinero que presta y el que necesita para su funcionamiento a nivel de gastos de operación y permitirles a sus clientes retirar su dinero cuando sea necesario.

Para mantener una buena solvencia estas entidades requieren que las personas paguen puntualmente sus deudas hacia el Banco de manera que se tenga liquidez para cubrir los gastos del Banco y poder obtener más ganancias prestando nuevamente el dinero que ingresan.

Sin embargo, ya que no todos los deudores pagan sus obligaciones a tiempo. Se requiere de un proceso adicional de cobranza que se encargue de lograr que aquellas personas que se atrasan en sus obligaciones se pongan al día lo antes posible. La efectividad de este proceso es muy importante ya que representa un gasto importante para los Bancos y cuando este no es efectivo este gasto es en vano.

Por esta razón se requiere una manera de predecir cómo será el comportamiento de pago de los deudores para determinar si se requiere o no presionar para el pago ya sea porque de todas maneras no van a pagar o porque, aunque se retrasaron en la cuota eventualmente igualarán. Adicional si se logra determinar a tiempo que deudores dejarán de pagar sus obligaciones de manera definitiva se pueden tomar acciones como cobrar a los garantes, aplicar garantías hipotecarias y vender carteras a mejores precios ya que se identifica un mal pagador antes que otras instituciones lo cataloguen como tal.

## **1.1. Pregunta de investigación**

¿Es posible Desarrollar un modelo predictivo con el uso de aprendizaje de máquina para la determinación del comportamiento de pago de los clientes con los datos de un Banco Ecuatoriano que funcione mejor que las cadenas de Márkov?

## **1.2. Objetivo general**

Desarrollar un modelo predictivo con el uso de aprendizaje de máquina para la determinación del comportamiento de pago de los clientes con los datos de un Banco Ecuatoriano.

## **1.3. Objetivos específicos**

- Diseñar un modelo predictivo que utilice aprendizaje de máquina para la determinación del comportamiento de pago de los clientes.
- Entrenar el modelo predictivo para la determinación del comportamiento de pago de los clientes con datos de entrenamiento obtenidos de la cartera de clientes de un Banco Ecuatoriano.
- Comparar el comportamiento del modelo predictivo que utilice aprendizaje de máquina para la determinación del comportamiento de pago de los clientes con el modelo obtenido mediante el uso de cadenas de Markov, utilizando datos de prueba obtenidos de la cartera de clientes de un Banco Ecuatoriano.

## **1.4. Marco Teórico**

### **Cadenas de Markov**

En la actualidad el sector financiero necesita técnicas que le permitan predecir el comportamiento de pago de sus acreedores. De esta manera pueden tomar decisiones a tiempo para el bienestar de la institución. En la actualidad uno de los métodos utilizados son las cadenas de Markov ya que muchos autores incluyendo Kosubud y Stokes, sugieren que su aplicación es rica en términos de implicaciones económicas y políticas [1]. Los procesos aleatorios de Markov son utilizados para describir muchos otros sistemas físicos, técnicos y económicos [2].

Las Cadena de Markov Monte Carlo son un método general para la simulación de procesos estocásticos que tienen densidades de probabilidad conocidas hasta una constante de proporcionalidad [3].

La idea básica es muy simple. Si uno no puede encontrar una forma de simular ocurrencias independientes de algunos procesos estocástico complicados, es útil para poder simular realizaciones dependientes  $X_1, X_2, \dots$  formando una cadena de Markov irreducible que tiene la distribución de interés  $P$  como su distribución estacionaria. [3]

Este tipo de técnicas se utilizan ya que se considera que el comportamiento de pago de los créditos es aleatorio y no depende de la historia de pagos [4]. Una de las técnicas más utilizadas para el modelado de portafolios de créditos son las cadenas de Markov con tiempo discreto y número finito de estados [5].

Un proceso estocástico de tiempo discreto especifica cómo una variable aleatoria cambia en puntos discretos en el tiempo. Sea  $X_T$  una variable aleatoria que representa el estado de un sistema en el tiempo  $t$ , donde  $t = 0, 1, 2, \dots$ . La cadena de Markov estacionaria es un tipo especial de proceso estocástico de tiempo con los siguientes supuesto [6]:

- La distribución de probabilidad del estado en el momento  $t + 1$  depende del estado en el tiempo  $t$ , y no dependen de los estados anteriores que conducen al estado en el momento  $t$ .
- Una transición de estado del tiempo  $t$  al tiempo  $t + 1$  es independiente del tiempo.

Si  $P_{ij}$  es la probabilidad de que un sistema se encuentre en estado  $j$  en un tiempo  $t+1$  dado que el sistema está en estado  $i$  en un tiempo  $t$ , Si es sistema tiene un numero finito de estados  $1, 2, 3, \dots, n$ , La cadena de Markov estacionaria se puede definir por una matriz de transición:

$$\begin{bmatrix} P_{11} & \dots & P_{1n} \\ \vdots & \ddots & \vdots \\ P_{n1} & \dots & P_{nn} \end{bmatrix}$$

La matriz de probabilidad de transición de una cadena de Markov estacionaria se puede aprender de las observaciones del sistema estado en el pasado. Provisto de las observaciones del estado del sistema  $x_1, x_2, \dots, x_{N-1}$  en el tiempo  $t = 0, \dots, N-1$ , aprendemos la matriz de probabilidad de transición. [7]

Sin Embargo, el problema de las cadenas de Markov es que asumen que para predecir el comportamiento del portafolio en un periodo, sólo depende del periodo anterior y no del historial completo de pagos del acreedor [8]. Por esta razón da la impresión de que mucha información no se toma en cuenta al momento de la predicción. Además, las cadenas de



Markov son modelos predictivos de corto alcance. Es decir, no puede predecir el comportamiento del portafolio en un largo periodo sin importar la cantidad de datos históricos disponibles, ya que después de cierto número de períodos las predicciones se estabilizan [8].

En la actualidad existen estudios acerca de la predicción de pago de créditos en Mora, que permiten determinar cuáles deudas podrán ser recuperadas con mayor facilidad una vez que se tiene una cartera vencida. Belloti et all [9] Intentan determinar intentan determinar qué características se deben tomar en cuenta al momento de determinar si un cliente en Mora va a pagar una deuda o no, Mediante el uso de hasta 20 diferentes algoritmos de Aprendizaje de Máquina, intenta determinar el que mejor permita determinar la voluntad de pago de Deudores que ya se encuentran en Mora.

Tenemos estudios que intentan determinar la perdida por mora de los créditos tomando en cuenta factores Macroeconómicos que afectan el pago de una deuda [10]. Se toma en cuenta características de los deudores además de los factores macroeconómicos para poder calcular que porcentaje de la deuda se puede recuperar. Pero una vez más esto se lo realiza una vez que la deuda ya se encuentra en Mora.

En este trabajo se propone el desarrollo de un modelo predictivo con el uso de herramientas de aprendizaje de máquina que tome en cuenta la data histórica del comportamiento de los clientes para determinar su comportamiento de pagos futuros a corto y mediano plazo de manera más precisa. Además, se busca predecir el comportamiento de pago de los clientes de manera individual para determinar cuáles tienen mayor o menor probabilidad de pagar tomando en cuenta características que no pueden describirse con un modelo simplemente estadístico como el de Markov. Pero También se quiere obtener una predicción que nos permita establecer clientes que entraran en Mora, antes de que suceda para tomar acciones preventivas y no reactivas.

## **Redes Neuronales Convolucionales**

Los algoritmos de aprendizaje supervisado realizan una predicción en base a un conjunto de datos de entrada y el resultado puede ser categórico o continuo. Dentro de este tipo de algoritmos las Redes Neuronales son unob de los más utilizados. Una red es un sistema de sumas ponderadas y funciones diferenciables que pueden aprender cosas asombrosamente complejas. Por lo general, las variantes de descenso de gradiente junto con la retro propagación se utilizan para encontrar los valores óptimos de los pesos de la red. Esto es simple e intuitivo, pero difícil de comprender para la gente. Hay tantos pesos y conexiones que simplemente no entendemos cómo el sistema produjo los resultados.

Las redes Neuronales pueden aprender funciones arbitrariamente complejas y frecuentemente proporcionan excelentes predicciones para problemas de aprendizaje automático bastante difíciles. [11]

Las Redes Neuronales Recurrentes son redes neuronales para datos secuenciales, por lo que se las puede aplicar a las series temporales. La idea principal detrás de las redes neuronales recurrentes es usar no solo los datos de entrada sino también resultados anteriores para hacer nuevas predicciones.[11]

Existen 2 tipos de RNN que pueden trabajar de mejor manera que la forma clásica o Vainilla La memoria de corto plazo (LSTM) y Unidades Recurrentes Cerradas (GRU).

La memoria a corto plazo tiene 3 puertas que gestionan el contenido de la memoria. Estas puertas son funciones logísticas simples de sumas ponderadas, donde los pesos pueden aprenderse mediante retro propagación. Es decir que a pesar de que parece un poco complicado, el LSTM encaja perfectamente en la red neuronal y su proceso de formación. Puede aprender lo que necesita aprender, recordar lo que necesita recordar, y utilizar lo que necesita utilizar, sin ningún entrenamiento especial u optimización. La puerta de entrada (1) y la puerta de olvido (2) gestionan la celda estado (4), que es la memoria a largo plazo. La puerta de salida (3) produce el vector de salida o estado oculto (5), que es la memoria enfocada para su uso. El sistema de memoria permite que la red recuerde durante mucho tiempo, lo cual falta mucho en las redes neuronales recurrentes de vainilla. [12]

$$\begin{aligned} (1) \quad & i_t = \text{sigmoid}(W_i x_t + U_i h_{t-1} + b_i) \\ (2) \quad & f_t = \text{sigmoid}(W_f x_t + U_f h_{t-1} + b_f) \\ (3) \quad & o_t = \text{sigmoid}(W_o x_t + U_o h_{t-1} + b_o) \\ (4) \quad & c_t = f_t c_{t-1} + i_t \tanh(W_c x_t + U_c h_{t-1} + b_c) \\ (5) \quad & h_t = o_t \tanh(c_t) \end{aligned}$$

La unidad recurrente cerrada es esencialmente una LSTM simplificada. La principal diferencia está en el número de puertas y pesos: GRU tiene 2 puertas, ya que no tiene una puerta de salida, no hay control sobre el contenido de la memoria. La puerta de

actualización (6) controla el flujo de información de la activación anterior, y la adición de nueva información también (8), mientras que la puerta de reinicio (7) se inserta en la activación del candidato. En general, es bastante similar a LSTM. [13]

( 6 )

$$z_t = \text{sigmoid}(W_z x_t + U_z h_{t-1} + b_z)$$

( 7 )

$$r_t = \text{sigmoid}(W_r x_t + U_r h_{t-1} + b_r)$$

( 8 )

$$h_t = z_t h_{t-1} + (1 - z_t) \tanh(W_h x_t + U_h(r_t h_{t-1}) + b_h)$$

La utilización de Redes Neuronales Recurrentes en series de tiempo es cada vez más utilizada por ejemplo [11] describe un método basado en un estudio empírico que utiliza tanto Redes LSTM como GRU. [14] Propone una red neuronal recurrente estocástica para la detección de anomalías de series temporales multivariadas que funciona bien de forma robusta para varios dispositivos. Su idea central es capturar los patrones normales de series de tiempo multivariadas mediante el aprendizaje de sus representaciones robustas con técnicas clave como la conexión de variables estocásticas y el flujo de normalización de planos. [15] Propone un algoritmo de aprendizaje robusto aplicado a redes neuronales recurrentes. Este algoritmo se basa en filtrar los valores atípicos de los datos y luego estimar los parámetros de los datos filtrados. El filtrado elimina los valores atípicos tanto de la función de destino como de las entradas de la red neuronal.

## **Redes Temporales Convolucionales**

Se entrena una red convolucional temporal para predecir los siguientes valores de la serie temporal de entrada. La principal restricción es que, para predecir la salida para algún paso de tiempo, solo puede usar las entradas que se han observado anteriormente. Las TCN tienen dos restricciones principales: la salida de la red debe tener la misma longitud que su entrada, y la red solo puede usar la información de pasos de tiempo pasados. [16]

Las TCN se ha utilizado en series de tiempo para la detección de anomalías como en [16]. También en otros estudios como en [17] se ha utilizado para realizar predicciones sobre series de tiempo Multivariantes y mejorar los resultados de estudios hechos sólo utilizando RNN o LSTM. Por último, se tienen estudios como [18] donde se propone un modelo de aprendizaje profundo basado en TCN para mejorar el rendimiento predictivo en la previsión de la demanda de energía

## **Modelo N-BEATS**

La arquitectura N-BEATS en lugar de tratar las predicciones como un problema de secuencia a secuencia, lo trata como un problema de regresión multivariante no lineal. Por lo tanto, la arquitectura es un regresor no lineal completamente conectado que acepta los datos históricos de una serie de tiempo y produce una predicción de múltiples puntos en el futuro. [19]

No existen muchos estudios con el uso de este modelo para predicciones en series de Tiempo pero se pueden resaltar [19] donde se utiliza N-BEATS para resolver el problema de pronóstico de carga de electricidad a mediano plazo. También el mismo autor en [20] demuestra que se tiene una mejora en las predicciones utilizando este modelo en series temporales.

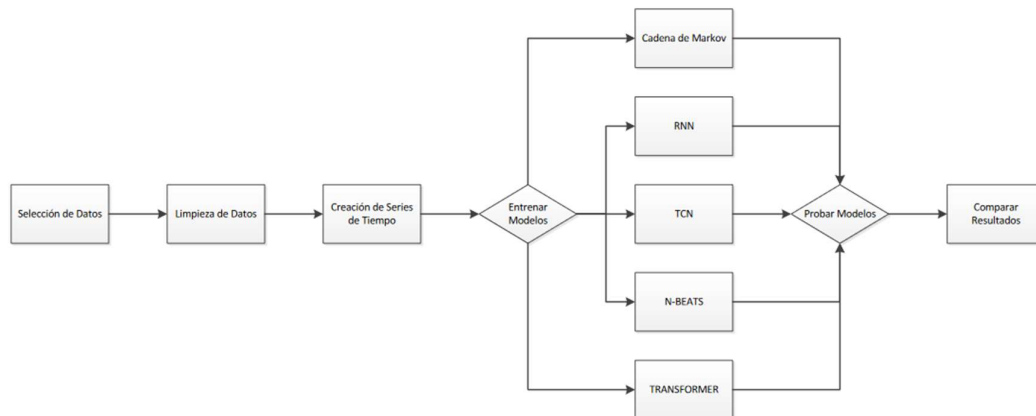
## **2. METODOLOGÍA**

Como se ha descrito anteriormente en este trabajo se busca desarrollar un modelo predictivo para la determinación del comportamiento de pago de los clientes con los datos de un Banco Ecuatoriano. Es decir, busca diseñar una nueva solución más efectiva que las ya antes mencionadas cadenas de Markov. Para ello se decidió utilizar la metodología Ciencias del diseño ya que según Hevner en el paradigma de la ciencia del diseño, el conocimiento y la comprensión del dominio de un problema y su solución se logran en la construcción y aplicación de un artefacto [21].

El desarrollo de este artefacto que, en nuestro caso, se trata de un modelo predictivo que no pretende solucionar un problema puntual de una organización sino brindar una mejor solución para el problema de predecir el comportamiento del portafolio de cartera de los bancos. El objetivo de este artefacto es intentar encontrar una mejor solución a este problema. Es decir, cae dentro de la definición de los objetivos de la ciencia del diseño que indica Hevner: Los artefactos de TI resultantes amplían los límites de la resolución de problemas humanos y las capacidades organizativas al proporcionar herramientas intelectuales y computacionales. Las teorías sobre su aplicación e impacto seguirán su desarrollo y uso [21].

Por último, se eligió esta metodología ya que propone una base matemática para muchos tipos de evaluaciones cuantitativas de un artefacto de TI, incluidas las pruebas de optimización, la simulación analítica y las comparaciones cuantitativas con diseños alternativos [21]. En este trabajo se ha decidido realizar una comparación entre nuestro

modelo predictivo con la solución clásica de cadenas de Markov. Utilizando la misma metodología se podrían realizar trabajos futuros para la evaluación del modelo en un contexto organizacional dado brindando la oportunidad de aplicar métodos empíricos y cualitativos [21].



**Figura 1 – Diagrama de Metodología**

## 2.1 Datos

Los Datos utilizados para este proyecto corresponden al pago de los préstamos de clientes de un Banco Ecuatoriano el cual no se mencionará su nombre. Los datos contienen información de las fechas y cantidades de pago de las cuotas, así como datos sobre los tipos de préstamos e información de los clientes. Se dispone de información sobre más de 570000 cuotas pagadas que corresponden a más de 22000 créditos entregados. A continuación, se indican las columnas incluidas en el set de Datos:

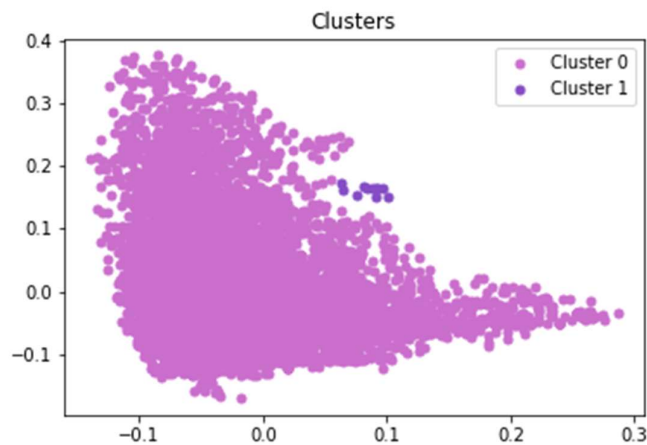
*idOperacion, idCliente, numeroCuota, fechaPagoCuota, fechaVencimientoCuota, montoCapitalCuota, montoCuota, numeroCuotasInicioOperacion, tipoOperacion, porcentajeEntradaOperacion, montoOperacion, montoCuotaOperacion, tasaOperacion, plazoOperacion, numeroCuotasOperacion, esVehiculo, claseVehiculo, marcaVehiculo, valorVehiculo, carteraVendida, carteraMala, carteraCastigada, codigoSexoCliente, edadCliente, codigoNivelEstudiosCliente, codigoEstadoCivilCliente, tipoResidenciaCliente, codigoProvinciaCliente, codigoCiudadCliente, ingresosCliente, gastosCliente, carteraVencidaSinCuotasPorVencer*

## Selección de Datos

Entre todos los datos que se tienen de los préstamos se observa que la gran mayoría corresponden a créditos para la compra de vehículos, por esta razón se utilizó solo créditos que indiquen SI en la columna esVehiculo, tras filtrado se obtienen 414517 cuotas que corresponden a 12573 créditos.

## Limpieza de Datos:

Para la limpieza de los datos debemos tomar en cuenta que dentro del set de datos existen 2 tipos de información, la Primera es la que hace referencia a las características del crédito y del cliente que lo solicito y la segunda hace referencia a las cuotas que se han pagado de ese crédito. Para crear las Series de tiempo de los pagos de los créditos solo necesitamos el primer tiempo de información, pero para asegurar que los créditos sean parecidos entre si utilizaremos un algoritmo de clusterización DBSCAN, el cual nos permite determinar los clústeres en base a un mínimo número de muestras para ser considerado un clúster. Intentando minimizar la cantidad de préstamos que se consideran como valores atípicos se determinó que el número mínimo de muestras debe ser 10 y se consiguen 2 clústeres los cuales se muestran a continuación.



**Figura 2 – Clúster DBSCAN**

Como se puede observar en la Figura1 no se tienen muchos préstamos en el clúster 1 por lo que solo trabajaremos con los préstamos correspondientes al clúster 0.

Finalmente, ya que se valida que existen varios créditos que fueron pagado de manera muy rápida de lo que no se puede aprender el comportamiento de los pagadores se utilizarán únicamente los créditos que duraron más de 18 meses en pagarse con esto utilizaremos 8843 créditos para entrenar nuestros modelos de Aprendizaje de Máquina.

### **Creación de Series de Tiempo**

Para la predicción del comportamiento de pagos de los clientes se utilizarán series de tiempo para lo cual en base a los datos que se tiene se determinara una categoría de Mora en la que se encuentra el cliente en cada cuota. Primero se determina el tiempo de Mora que tiene al momento de pagar la cuota para o cual se restan las columnas fechaVencimientoCuota menos fechaPagoCuota, en caso de ser menor a 0 se toma como 0 y se determina la categoría a la que pertenece en base a la Tabla 1.

**Tabla 1** – Categorías de Mora según días de Mora

<b>Número de días de Mora</b>	<b>Categoría Mora</b>
0	0
1-7	1
8-30	2
31-60	3
61-90	4
91-120	5
121-180	6
Mayor a 180	7

En base a las categorías indicadas a cada cuota que se tiene registrada de cada uno de los créditos que se dispone se le asigna una categoría y se crea una serie temporal en base a la cual se podrá generar modelos de predicción utilizando las cadenas de Markov y Algoritmos de aprendizaje de Máquina.

## **2.2 Cadenas de Markov**

### **Creación de la Matriz de transición**

Como se indicó anteriormente es posible calcular la matriz de transición en base a la observación histórico que se tiene sobre un evento, se genera la siguiente matriz:

$$MT = \begin{bmatrix} P_{00} & P_{01} & P_{02} & P_{03} & P_{04} & P_{05} & P_{06} & P_{07} \\ P_{10} & P_{11} & P_{12} & P_{13} & P_{14} & P_{15} & P_{16} & P_{17} \\ P_{20} & P_{21} & P_{22} & P_{23} & P_{24} & P_{25} & P_{26} & P_{27} \\ P_{30} & P_{31} & P_{32} & P_{33} & P_{34} & P_{35} & P_{36} & P_{37} \\ P_{40} & P_{41} & P_{42} & P_{43} & P_{44} & P_{45} & P_{46} & P_{47} \\ P_{50} & P_{51} & P_{52} & P_{53} & P_{54} & P_{55} & P_{56} & P_{57} \\ P_{60} & P_{61} & P_{62} & P_{63} & P_{64} & P_{65} & P_{66} & P_{67} \\ P_{70} & P_{71} & P_{72} & P_{73} & P_{74} & P_{75} & P_{76} & P_{77} \end{bmatrix}$$

Para calcular  $P_{ij}$  que es la probabilidad de que el próximo estado sea  $j$  dado que el estado actual es  $i$  y se calcula según (9).

(9)

$$P_{ij} = \frac{N_{ij}}{N_i}$$

Donde  $N_{ij}$  es la cantidad de veces que el próximo estado sea  $j$  dado que es estado actual es  $i$ ,  $N_i$  es la cantidad de veces que se da el evento  $i$ . Para calcular la matriz de transición utilizamos el 70% de los créditos de vehículos que tenemos y el 30% de créditos los utilizaremos para probar este modelo.

Al calcular la matriz de transición que describe el evento del pago de créditos de vehículos de este Banco Ecuatoriano, podemos realizar una predicción de cómo será el comportamiento de pago de los clientes de los créditos que separamos para probar el modelo. Para probar el modelo intentaremos calcular los últimos 6 pagos de los créditos que separamos para probar el modelo de las cadenas de Markov. Para calcular el estado de Mora de un crédito en un tiempo  $t+1$  se lo hace según (10).

(10)

$$e_{t+1} = e_t MT$$

Donde  $e_{t+1}$  es un vector de 8 componente que indica el estado del sistema en un tiempo  $t+1$ ,  $e_t$  es un vector de 8 componente que indica el estado del sistema en un tiempo  $t$  y  $MT$  es la matriz de transición de  $8 \times 8$ . El estado en el tiempo  $t$  está definido por (11).

(11)

$$e_t = [c_0 \quad c_1 \quad c_2 \quad c_3 \quad c_4 \quad c_5 \quad c_6 \quad c_7]$$



Donde  $c_n$  corresponde a categoría  $n$ , en donde es igual a 1 cuando en el tiempo  $n$  el evento se encuentra en la categoría  $n$  y 0 para todas las demás es decir si en el tiempo  $t$  el evento se encuentra en la categoría 4 el estado estaría dado por (12).

(12)

$$e_t = [0 \ 0 \ 0 \ 0 \ 1 \ 0 \ 0 \ 0]$$

Es decir, para calcular las predicciones del comportamiento de la serie temporal en un tiempo  $t+k$  se lo hace según (13).

(13)

$$e_{t+k} = [c_0 \ c_1 \ c_2 \ c_3 \ c_4 \ c_5 \ c_6 \ c_7]MT^k$$

Con los estados del sistema calculado podemos crear una serie de tiempo y comparar la real con la calculada para determinar qué tan bueno es nuestro modelo de cadenas de Markov.

## 2.3 Modelos con Aprendizaje de Máquina

Como se indicó anteriormente se utilizarán series de tiempo para la predicción del comportamiento de pago de los clientes, para el manejo de las series de tiempo se utilizará la librería Darts de Python, la cual nos permite manipular y realizar predicciones sobre series de tiempo utilizando algoritmos de Aprendizaje de Máquina optimizadas para este tipo de datos.

Dentro de los diferentes algoritmos de aprendizaje de máquina que de los que dispone esta librería se utilizarán 4 en específico ya que son los que nos permiten entrenar los modelos utilizando múltiples series de tiempo, los modelos que se utilizarán son los siguientes:

- Modelo de Pronóstico de series de tiempo de análisis de expansión de base neuronal (NBEATS)
- Modelo de Redes Neuronales Recurrentes (RNNs)
- Modelo Transformer
- Modelo de Redes Convolucionales Temporales (TCN)

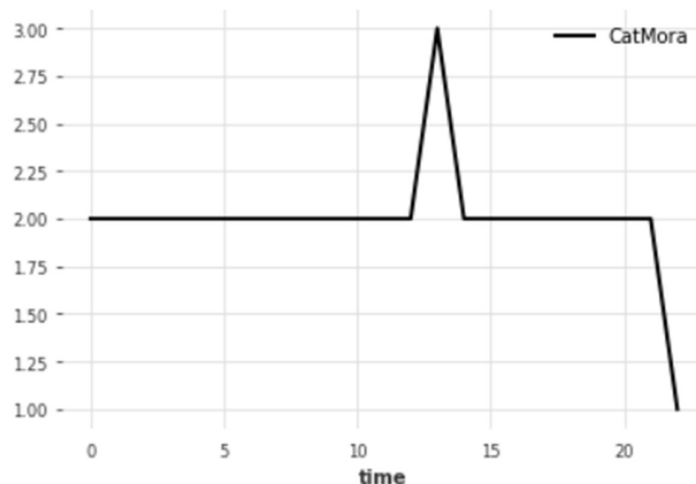
Para entrenar cada uno de estos modelos se debe generar una serie de tiempo con los datos obtenidos anteriormente, en este caso ya que no intentaremos obtener predicciones

utilizando estacionalidad no vamos a utilizar las fechas del pago de cada cuota, sino que se utilizara solo el número de cuota que se paga para generar la serie de tiempo.

Cada modelo requiere diferentes parámetros, pero a todos se los entrenara con los mismos datos, los cuales están conformados por una lista en el que cada elemento corresponde a una serie de tiempo que representa el comportamiento de pago de un préstamo del Banco Ecuatoriano de el que se obtuvieron los datos.

Los Datos de entrenamiento fueron obtenidos al seleccionar aleatoriamente el 70% de los 8843 créditos que fueron seleccionados como aptos para nuestra investigación. Es decir, se utilizarán 6190 créditos representados como series de tiempo para entrenar a nuestros modelos de aprendizaje de máquina. Para el entrenar nuestros modelos se debe convertir los datos en tipo “TimeSeries” el cual es propio de la biblioteca Darts y se maneja de manera óptima con los modelos propios de la misma.

Para entrenar los modelos se crea una lista donde cada uno de los miembros es una serie de tiempo que representa a cada uno de los créditos que fueron seleccionados para entrenar los modelos. En los datos tipo serie de tiempo se guarda información del tiempo y del valor de cada punto en ese tiempo, ya que como se indicó no se maneja estacionalidad para este estudio la información de tiempo representa el número de la cuota que se pagó, y en el estado se guarda el valor correspondiente a la categoría de mora en la que se encuentra al pagar esa cuota.



**Figura 3** – Serie de Tiempo del pago de un Crédito

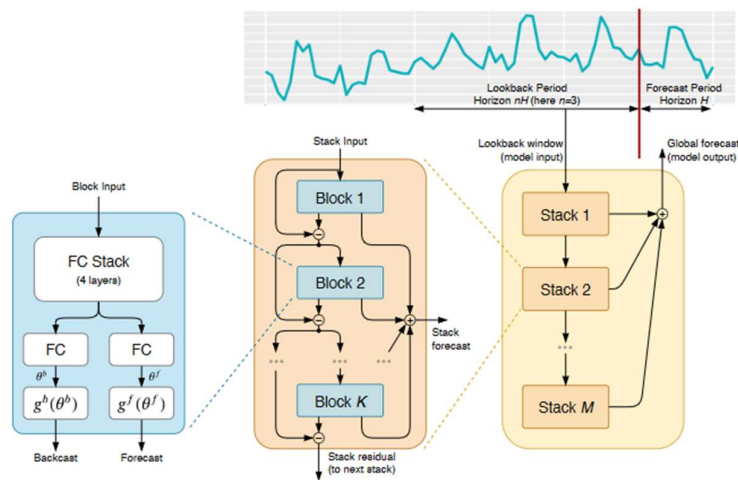
La información representada en la Figura 3 corresponde a 1 de los 6190 elementos de los cuales está conformada la lista con al que se entrenaran los modelos de aprendizaje de máquina. Cada modelo requiere de diferentes parámetros los cuales se obtuvieron por el método de tanteo, en el cual se fue modificando los diferentes parámetros para minimizar las pérdidas de entrenamiento y de validación que se obtienen al entrenar a cada uno de los modelos.

### Neural Basis Expansion Analysis Time Series Forecasting (N-BEATS)

Primero se valida que los datos se tratan de series que requieren una predicción determinística, tomando en cuenta esto se modificó los siguientes parámetros del modelo para crearlo y posteriormente entrenarlo:

- **input\_chunk\_length=6**
- **output\_chunk\_length=3**
- **n\_epochs=100**
- **batch\_size=64,**
- **random\_state=0**

El resto de los parámetros se mantuvieron en los valores por defecto. A continuación se muestra la arquitectura [20] presentado en la Figura 4 en la cual se basa la programación del Modelo N-BEATS de la Biblioteca Darts.



**Figura 4 – Arquitectura Modelo N-BEATS**

En base a la Figura 4 nuestra arquitectura final está dada por 4 capas, en número de bloques  $K=1$ , el número de Pilas  $M=30$ , el periodo de bucle invertido  $n=6$  y el periodo de predicción  $H=3$ , se utiliza un coeficiente de expansión hacia adelante  $f$  y hacia atrás  $b = 5$ , Adicional se utiliza un polinomio de grado 2 como tendencia.

### **Recurrent Neural Network Model (RNNs)**

En este modelo también se tomó en cuenta que es una predicción determinística y se mantuvieron los parámetros por defecto del modelo y se modificaron los siguientes parámetros con los valores a continuación:

- **model='RNN',**
- **hidden\_dim=20**
- **dropout=0,**
- **batch\_size=64**
- **n\_epochs=100**
- **random\_state=0**
- **n\_rnn\_layers=5**
- **training\_length=9**
- **input\_chunk\_length=6**

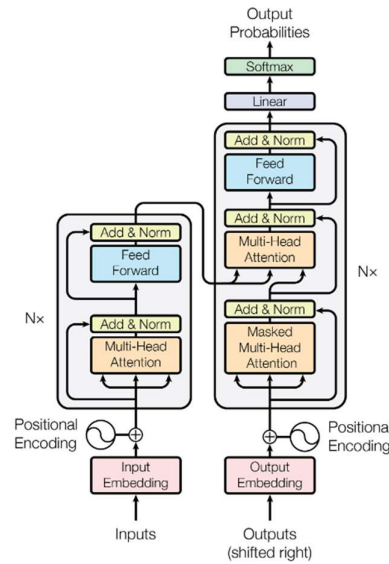
Como se observa se utiliza una Red de 20 Capas del Tipo Vainilla mencionada anteriormente.

### **Transformer Model**

También se tomó en cuenta que es una predicción determinística se modificaron los siguientes parámetros:

- **input\_chunk\_length = 6**
- **output\_chunk\_length = 1**
- **batch\_size = 64**
- **n\_epochs = 100**
- **random\_state=0**

El modelo Transformer está basado en los mecanismos de atención, prescindiendo de la recurrencia y las circunvoluciones, el modelo que utiliza el DARTS está basado en la arquitectura que presenta [22] el cual se observa en la Figura 5.



**Figura 5** – Arquitectura Modelo TRANSFORMER

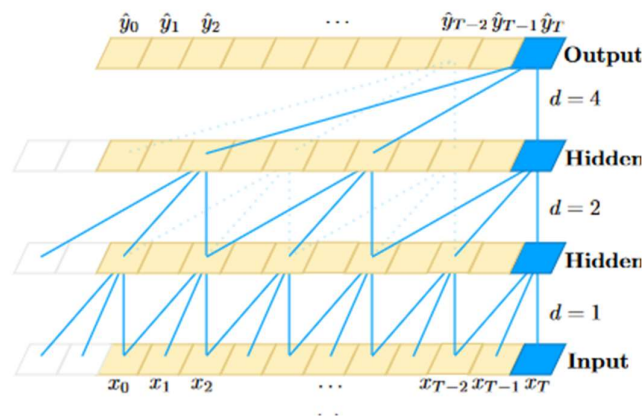
El modelo consta de un codificador y un decodificador, el primero asigna una secuencia de entrada de representaciones de símbolos ( $x_1, \dots, x_n$ ) a una secuencia de representaciones continuas  $z = (z_1, \dots, z_n)$ . Dado  $z$ , el decodificador genera una salida secuencia ( $y_1, \dots, y_m$ ) de símbolos un elemento a la vez. En cada paso el modelo es autorregresivo, consumiendo los símbolos generados previamente como entrada para generar los siguientes.[22] En nuestro Caso utilizamos los siguientes Parámetros  $N=3$ , dimensión de modelo=64, se utiliza una función de activación Relu,  $n=6$ ,  $m=1$ , dimensión de avance de 512 y un valor de dropout de 0.2.

### **Temporal Convolutional Network Model (TCN)**

En este modelo también se tomó en cuenta que es una predicción determinística y se mantuvieron los parámetros por defecto del modelo y se modificaron los siguientes parámetros con los valores a continuación:

- **batch\_size=64**
- **input\_chunk\_length=6**
- **output\_chunk\_length=1**
- **n\_epochs=100**
- **nr\_epochs\_val\_period=1**
- **random\_state=0**

El modelo TCN se basa en dos principios: la red produce una salida de la misma longitud que la entrada, y no puede haber fugas del futuro al pasado. Para esto utiliza una arquitectura de red totalmente convolucional donde cada capa oculta es de la misma longitud que la capa de entrada. Para lograr el segundo punto, utiliza convoluciones causales, donde la salida en el tiempo  $t$  está convolucionada solo con elementos del tiempo  $t$  u anteriores. [23]



**Figura 6 – Arquitectura Modelo TCN**

En nuestro caso utilizamos una base de dilatación  $d=2$  según la arquitectura de la Figura 6 [23], en la cual se base la programación del modelo TCN en la Librería DARTS.

### **Entrenamiento de los Modelos**

Para todos los modelos de aprendizaje de máquina se utilizan los mismos datos de entrenamiento para entrenar todos los modelos, se debe tomar en cuenta que no es necesario escalar los datos ya que al crear las series de tiempo se categorizó en base a los rangos de días de mora el comportamiento de pago.

Una vez que tenemos los modelos entrenados se utilizaron los datos de prueba para predecir el comportamiento de pago de los clientes, para esto se procede a quitar los

últimos 6 pagos de cada una de las series de tiempo correspondiente a los pagos de cada uno de los clientes. Estos nos servirán para validar las predicciones que se obtuvieron. Una vez que se aplicó el modelo entrenado sobre los datos de prueba se procede a redondear el resultado obtenido ya los datos de las series de tiempo deben ser categóricos en este caso tenemos 8 categorías por lo cual en caso de que el resultado sea mayor a 7 se asume que cae dentro de la categoría 7.

### **3. RESULTADOS Y DISCUSIÓN**

A continuación, se presentarán los resultados obtenidos al comparar los 4 diferentes modelos de aprendizaje de máquina comparados con el modelo de cadenas de Markov, junto con una interpretación de estos en base a nuestra experiencia y al conocimiento que se adquirió sobre los datos del Banco durante la ejecución de este trabajo.

#### **3.1. Resultados**

Para medir los resultados de las predicciones realizadas por los 5 modelos que vamos a comparar. Se procedió a aplicar cada uno de los modelos ya entrenados sobre el 30% de los prestamos disponibles los cuales hemos denominado datos de prueba. Para realizar las predicciones utilizando los modelos procedemos a retirar la información de las 6 últimas cuotas de cada uno de los préstamos de los datos de prueba y aplicamos los modelos para predecir esas 6 cuotas.

Los resultados obtenidos se comparan con los datos reales, se utilizaron 3 medidas para determinar la efectividad de los modelos de predicción. El primero es el Error el cual mide el porcentaje de predicciones erróneas que obtuvo el modelo, el segundo es el F-score que nos permite medir la precisión del modelo. Por último, se calcula la Matriz de confusión la cual nos permite ver de mejor forma la relación de error entre el valor predicho y el valor obtenido.

Cada una de las medidas mencionadas anteriormente fueron calculadas para los modelos realizando la predicción de 3 y 6 meses. A continuación, se presenta 1 tabla para cada uno de los modelos con el resumen del Error, Aciertos y F-score, aplicados para las predicciones realizadas en los datos de prueba y de entrenamiento.

**Tabla 2** - Resumen del Error, Aciertos y F-score para el Modelo de Cadenas de Markov con Datos de Entrenamiento y Prueba.

	Correcto Entrenamiento	Correcto Prueba	Equivocado Entrenamiento	Equivocado Prueba	F-Score Entrenamiento	F-Score Prueba
<b>Predicción 3 meses</b>	0,4664	0,4648	0,5336	0,5352	0,6806	0,6829
<b>Predicción 6 meses</b>	0,3601	0,3530	0,6399	0,6470	0,5679	0,5717

**Tabla 3** – Resumen del Error, Aciertos y F-score para el Modelo RNN con Datos de Entrenamiento y Prueba.

	Correcto Entrenamiento	Correcto Prueba	Equivocado Entrenamiento	Equivocado Prueba	F-Score Entrenamiento	F-Score Prueba
<b>Predicción 3 meses</b>	0,4465	0,4172	0,5535	0,5828	0,5784	0,5856
<b>Predicción 6 meses</b>	0,3824	0,3635	0,6176	0,6365	0,5473	0,5474

**Tabla 4** – Resumen del Error, Aciertos y F-score para el Modelo TCN con Datos de Entrenamiento y Prueba.

	Correcto Entrenamiento	Correcto Prueba	Equivocado Entrenamiento	Equivocado Prueba	F-Score Entrenamiento	F-Score Prueba
<b>Predicción 3 meses</b>	0,3069	0,3136	0,6931	0,6864	0,5316	0,5441
<b>Predicción 6 meses</b>	0,2841	0,2827	0,7159	0,7173	0,5048	0,5091

**Tabla 5** – Resumen del Error, Aciertos y F-score para el Modelo NBEATS con Datos de Entrenamiento y Prueba.

	Correcto Entrenamiento	Correcto Prueba	Equivocado Entrenamiento	Equivocado Prueba	F-Score Entrenamiento	F-Score Prueba
<b>Predicción 3 meses</b>	0,3310	0,3086	0,6690	0,6914	0,4988	0,4890
<b>Predicción 6 meses</b>	0,2912	0,2755	0,7088	0,7245	0,4737	0,4707



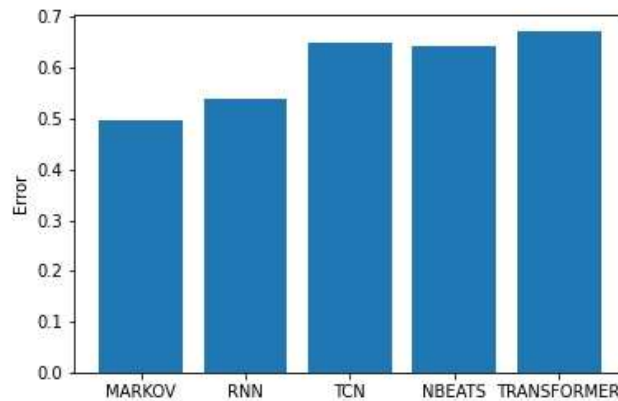
**Tabla 6** – Resumen del Error, Aciertos y F-score para el Modelo TRANSFORMER con Datos de Entrenamiento y Prueba.

	Correcto Entrenamiento	Correcto Prueba	Equivocado Entrenamiento	Equivocado Prueba	F-Score Entrenamiento	F-Score Prueba
<b>Predicción 3 meses</b>	0,2962	0,2939	0,7038	0,7061	0,5116	0,5033
<b>Predicción 6 meses</b>	0,2698	0,2646	0,7302	0,7354	0,4935	0,4903

En base a los resultados de las tablas de la 2 a la 6 se pueda validar que no existe overfitting, ya que no existe una diferencia considerable entre los errores obtenidos de las predicciones en los datos de entrenamiento y de prueba para ninguno de los modelos de Aprendizaje de maquina ni de Cadenas de Markov. A continuación, se procede a comparar los resultados de cada una de las medidas descritas anteriormente.

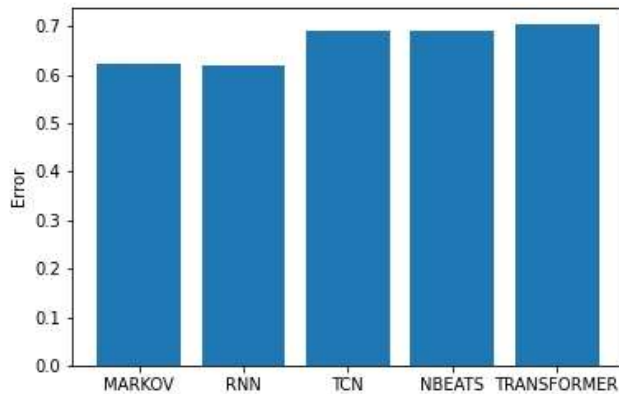
### Error

En la siguiente figura se muestra el error que se obtiene para cada uno de los modelos para una predicción de 3 meses, aplicados sobre los datos de prueba:



**Figura 7** – Error por Modelo en predicción de 3 meses.

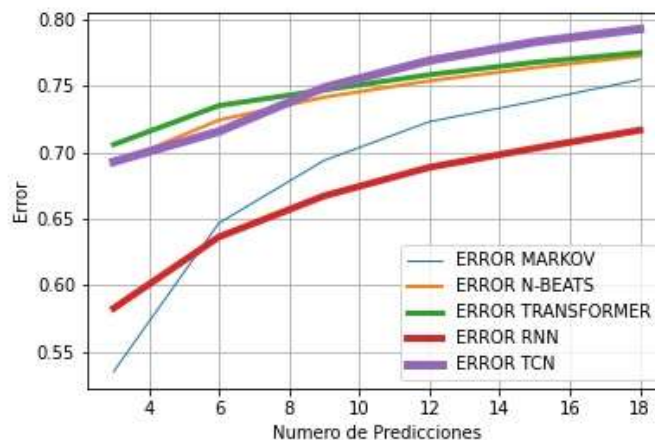
Como se observa en la Figura 7 el error es similar entre los modelos RNN y las Cadena de Markov y son los más bajos alrededor del 50%, mientras que los errores de los otros 3 modelos son mayores y están cerca del 65%. En la Figura 8 se muestra el error que se obtiene para cada uno de los modelos para una predicción de 6 meses, aplicados sobre los datos de prueba.



**Figura 8** – Error por Modelo en predicción de 6 meses

Como se observa en la Figura 8 el error es similar entre los modelos RNN y la Cadena de Markov y son los más bajos alrededor del 60%, mientras que los errores de los otros 3 modelos son mayores y están cerca del 70%.

También es interesante comparar cómo se comporta el error al ir aumentando el número de meses que vamos a predecir, para esto se eliminó las últimas 18 cuotas de cada uno de los préstamos. Adicional como se vio en los parámetros con los que se crearon los modelos de Aprendizaje de Máquina se requieren por lo menos 6 meses de datos para realizar las predicciones, por esta razón solo se utilizan préstamos que tengan por lo menos 24 cuotas.



**Figura 9** – Error de cada Modelo por Numero de predicciones

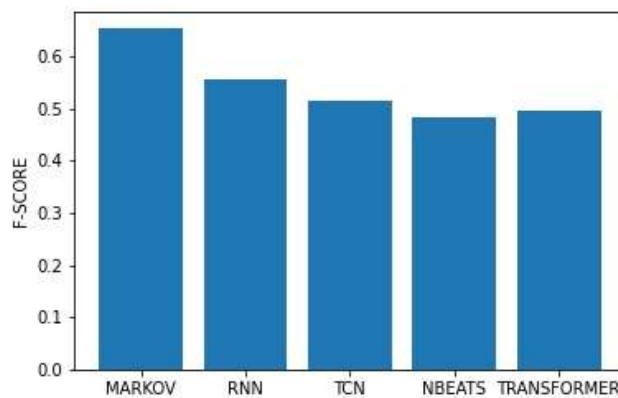
Como se puede observar en la Figura 9, los errores de los Modelos NBEATS, TRANSFORMER y TCN siempre es mayor que el error de las cadenas de Markov, mientras que el modelo RNN tiene un error mayor solo para predicciones de hasta 6 meses y de ahí en adelante tiene un error menor y con un comportamiento casi lineal y con una pendiente muy baja.

En base a los resultados obtenidos midiendo el error se valida que el modelo de Cadenas de Markov y el modelo RNN son los mejores. Markov presenta un mejor comportamiento con pocas predicciones mientras que el Modelo RNN demuestra ser mejor para realizar un mayor número de predicciones. El resto de los modelos demuestran tener un error mucho mayor que los otros dos mencionados anteriormente, para pocas predicciones y este comportamiento se mantiene mientras se aumenta el número de predicciones.

### F-score

El coeficiente F-score es un valor entre 0 y 1 que nos permite calcular la precisión al comparar 2 resultados, en este caso comparamos los valores reales de las cuotas de cada uno de los préstamos, con los valores predichos utilizando cada uno de los modelos de aprendizaje de máquina y el Modelo de cadenas de Markov. El valor de 0 es la peor precisión posible mientras que 1 indica que ambos valores son iguales, es decir la precisión es total.

A continuación, se presentan la comparación de los resultados del F-score para cada uno de los 5 modelos en las predicciones realizadas para 3 meses aplicados para los datos de prueba:

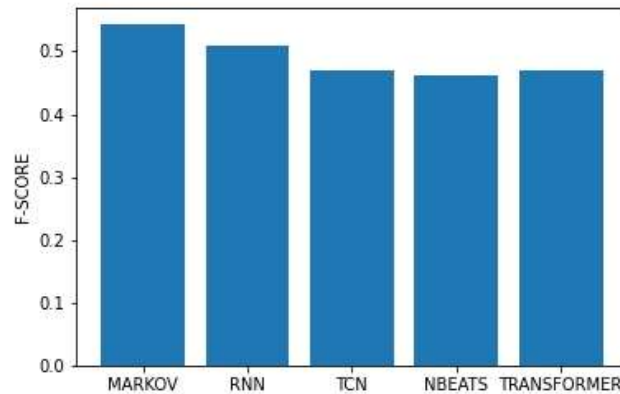


**Figura 10** – F-score por Modelo en predicción de 3 meses

Como se observa en la Figura 10 se valida que la precisión del modelo de cadenas de Markov es mayor a los modelos de aprendizaje de máquina es alrededor de 0,65 mientras

que de estos modelos el Modelo RNN es el mejor con un F-score de 0,55 el resto está alrededor del 0,5.

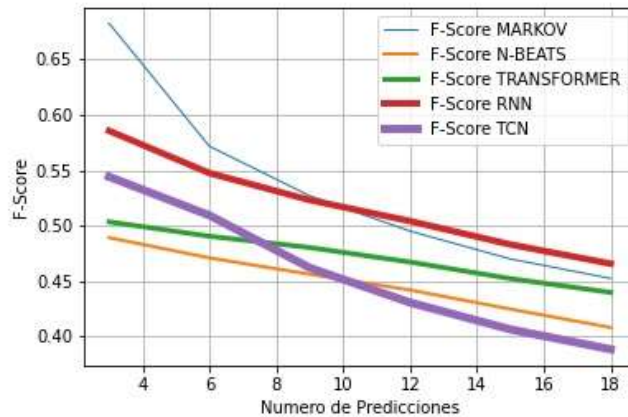
También se procede a comparar el F-score de cada modelo cuando se realiza una predicción de 6 meses sobre los datos de prueba.



**Figura 11** – F-score por Modelo en predicción de 6 meses

Como se observa en la Figura 11 la tendencia se mantiene y el modelo de cadenas de Markov presenta el F-score y el modelo RNN está en segundo lugar, aunque ya la diferencia se reduce mientras que con una predicción de 3 meses se tenía una diferencia de alrededor de 0,1 en 6 meses esta diferencia se reduce a 0,05. Markov presenta un F-score de alrededor de 0,55 y El modelo RNN de al redor de 0,5, mientras que el resto de las modelos presentan un f-score de alrededor de 0,46.

Como se realizó con el análisis del error es interesante comparar cómo se comporta el coeficiente de F-score al ir aumentando el número de meses que vamos a predecir. De igual manera se realizará una predicción de hasta 18 meses y se compara el valor de F-score para cada modelo, de igual manera se utilizarán prestamos que tienen al menos 24 cuotas.



**Figura 12**– F-score de cada Modelo por Numero de predicciones

En la Figura 12 se puede validar que la precisión de los modelos va disminuyendo mientras aumenta la cantidad de predicciones. El modelo de cadenas de Markov tiene un mayor F-score que los modelos de aprendizaje máquina hasta la predicción con 9 meses cuando el Modelo RNN presenta un F-score mayor que el resto de modelo y esto se mantiene hasta los 18 meses. El resto de las modelos siempre presentan un F-Score menor que el modelo de cadenas de Markov.

Al analizar la precisión del modelo mediante el uso del coeficiente F-score se observó que el modelo de cadenas de Markov es el mejor ya que presenta una mayor fidelidad que los modelos de aprendizajes de máquina. Y una vez más se puede observar que el modelo RNN es el único de los de aprendizaje máquina que se comporta mejor cuando aumenta la cantidad de predicciones que realizamos

### Matriz de Confusión

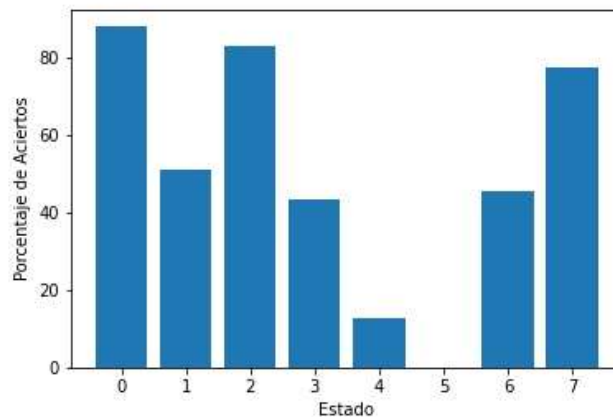
La matriz de confusión de un modelo nos permite representar más información importante sobre el comportamiento de el mismo ya que nos permite representar como el mismo predice cada uno de los estados y con qué estados se confunden entre si el momento de realizar una predicción, la matriz de confusión en nuestro caso está dado por la siguiente.

$$\begin{bmatrix}
 P_{00} & P_{01} & P_{02} & P_{03} & P_{04} & P_{05} & P_{06} & P_{07} \\
 P_{10} & P_{11} & P_{12} & P_{13} & P_{14} & P_{15} & P_{16} & P_{17} \\
 P_{20} & P_{21} & P_{22} & P_{23} & P_{24} & P_{25} & P_{26} & P_{27} \\
 P_{30} & P_{31} & P_{32} & P_{33} & P_{34} & P_{35} & P_{36} & P_{37} \\
 P_{40} & P_{41} & P_{42} & P_{43} & P_{44} & P_{45} & P_{46} & P_{47} \\
 P_{50} & P_{51} & P_{52} & P_{53} & P_{54} & P_{55} & P_{56} & P_{57} \\
 P_{60} & P_{61} & P_{62} & P_{63} & P_{64} & P_{65} & P_{66} & P_{67} \\
 P_{70} & P_{71} & P_{72} & P_{73} & P_{74} & P_{75} & P_{76} & P_{77}
 \end{bmatrix}$$

En donde  $P_{xy}$ , está dado por que la predicción sea  $x$  dado que el valor real sea  $y$ , quiere decir que cuando  $x=y$  es el porcentaje de predicciones correctas y se encuentra en la diagonal de la matriz. A continuación, se muestra las matrices de confusión de cada modelo y luego se comparan entre ellas.

**Tabla 7** – Matriz de confusión para el Modelo de Cadenas de Markov para predicción de 3 meses.

88,31	6,88	4,81	0,00	0,00	0,00	0,00	0,00
33,59	51,31	15,10	0,00	0,00	0,00	0,00	0,00
10,74	5,86	83,24	0,15	0,00	0,00	0,00	0,00
4,59	1,67	49,95	43,59	0,21	0,00	0,00	0,00
2,96	0,27	37,20	46,63	12,94	0,00	0,00	0,00
1,01	1,01	27,70	11,49	58,45	0,00	0,00	0,34
0,72	0,36	11,15	7,91	29,14	0,00	45,68	5,04
0,00	0,00	13,33	3,33	5,83	0,00	0,00	77,50

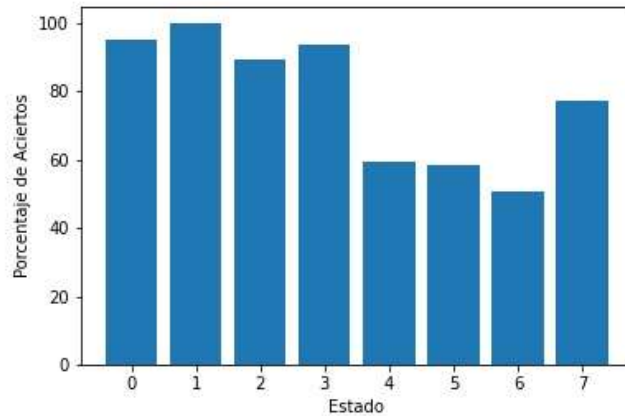


**Figura 13** – Porcentaje de aciertos del modelo de cadenas de Markov por estado para predicción de 3 meses

Lo primero que se puede observar en la Figura 13 es que la matriz no está balanceada ya que los valores de la diagonal son muy diferentes, ya que para los estados 0, 2 y 7 son cercanos al 80% mientras que los estados 1,3 y 6 son cercanos al 45% adicional para el estado 4 es apenas del 12% y por último el estado 5 tiene un acierto de 0%, es decir que el modelo de Cadenas de Markov es incapaz de predecir el estado 5.

También es interesante hacer un gráfico de aciertos aumentado en el cual para cada estado tomaremos dentro de los aciertos cuando el estado predicho es  $x$  pero el real es  $x-1$  y  $x+1$ .

Ya que no es lo mismo que me prediga un estado 1 cuando el valor real es 7 a que prediga un estado 1 cuando el real es 2.

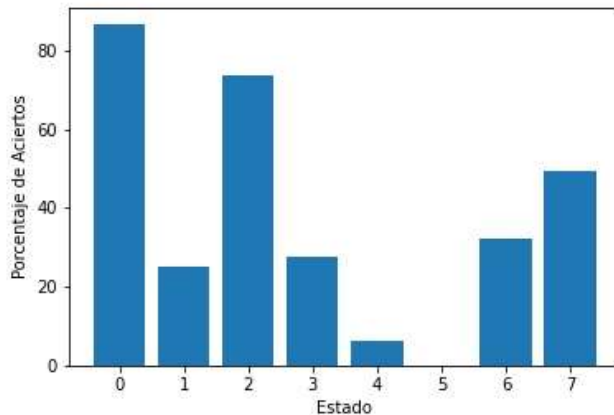


**Figura 14** – Porcentaje de aciertos aumentado del modelo de cadenas de Markov por estado para predicción de 3 meses

Analizando el porcentaje de aciertos aumentado de la Figura 17 se valida que los porcentajes de error suben considerablemente en especial en el estado 1 que sube de 50% a casi 100% y en el estado 5 que sube de 0 a 58%. Esto produce una diferencia entre el error que tiene el modelo de 49,68% a un error de acierto aumentado de 21,95% para una predicción de 3 meses. Se puede realizar un análisis similar con la predicción de 6 meses.

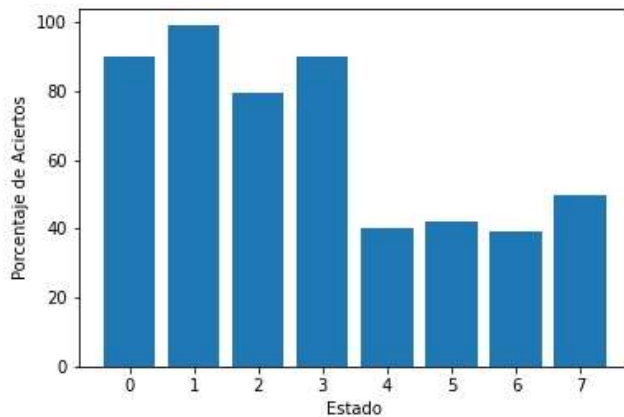
**Tabla 8** – Matriz de confusión para el Modelo de Cadenas de Markov para predicción de 6 meses.

86,59	3,40	9,30	0,71	0,00	0,00	0,00	0,00
51,46	24,99	22,65	0,90	0,00	0,00	0,00	0,00
20,70	2,91	73,59	2,74	0,00	0,00	0,00	0,05
9,02	0,81	62,27	27,56	0,10	0,00	0,00	0,25
6,18	0,13	52,56	33,90	6,31	0,00	0,00	0,92
3,41	0,73	40,88	10,46	42,09	0,00	0,00	2,43
2,53	0,25	27,27	10,10	20,45	0,00	32,07	7,32
0,91	0,00	38,60	8,81	2,13	0,00	0,00	49,54



**Figura 15** – Porcentaje de aciertos del modelo de cadenas de Markov por estado para predicción de 6 meses

También se puede observar en la Figura 15 que la matriz no está balanceada ya que los valores de la diagonal son muy diferentes, ya que para los estados 0, 2 y 7 son mayores al 50% mientras que los estados 1,3 y 6 son cercanos al 25% adicional para el estado 4 es apenas del 6% y una vez más el estado 5 tiene un acierto de 0% es decir que tampoco puede predecir el estado 5. Una vez más se realizó un gráfico de aciertos aumentado.



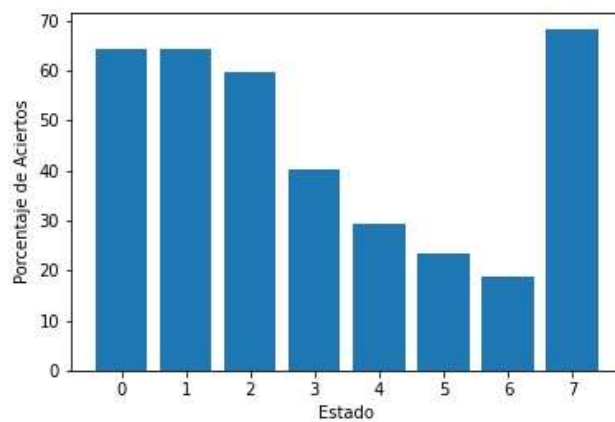
**Figura 16** – Porcentaje de aciertos aumentado del modelo de cadenas de Markov por estado para predicción de 6 meses

Al analizar nuevamente el porcentaje de aciertos aumentado esta vez de la Figura 16 se valida que los porcentajes de error suben considerablemente en especial en el estado 1 que sube de 25% a casi 100%, en el estado 3 que sube de 27% a 90% y el estado 5 que subió de 0 a 50%. Esto produce una diferencia entre el error que tiene el modelo de 62,42% a un error de acierto aumentado de 21,35% para una predicción de 6 meses.



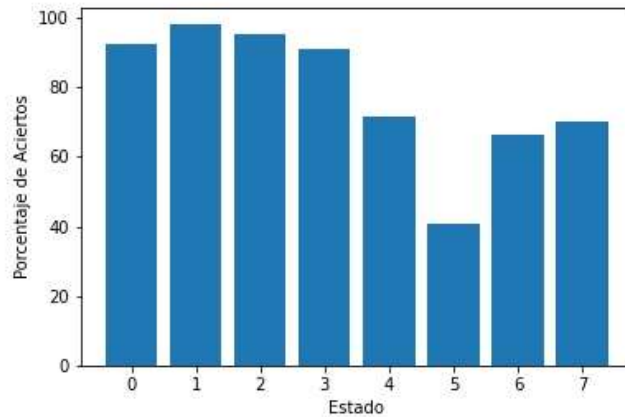
**Tabla 9** – Matriz de confusión para el Modelo RNN para predicción de 3 meses.

64,43	27,83	6,43	1,21	0,09	0,00	0,00	0,00
16,23	64,27	17,60	1,66	0,24	0,00	0,00	0,00
3,65	22,72	59,68	12,62	1,23	0,10	0,00	0,00
0,63	7,72	42,23	40,15	8,65	0,52	0,10	0,00
1,08	2,16	24,53	35,31	29,38	6,74	0,27	0,54
0,34	1,69	15,88	25,00	14,86	23,31	2,36	16,55
0,00	0,36	8,27	14,03	11,15	9,35	18,71	38,13
0,00	2,50	7,50	13,33	3,33	3,33	1,67	68,33



**Figura 17** – Porcentaje de aciertos del modelo RNN por estado para predicción de 3 meses

Analizando la Figura 17 se valida que la matriz de confusión pese a tener porcentajes de acierto menores a los del Modelo de cadenas de Markov, es un poco más balanceada ya que para empezar hay 4 estados, 0,1,2,7 con porcentaje de aciertos similar cercano al 60%, Adicional no hay ningún estado que tenga un acierto de 0 ya que el menor es del 19% para el estado 6. Una vez más analizaremos el porcentaje de acierto aumentado para el modelo RNN con una predicción de 3 meses.

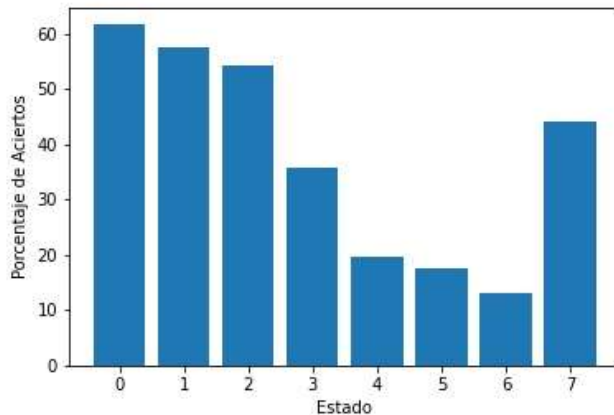


**Figura 18** – Porcentaje de aciertos aumentado del modelo RNN por estado para predicción de 3 meses

Al analizar la Figura 18 se valida que el mayor aumento se da en el estado 6 que pasa de un acierto del 19% al 65% y ahora el menor es el estado 5 que es alrededor del 40%, de la misma manera se observa que es más balanceado que para la predicción de 3 meses que el modelo de cadenas de Markov pese a que el error es mayor 25,51%.

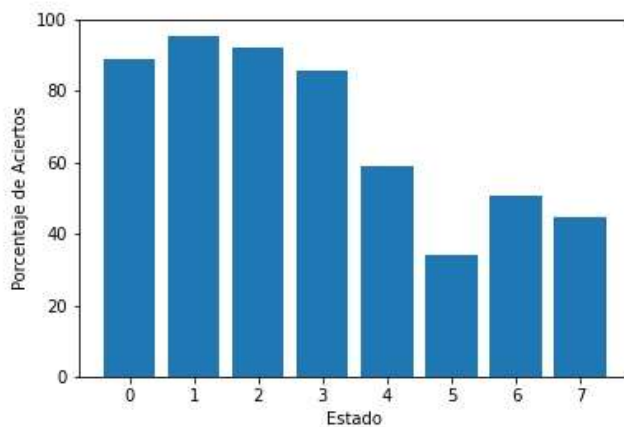
**Tabla 10** – Matriz de confusión para el Modelo RNN para predicción de 6 meses.

61,73	27,13	7,92	2,80	0,38	0,02	0,00	0,02
17,78	57,46	20,24	3,76	0,41	0,03	0,00	0,32
4,94	23,74	54,11	14,32	1,76	0,24	0,02	0,86
1,56	9,02	42,37	35,87	7,61	0,96	0,10	2,52
1,71	4,20	27,33	34,95	19,71	4,47	0,26	7,36
0,97	1,70	18,25	30,66	15,09	17,52	1,70	14,11
0,76	1,52	14,14	20,20	12,63	7,32	13,13	30,30
0,00	2,43	9,73	34,95	6,08	2,13	0,61	44,07



**Figura 19** – Porcentaje de aciertos del modelo RNN por estado para predicción de 6 meses

La Figura 19 permite ver que al igual que para la predicción de 3 meses se valida que la matriz de confusión se valida más balanceada que en el modelo de cadenas de Markov para una predicción de 6 meses, aunque el error es similar para el Modelo de cadenas de Markov y el modelo RNN, también se analizó el porcentaje de acierto aumentado.

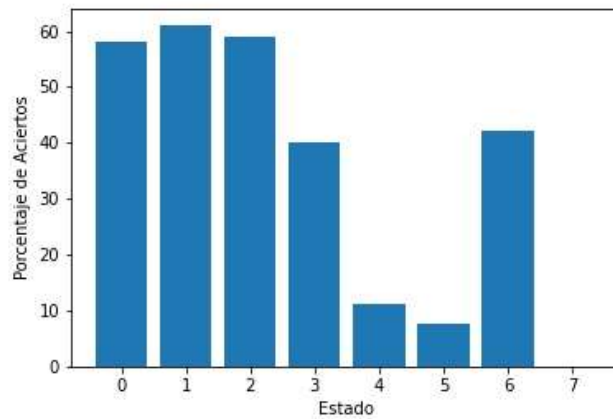


**Figura 20** – Porcentaje de aciertos Aumentado del modelo RNN por estado para predicción de 6 meses

Al analizar la Figura 19 se verifica que el porcentaje de acierto es más balanceado que para el modelo de Cadenas de Markov aunque también se nota que pese a que el error en el caso de las cadenas de Markov y el modelo RNN es casi igual en el caso del error de aciertos aumentado si existe una diferencia ya que para el modelo RNN es 29,07%.

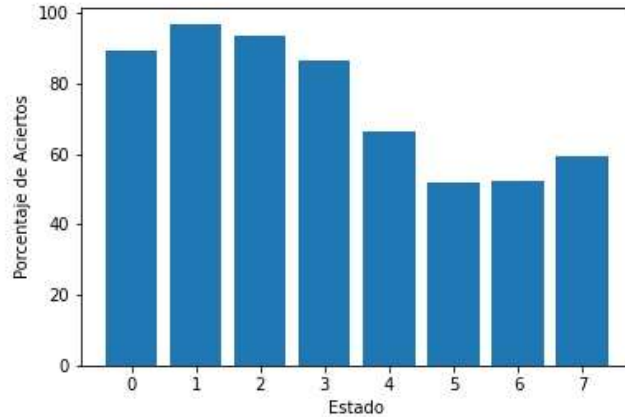
**Tabla 11** – Matriz de confusión para el Modelo TCN para predicción de 3 meses.

58,14	31,07	8,45	1,98	0,31	0,04	0,00	0,00
14,45	61,06	21,28	2,68	0,42	0,12	0,00	0,00
3,35	20,80	59,04	13,60	2,41	0,79	0,00	0,00
1,15	8,03	40,56	40,15	5,74	4,38	0,00	0,00
1,35	2,96	28,03	40,16	11,32	14,82	1,35	0,00
0,68	0,68	19,59	27,03	15,54	7,77	28,72	0,00
0,36	1,44	13,31	21,22	11,15	10,43	42,09	0,00
0,00	1,67	10,00	12,50	8,33	8,33	59,17	0,00



**Figura 21** – Porcentaje de aciertos del modelo TCN por estado para predicción de 3 meses

Se puede observar en la Figura 21 que la matriz de confusión está desequilibrada ya que se tienen por ejemplo para el estado 7 el porcentaje de acierto es 0% es decir que este modelo no puede predecir el estado 7. Para los estados 4 y 5 el porcentaje de acierto es menor a 12%, también se observa que para los estados 0,1,2 el porcentaje de acierto es cercano al 60% y para los estados 3,6 el porcentaje de acierto es cerca del 40%.

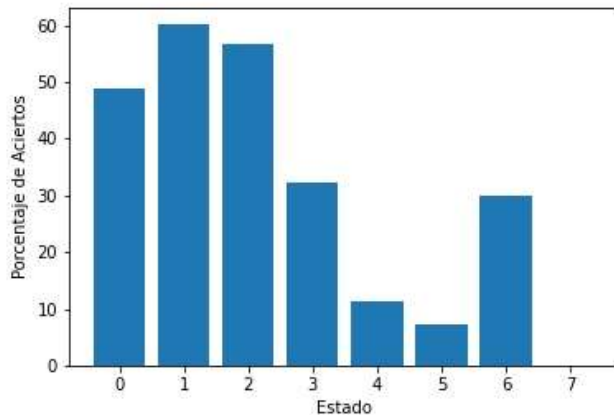


**Figura 22** – Porcentaje de aciertos aumentado del modelo TCN por estado para predicción de 3 meses

En la Figura 22 se observa más equilibrado el porcentaje de aciertos, y los aumentos más drásticos se dan en los estados 4,5,7 que pasan de menores al 12% a superar el 50% de aciertos al tomar el acierto aumentado. El error de porcentaje de acierto aumentado aun es 26,44% que es mayor al del modelo de cadenas de Markov.

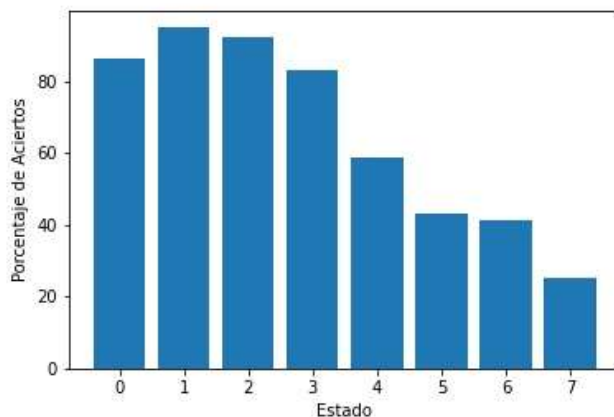
**Tabla 12** – Matriz de confusión para el Modelo TCN para predicción de 6 meses.

48,83	37,60	9,76	2,40	0,62	0,78	0,00	0,00
11,18	60,18	23,60	3,56	0,72	0,72	0,03	0,00
3,13	22,52	56,78	12,78	2,47	2,30	0,02	0,00
1,11	9,17	45,14	32,14	5,89	6,55	0,00	0,00
1,18	4,73	31,41	34,95	11,43	12,09	4,20	0,00
0,97	0,73	22,14	33,09	14,60	7,30	21,17	0,00
0,76	2,02	18,18	25,76	12,12	11,11	30,05	0,00
0,00	1,52	13,37	24,62	16,72	18,54	25,23	0,00



**Figura 23** – Porcentaje de aciertos del modelo TCN por estado para predicción de 6 meses

Se valida que para 6 meses como se observa en la figura 23 se sigue teniendo una matriz de confusión desbalanceada, aun se tiene un muy bajo porcentaje de error para los estados 4 y 5 y para el estado 7 el porcentaje de acierto sigue siendo 0%, es decir que tampoco puede predecir el estado 7. Por último, el mayor porcentaje de acierto los tienen los estados 1 y 2 que es cercano al 60%.

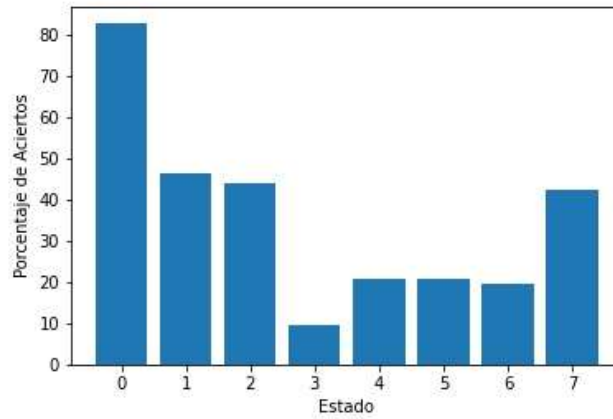


**Figura 24** – Porcentaje de aciertos aumentado del modelo TCN por estado para predicción de 6 meses

En base a la Figura 24 se validan aumentos considerables en el porcentaje de acierto de todos los estados, pero en especial en los estados 4 y 5. Adicionalmente se valida que si se tiene un aumento considerable en el error comparado con el del modelo de Cadenas de Markov ya que es del 33,81%.

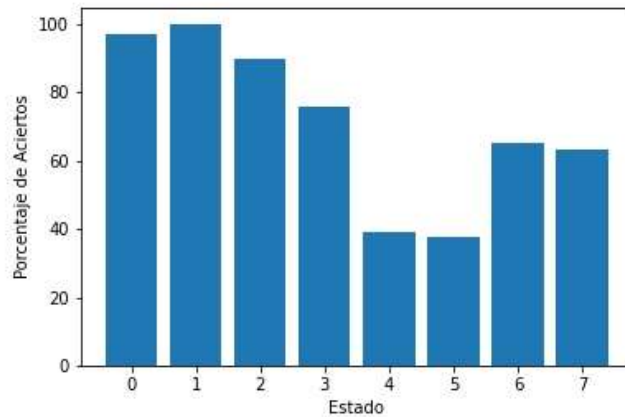
**Tabla 13** – Matriz de confusión para el Modelo NBEATS para predicción de 3 meses.

82,64	14,07	3,19	0,04	0,04	0,00	0,00	0,00
47,38	46,25	6,18	0,12	0,06	0,00	0,00	0,00
9,96	44,60	43,91	1,13	0,39	0,00	0,00	0,00
2,19	21,38	63,40	9,59	2,92	0,52	0,00	0,00
2,16	8,89	49,33	14,82	20,75	3,50	0,27	0,27
0,68	7,77	32,43	10,81	12,50	20,95	4,39	10,47
0,00	3,96	17,99	5,04	7,91	24,82	19,42	20,86
0,83	4,17	15,00	2,50	5,83	8,33	20,83	42,50



**Figura 25** – Porcentaje de aciertos del modelo NBEATS por estado para predicción de 3 meses

Se puede observar en la Figura 25 que la matriz de confusión está desequilibrada ya que para el estado 1 tiene un porcentaje alto de acierto y para el resto de los estados es menor al 50% e incluso para los estados 3, 4, 5 y 6 se tiene un porcentaje de acierto menor al 21%, adicional se observa que no existe ningún estado que tenga acierto de 0%.



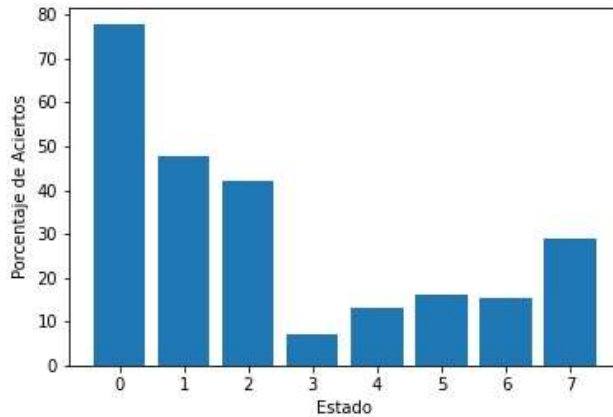
**Figura 26** – Porcentaje de aciertos aumentado del modelo NBEATS por estado para predicción de 3 meses

En la Figura 26 se observa más equilibrado el porcentaje de aciertos, y los aumentos más drásticos se dan en los estados 3 que pasan de menores al 10% a superar el 75% de aciertos al tomar el acierto aumentado. El error de porcentaje de acierto aumentado aun es 31,1% que es mayor al del modelo de cadenas de Markov.

**Tabla 14** – Matriz de confusión para el Modelo NBEATS para predicción de 6 meses.

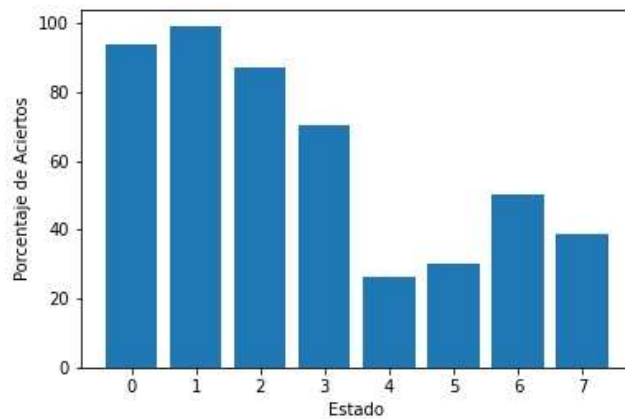
77,79	16,12	5,63	0,22	0,13	0,04	0,04	0,02
41,67	47,64	9,88	0,38	0,09	0,03	0,12	0,20
10,89	43,44	42,22	1,71	0,59	0,29	0,20	0,66
3,58	22,92	59,55	7,15	3,58	0,81	0,55	1,86
2,76	12,88	51,51	9,86	13,14	3,42	1,18	5,26
1,22	9,49	39,42	10,95	10,46	16,30	3,65	8,52
1,26	6,82	27,78	5,81	8,08	18,18	15,40	16,67
1,22	4,56	39,82	4,26	6,99	4,56	9,73	28,88





**Figura 27** – Porcentaje de aciertos del modelo NBEATS por estado para predicción de 6 meses

En base a la Figura 27 se valida que para 6 meses se sigue teniendo una matriz de confusión desbalanceada, aun se tiene un muy bajo porcentaje de error para los estados 3,4,5 y 6 y el porcentaje de acierto para el estado 1 sigue siendo muy alto cercano al 80%.

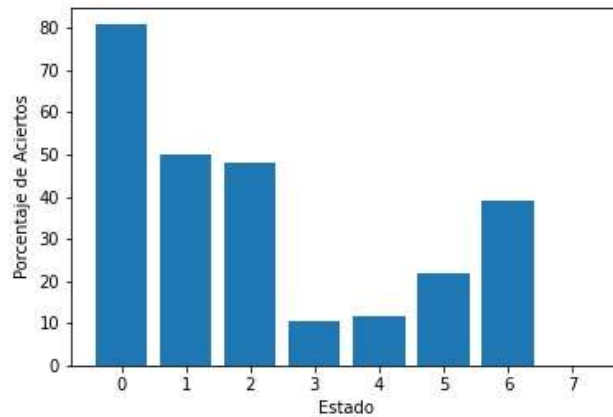


**Figura 28** – Porcentaje de aciertos aumentado del modelo NBEATS por estado para predicción de 6 meses

En base a la Figura 28 se validan aumentos considerables en el porcentaje de acierto de todos los estados, pero en especial en el estado 3. Adicionalmente se valida que si se tiene un aumento considerable en el error comparado con el del modelo de Cadenas de Markov ya que es del 34.43%.

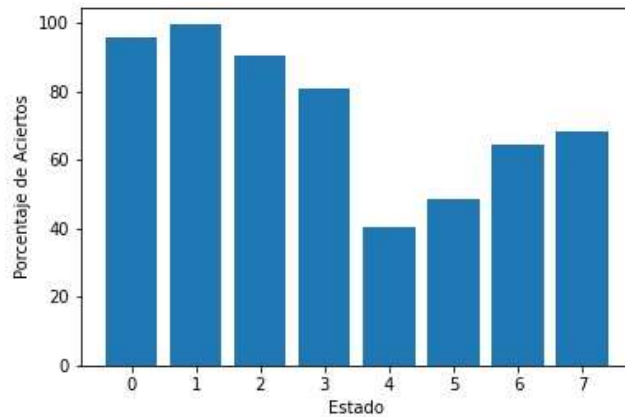
**Tabla 15** – Matriz de confusión para el Modelo TRANSFORMER para predicción de 3 meses.

80,85	14,84	4,23	0,09	0,00	0,00	0,00	0,00
41,50	50,12	8,03	0,30	0,06	0,00	0,00	0,00
9,12	40,81	48,10	1,72	0,25	0,00	0,00	0,00
2,09	16,16	68,20	10,43	2,09	1,04	0,00	0,00
1,62	5,66	51,48	22,37	11,59	6,47	0,81	0,00
0,68	5,74	33,45	11,49	9,80	21,96	16,89	0,00
0,00	2,52	18,71	5,76	8,63	25,54	38,85	0,00
0,83	4,17	15,00	1,67	2,50	7,50	68,33	0,00



**Figura 29** – Porcentaje de aciertos del modelo TRANSFORMER por estado para predicción de 3 meses

Se puede observar en la Figura 29 que la matriz de confusión esta desequilibrada ya que para el estado 0 tiene un porcentaje alto de acierto y para el estado 7 se tiene un porcentaje de acierto de 0%. Los estados 1 y 2 tiene un acierto de alrededor del 50% y los estados 3,4 y 5 tiene un acierto menor al 22%.

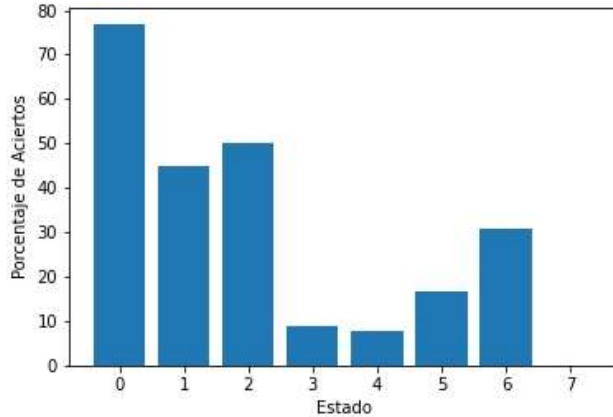


**Figura 30** – Porcentaje de aciertos aumentado del modelo TRANSFORMER por estado para predicción de 3 meses

En la Figura 30 se observa más equilibrado el porcentaje de aciertos, y los aumentos más drásticos se dan en los estados 1 que pasan de menores al 50% a cercano al 100% de aciertos al tomar el acierto aumentado, el estado 7 pasa de 0% a más del 60%. El error de porcentaje de acierto aumentado es 37,95% que aún es mayor al del modelo de cadenas de Markov.

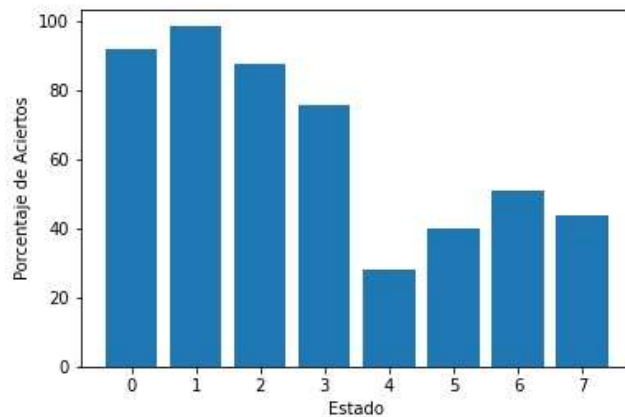
**Tabla 16** – Matriz de confusión para el Modelo TRANSFORMER para predicción de 6 meses.

76,90	15,12	7,23	0,47	0,02	0,22	0,04	0,00
38,98	45,09	14,74	0,49	0,17	0,20	0,32	0,00
10,30	35,61	50,17	1,93	0,44	0,66	0,88	0,00
3,58	16,22	64,84	8,92	2,12	1,66	2,67	0,00
2,63	8,80	52,69	15,77	7,62	4,86	7,62	0,00
1,22	6,33	41,12	11,44	9,00	16,55	14,36	0,00
1,26	3,79	28,54	7,83	7,58	20,20	30,81	0,00
1,22	3,04	38,91	4,26	2,43	6,08	44,07	0,00



**Figura 31** – Porcentaje de aciertos del modelo TRANSFORMER por estado para predicción de 6 meses

En base a la Figura 31 se valida que para 6 meses se sigue teniendo una matriz de confusión desbalanceada, aun se tiene un muy bajo porcentaje de error para los estados 3,4 y 5. El porcentaje de acierto para el estado 0 sigue siendo 0% y el acierto del estado 0 sigue siendo alto cercano al 80%.

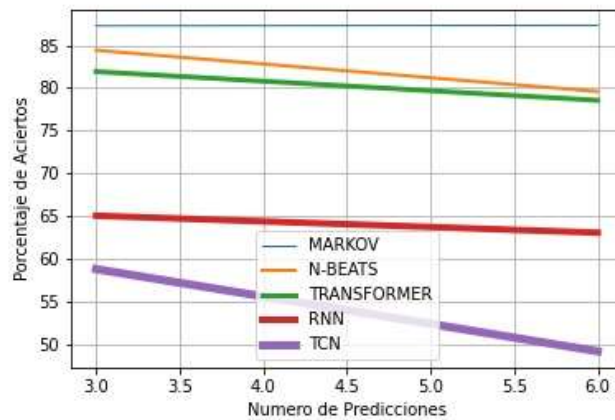


**Figura 32** – Porcentaje de aciertos aumentado del modelo TRANSFORMER por estado para predicción de 6 meses

En base a la Figura 32 se validan aumentos considerables en el porcentaje de acierto de todos los estados, pero en especial en los estados 1,3 y 7. Adicionalmente se valida que si se tiene un aumento considerable en el error comparado con el del modelo de Cadenas de Markov ya que es del 35.29%, es el único modelo en el que se observa que se tiene un error de aciertos aumentados menor para una predicción de 6 meses que para 3 meses.

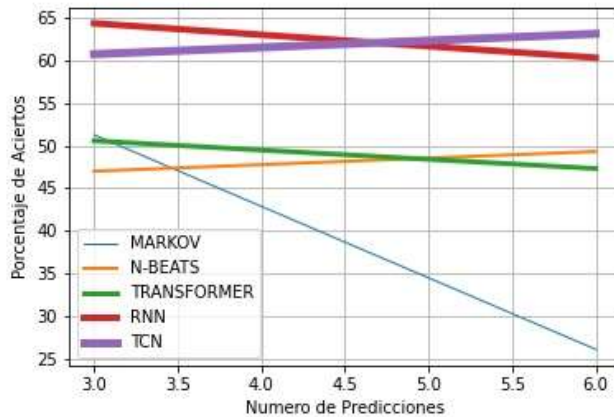
En base a lo que se observó en el análisis de la matriz de confusión de los 5 modelos que aplicamos para predicciones de 3 y 6 meses se observa que el modelo RNN es el mejor ya que tiene una matriz de confusión más equilibrada es decir que es capaz de predecir cada uno de los estados de manera similar, pese a que tiene un error de predicción un poco mayor, tiene un mejor comportamiento con los datos.

Por último, vamos a analizar que tan bien predice cada modelo a cada uno de los estados posibles y como este porcentaje de precisión va cambiando con el aumento de la cantidad de predicciones.



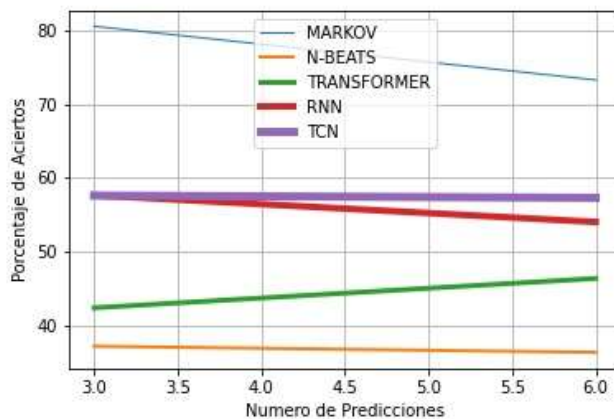
**Figura 33** – Porcentaje de aciertos de cada Modelo para estado 0 por número de predicciones.

En base a la Figura 33 se valida que el modelo de cadena de Markov es el que mejor predice el estado 0 y es casi invariante la precisión con la cantidad de predicciones, mientras que los modelos de aprendizaje de máquina que mejor hacen la predicción de este estado son TRANSFORMER y NBEATS, el modelo RNN también tiene una precisión casi invariable cuando aumentan el número de predicciones, aunque es menor a los otros 2.



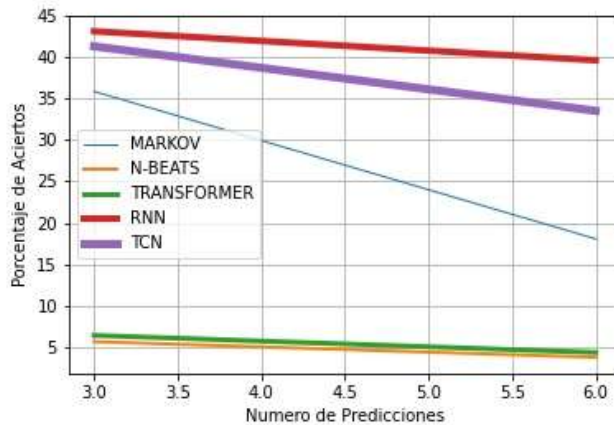
**Figura 34** – Porcentaje de aciertos de cada Modelo para estado 1 por número de predicciones.

En la figura 34 se valida que los modelos TCN y RNN son los que mejor predicen el estado 1, y no disminuyen mucho con el aumento de numero de predicciones. Los modelos NBEATS y TRANSFORMER tienen una precisión menor pero también son invariantes con el aumento de numero de predicciones. Por último, el modelo de cadenas de Markov tiene una precisión menor y disminuye drásticamente con el aumento del número de predicciones.



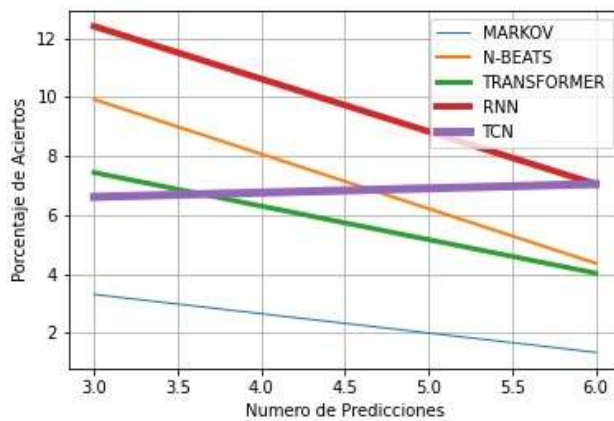
**Figura 35** – Porcentaje de aciertos de cada Modelo para estado 2 por número de predicciones.

Para el estado 2 en base a la Figura 35 se valida que Markov es el que mejor predice, pero si tiene una disminución con el aumento de número de predicciones mientras que los modelos TCN y RNN tienen un porcentaje de aciertos menor pero no tan bajo como los otros modelos de aprendizaje de máquina.



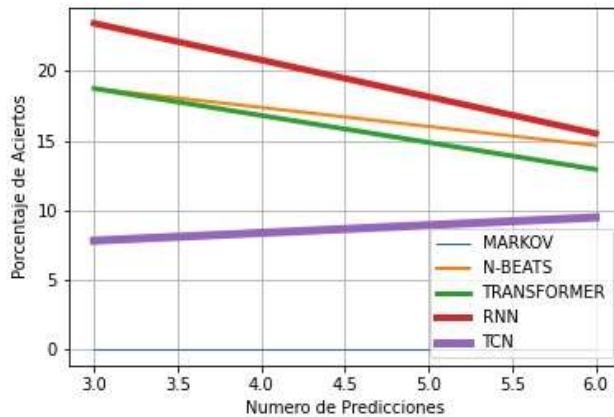
**Figura 36** – Porcentaje de aciertos de cada Modelo para estado 3 por número de predicciones.

Para el estado 3 en base a la Figura 36 se valida que el modelo RNN es el que mejor predice y no varía mucho la precisión al aumentar la cantidad de predicciones. El modelo TCN tiene una disminución mayor, pero la disminución más drástica la tiene el modelo de cadenas de Markov, pero la precisión es mayor que la de los otros modelos de aprendizaje de máquina a todo momento.



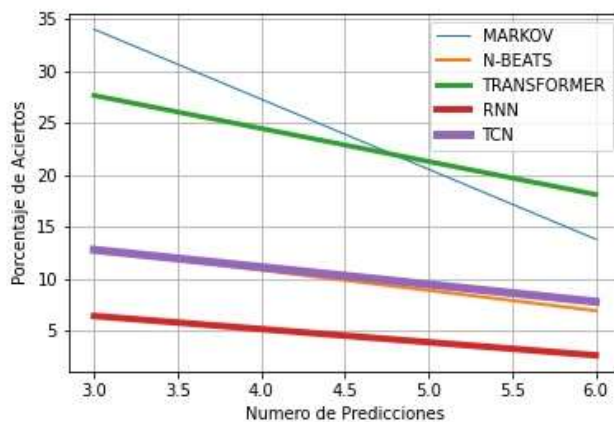
**Figura 37** – Porcentaje de aciertos de cada Modelo para estado 4 por número de predicciones.

Para el estado 4 en base a la Figura 37 se observa que todos los modelos tienen una precisión muy baja, aunque la mejor es la del modelo RNN, aunque si se tiene una disminución pronunciada con el aumento de numero de predicciones.



**Figura 38** – Porcentaje de aciertos de cada Modelo para estado 5 por número de predicciones.

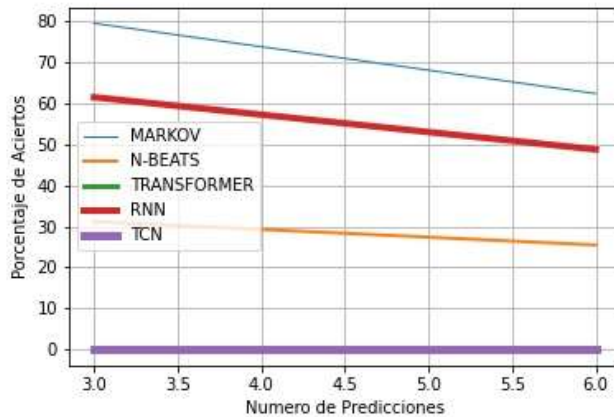
Para el estado 5 en base a la Figura 38 se observa que el modelo de Markov tiene una precisión de 0% mientras que el modelo RNN tiene una precisión mayor, aunque no es mucho mayor a 20% por lo cual no es muy preciso incluso con pocas predicciones.



**Figura 39** – Porcentaje de aciertos de cada Modelo para estado 6 por número de predicciones.

Para el estado 6 como se observa en la figura 39 se observa que con pocas predicciones el modelo de cadenas de Markov es el más preciso, pero baja rápidamente al aumentar el número de predicciones. De los modelos de aprendizaje de máquina se valida que el modelo TRANSFORMER es el mejor.





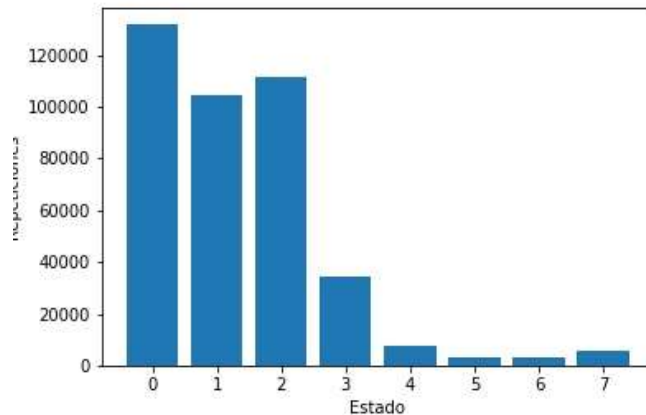
**Figura 40** – Porcentaje de aciertos de cada Modelo para estado 7 por número de predicciones.

En la figura 40 se valida que el modelo de cadenas de Markov es el más preciso, seguido del modelo RNN y ambos tienen un decaimiento no tan pronunciado al aumentar el número de predicciones.

### 3.2. Discusiones

Se observó mediante las 4 medidas que se utilizó el modelo que tiene menor error es del modelo de cadenas Markov, también es el modelo que presenta mayor precisión ya que tiene un F-score más alto. Sin embargo, el modelo RNN es el que tiene una matriz de confusión más equilibrada.

Pero también se valida que ninguno de los modelos tiene un error muy bajo ni un F-score o coeficiente de determinación altos que nos indiquen que tenemos un modelo robusto. Si se analiza la cantidad de veces que se repite cada uno de los estados dentro del set de datos disponibles se puede identificar porque no es posible entrenar un modelo robusto.



**Figura 41** – Histograma de repeticiones 8 estados en el set de datos

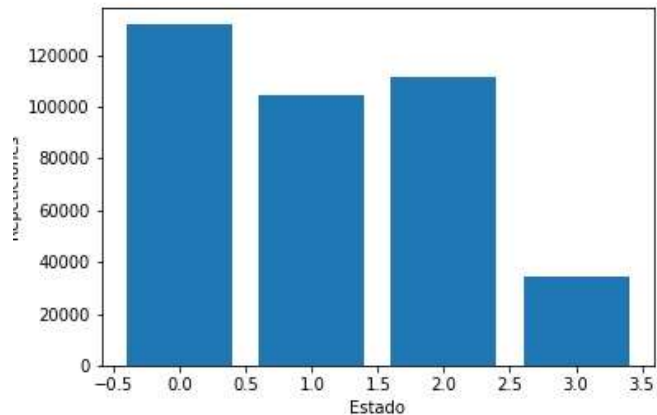
En base a la Figura 41 es fácil verificar que los datos no se encuentran equilibrados ya que existen muchas más observaciones de estados 0,1 y 2 y el resto de los estados no tienen suficientes observaciones por esta razón al intentar equilibrar los datos se pierde demasiada información y no se tienen suficientes datos para entrenar ninguno de los modelos ni el de las cadenas de Markov, ni de los de aprendizaje de máquina.

Una de las posibles soluciones sería disminuir el número de estado de 8 a 4 para que los últimos 4 estados se junten en uno solo. La división de estado estaría dada por la siguiente tabla.

**Tabla 17** – Categorías de Mora según días de Mora para 4 estados.

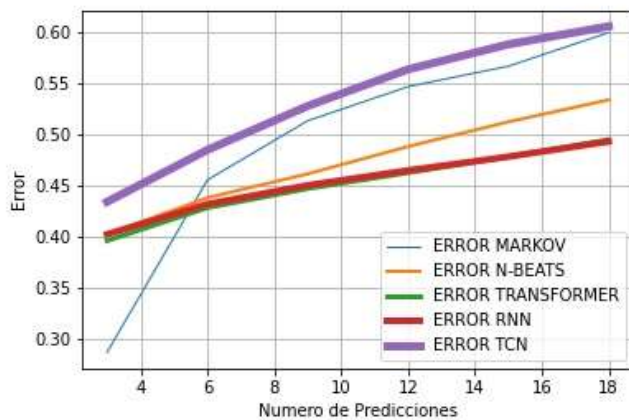
Número de días de Mora	Categoría Mora
0	0
1-7	1
8-30	2
Mayor a 31	3

Se puede hacer un histograma de los datos con la nueva categorización.



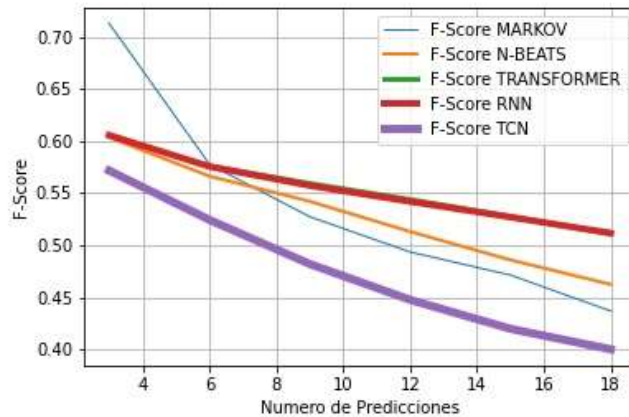
**Figura 42** – Histograma de repeticiones 4 estados en el set de datos

En la figura 42 se valida que la muestra está más equilibrada pero aún se tiene un mucho menor de muestra de la categoría 3. Con esta nueva categorización de estados se puede entrenar nuevamente los modelos y calcular varias de las medidas que se obtuvo para 8 estados.



**Figura 43** – Error de cada modelo para 4 estados por número de predicciones

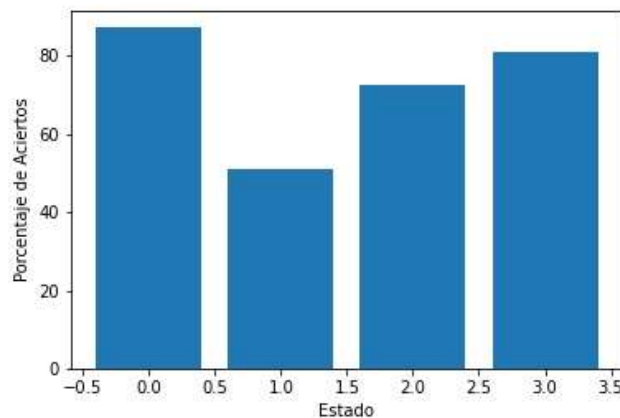
En la figura 43 se puede observar para 4 estados el error es menor que para 8, adicional se tiene un mejor comportamiento de los modelos TRANSFORMER y NBEATS ya que al igual que el modelo RNN después de 6 o más predicciones ya tienen un error menor que el modelo de cadenas de Markov.



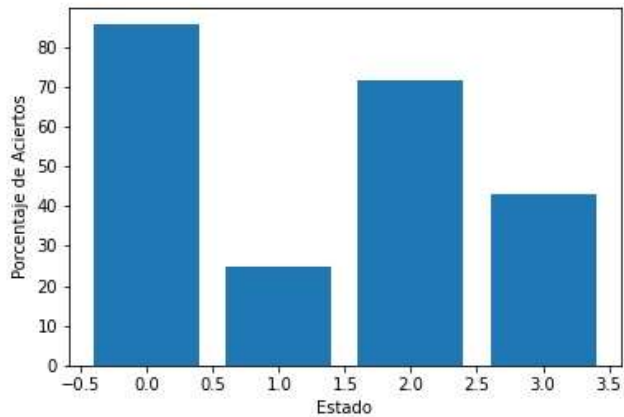
**Figura 44** – F-score de cada modelo para 4 estados por número de predicciones

En la figura 43 se observa que se tiene un mejor F-score para todos los modelos, aunque el aumento es menor que la disminución que se tuvo para el error, adicional se mantiene el mejor comportamiento de los modelos NBEATS y TRANSFORMER al igual que el modelo RNN para más de 6 predicciones.

También podemos analizar las matrices de confusión para los modelos con 4 estados tanto para 3 y 6 meses, particularmente analizaremos la diagonal para ver qué tan balanceada es la matriz.

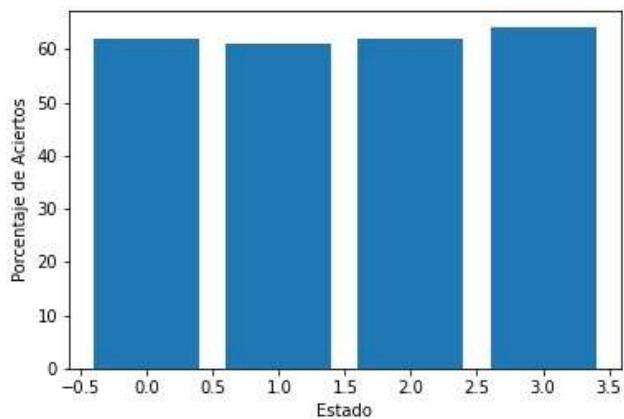


**Figura 45** – Porcentaje de aciertos del modelo de cadena de MARKOV para los 4 estados para predicción de 3 meses

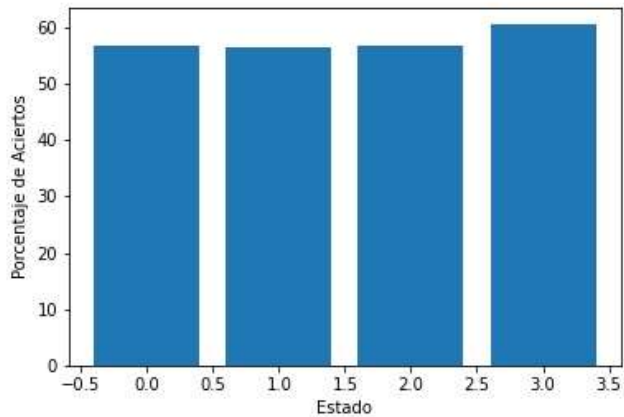


**Figura 46** – Porcentaje de aciertos del modelo de cadenas de MARKOV para los 4 estados para predicción de 6 meses

En la figura 45 se observa que para el modelo de cadenas de Markov con predicción de 3 meses se tiene una matriz más equilibrada en 4 estados que en 8, sin embargo, la matriz se desequilibra apenas se pasa a una predicción de 6 meses como se observa en la Figura 46, lo cual se complementa con los resultados anteriores que se observa un aumento drástico del error y disminución del F-score y coeficiente de determinación al aumentar el número de predicciones.

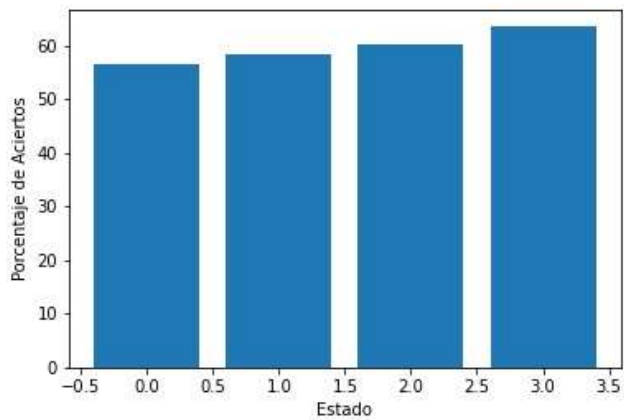


**Figura 47** – Porcentaje de aciertos del modelo RNN para los 4 estados para predicción de 3 meses

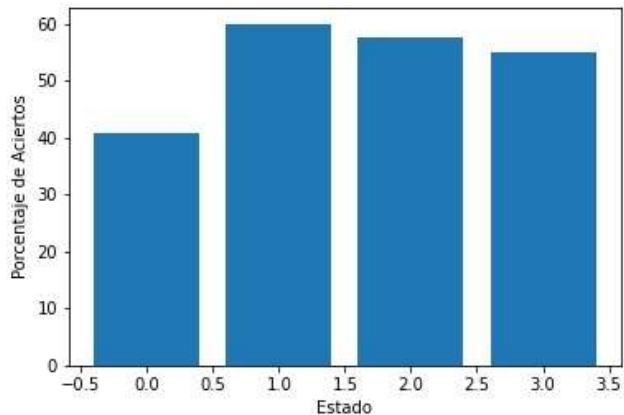


**Figura 48** – Porcentaje de aciertos del modelo RNN para los 4 estados para predicción de 6 meses

Para el modelo RNN se observa en la Figura 47 que con 4 estados se tiene la matriz de confusión más equilibrada de todos los modelos y esto se mantiene con 6 meses de predicción como se observa en la Figura 48.

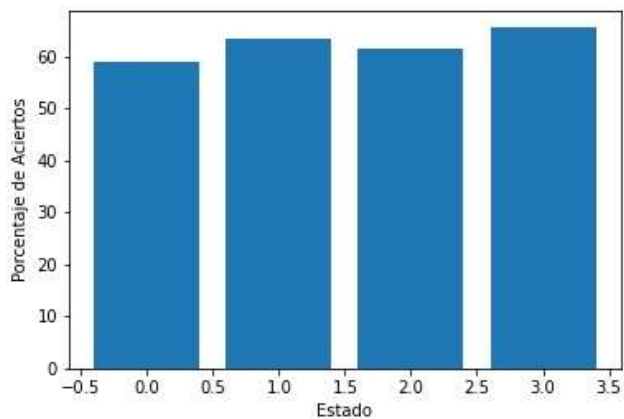


**Figura 49** – Porcentaje de aciertos del modelo TCN para los 4 estados para predicción de 3 meses

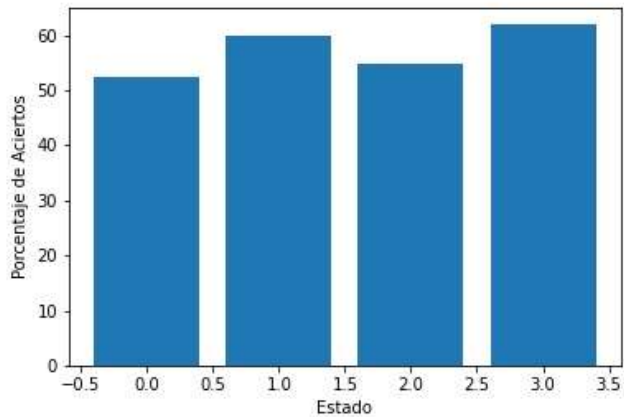


**Figura 50** – Porcentaje de aciertos del modelo TCN para los 4 estados para predicción de 6 meses

Para el modelo TCN se observa que de los modelos de aprendizaje de máquina es el que más se desequilibra la matriz de confusión al pasar de una predicción de 3 meses en la Figura 49 a una de 6 meses en la Figura 50, lo cual mantiene la tendencia de las otras medidas que indican que es el peor de los modelos de aprendizaje de máquina para 4 estados.

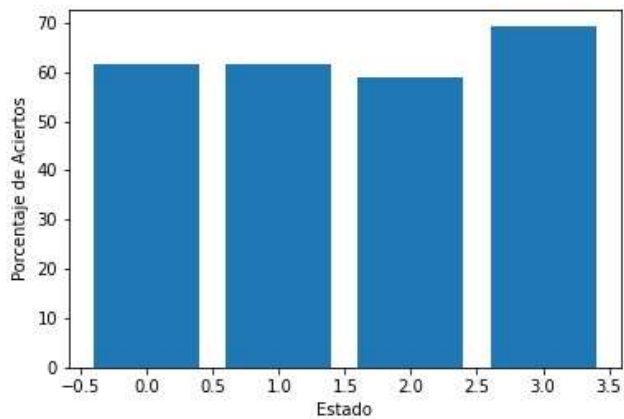


**Figura 51** – Porcentaje de aciertos del modelo NBEATS para los 4 estados para predicción de 3 meses



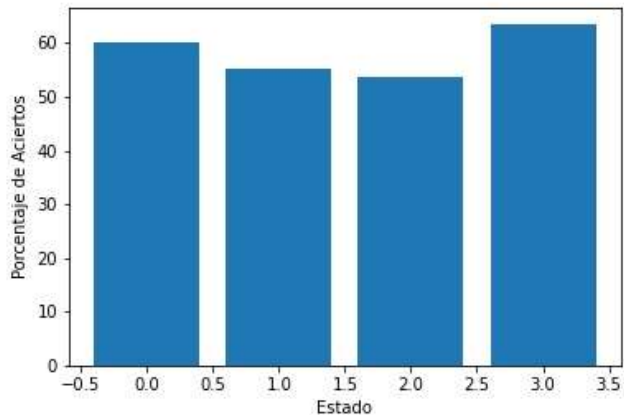
**Figura 52** – Porcentaje de aciertos del modelo NBEATS para los 4 estados para predicción de 6 meses

Para el modelo NBEATS se observa una matriz de confusión balanceada para 3 meses en la Figura 51 y 6 meses de predicción en la Figura 52.



**Figura 53** – Porcentaje de aciertos del modelo TRANSFORMER para los 4 estados para predicción de 3 meses





**Figura**

**54** – Porcentaje de aciertos del modelo TRANSFORMER para los 4 estados para predicción de 6 meses

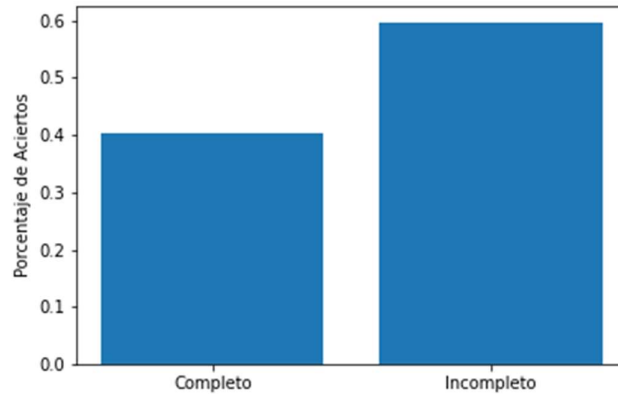
Para el modelo TRANSFORMER se observa una matriz de confusión balanceada para 3 en la Figura 53 y 6 meses de predicción en la Figura 54.

Al analizar las predicciones de los modelos con 4 estados se puede decir que tiene un mejor comportamiento que los modelos con 8 estados, pero como se dijo anteriormente se pierde mucha información del movimiento de las series de tiempo del comportamiento de pago de cada préstamo al reducir de 8 a 4 estados.

También el modelo pierde un poco de su utilidad en la práctica ya que solo me va a indicar si los clientes me van a pagar durante el mes que deberían ya que un estado 3 solo me indica si se van a demorar más de un mes en pagar la cuota, lo cual no es tan útil para las entidades financieras.

Adicional a lo desequilibrada que es la muestra que se tiene de el set de datos disponibles, se debe señalar que dentro de los registros de pagos de los prestamos hay información faltante en cuanto a las fechas ya que se observó pagos de cuotas con la fecha esperada de pago meses después del pago de la cuota anterior. Esta información errónea provocó que no se pueda utilizar las fechas para describir las series de tiempo lo cual le quita información al modelo de aprendizaje de máquina para entrenarse ya que no permite tomar en cuenta aspectos importantes como la estacionalidad.

Por último, en base a los datos disponibles se puede observar que hay muchos datos faltantes ya que existen muchos préstamos que se pagan en menos cuotas de las que originalmente estipulaba, y no son una o dos cuotas menos, sino que son 10 o 20 cuotas menos.



**Figura 55** – Porcentaje de préstamos que se pagaron completos e incompletos

Como se observa en la figura 55 la mayoría de los préstamos cerca del 60% se pagaron en menos cuotas de las pactadas originalmente, como indicamos al verificar los datos se observa que no se pagan 1 o 2 cuotas menos, sino que son 10 o más cuotas, lo que parece bastante improbable. Este estado de los datos nos da la impresión de que existen información faltante la cual nos podría permitir tener una muestra más equilibrada y brindar más muestras a los modelos para entrenarlos y realizar las predicciones con un mejor resultado final.

#### 4. CONCLUSIONES

Lo primero que se puede concluir es que con los datos que se tienen disponibles de un Banco Ecuatoriano, el modelo de Cadenas de Markov para una predicción de hasta 6 meses es la que tiene un menor error en las predicciones y muestran una mayor precisión, aunque no describe tan bien el comportamiento de los datos y tiene una matriz de confusión desequilibrada.

También se observó que de los 4 modelos de aprendizaje de máquina que se utilizaron el modelo RNN que son redes neuronales recurrentes es el que tiene el mejor comportamiento y es bastante similar al de las cadenas de Markov. Aunque tiene un error

mayor y una menor precisión, describe de mejor manera el comportamiento de los datos y tiene una matriz de confusión más equilibrada.

Los otros 3 modelos de aprendizaje de máquina al analizarlos con una segmentación de 8 estados para el pago de las cuotas no presentan buenos resultados. Sin embargo, al segmentar solo con 4 estados las predicciones de los modelos NBEATS y TRANSFORMER mejoran considerablemente.

En general todos los modelos tienen un mejor comportamiento al segmentar el estado de pago de cada cuota en 4 estados en lugar de 8. Es decir que tienen un mejor comportamiento al realizar predicciones. Pero como se indicó se reduce la utilidad para las entidades financieras de los modelos predictivos y se pierde información del comportamiento de la serie de tiempo que describe el pago de las cuotas de un cliente.

Se concluye que ninguno de los modelos al entrenarlos con 8 estados demuestra ser muy robustos, aunque el modelo de Cadenas de Markov tampoco presenta un comportamiento considerablemente mejor. Se valida que esto en parte se debe a que los datos disponibles no demuestran ser una muestra balanceada es decir que se tenga un similar número de observaciones de cada uno de los estados que puede tomar las predicciones.

También se observó que al parecer existe información faltante en los datos disponibles ya que existen problemas con las fechas en las que se esperan que se realicen los pagos y el número de la cuota. Adicionalmente al parecer existen prestamos en los que no se muestra toda la información del pago de las cuotas, sino que se trunca en cierto momento, lo cual genera una falta de datos que no nos permite tener una muestra de datos más balanceada.

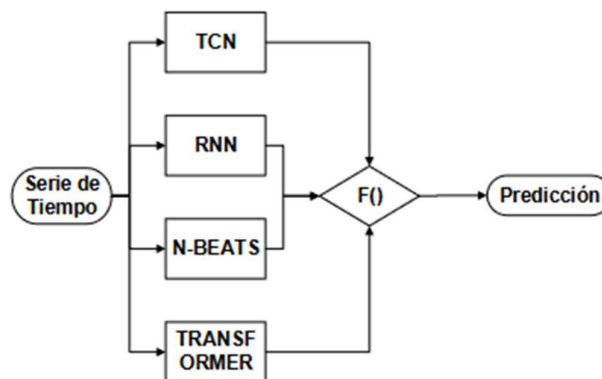
Por último, en base a los resultados obtenidos se puede decir que el modelo de cadenas de Markov, es el que da mejores resultados con los datos disponibles del Banco Ecuatoriano del cual se obtuvieron los datos. Sin embargo, los modelos de aprendizaje de máquina en especial el modelo RNN demostró dar resultados muy similares por lo cual se puede deducir que en caso de que los datos se lograrían mantener de mejor manera y tenerlos completos los modelos de aprendizaje de máquina podrían darnos un mucho mejor resultado.

La recomendación principal que se puede dar es que se requiere una mayor rigurosidad el momento de mantener los datos por parte del Banco Ecuatoriano del cual se obtuvieron

los datos. Esto se lo puede lograr con un sistema de manejo de la información más riguroso que permita que el personal del Banco ingrese la información de manera más precisa y sin errores, y que sea complementado por un departamento de sistemas de la información que mantenga la tanto a las personas tanto del funcionamiento de su infraestructura, como de la importancia de tener información real y completa en sus bases de datos.

Adicionalmente cuando se analizó las matrices de confusión de cada uno de los modelos se observó que ciertos modelos daban mejores resultados para predecir ciertos estados. por esta razón para trabajos futuros se puede crear un modelo mixto que permita utilizar una mezcla de los 5 modelos, que utilice las fortalezas de cada uno para producir un modelo que permita obtener un mejor resultado en cuanto a las predicciones obtenidas.

Esto se lo puede realizar utilizando los 4 modelos de aprendizaje de máquina que se desarrollaron en este trabajo y en base a que tan bien predice cada modelo cada uno de los estados se puede desarrollar una función que permita elegir la mejor predicción de las 4 que se realizaron y así crear una serie temporal resultante que tenga una mayor precisión que la de cualquiera de los 4 modelos por separado. Esta solución sería similar a la de la Figura 56.



**Figura 56** – Diagrama Propuesto para Trabajos Futuros.

## REFERENCIAS BIBLIOGRÁFICAS

- [1] R. F. Kosobud and H. H. Stokes, “OPEC short-run market share behaviour: Implications, theories and facts,” *Energy Econ.*, vol. 2, no. 2, pp. 66–80, 1980.
- [2] A. A. Markov, “Extension of the law of large numbers to dependent quantities (in Russian),” *Izv Fiz-Matem Obs. Kazan Univ (2nd Ser)*, vol. 15, pp. 135–156, 1906.
- [3] C. J. Geyer, “Practical markov chain monte carlo,” *Stat. Sci.*, pp. 473–483, 1992.
- [4] T.-C. Lee, G. G. Judge, and A. Zellner, “Estimating the parameters of the Markov probability model from aggregate time series data,” 1970.
- [5] G. A. Timofeeva and N. A. Timofeev, “Forecasting credit portfolio components with a Markov chain model,” *Autom. Remote Control*, vol. 73, no. 4, pp. 637–651, 2012.
- [6] W. L. Winston and J. B. Goldberg, *Operations research: applications and algorithms*, vol. 3. Thomson Brooks/Cole Belmont, 2004.
- [7] T. Mitchell, “Machine learning,” 1997.
- [8] V. Thyagarajan and M. Saiful, “Retail banking loan portfolio equilibrium mix: A Markov Chain model analysis,” *Am. J. Appl. Sci.*, vol. 2, no. 1, pp. 410–419, 2005.
- [9] A. Bellotti, D. Brigo, P. Gambetti, and F. Vnins, “Forecasting recovery rates on non-performing loans with machine learning,” *Int. J. Forecast.*, vol. 37, no. 1, pp. 428–444, 2021.
- [10] T. Bellotti and J. Crook, “Loss given default models incorporating macroeconomic variables for credit cards,” *Int. J. Forecast.*, vol. 28, no. 1, pp. 171–182, 2012.
- [11] G. Petneházi, “Recurrent neural networks for time series forecasting,” *arXiv Prepr. arXiv1901.00069*, 2019.
- [12] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, 1997.
- [13] K. Cho *et al.*, “Learning phrase representations using RNN encoder-decoder for statistical machine translation,” *arXiv Prepr. arXiv1406.1078*, 2014.
- [14] Y. Su, Y. Zhao, C. Niu, R. Liu, W. Sun, and D. Pei, “Robust anomaly detection for multivariate time series through stochastic recurrent neural network,” in *Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining*, 2019, pp. 2828–2837.
- [15] J. T. Connor, R. D. Martin, and L. E. Atlas, “Recurrent neural networks and robust time series prediction,” *IEEE Trans. neural networks*, vol. 5, no. 2, pp. 240–254,

1994.

- [16] Y. He and J. Zhao, “Temporal convolutional networks for anomaly detection in time series,” in *Journal of Physics: Conference Series*, 2019, vol. 1213, no. 4, p. 42050.
- [17] R. Wan, S. Mei, J. Wang, M. Liu, and F. Yang, “Multivariate temporal convolutional network: A deep neural networks approach for multivariate time series forecasting,” *Electronics*, vol. 8, no. 8, p. 876, 2019.
- [18] P. Lara-Benitez, M. Carranza-Garcia, J. M. Luna-Romera, and J. C. Riquelme, “Temporal convolutional networks applied to energy-related time series forecasting,” *Appl. Sci.*, vol. 10, no. 7, p. 2322, 2020.
- [19] B. N. Oreshkin, G. Dudek, and E. Peřka Pawełand Turkina, “N-BEATS neural network for mid-term electricity load forecasting,” *Appl. Energy*, vol. 293, p. 116918, 2021.
- [20] B. N. Oreshkin, D. Carpov, N. Chapados, and Y. Bengio, “N-BEATS: Neural basis expansion analysis for interpretable time series forecasting,” *arXiv Prepr. arXiv1905.10437*, 2019.
- [21] A. R. Hevner, S. T. March, J. Park, and S. Ram, “Design science in information systems research,” *MIS Q.*, pp. 75–105, 2004.
- [22] A. Vaswani *et al.*, “Attention is all you need,” *Adv. Neural Inf. Process. Syst.*, vol. 30, 2017.
- [23] S. Bai, J. Z. Kolter, and V. Koltun, “An empirical evaluation of generic convolutional and recurrent networks for sequence modeling,” *arXiv Prepr. arXiv1803.01271*, 2018.

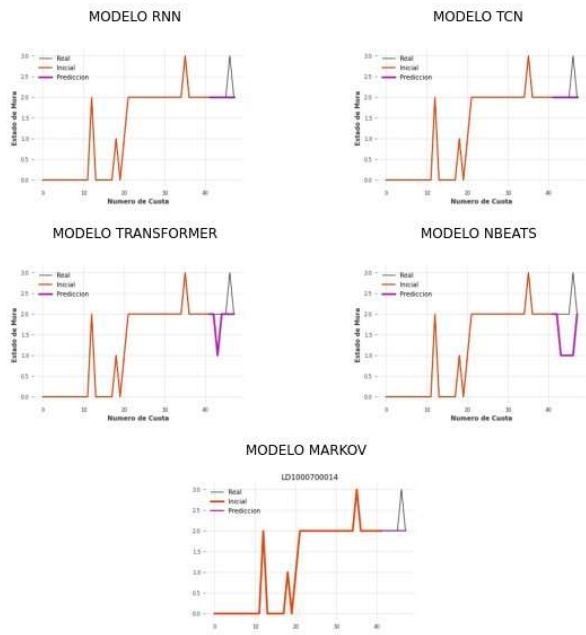


## **ANEXOS**

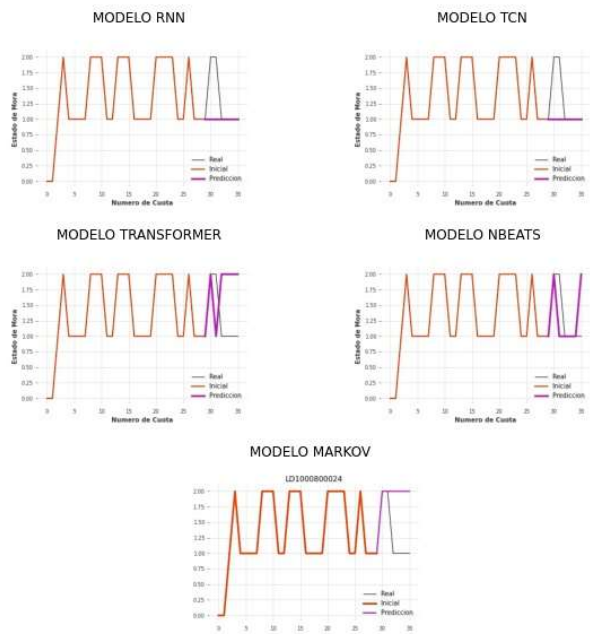


**Anexo 1** – Serie de tiempo real y predicción con 8 estados para los modelos de cadenas de Markov, RNN, TCN, NBEATS y TRANSFORMER de cada prestamos de los datos de prueba.

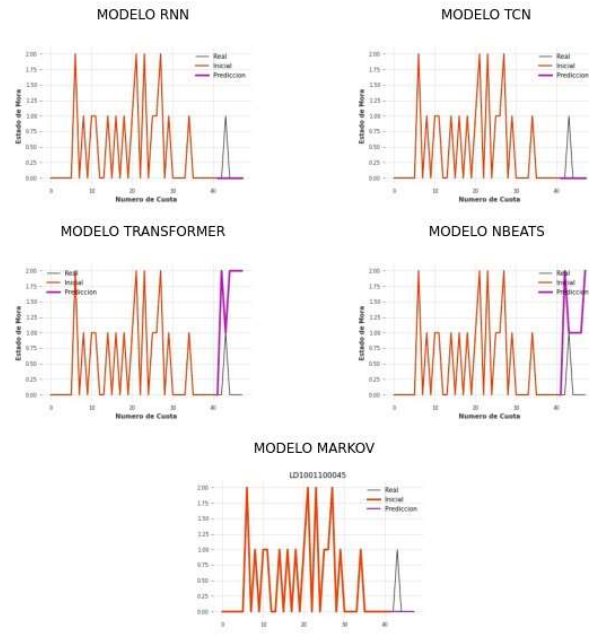
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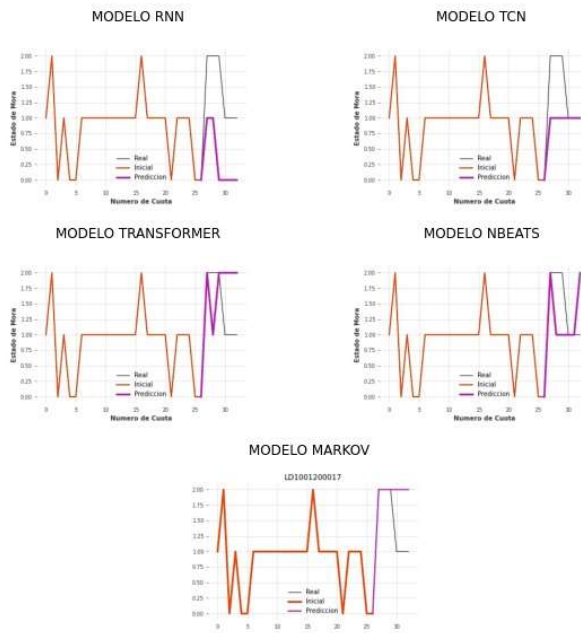
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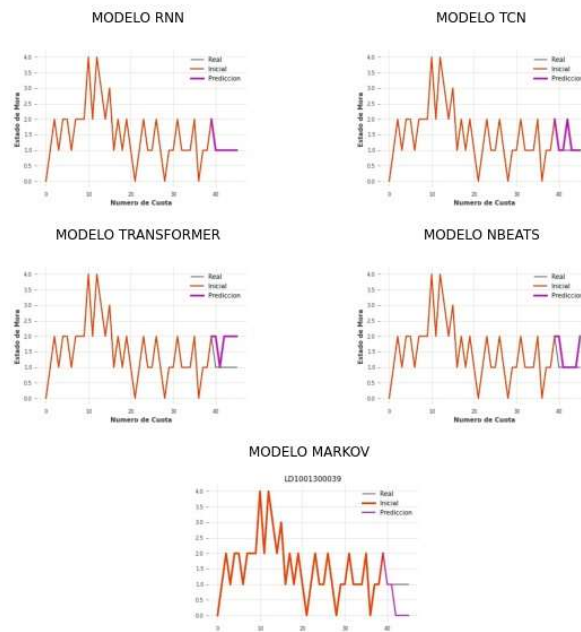
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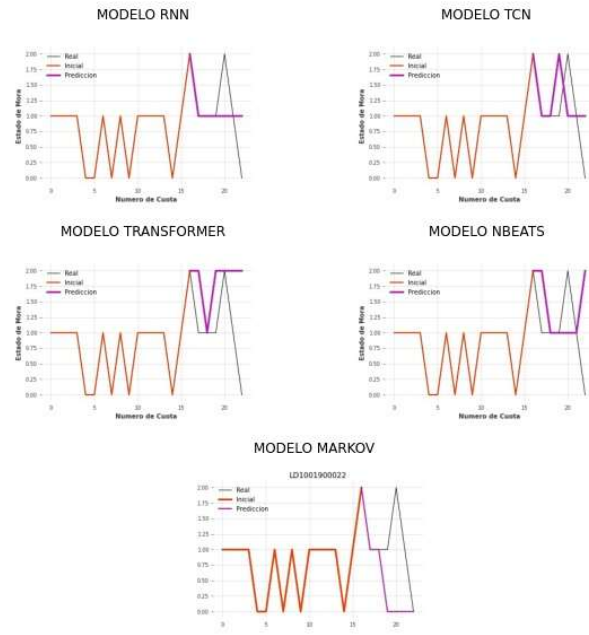
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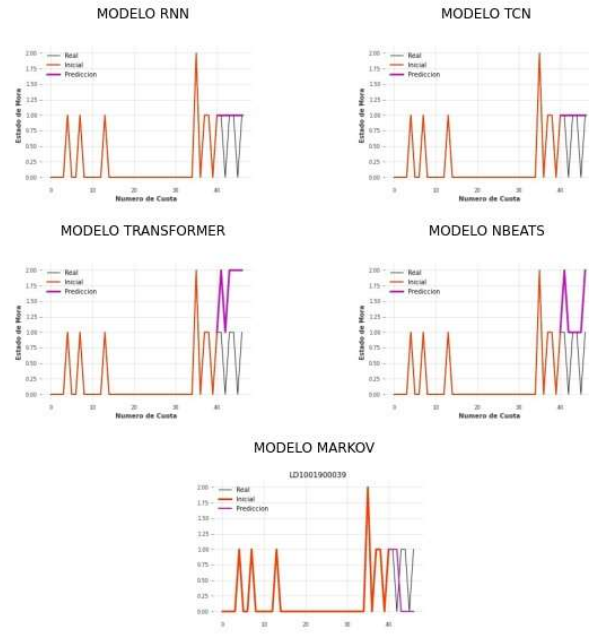
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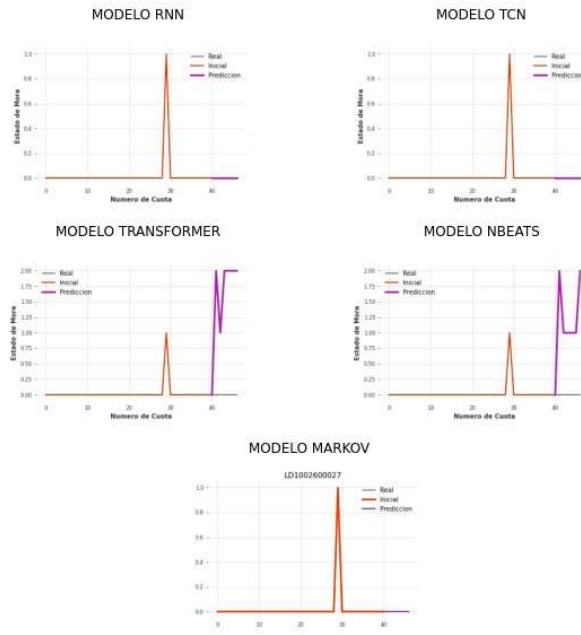
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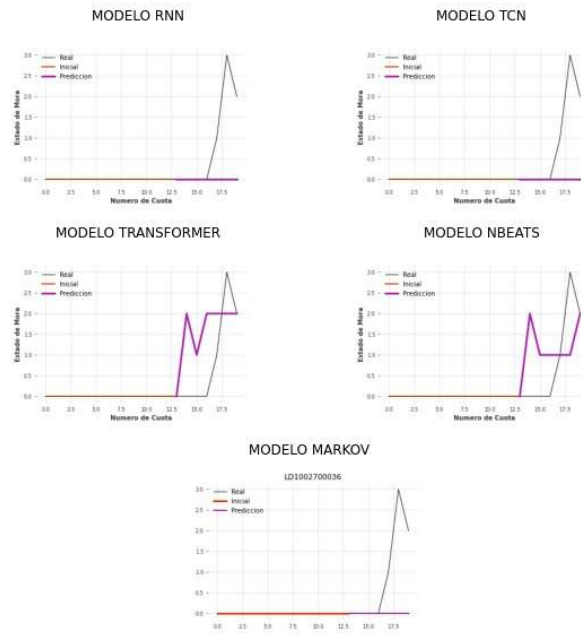
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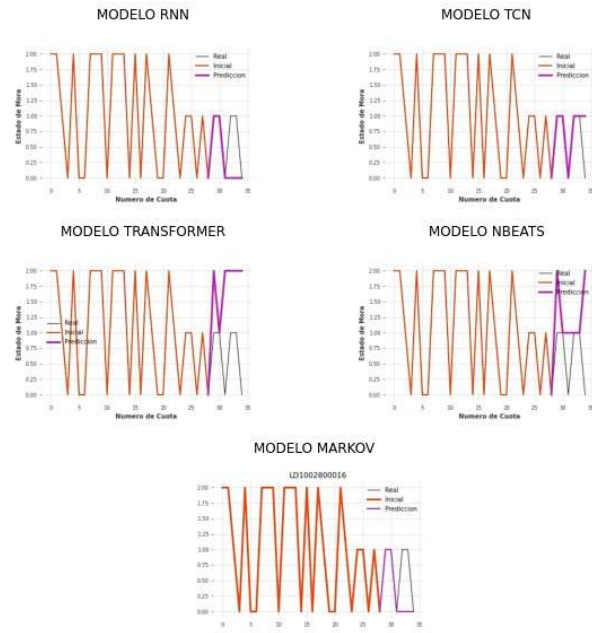
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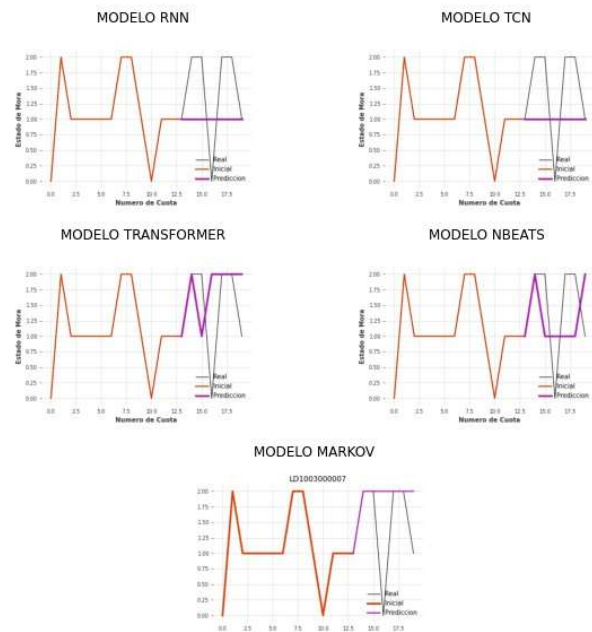
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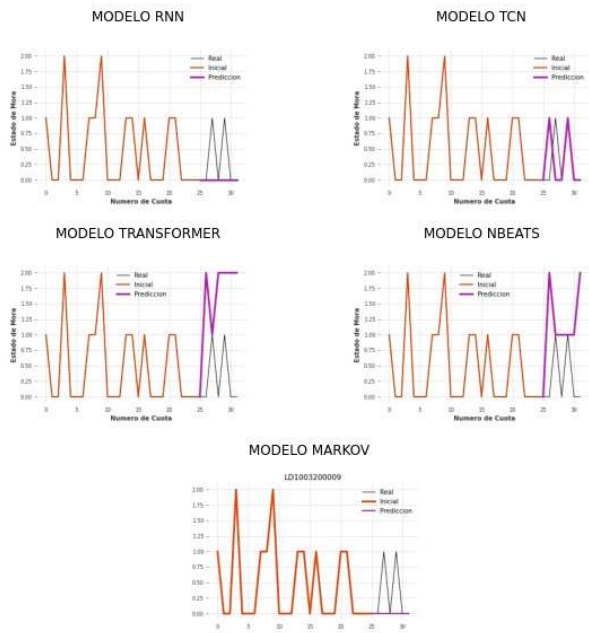
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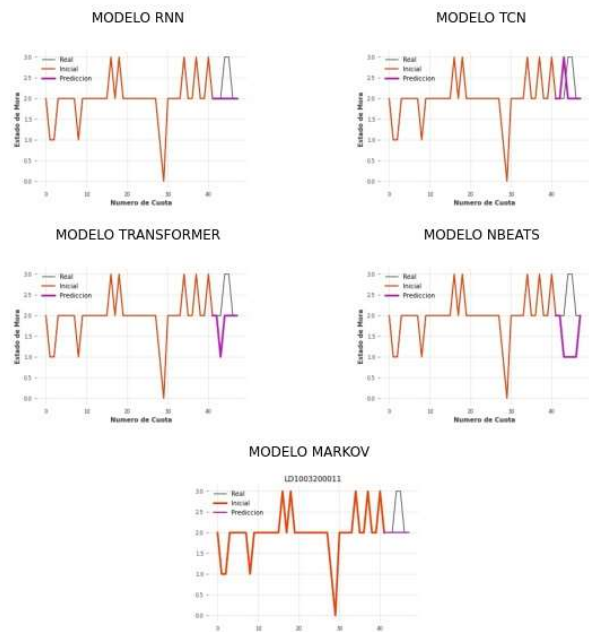
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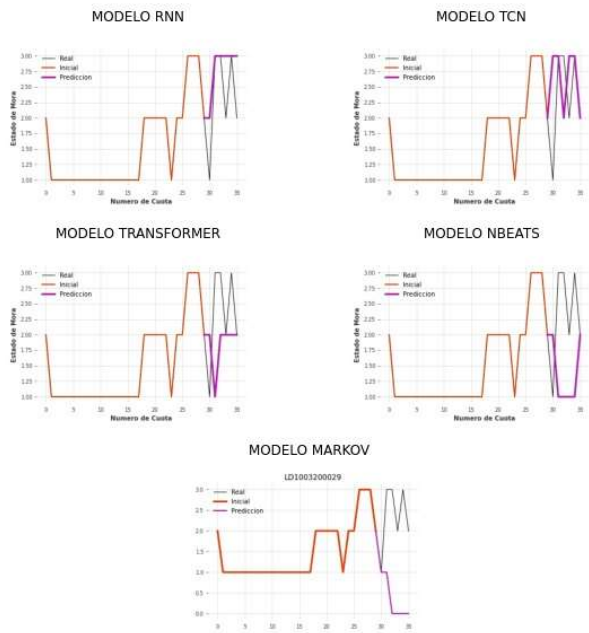


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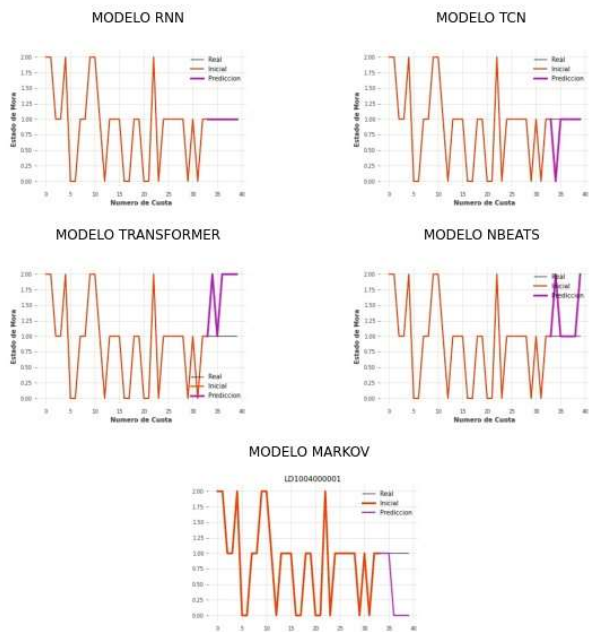




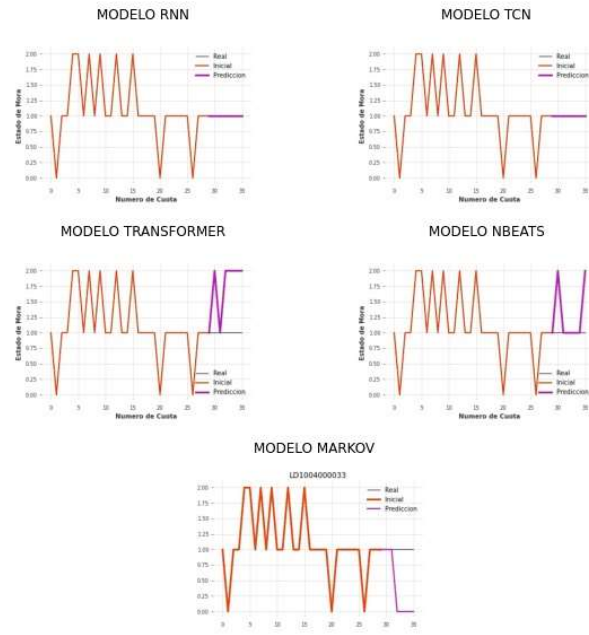
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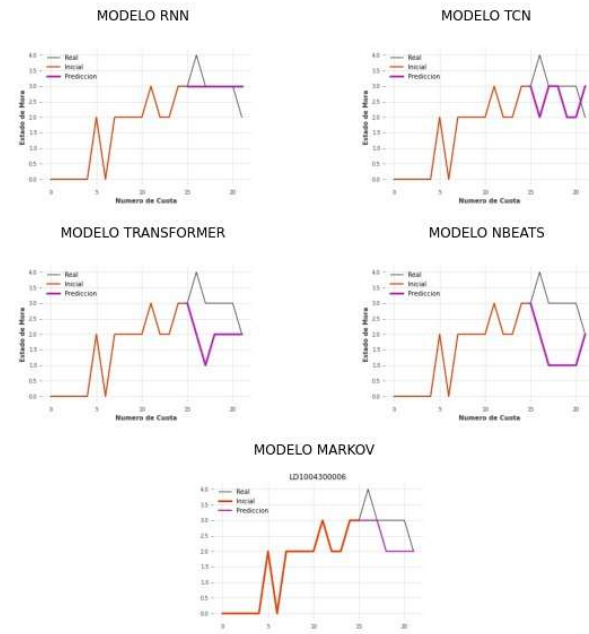
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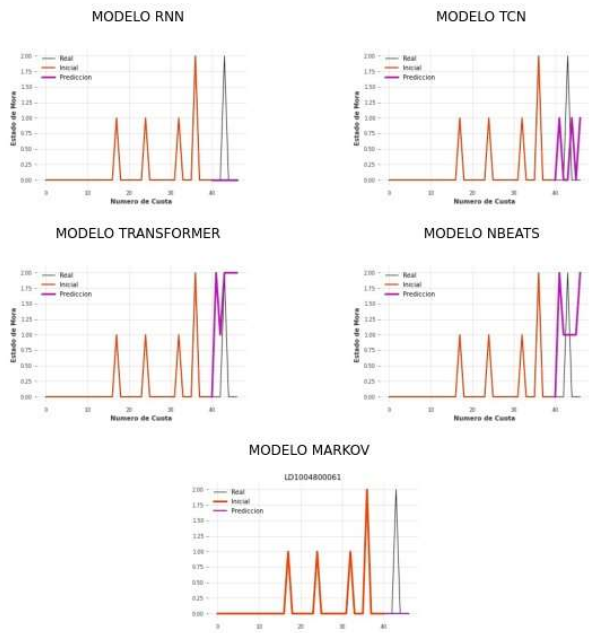
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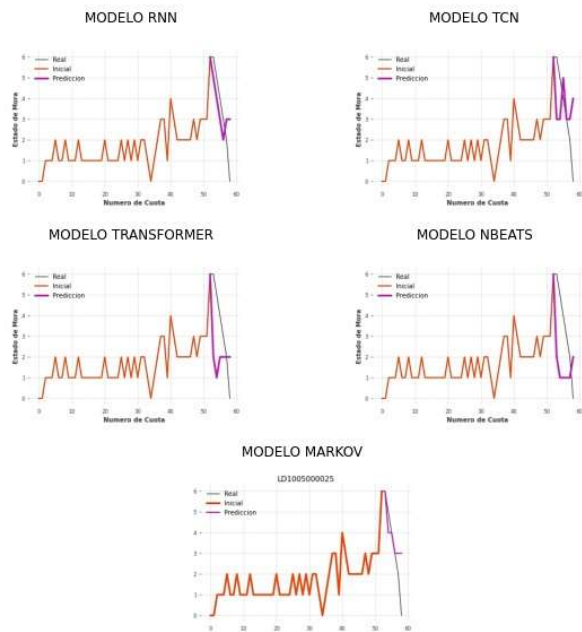
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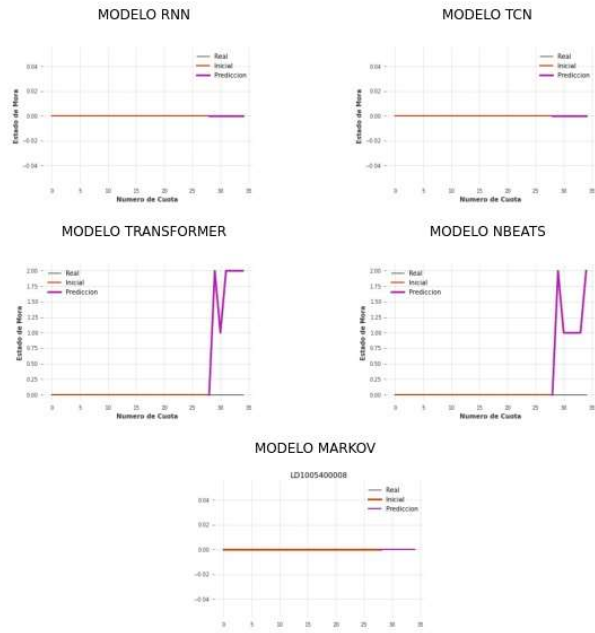
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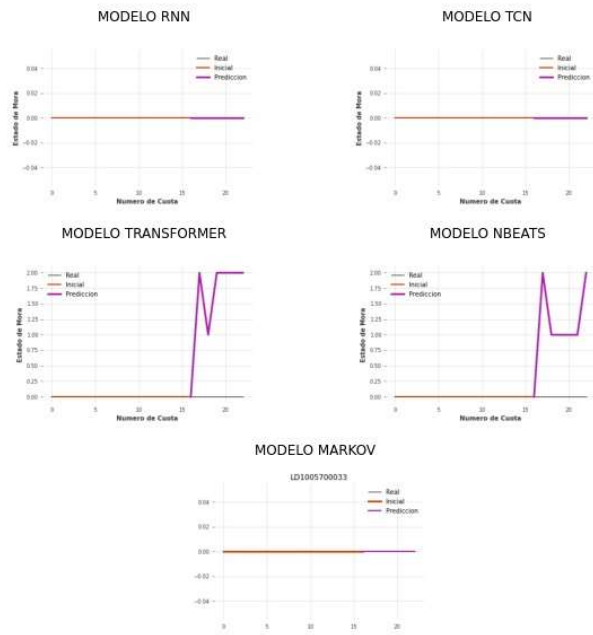
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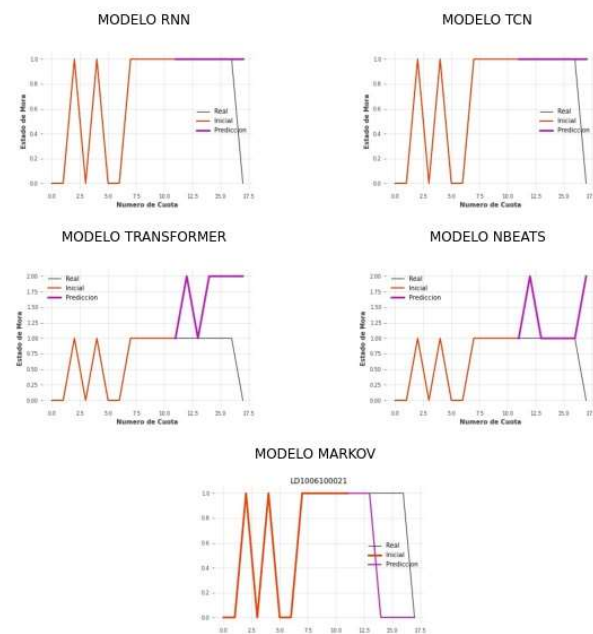
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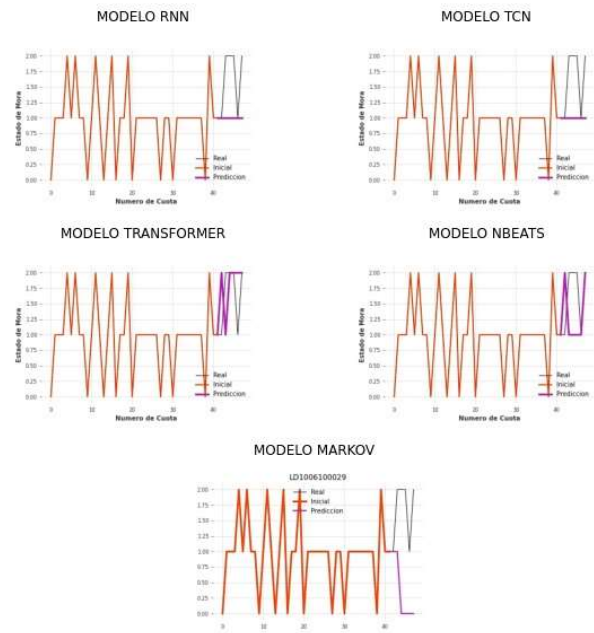
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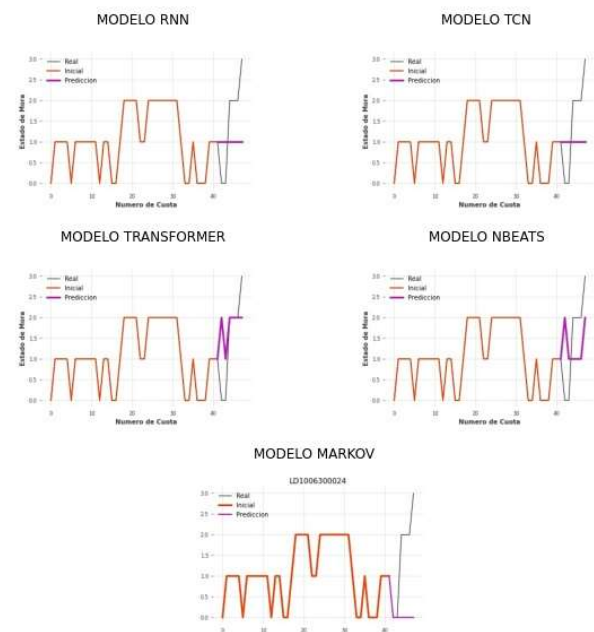
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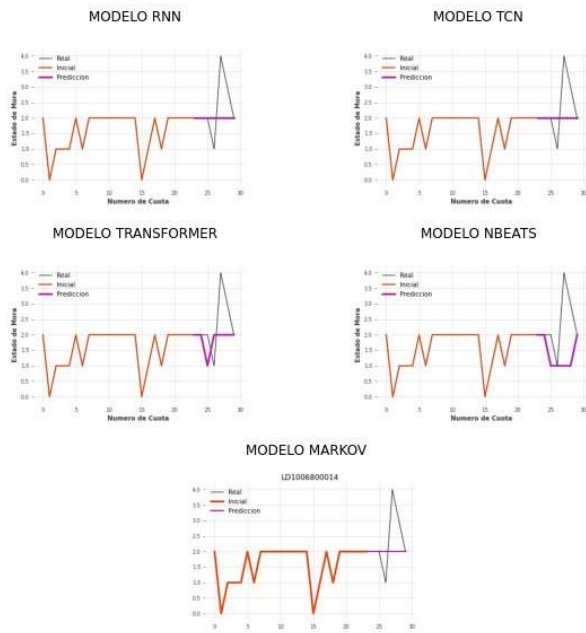
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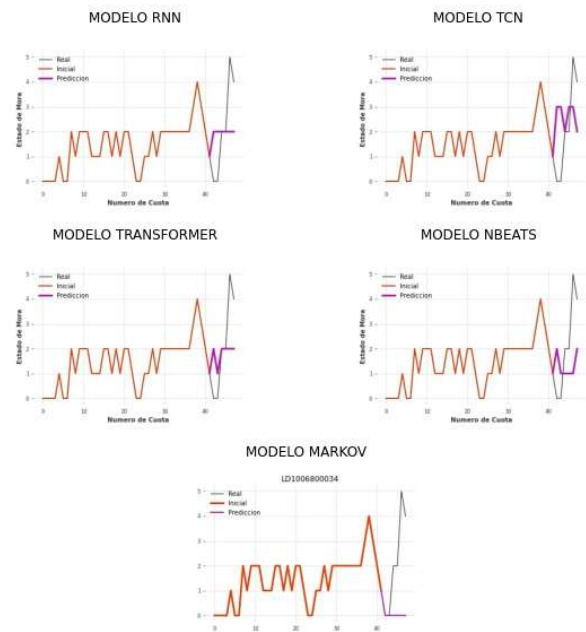
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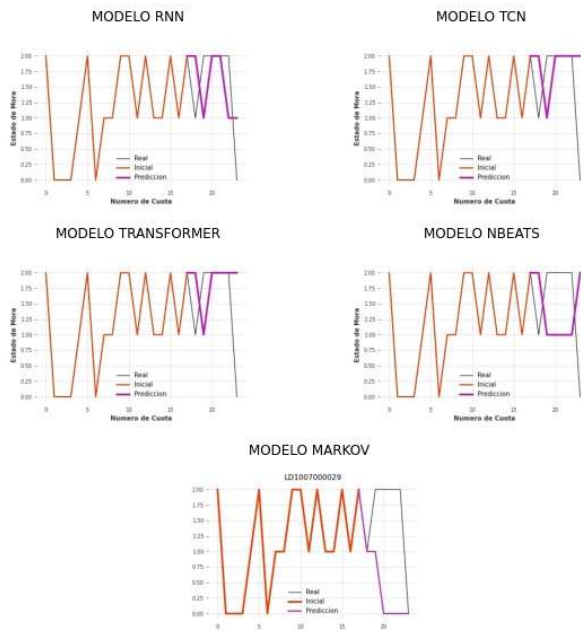
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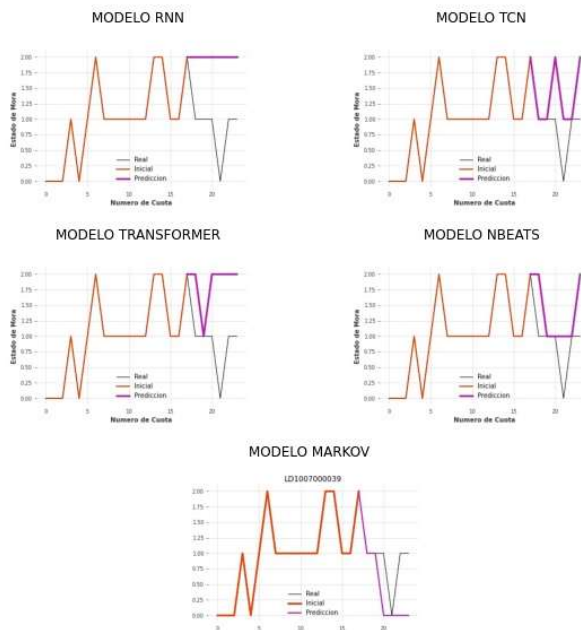




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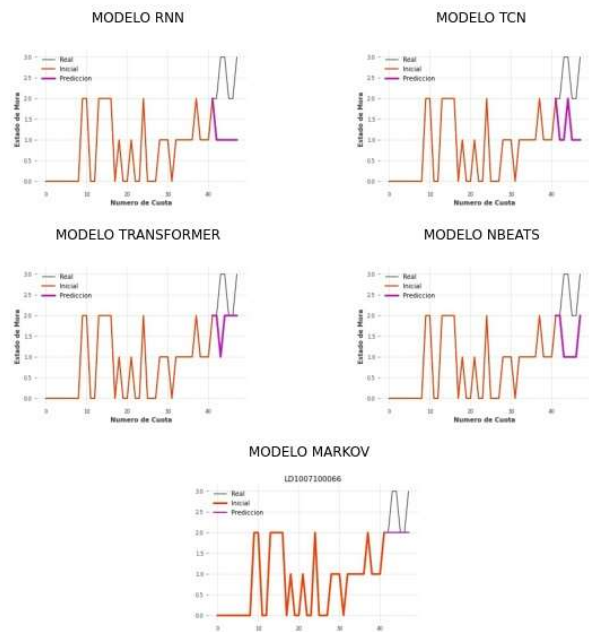
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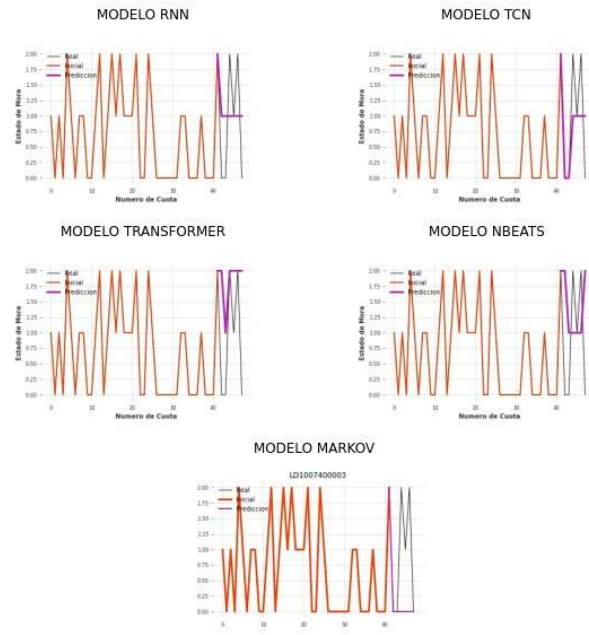
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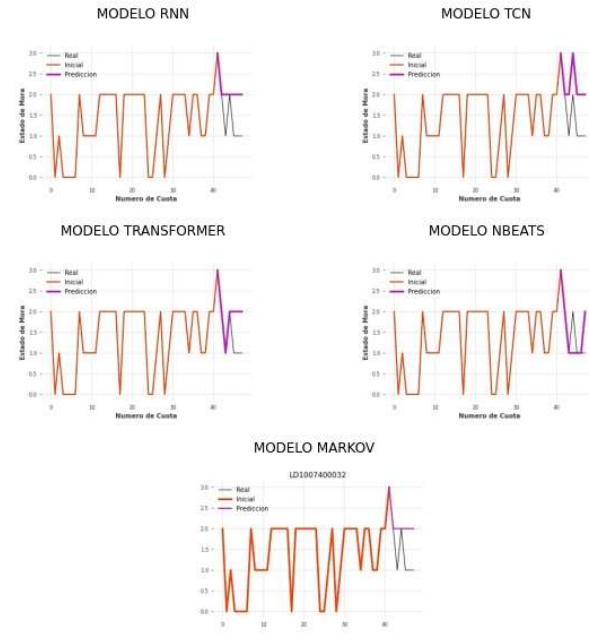
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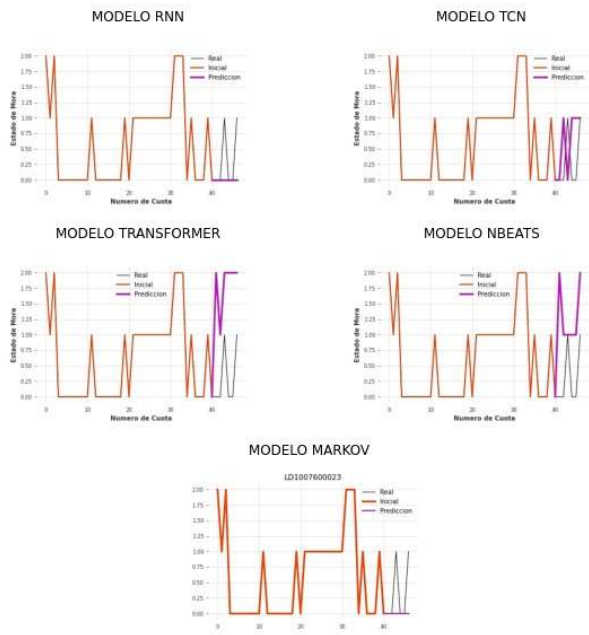
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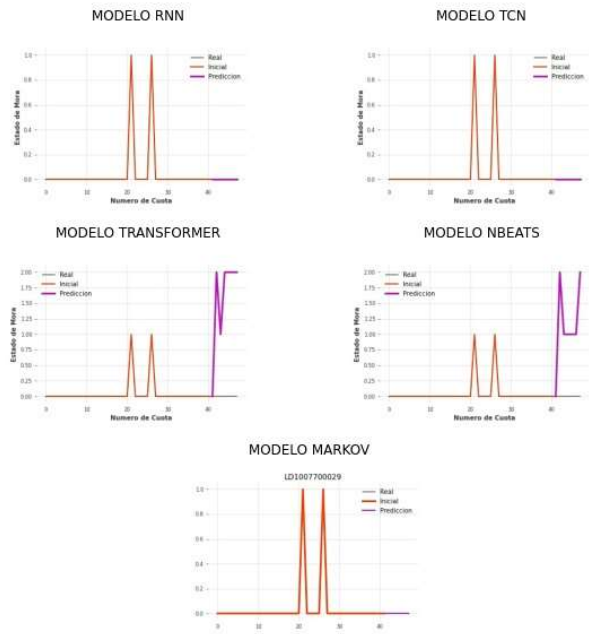
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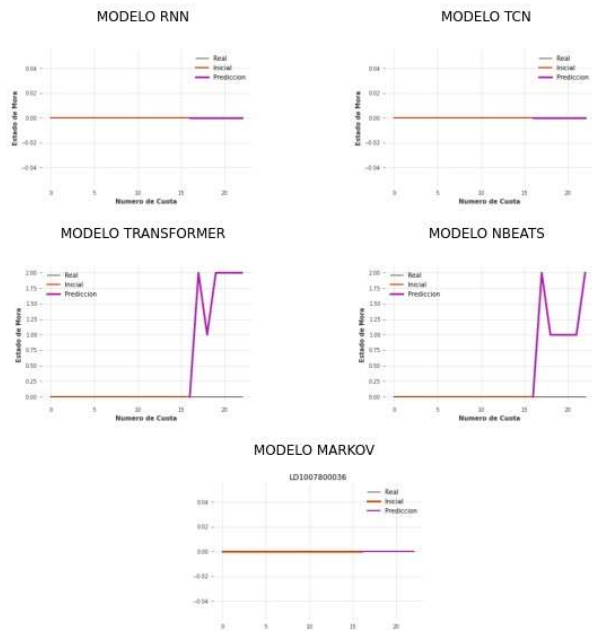
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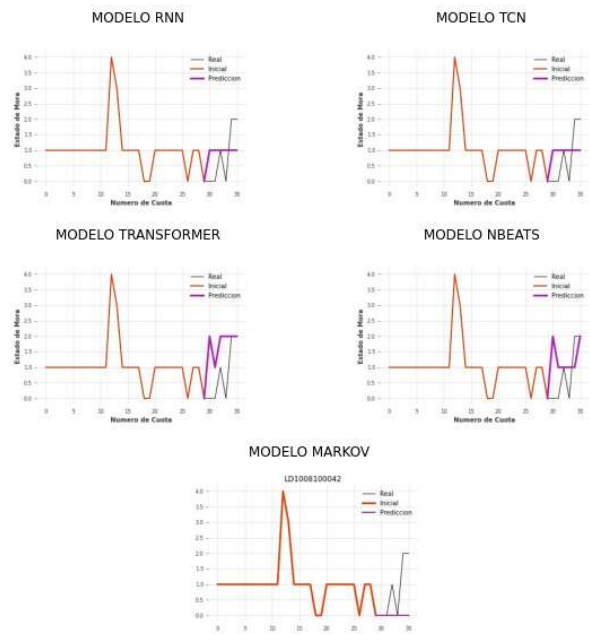
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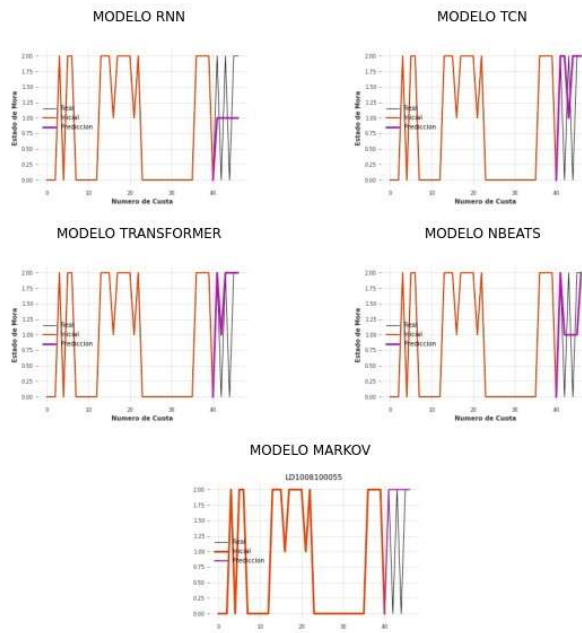
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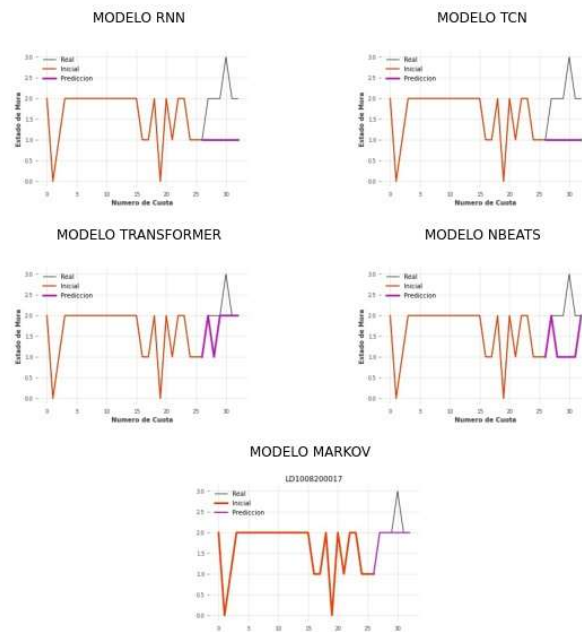
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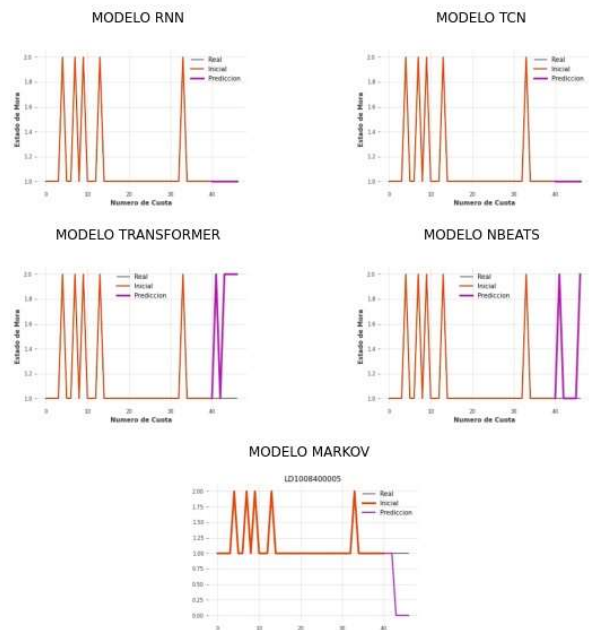
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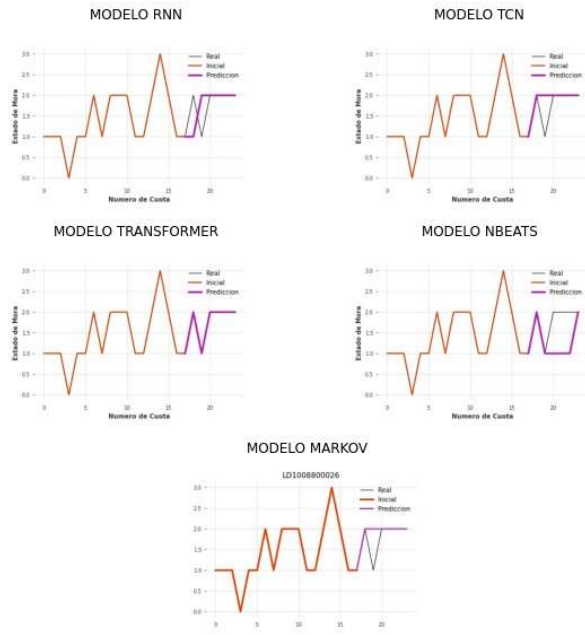


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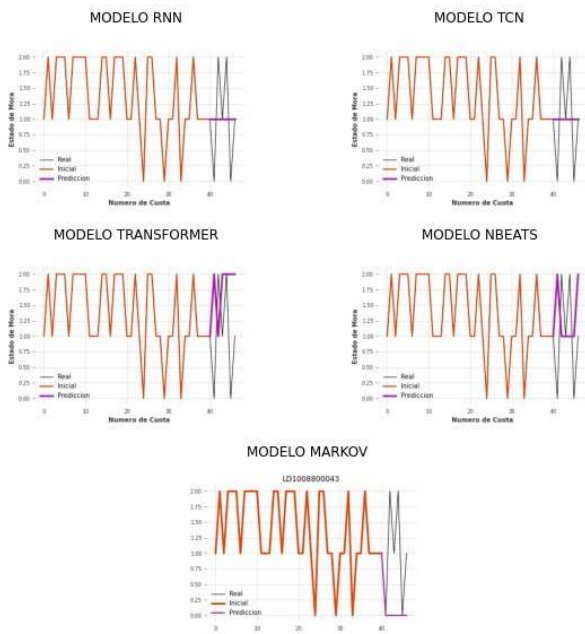




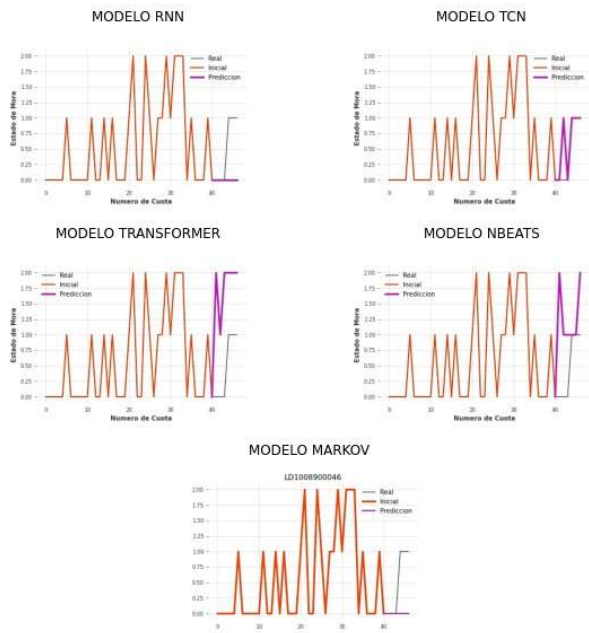
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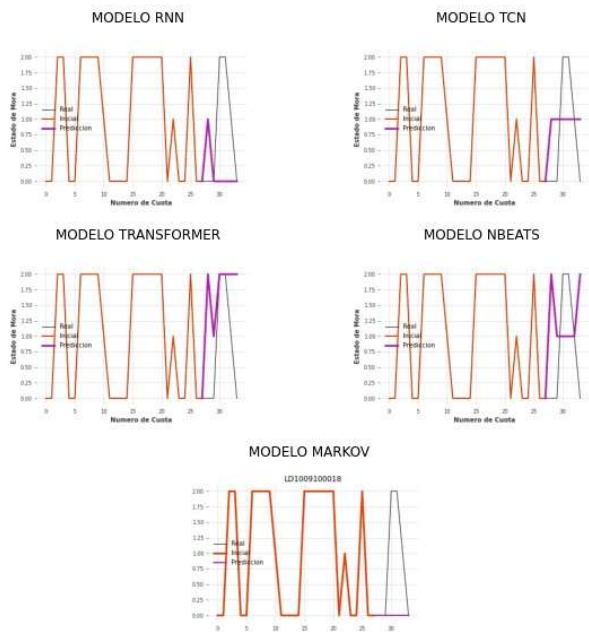
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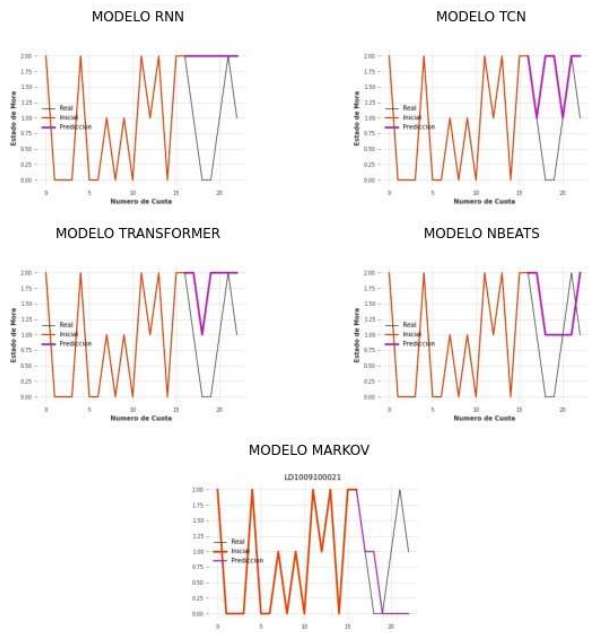
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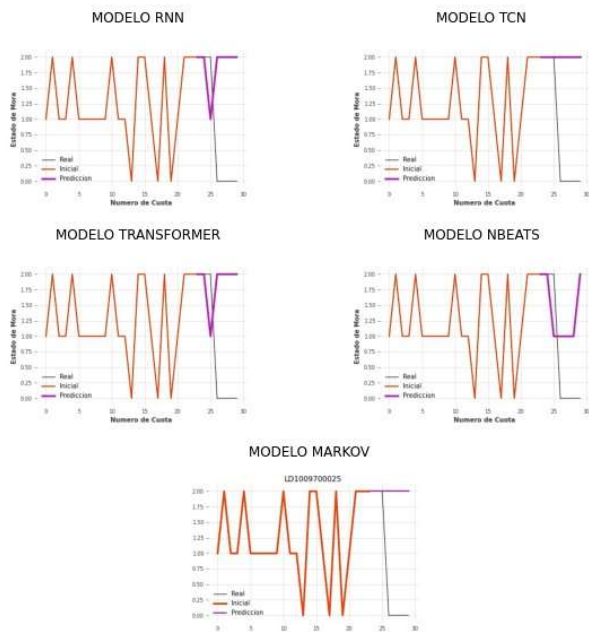
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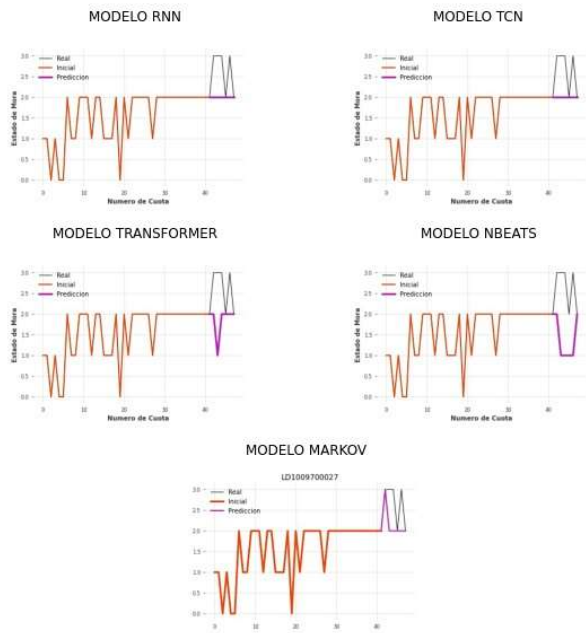
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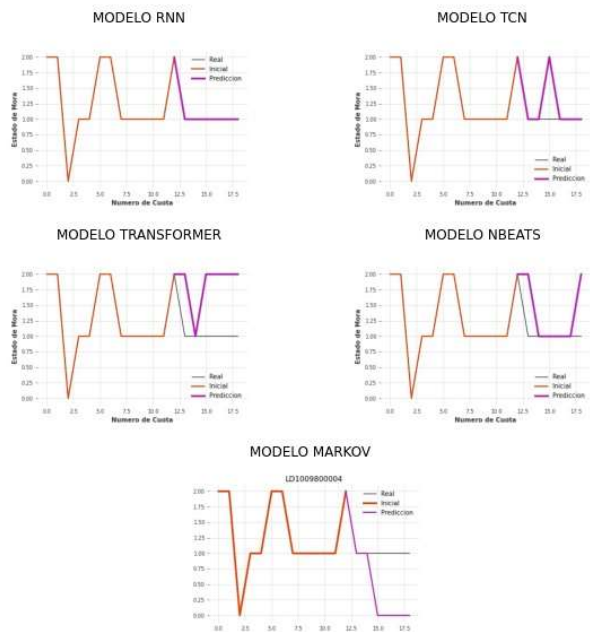
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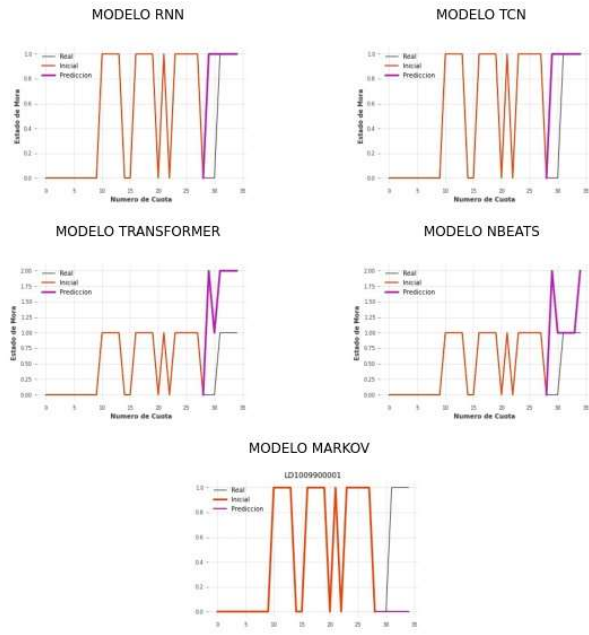
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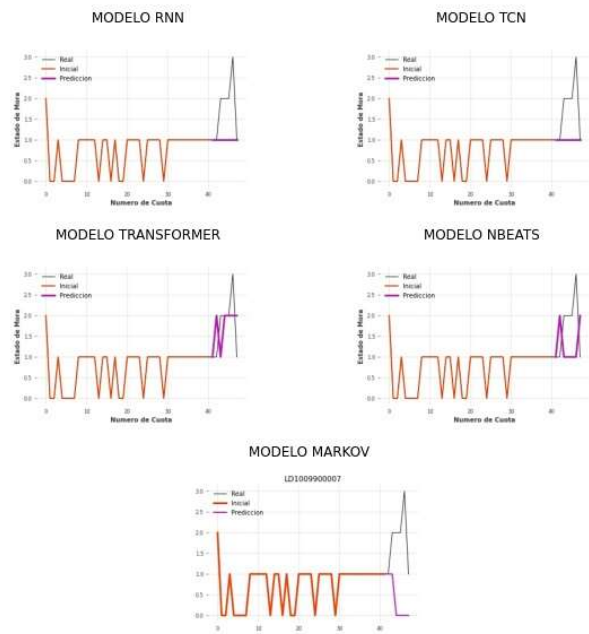
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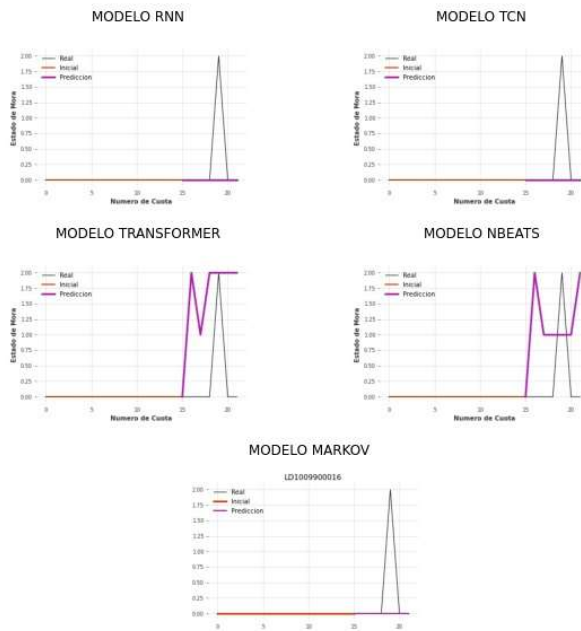
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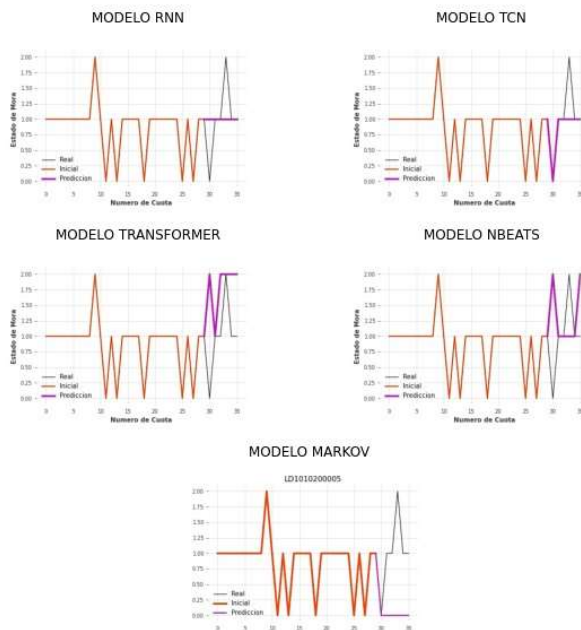
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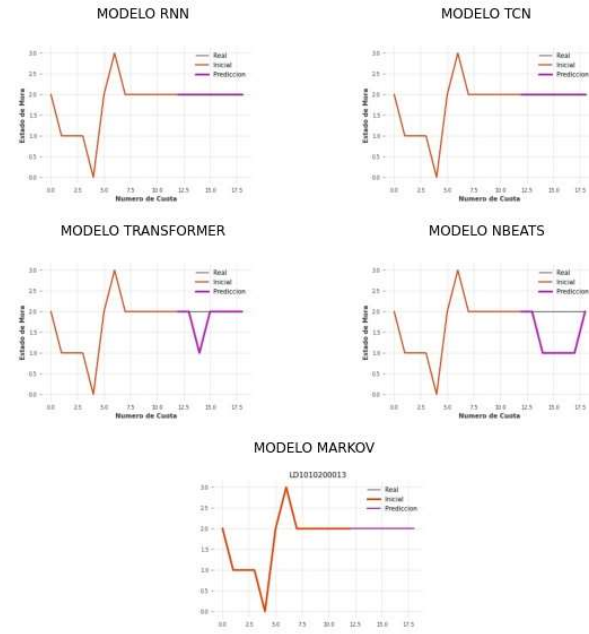
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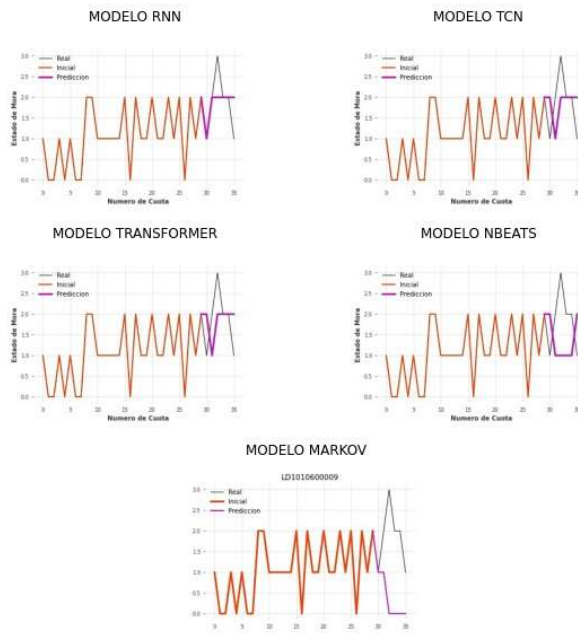
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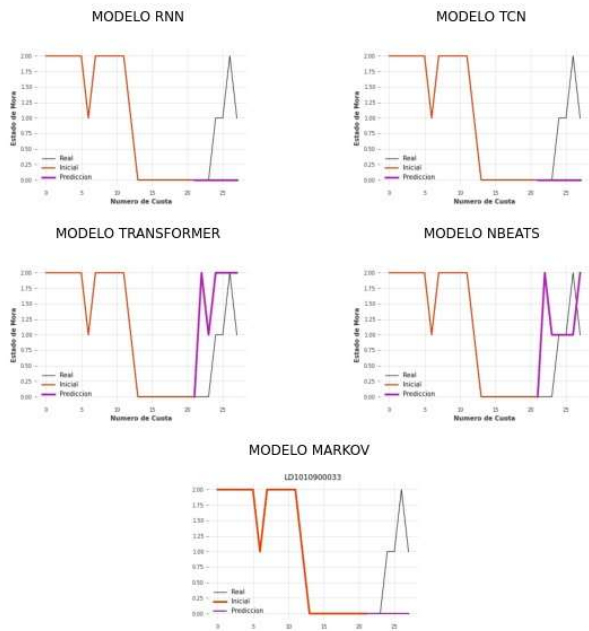


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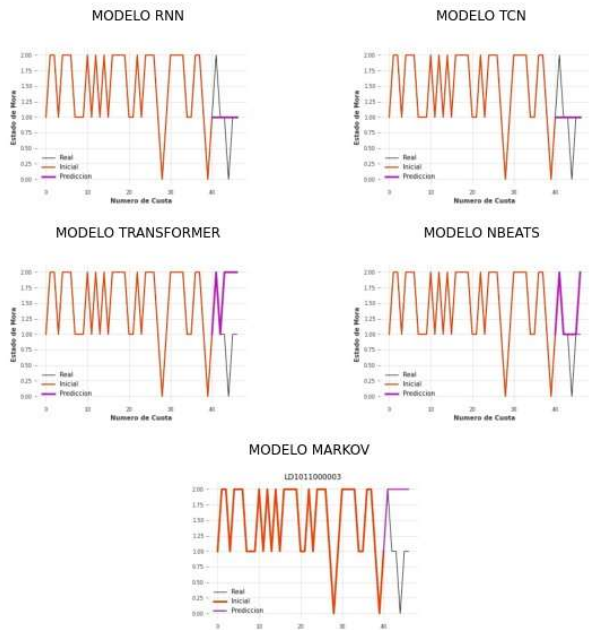




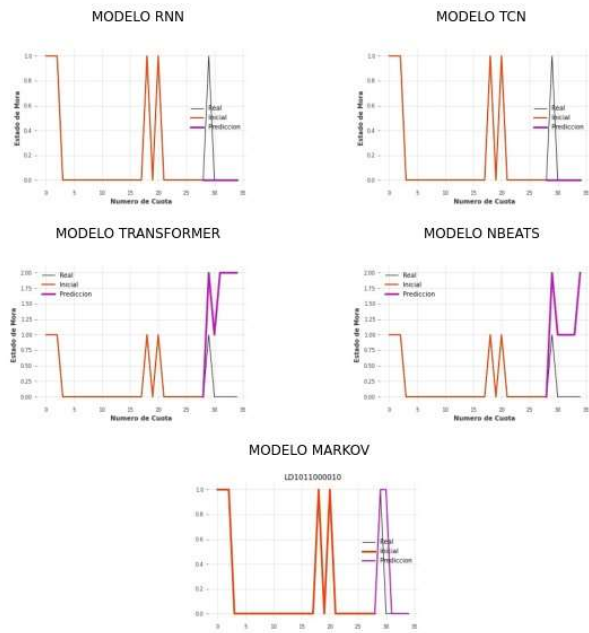
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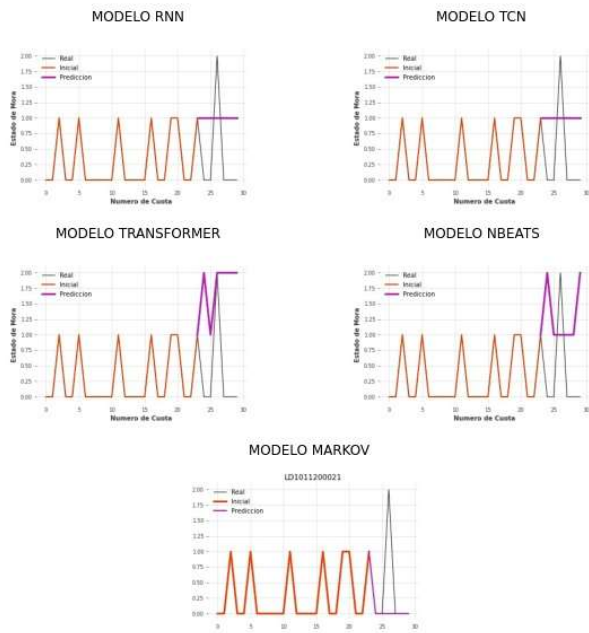
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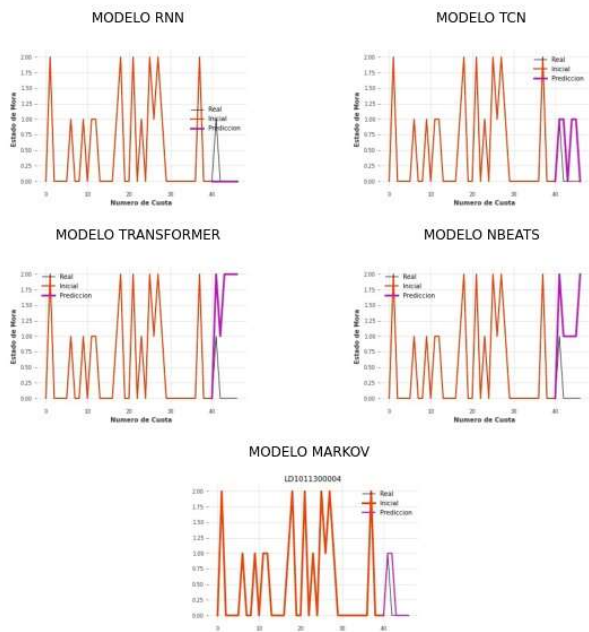
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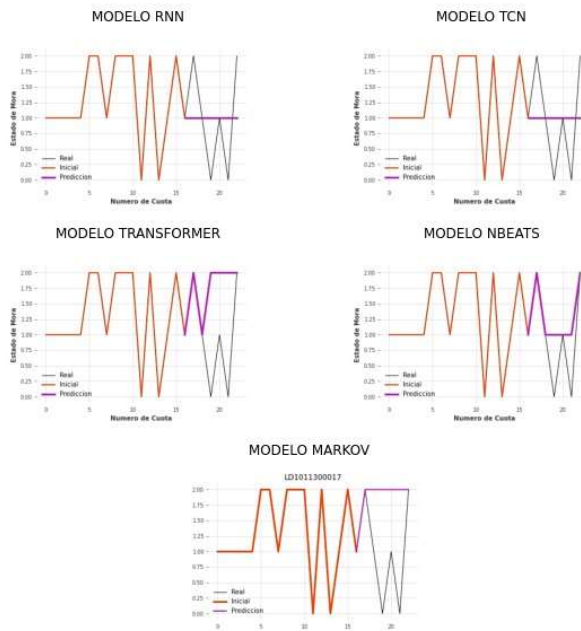
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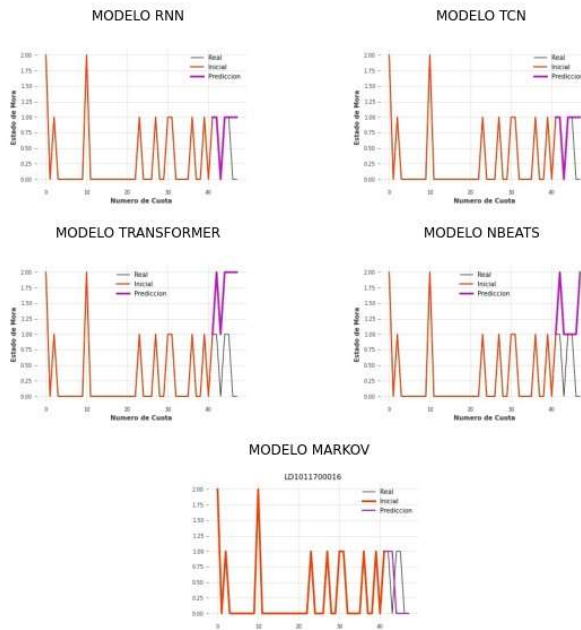
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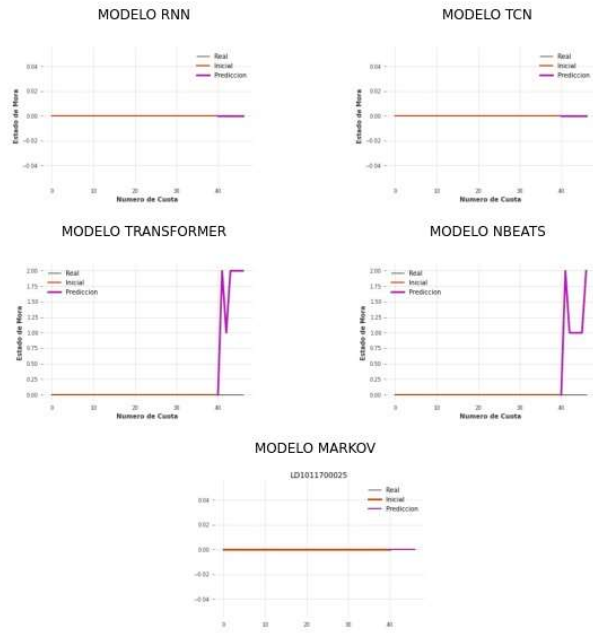
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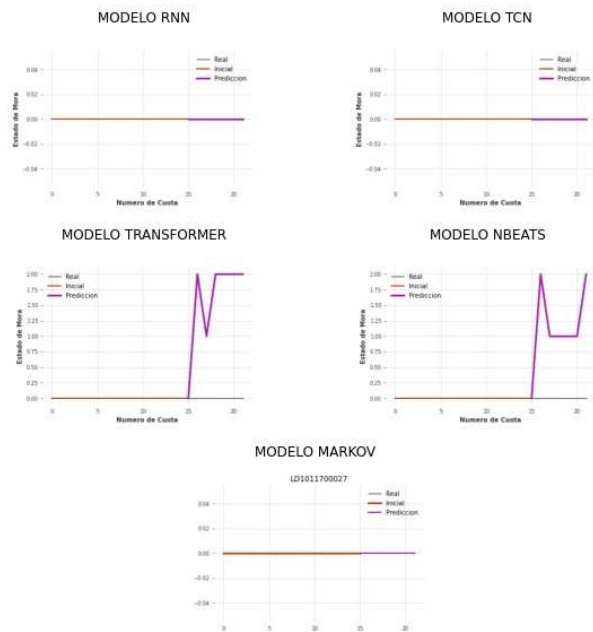
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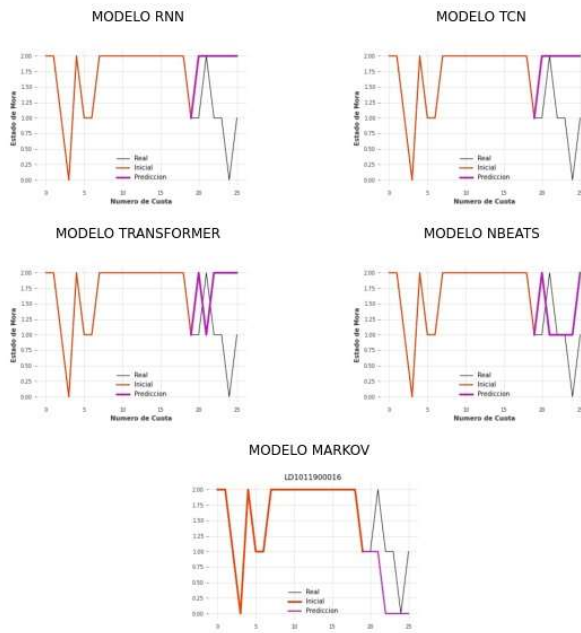
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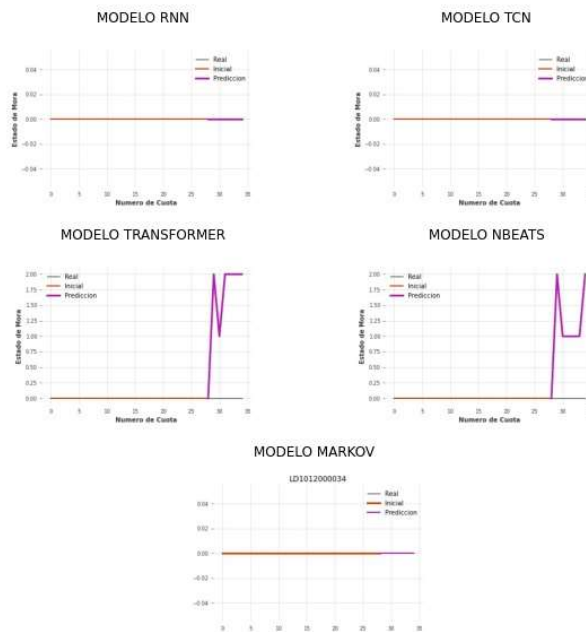
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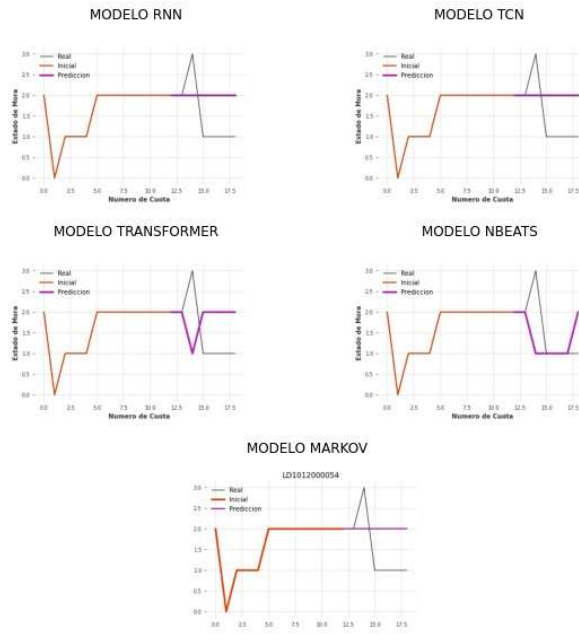
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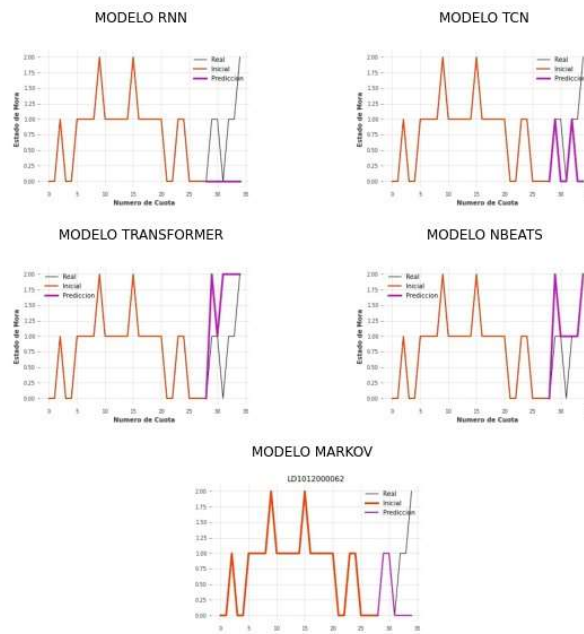
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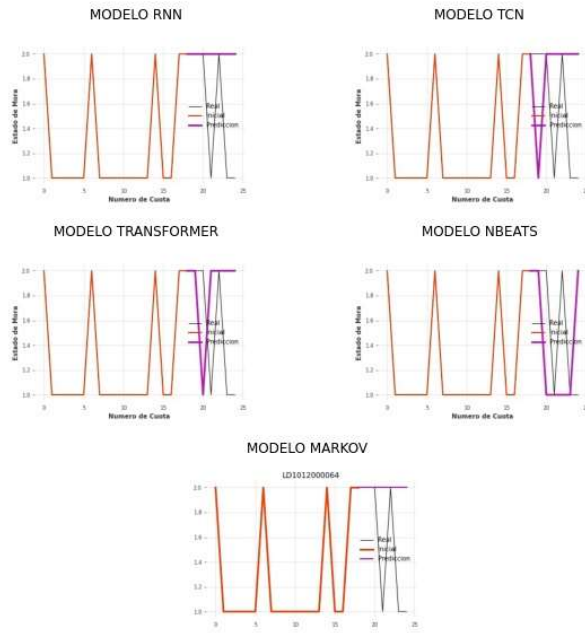
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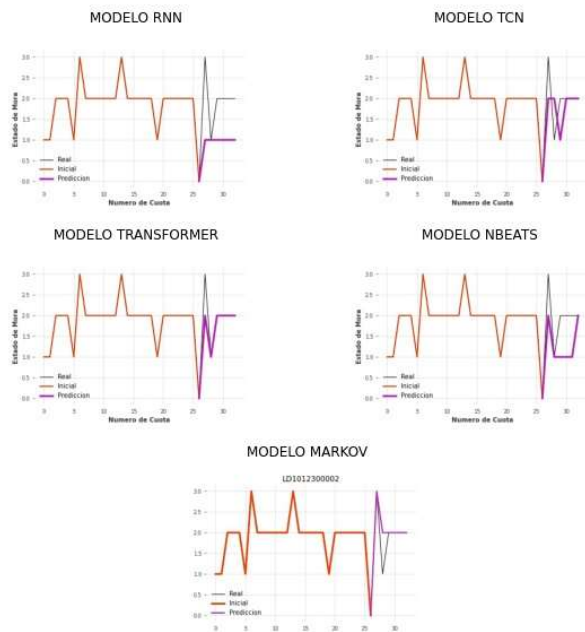
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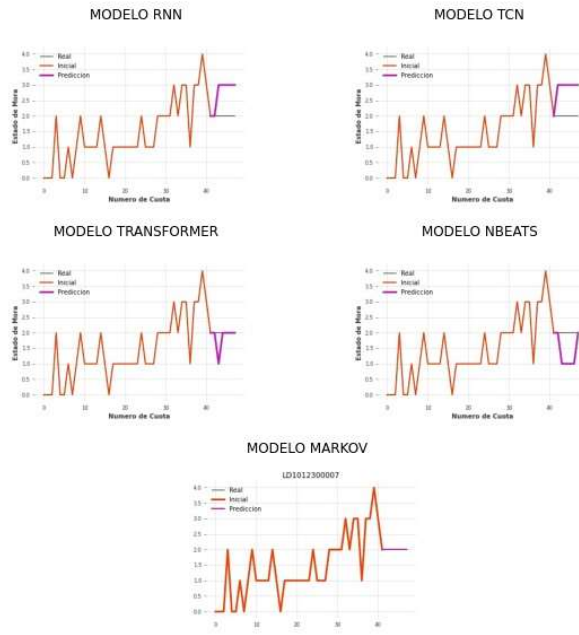


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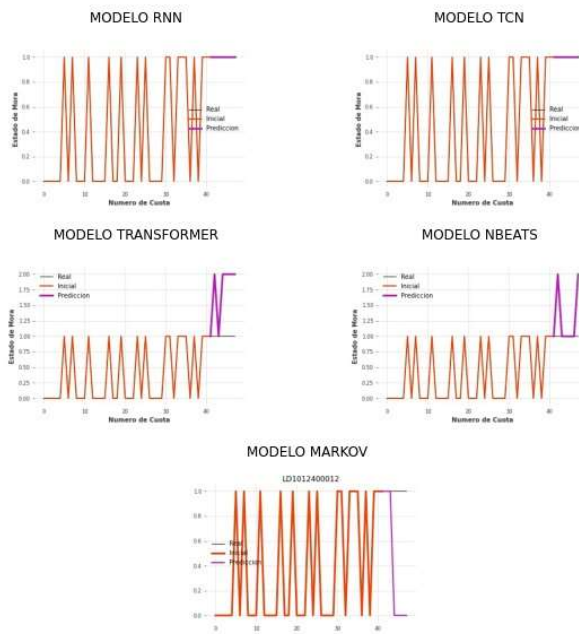




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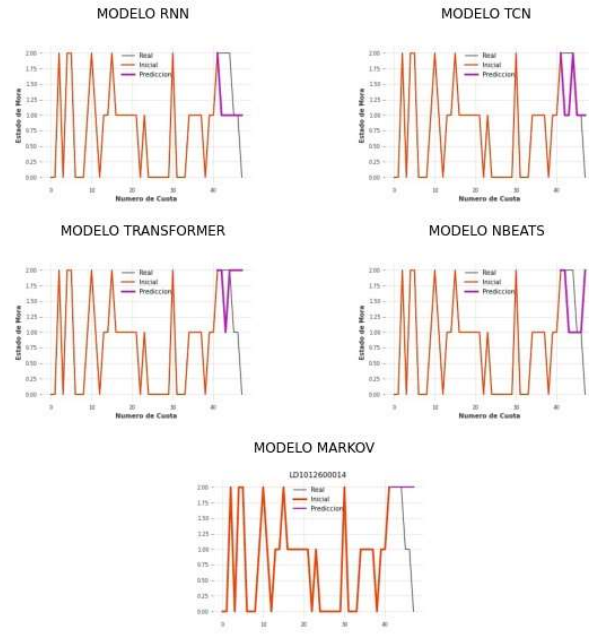
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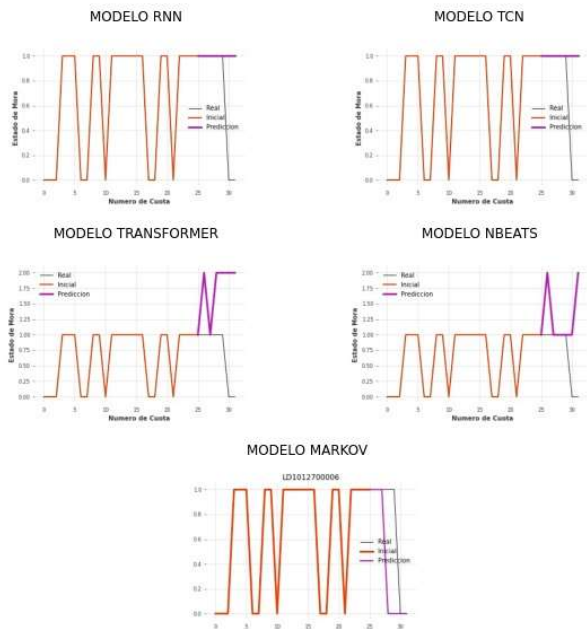
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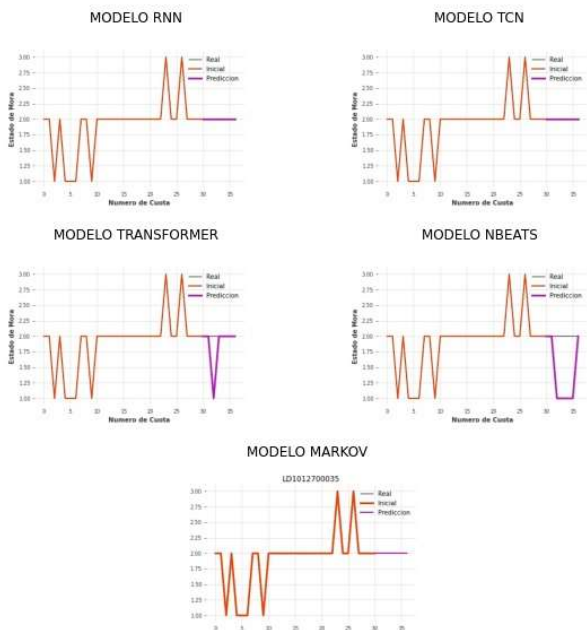
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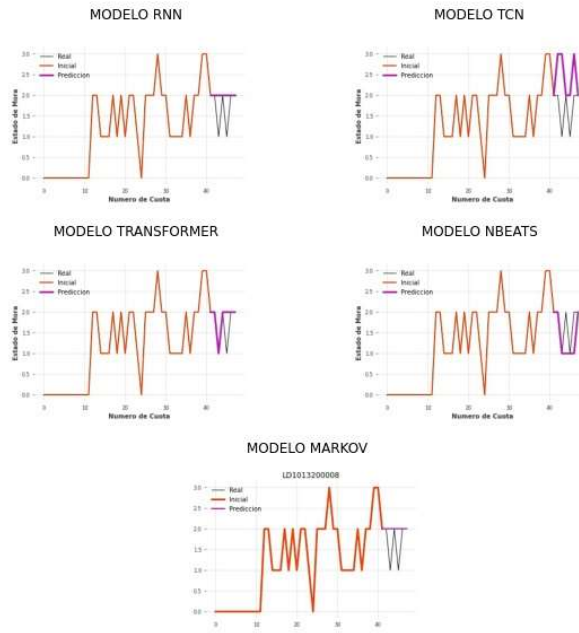
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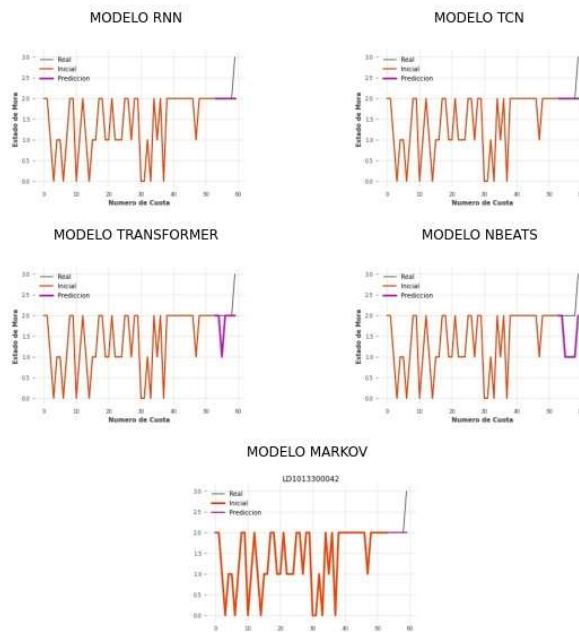
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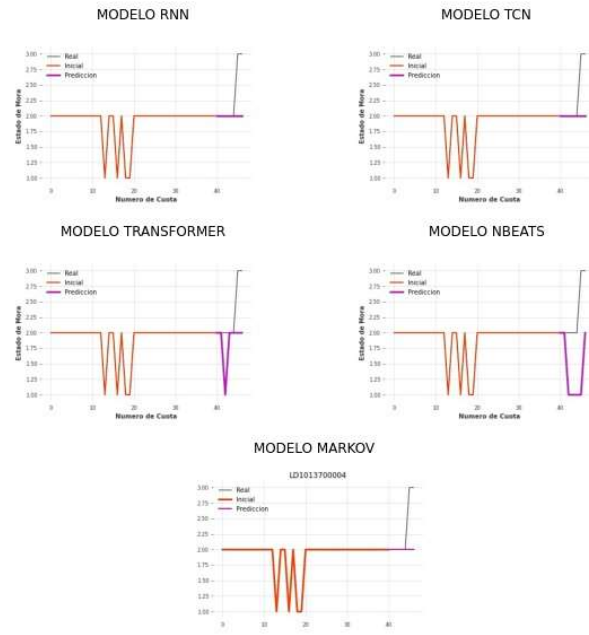
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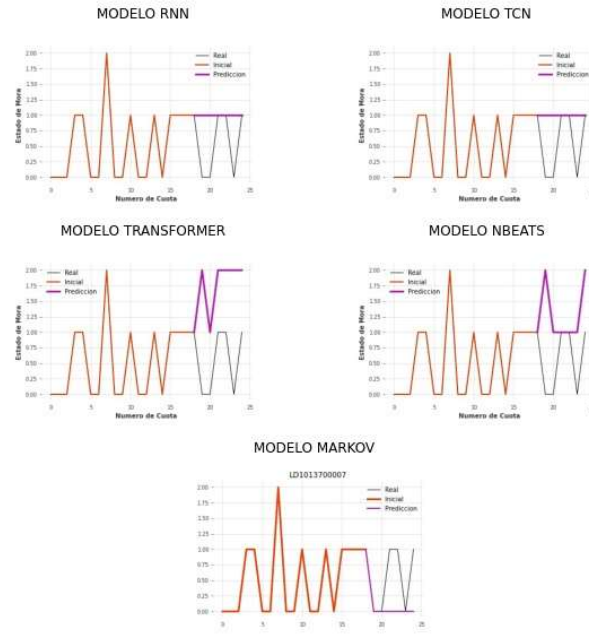
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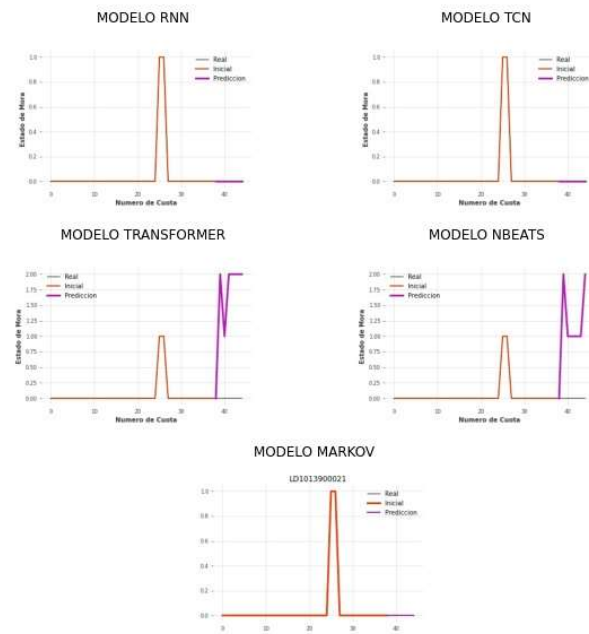
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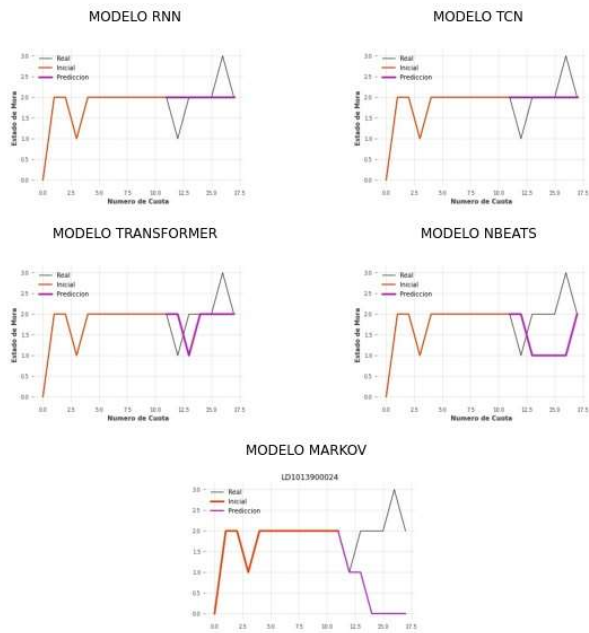
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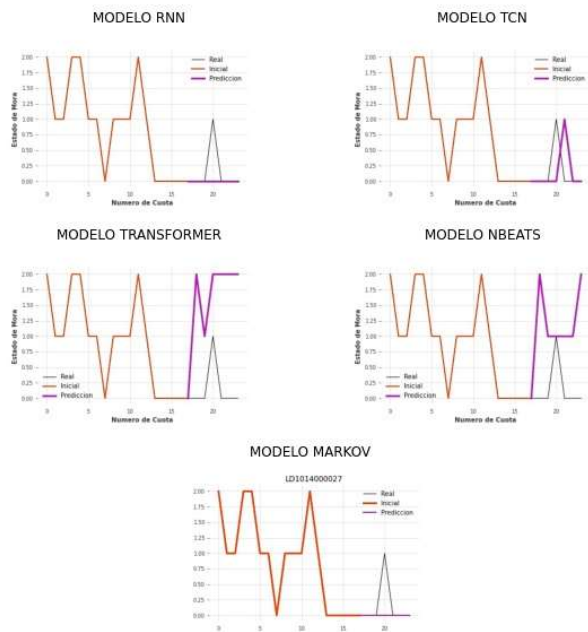
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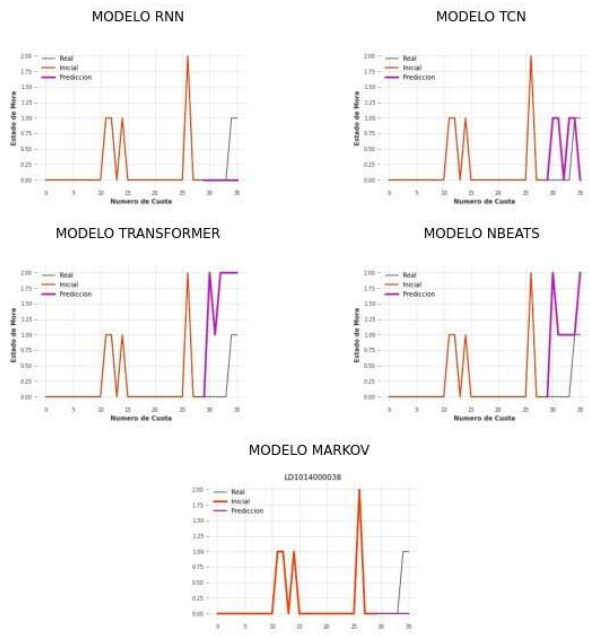
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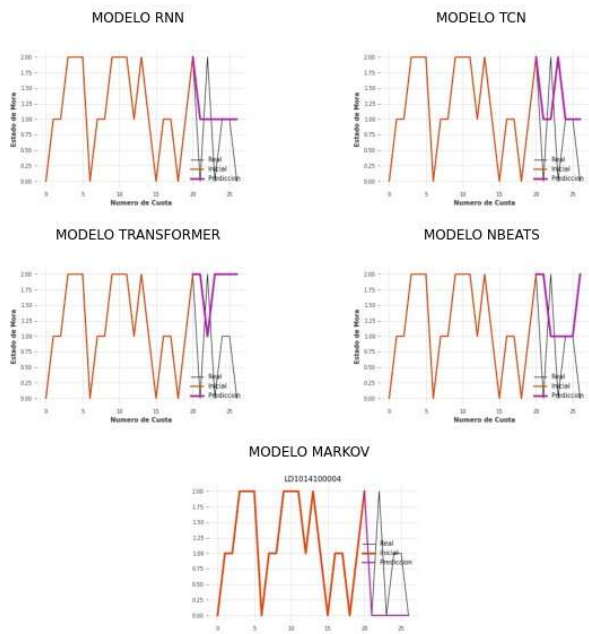
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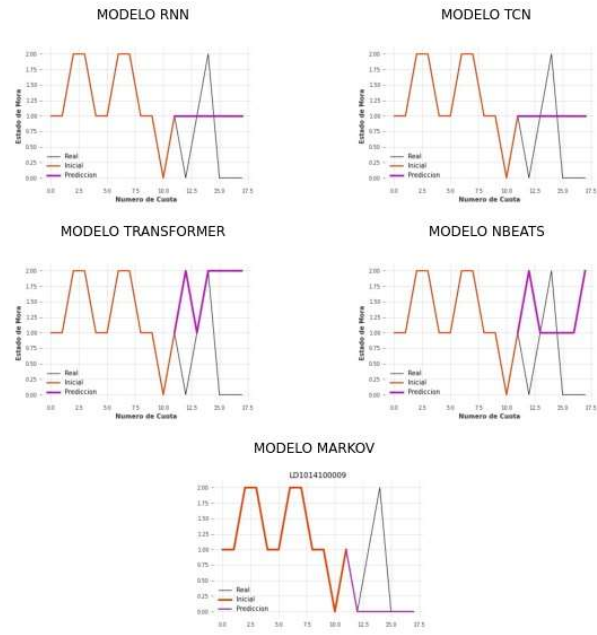


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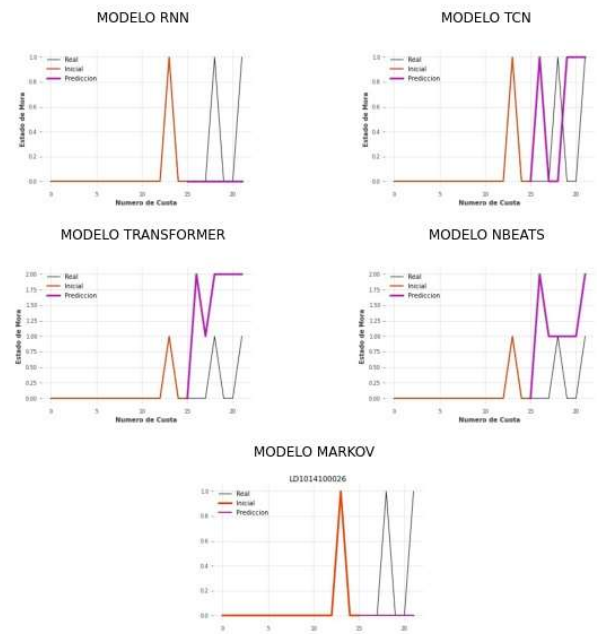




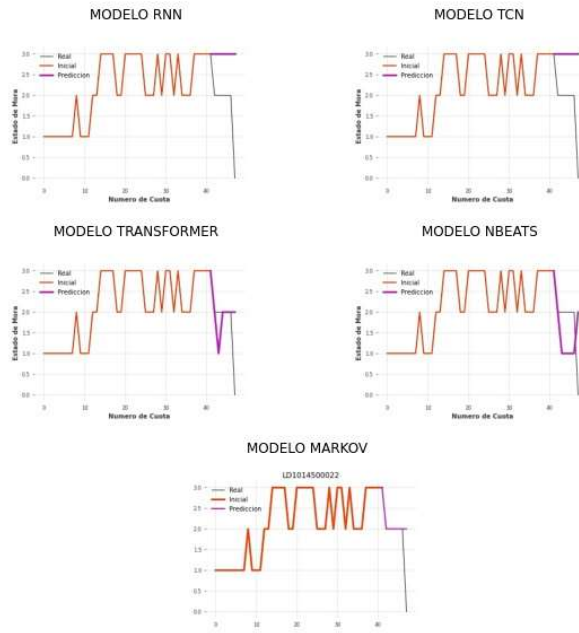
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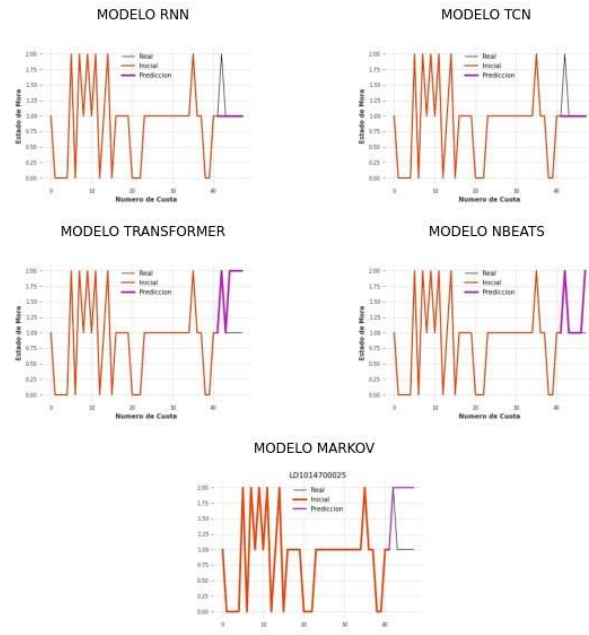
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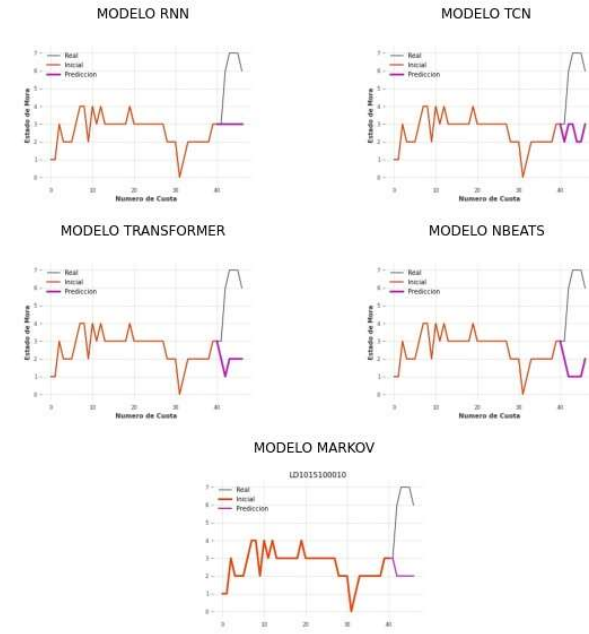
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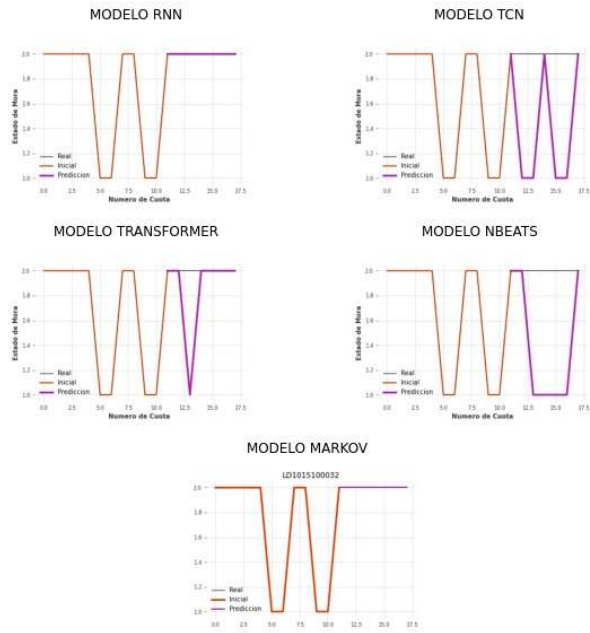
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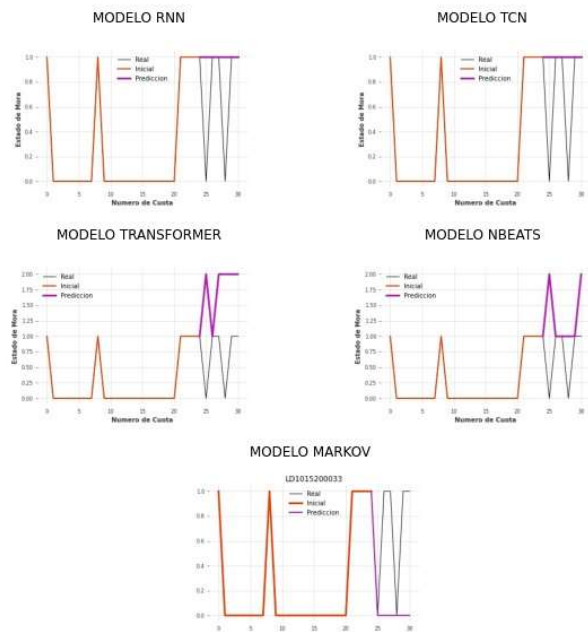
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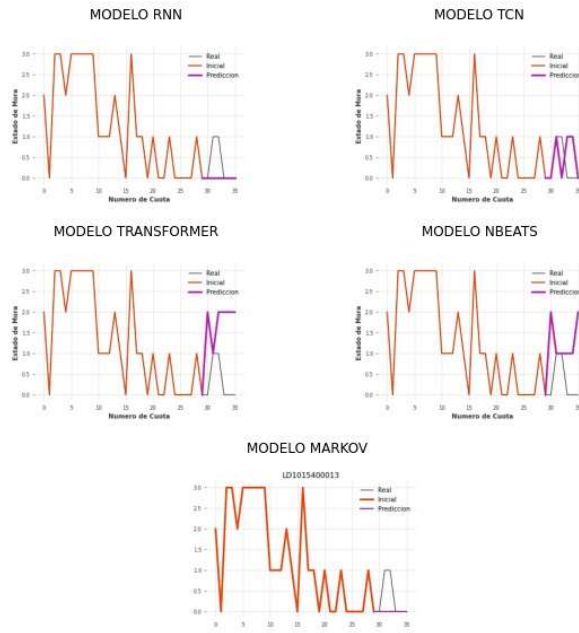
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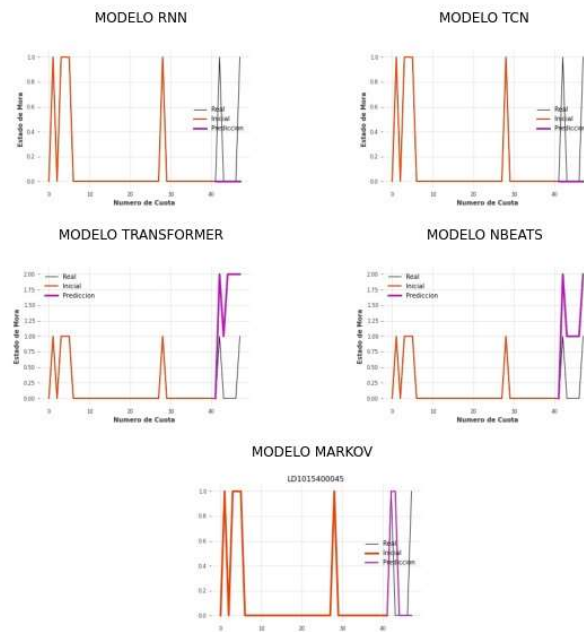
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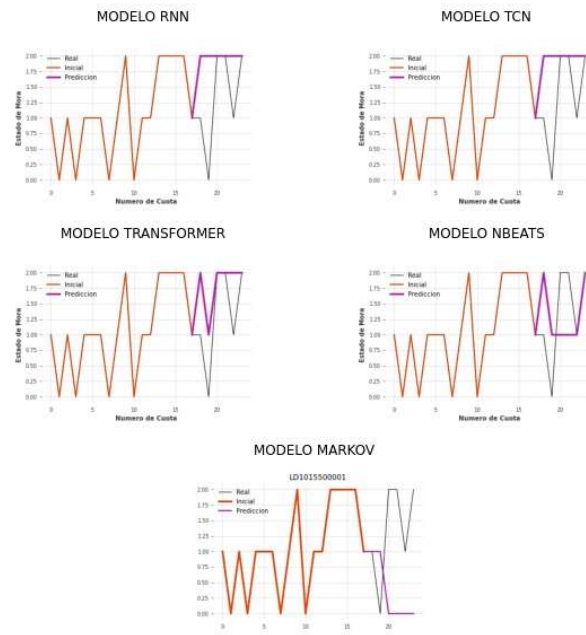
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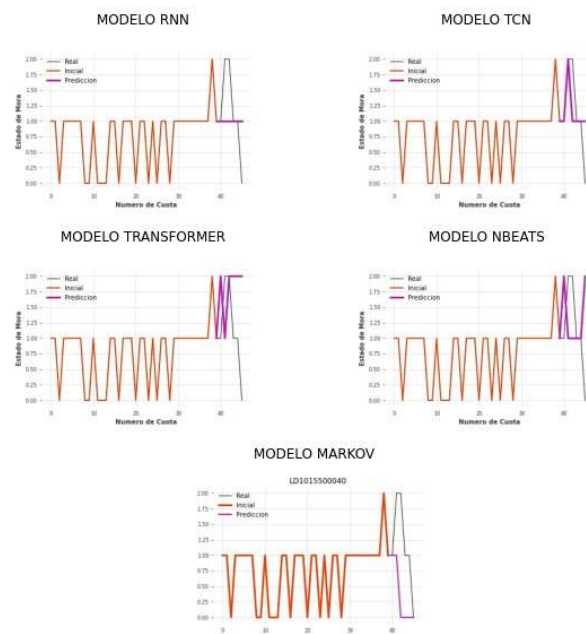
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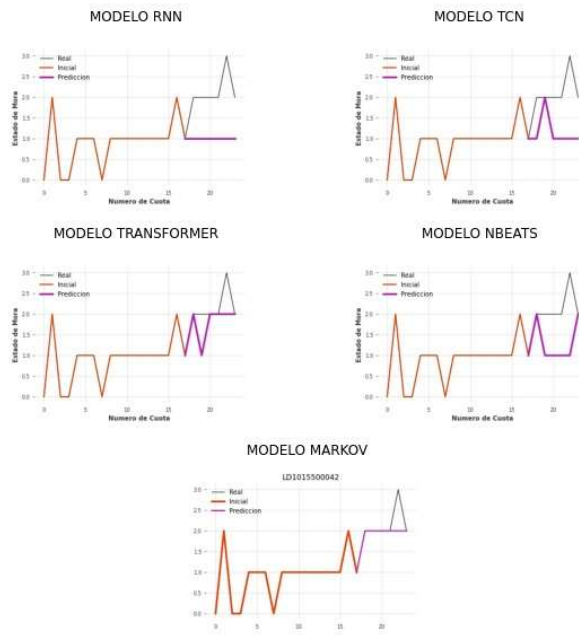
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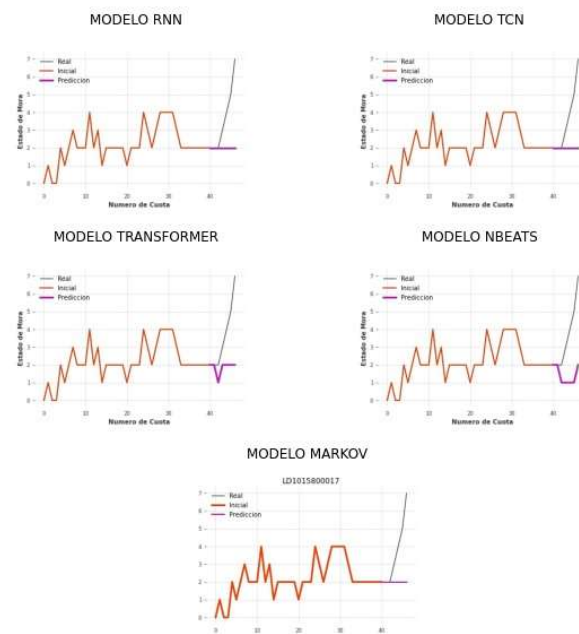
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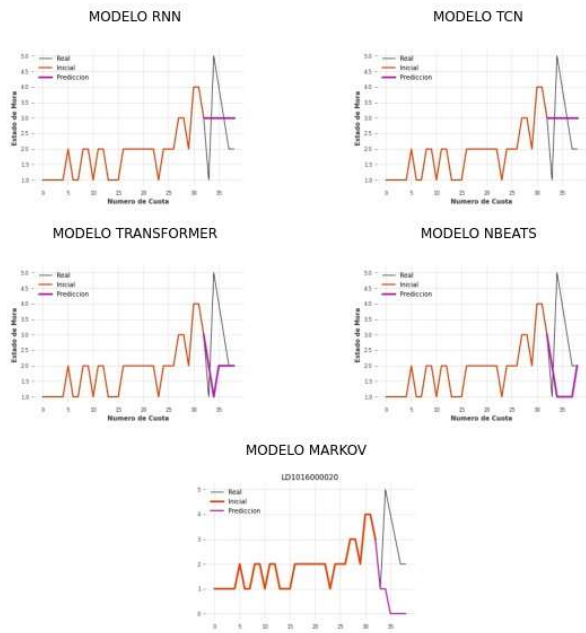
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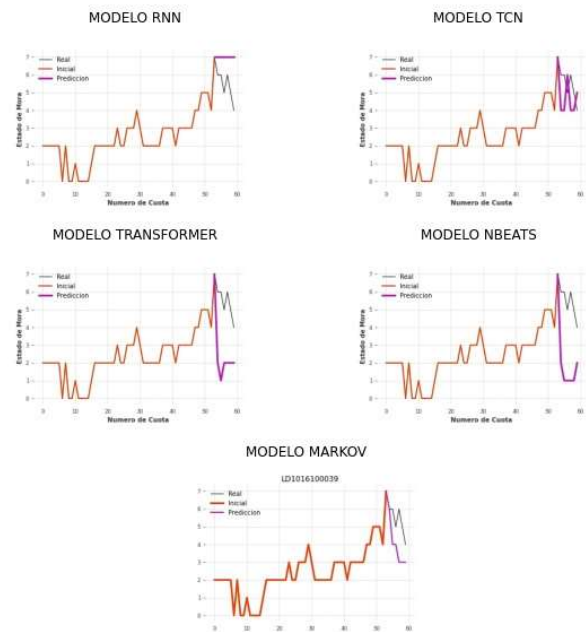
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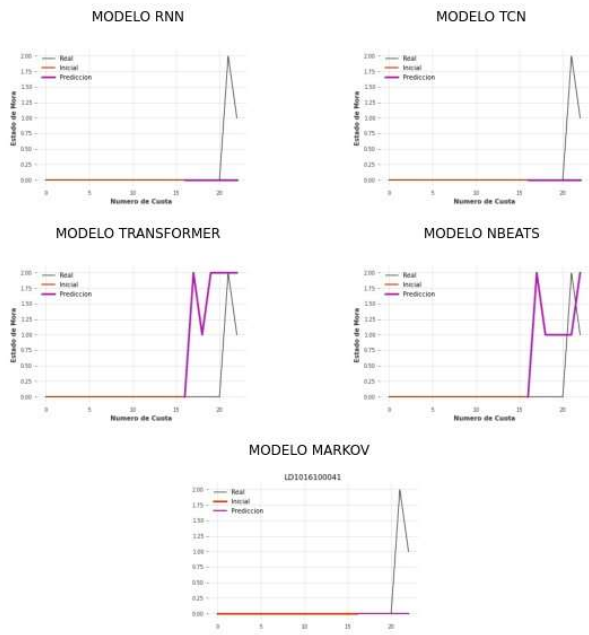


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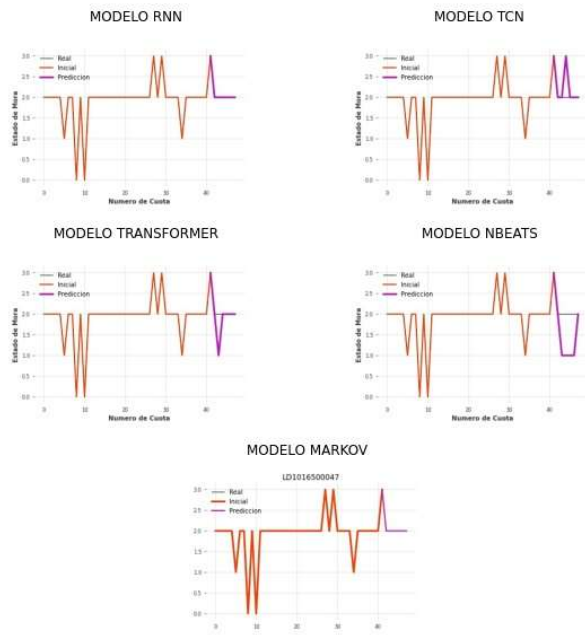
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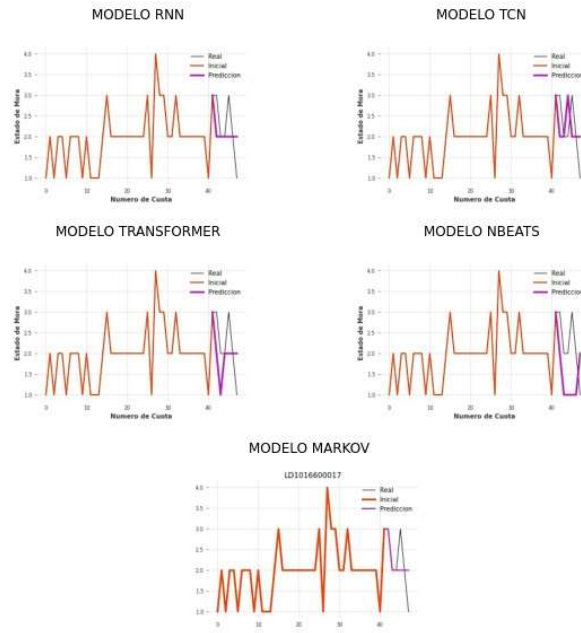
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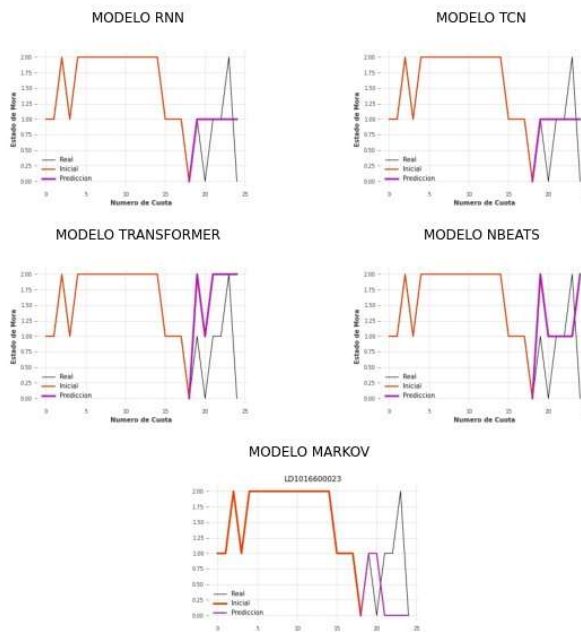
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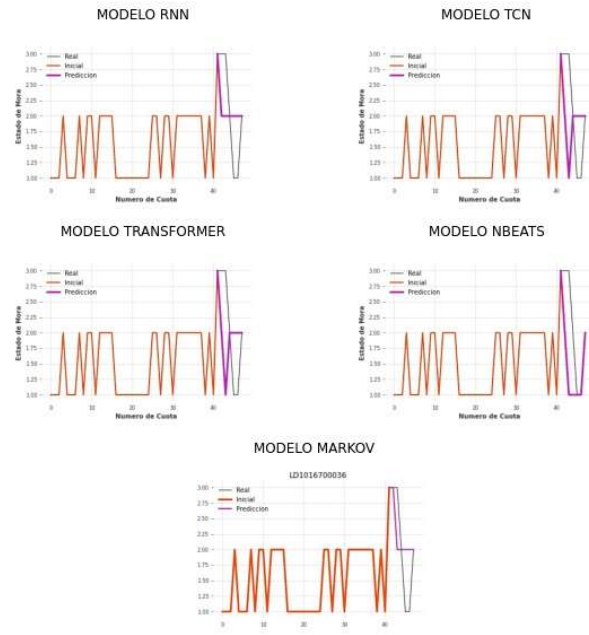
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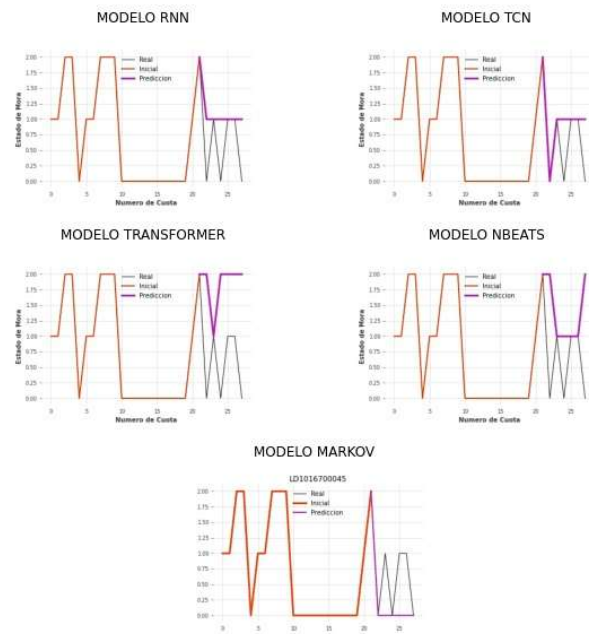
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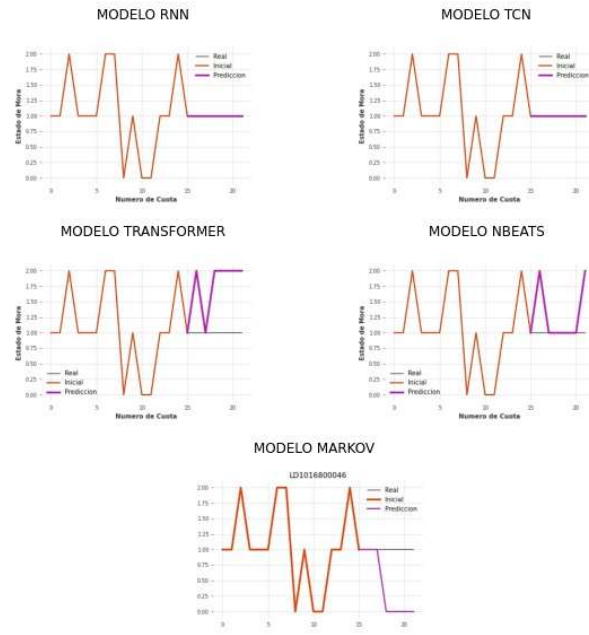
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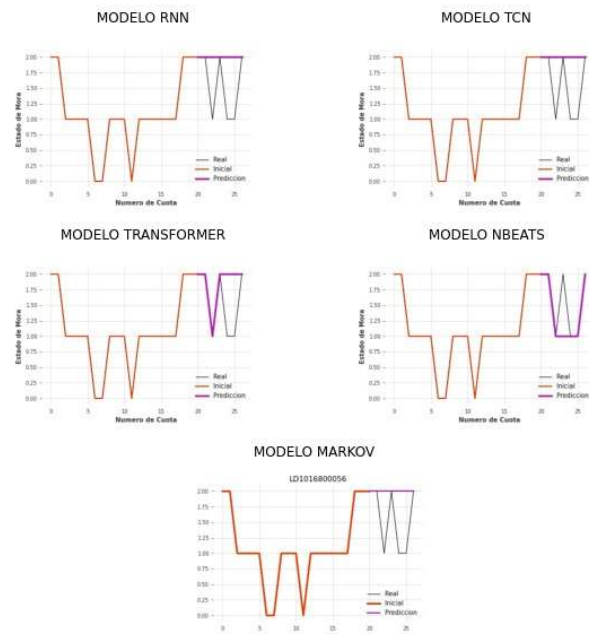
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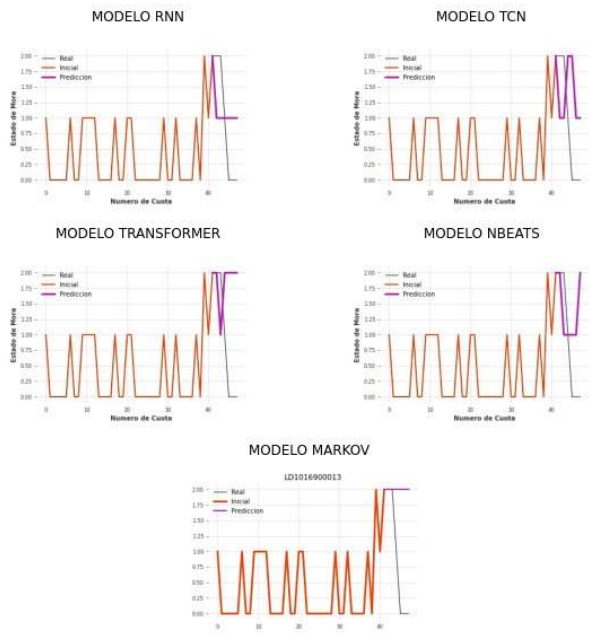
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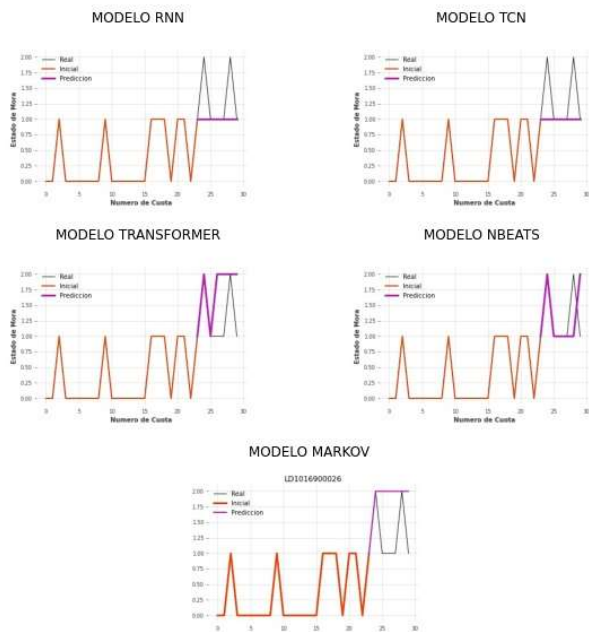
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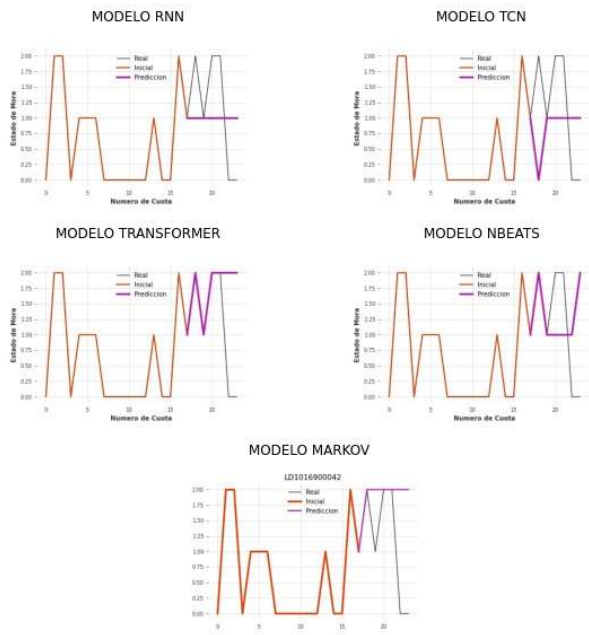
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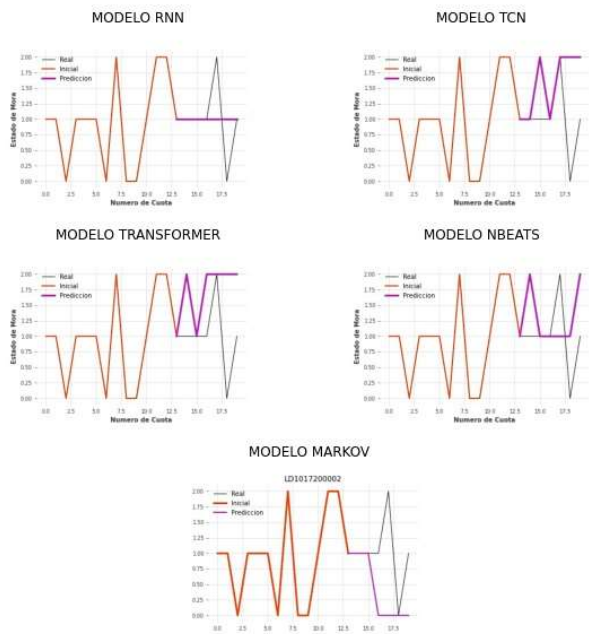
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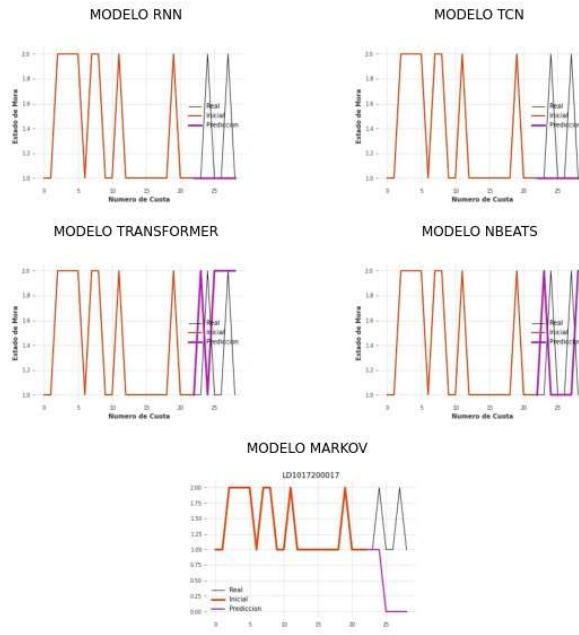
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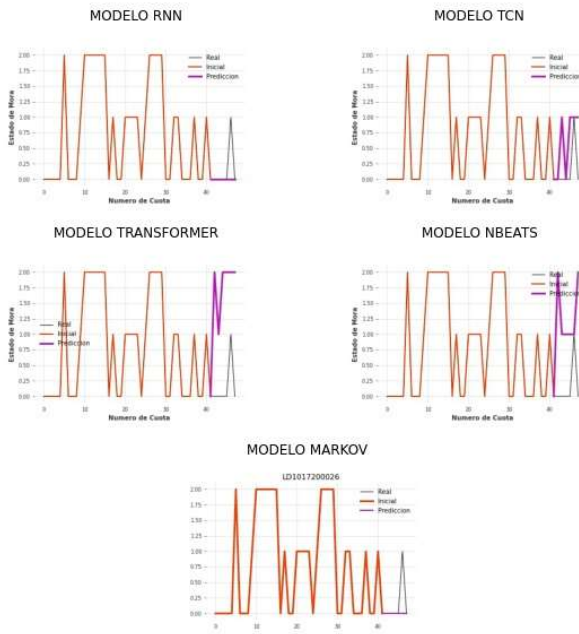
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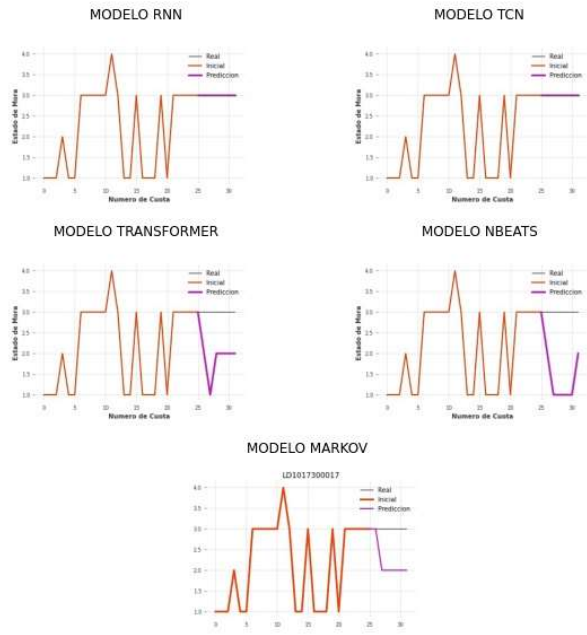


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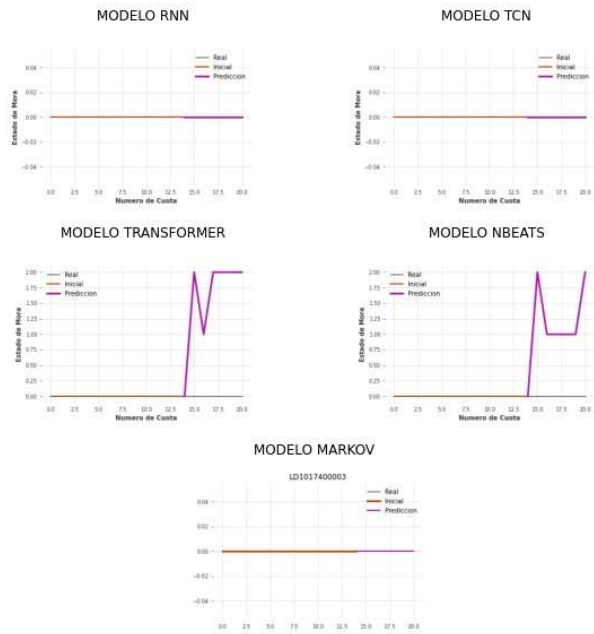




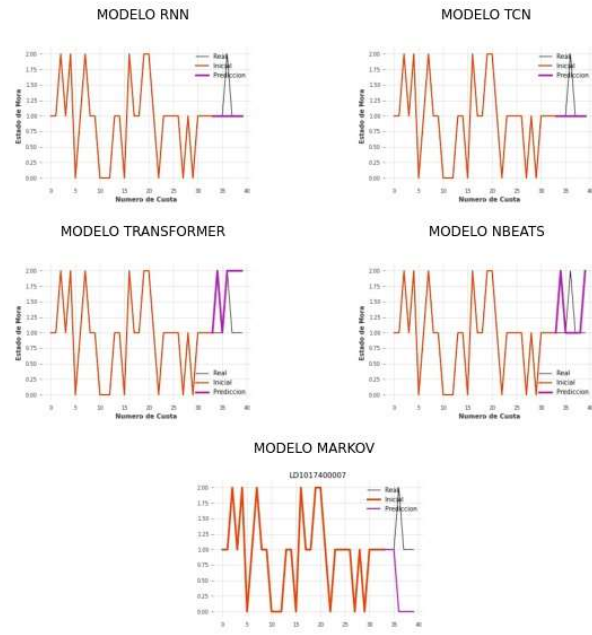
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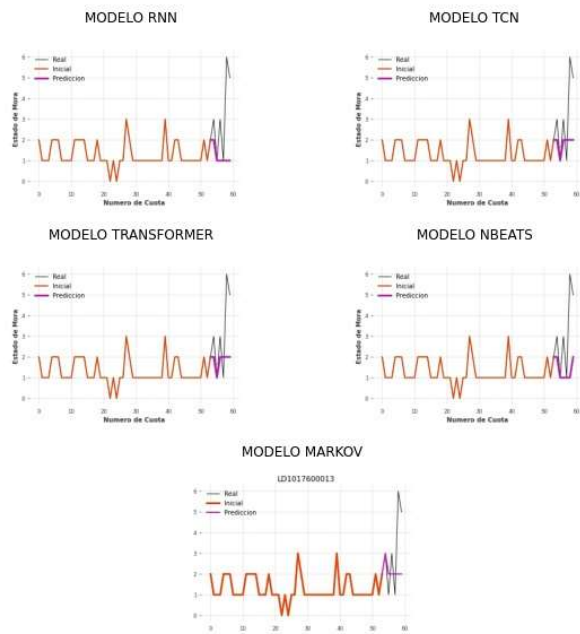
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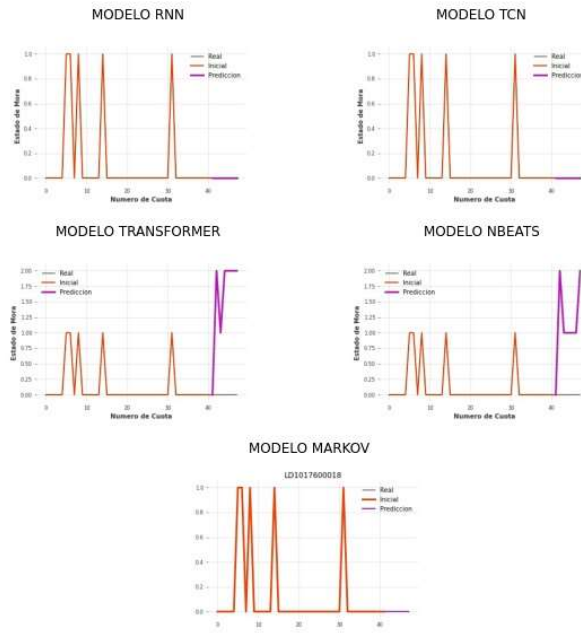
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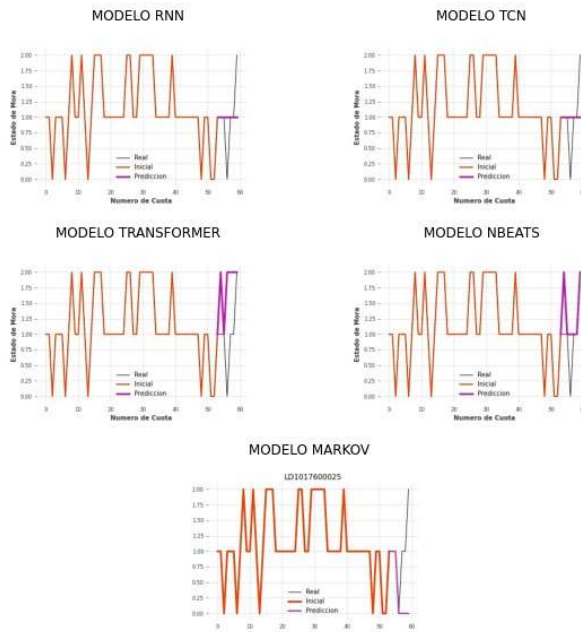
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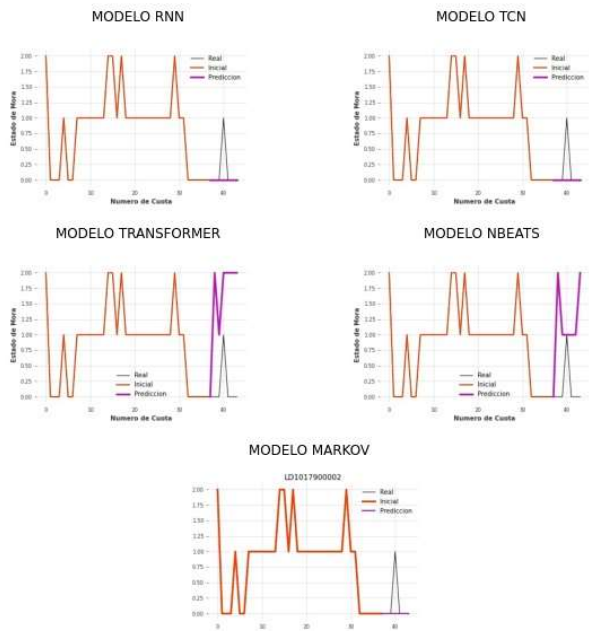
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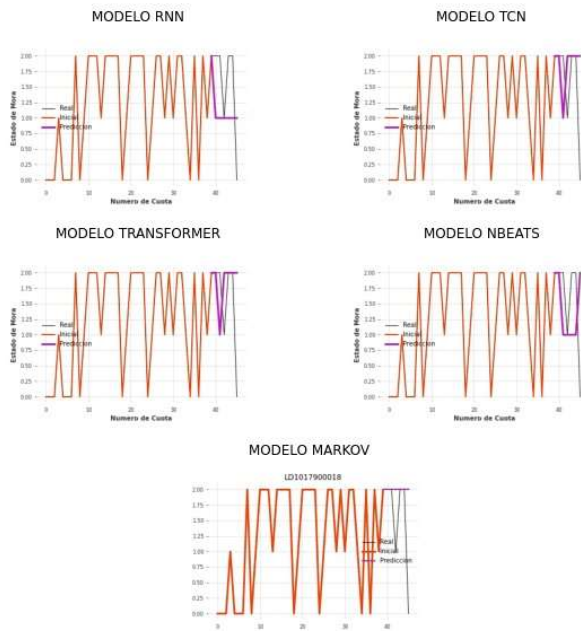
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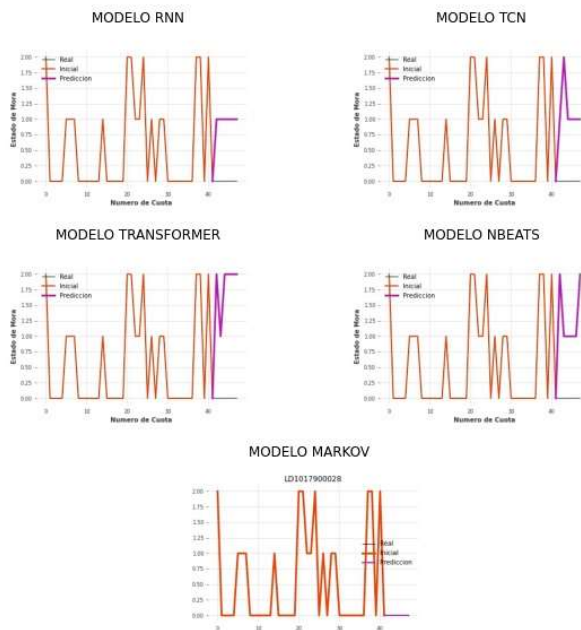
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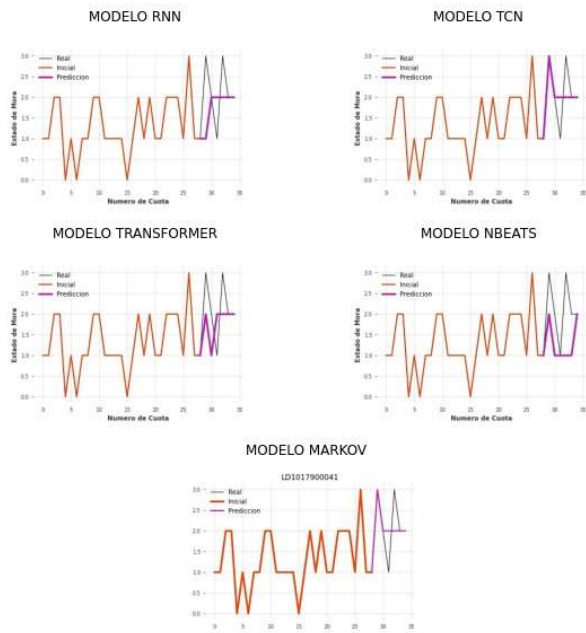
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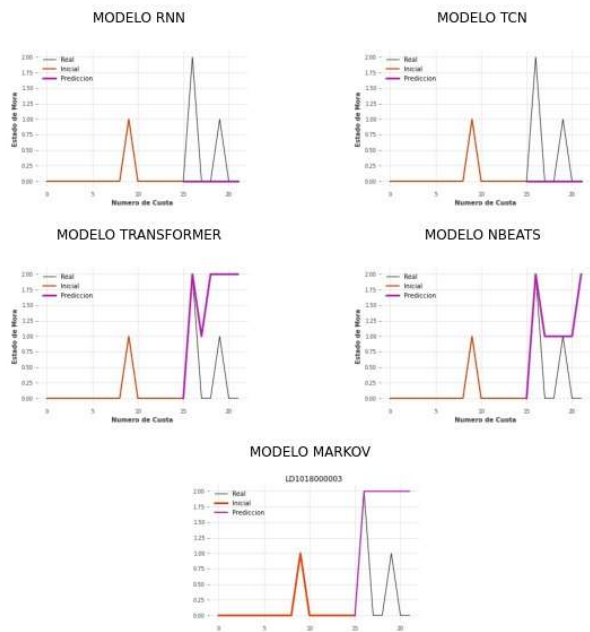
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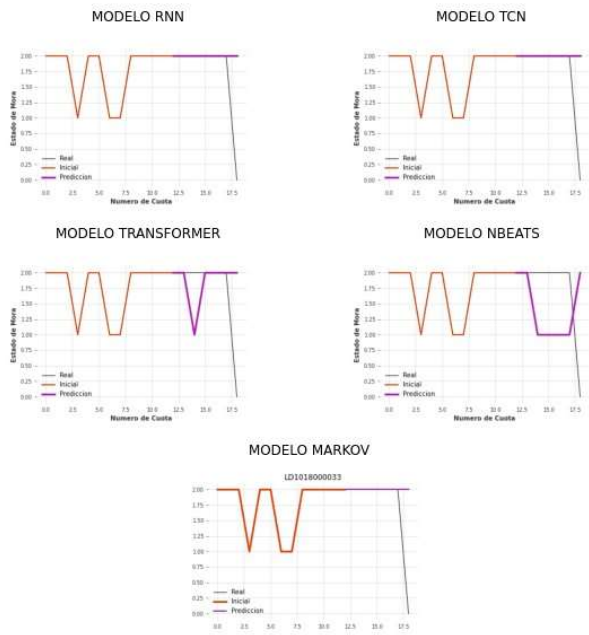
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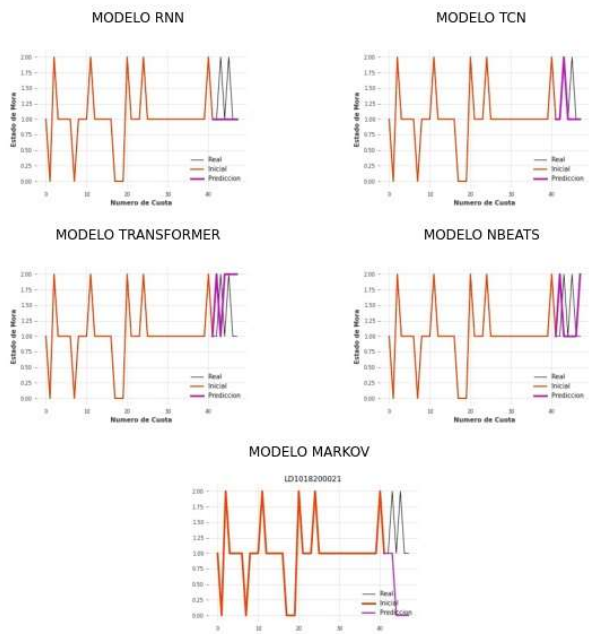
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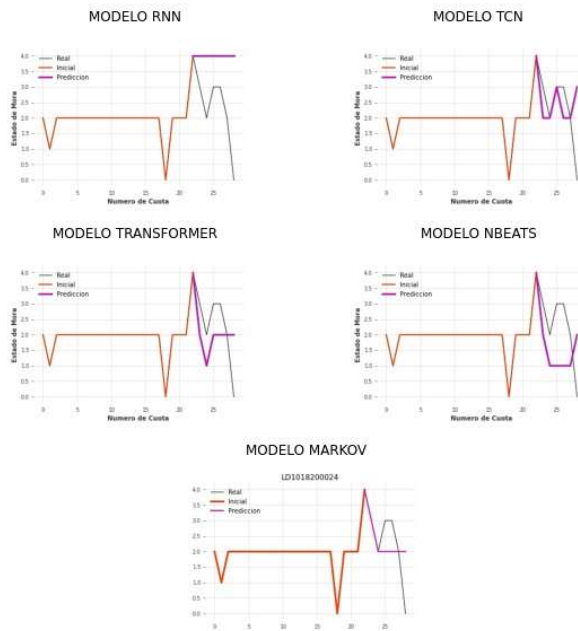
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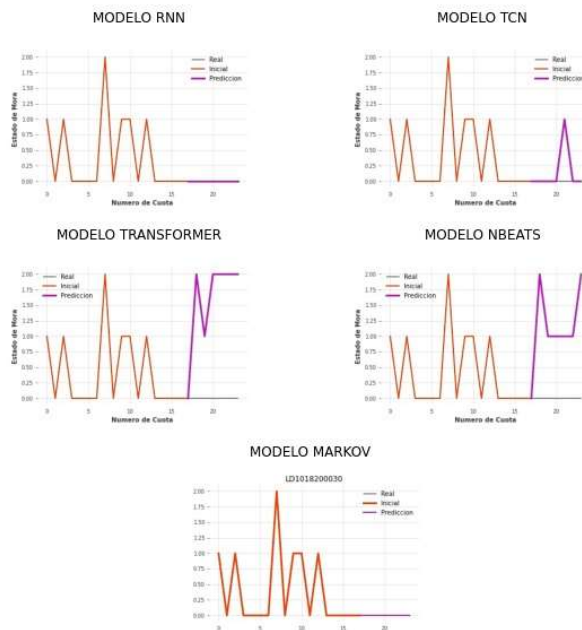
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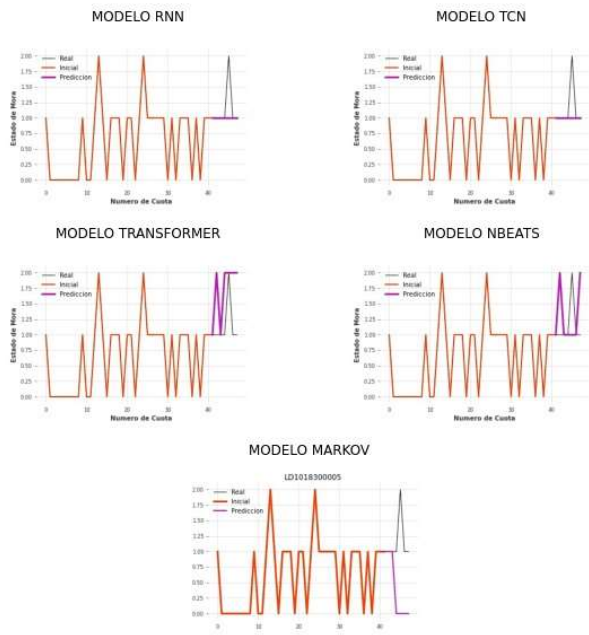


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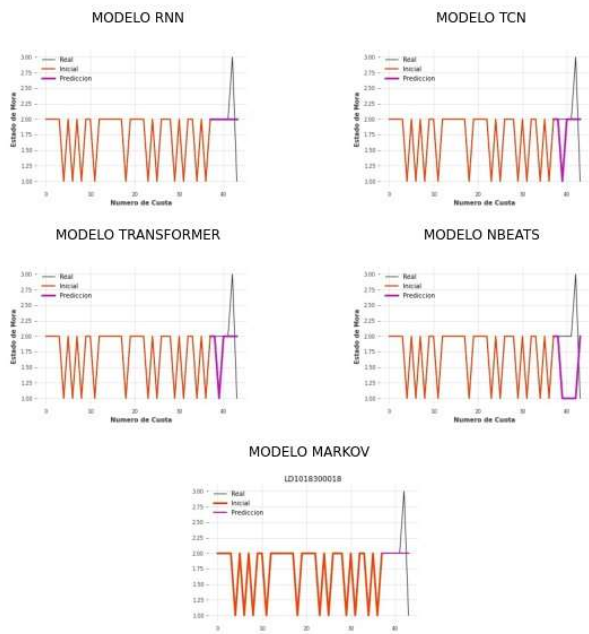




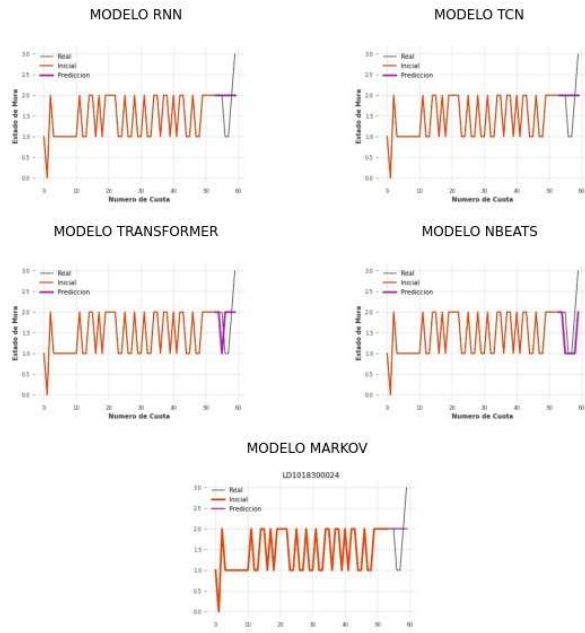
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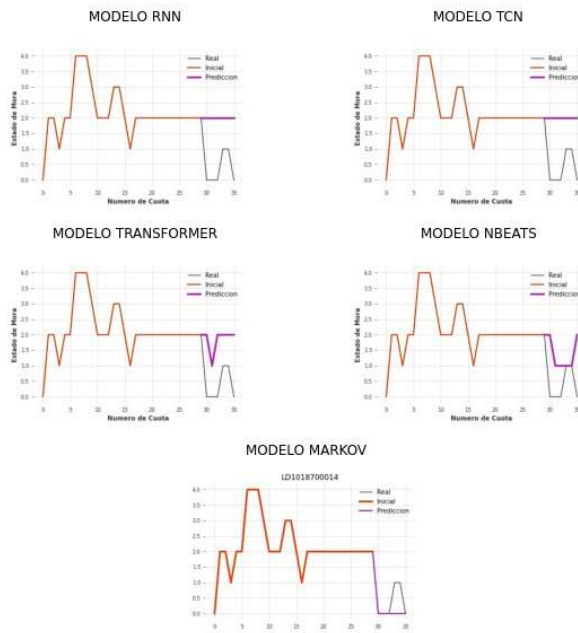
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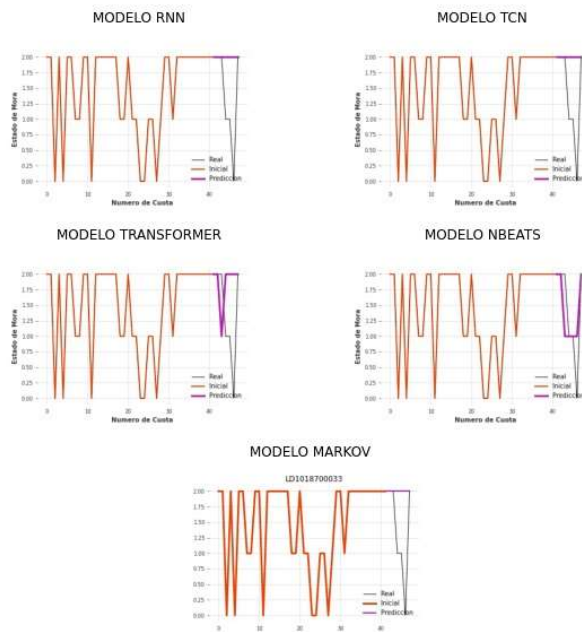
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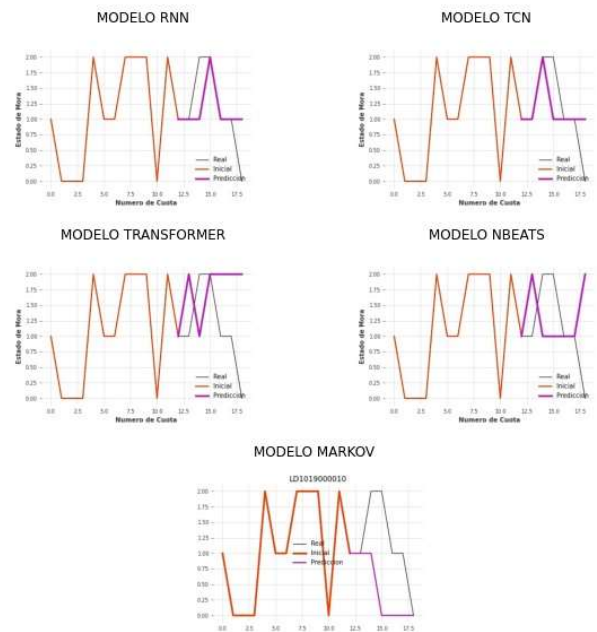
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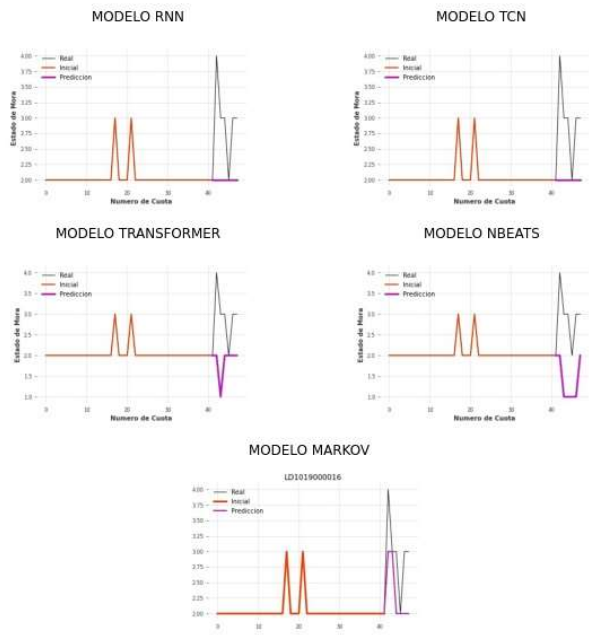
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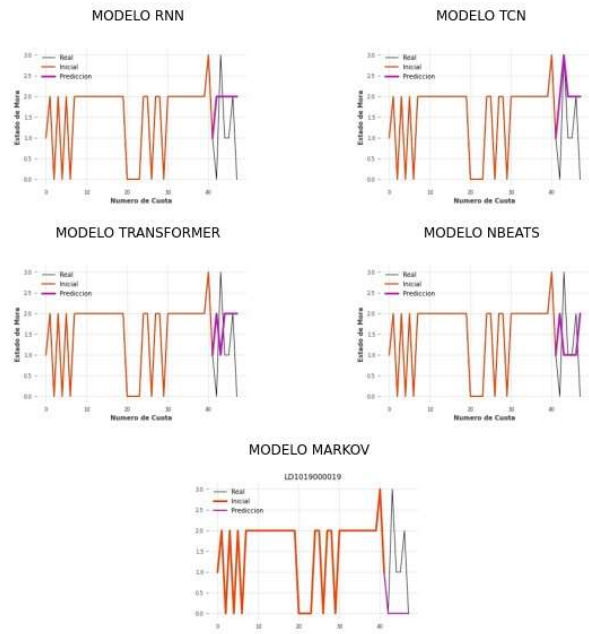
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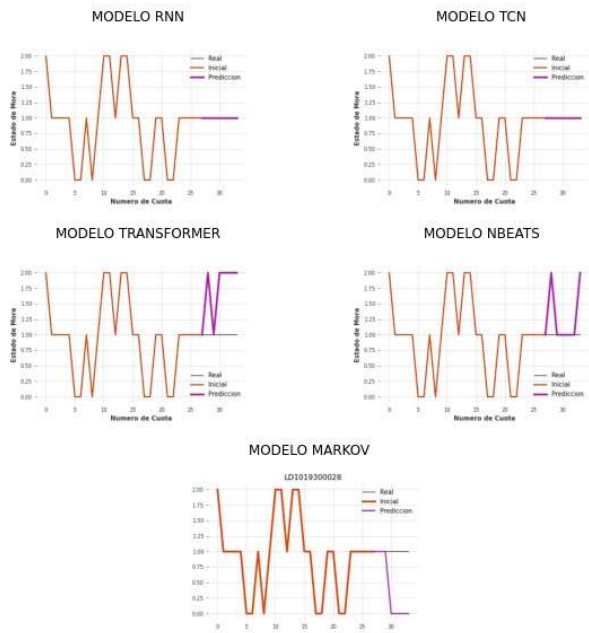
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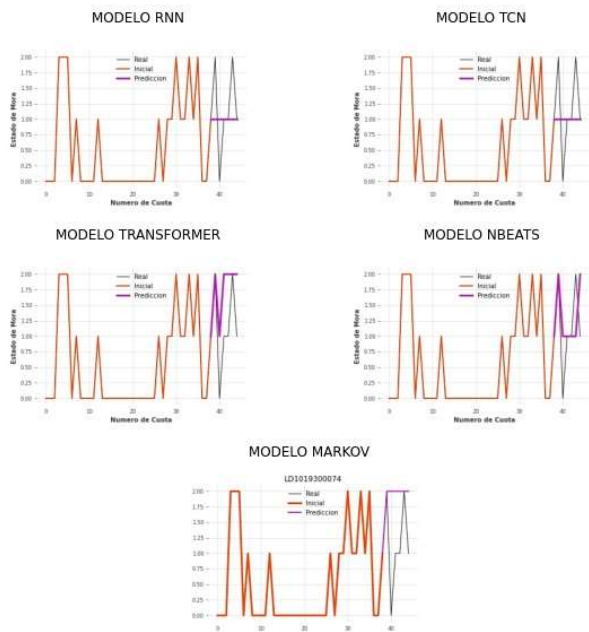
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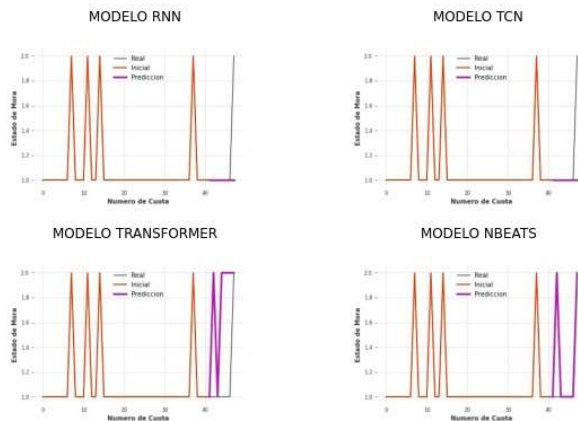
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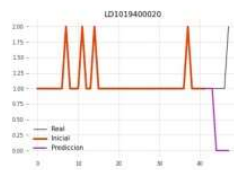
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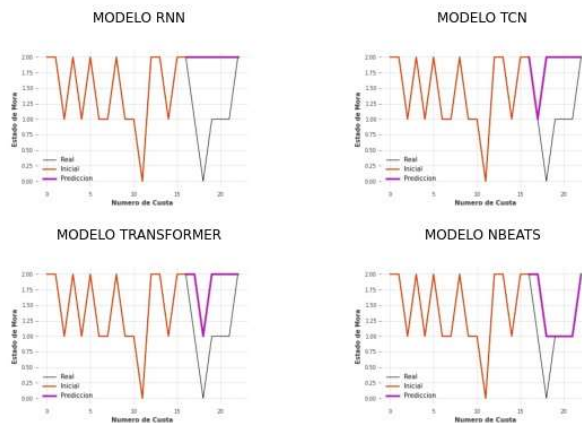
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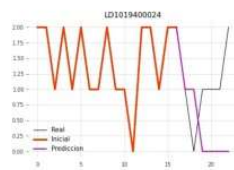
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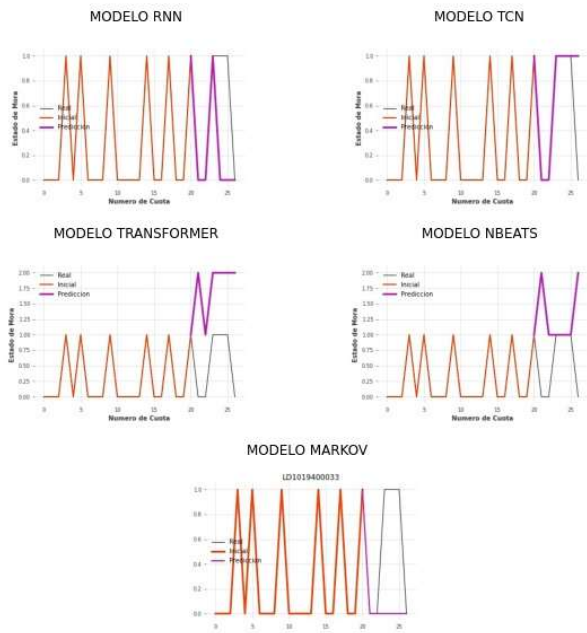
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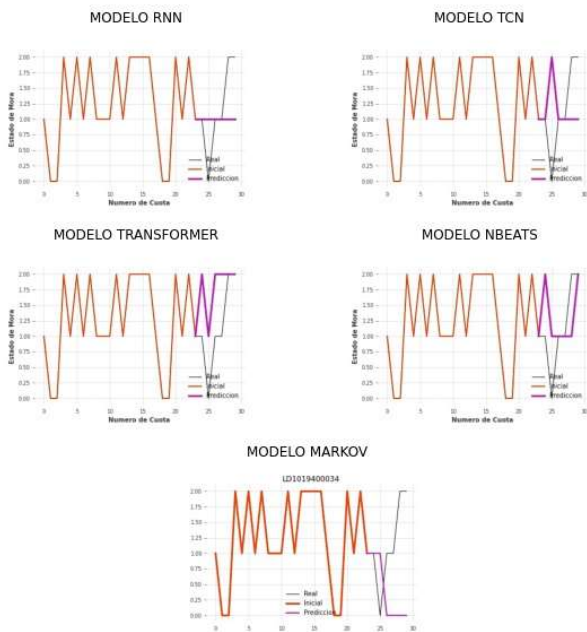
MODELO MARKOV



LD1019400033

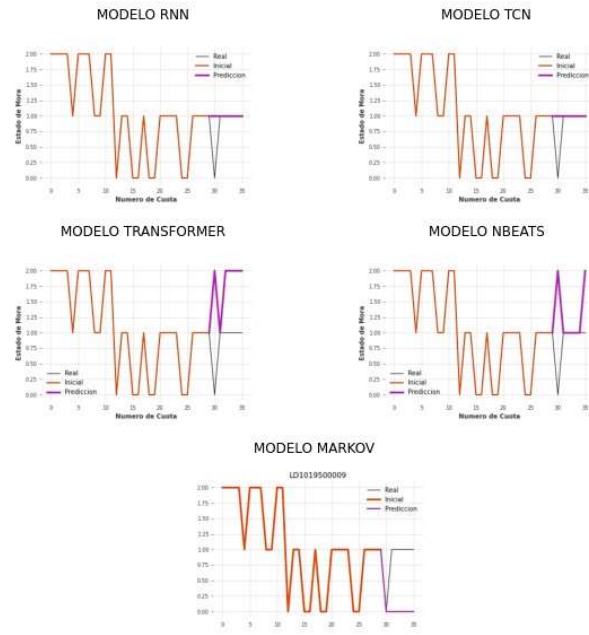


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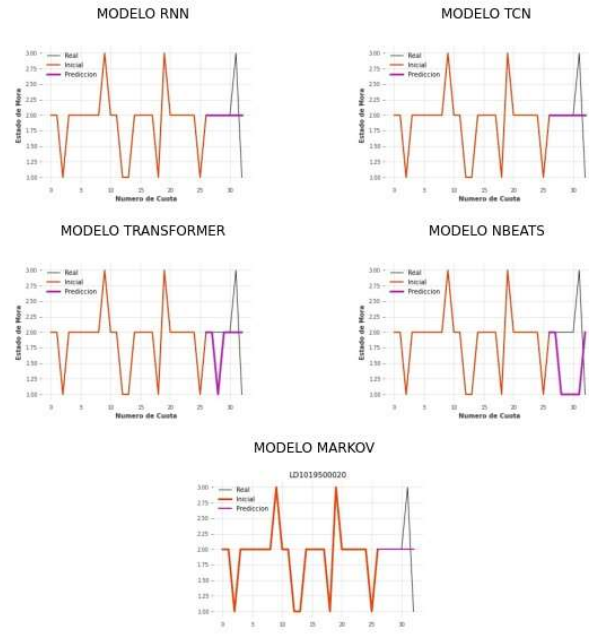




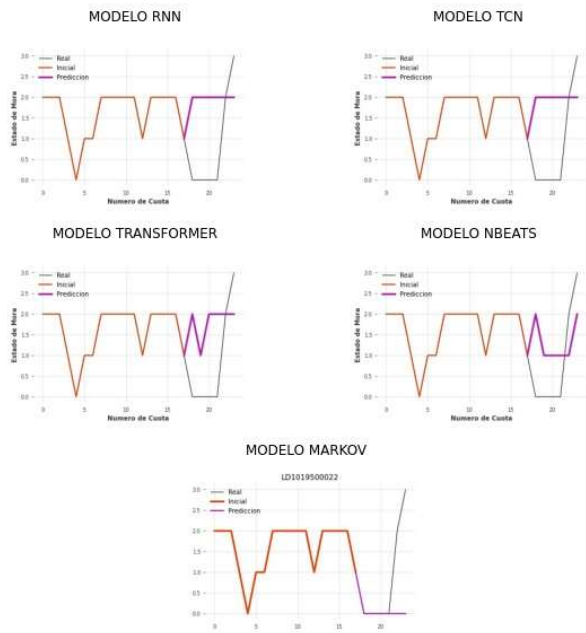
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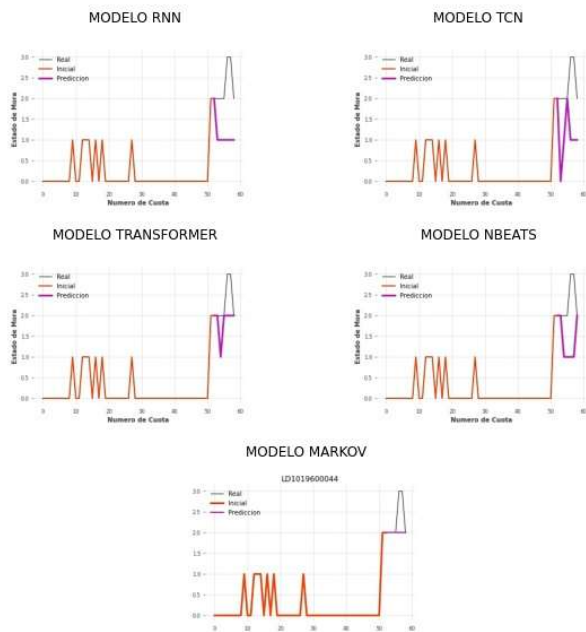
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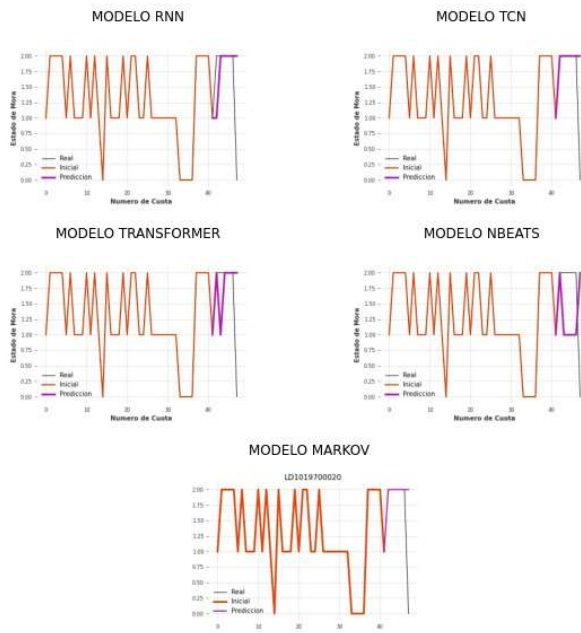
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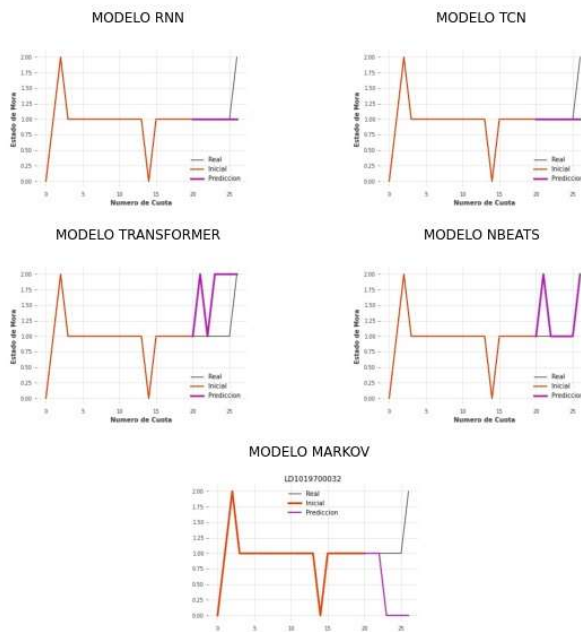
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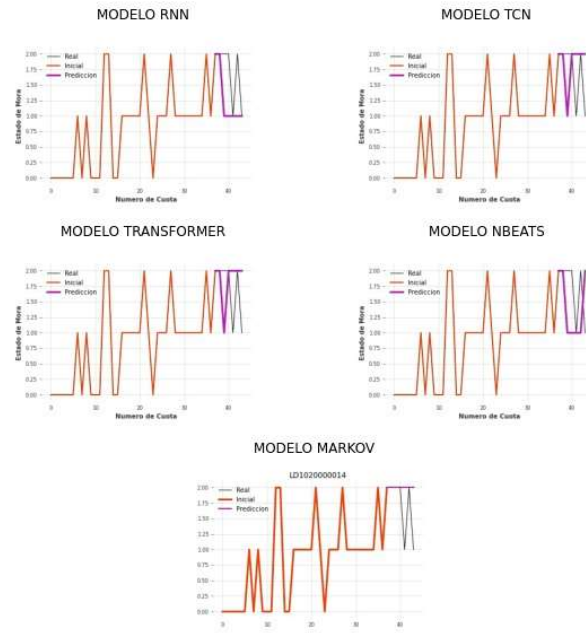
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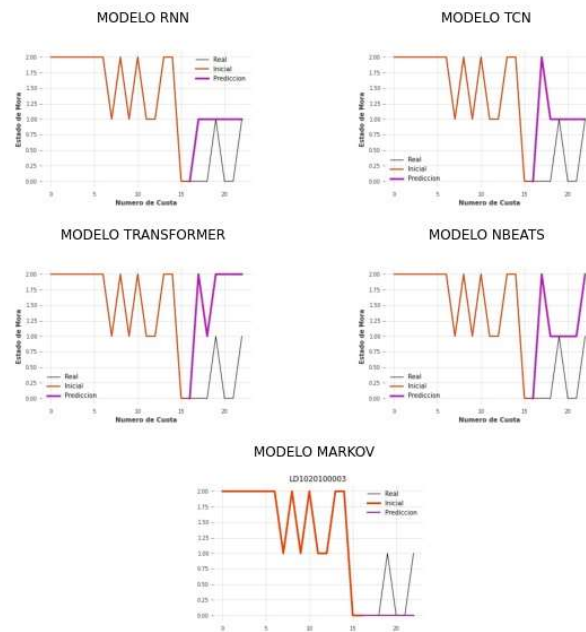
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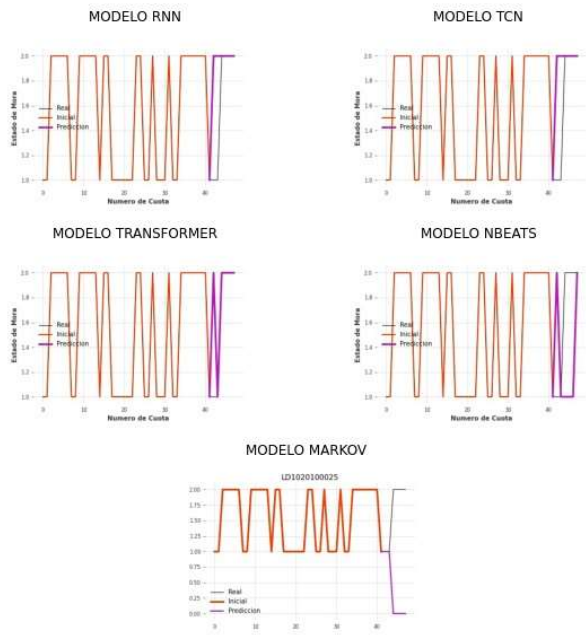
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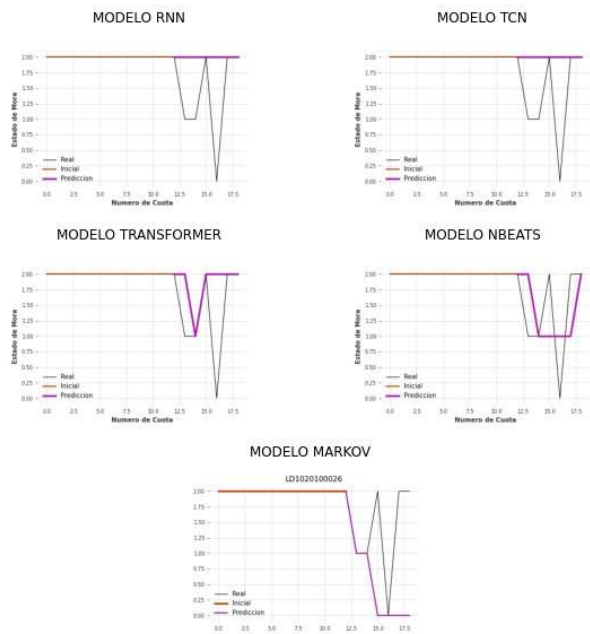
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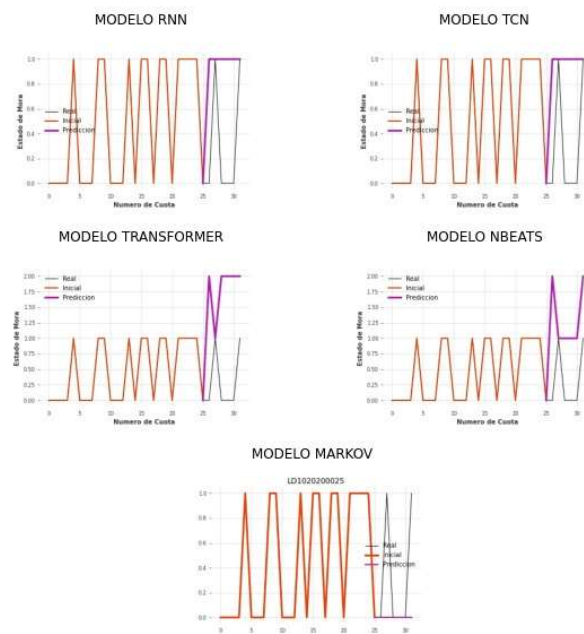
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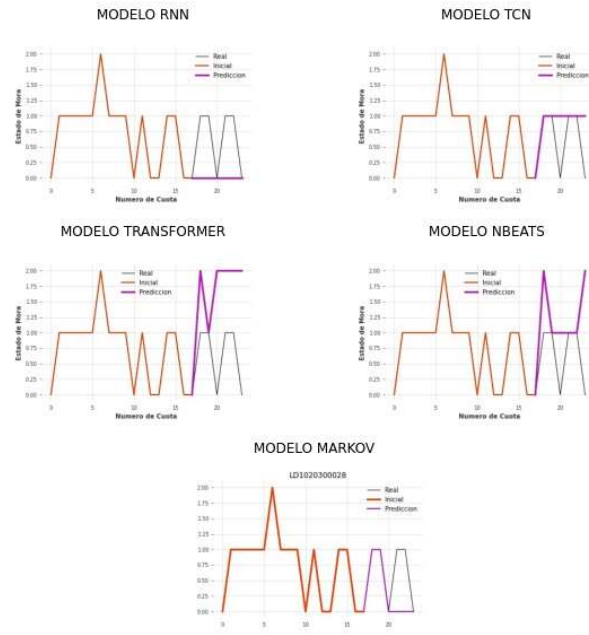
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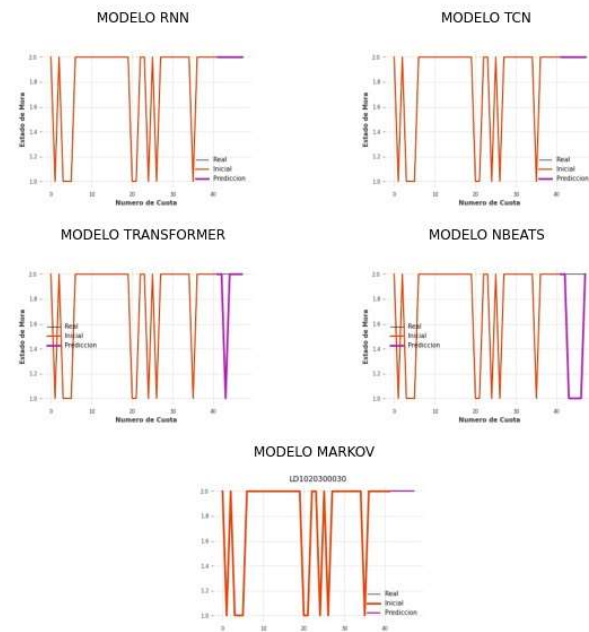
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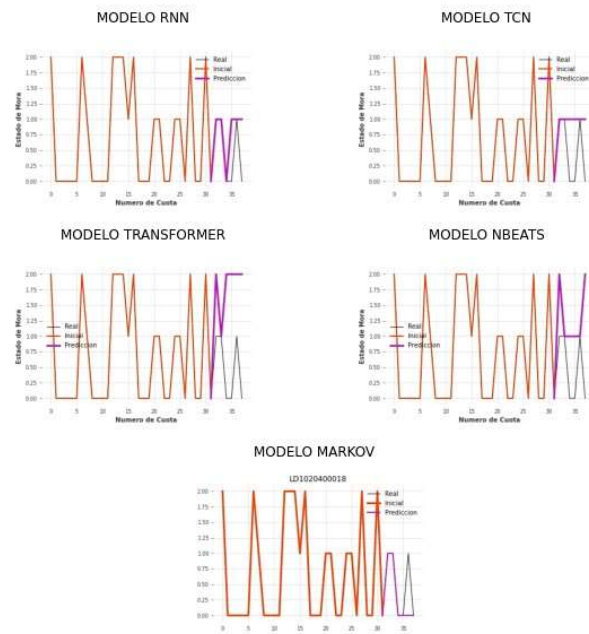
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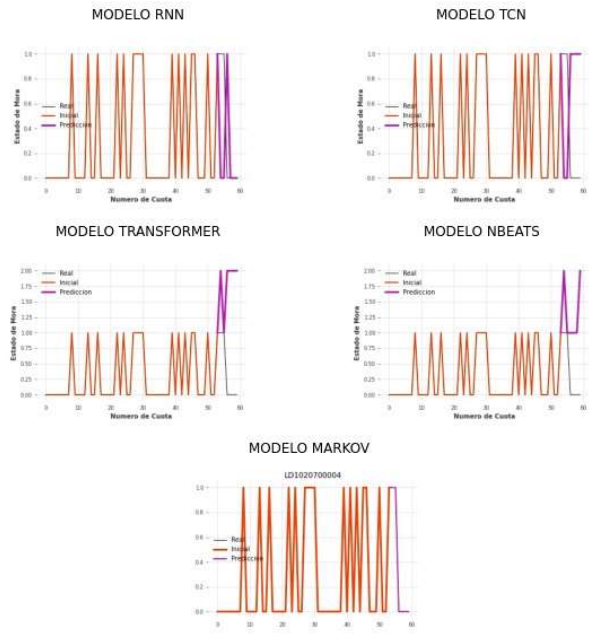


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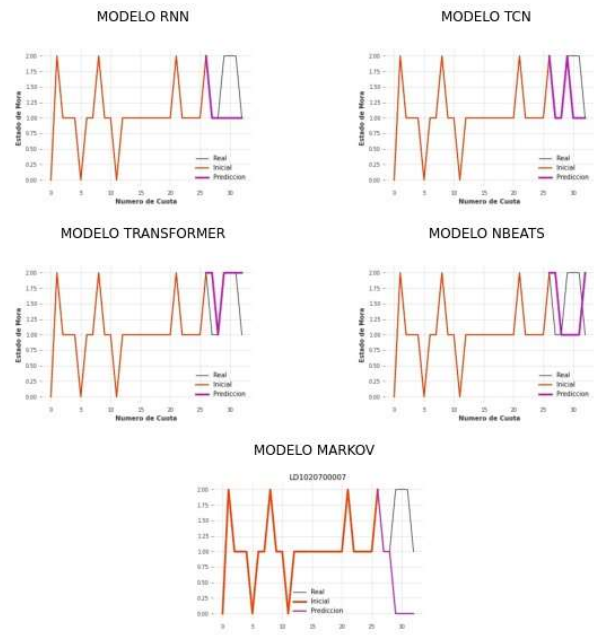
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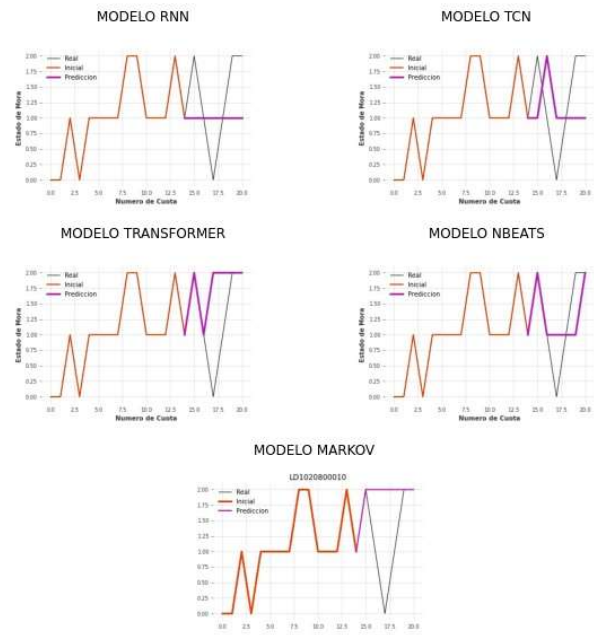
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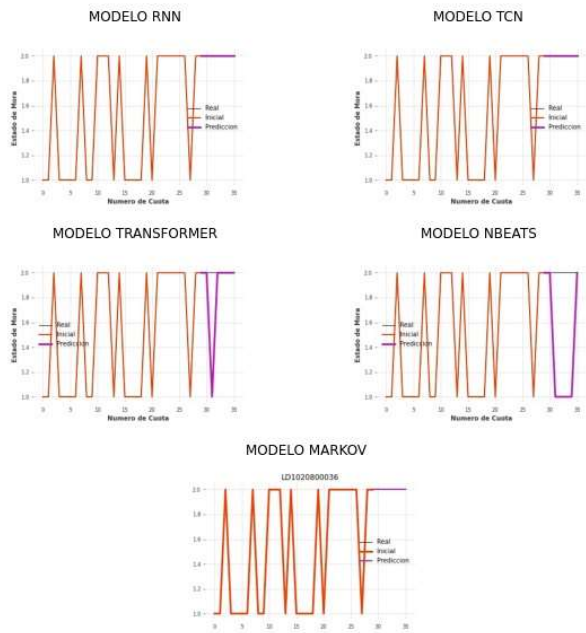
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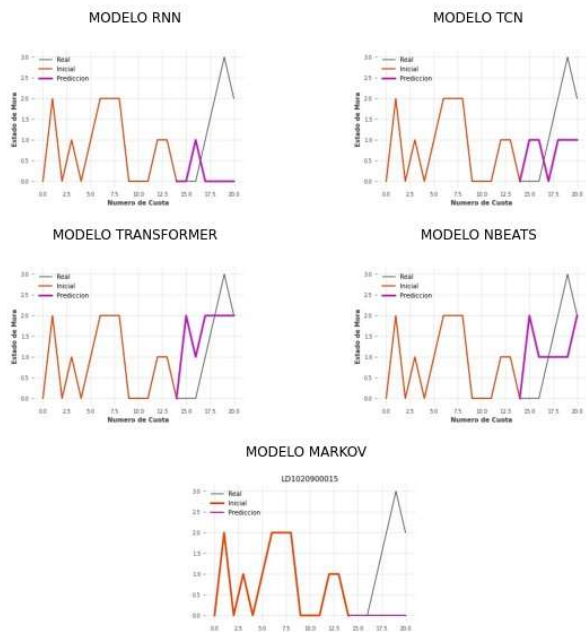
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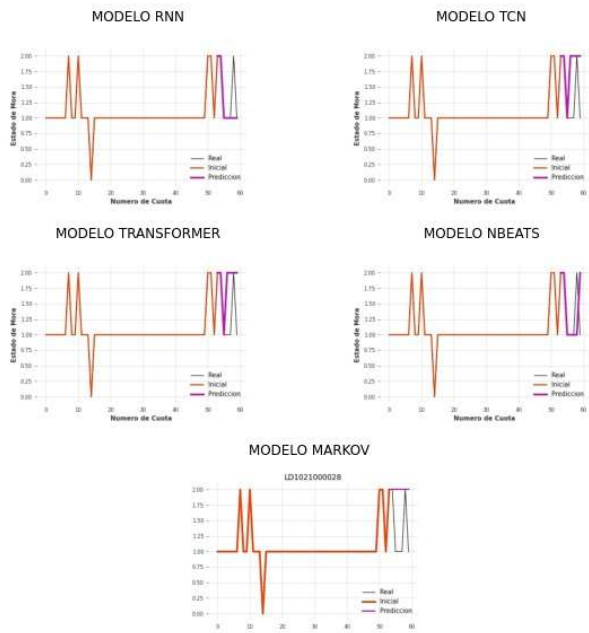
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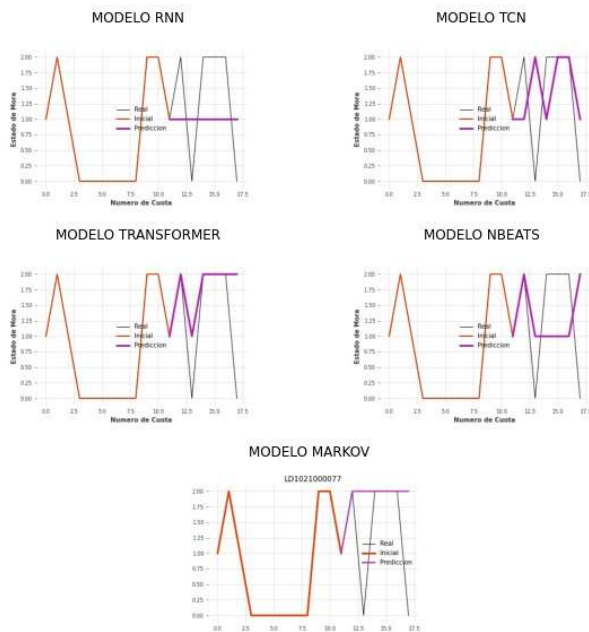
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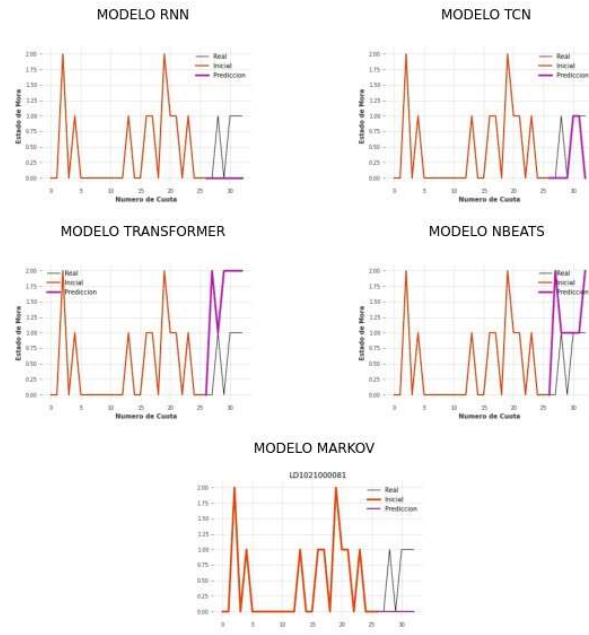
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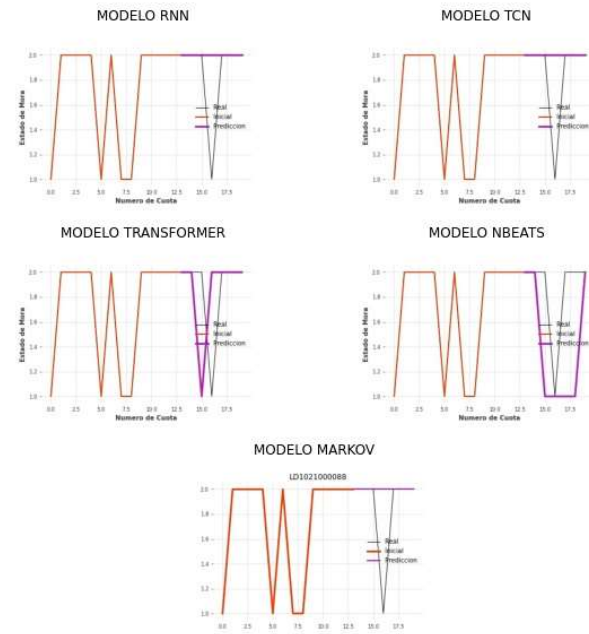
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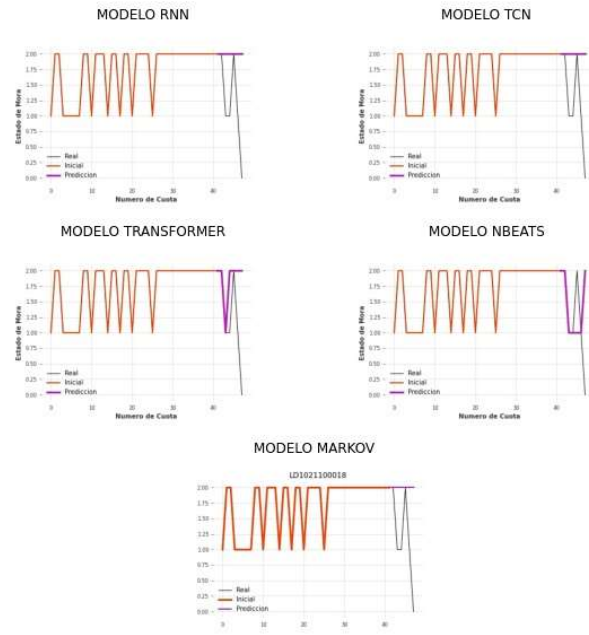
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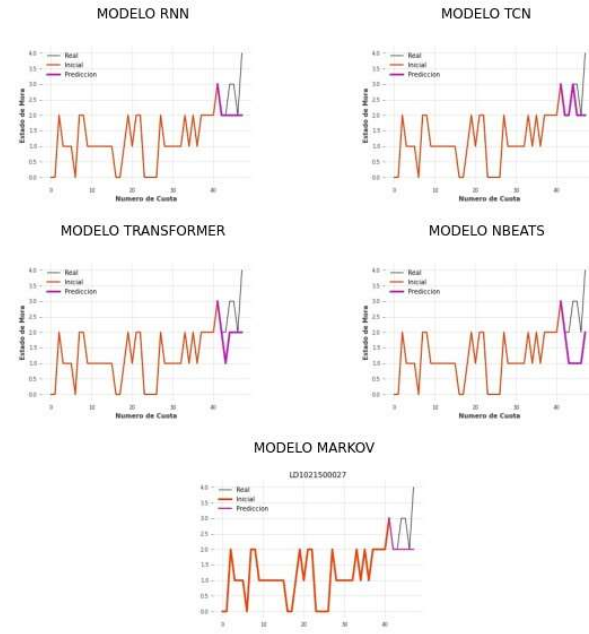
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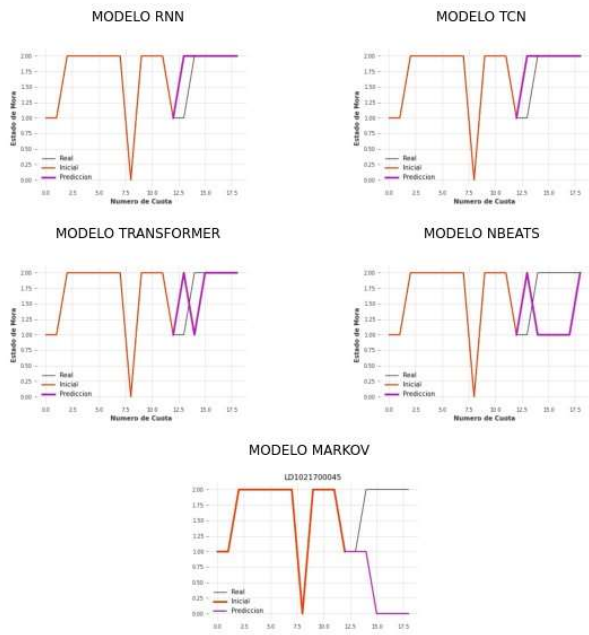
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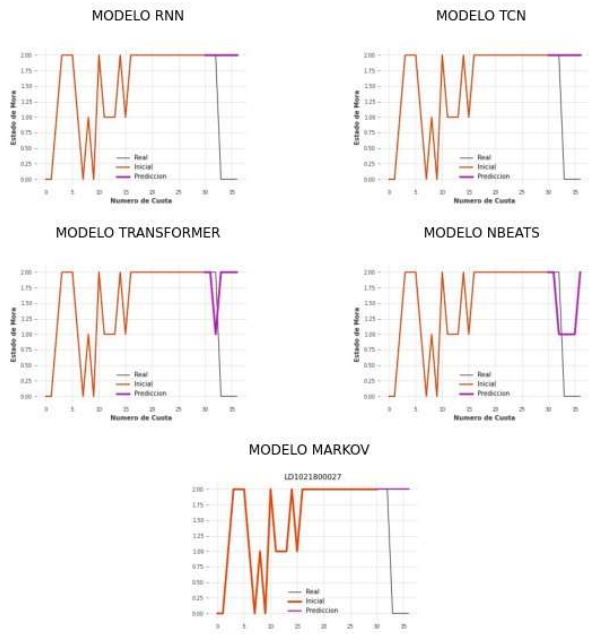
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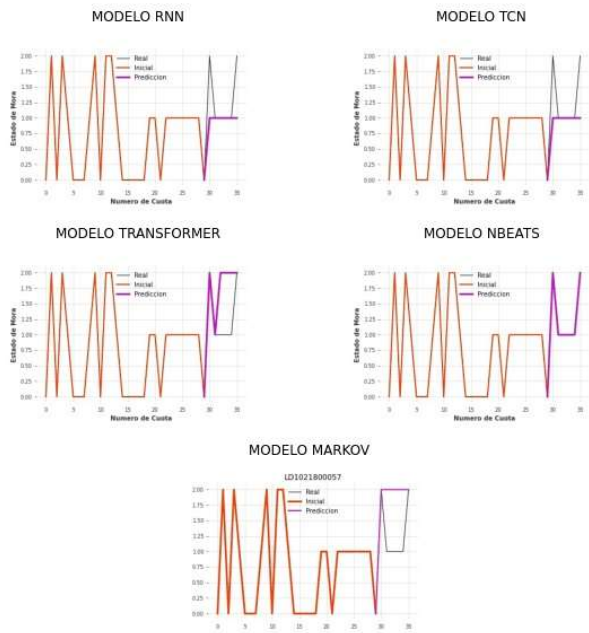


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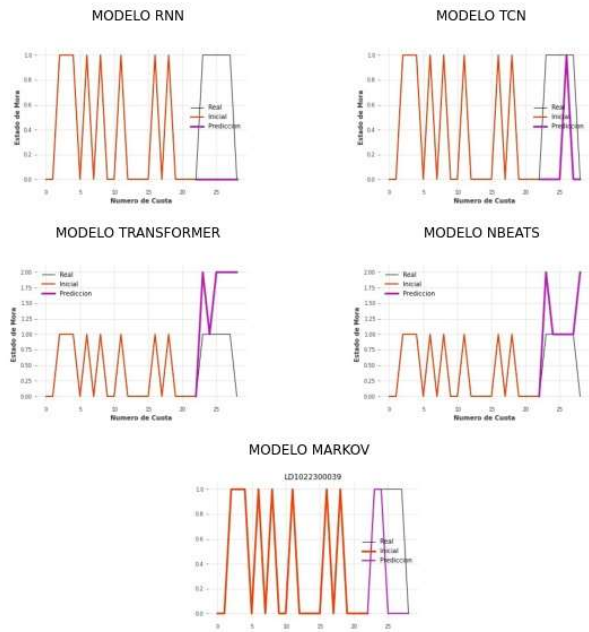




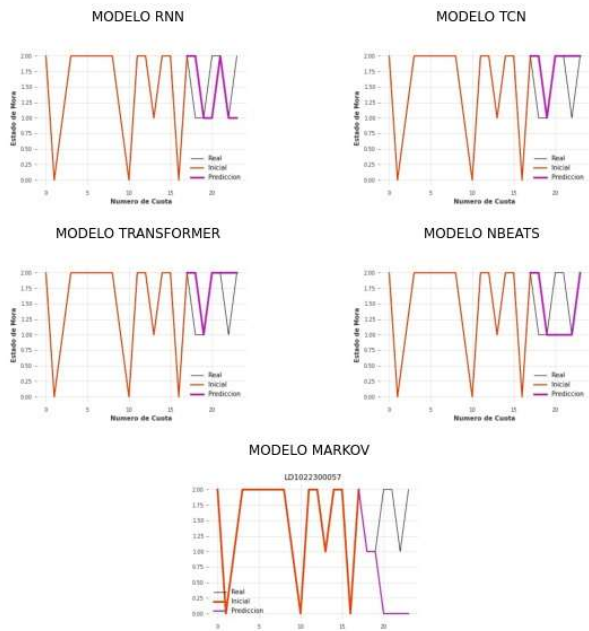
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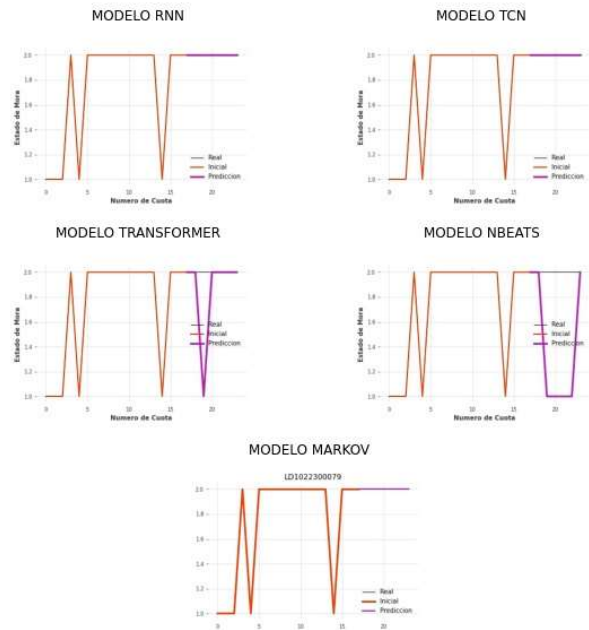
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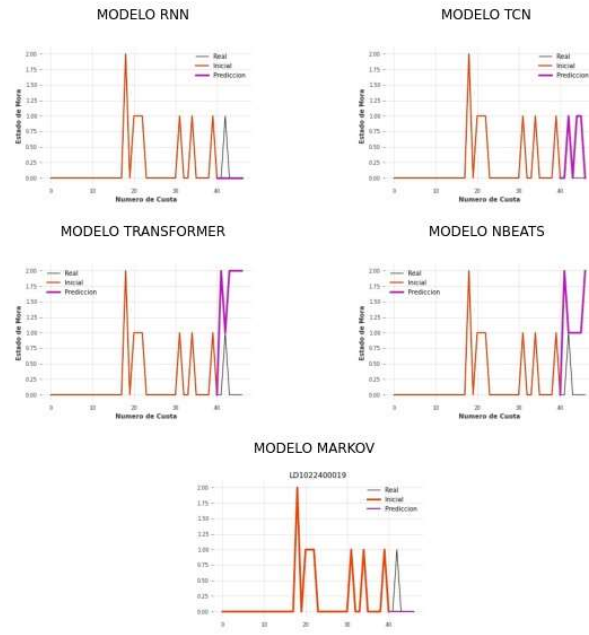
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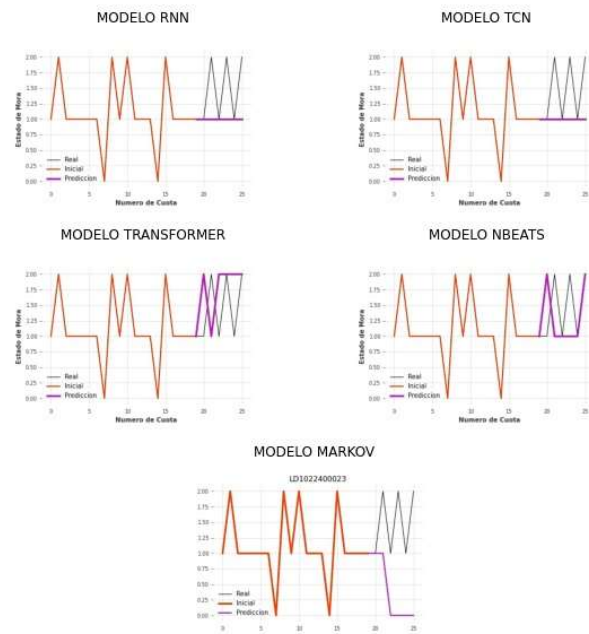
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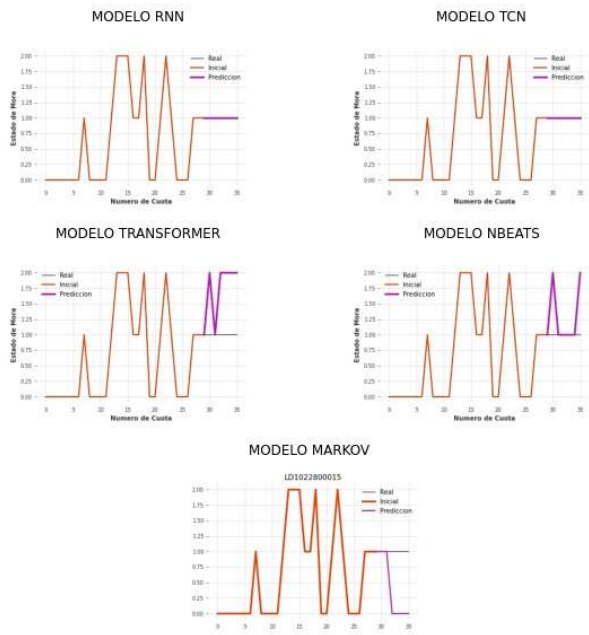
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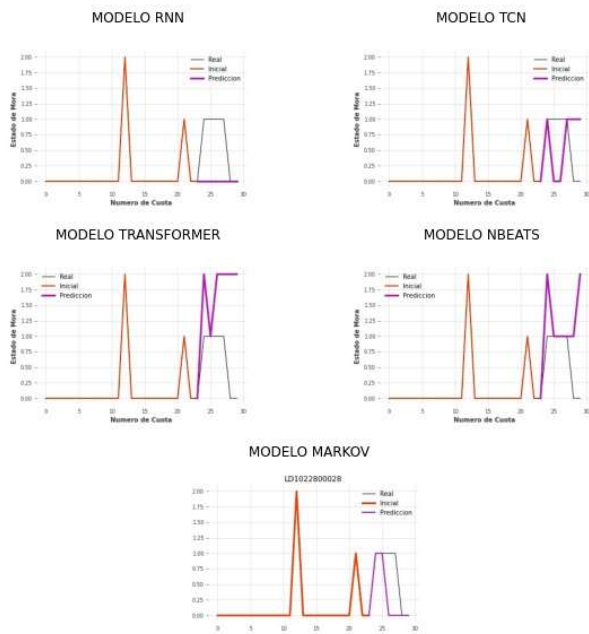
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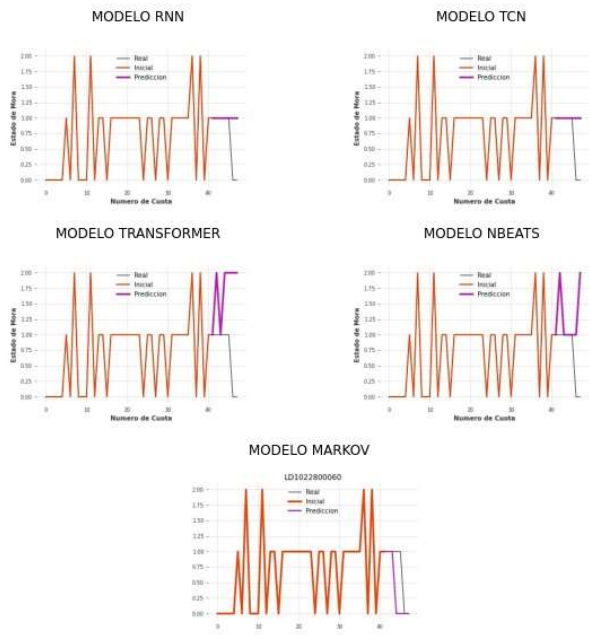
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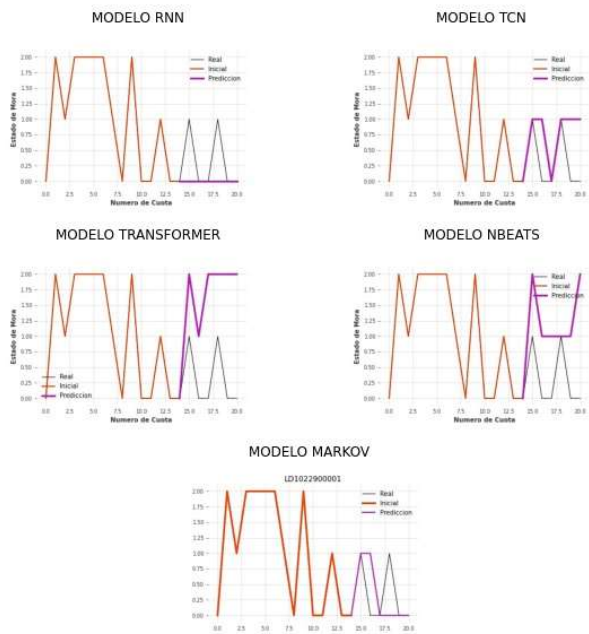
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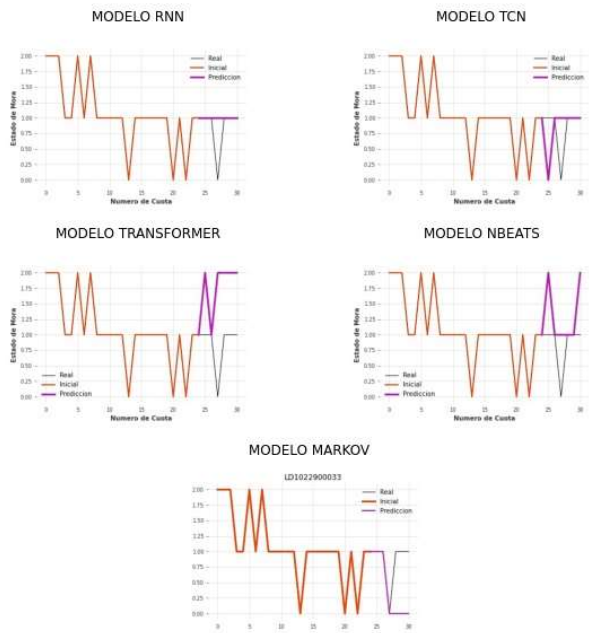
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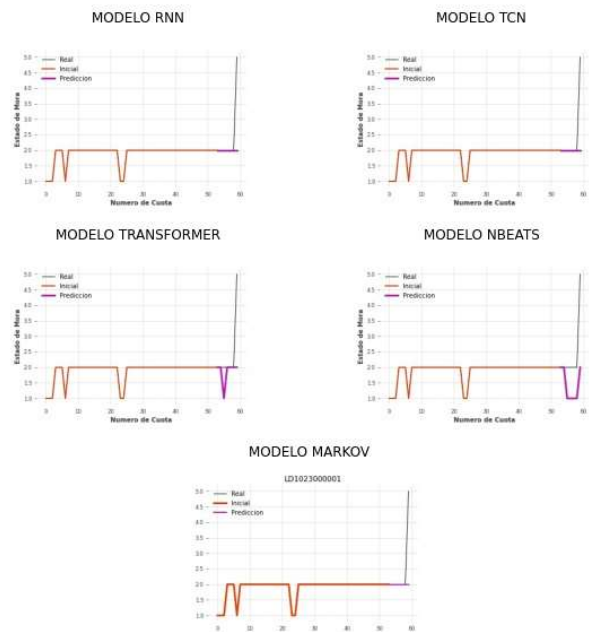
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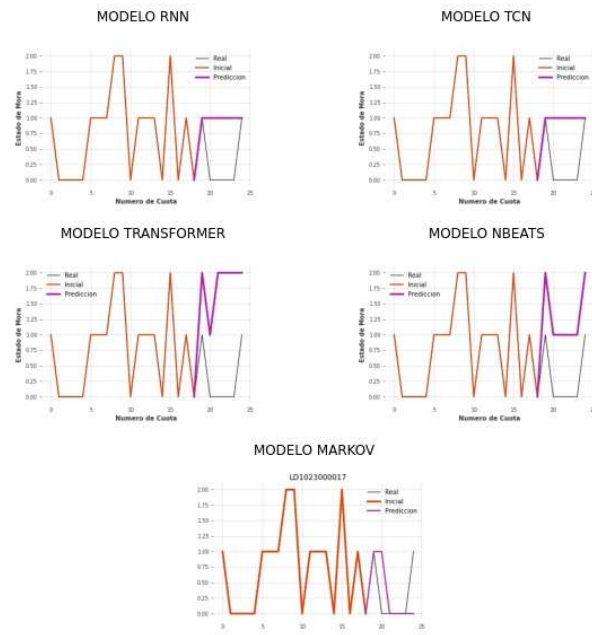
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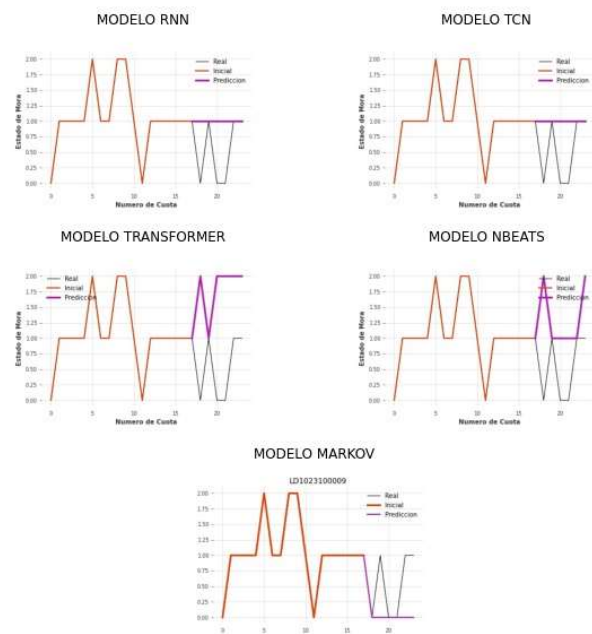
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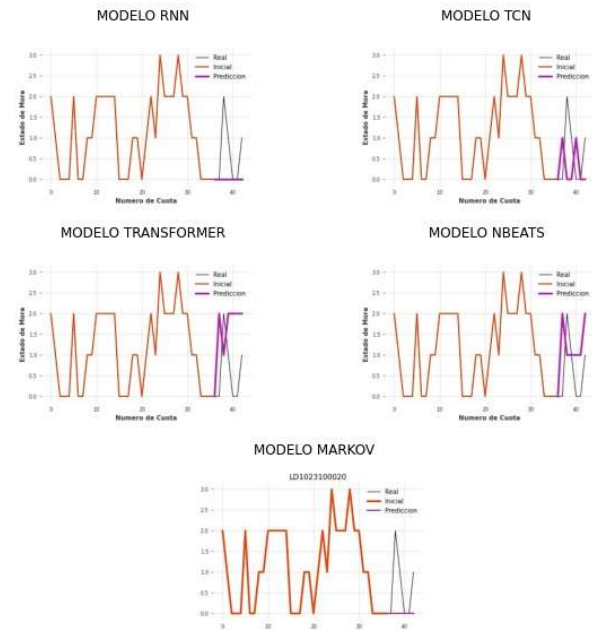




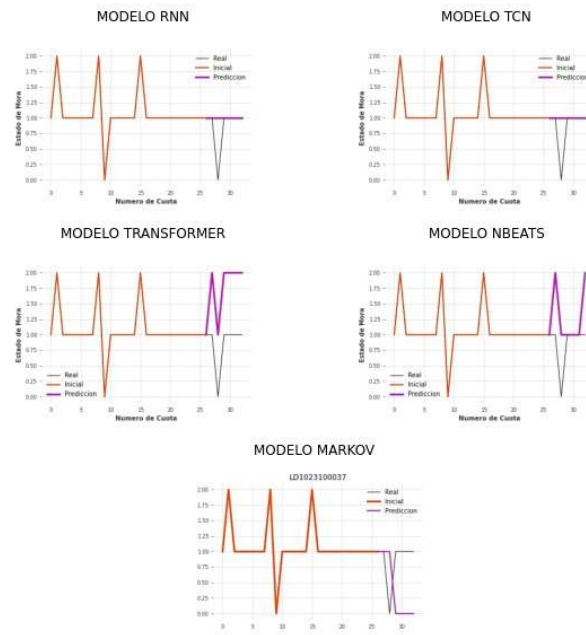
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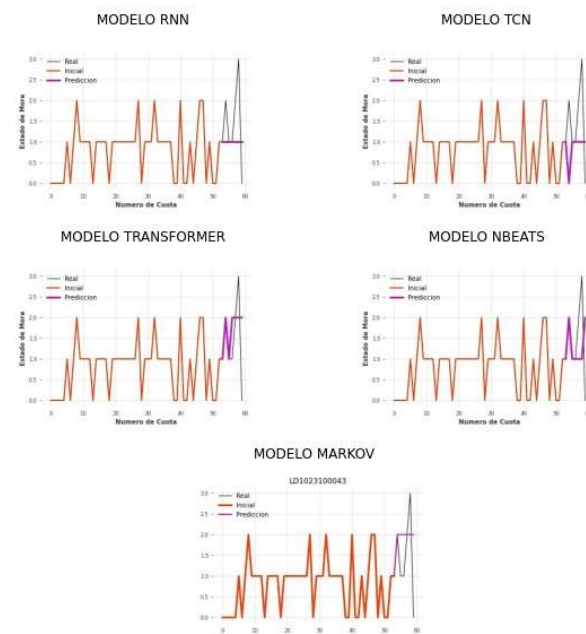
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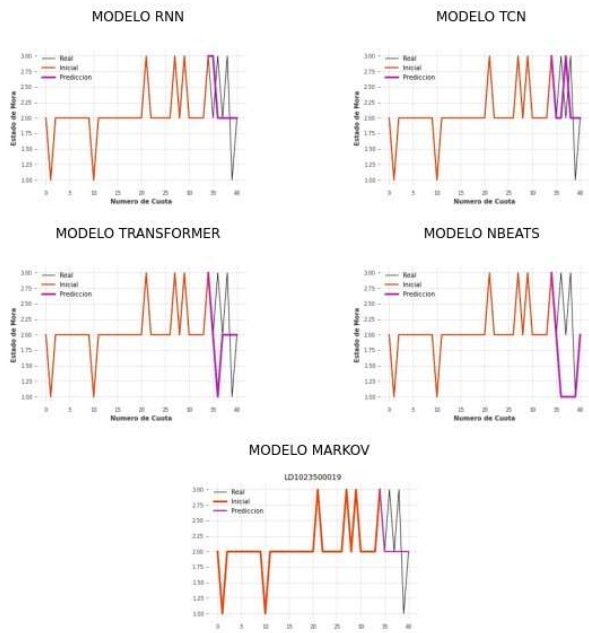
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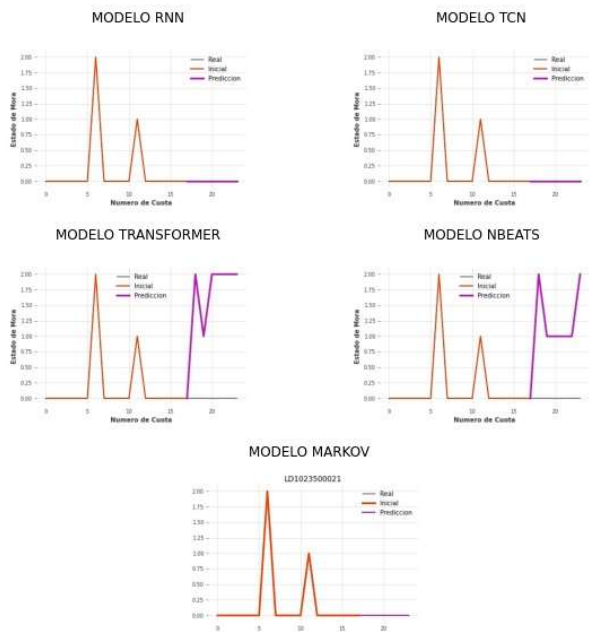
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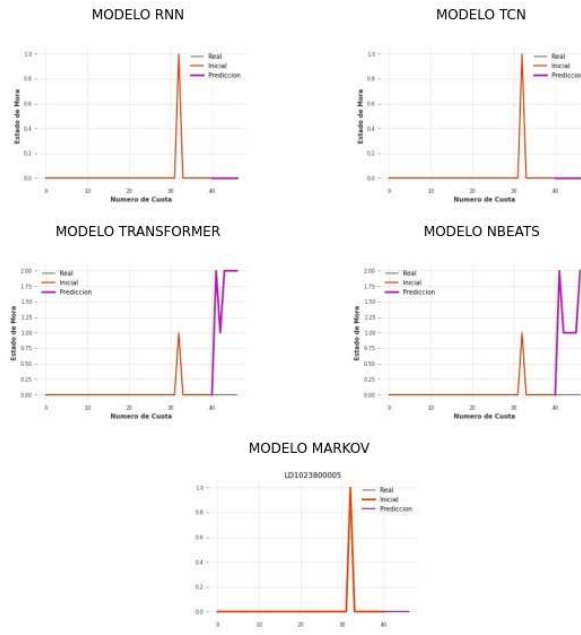
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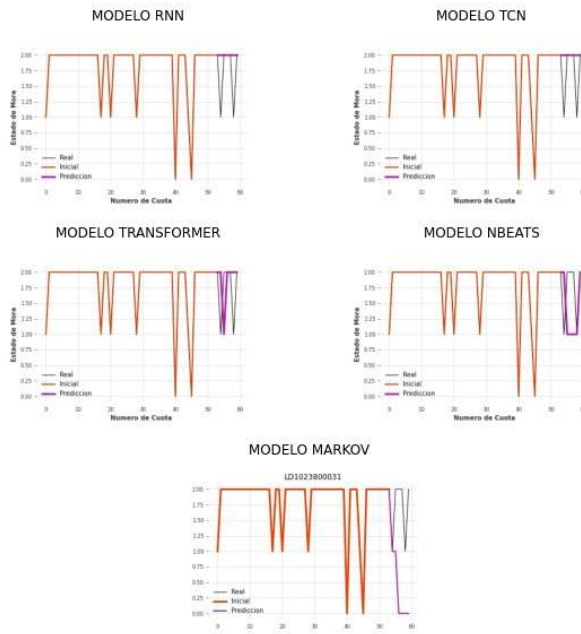
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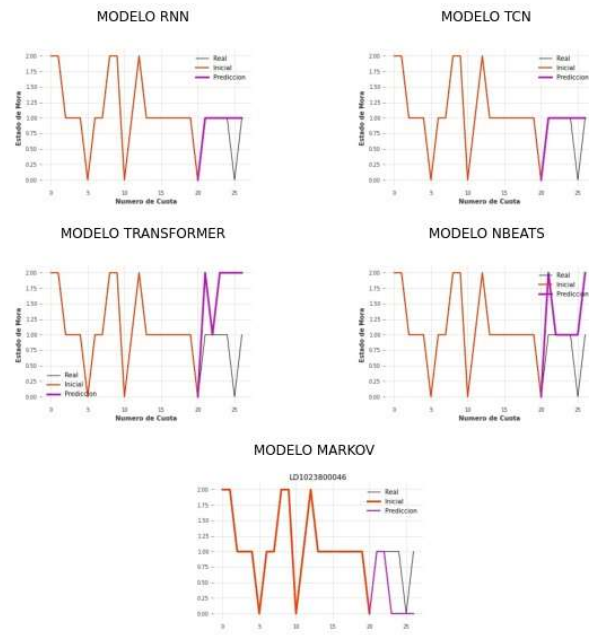
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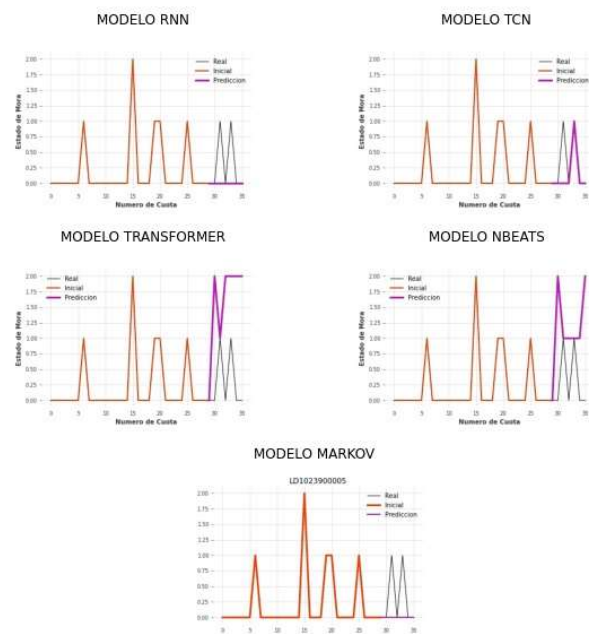
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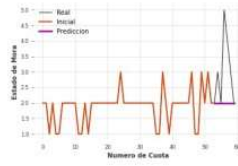


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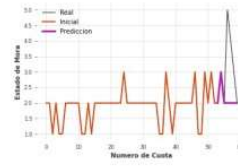


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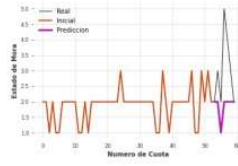
MODELO RNN



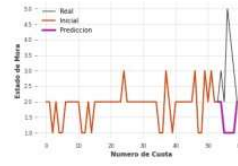
MODELO TCN



MODELO TRANSFORMER



MODELO NBEATS

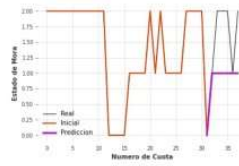


MODELO MARKOV

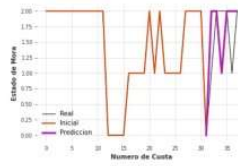


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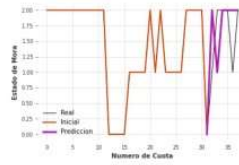
MODELO RNN



MODELO TCN



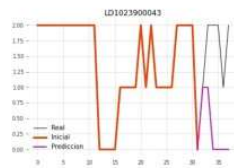
MODELO TRANSFORMER



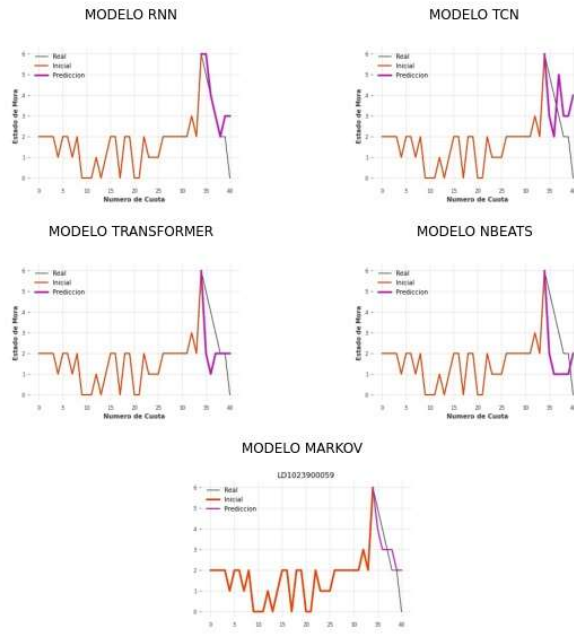
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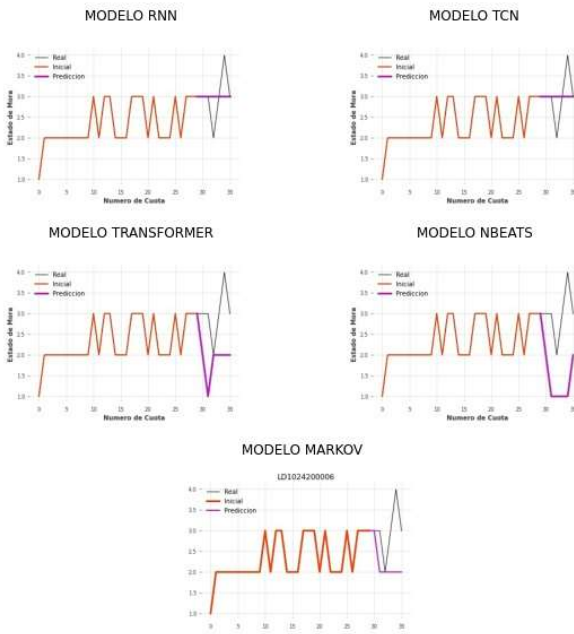
MODELO MARKOV



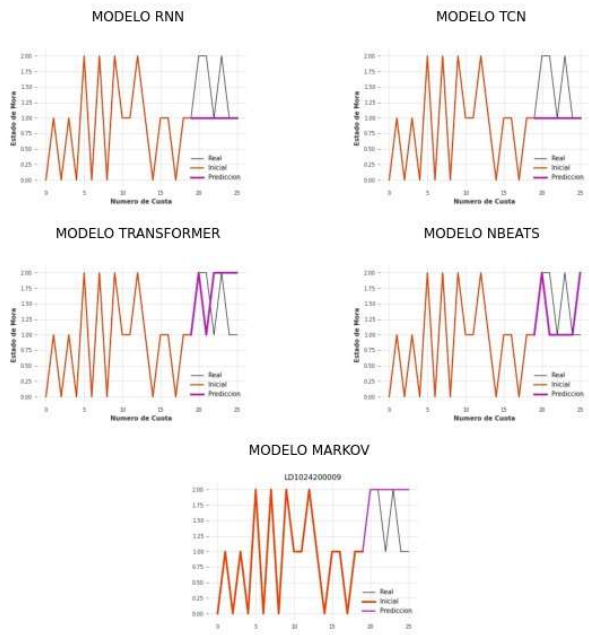
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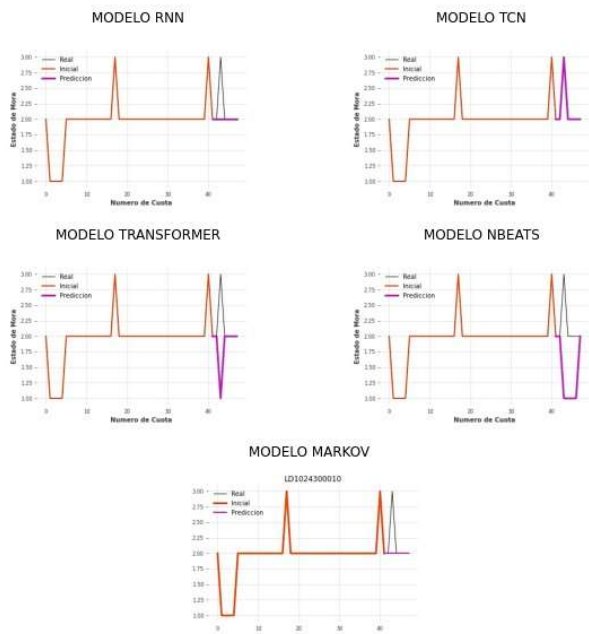
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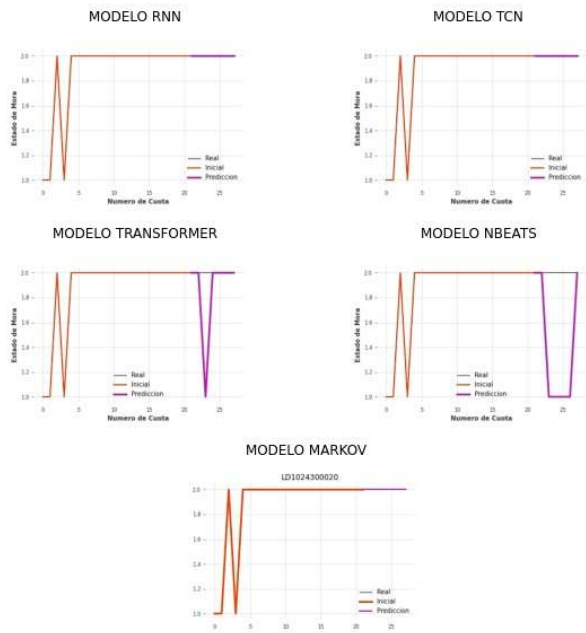


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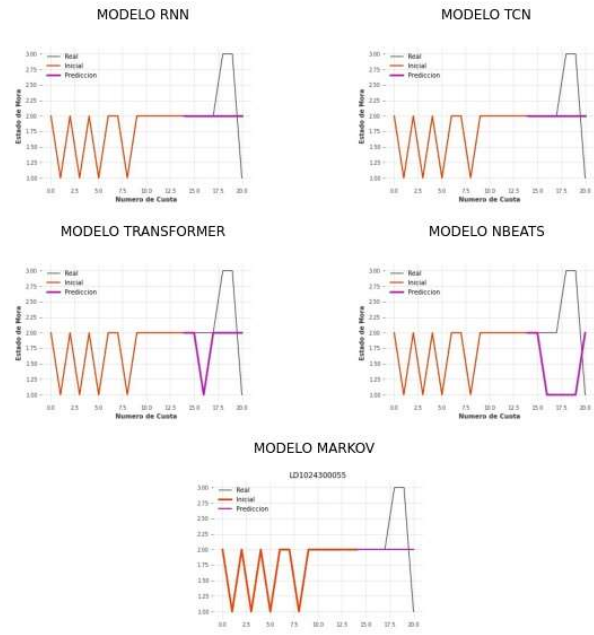
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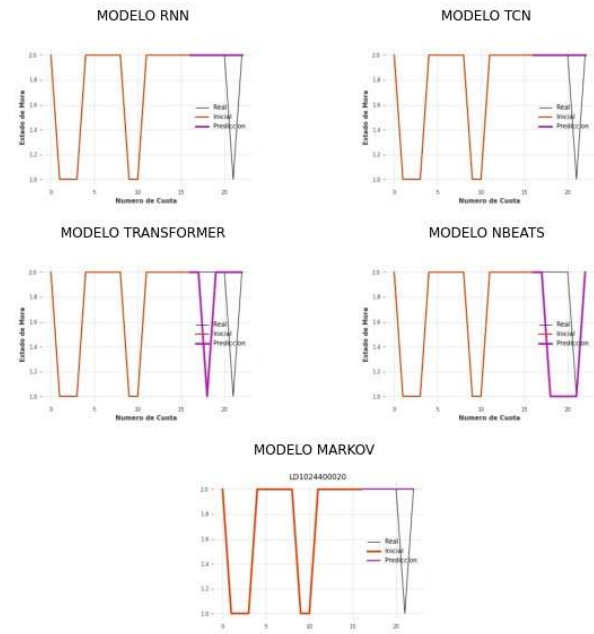
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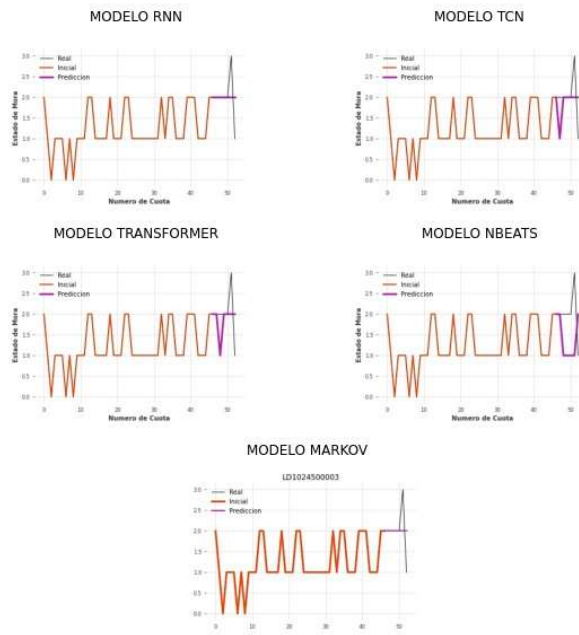
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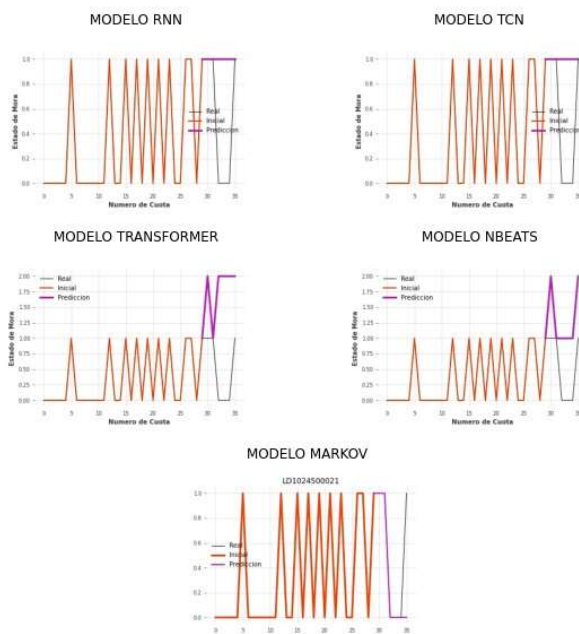
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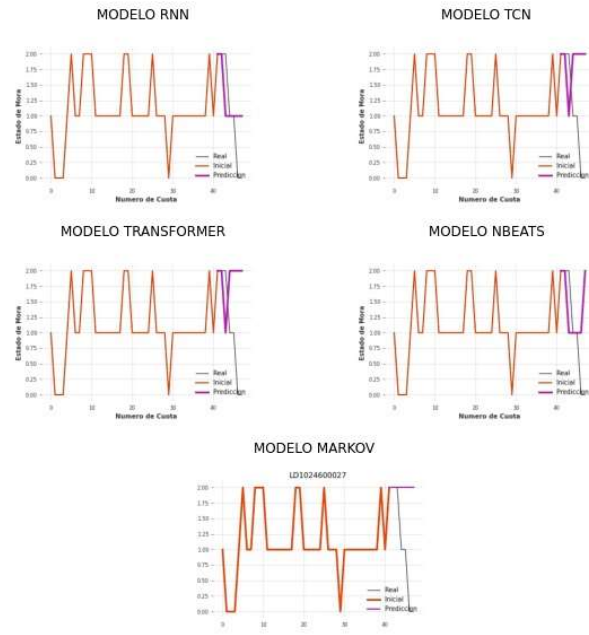
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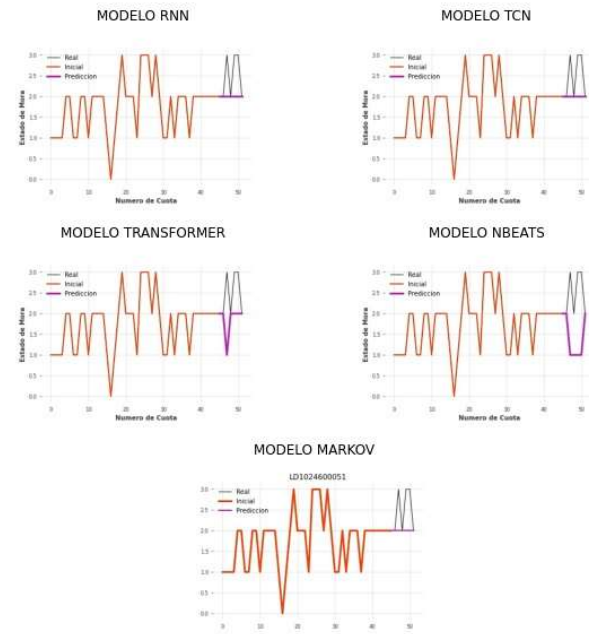
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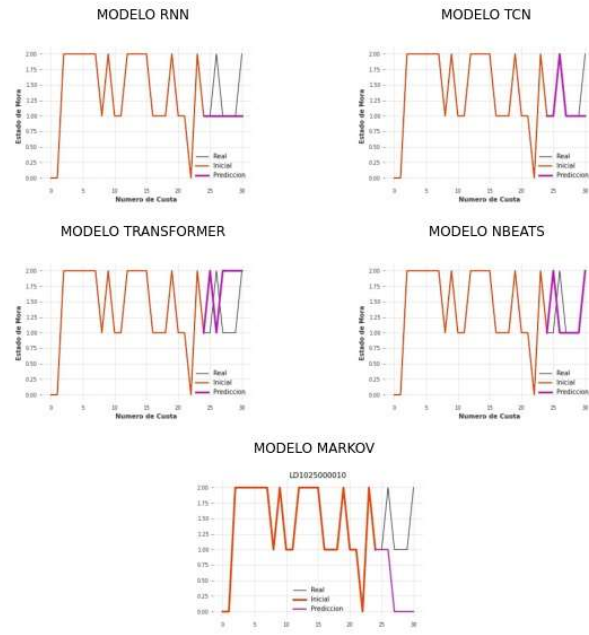
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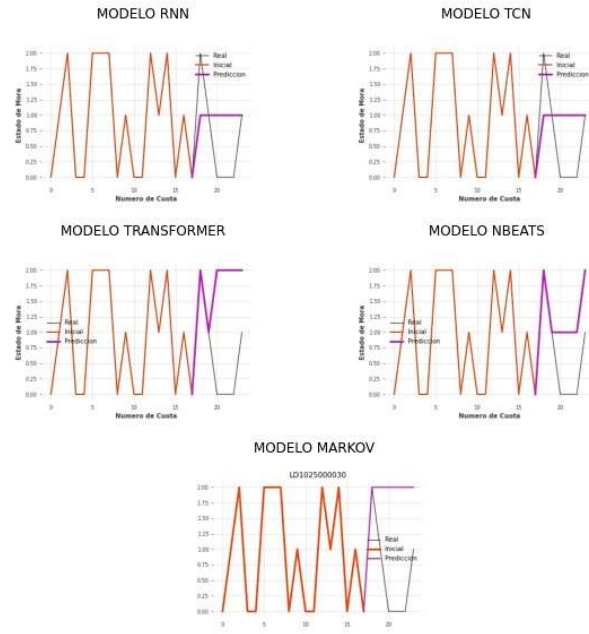
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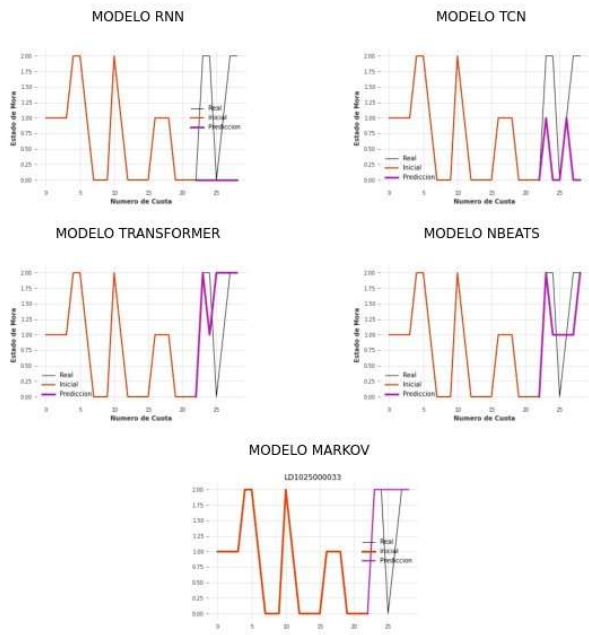
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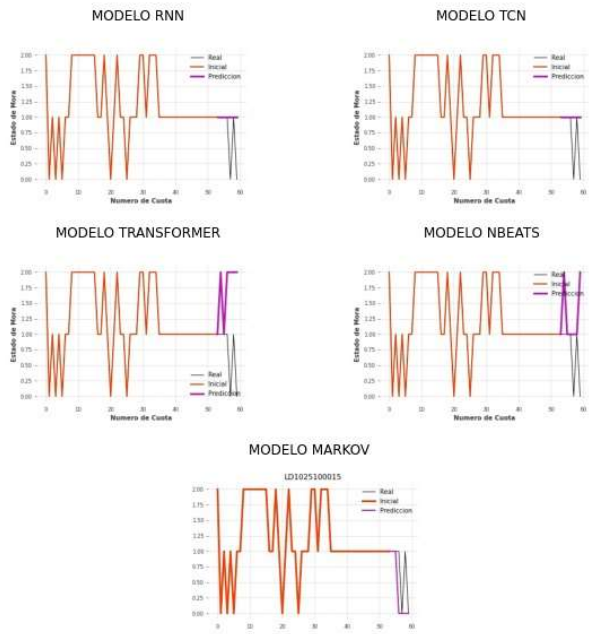
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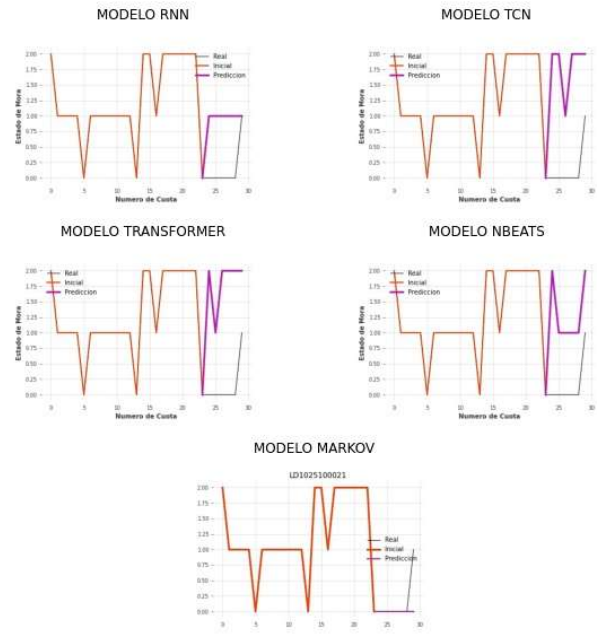
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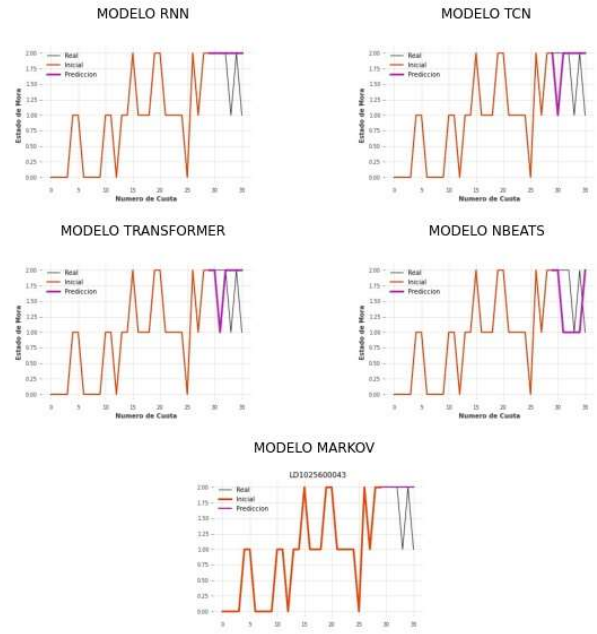
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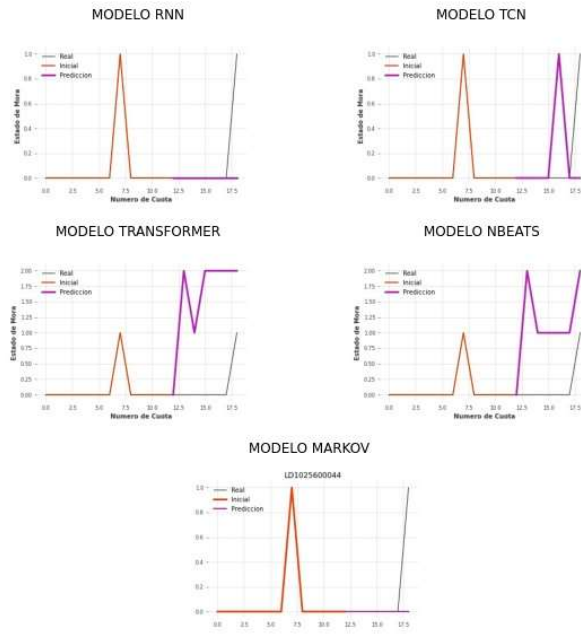
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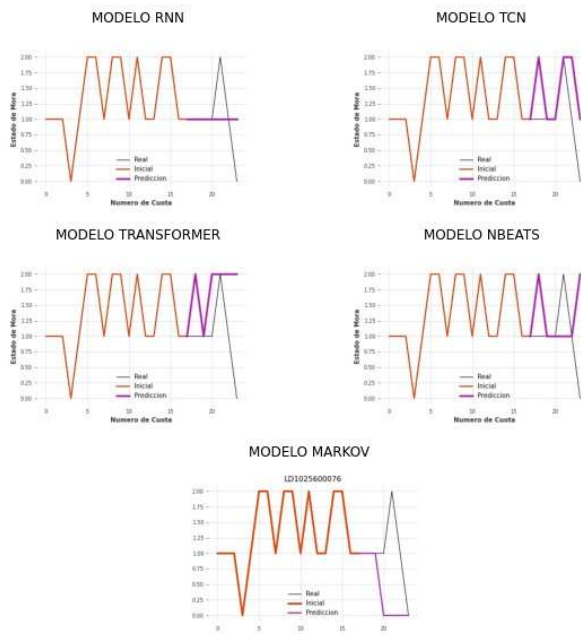
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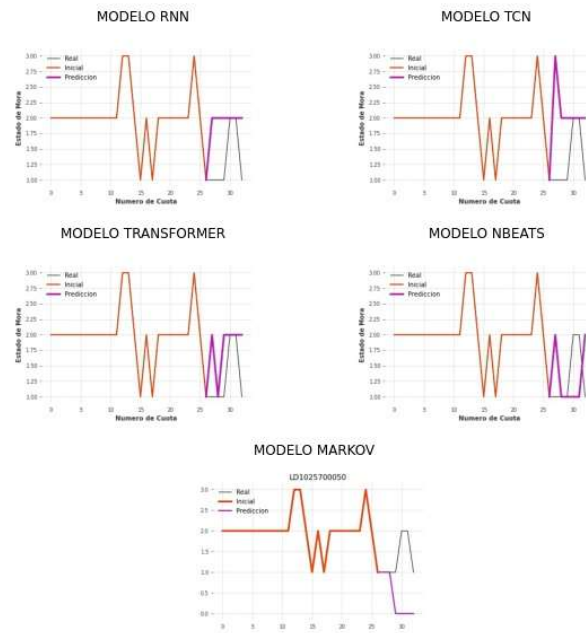


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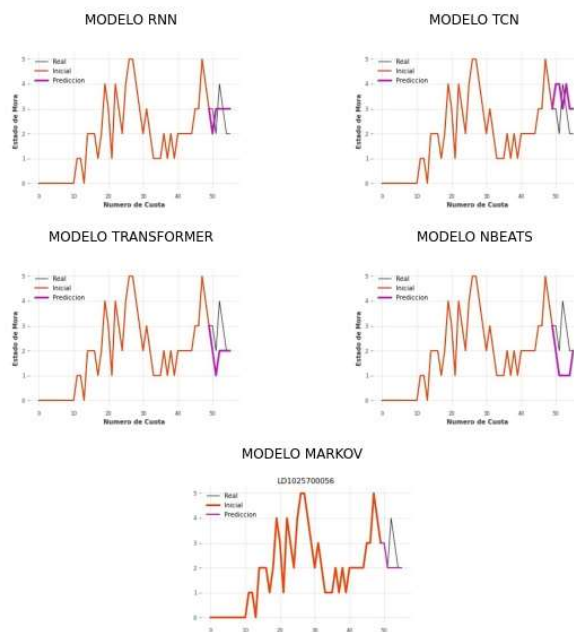




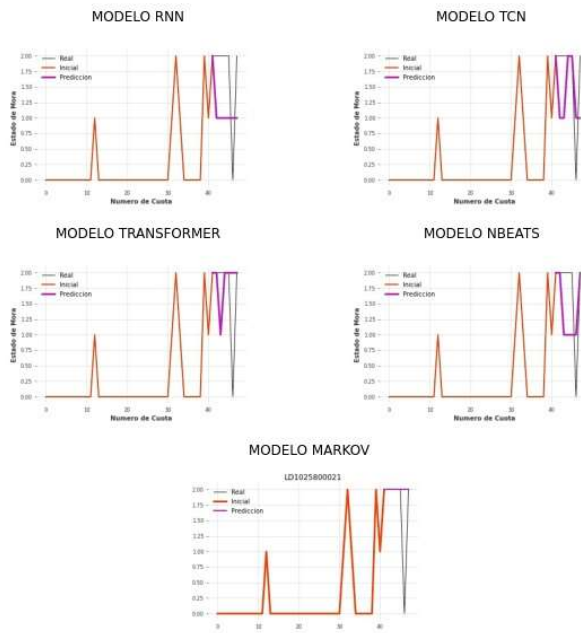
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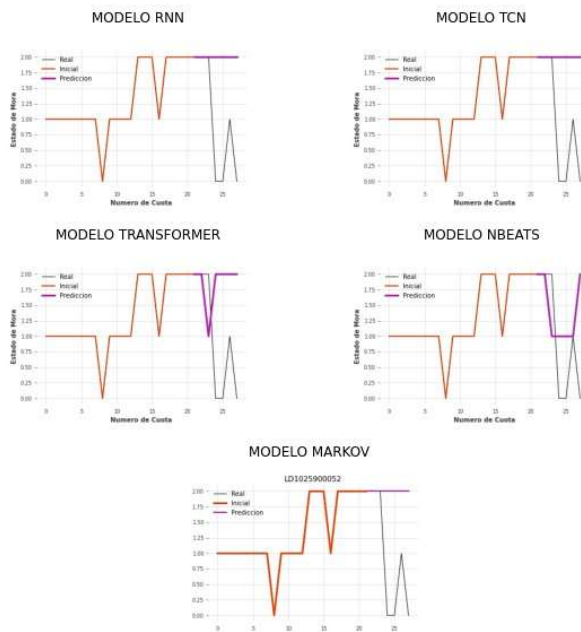
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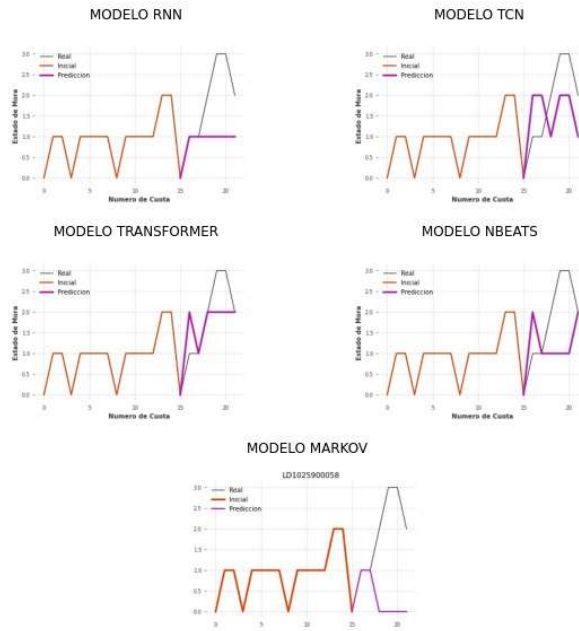
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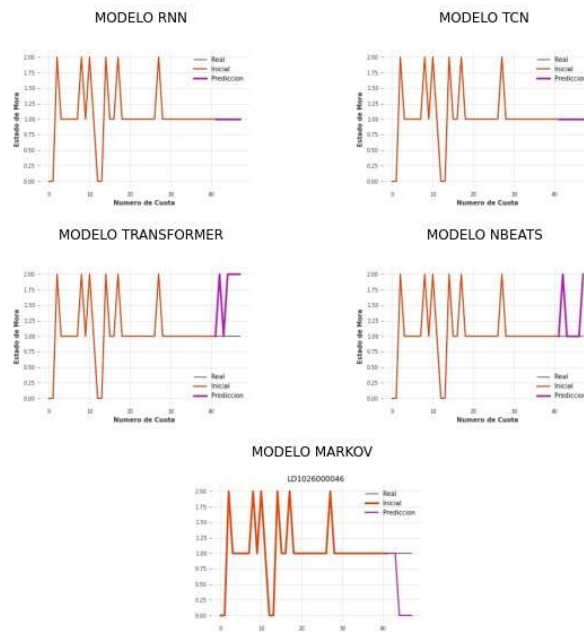
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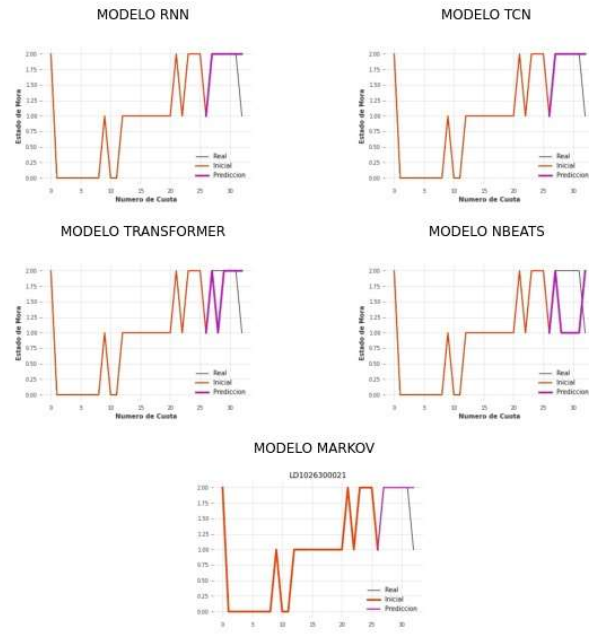
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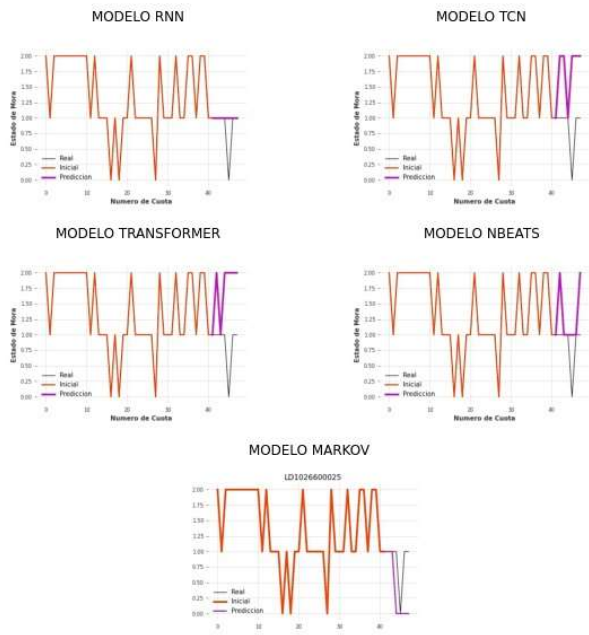


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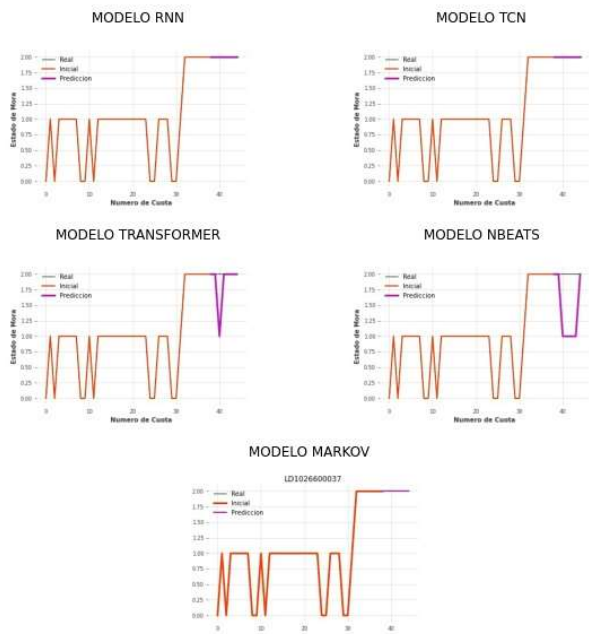




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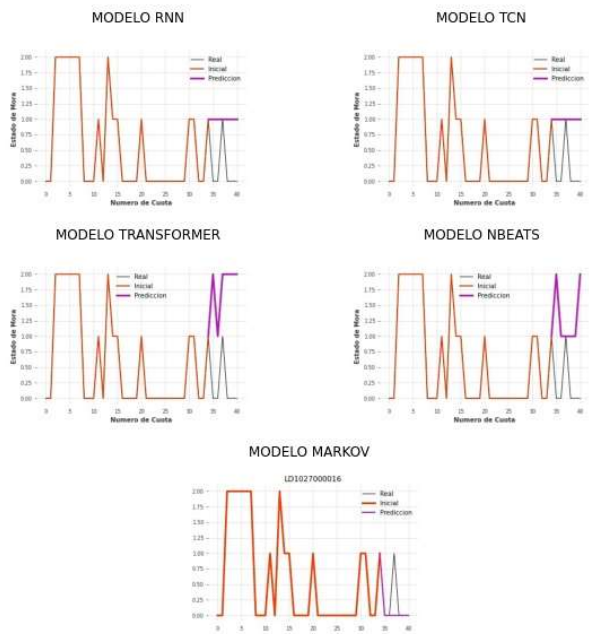
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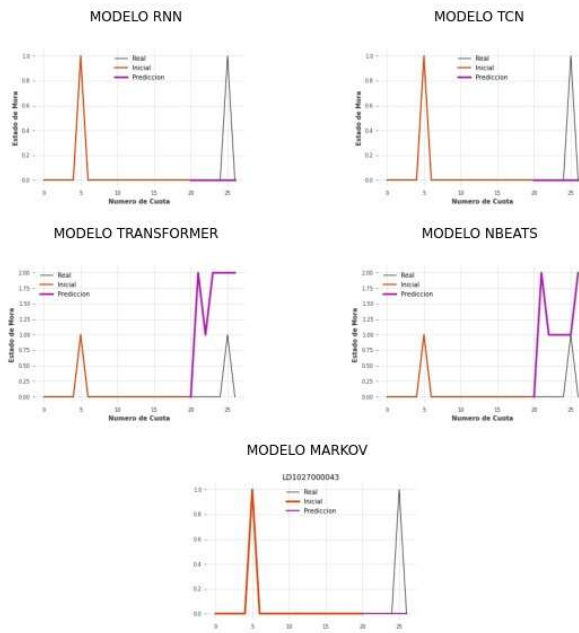
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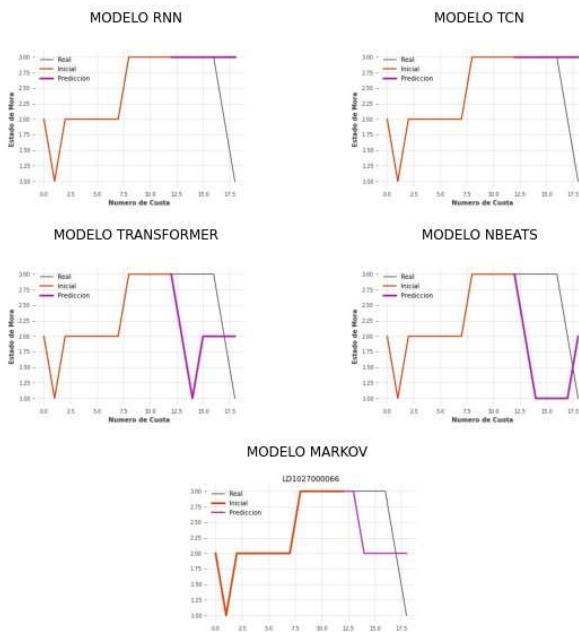
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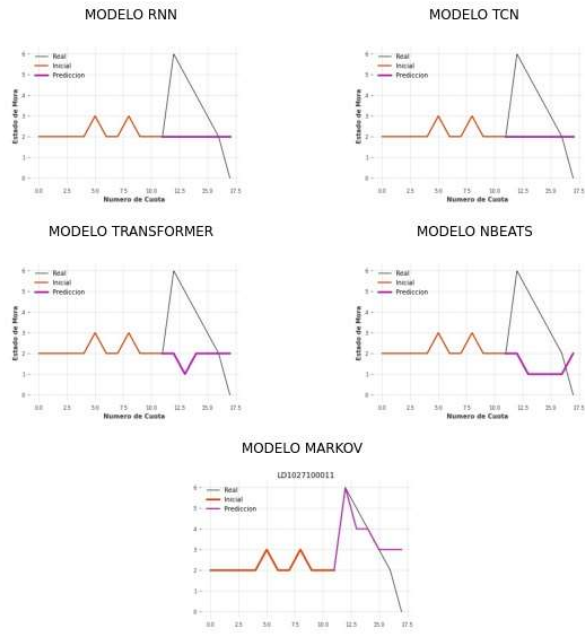


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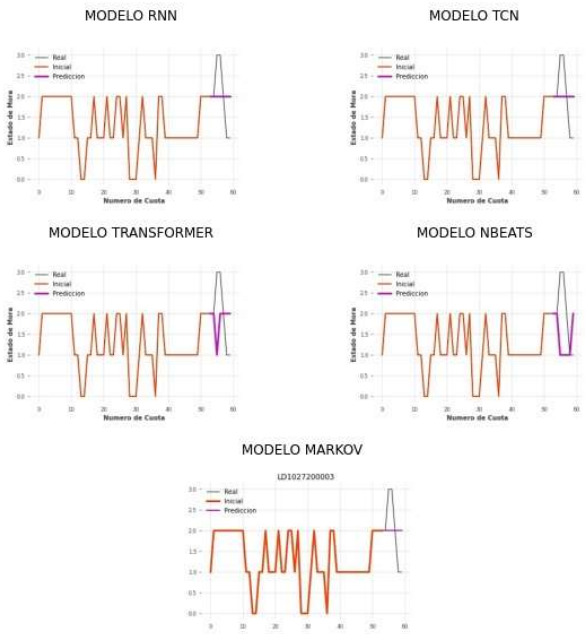




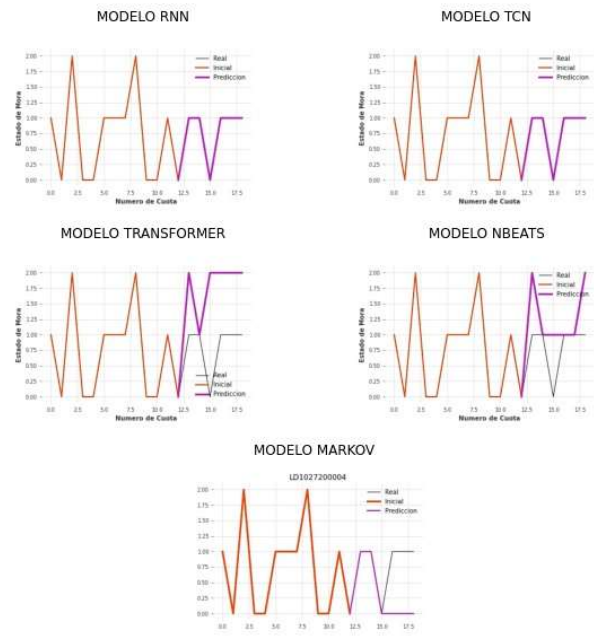
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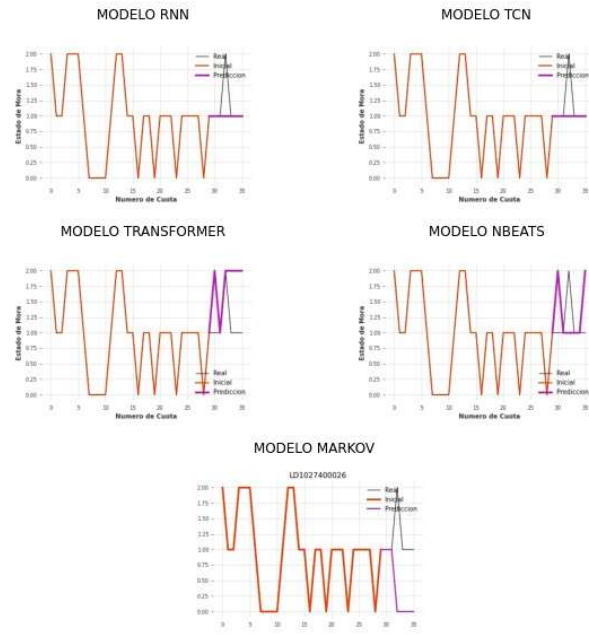
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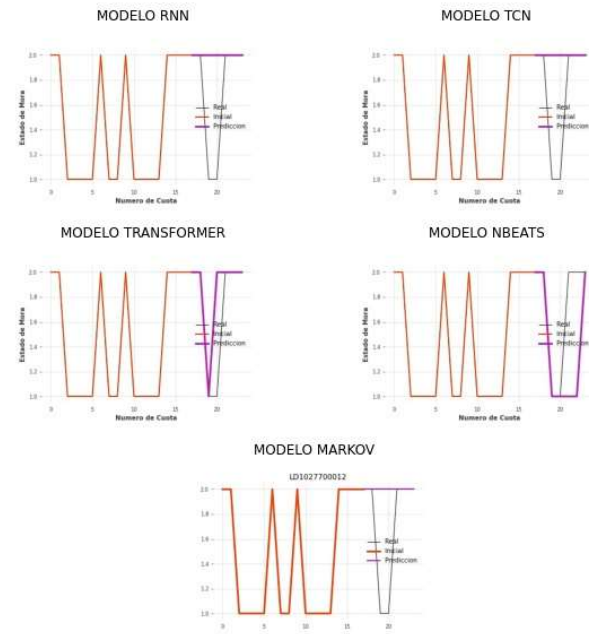
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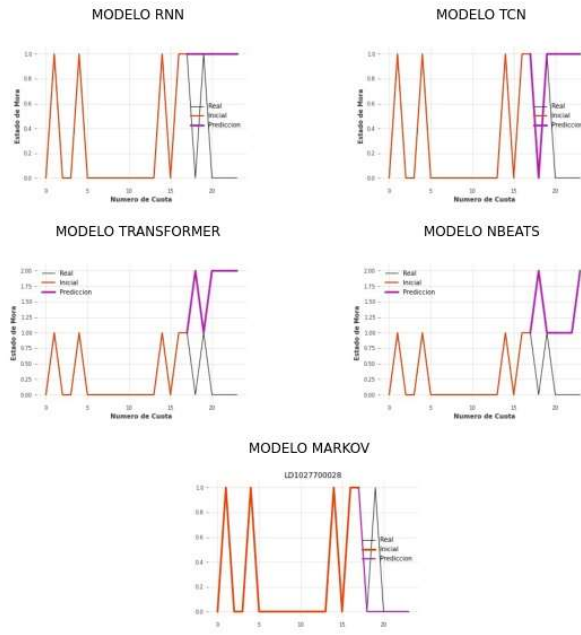
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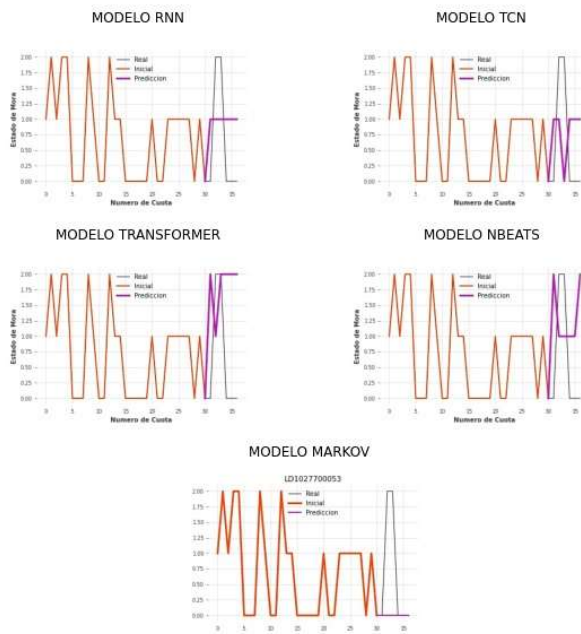
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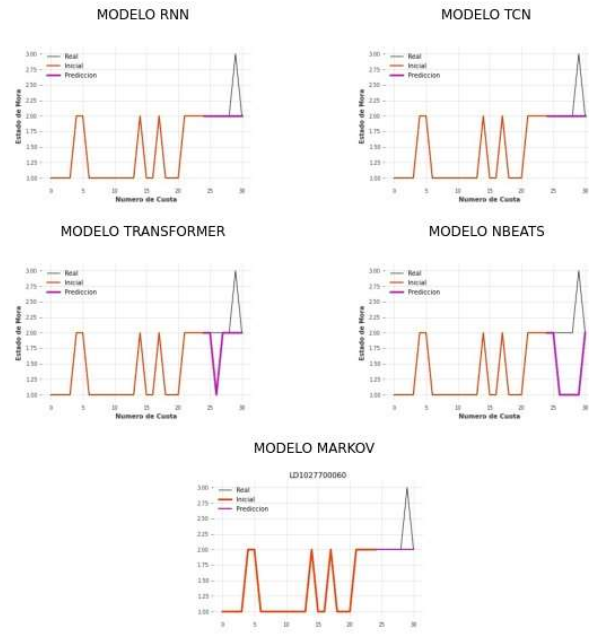
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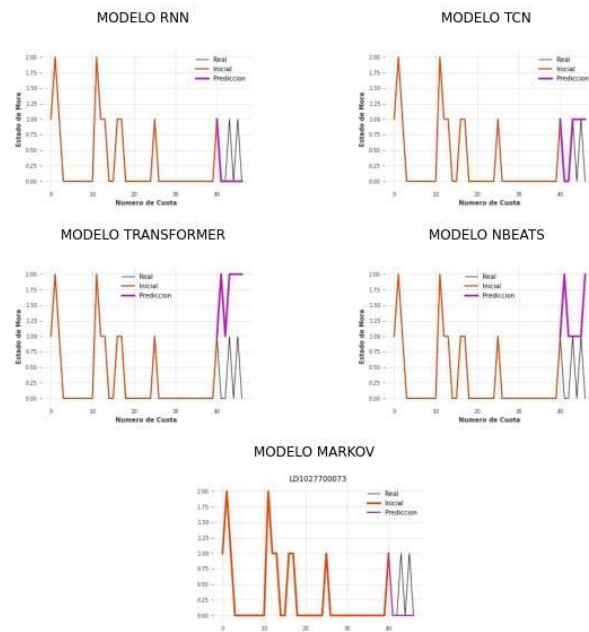
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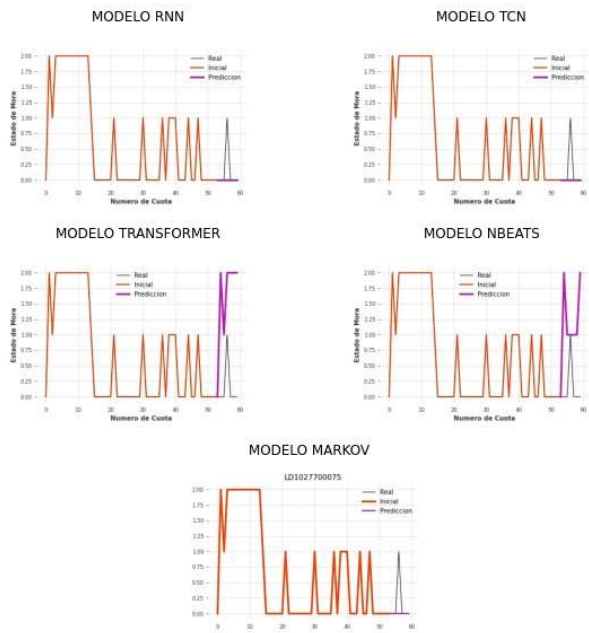
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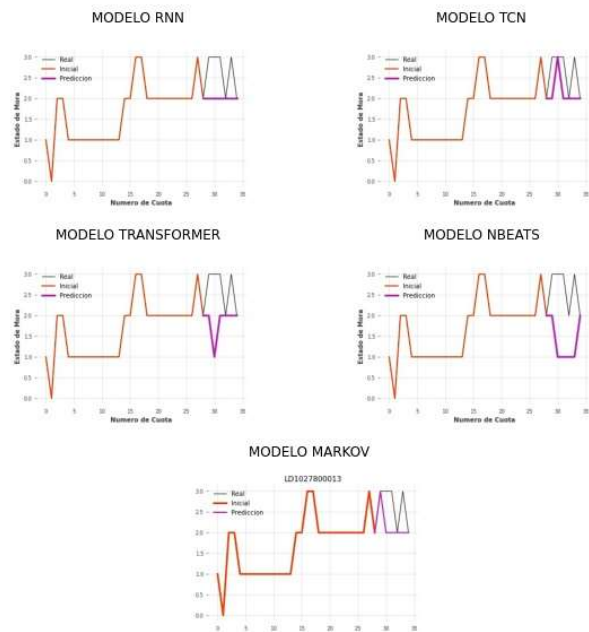
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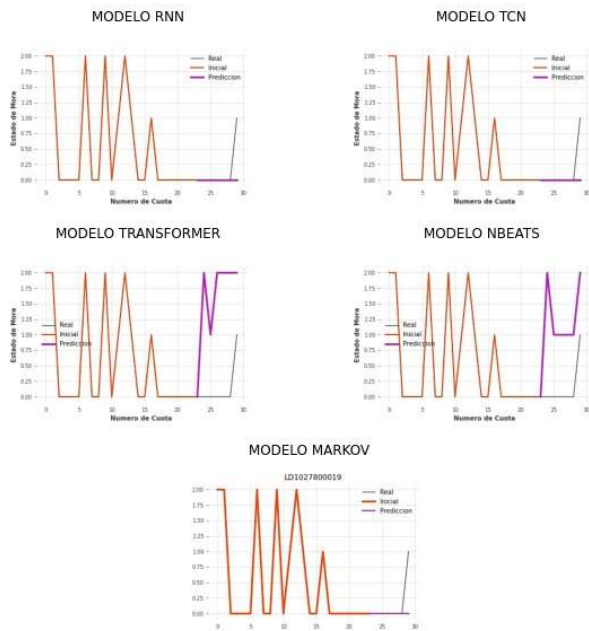
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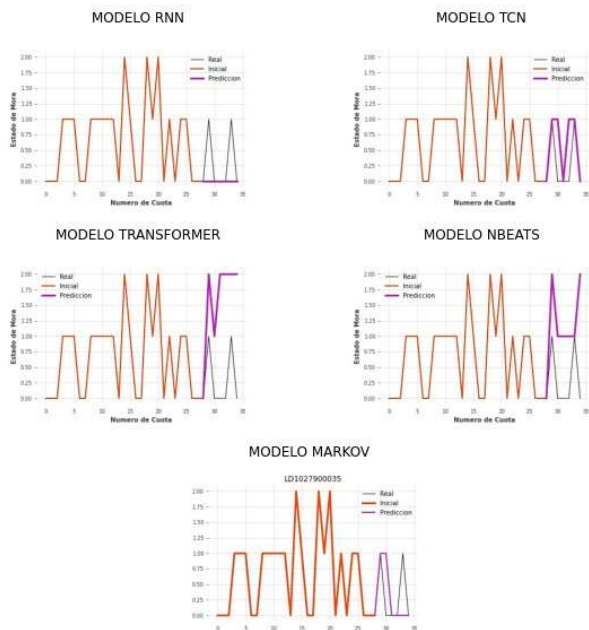
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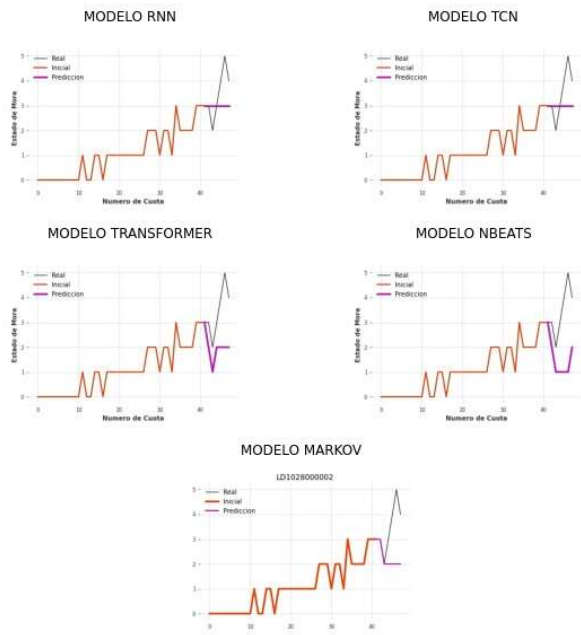
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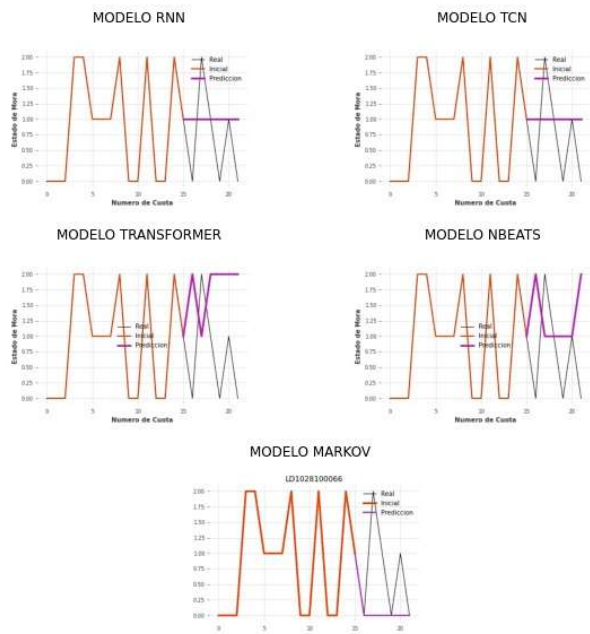
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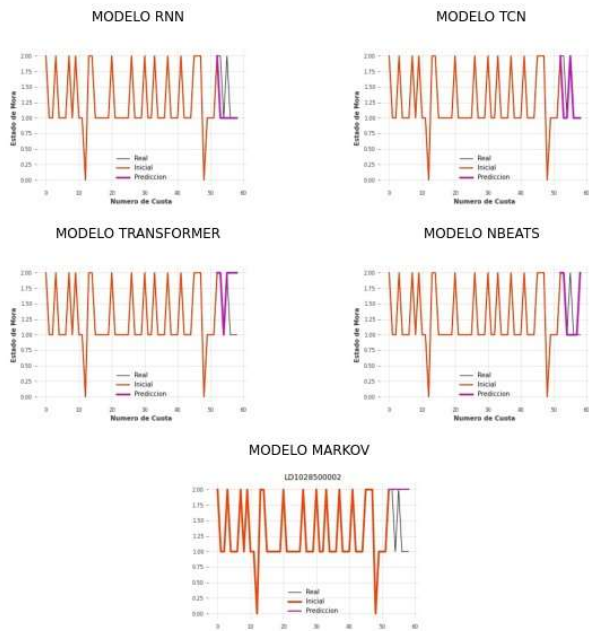


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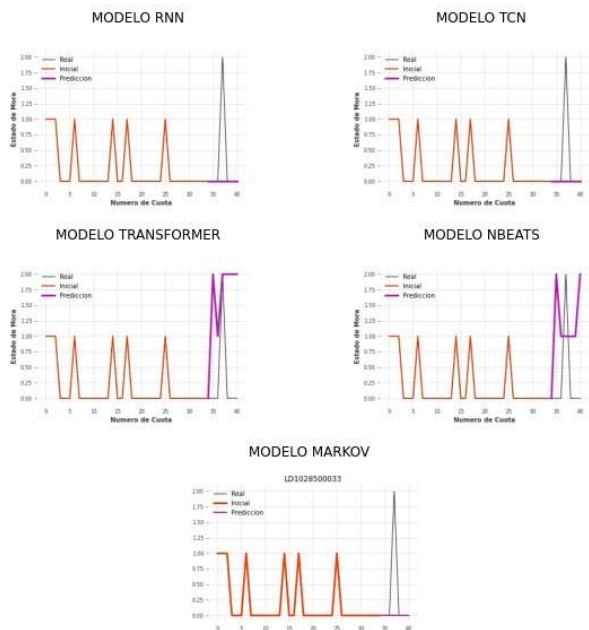




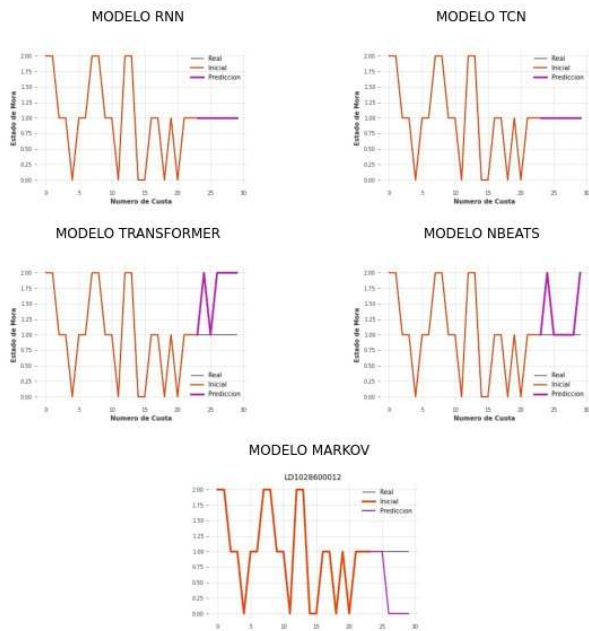
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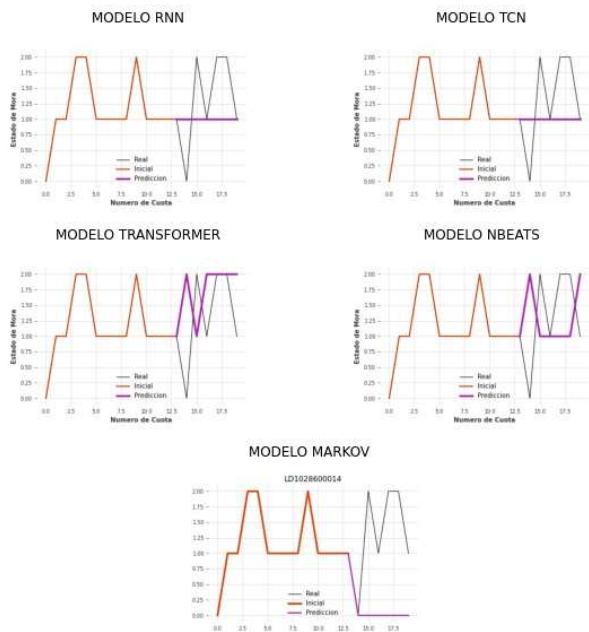
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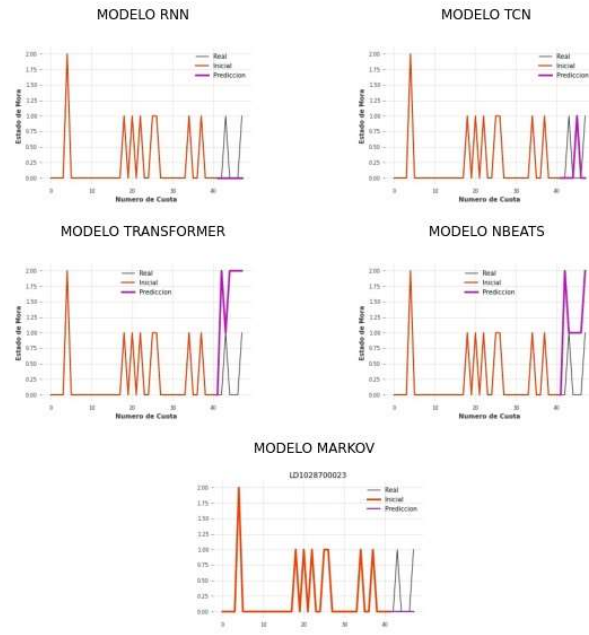
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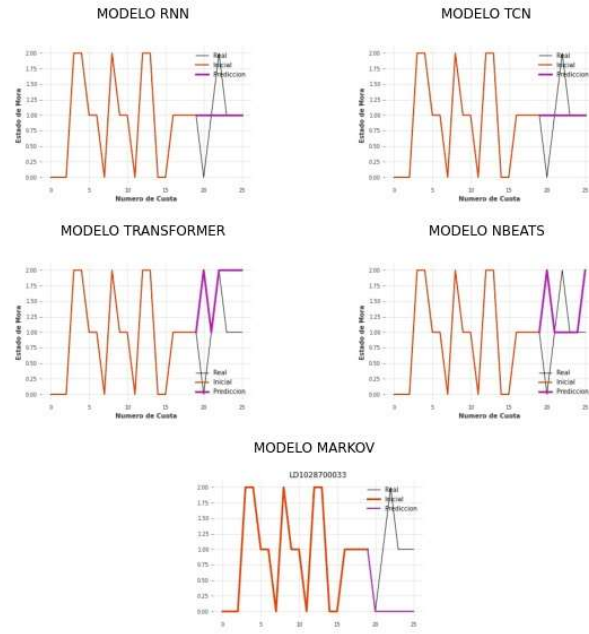
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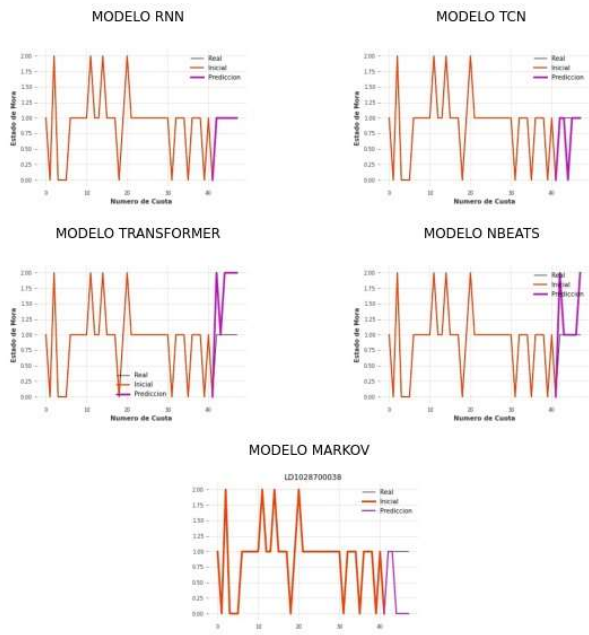
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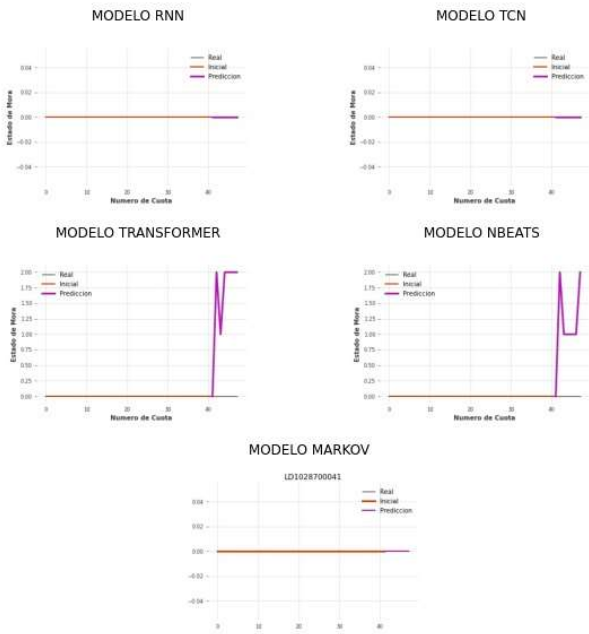
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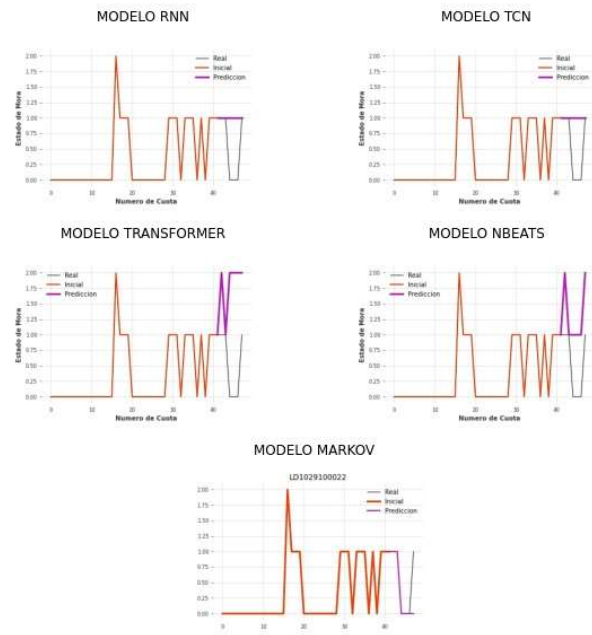
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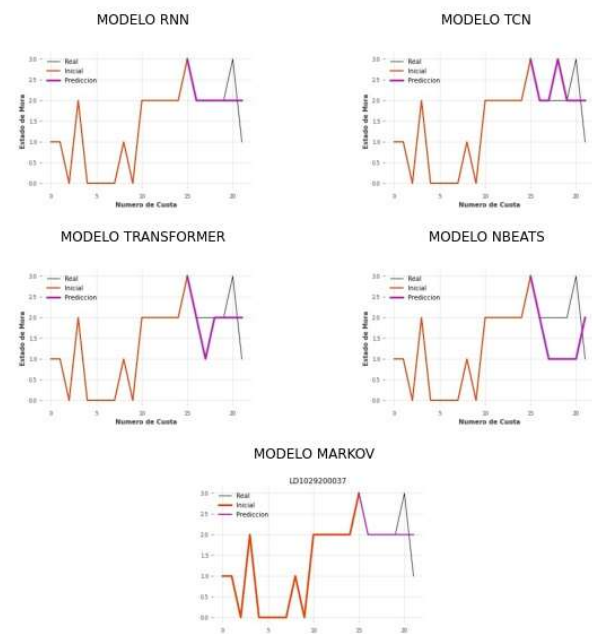
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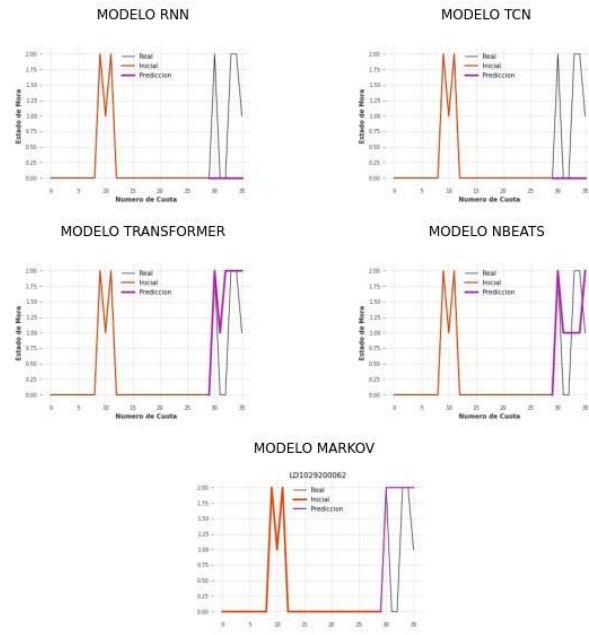
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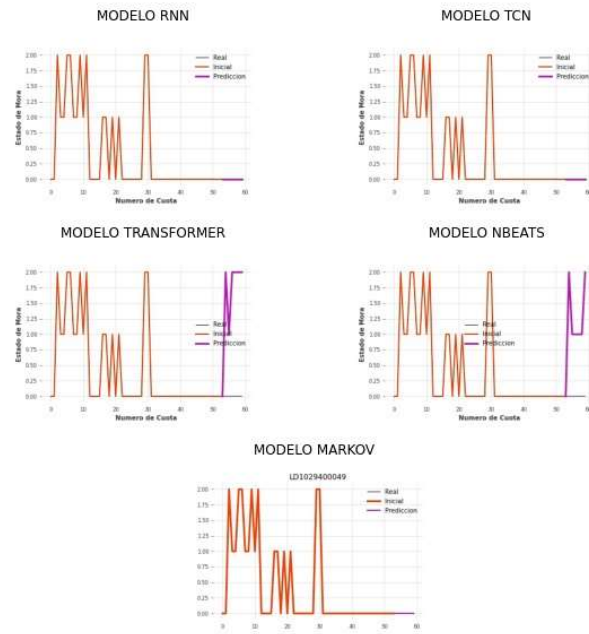
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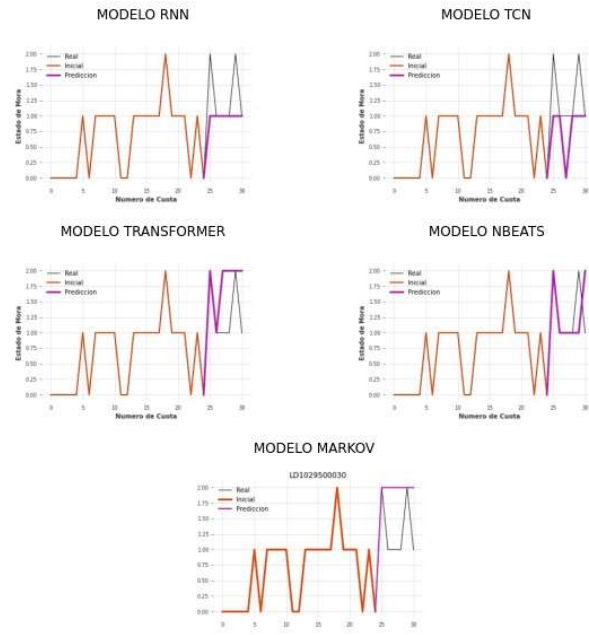
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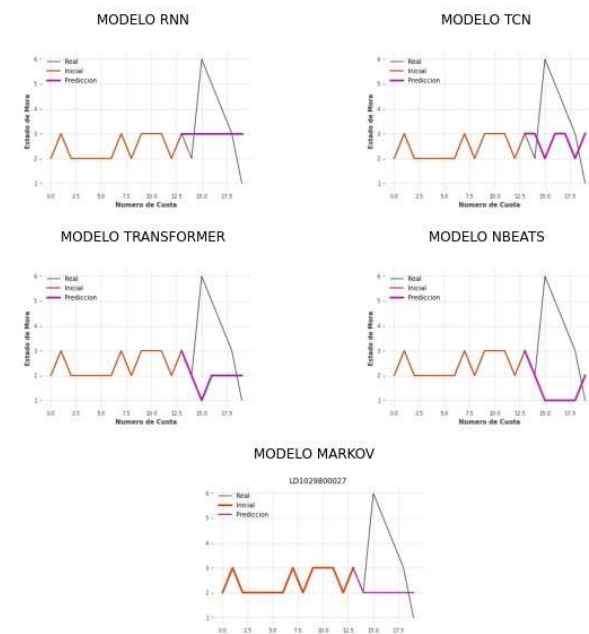
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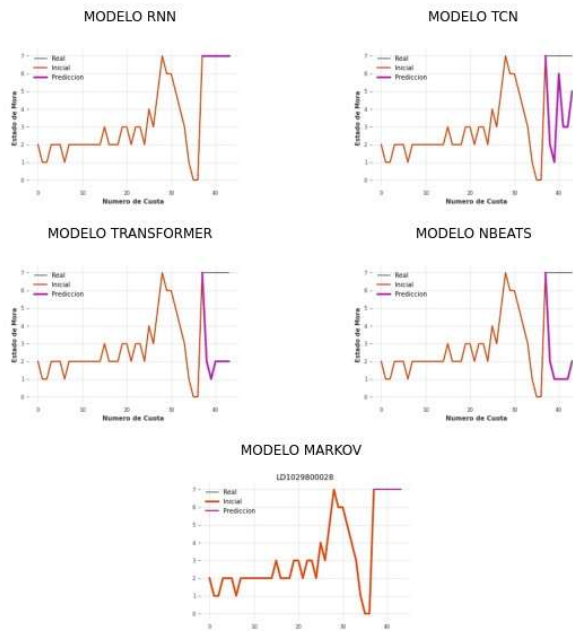
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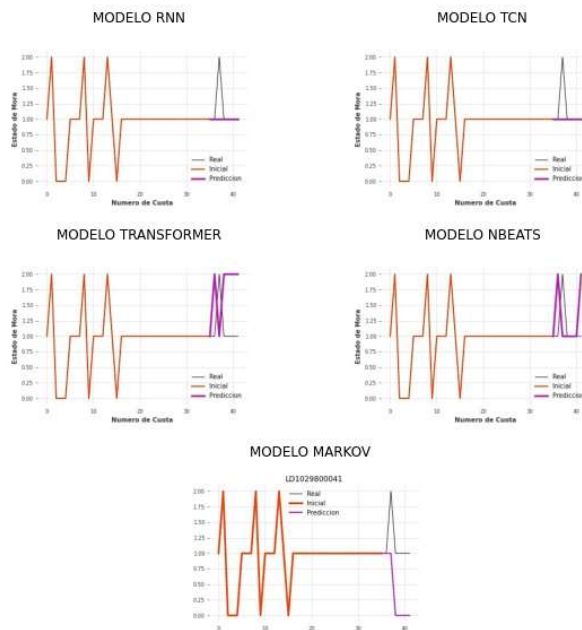
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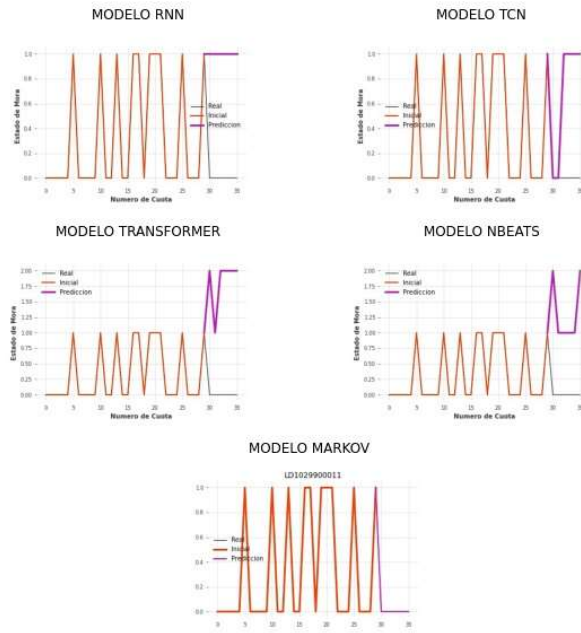


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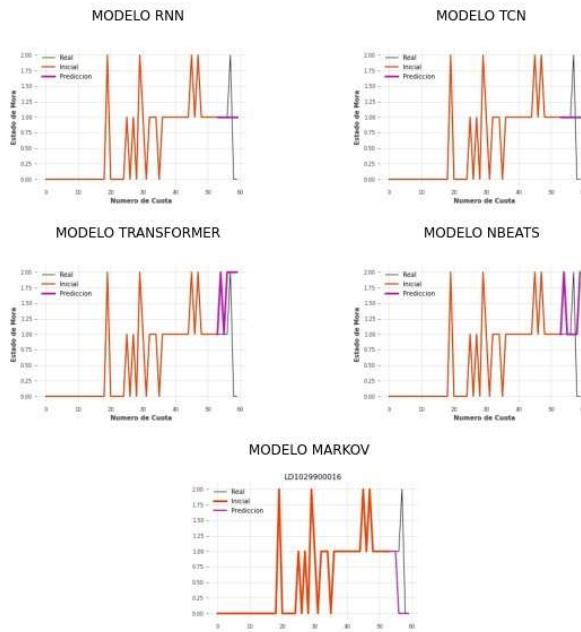




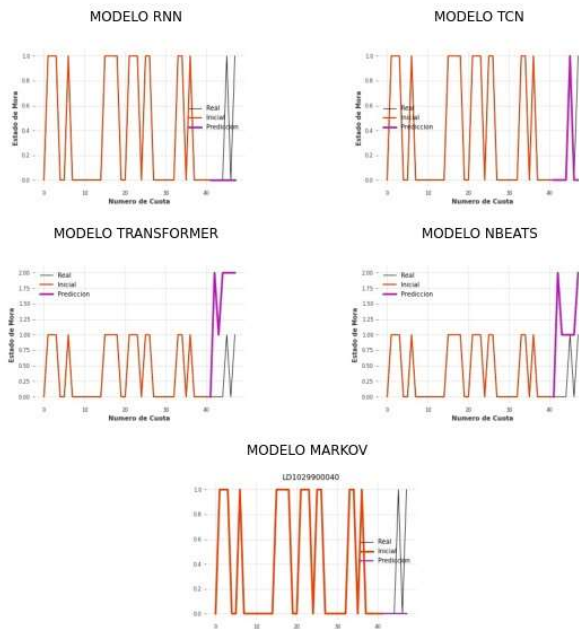
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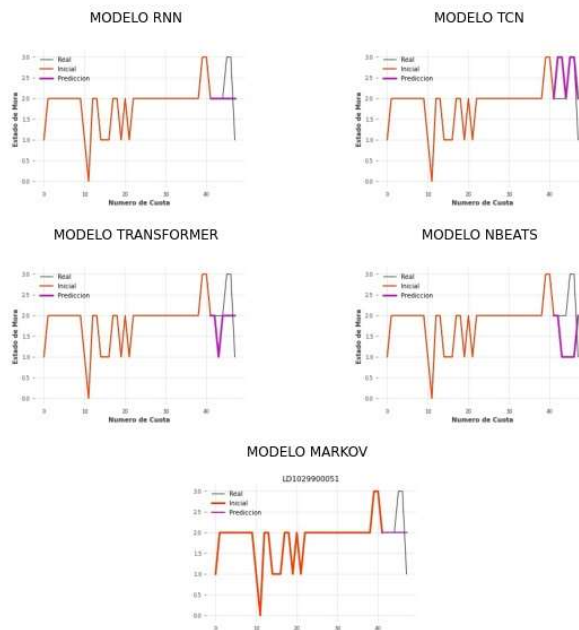
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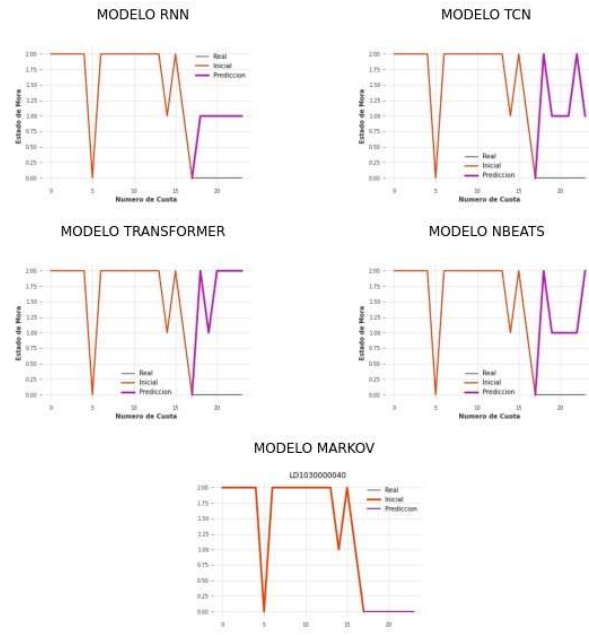
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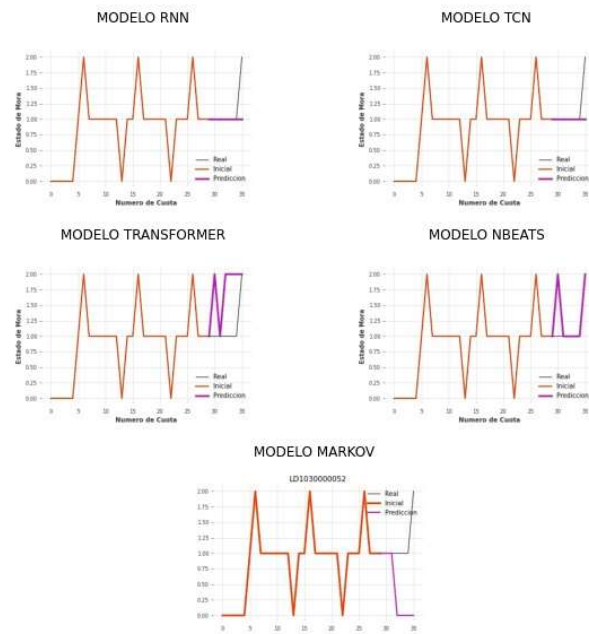
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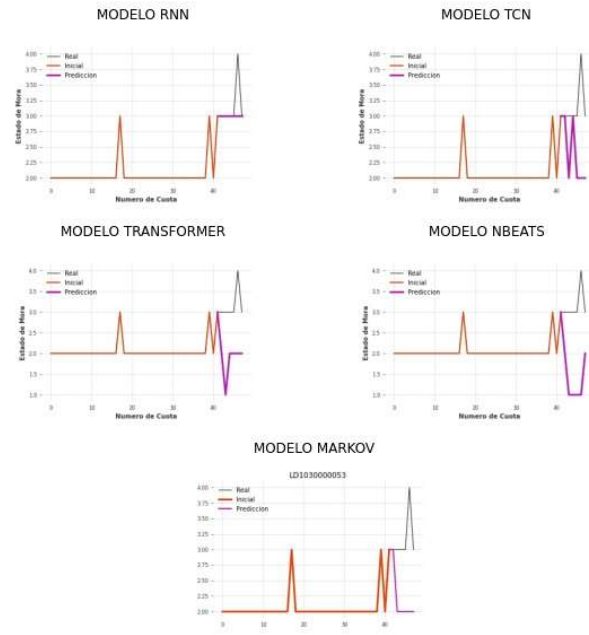
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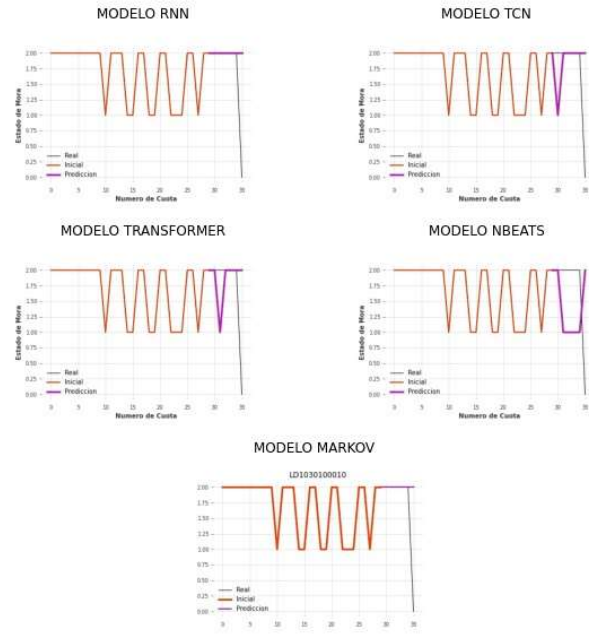
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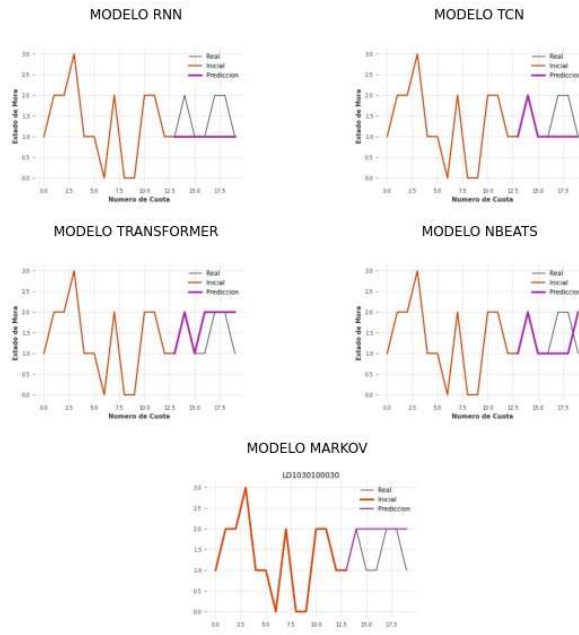
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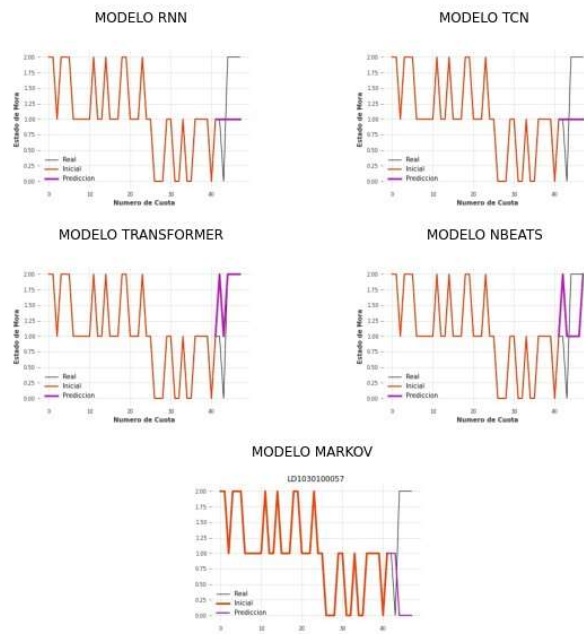
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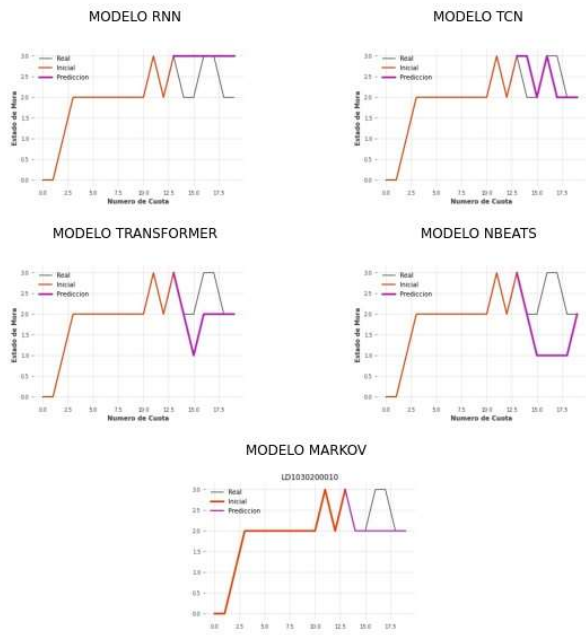
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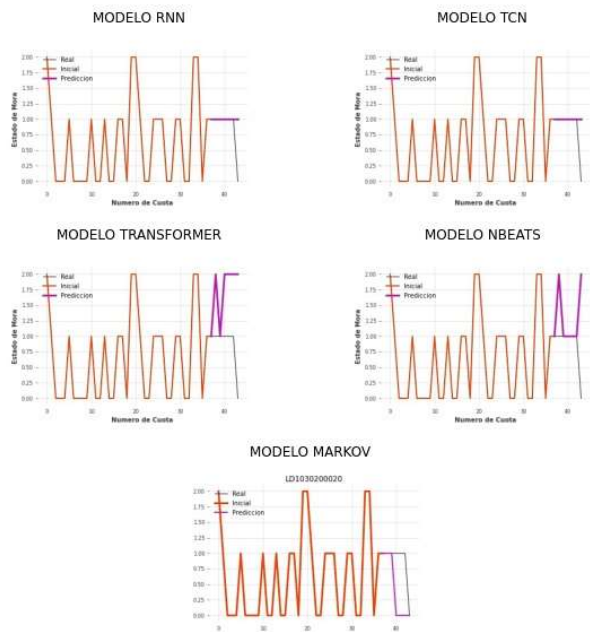
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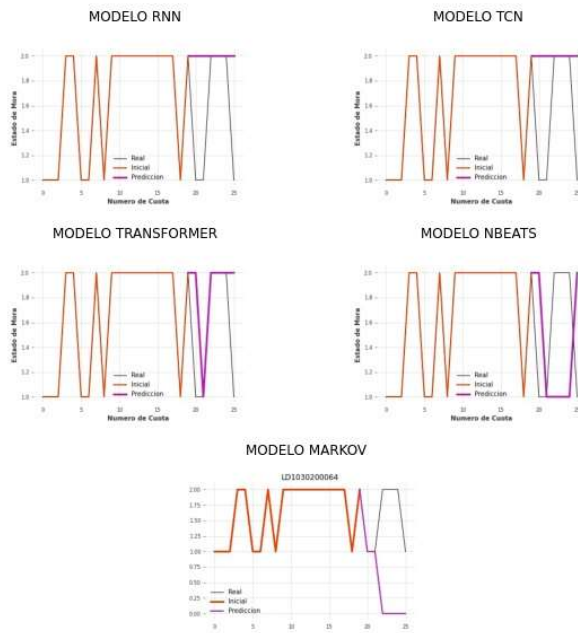
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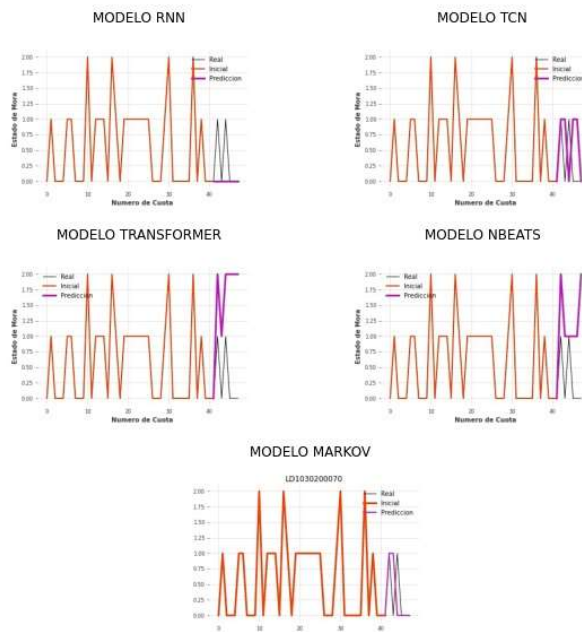
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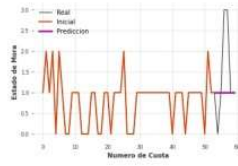


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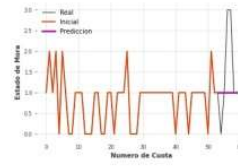


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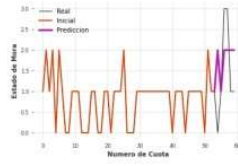
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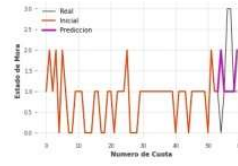
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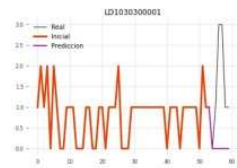
MODELO TRANSFORMER



MODELO NBEATS

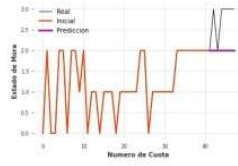


MODELO MARKOV

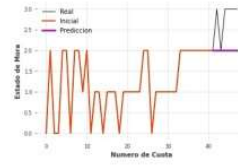


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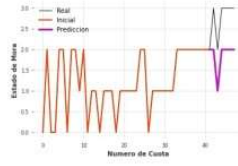
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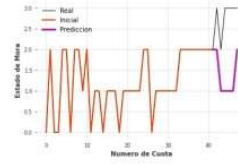
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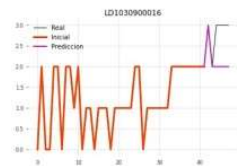
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MODELO NBEATS

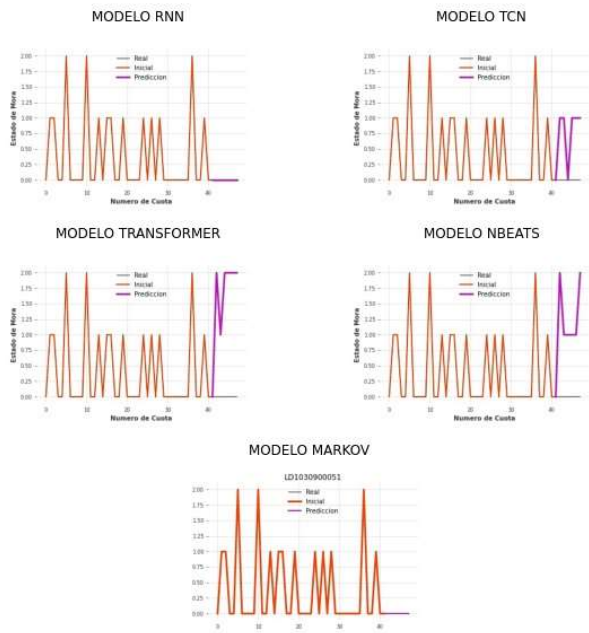


MODELO MARKOV

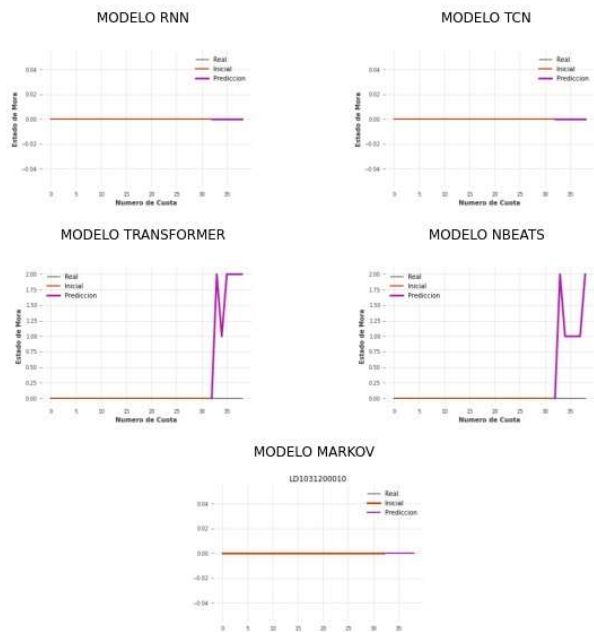




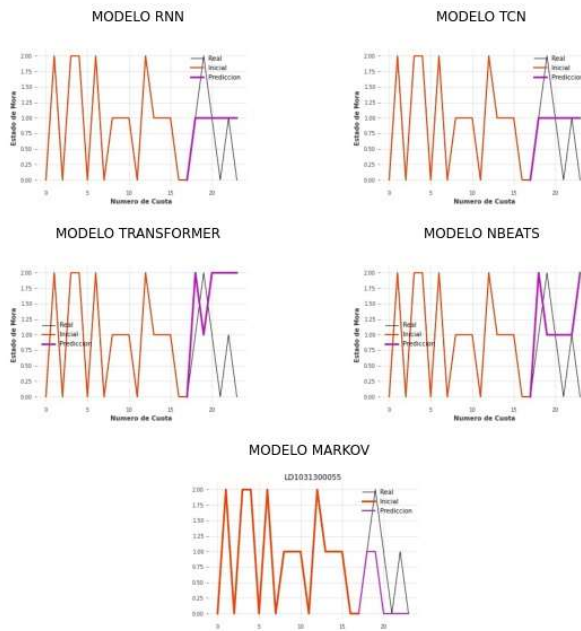
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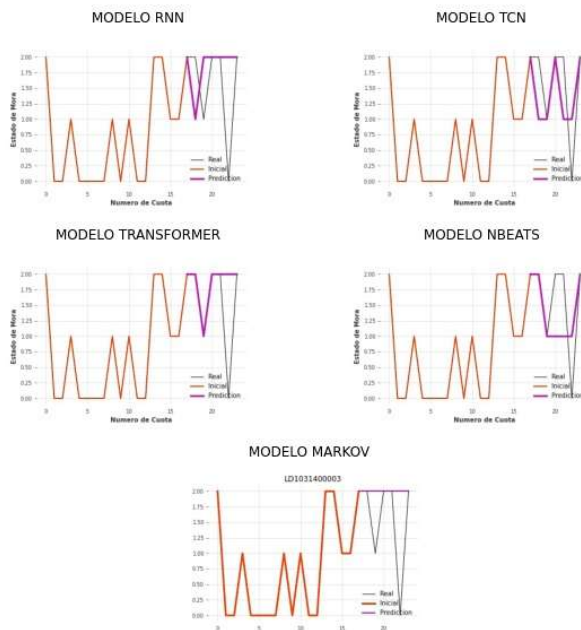
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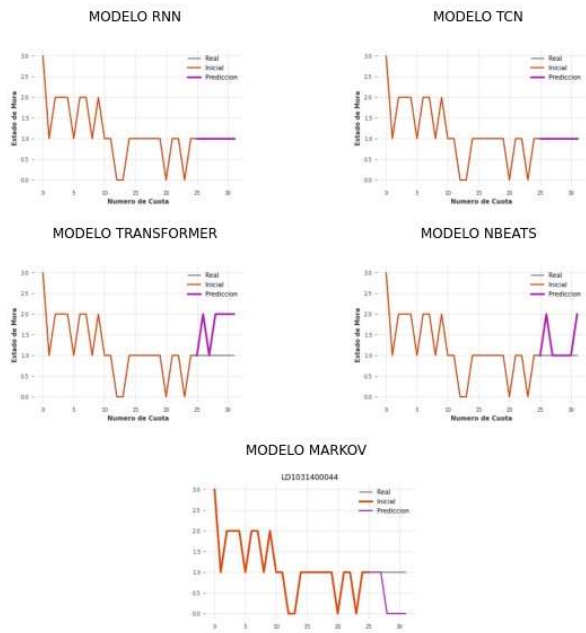
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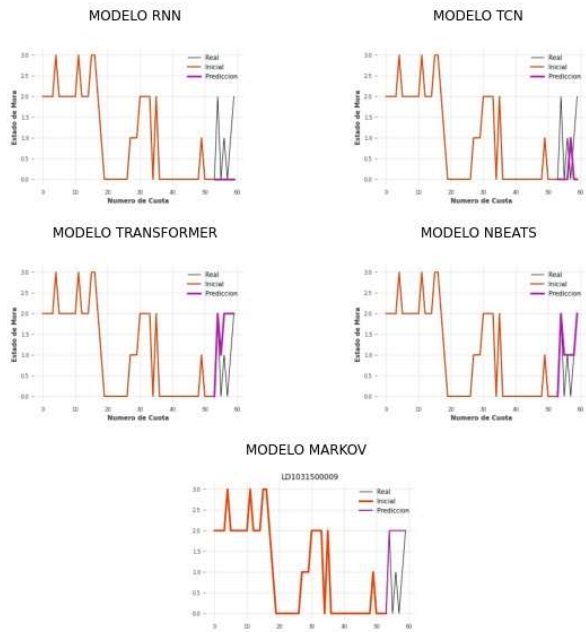
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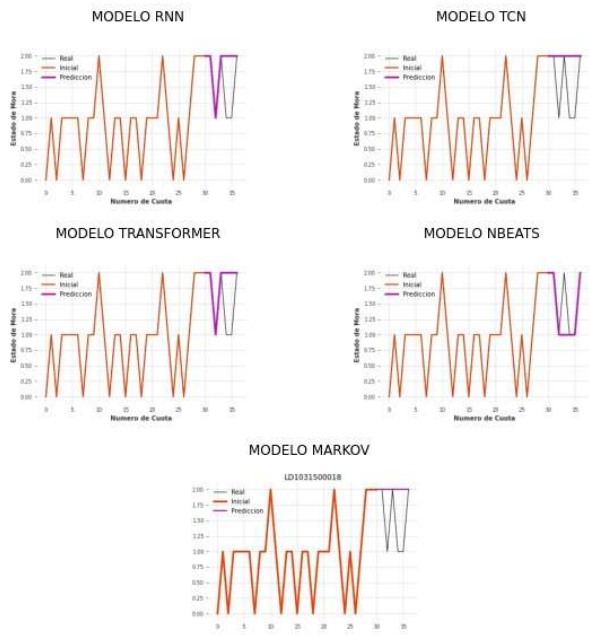
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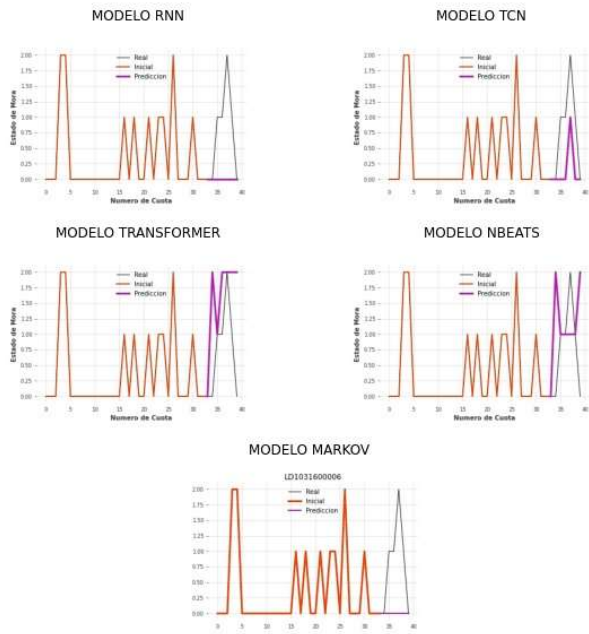
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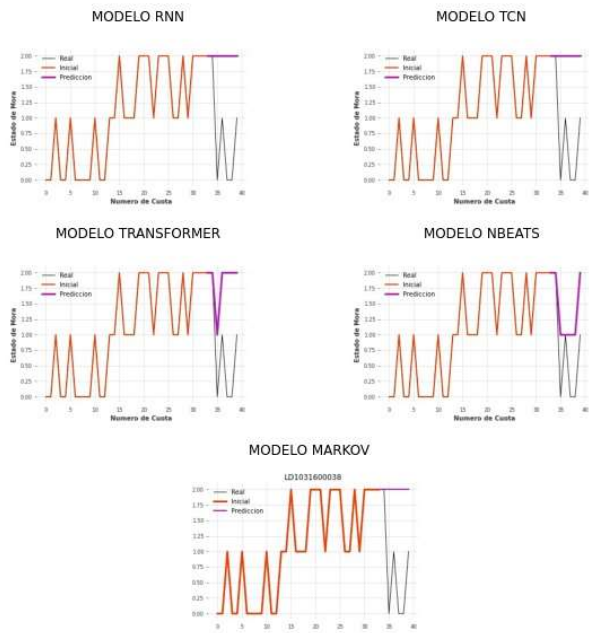
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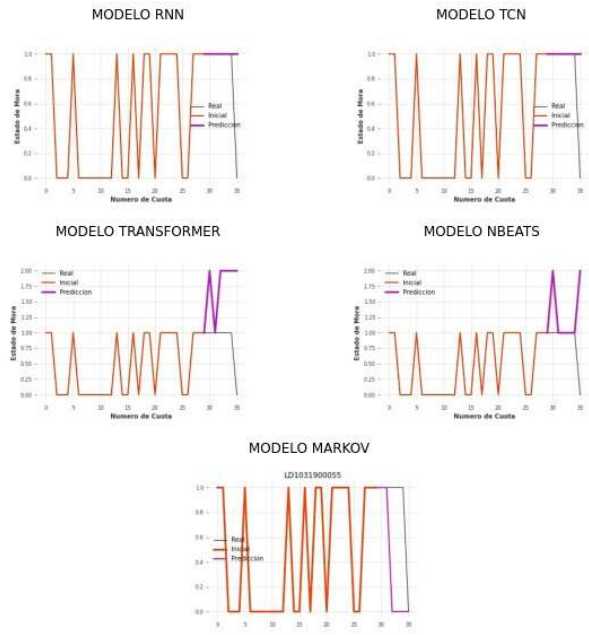
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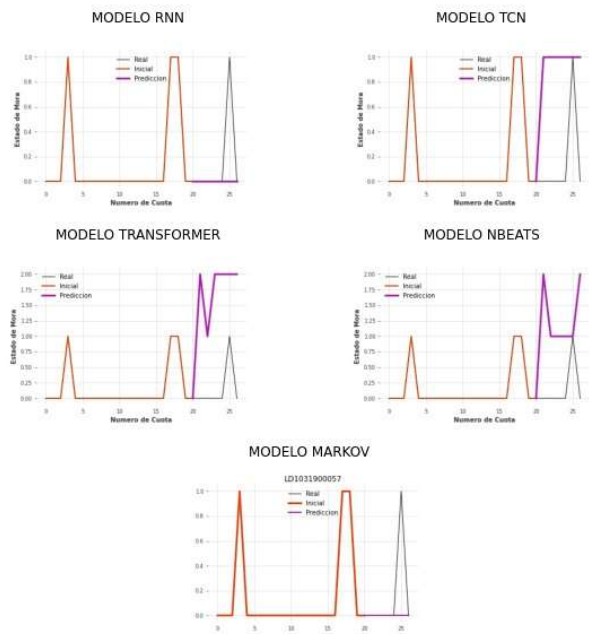
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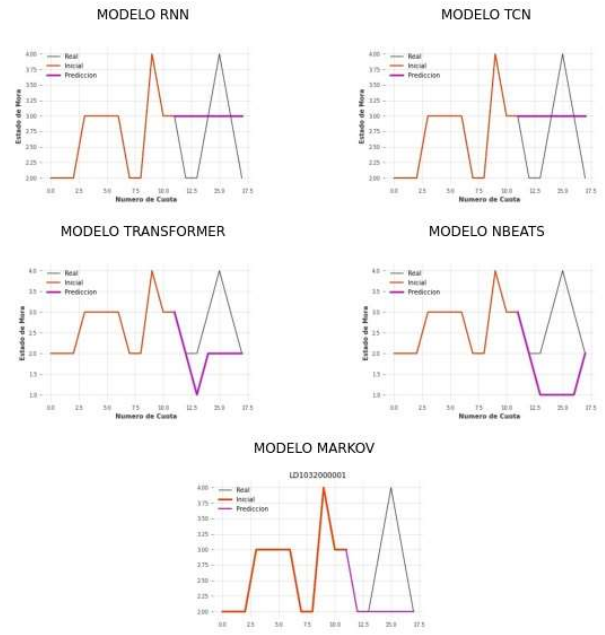
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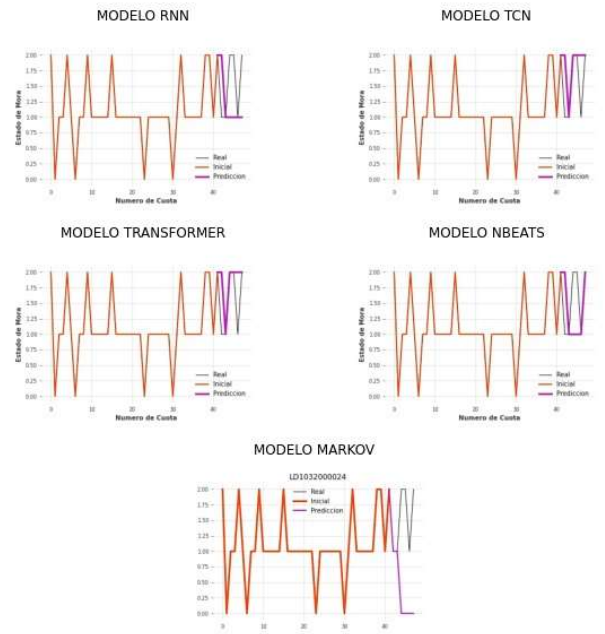
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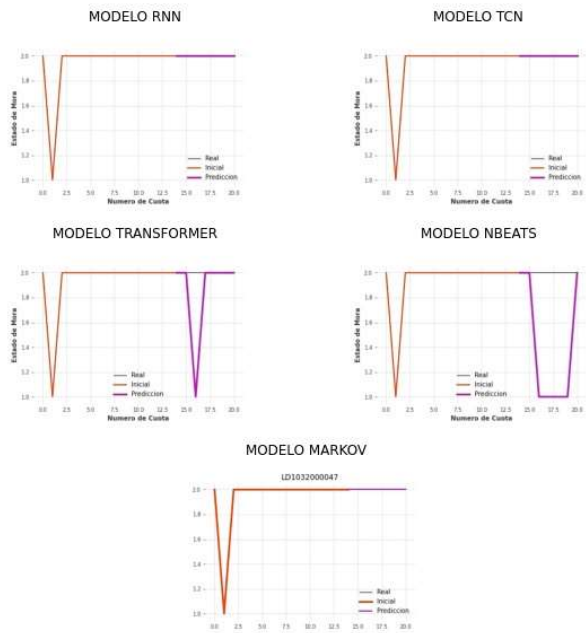
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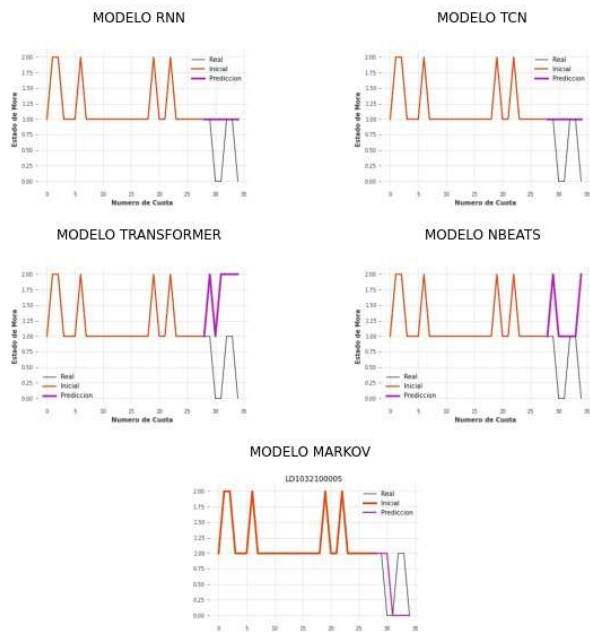
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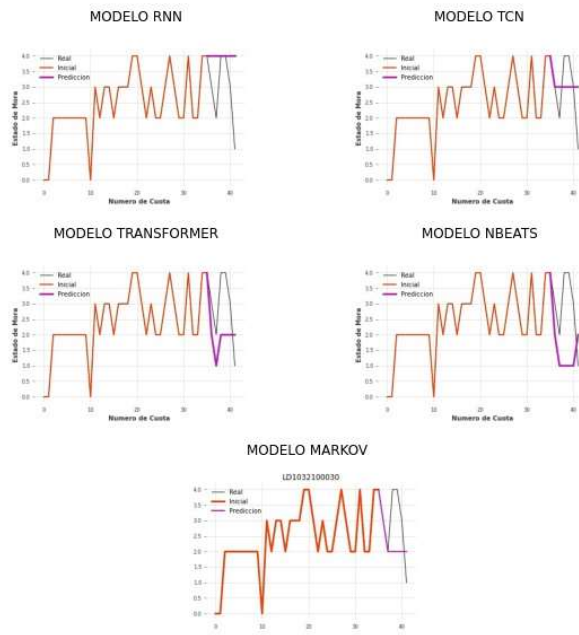


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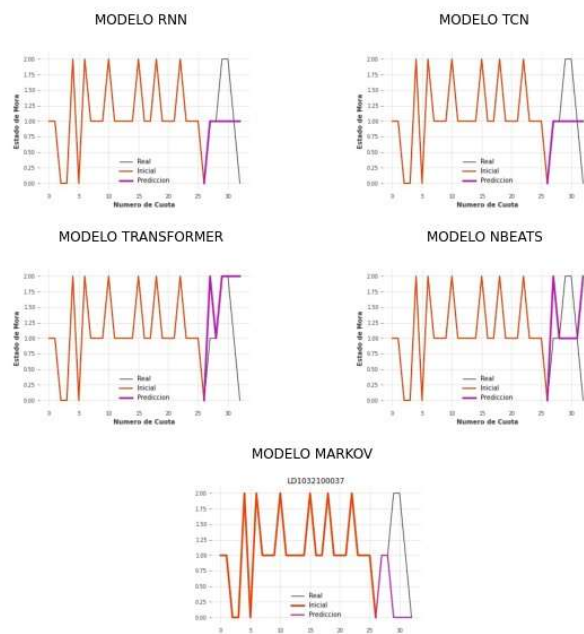




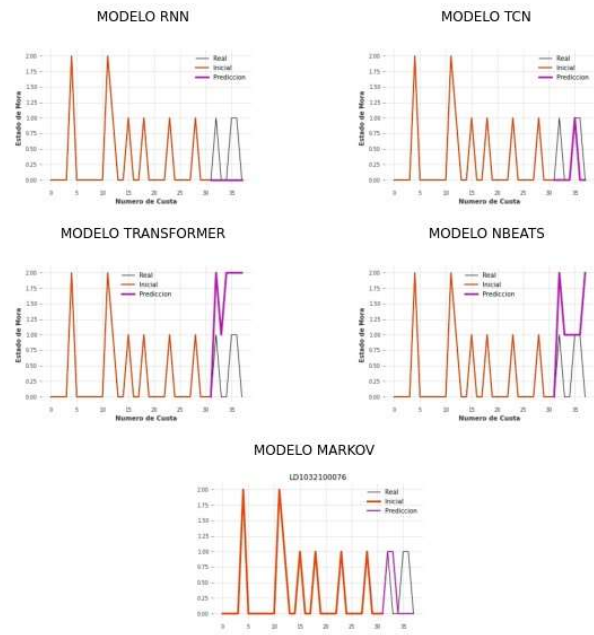
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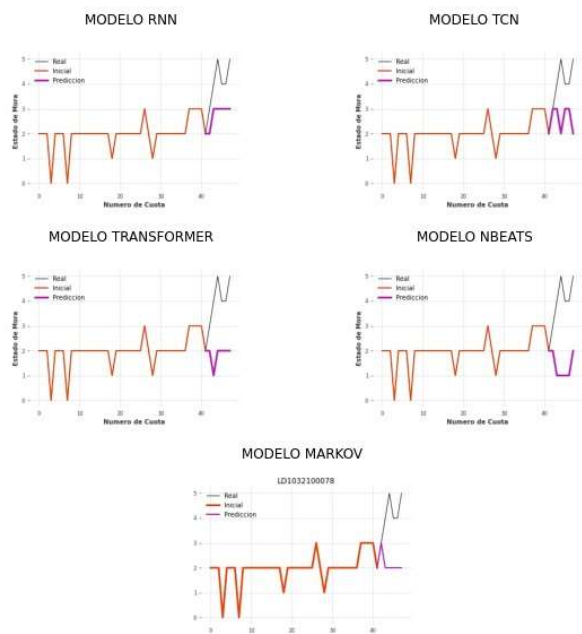
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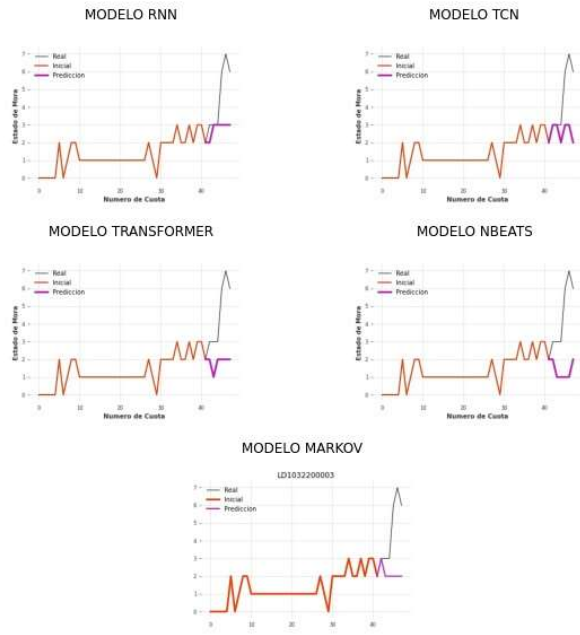
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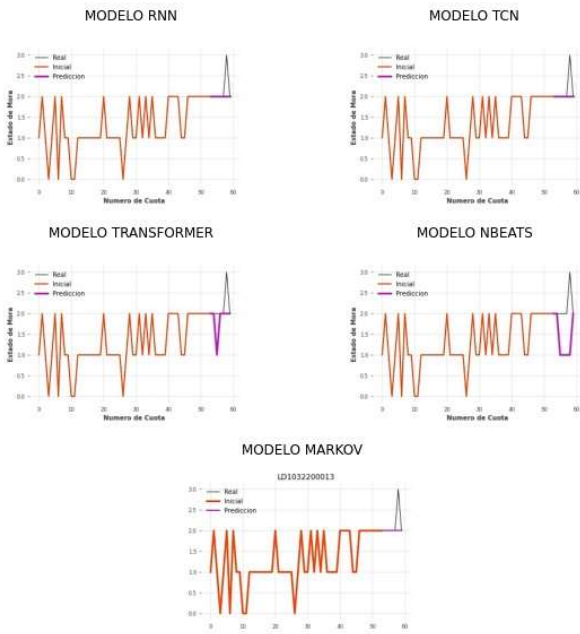
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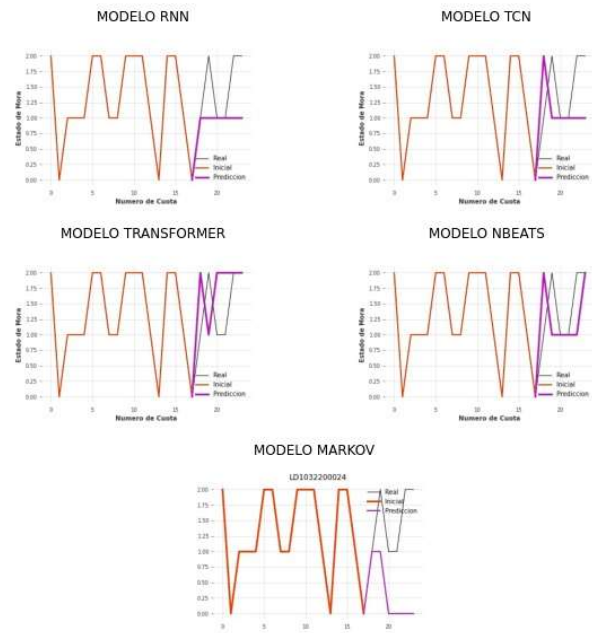
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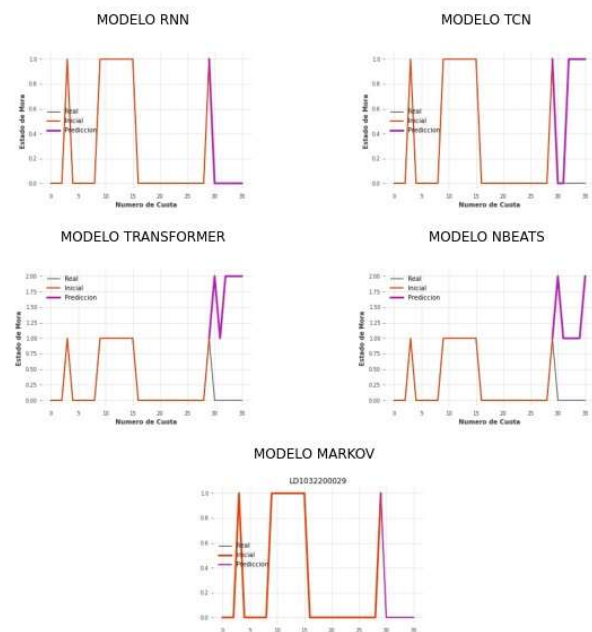
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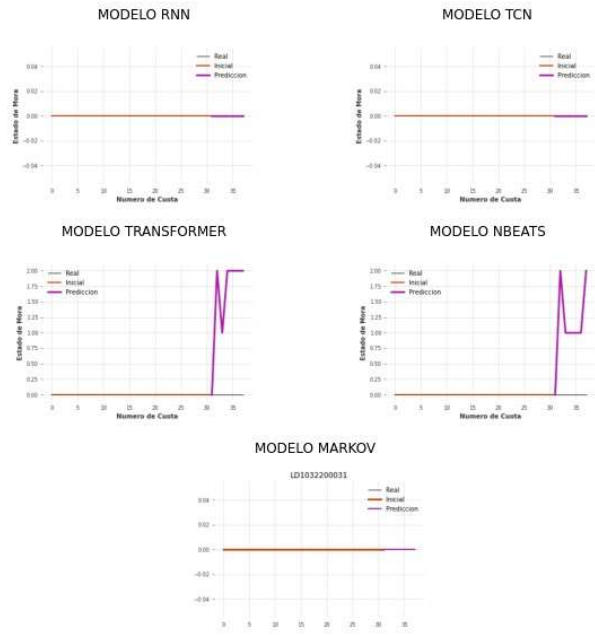
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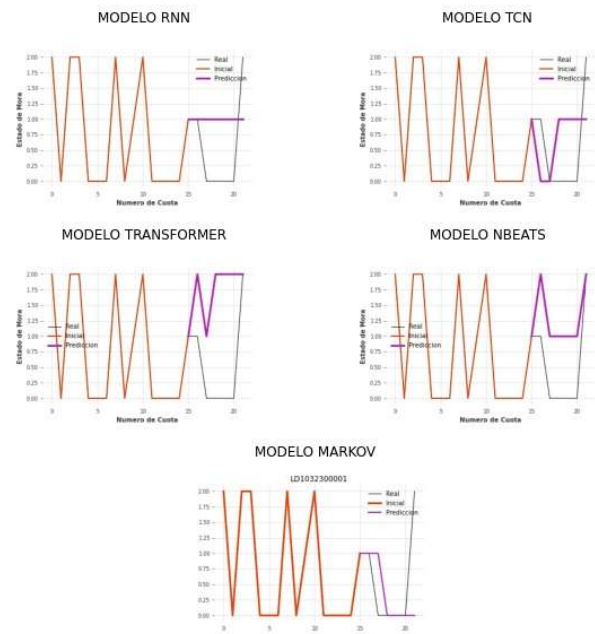
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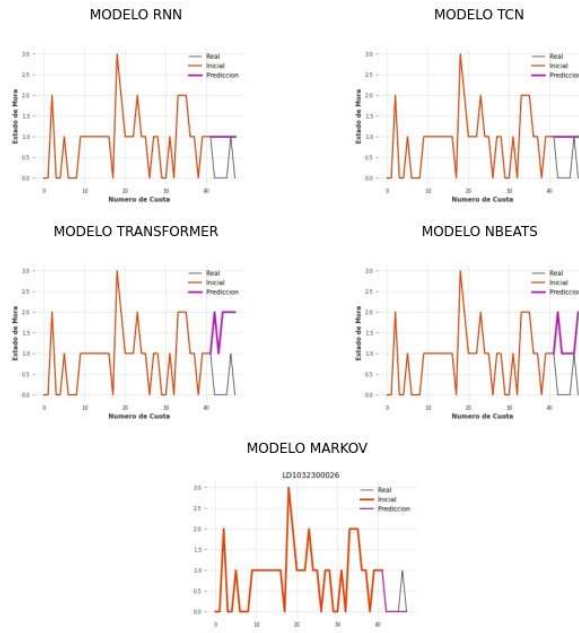
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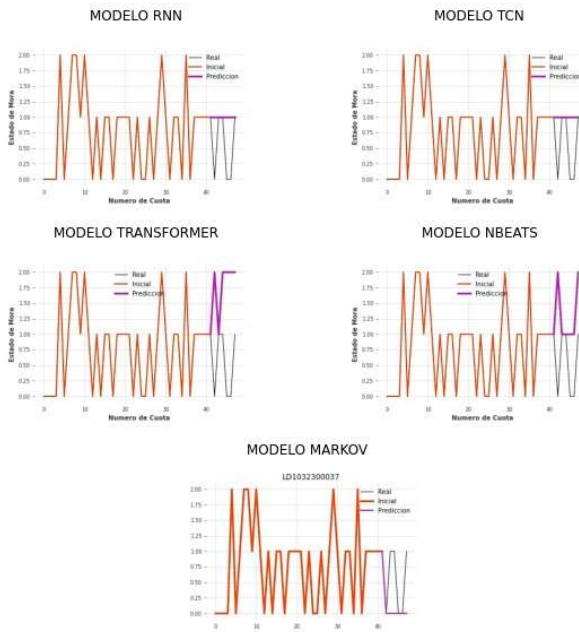
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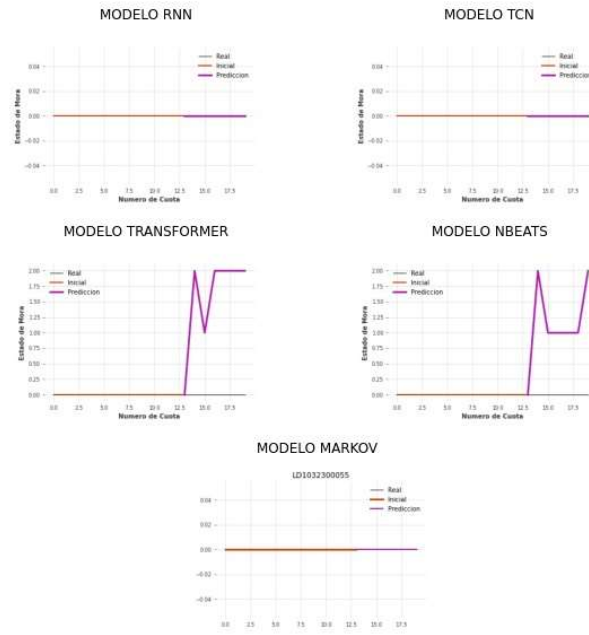
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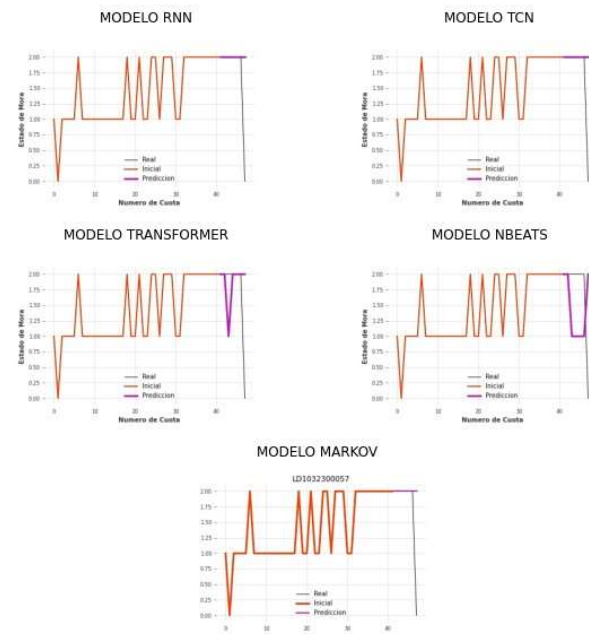
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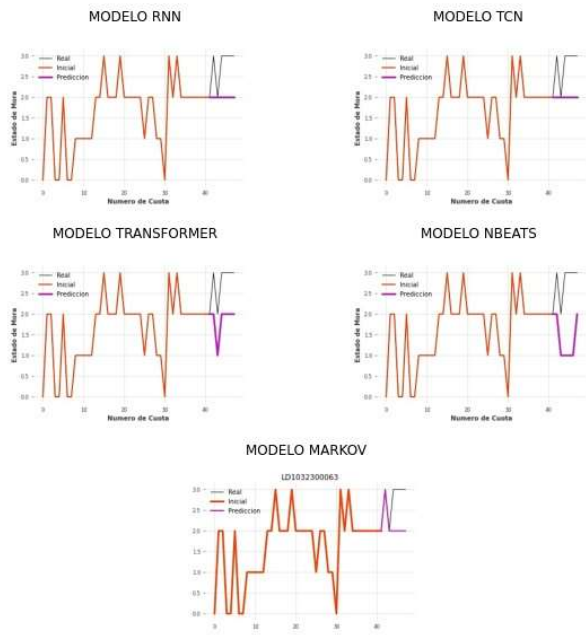
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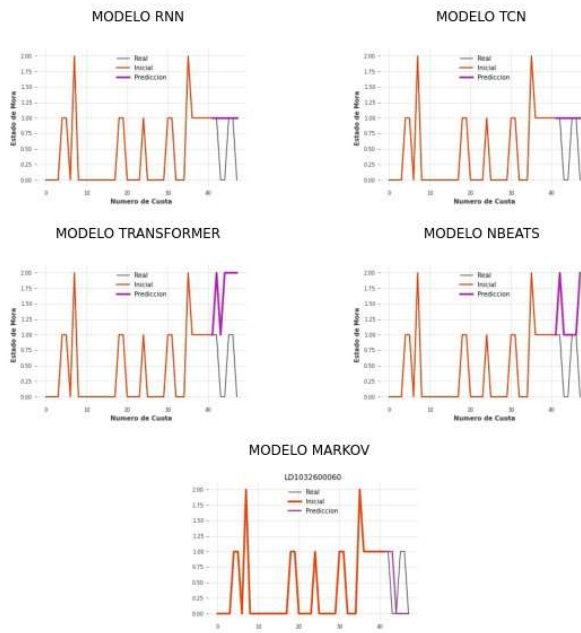


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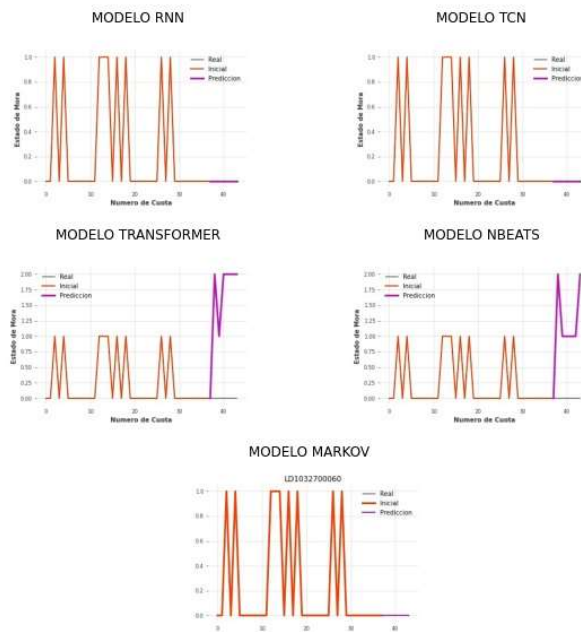




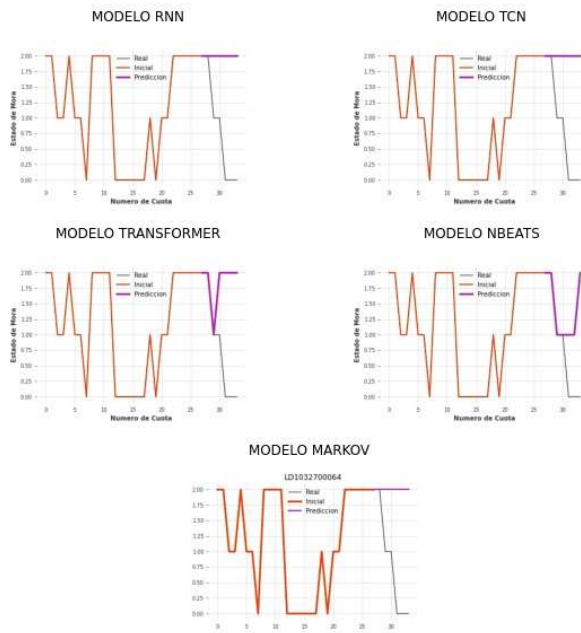
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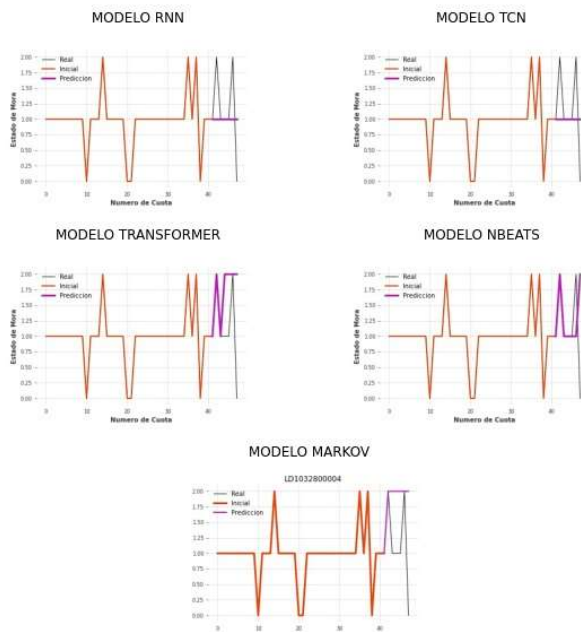
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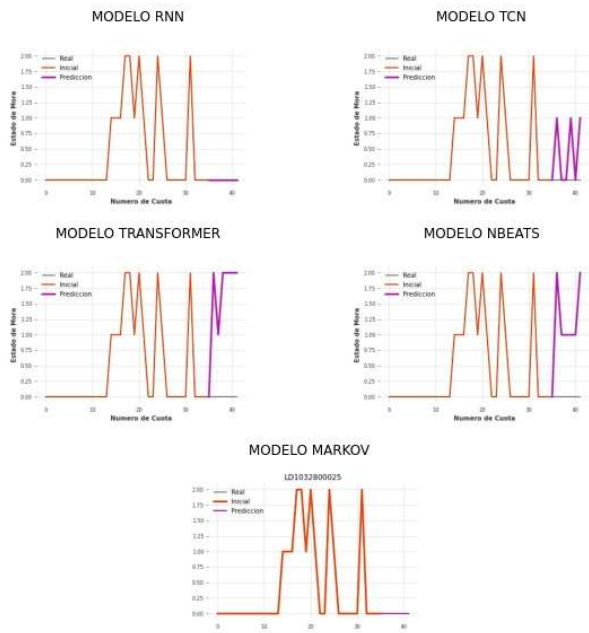
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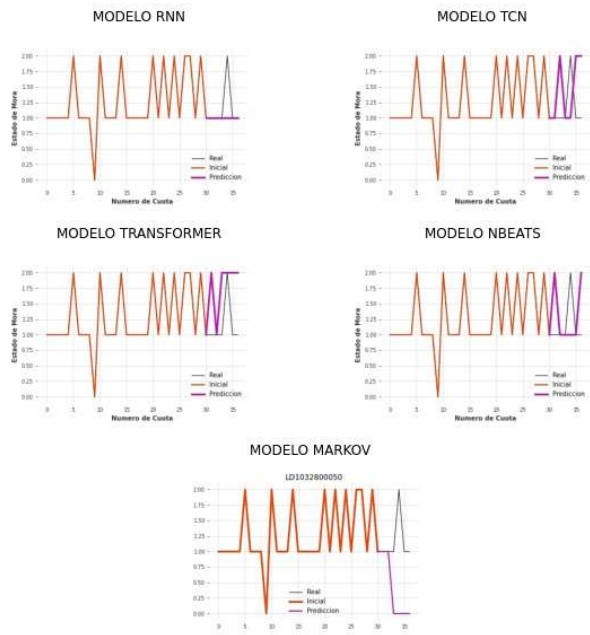
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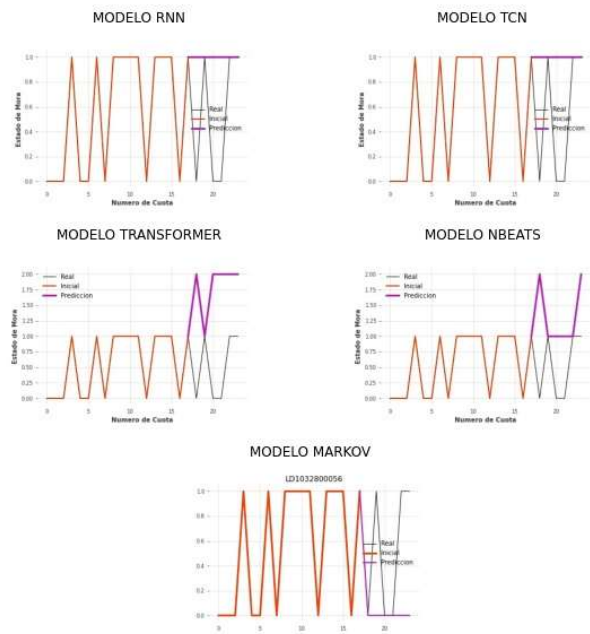
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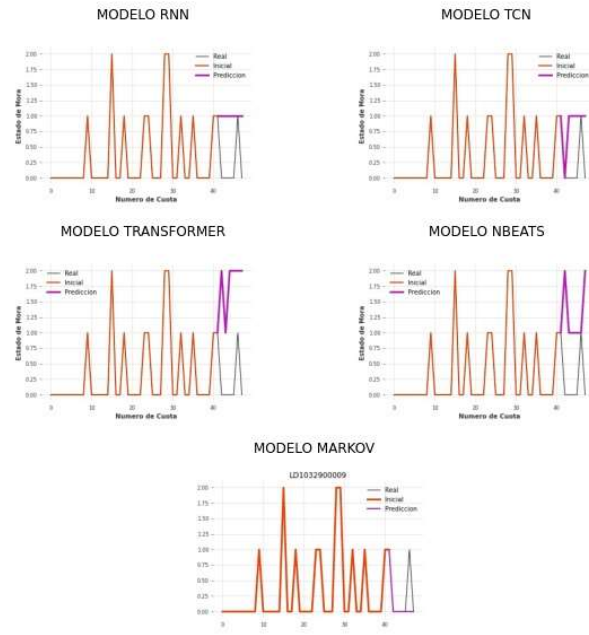
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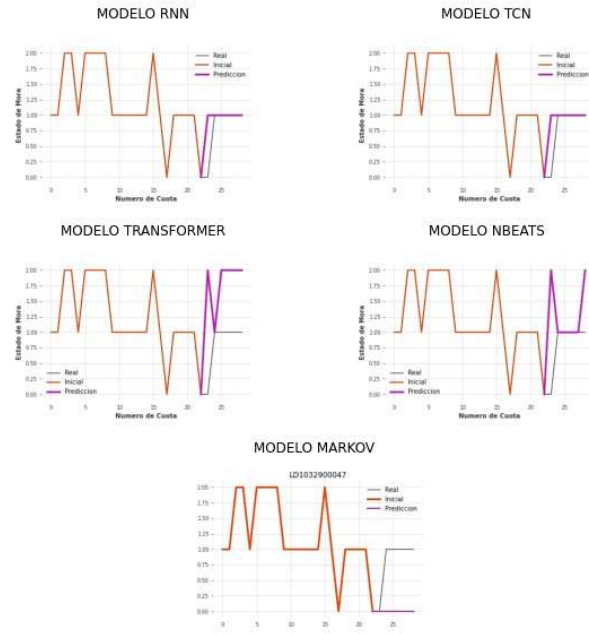
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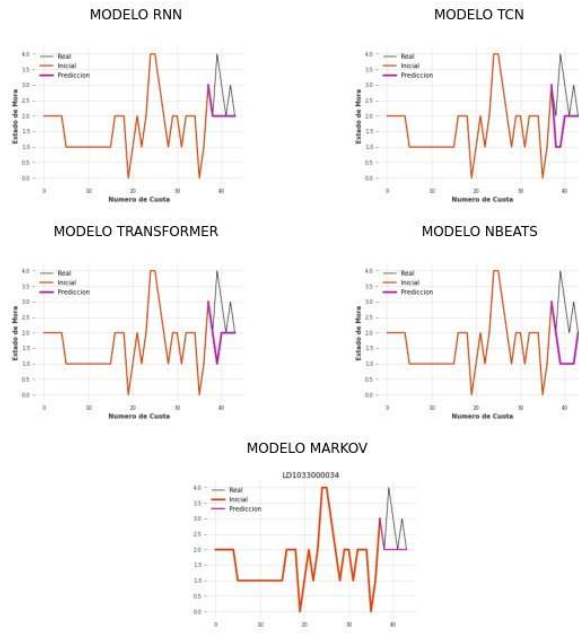
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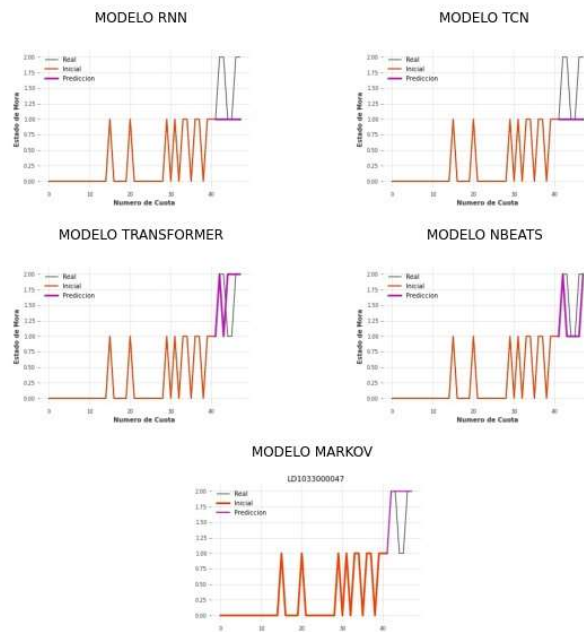
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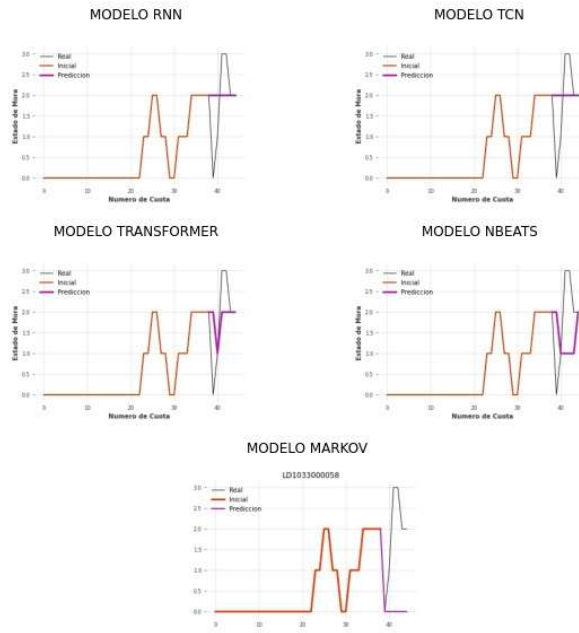
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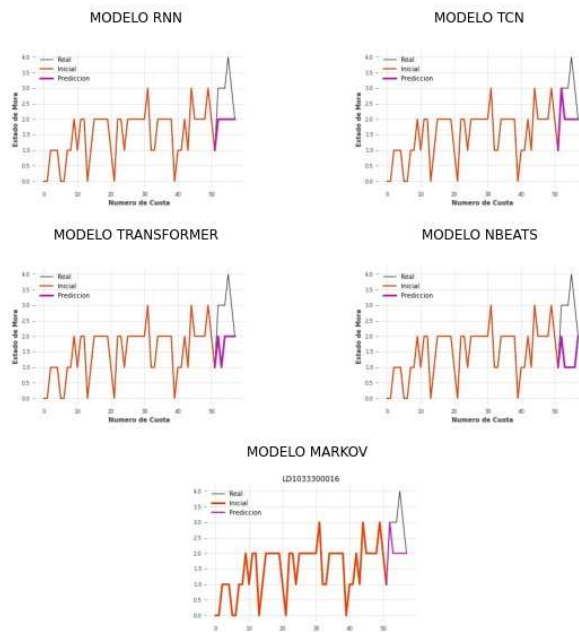
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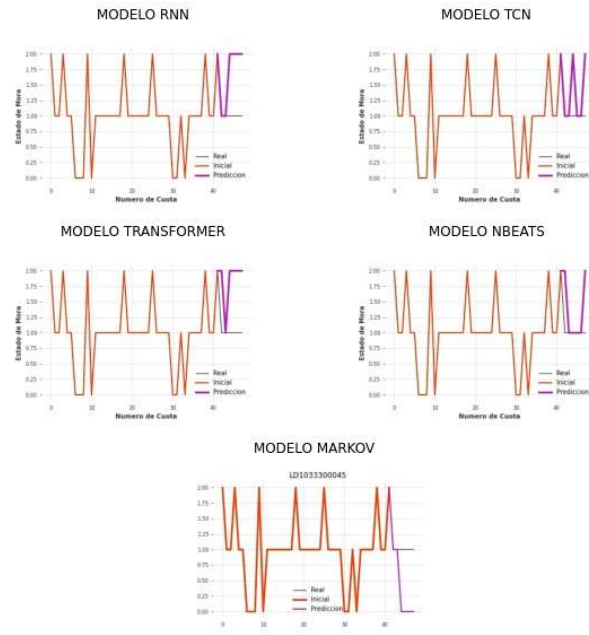
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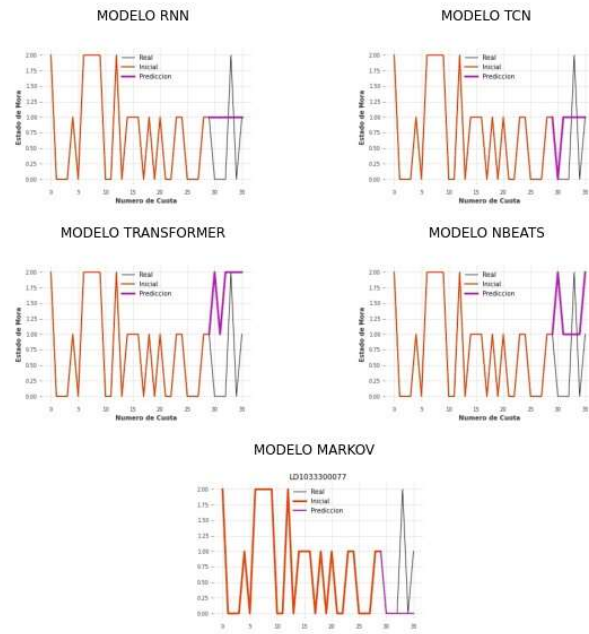
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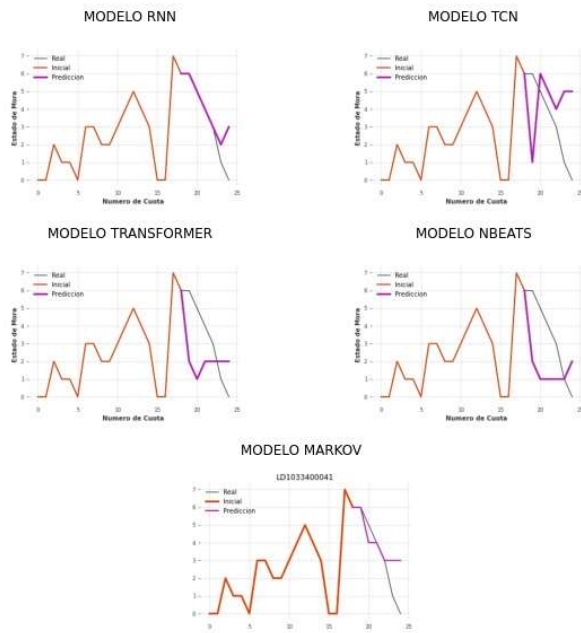


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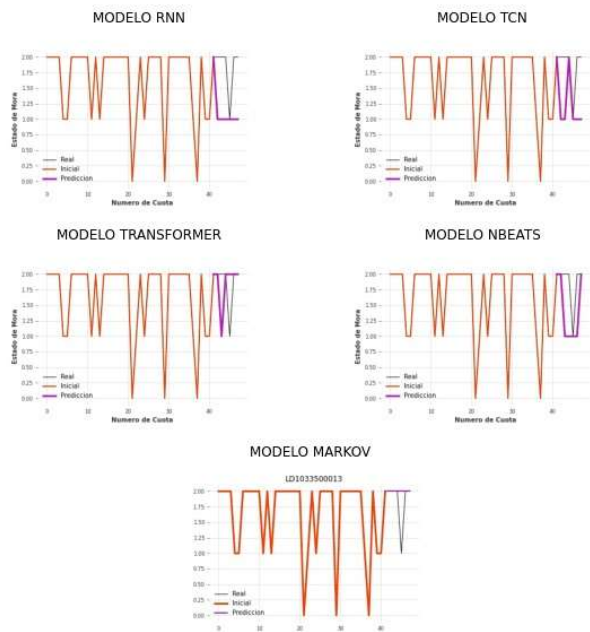




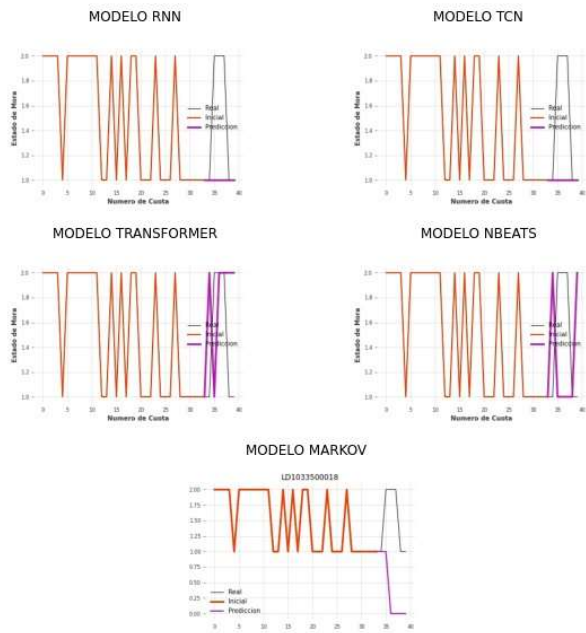
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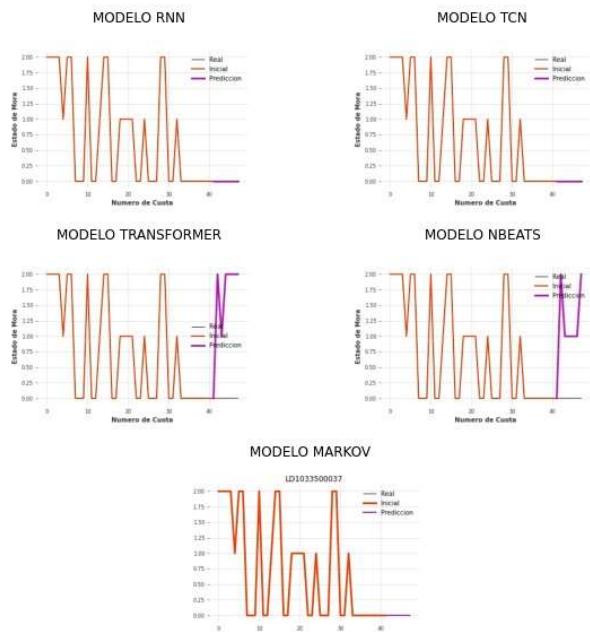
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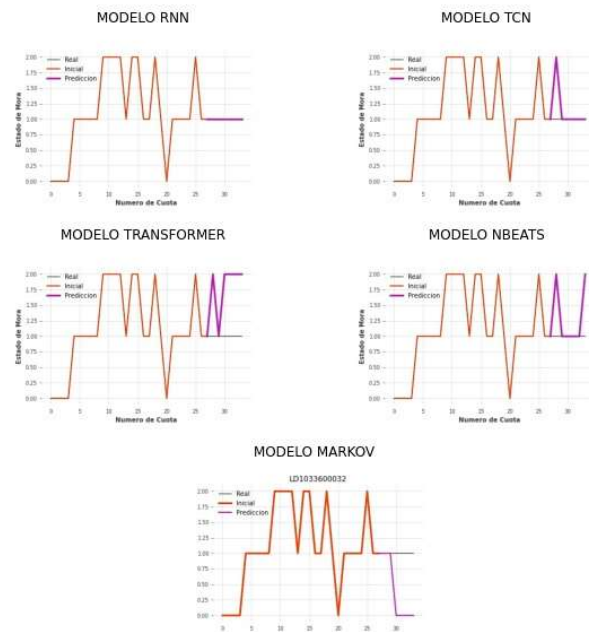
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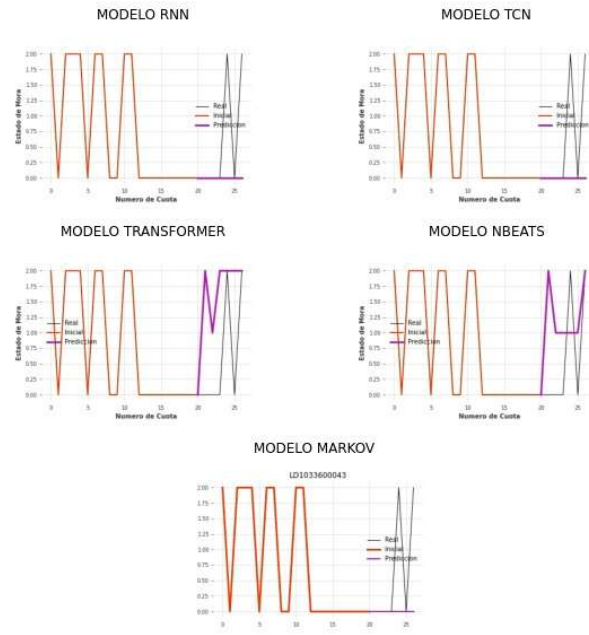
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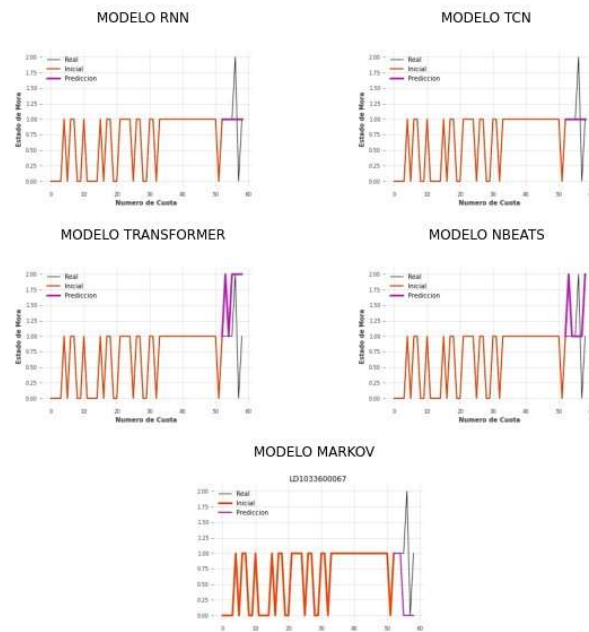
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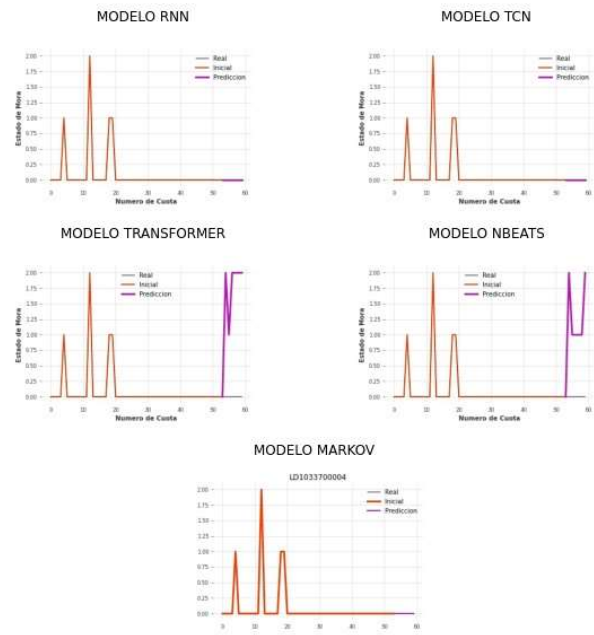
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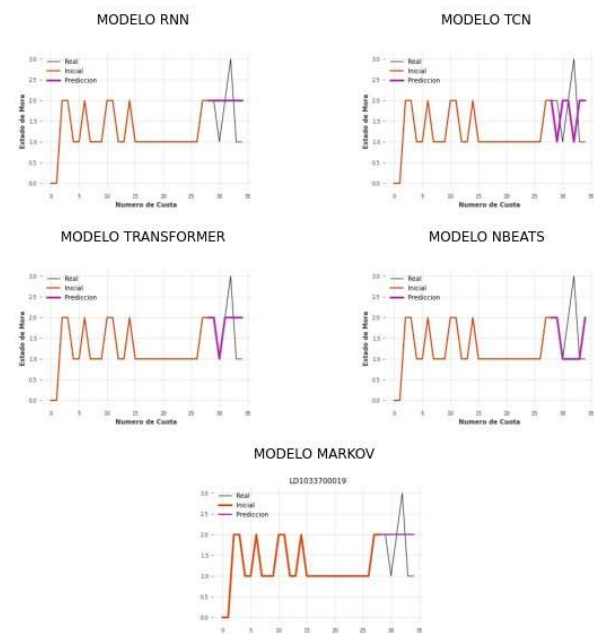
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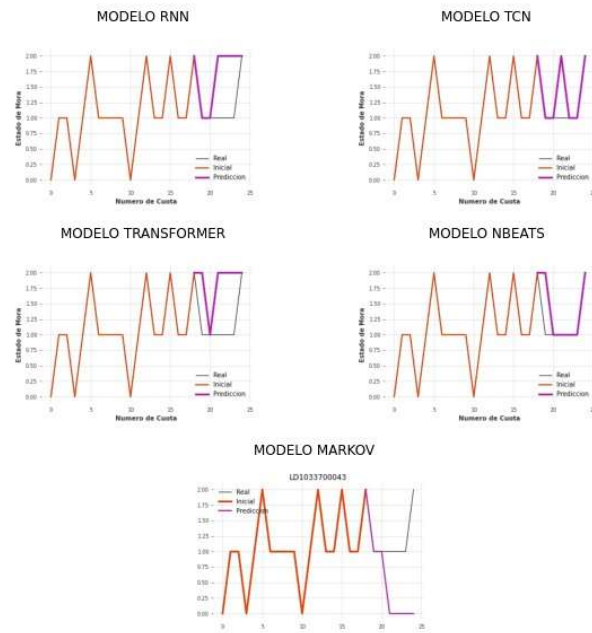
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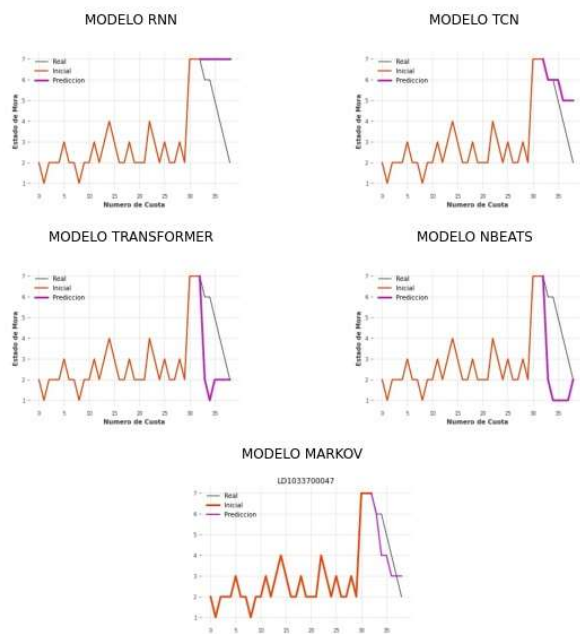
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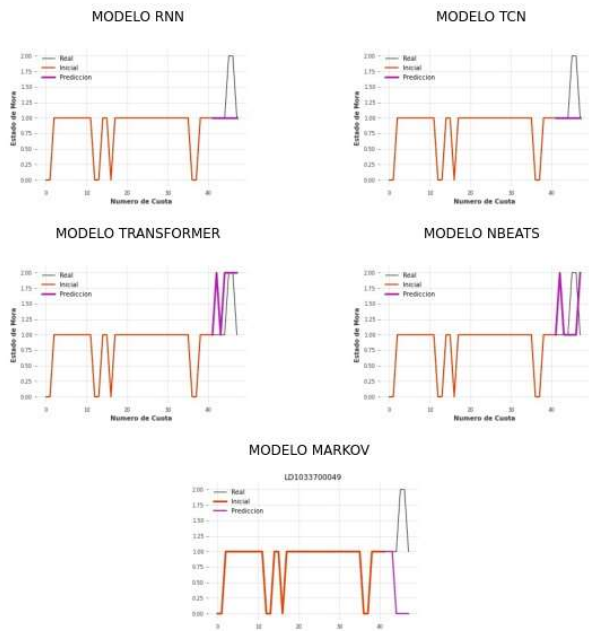
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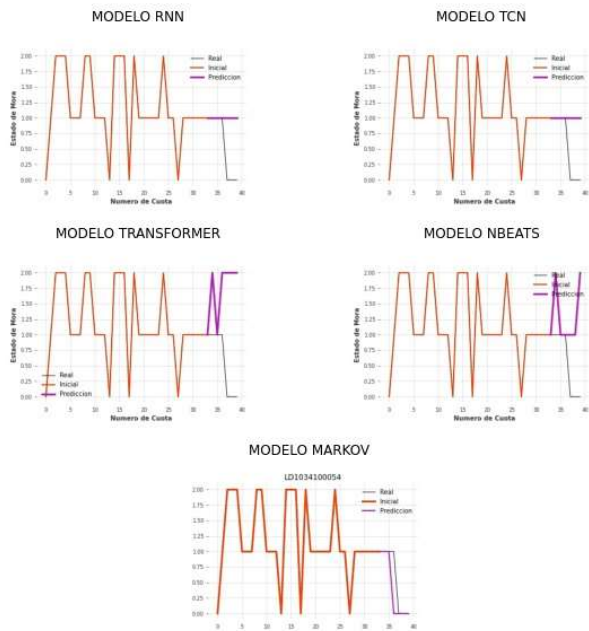
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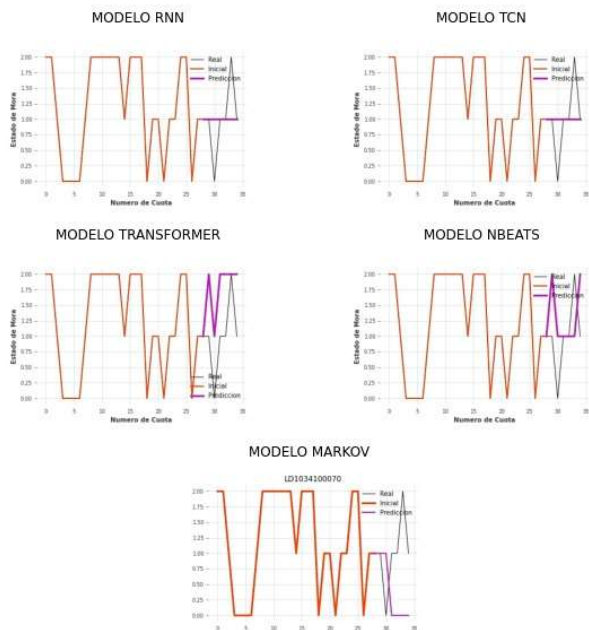
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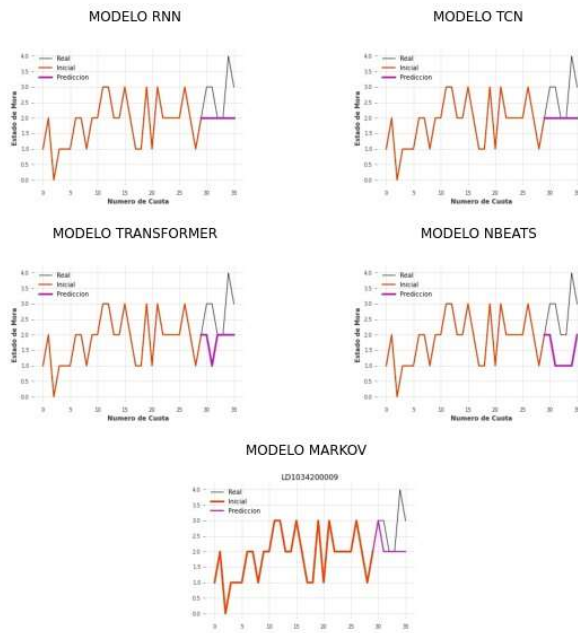


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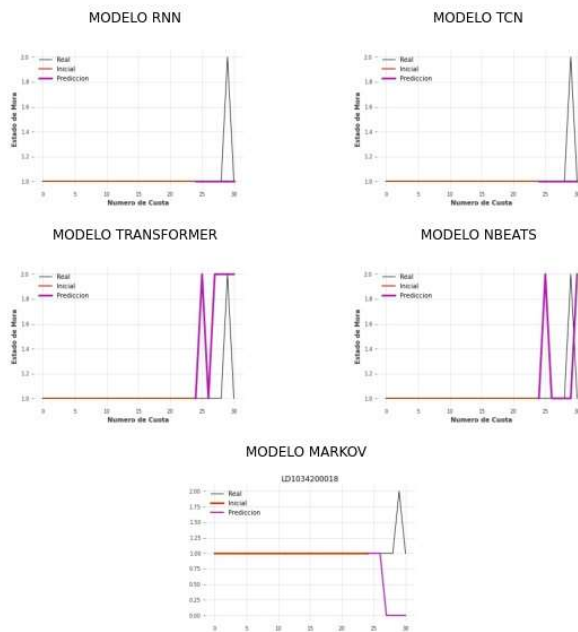




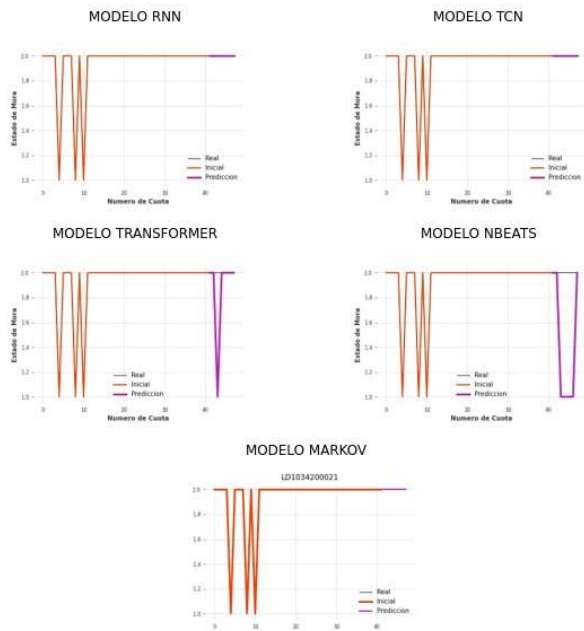
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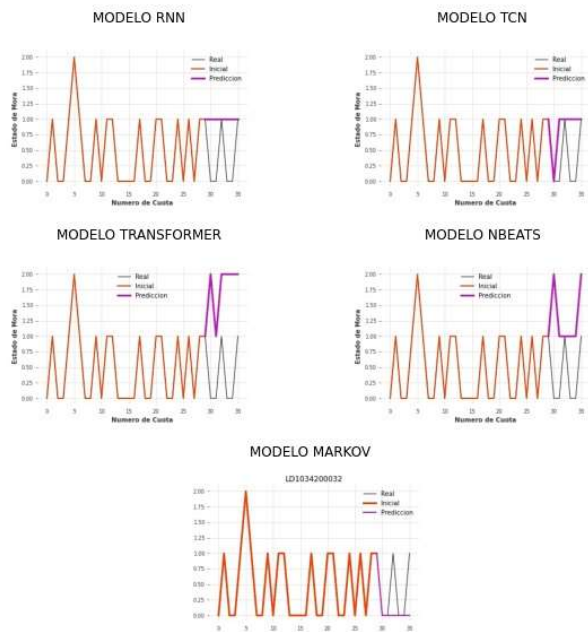
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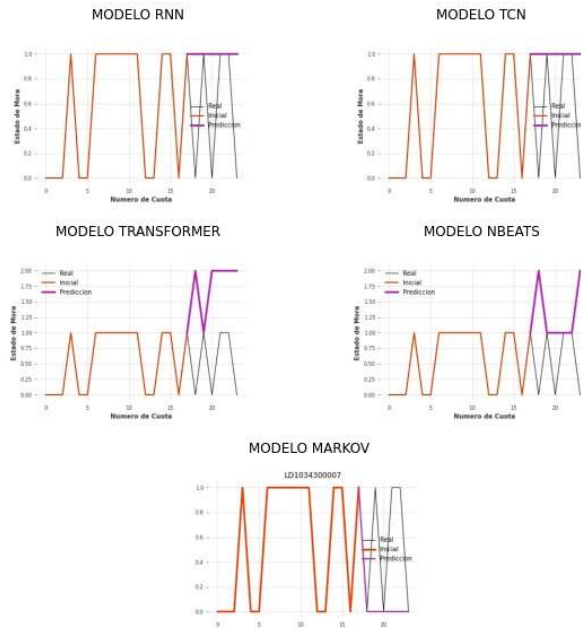
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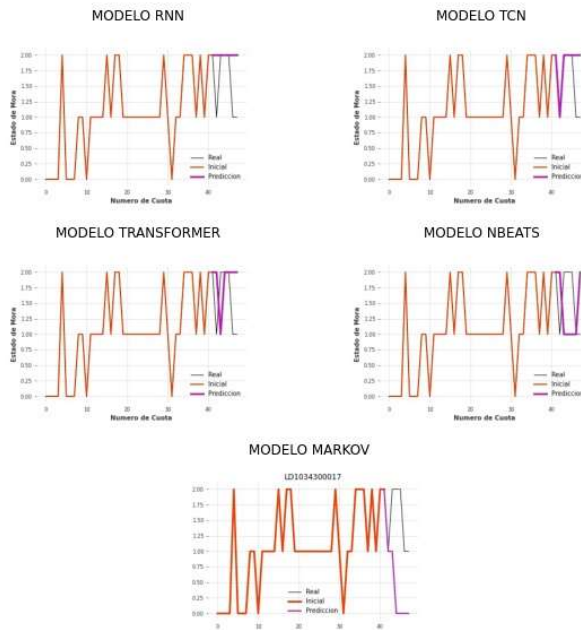
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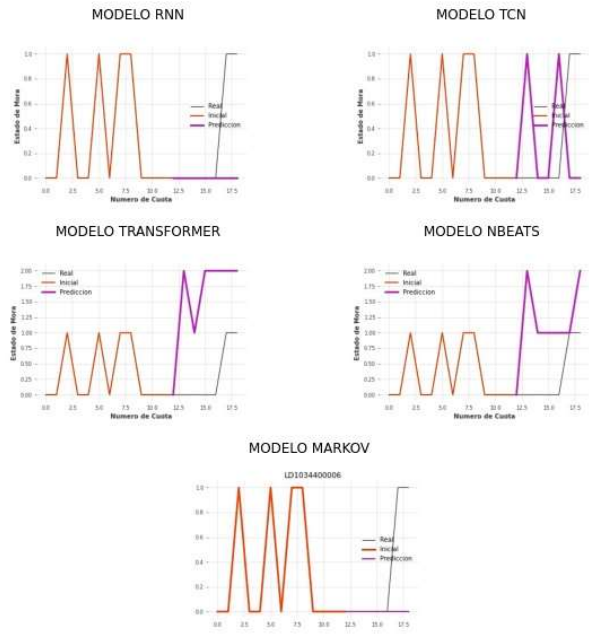
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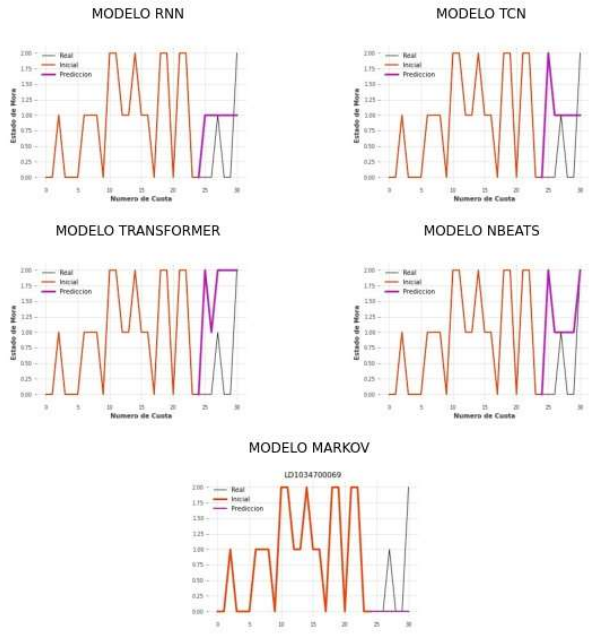
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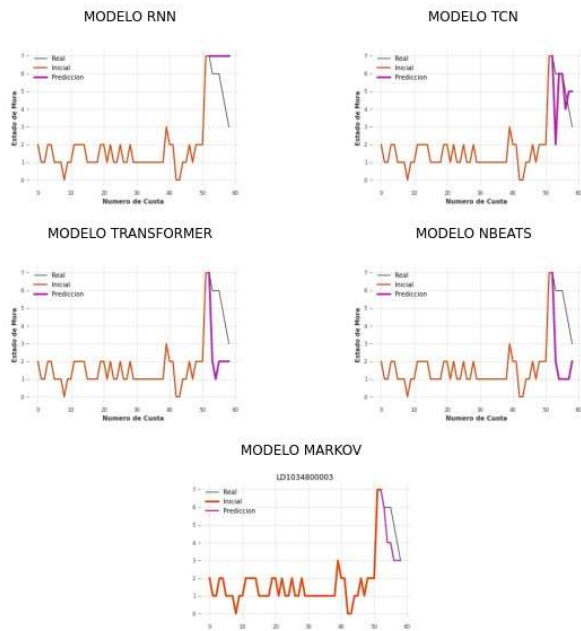
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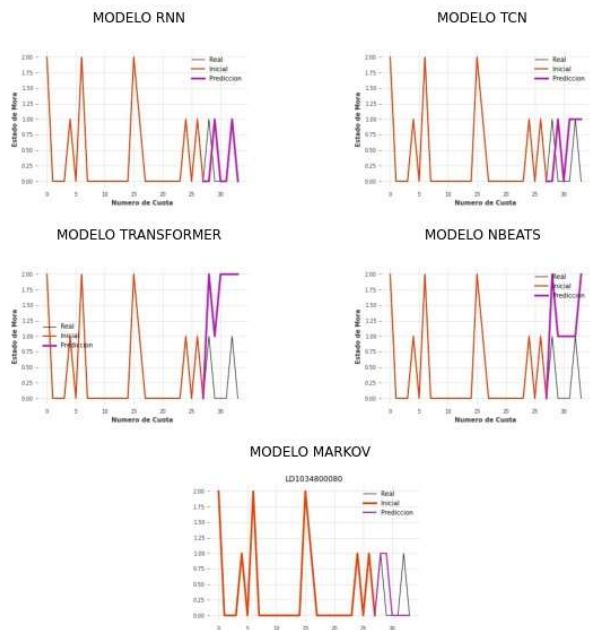
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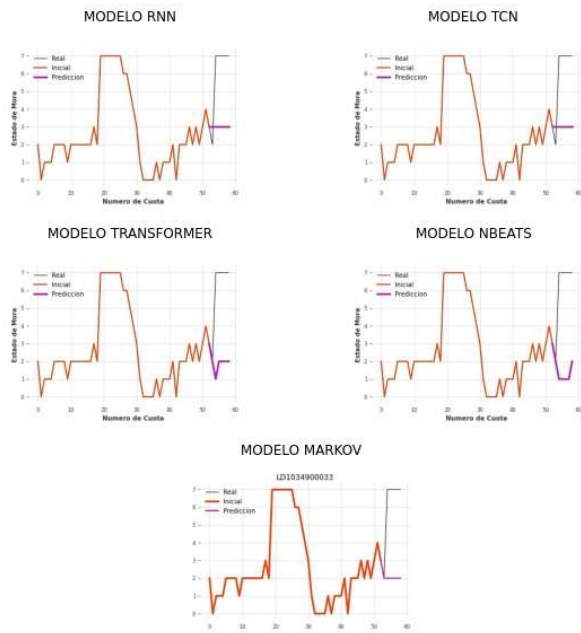
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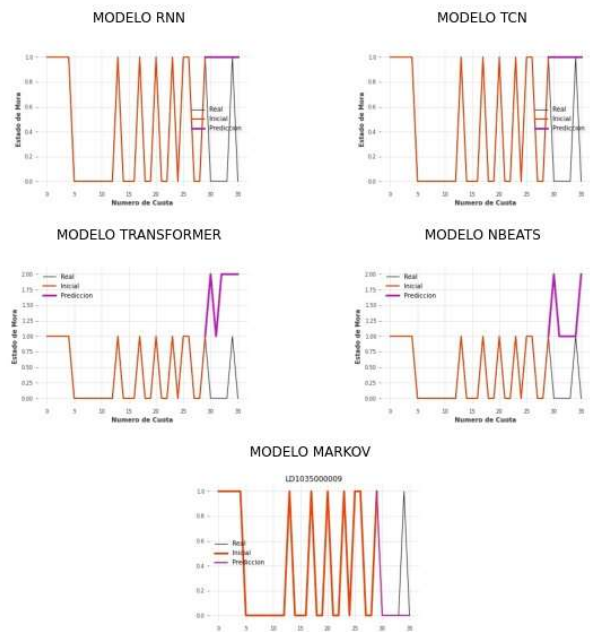
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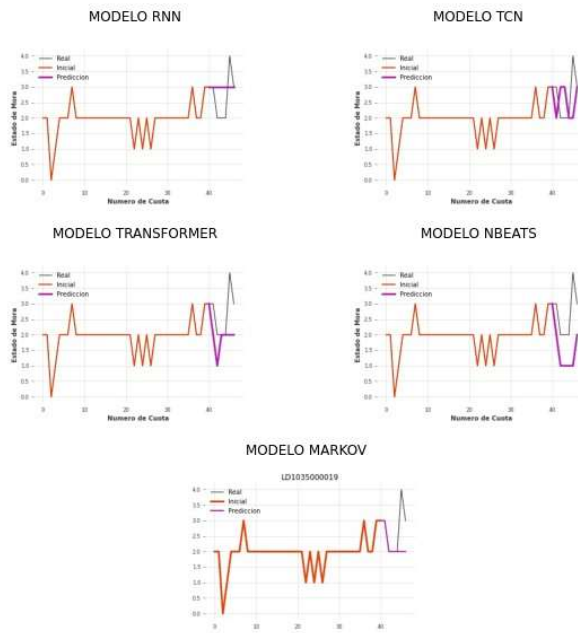
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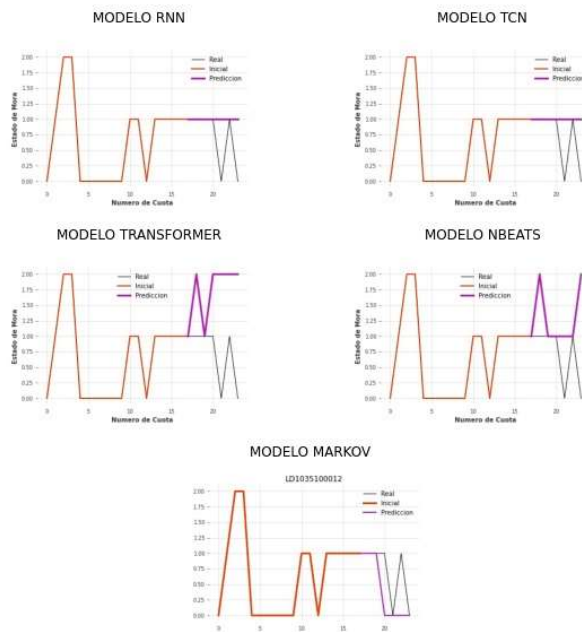
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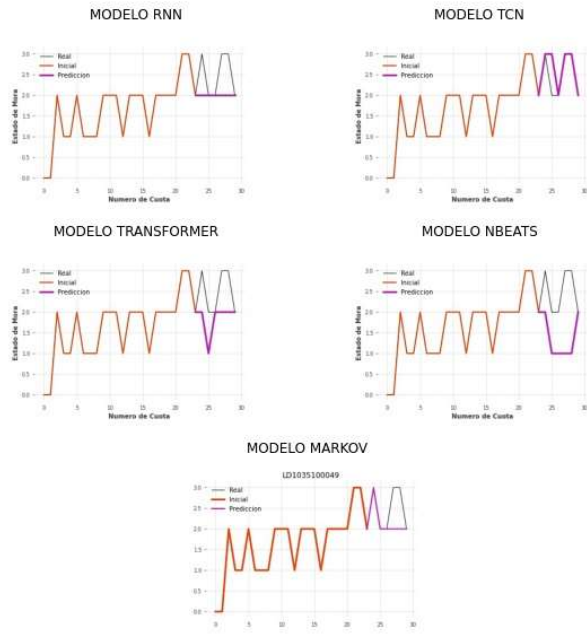
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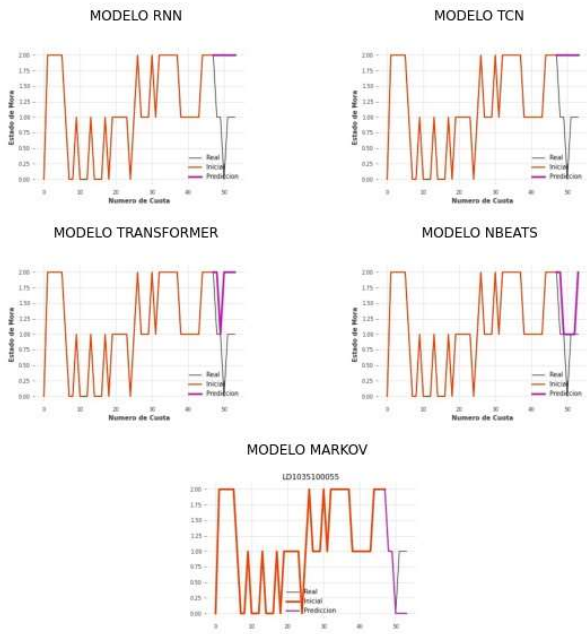
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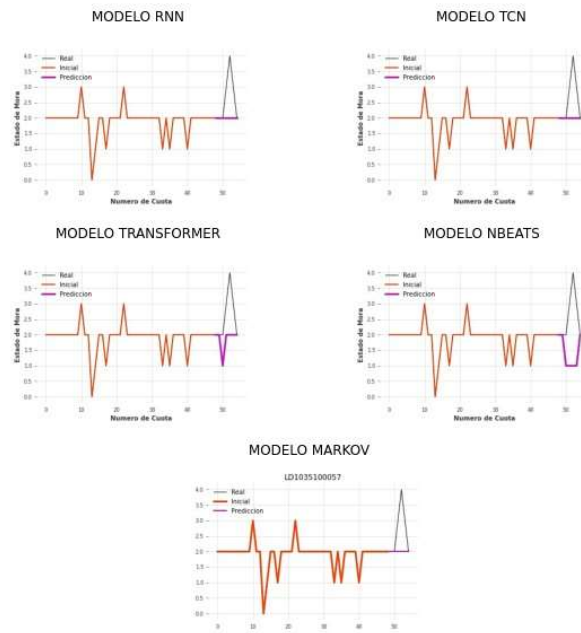


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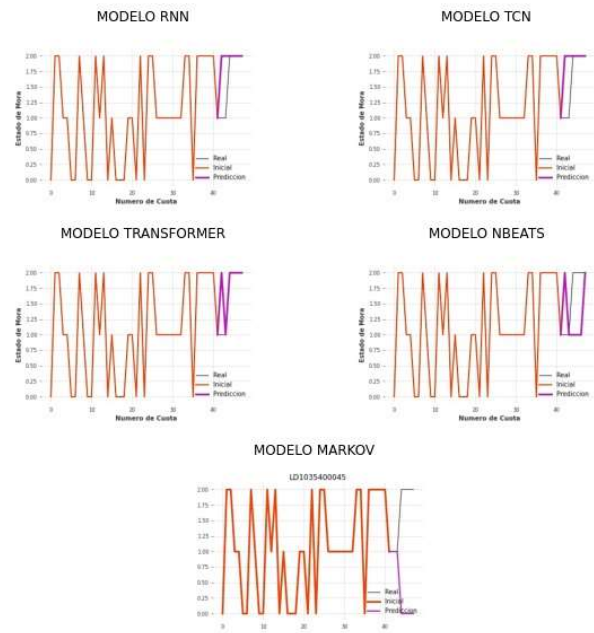
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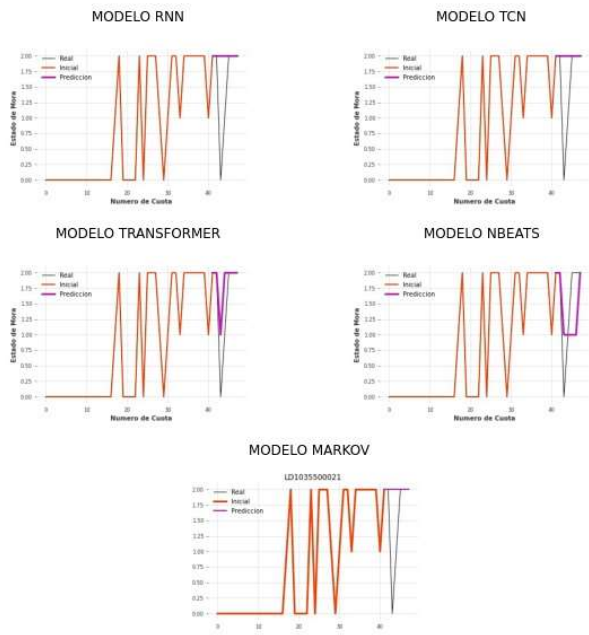
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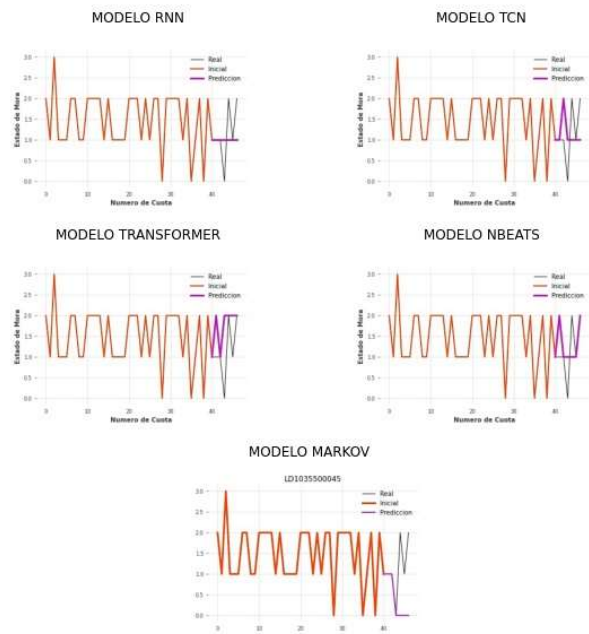
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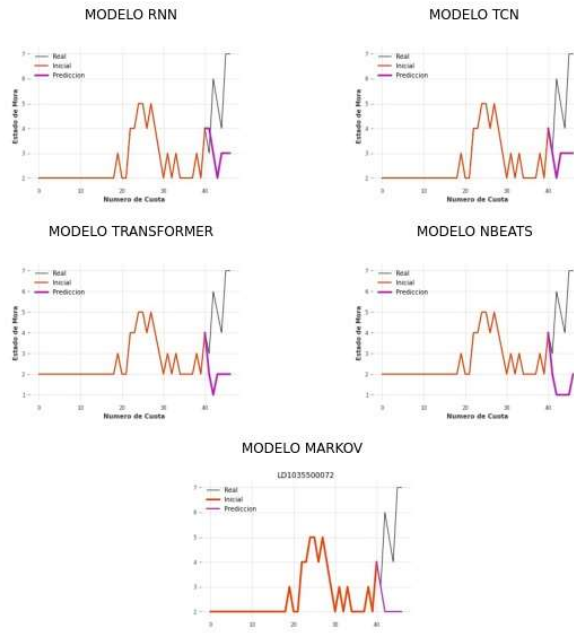
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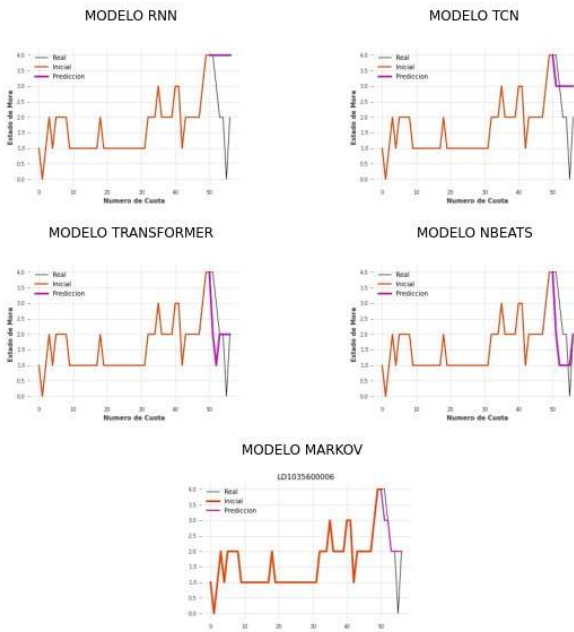
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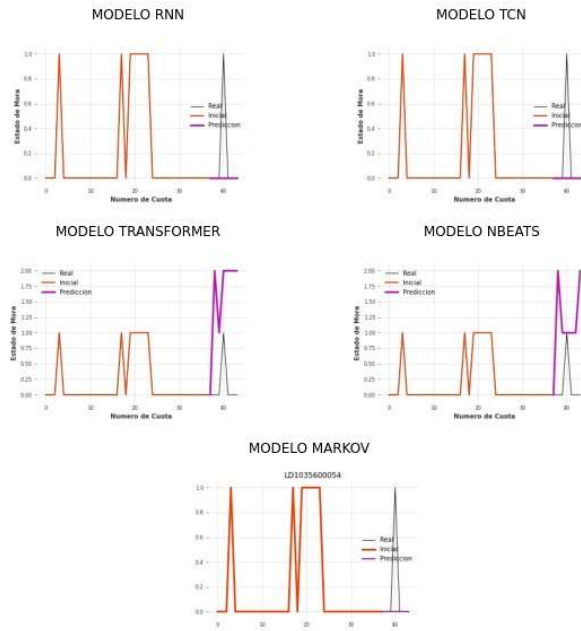
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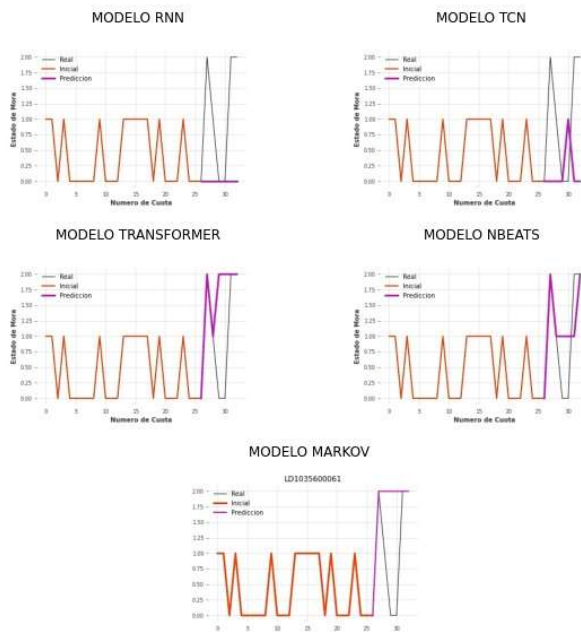
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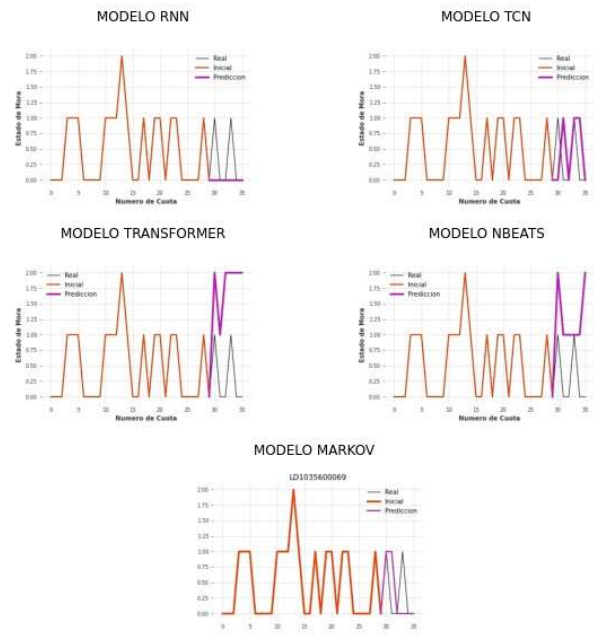
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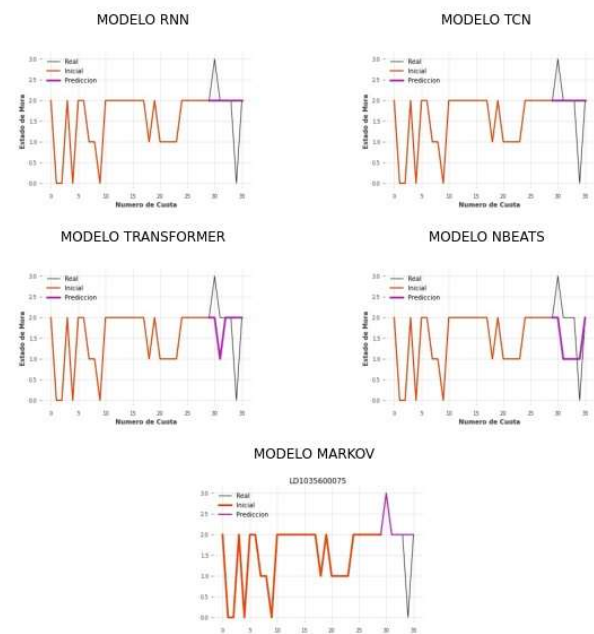
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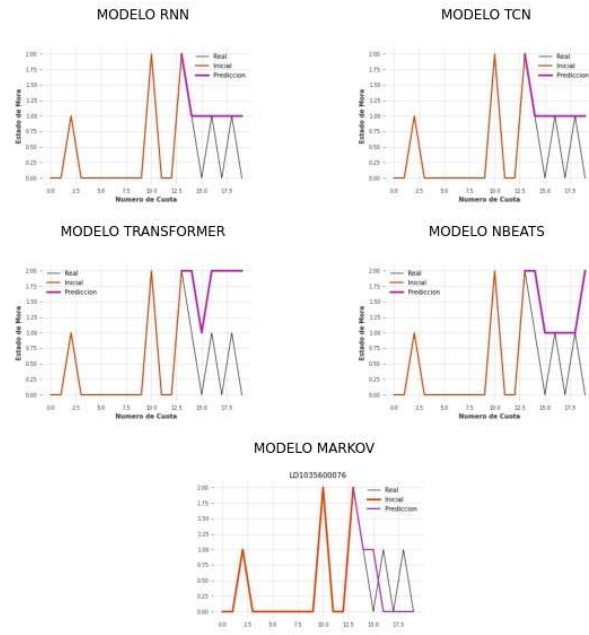
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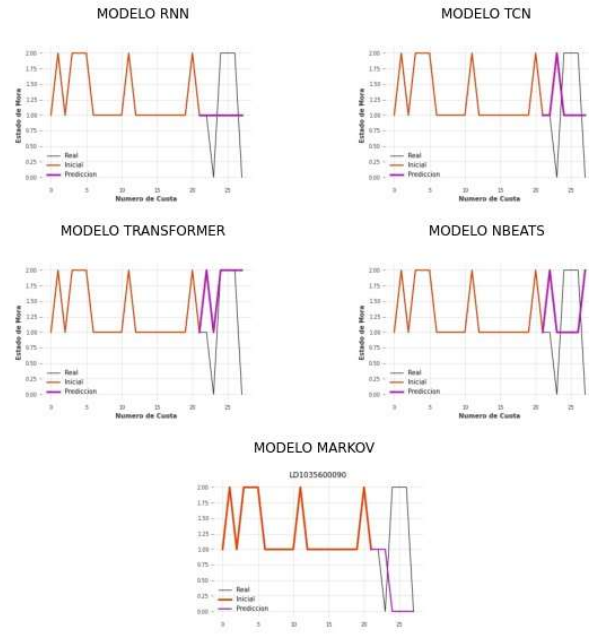
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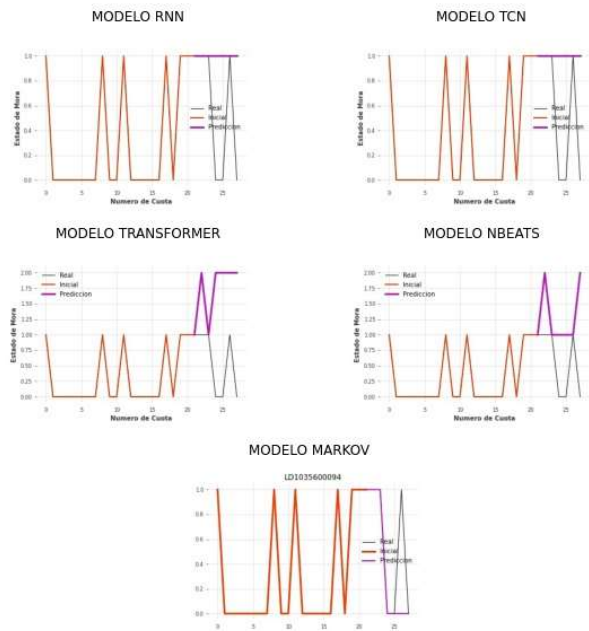
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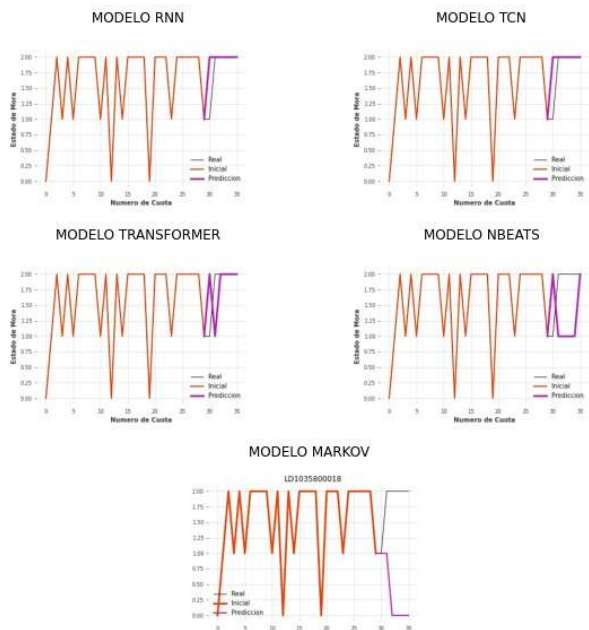




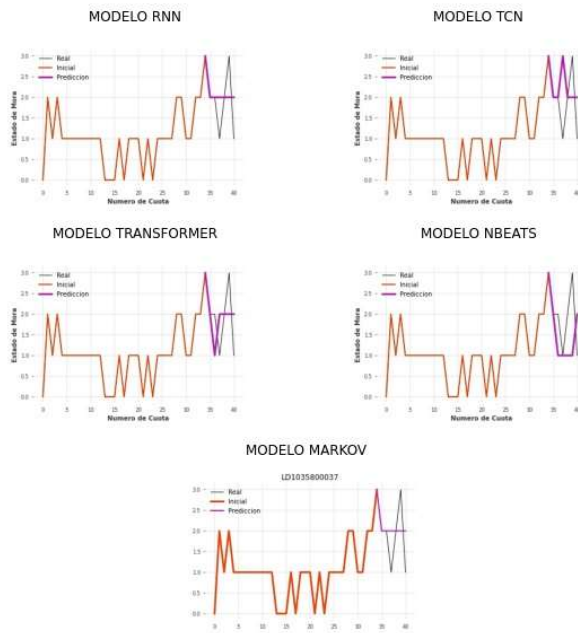
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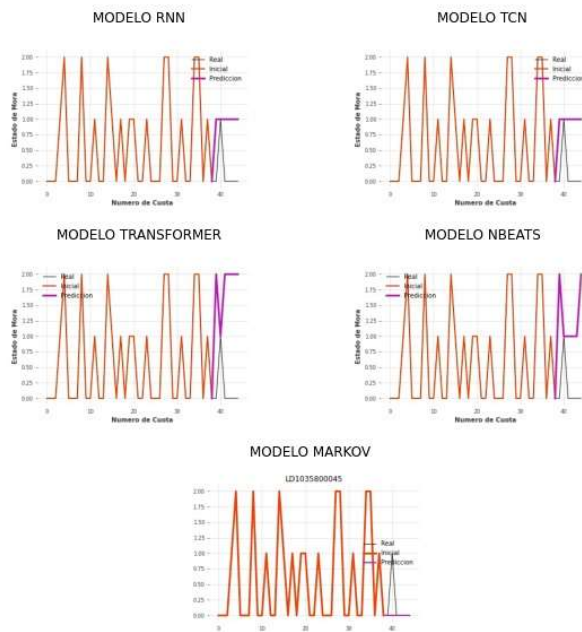
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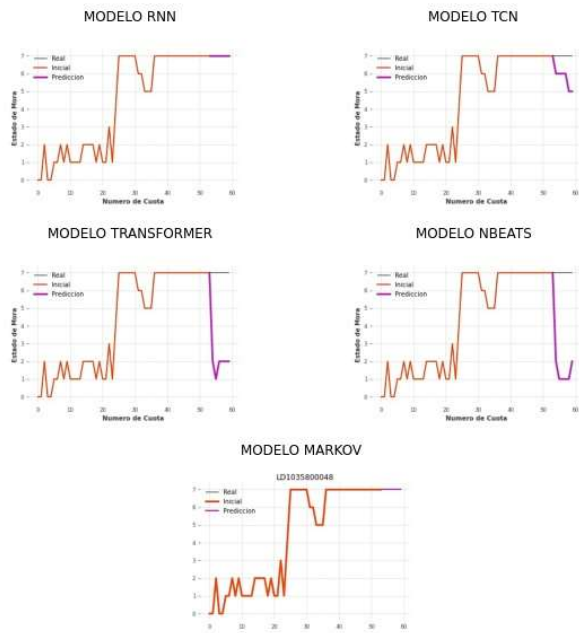
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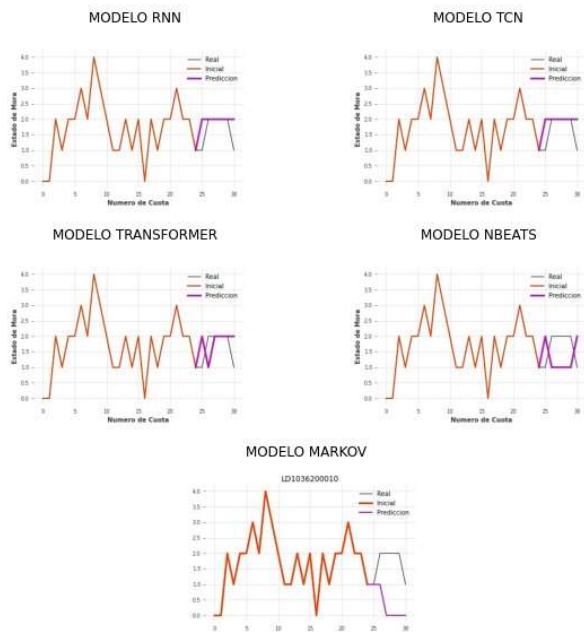
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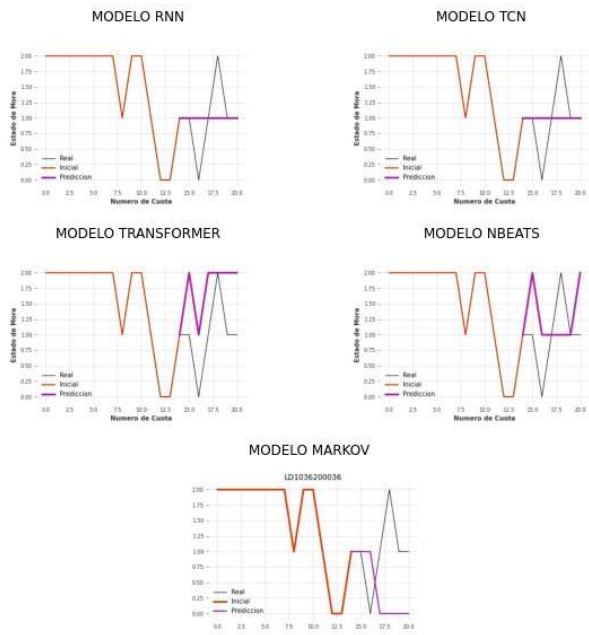
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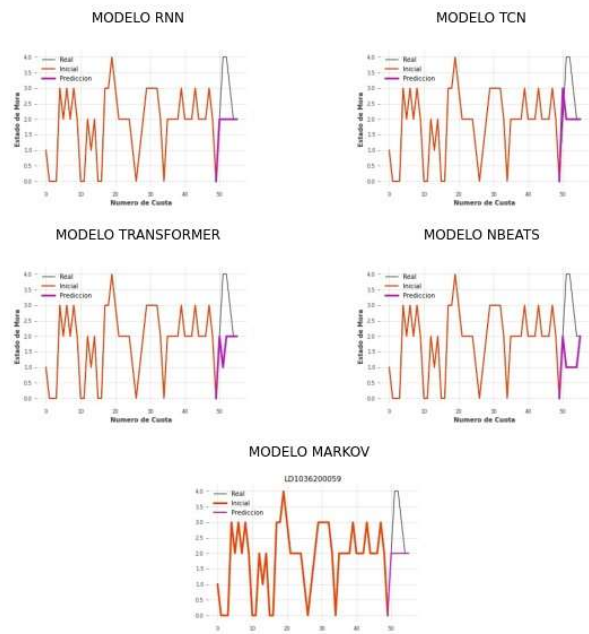
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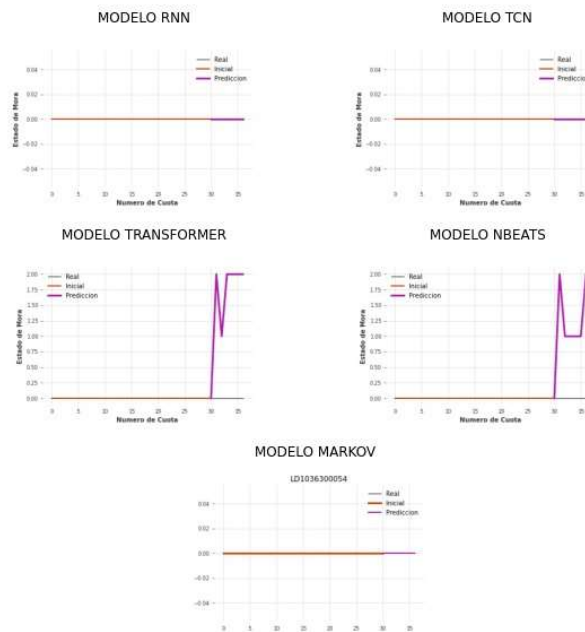
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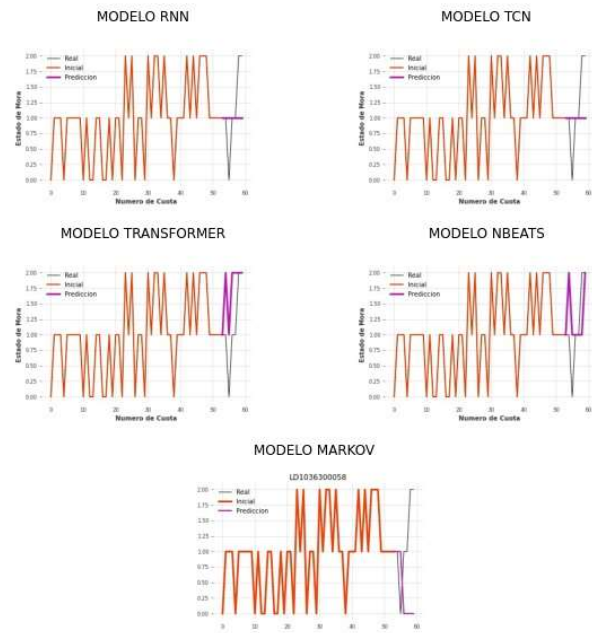
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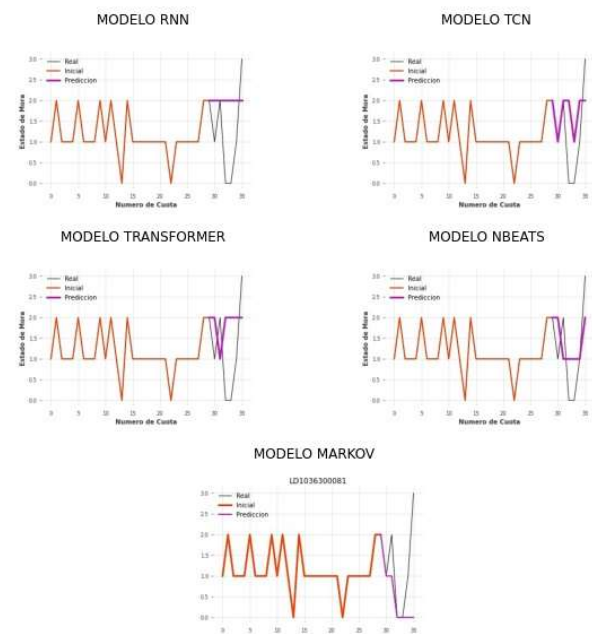
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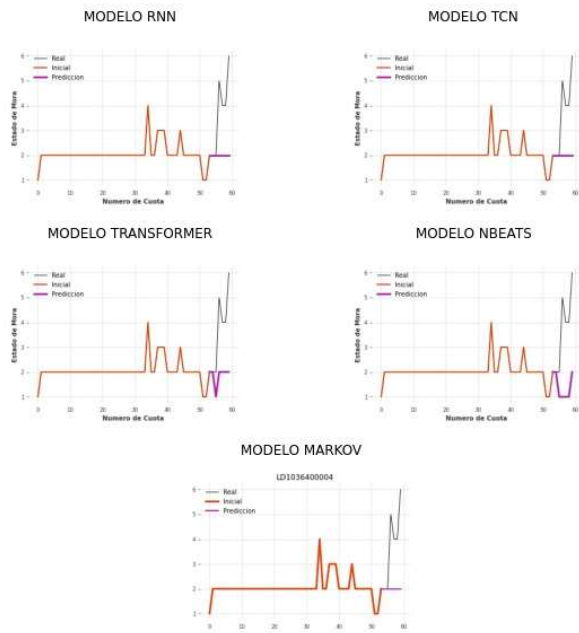
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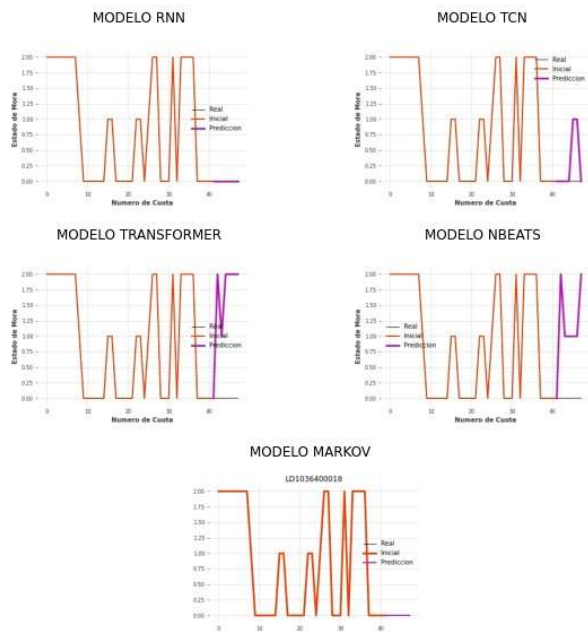
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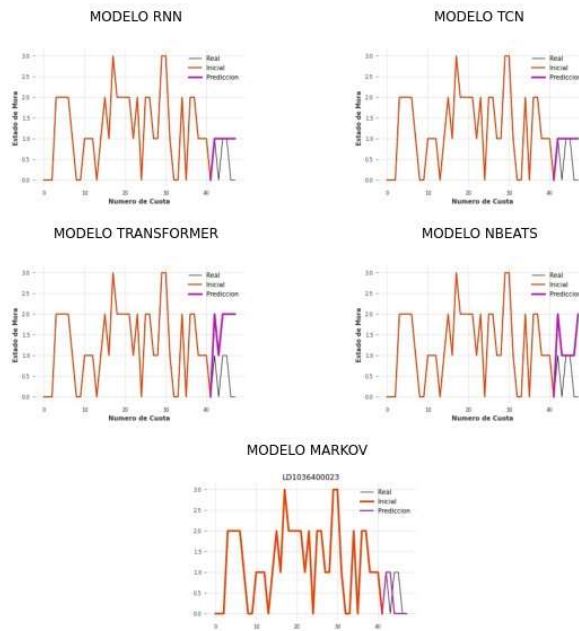
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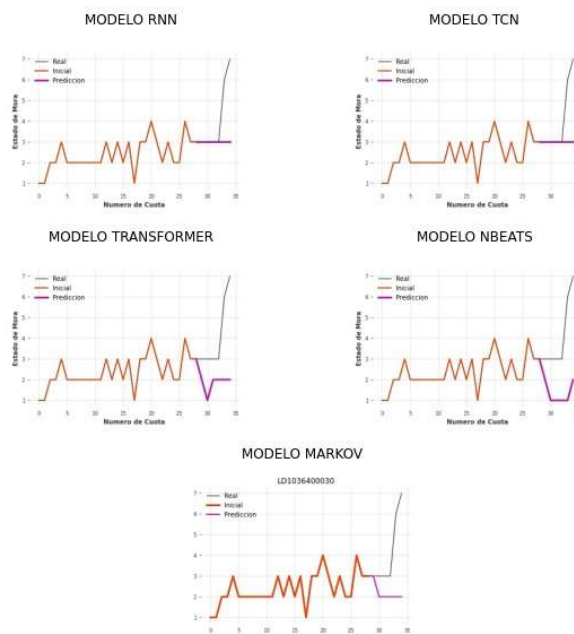
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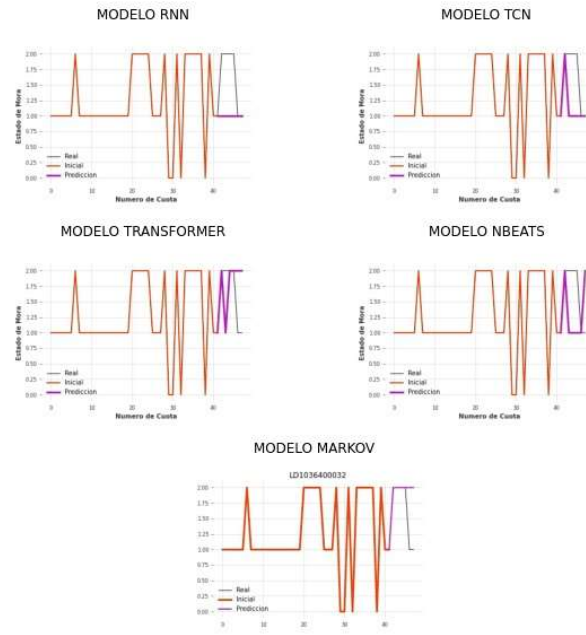


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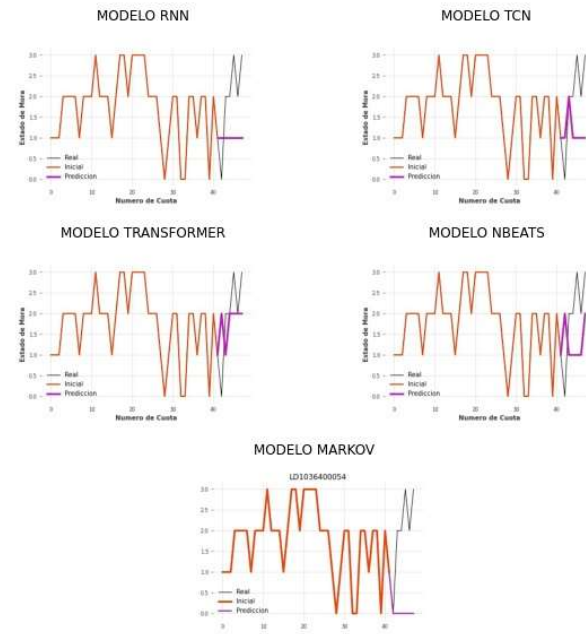




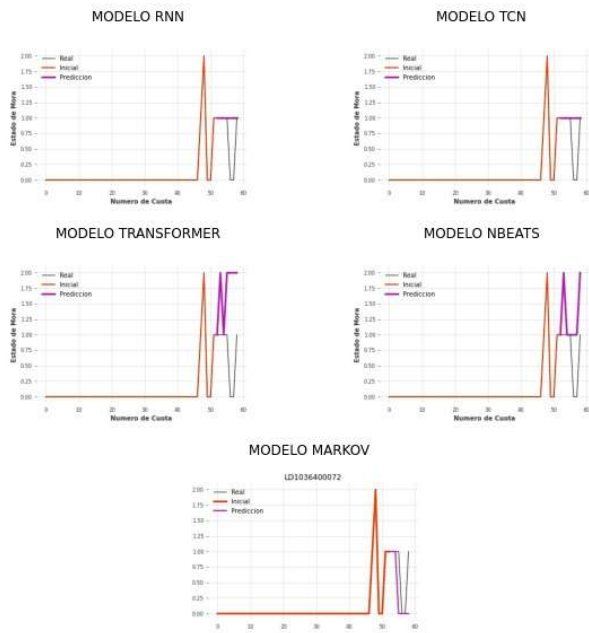
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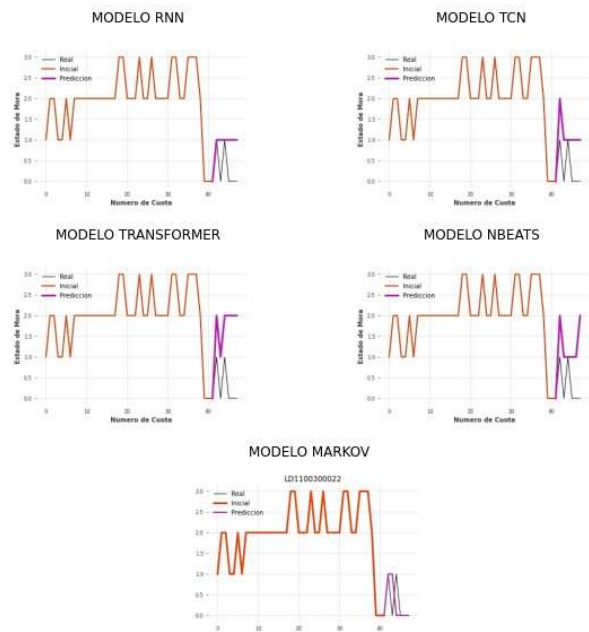
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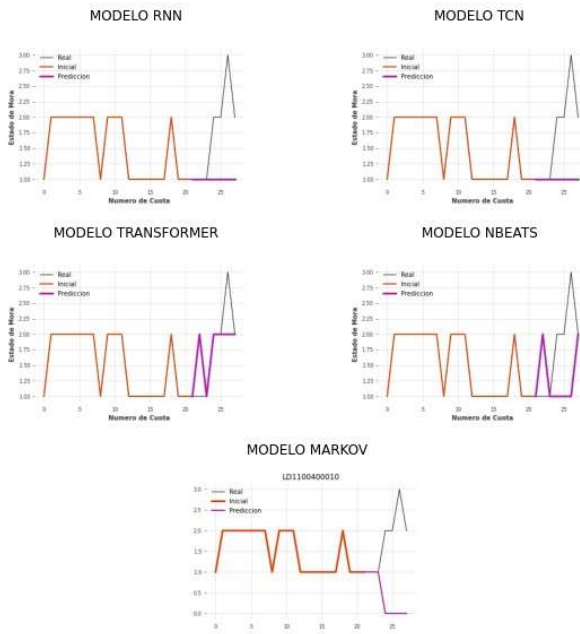
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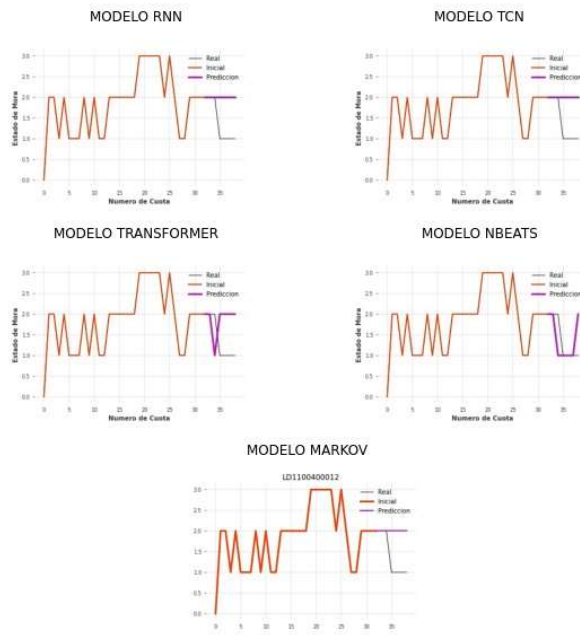
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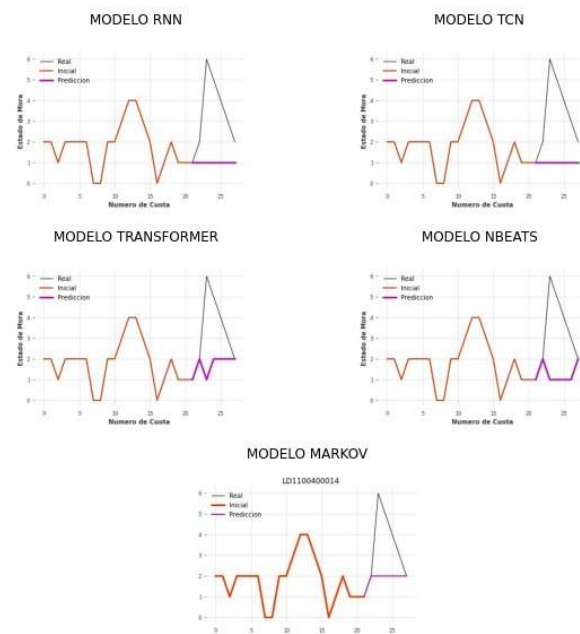
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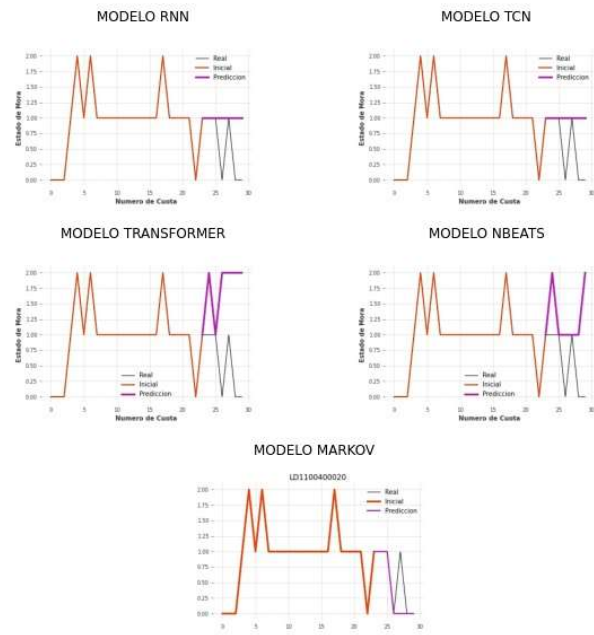
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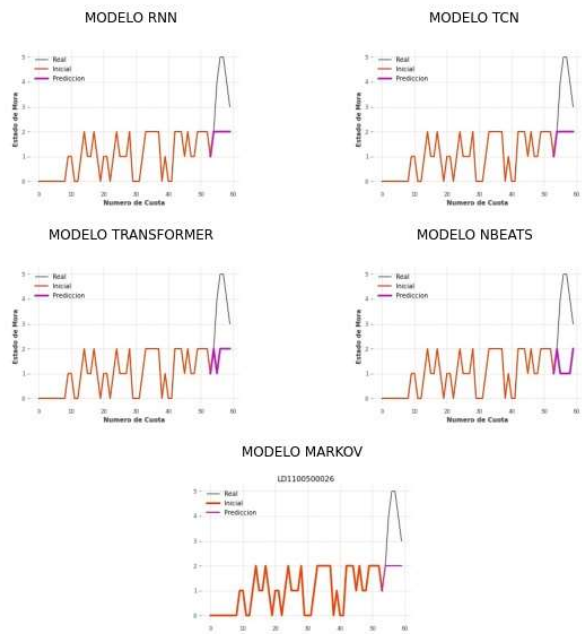
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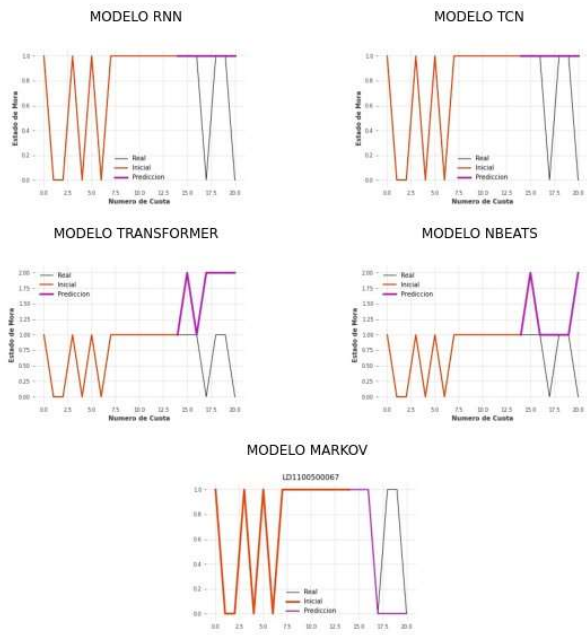
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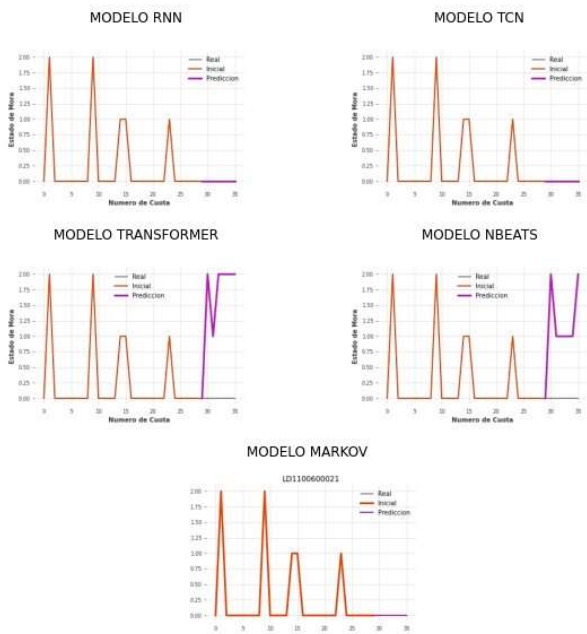
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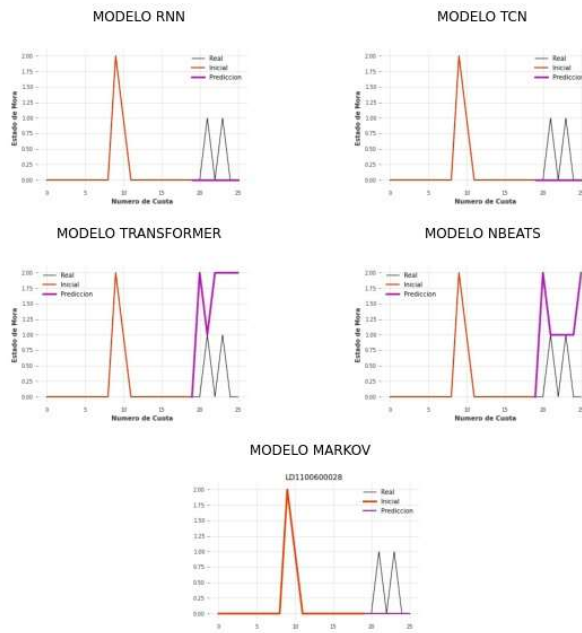
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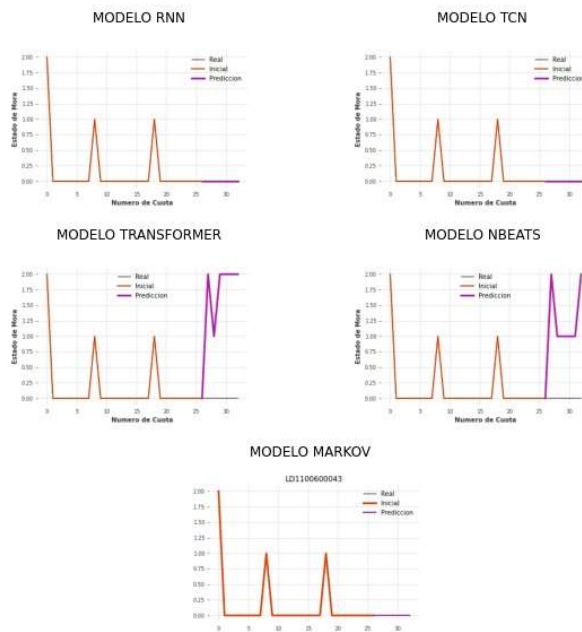
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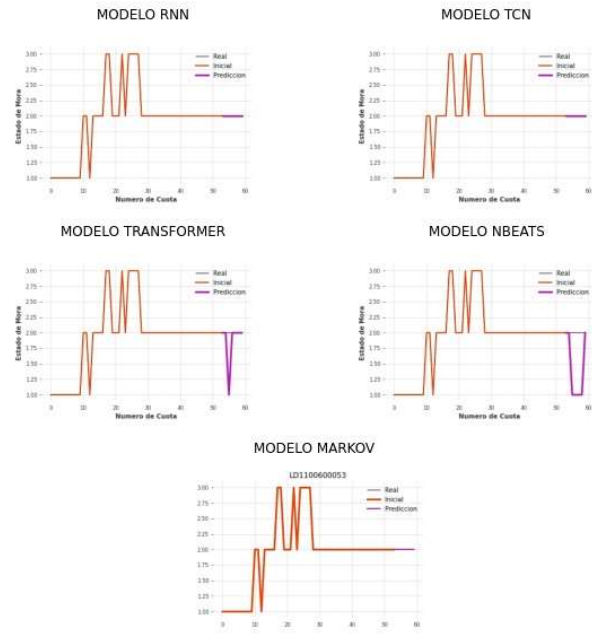
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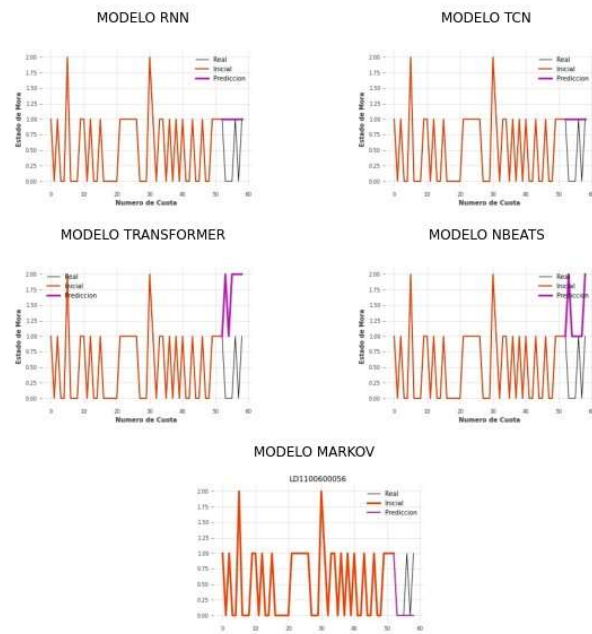
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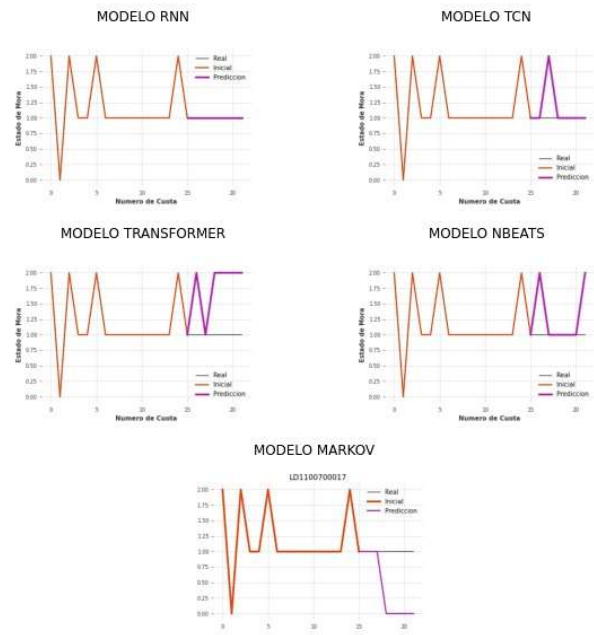


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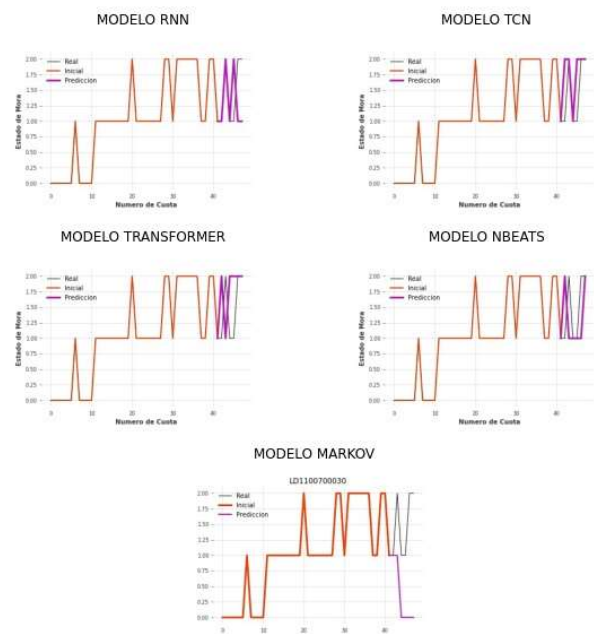




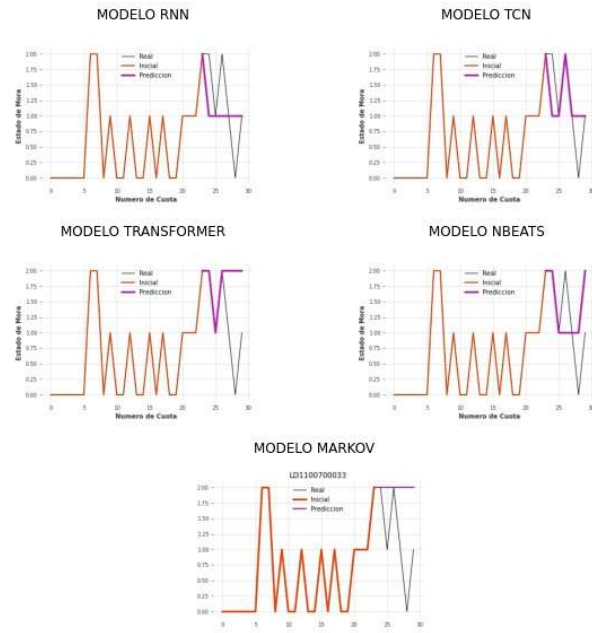
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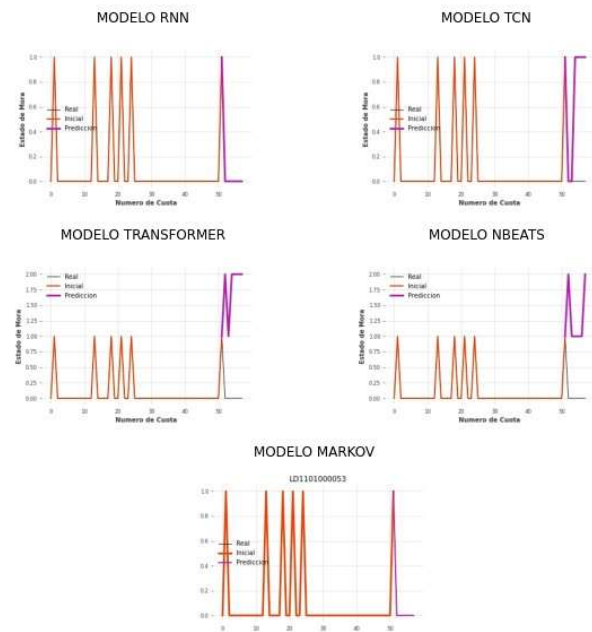
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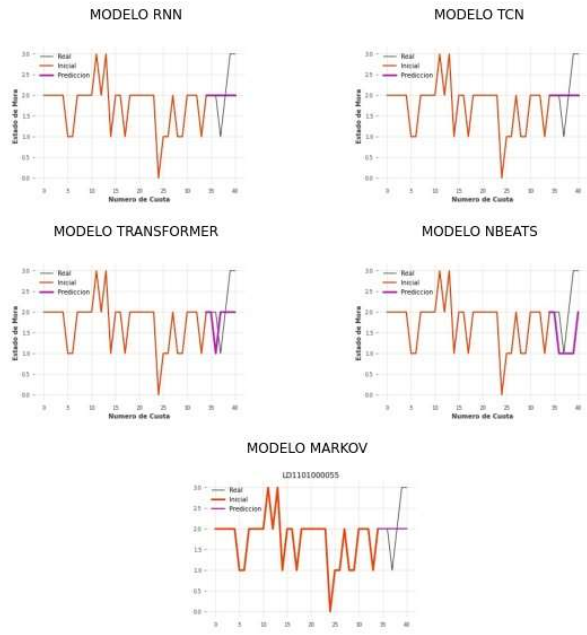
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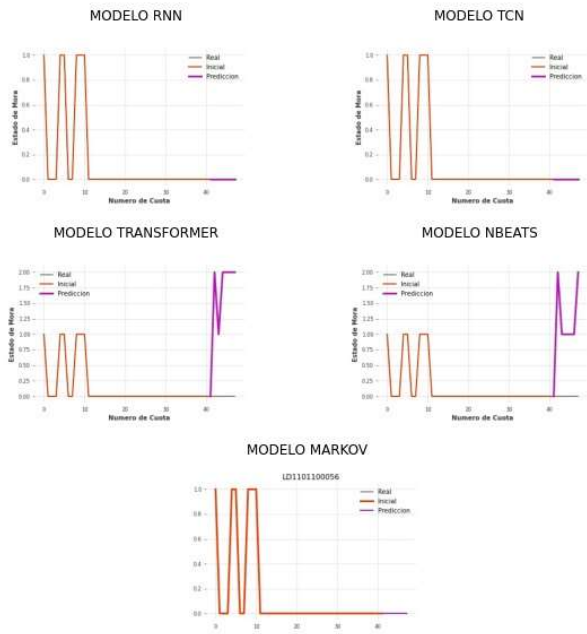
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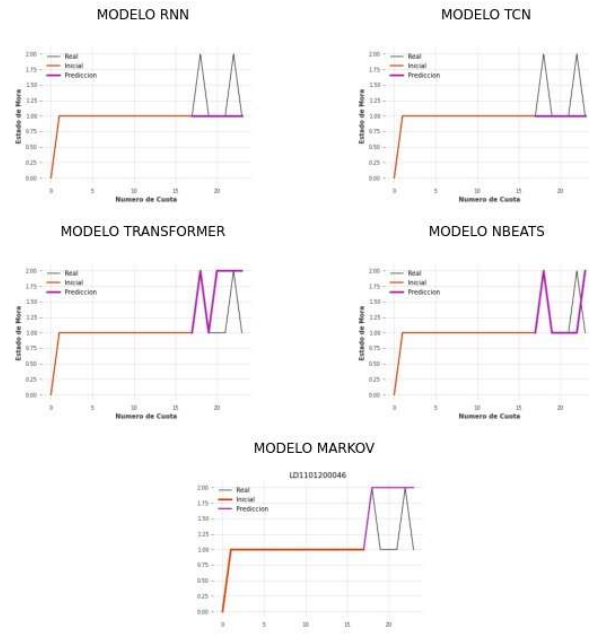
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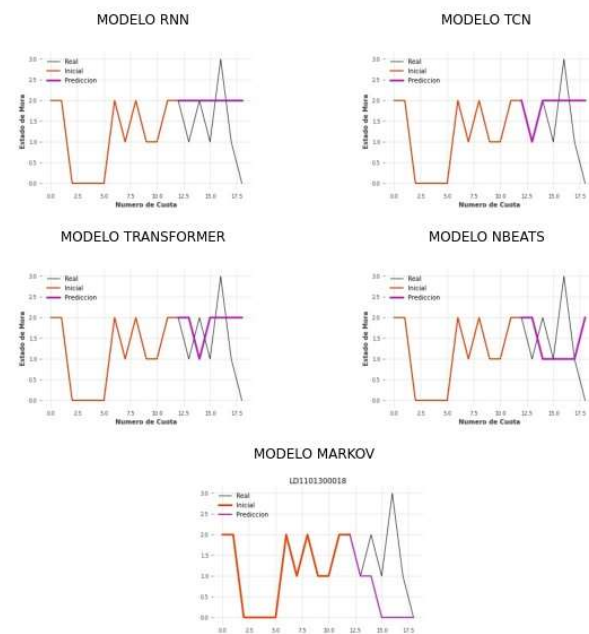
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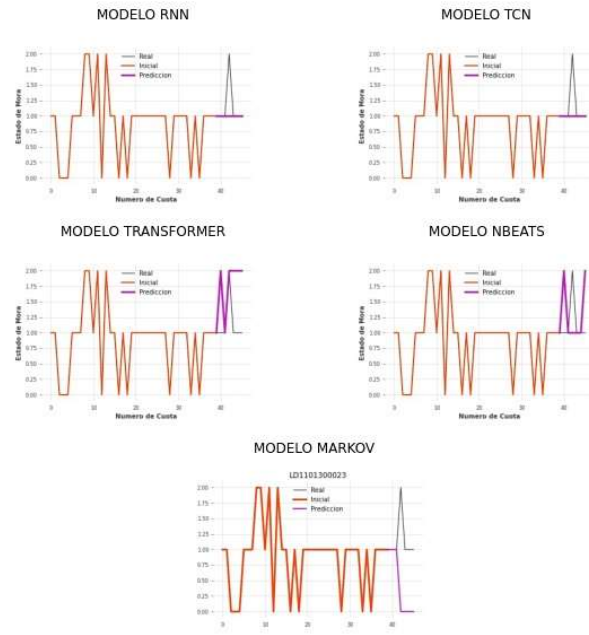
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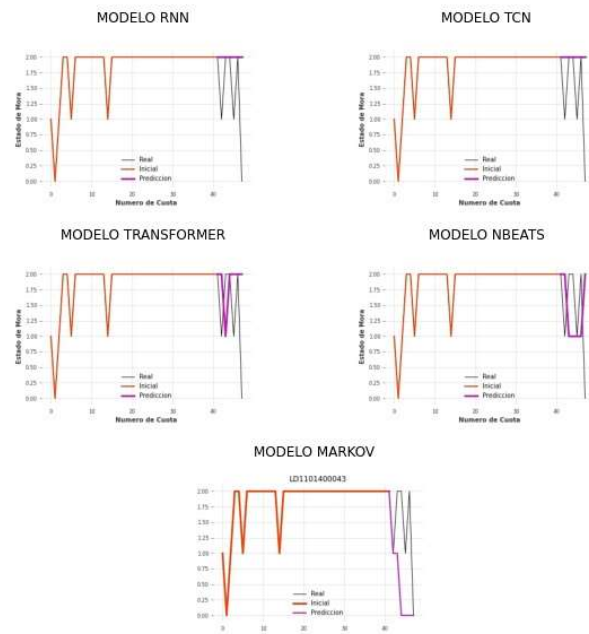
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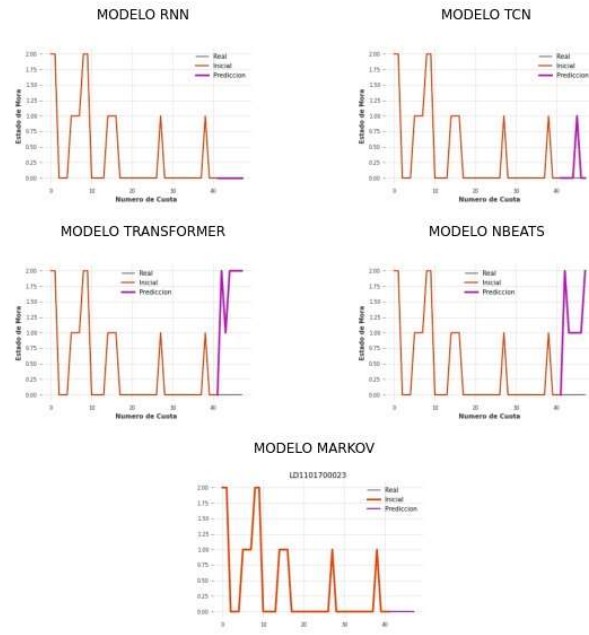
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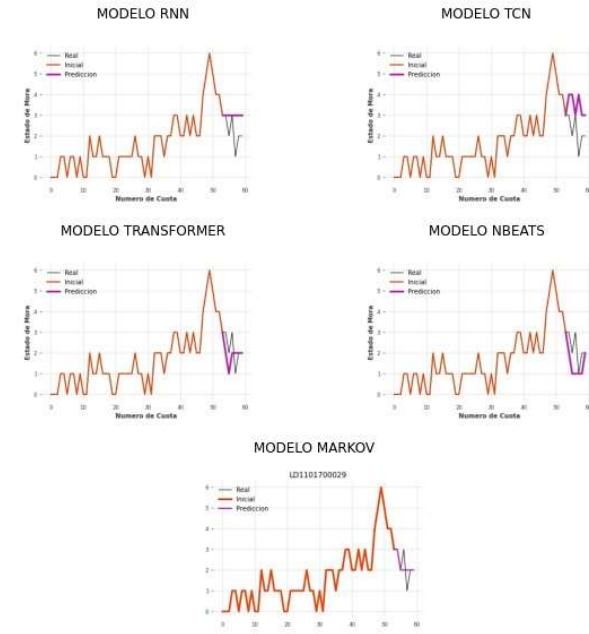
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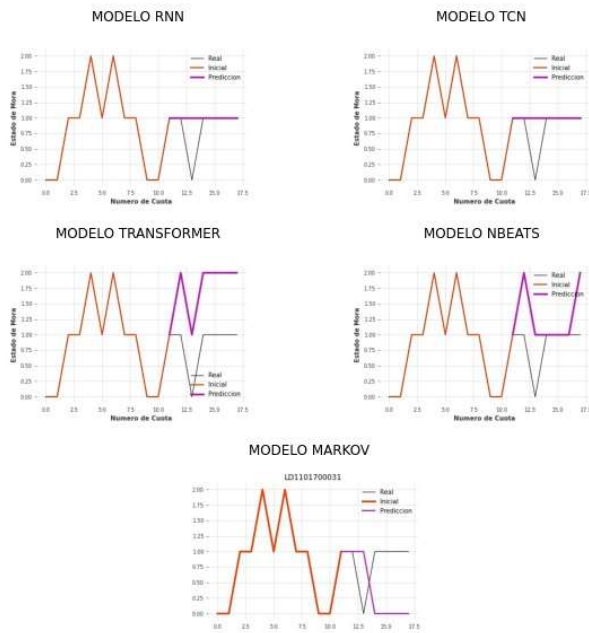
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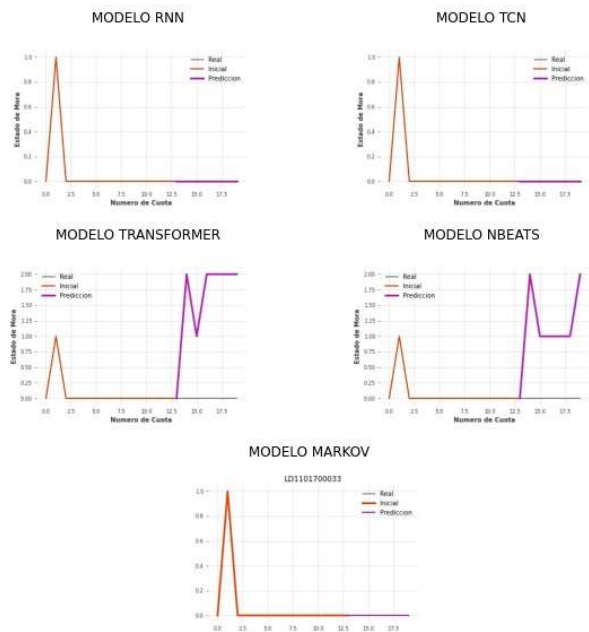
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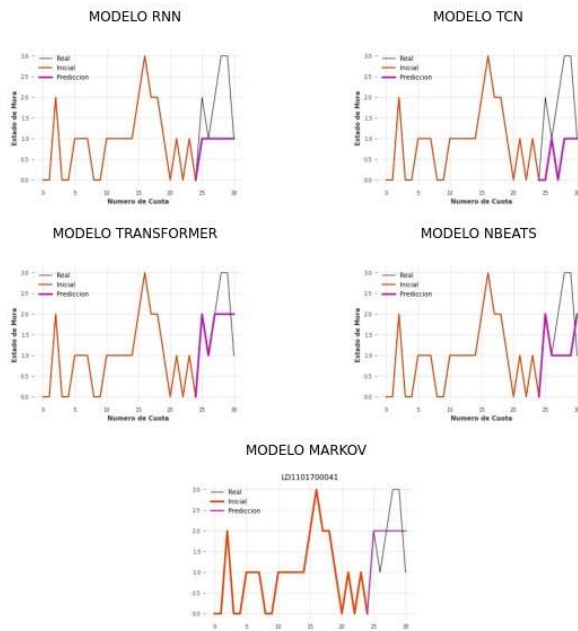
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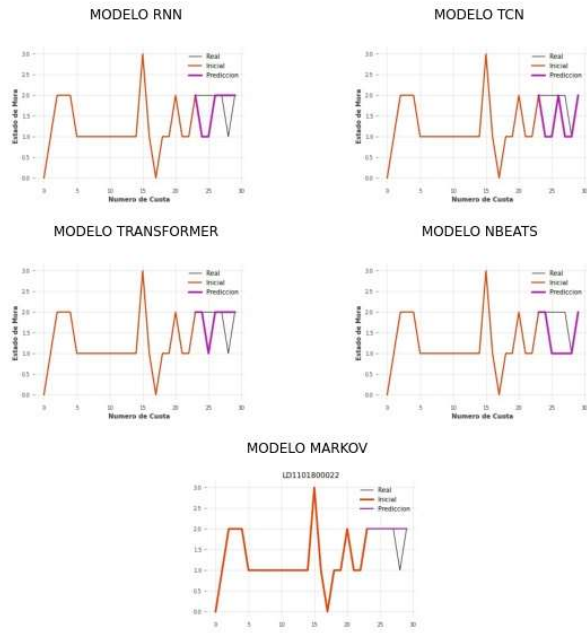


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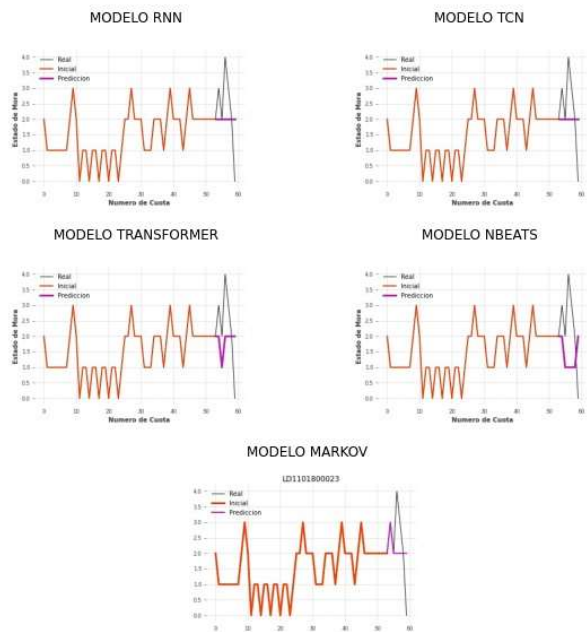




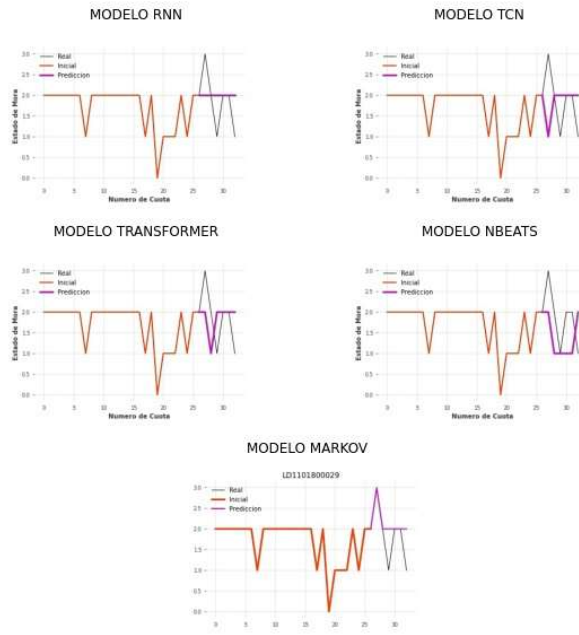
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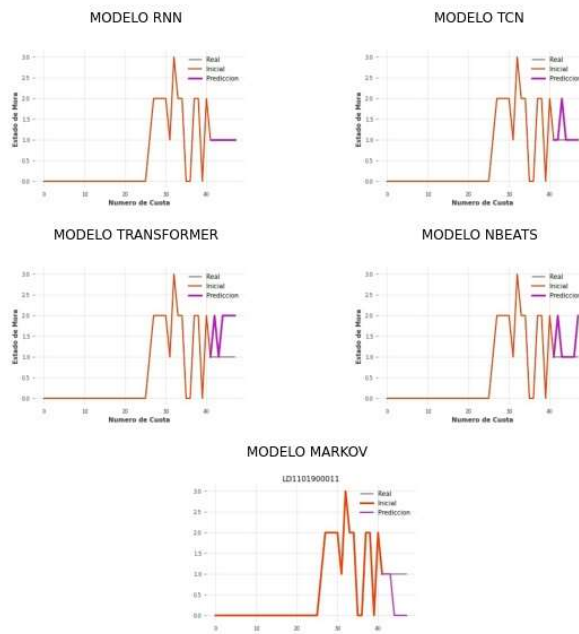
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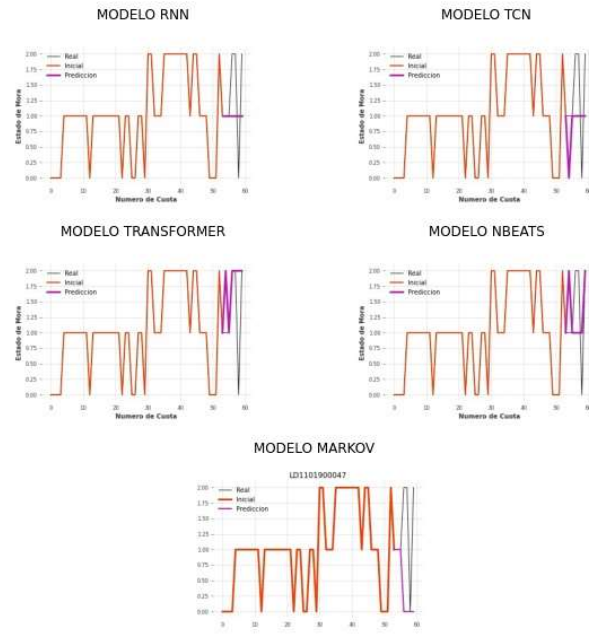
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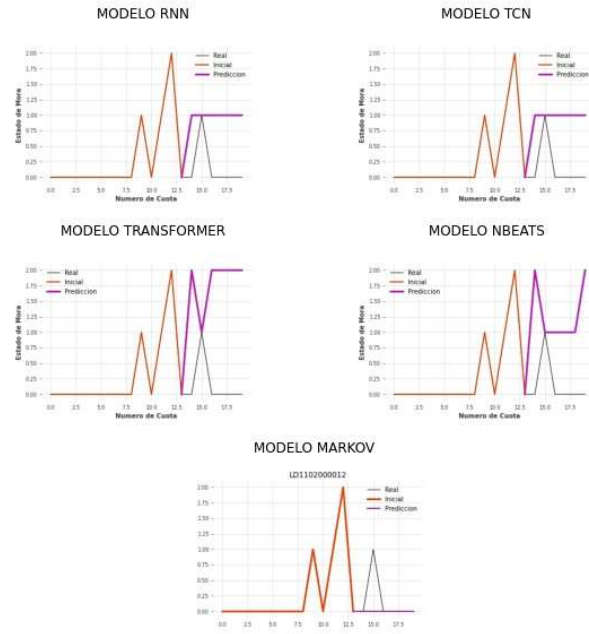
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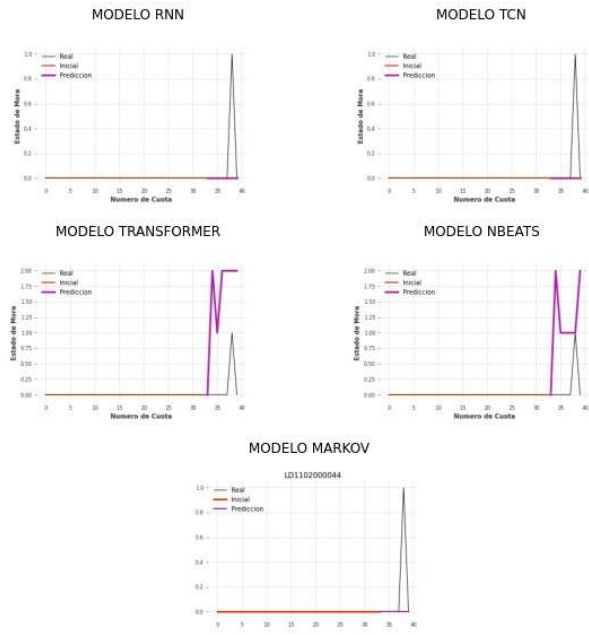
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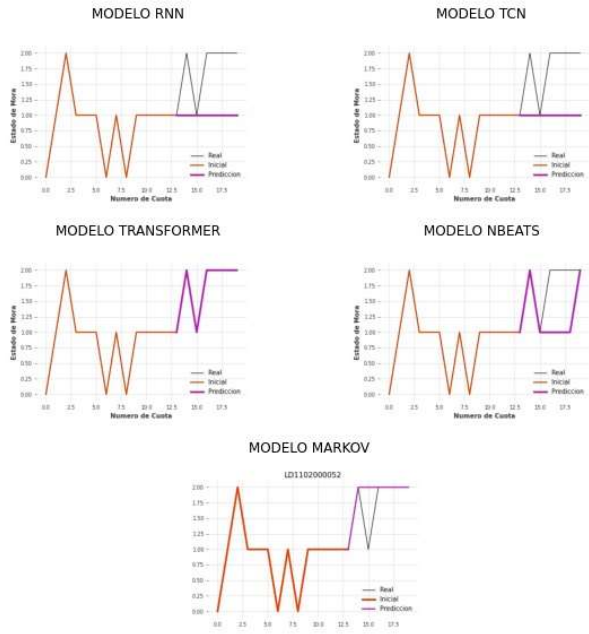
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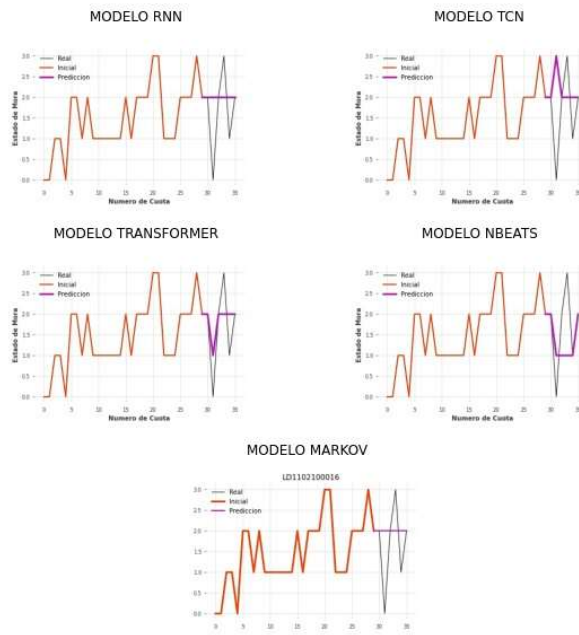
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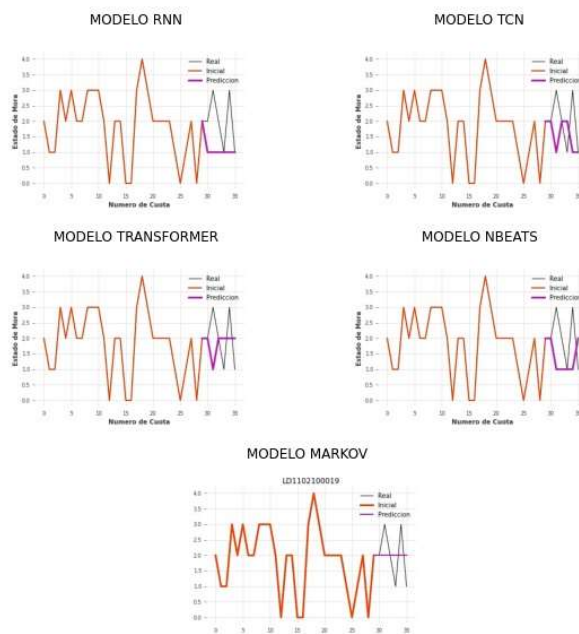
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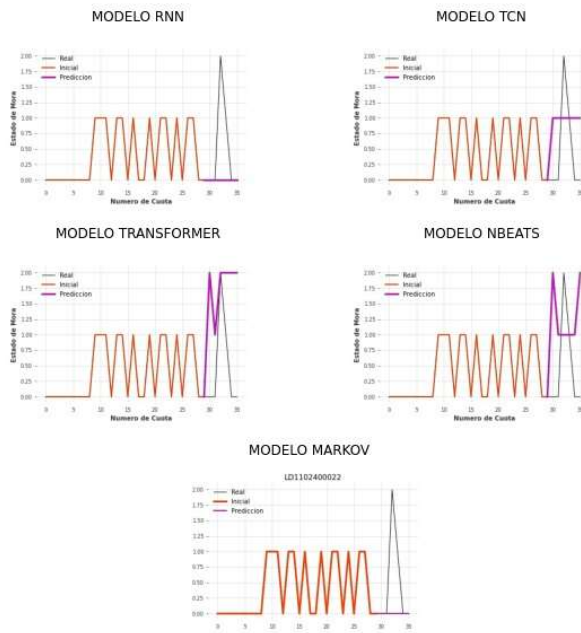
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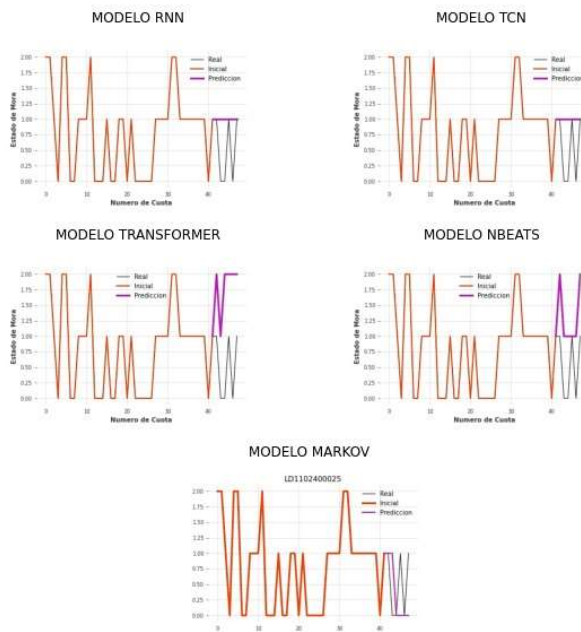
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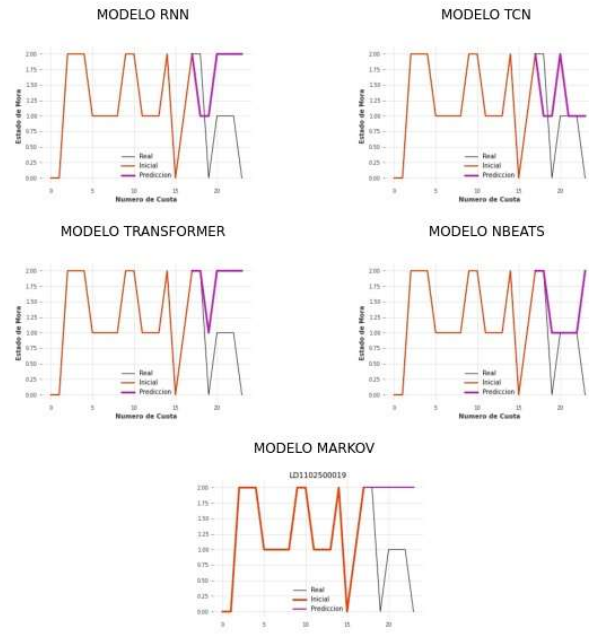
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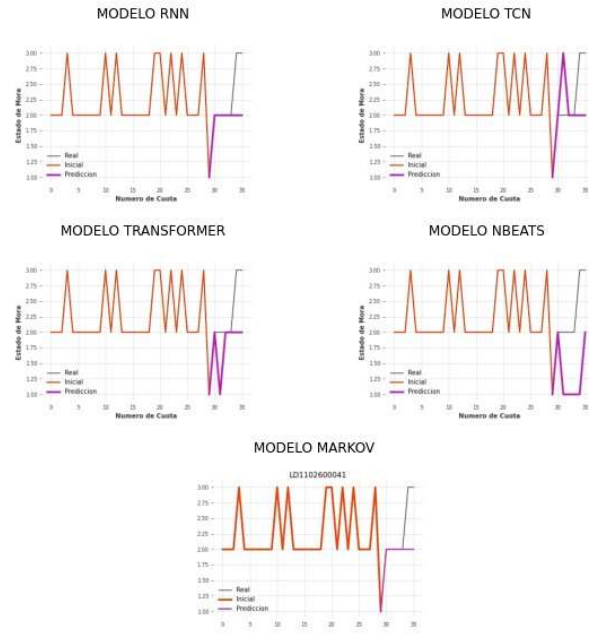
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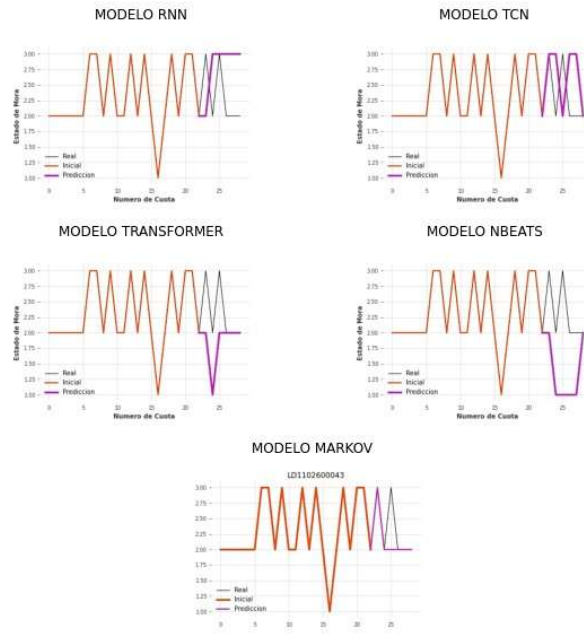
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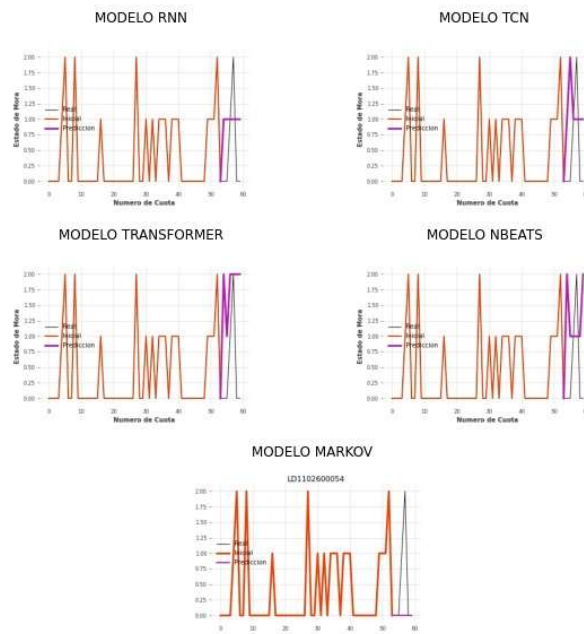
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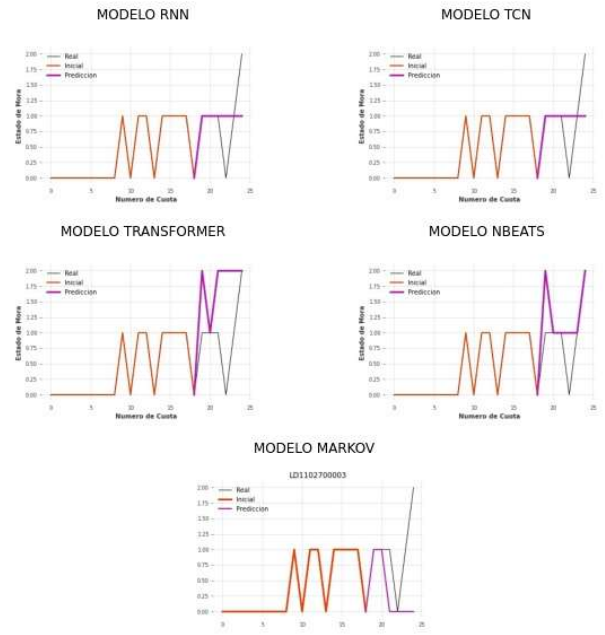


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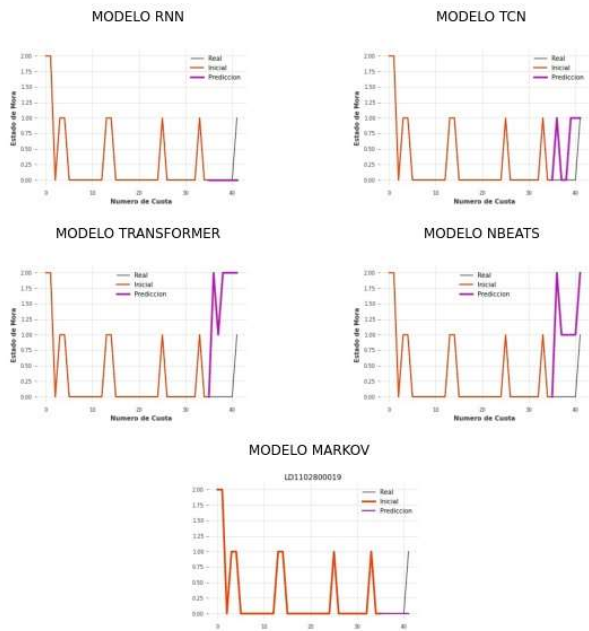
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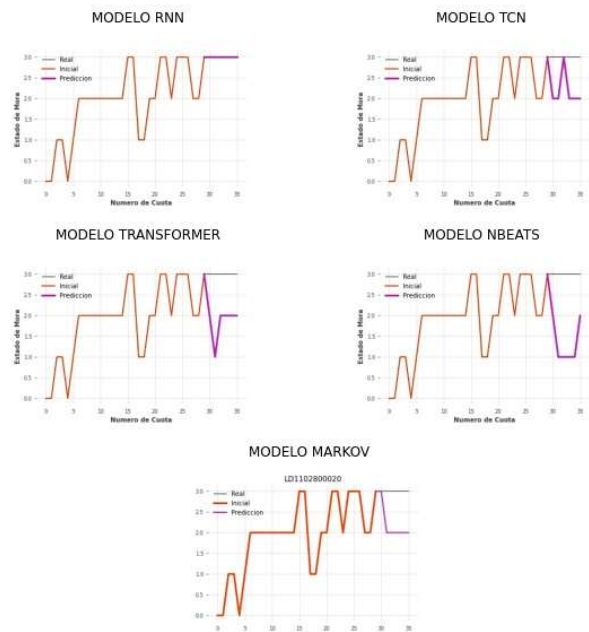
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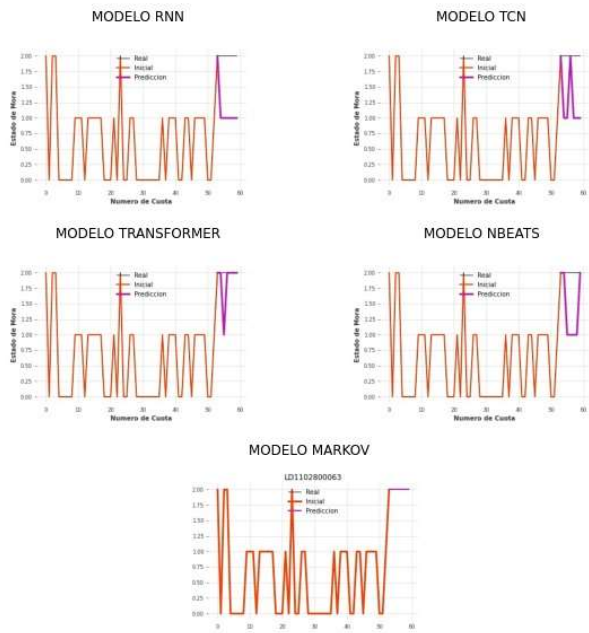
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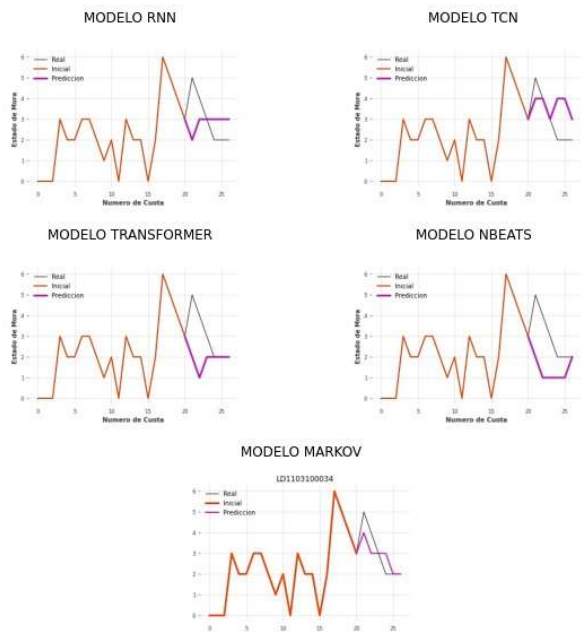
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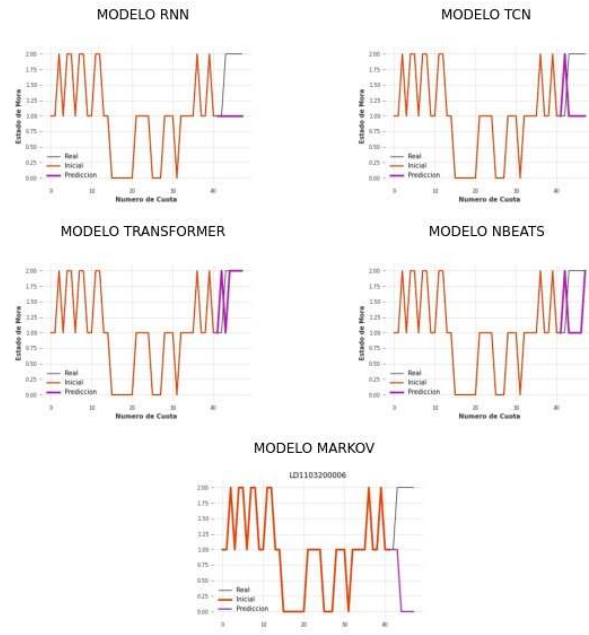
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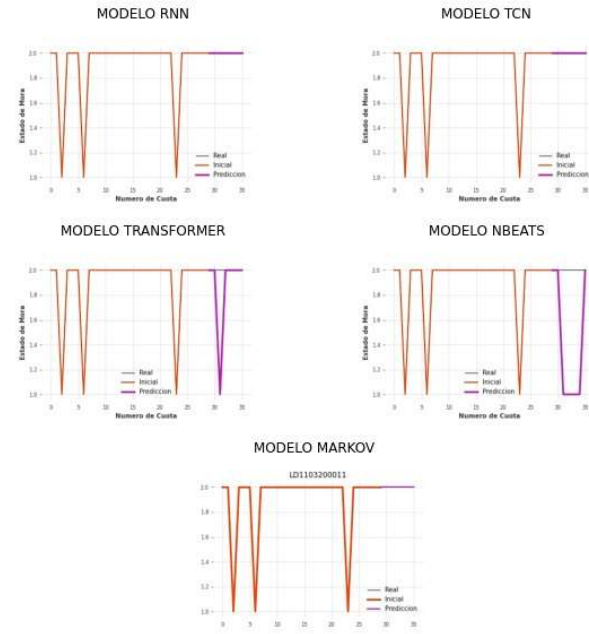
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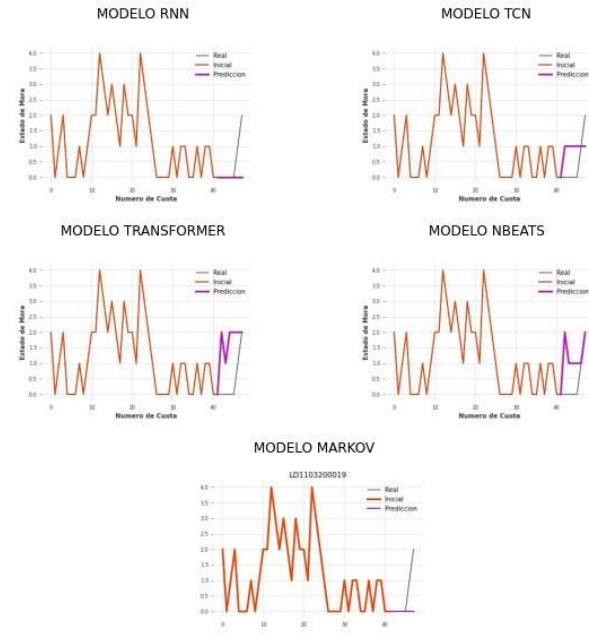
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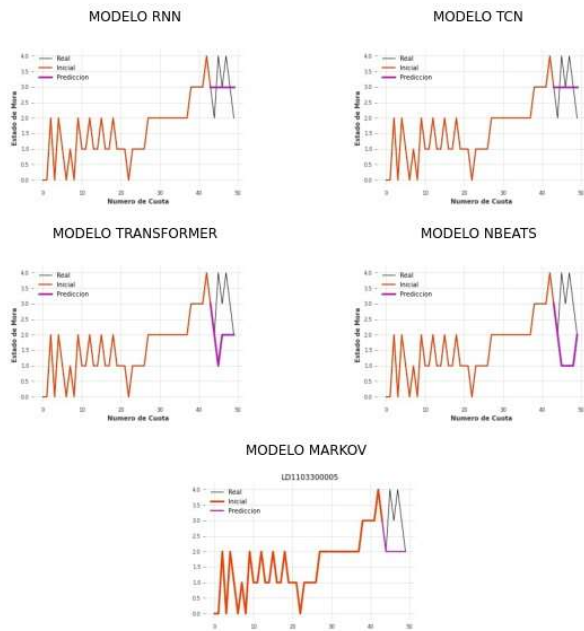
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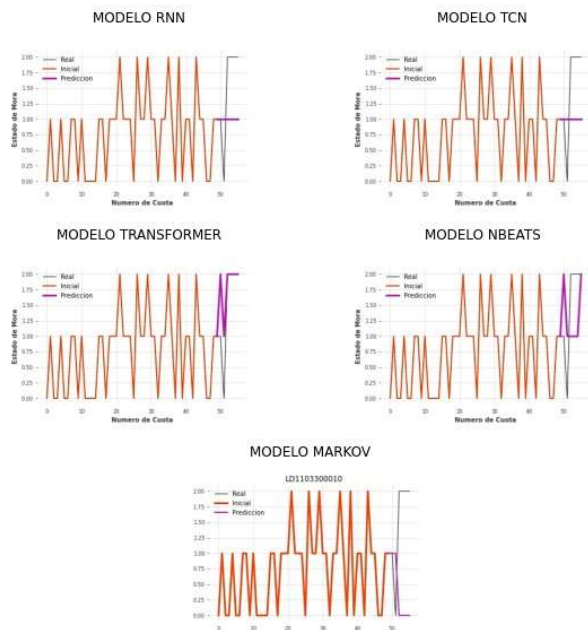
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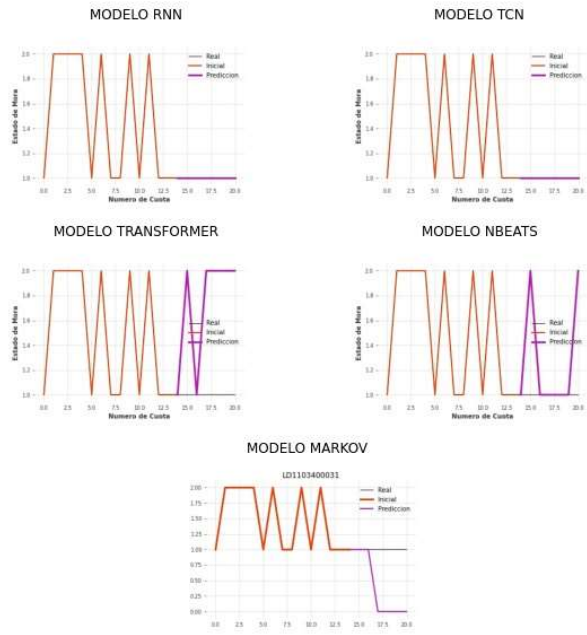
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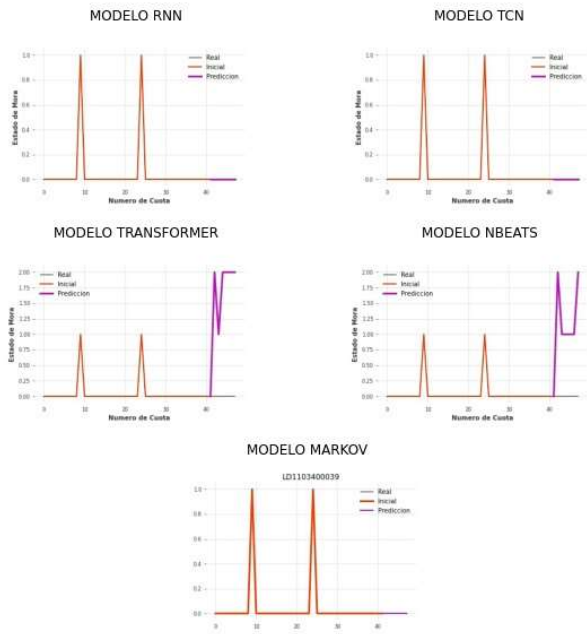
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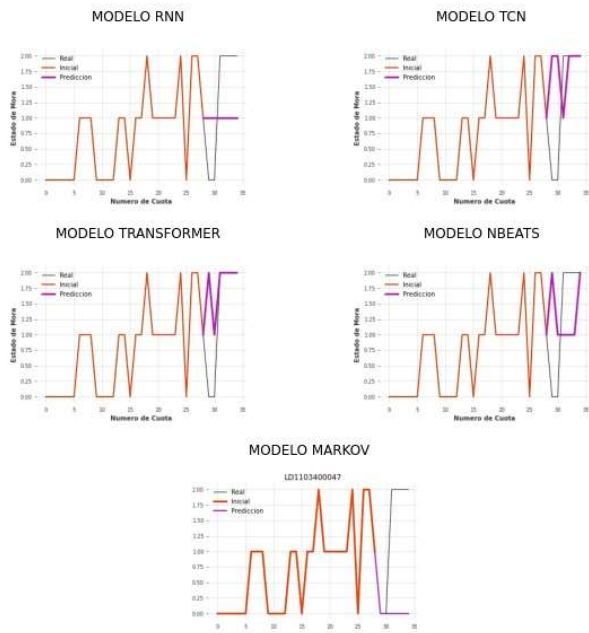
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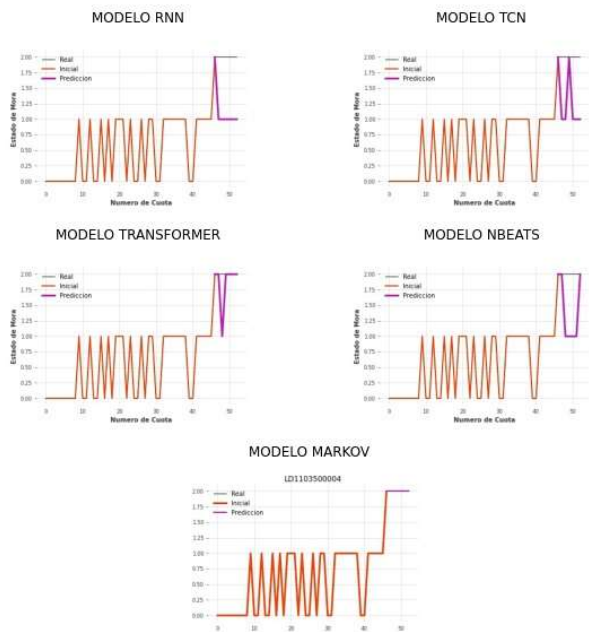
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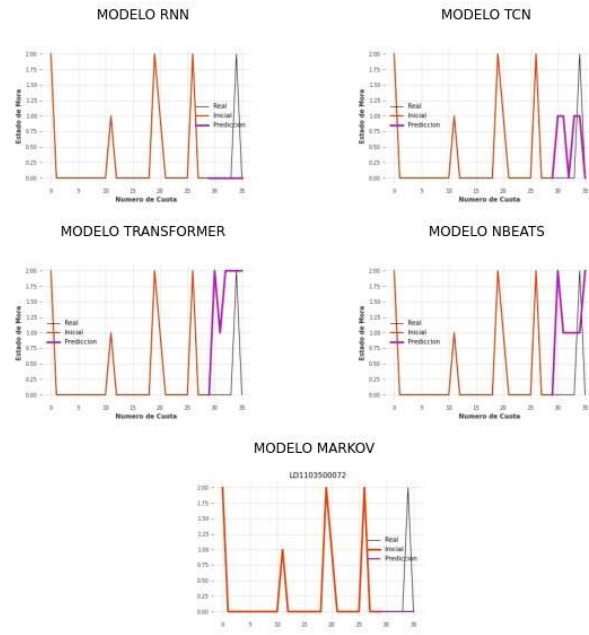


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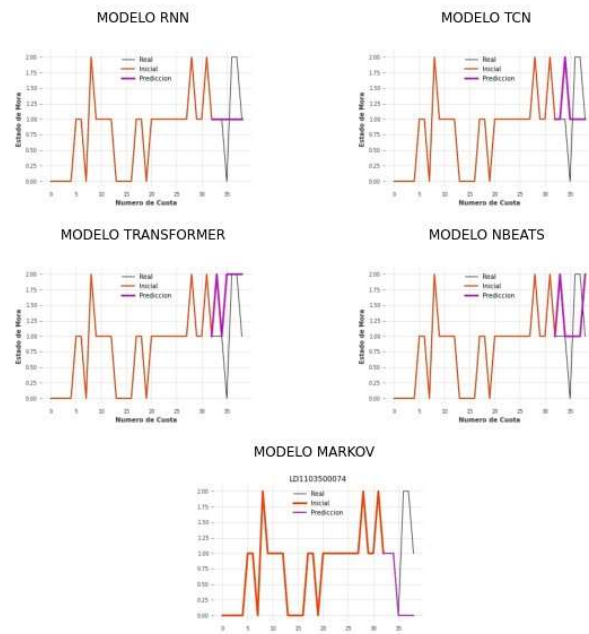




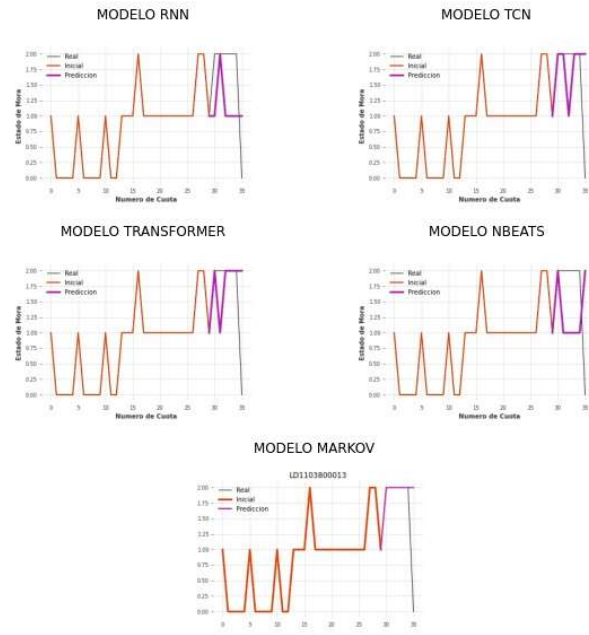
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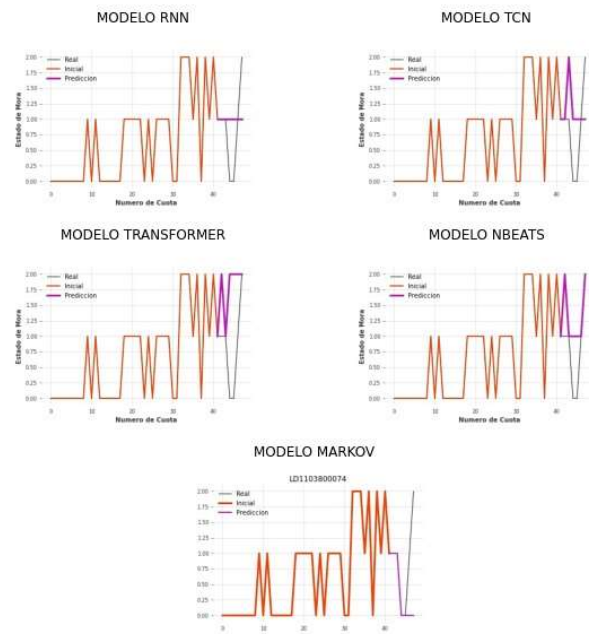
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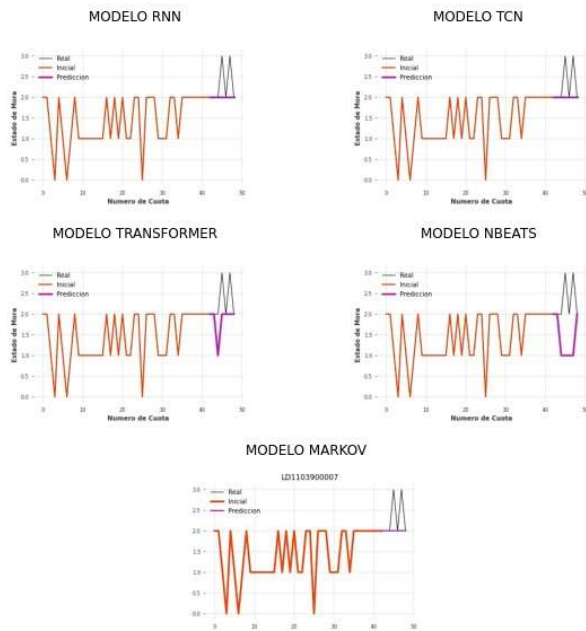
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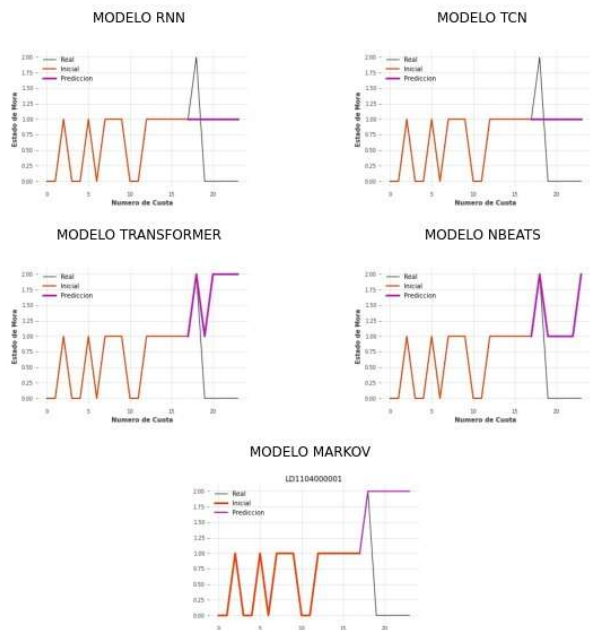
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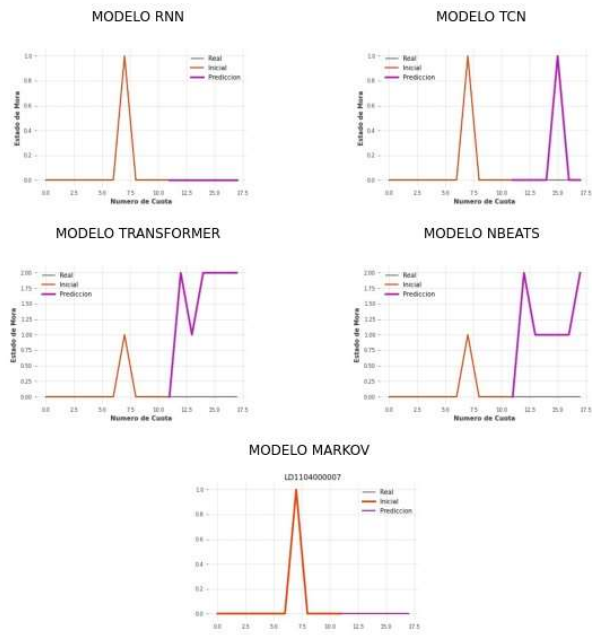
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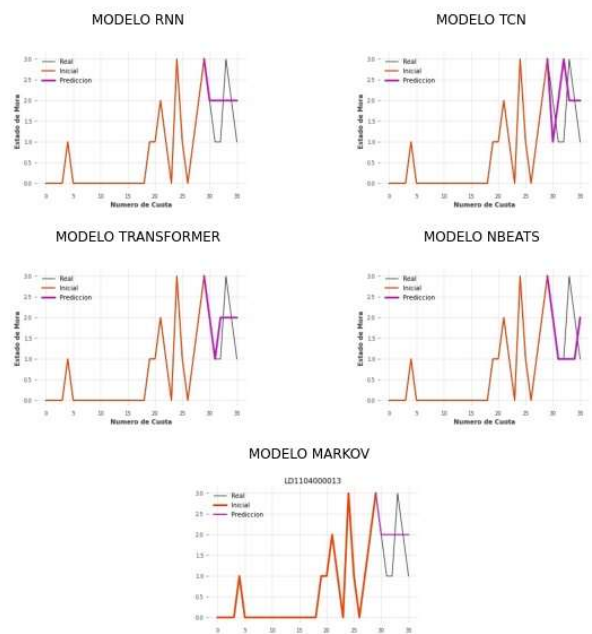
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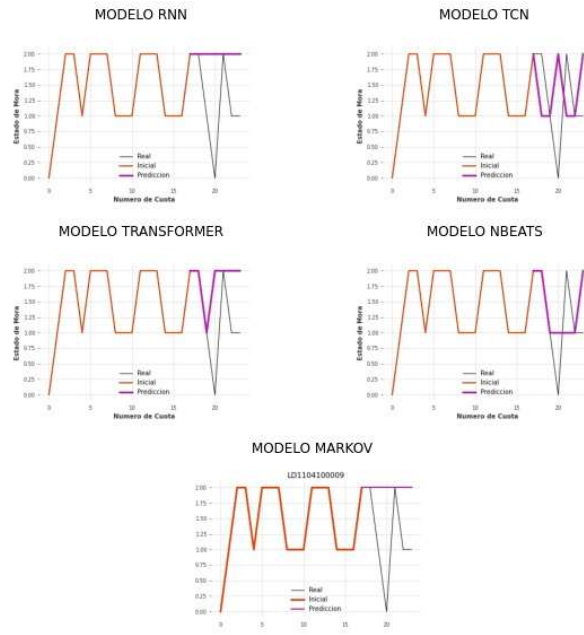
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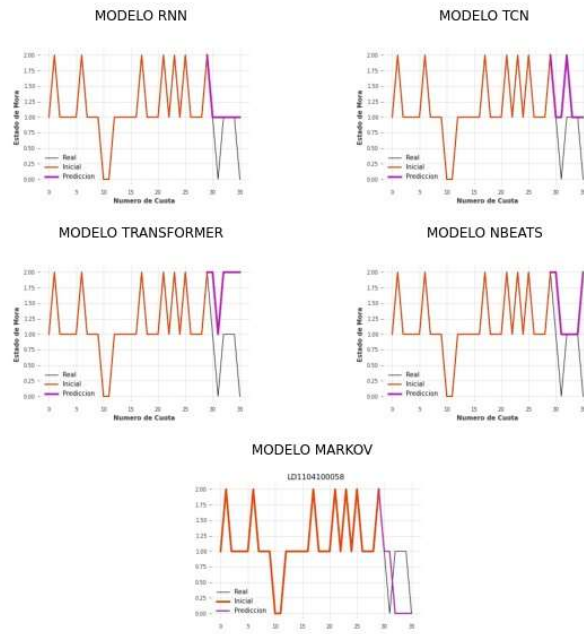
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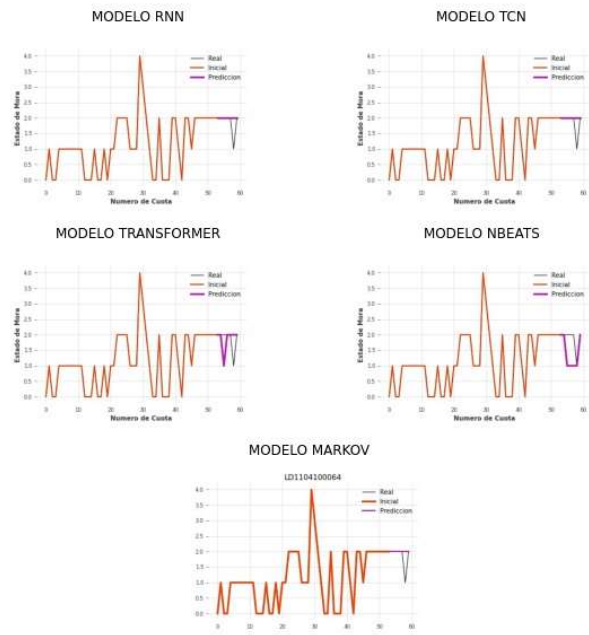
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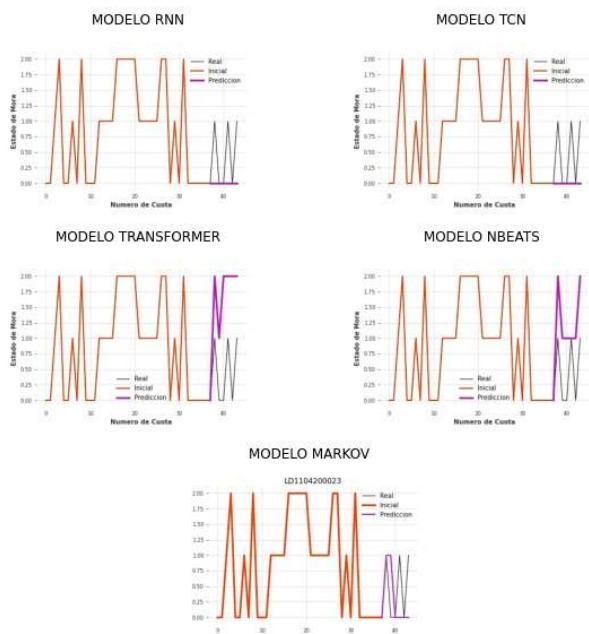
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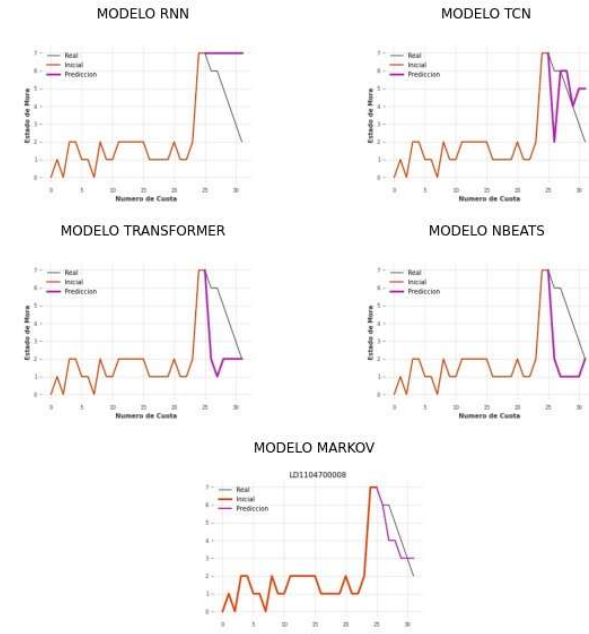
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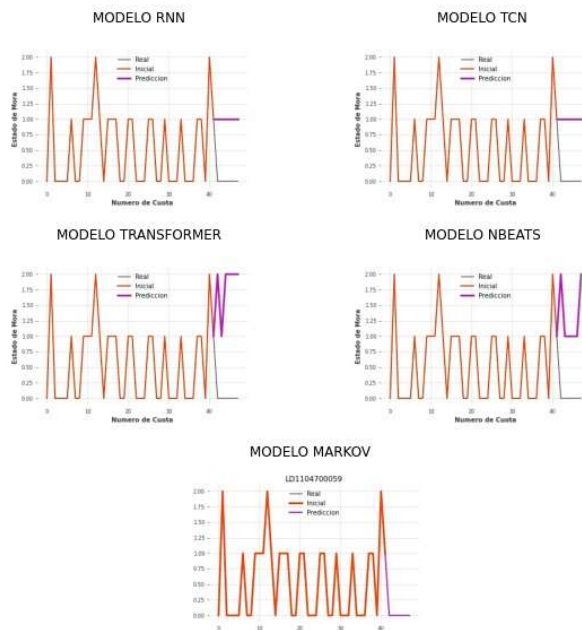
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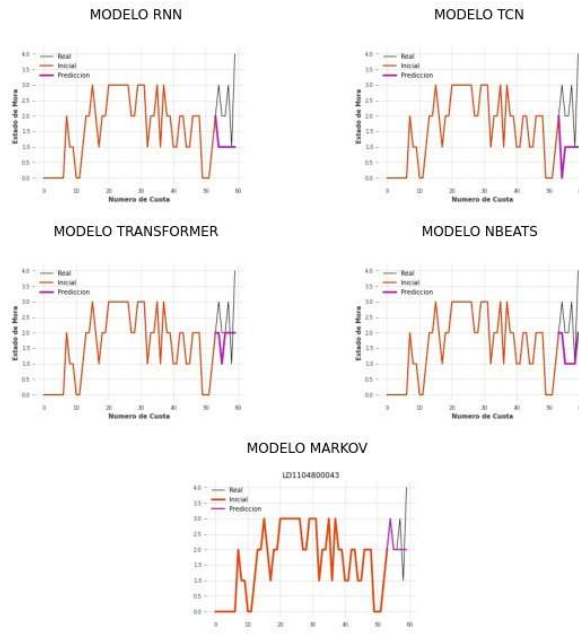


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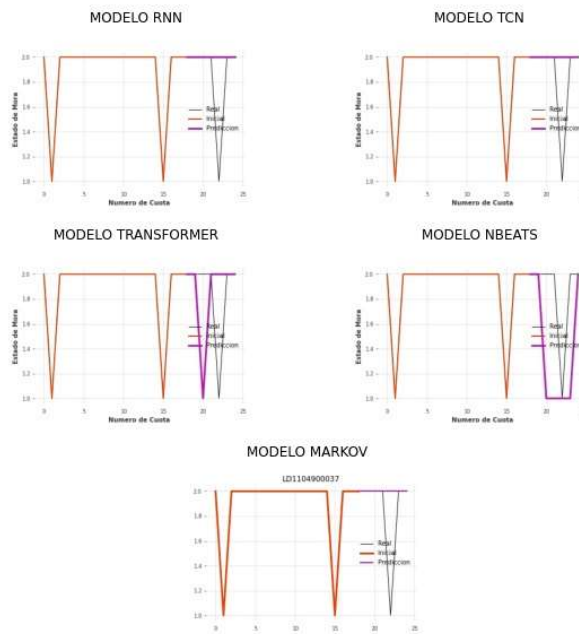




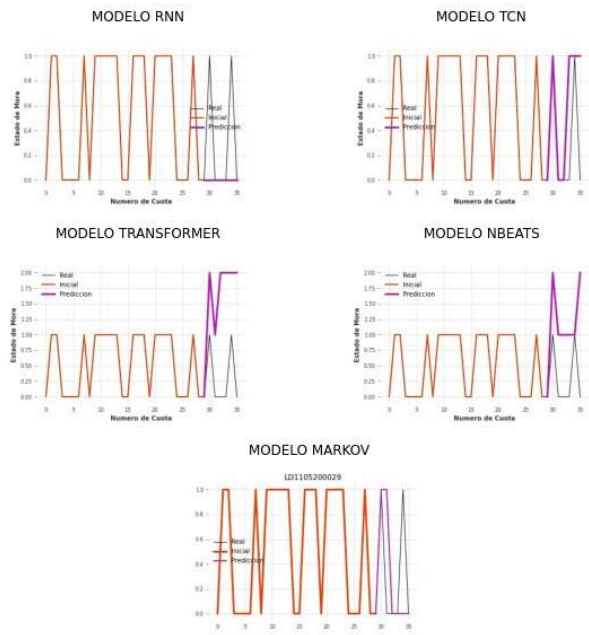
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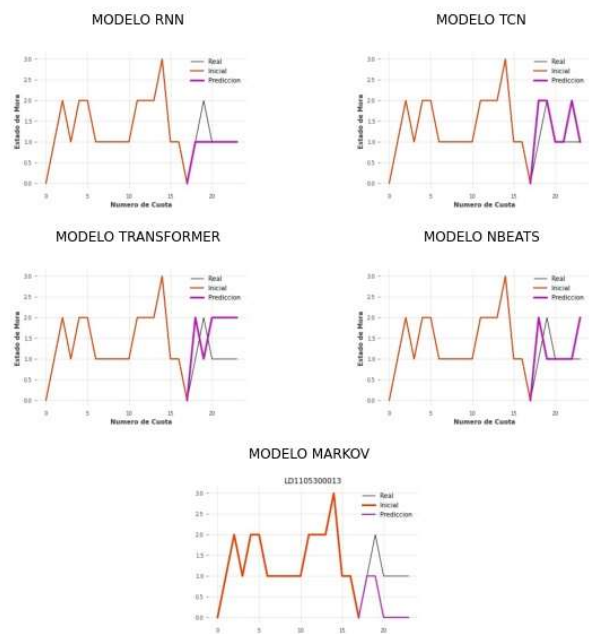
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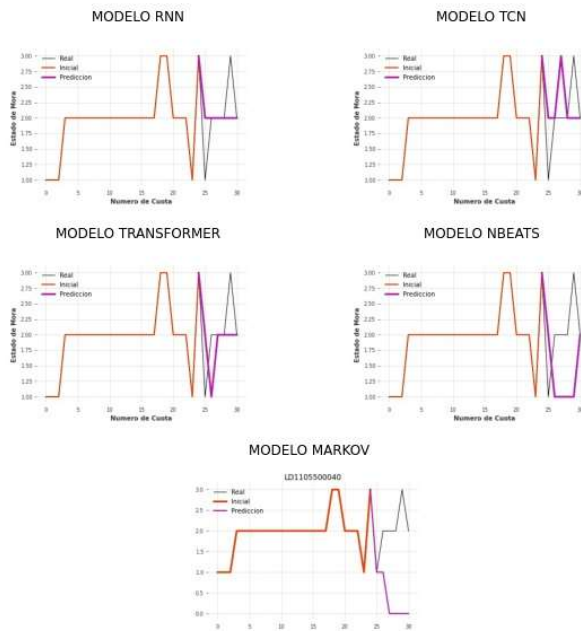
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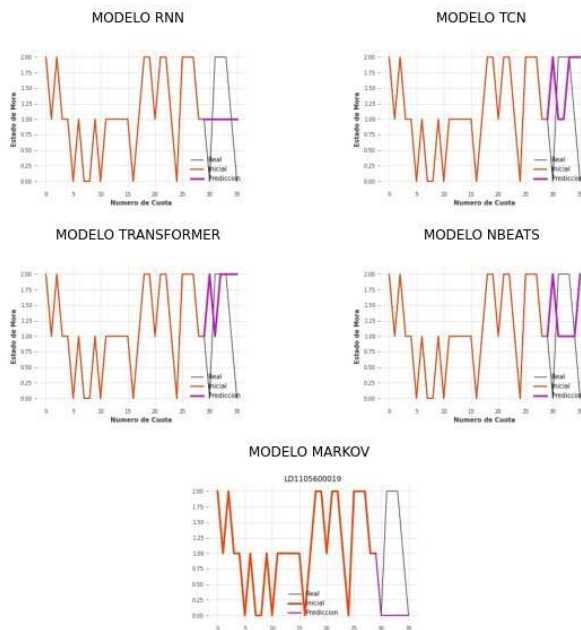
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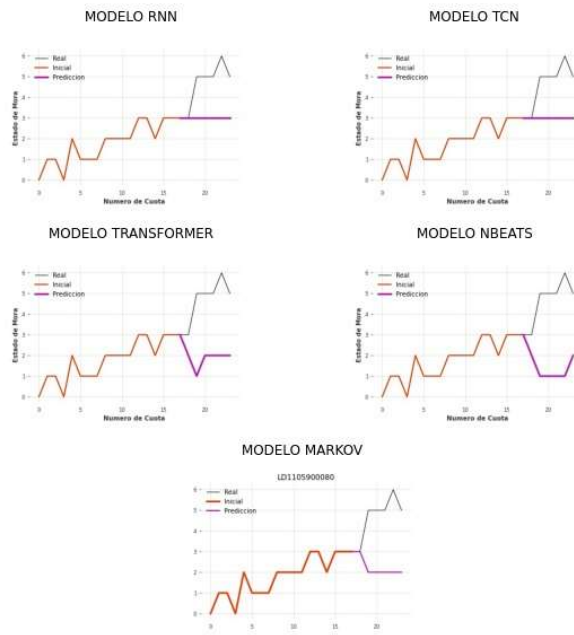
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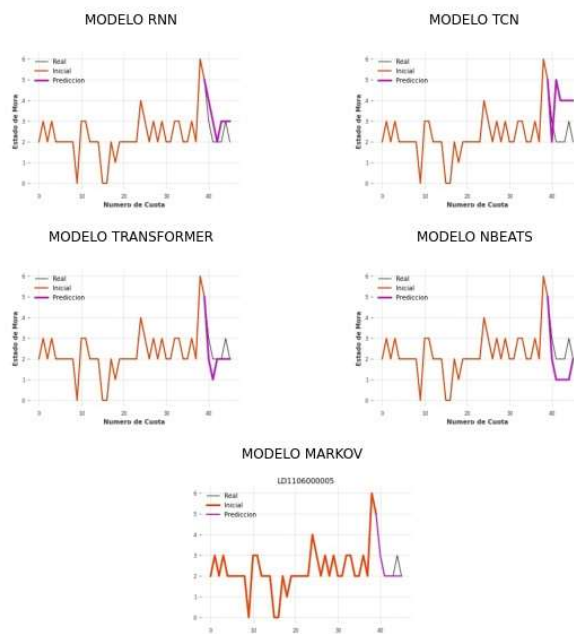
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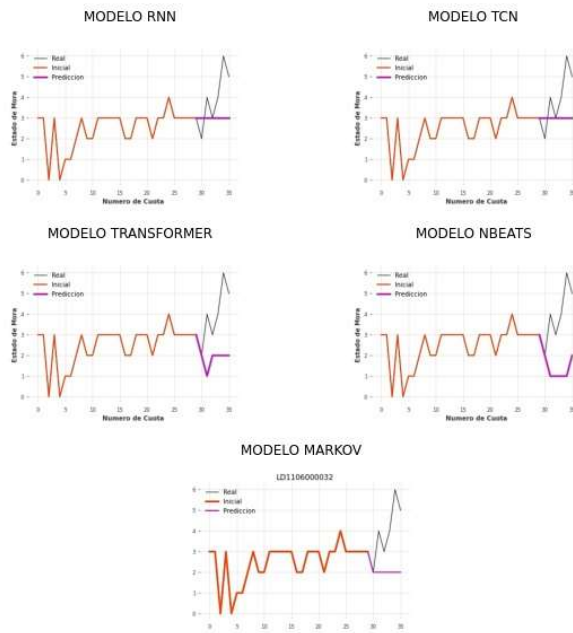
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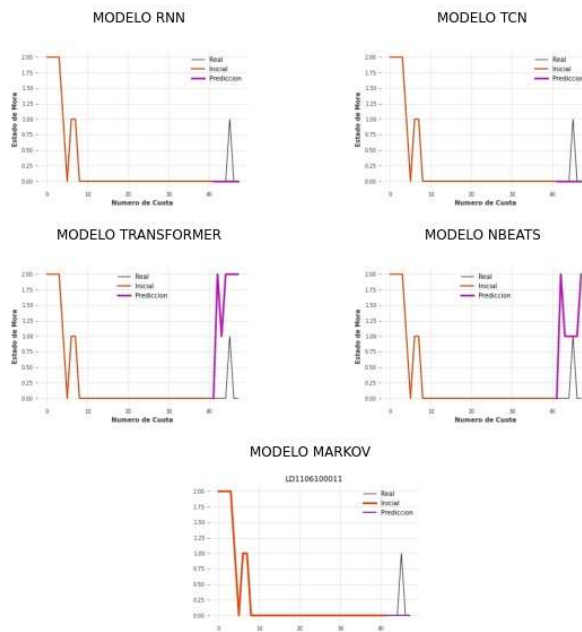
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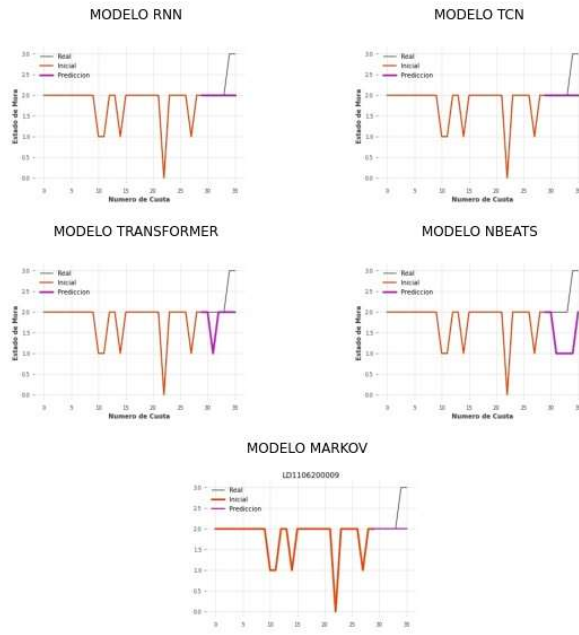
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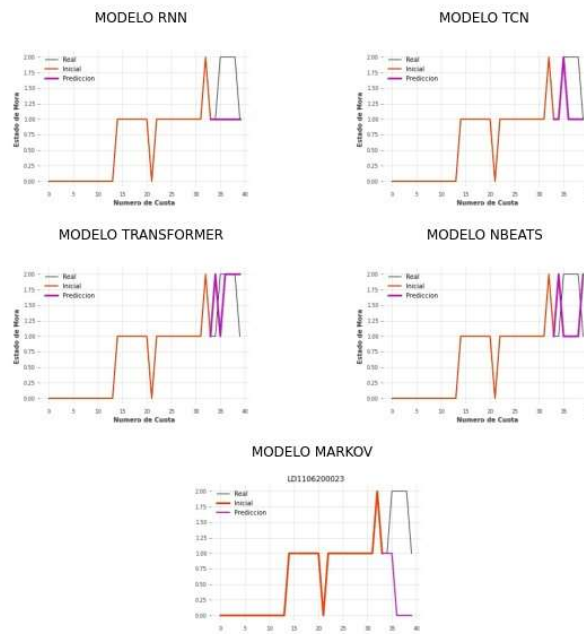
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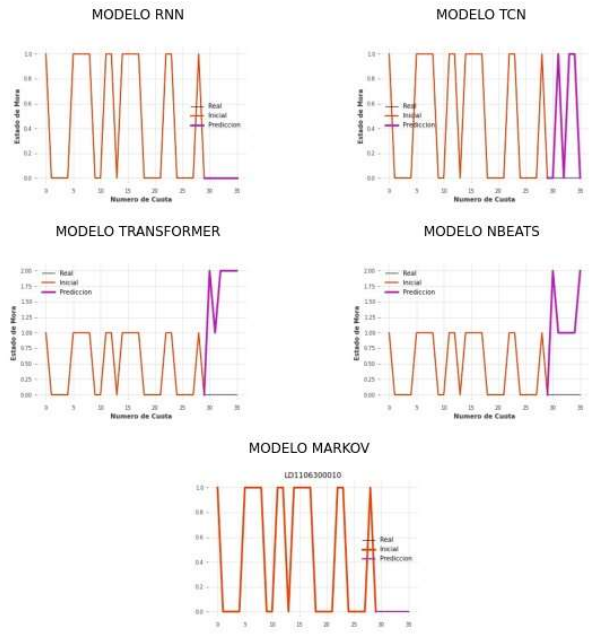
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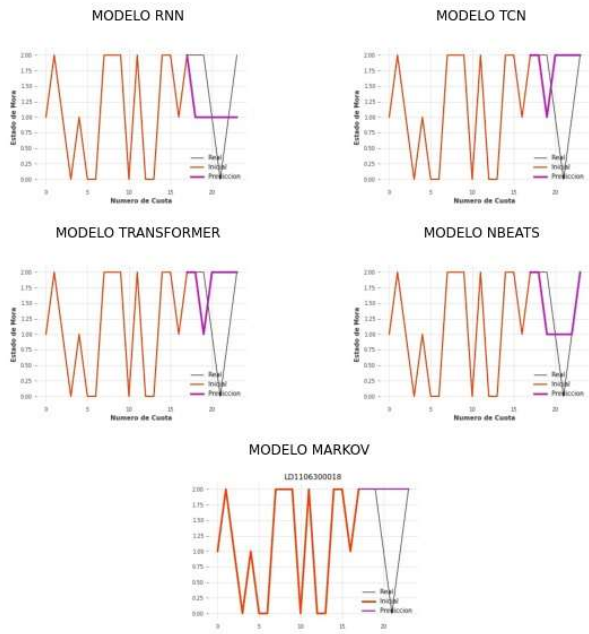
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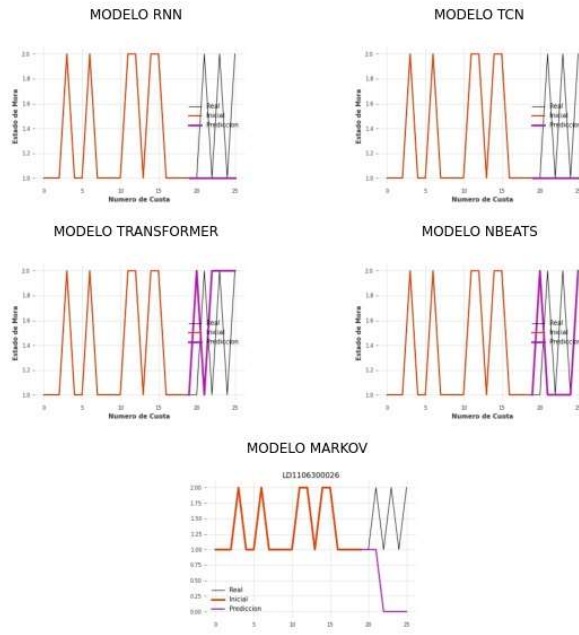
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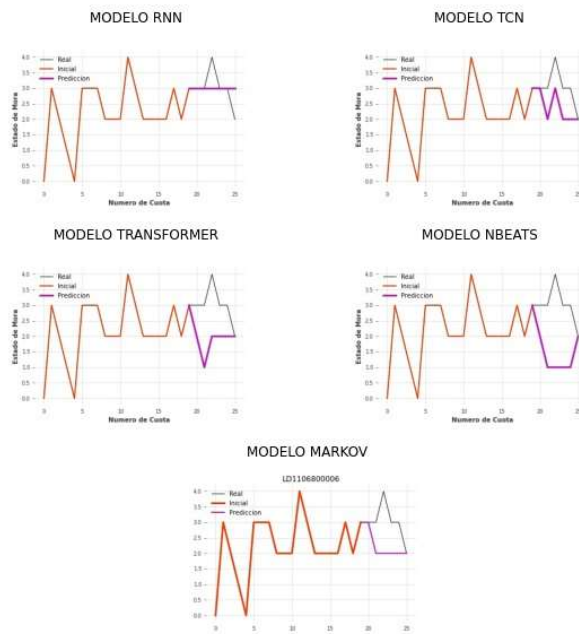
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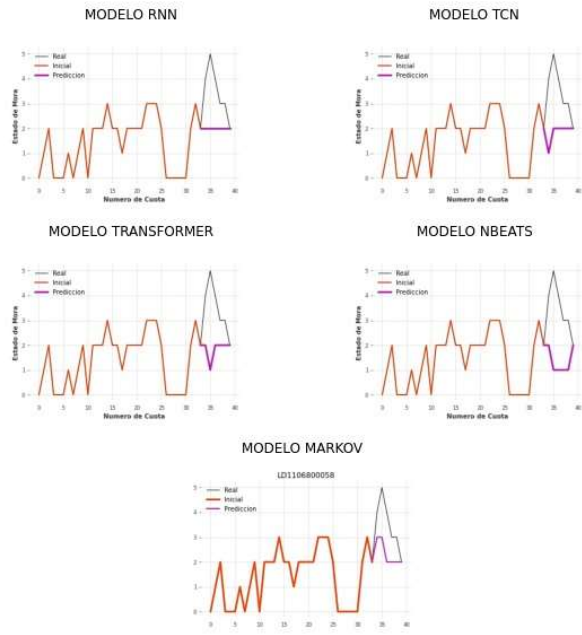


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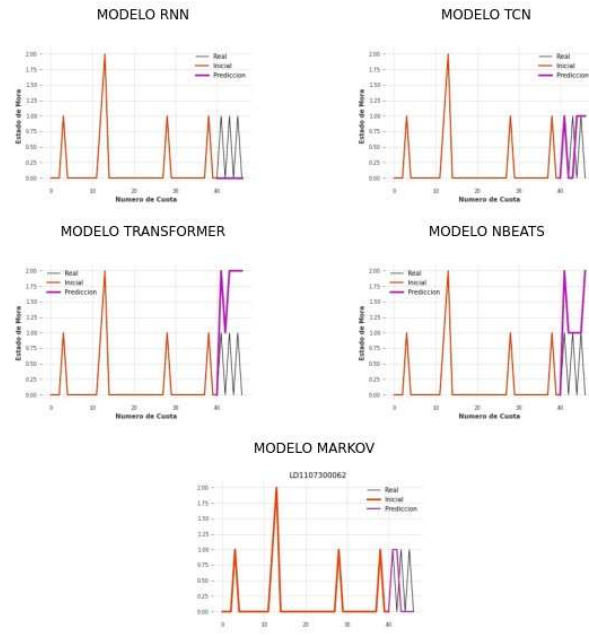
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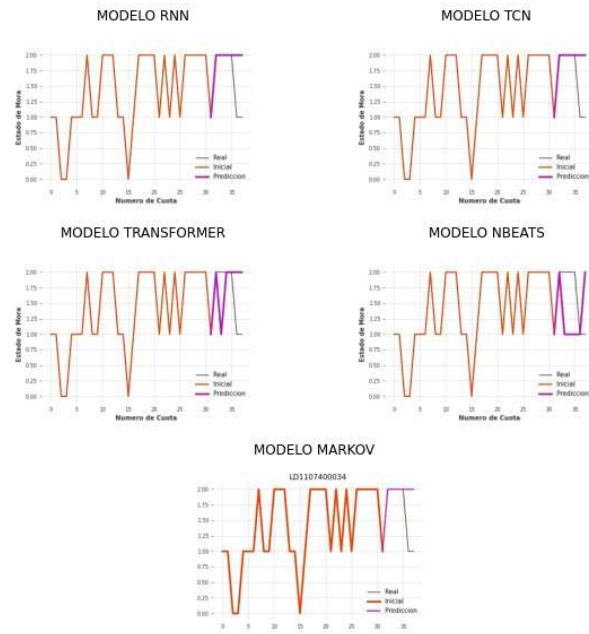
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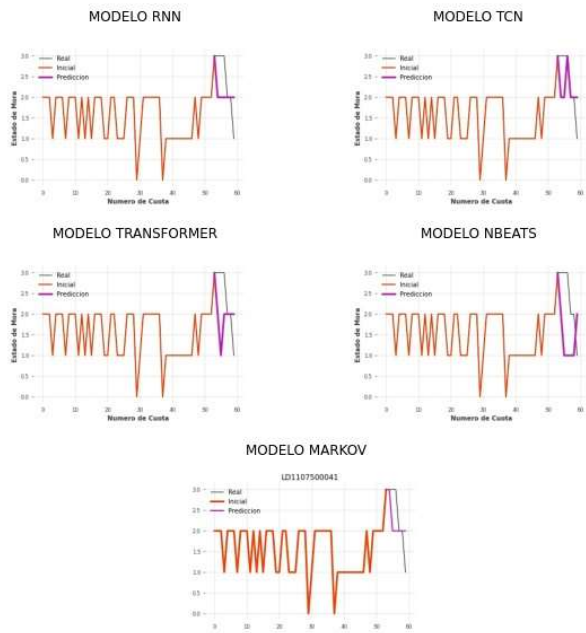
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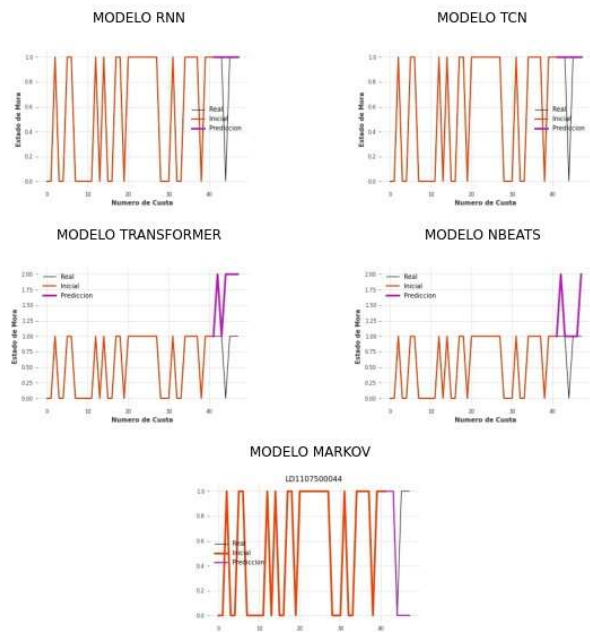
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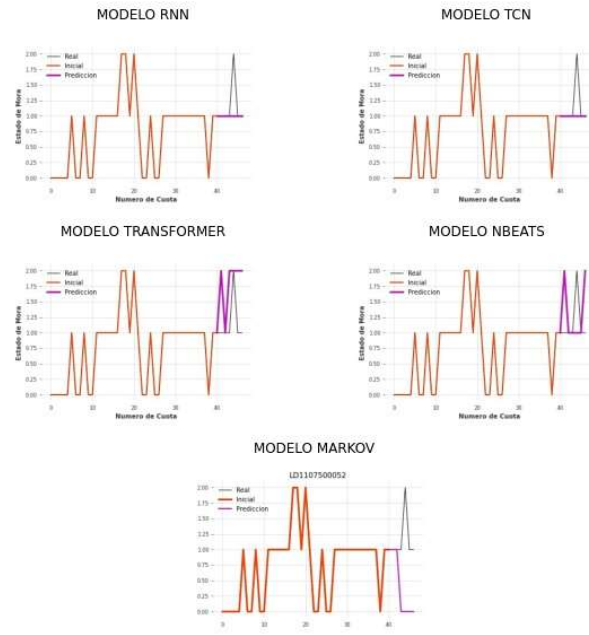
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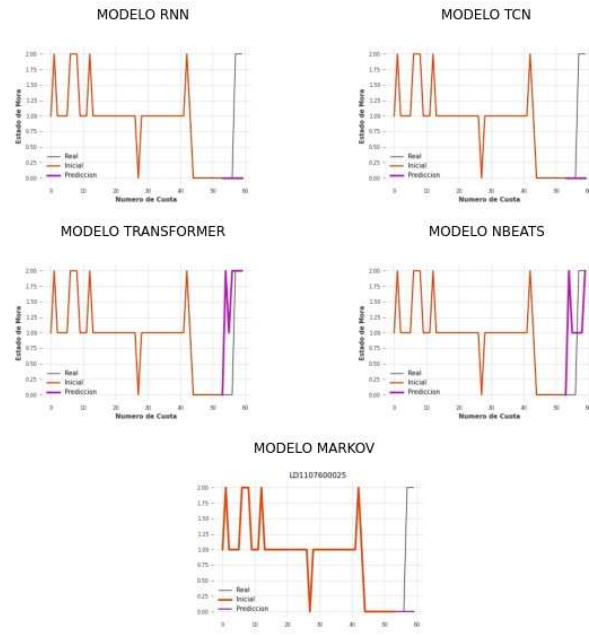
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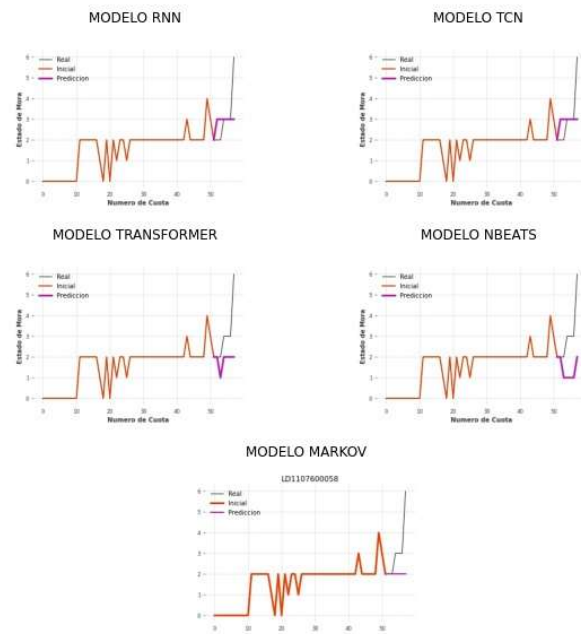
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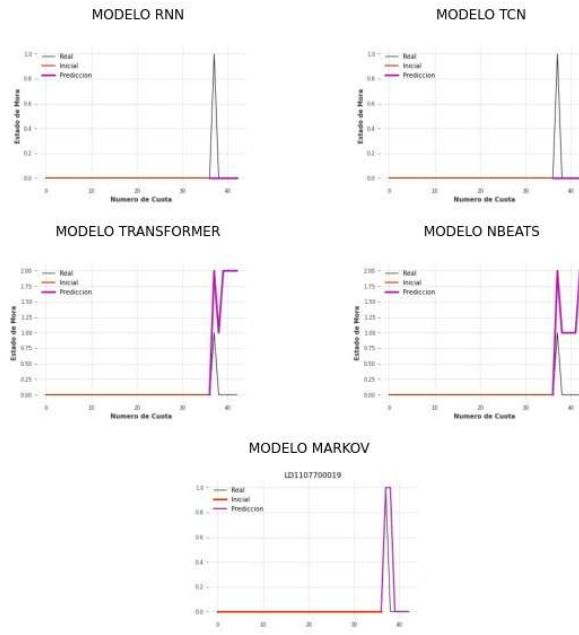
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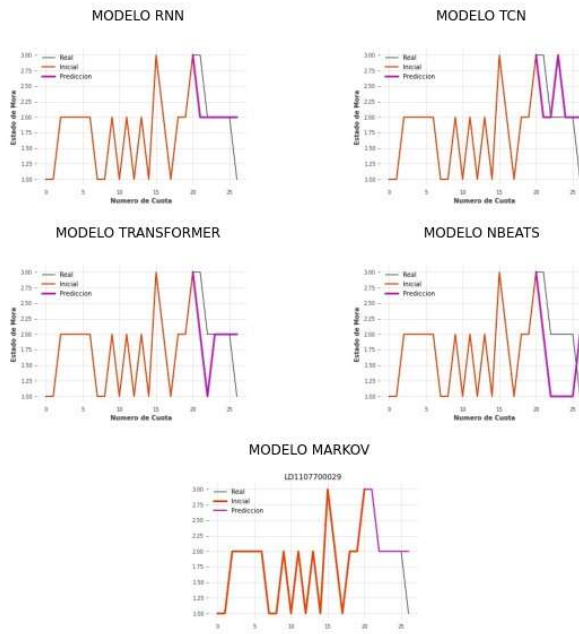
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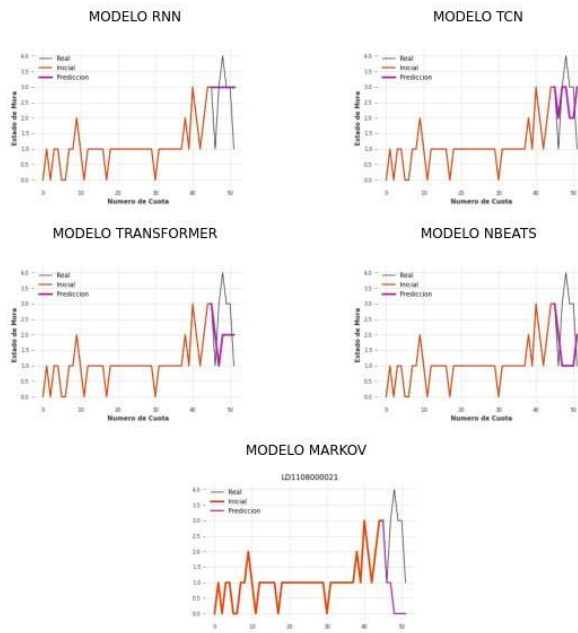
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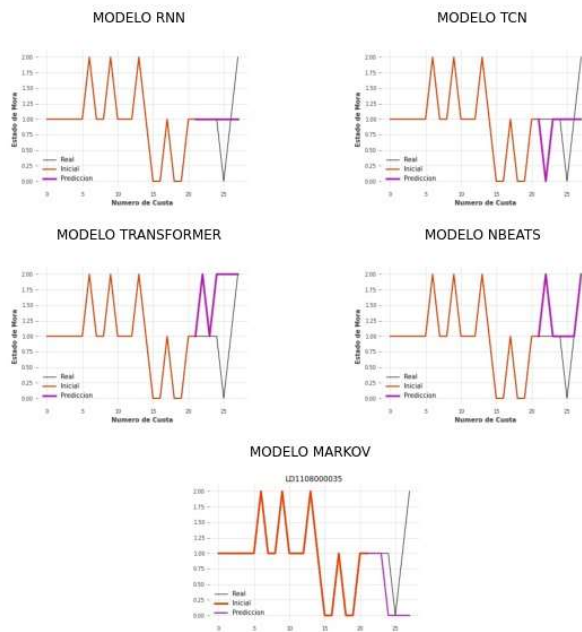
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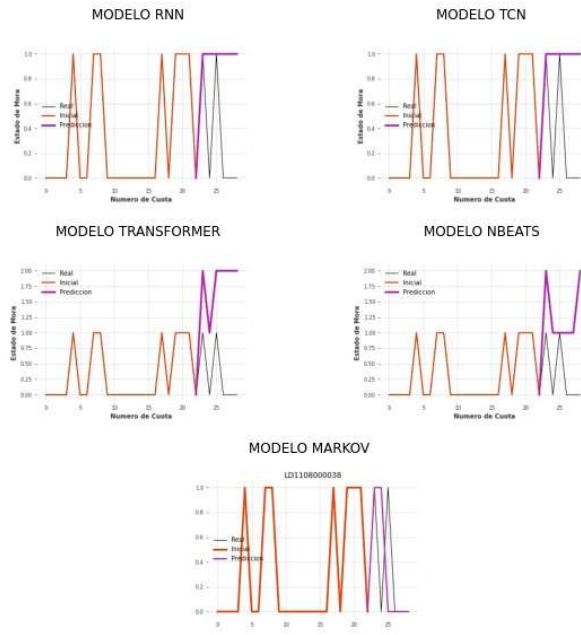
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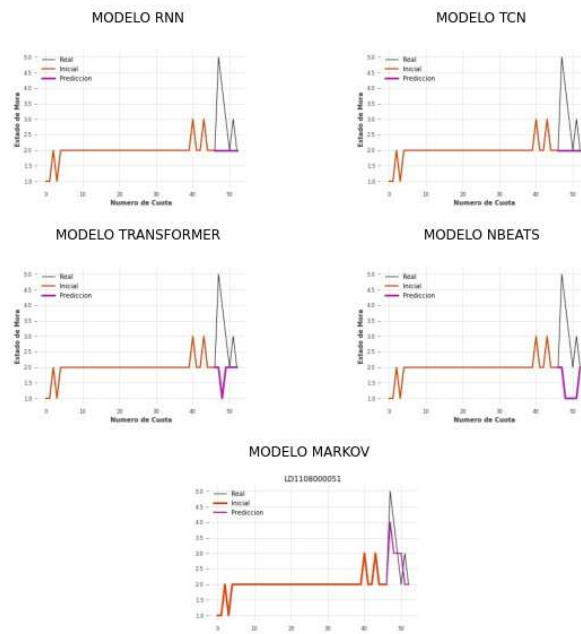
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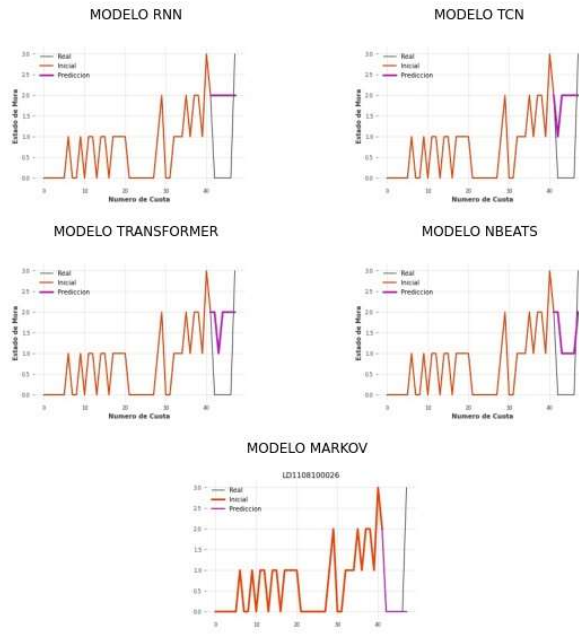


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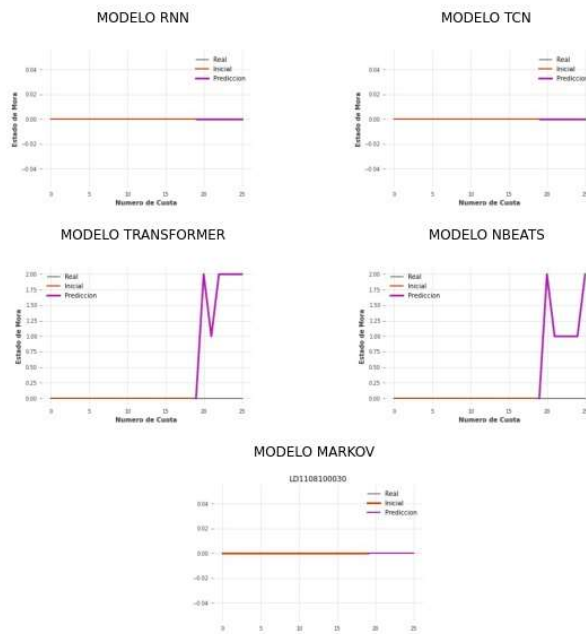




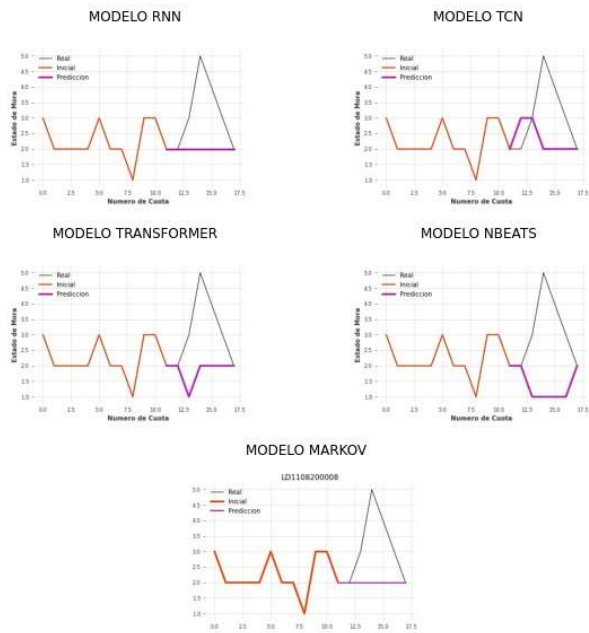
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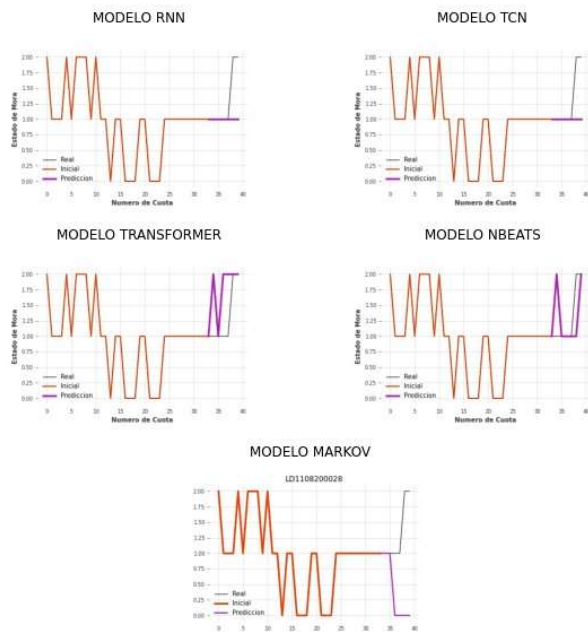
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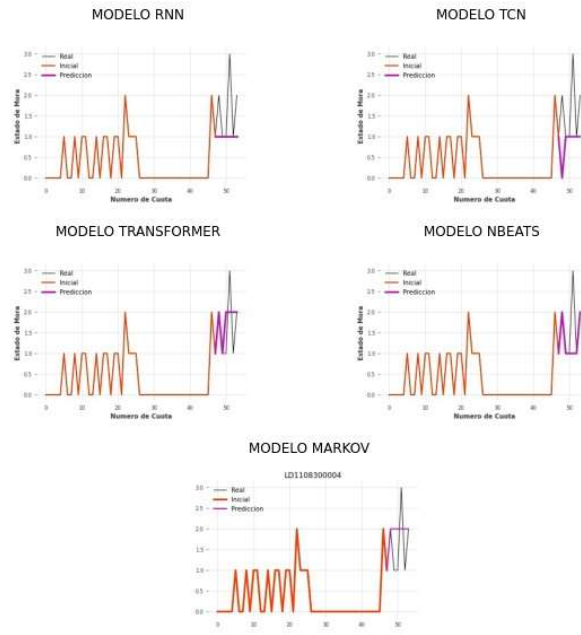
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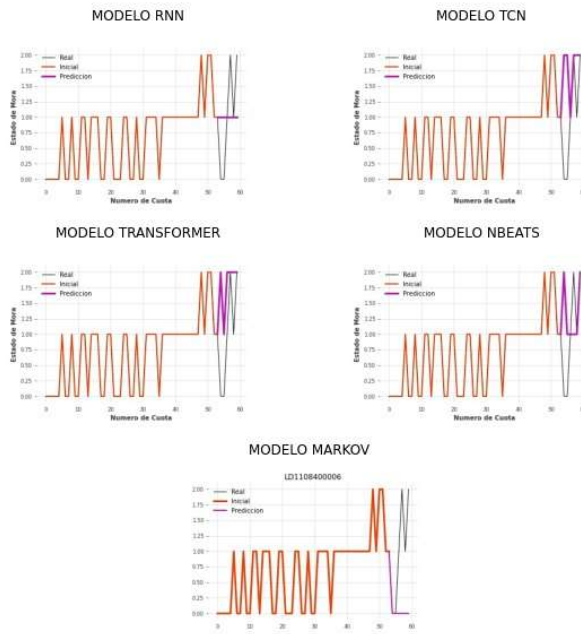
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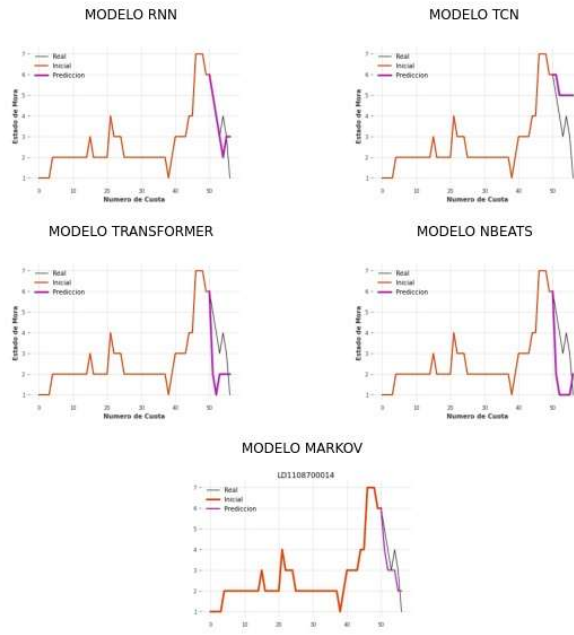
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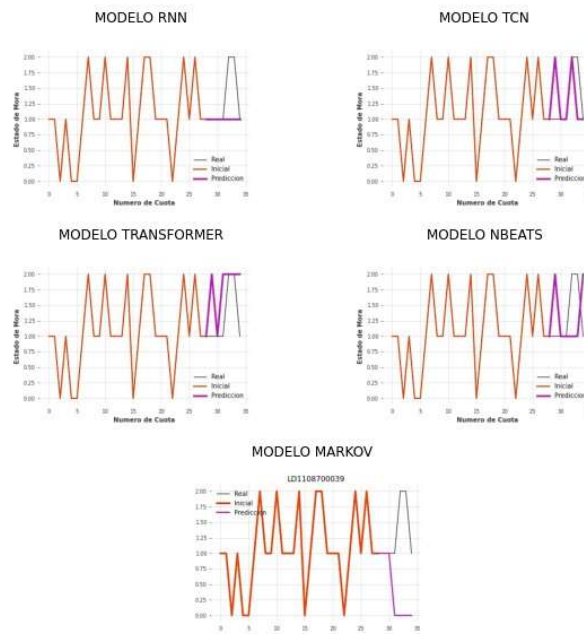
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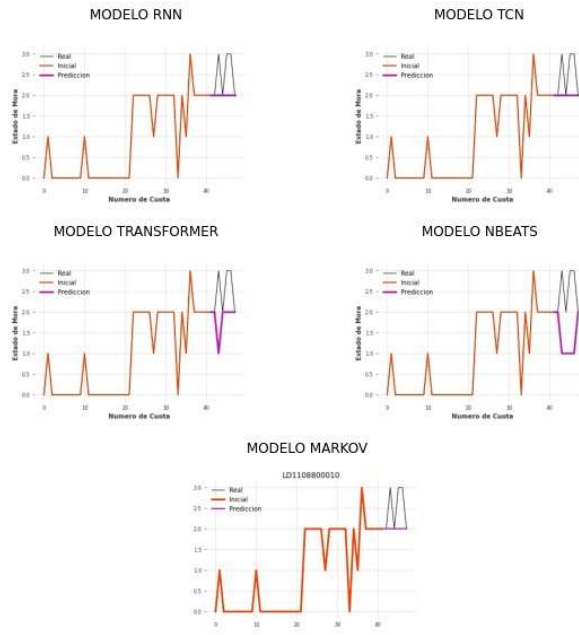
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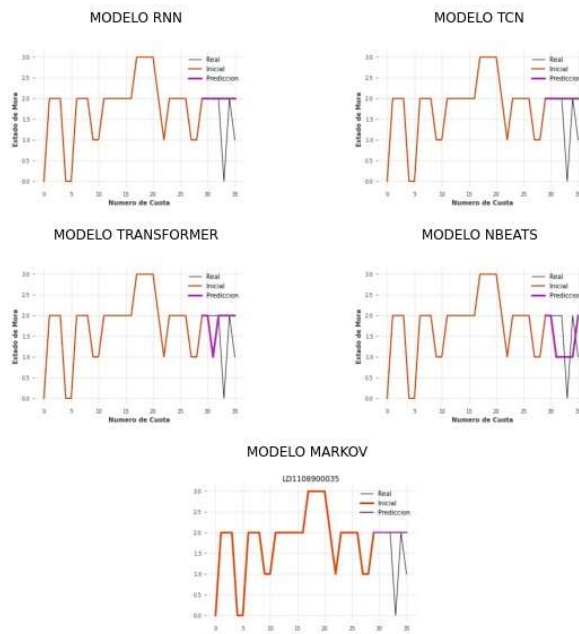
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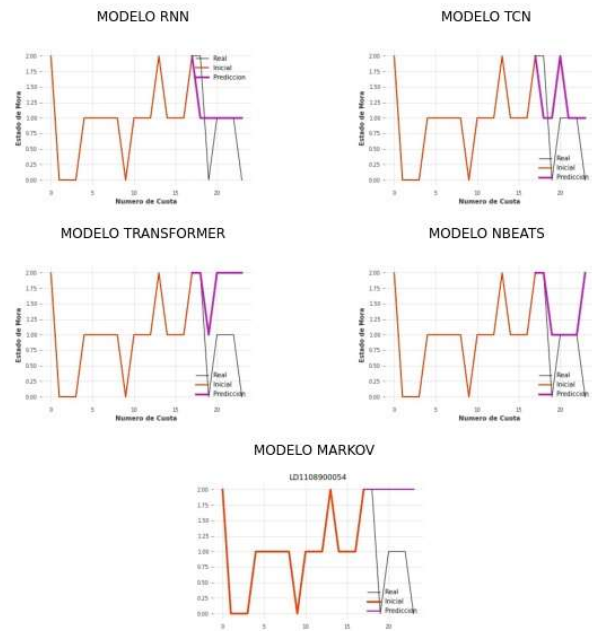
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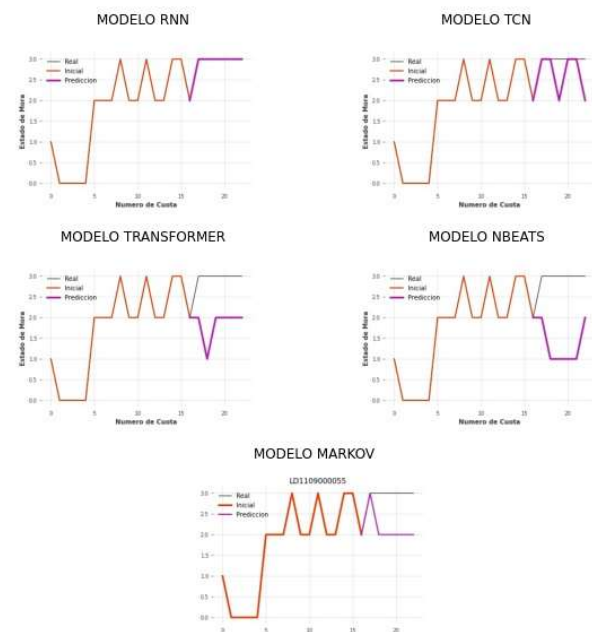
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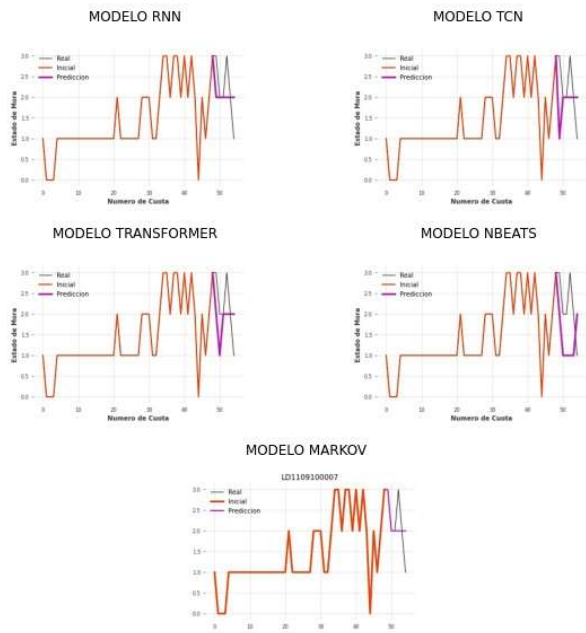
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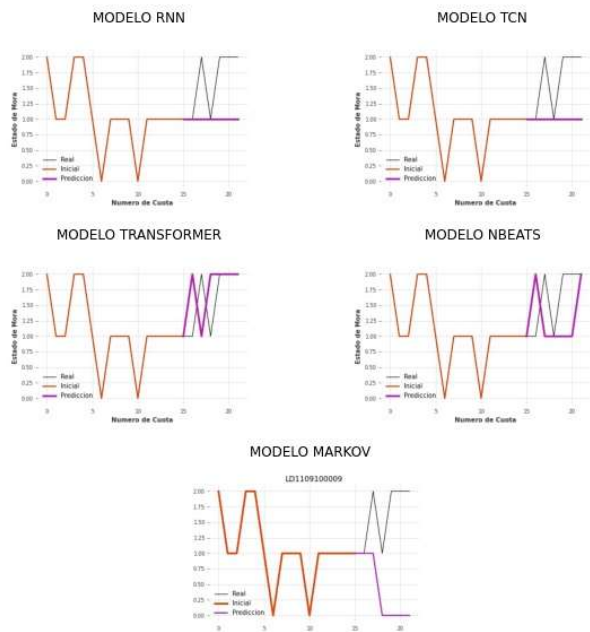
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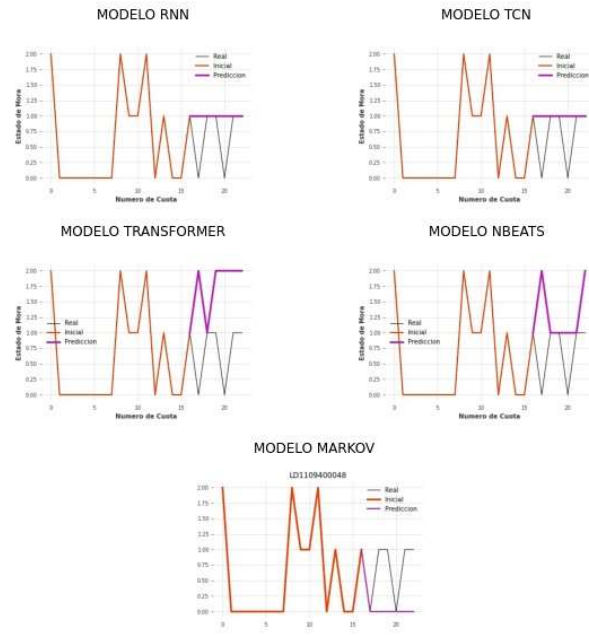
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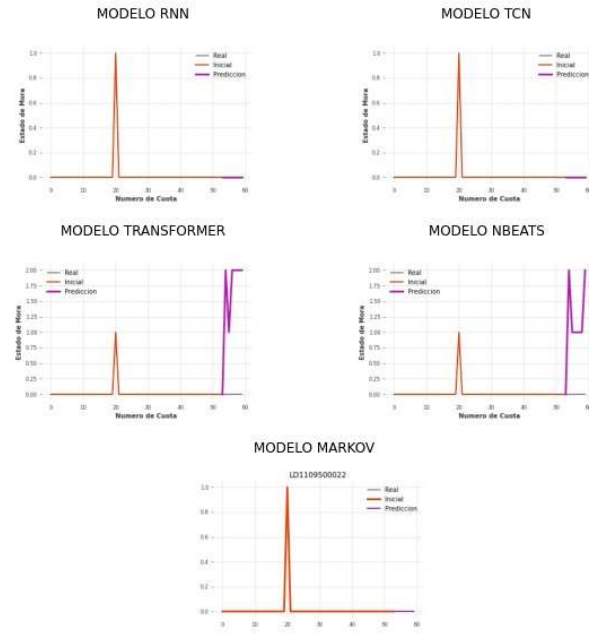
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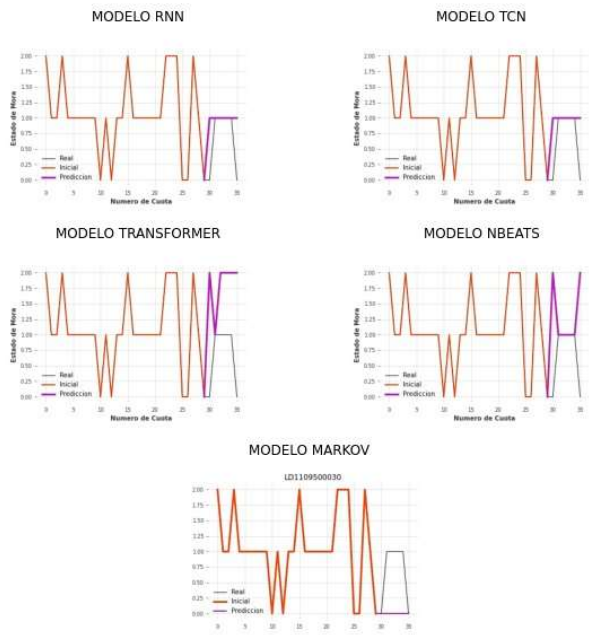


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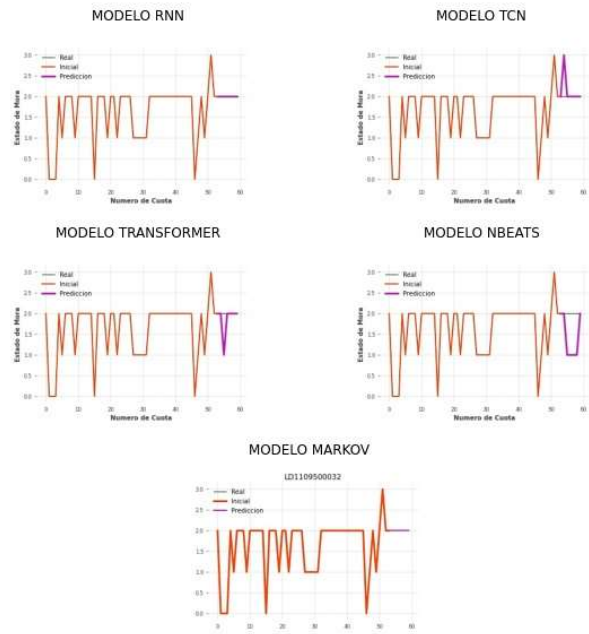




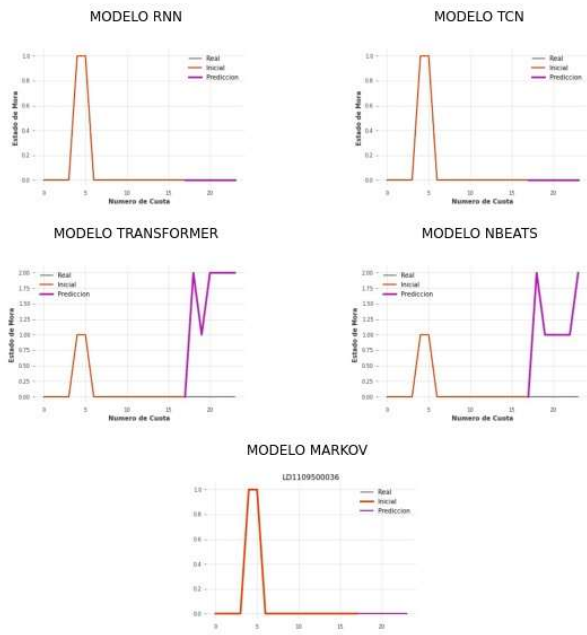
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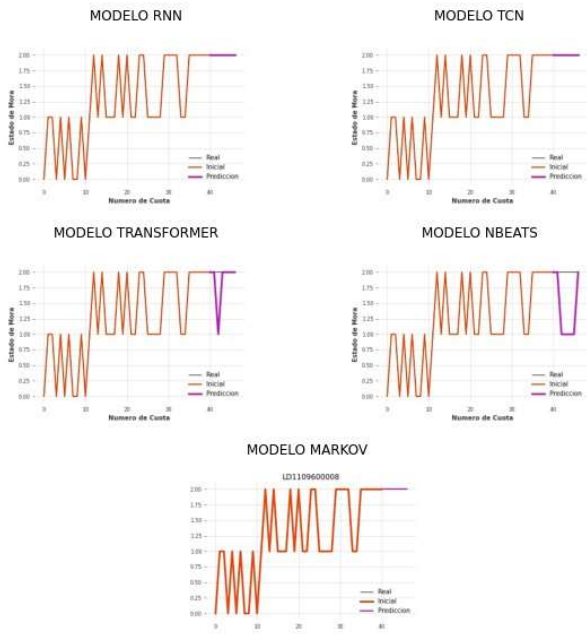
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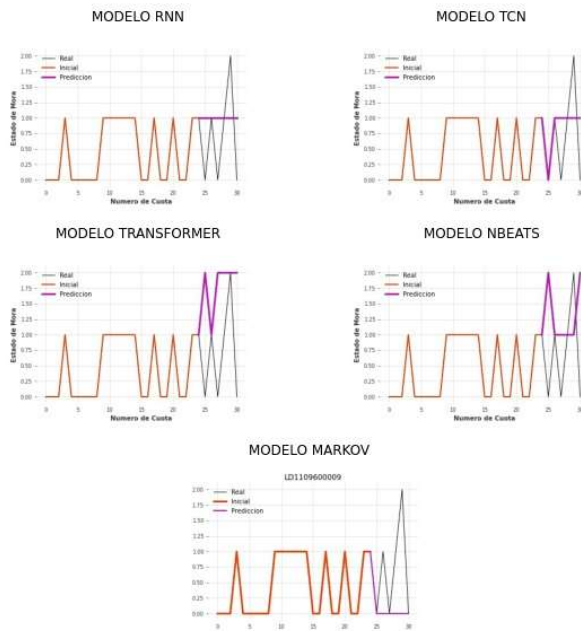
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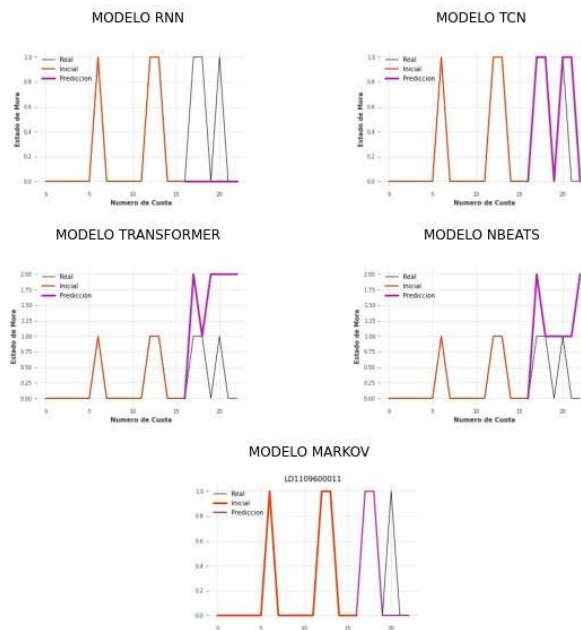
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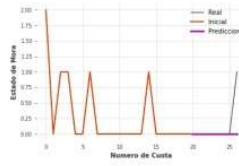


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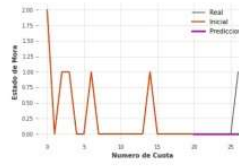


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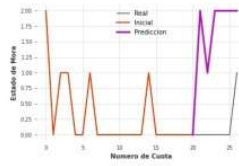
MODELO RNN



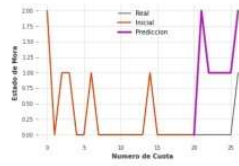
MODELO TCN



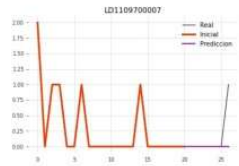
MODELO TRANSFORMER



MODELO NBEATS

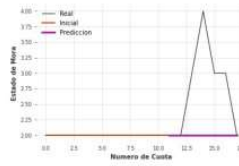


MODELO MARKOV

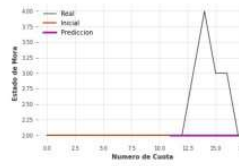


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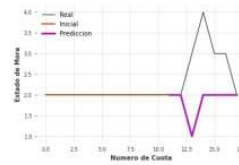
MODELO RNN



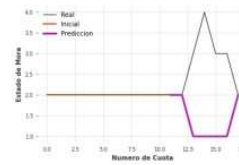
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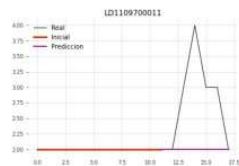
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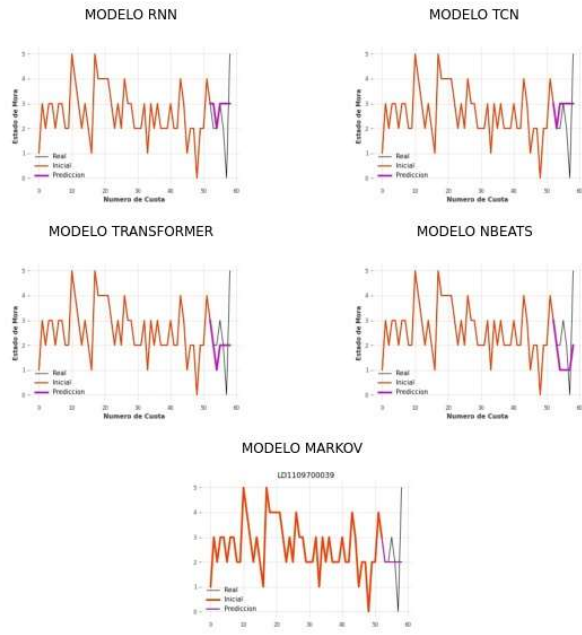
MODELO NBEATS



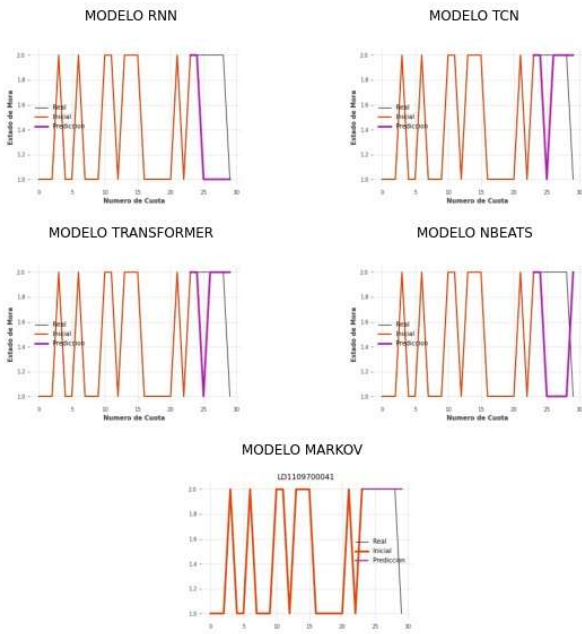
MODELO MARKOV



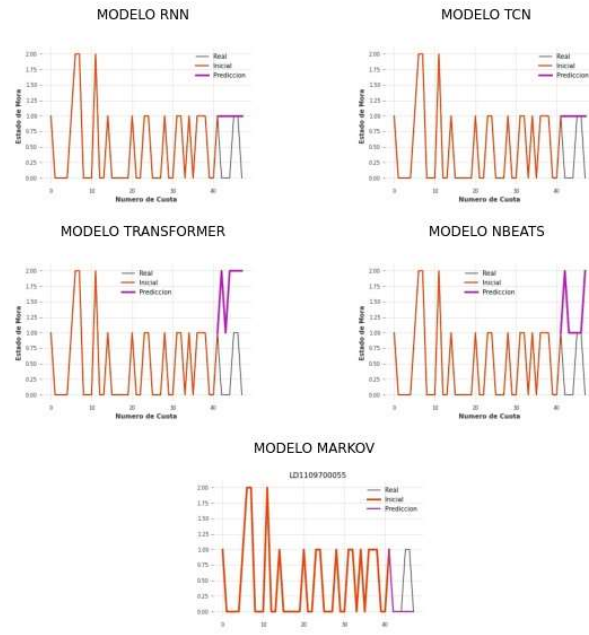
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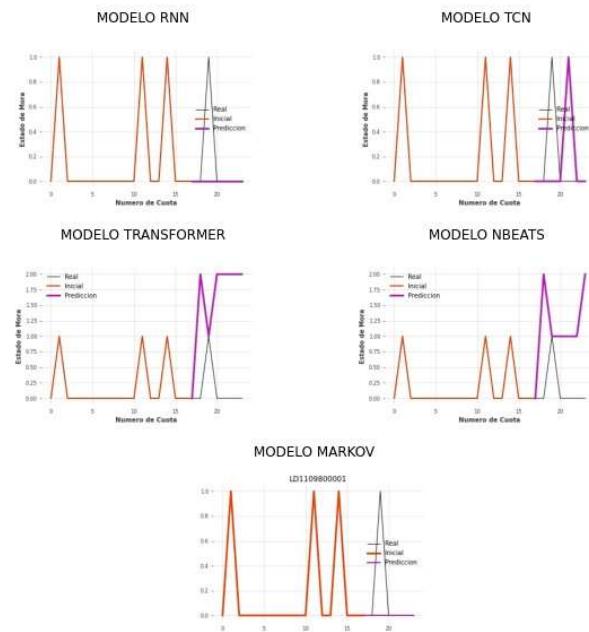
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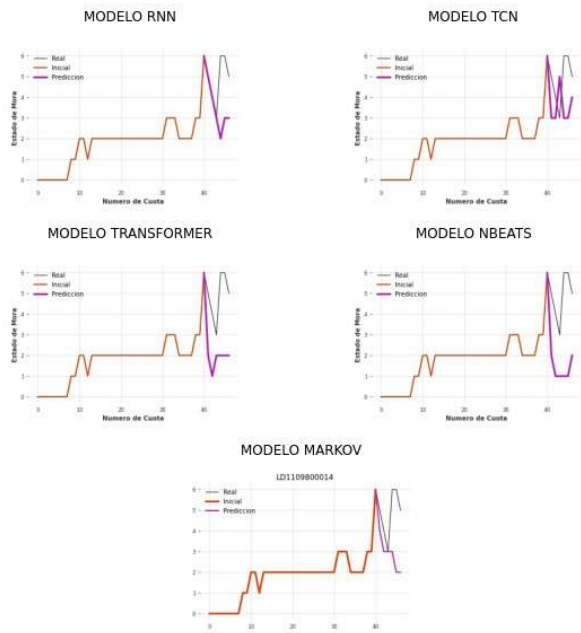
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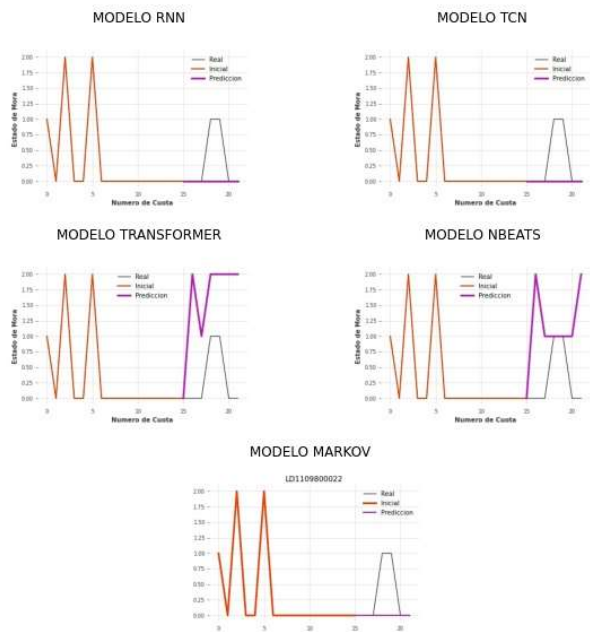
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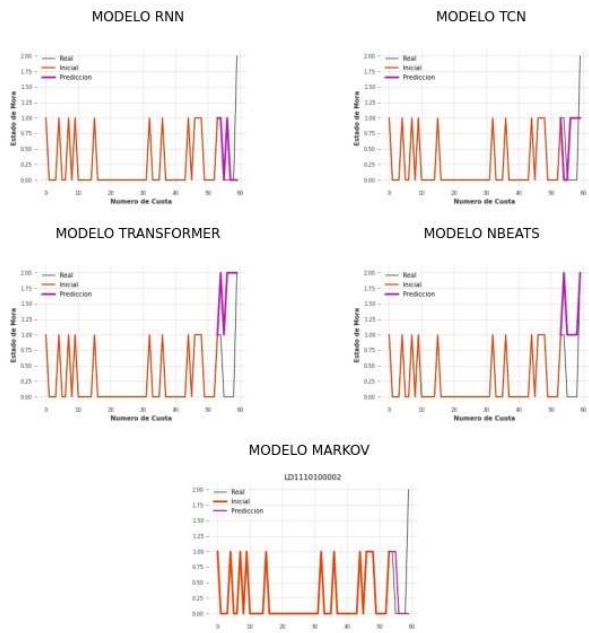
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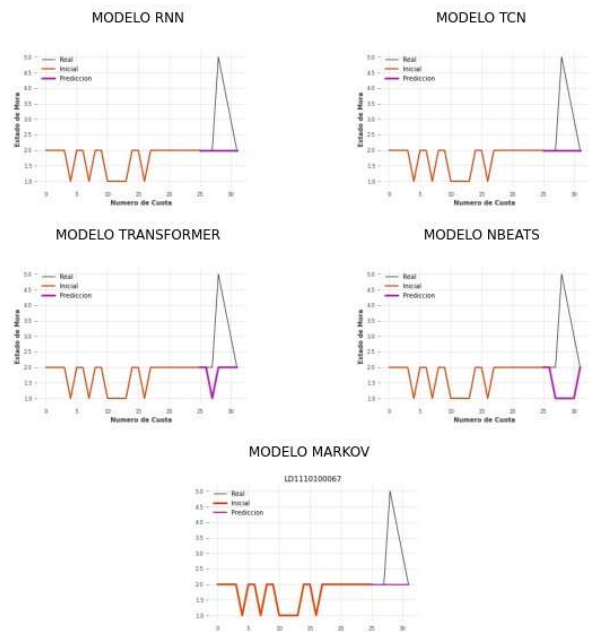
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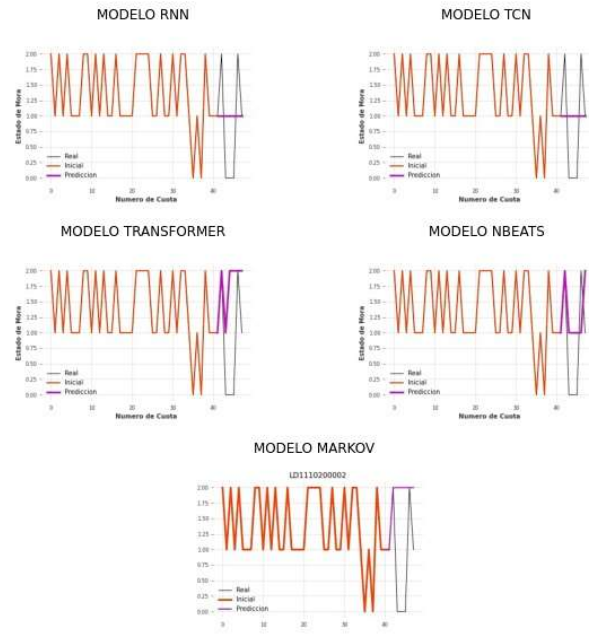


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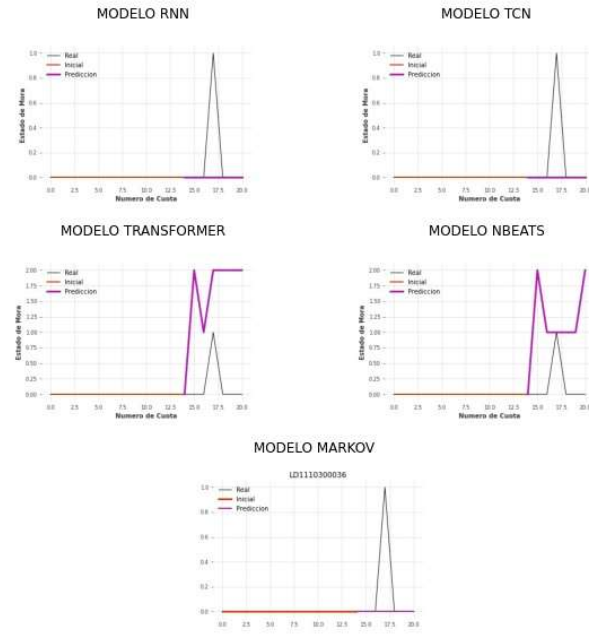




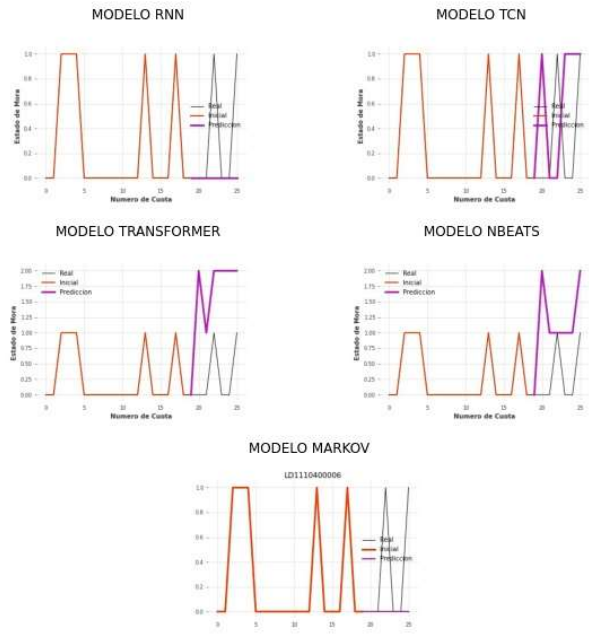
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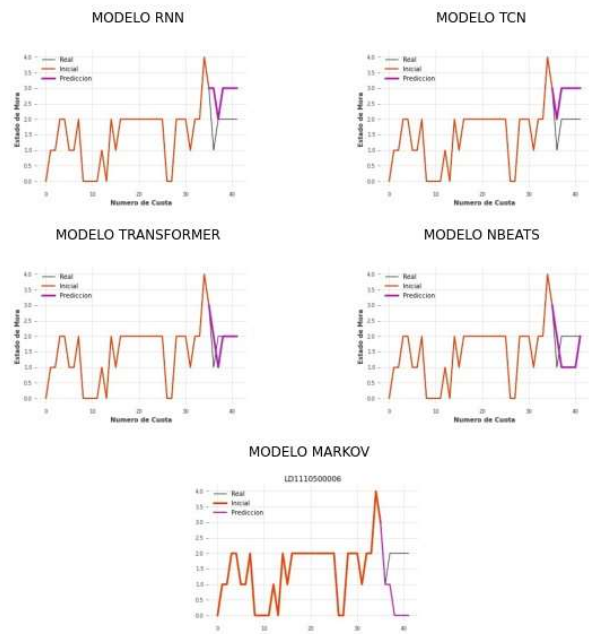
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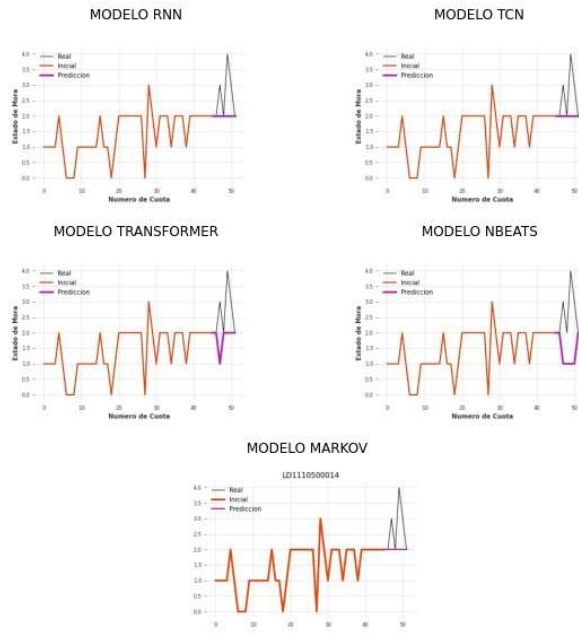
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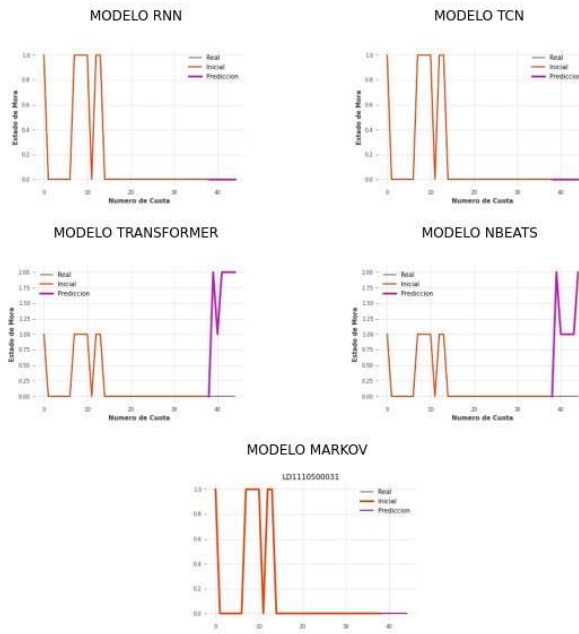
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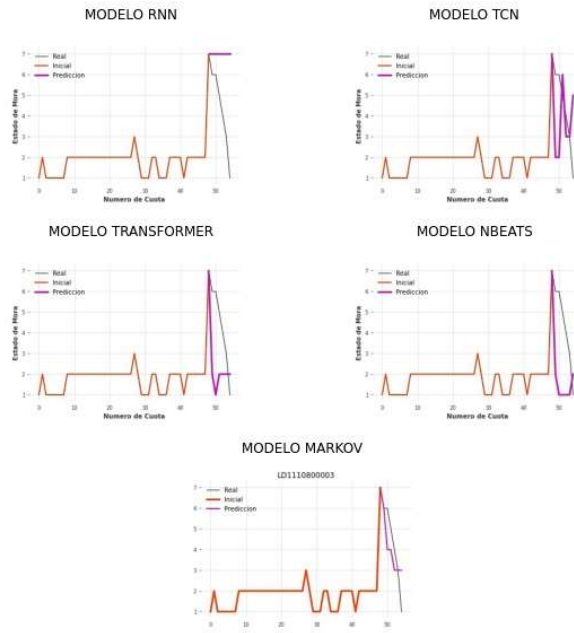
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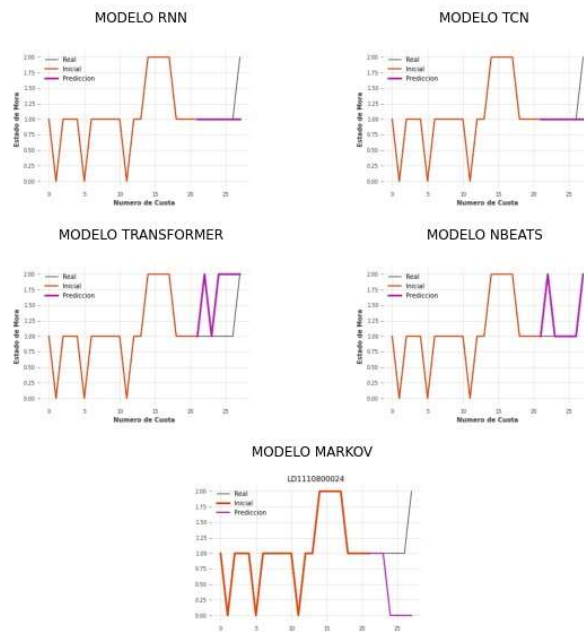
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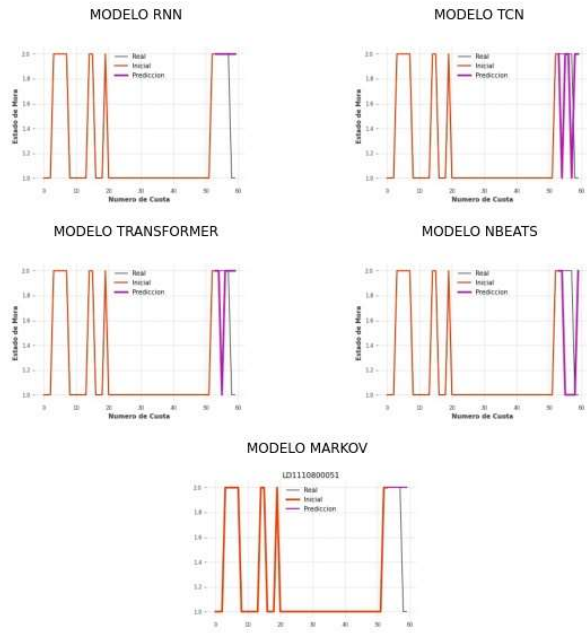
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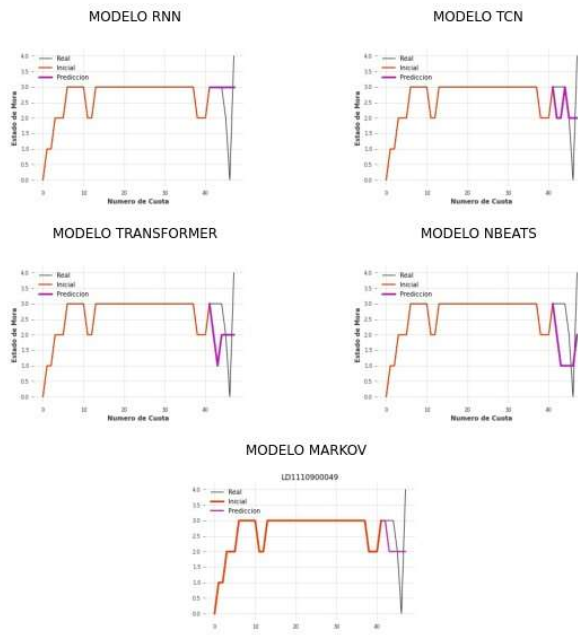
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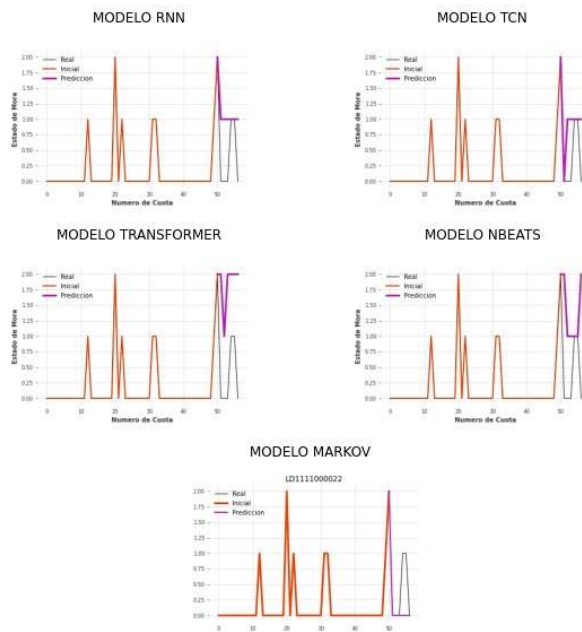
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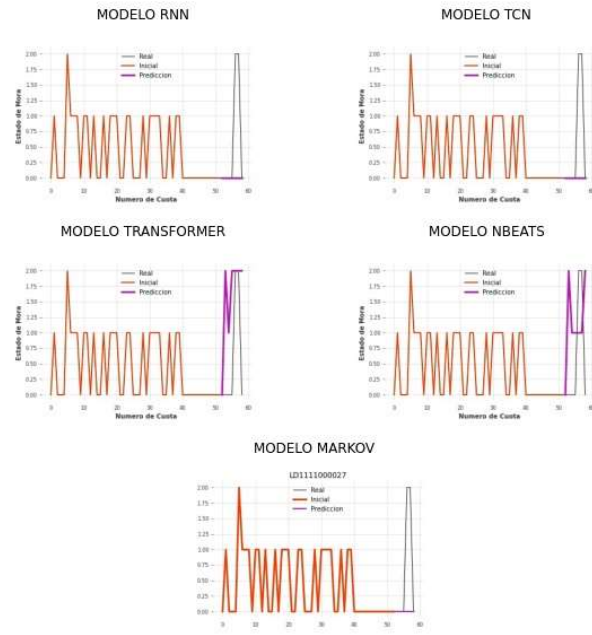
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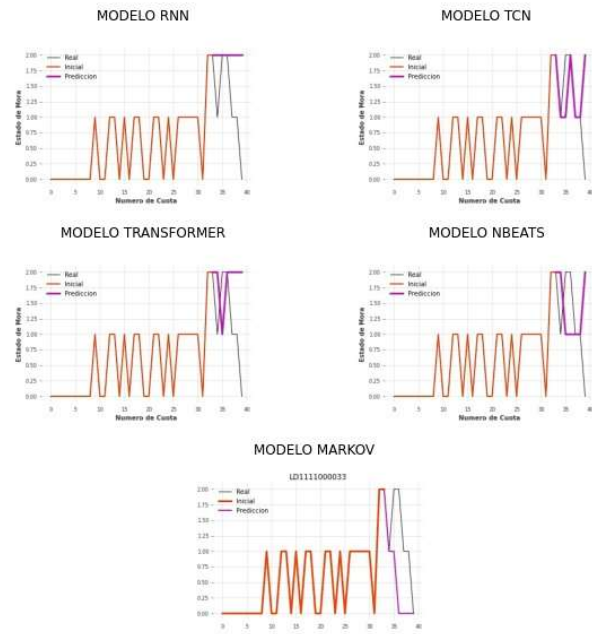
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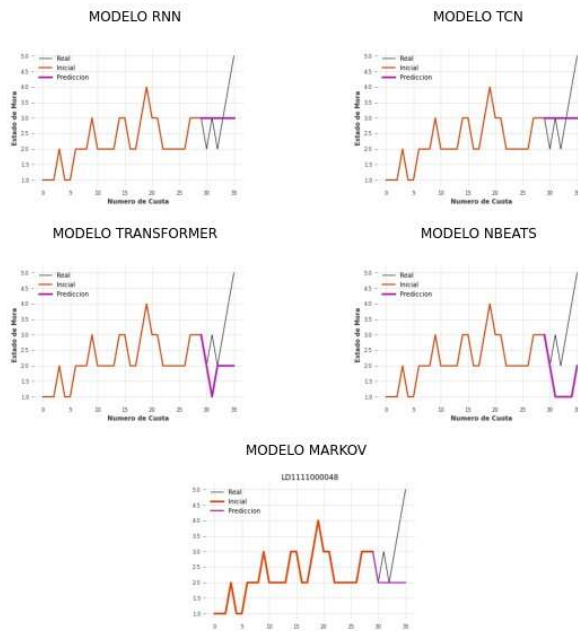
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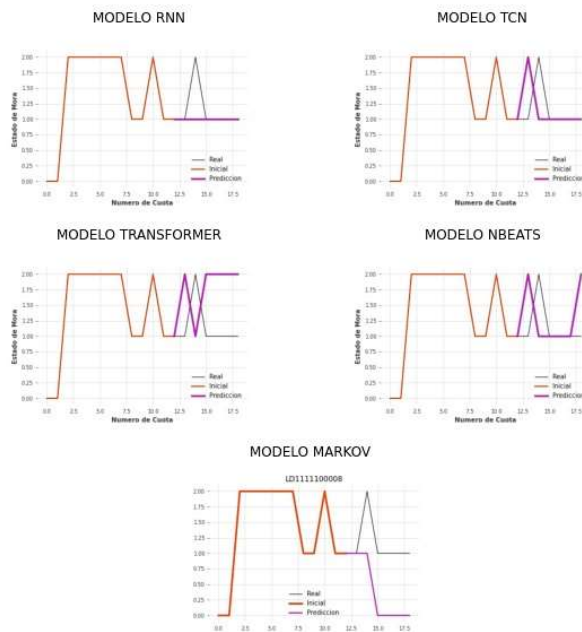
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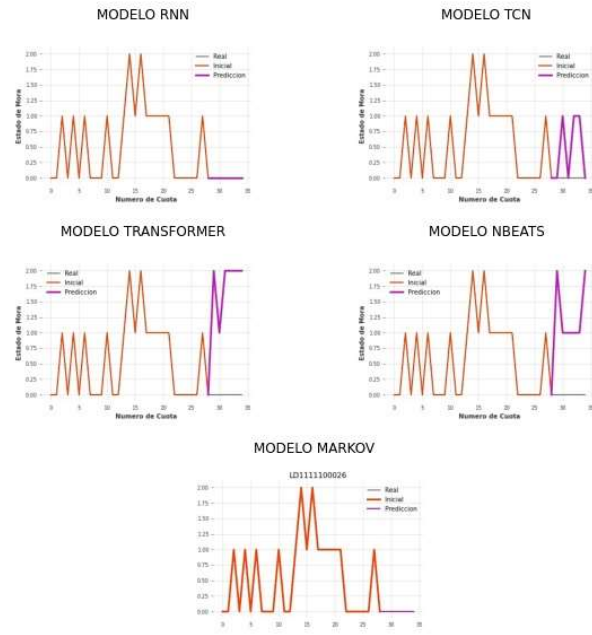


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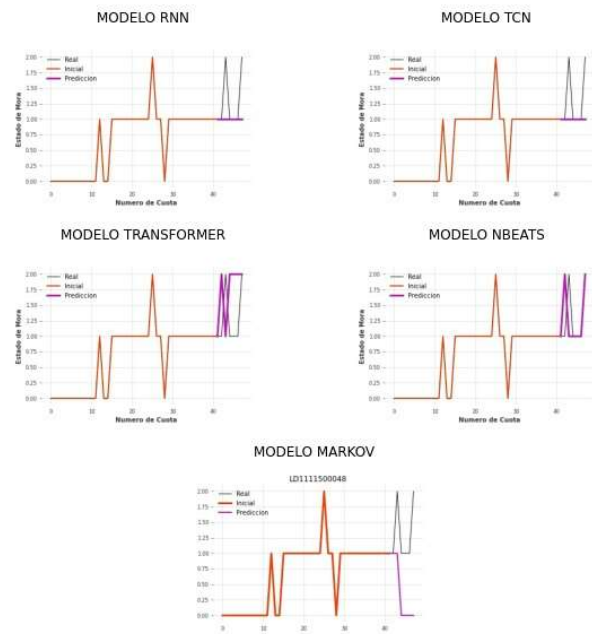




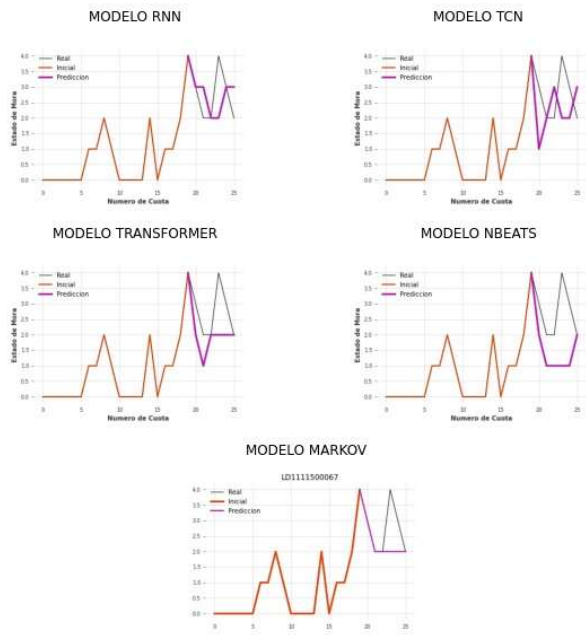
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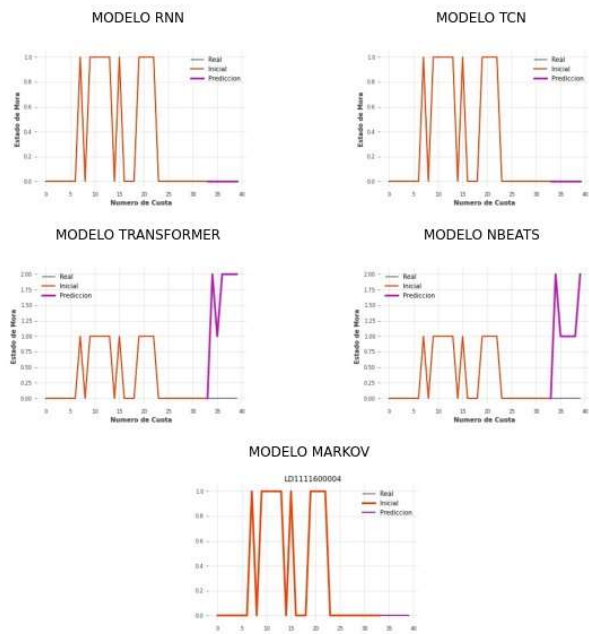
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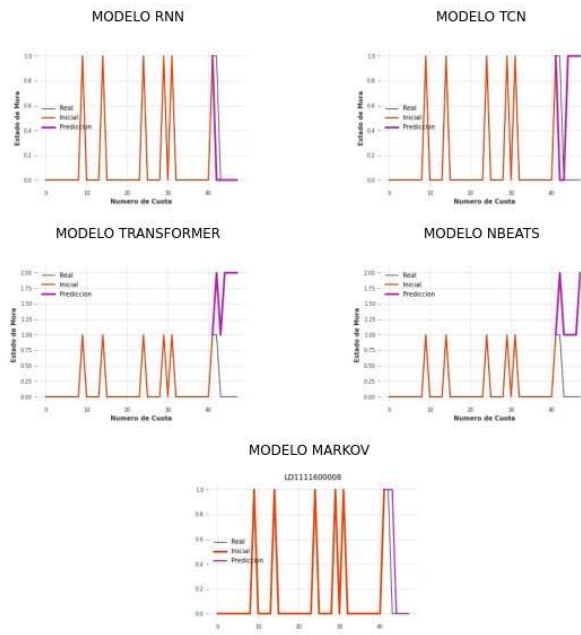
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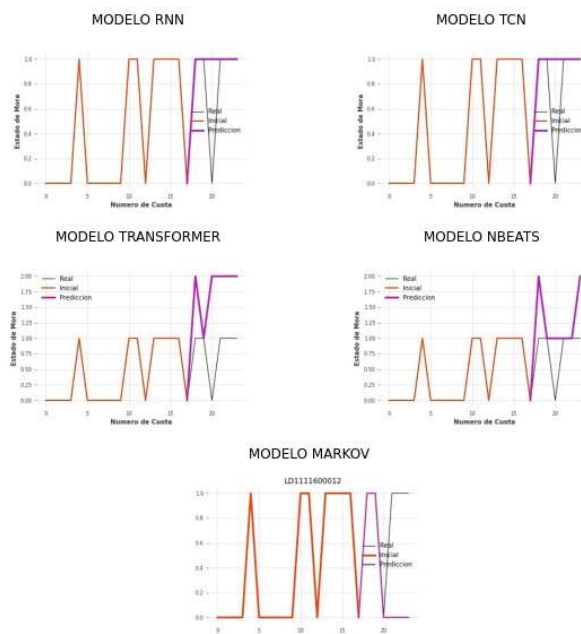
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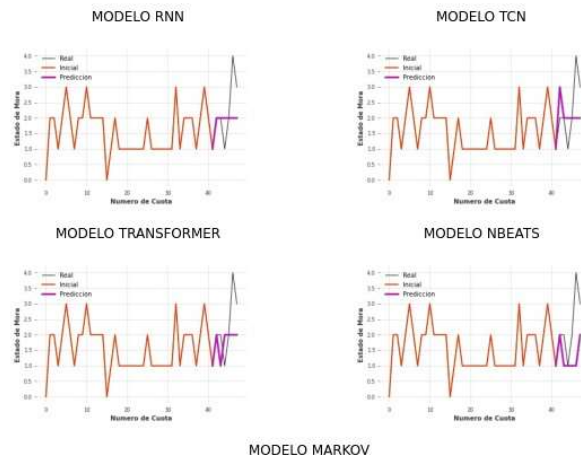
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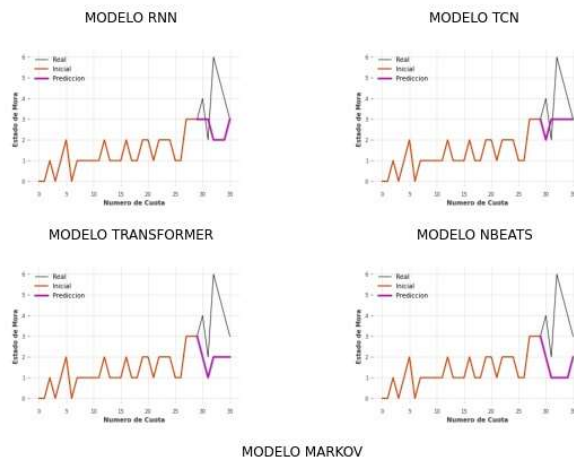
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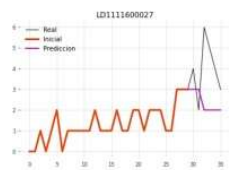
MODELO MARKOV



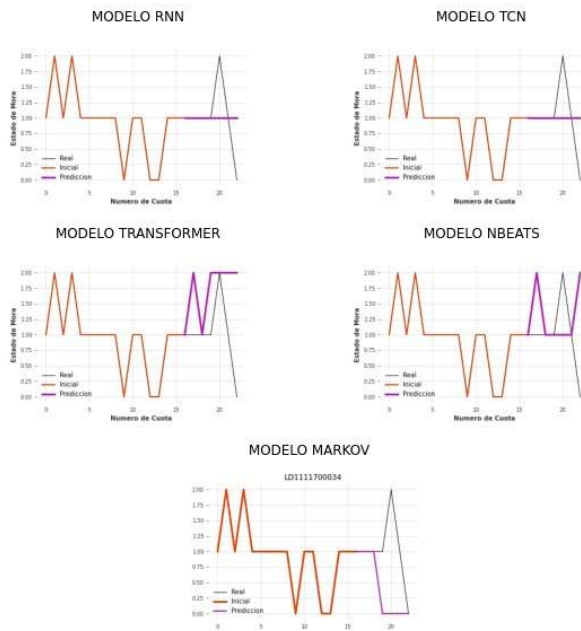
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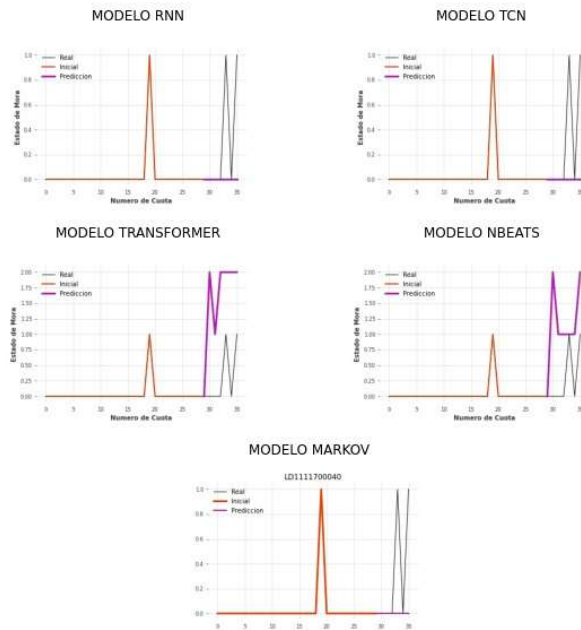
MODELO MARKOV



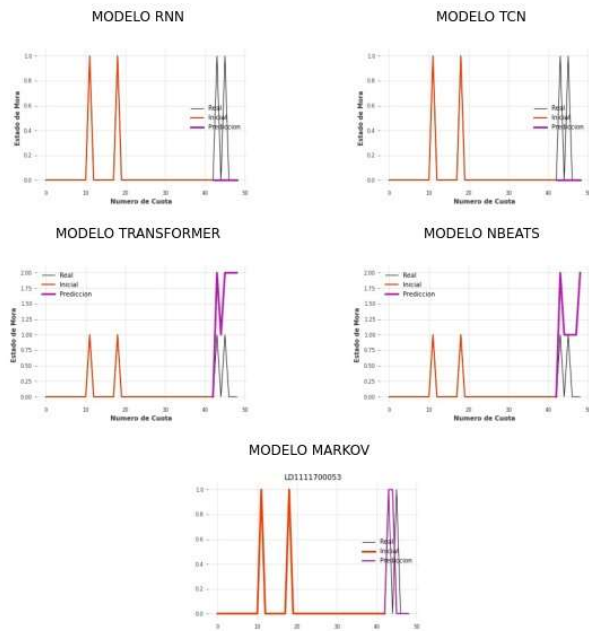
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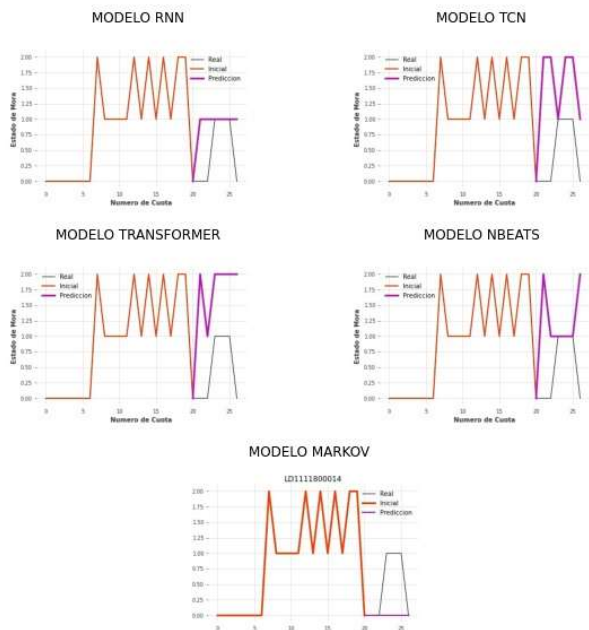
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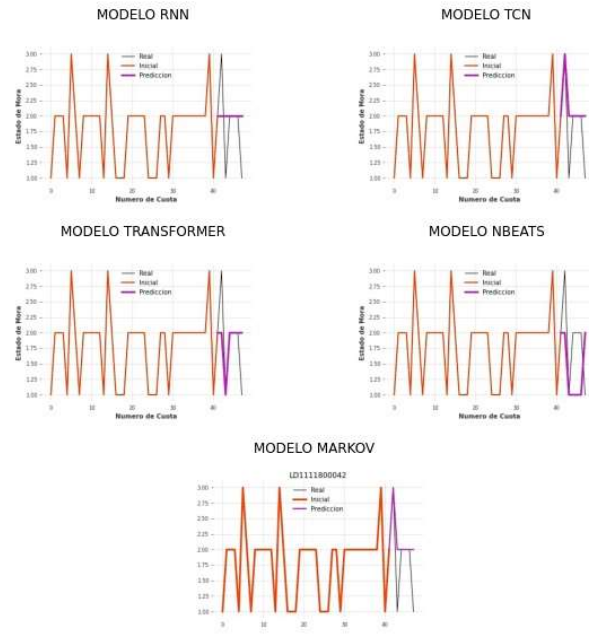
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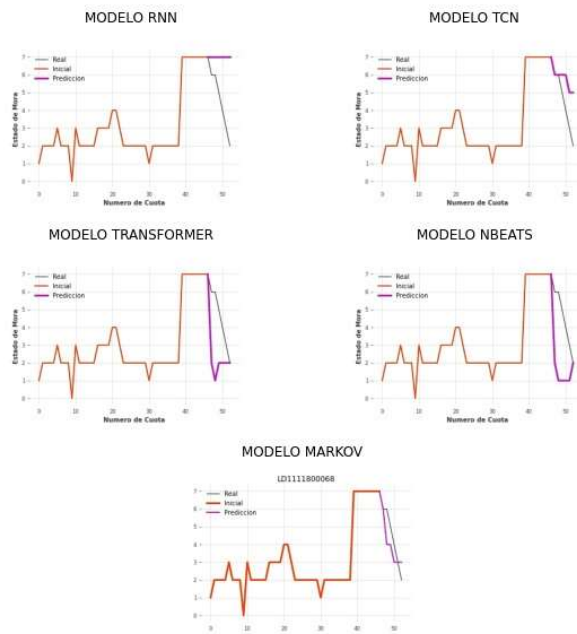
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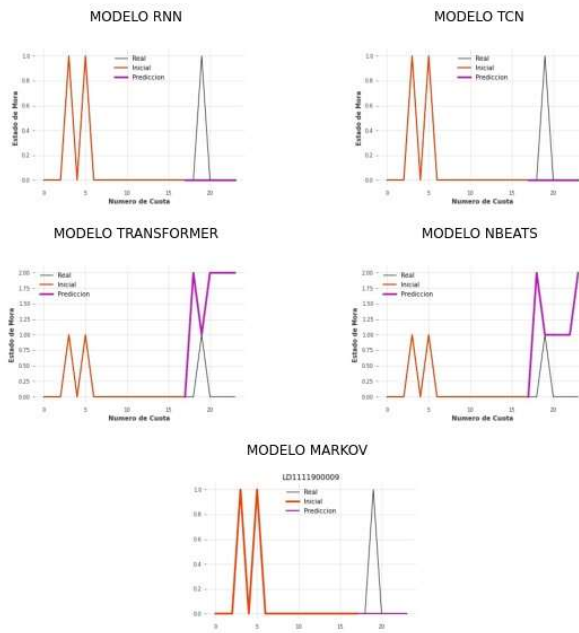
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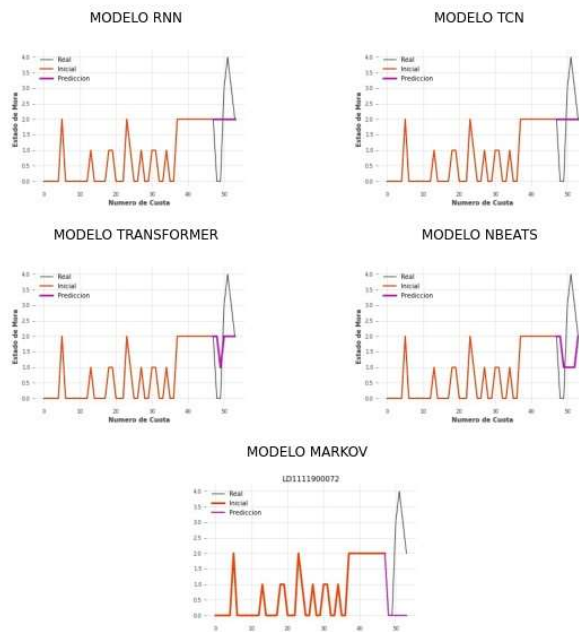
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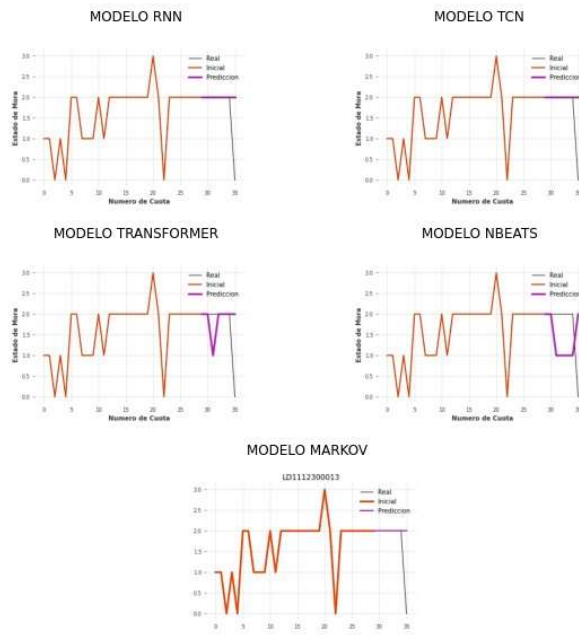


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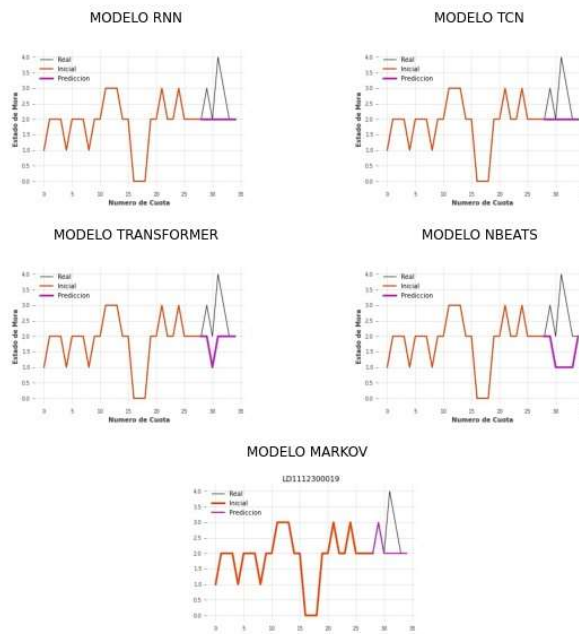




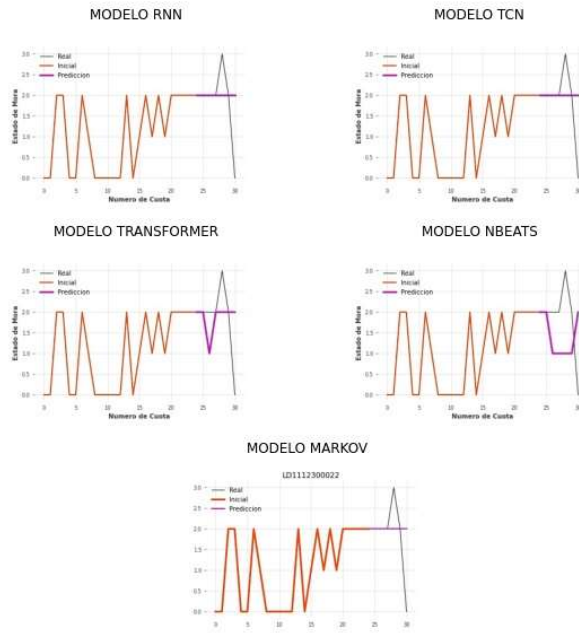
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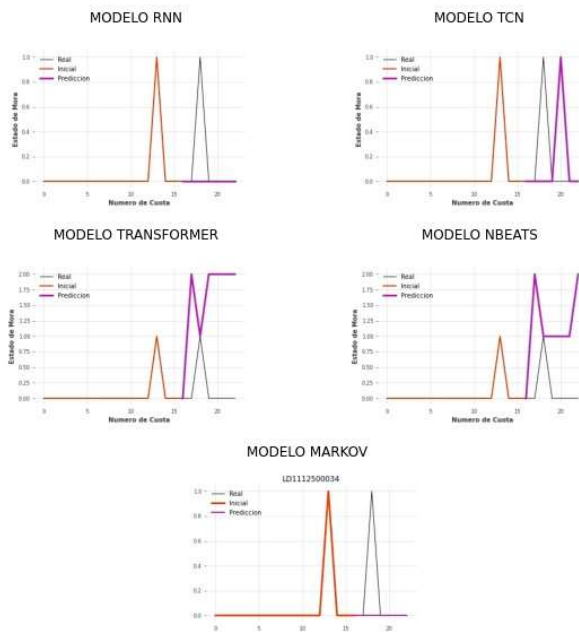
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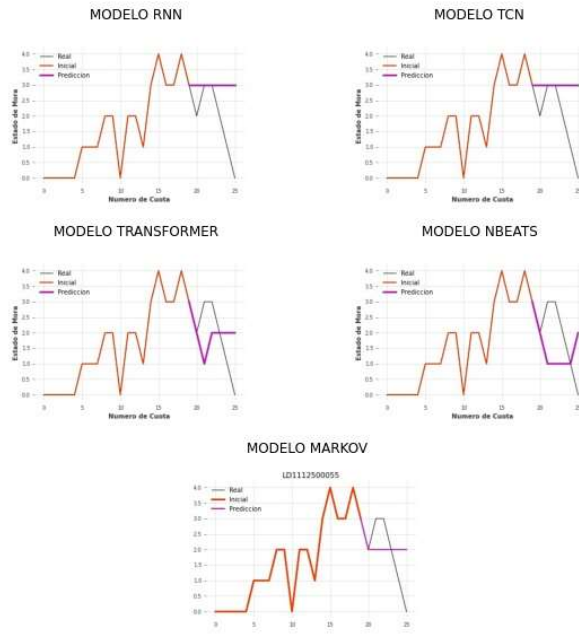
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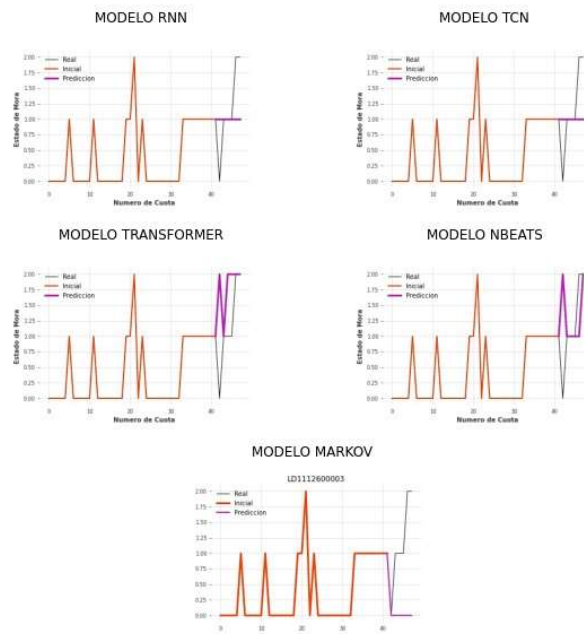
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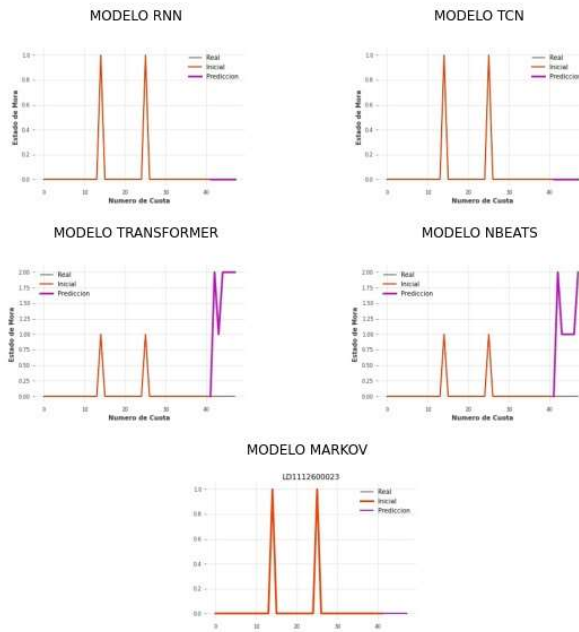
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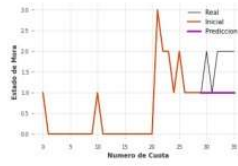


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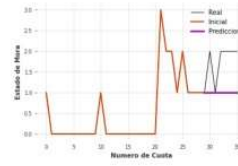


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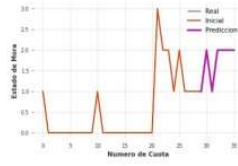
MODELO RNN



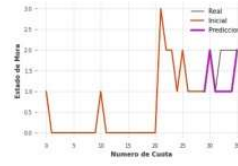
MODELO TCN



MODELO TRANSFORMER



MODELO NBEATS

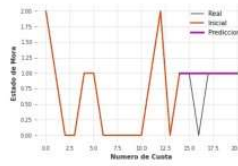


MODELO MARKOV

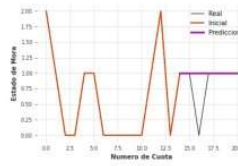


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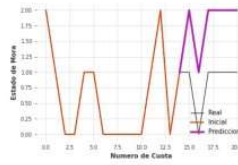
MODELO RNN



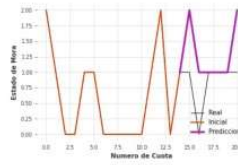
MODELO TCN



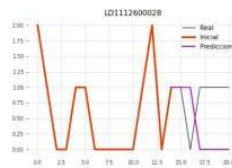
MODELO TRANSFORMER



MODELO NBEATS



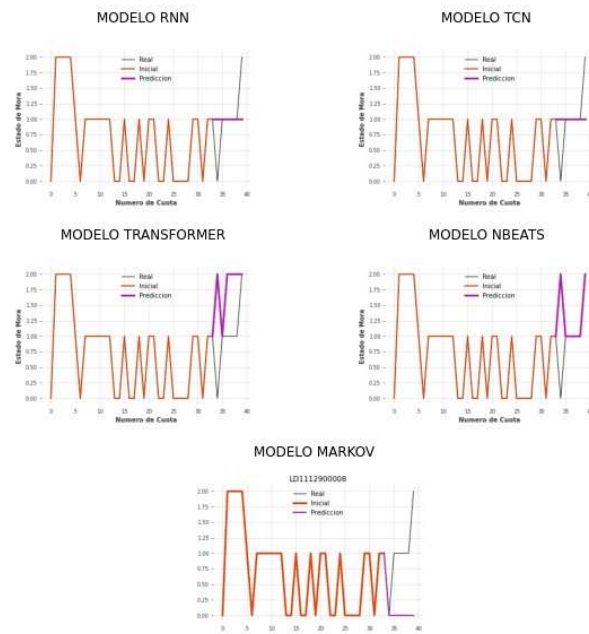
MODELO MARKOV



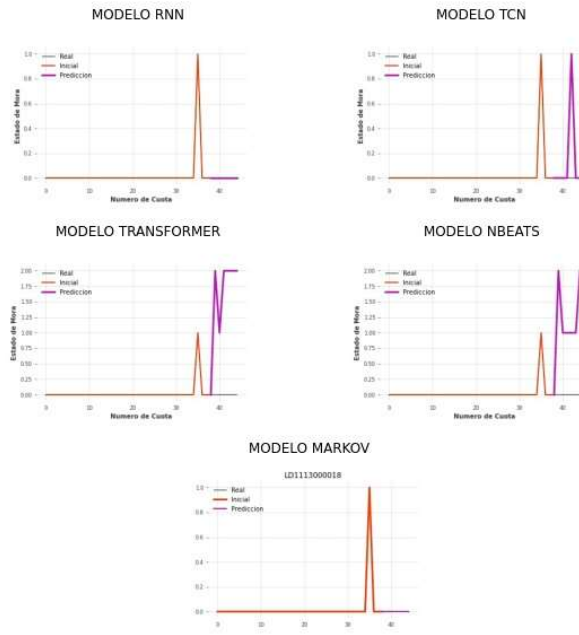
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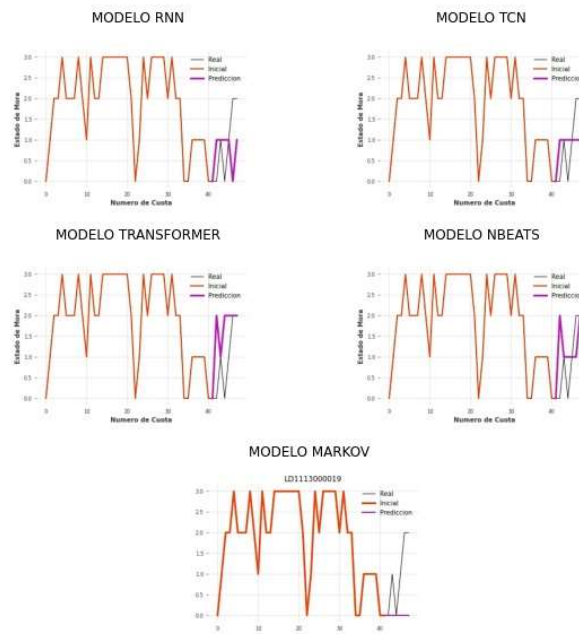
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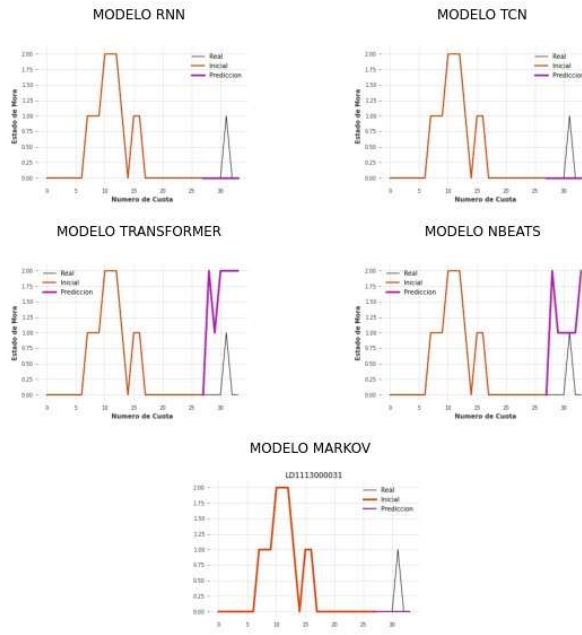
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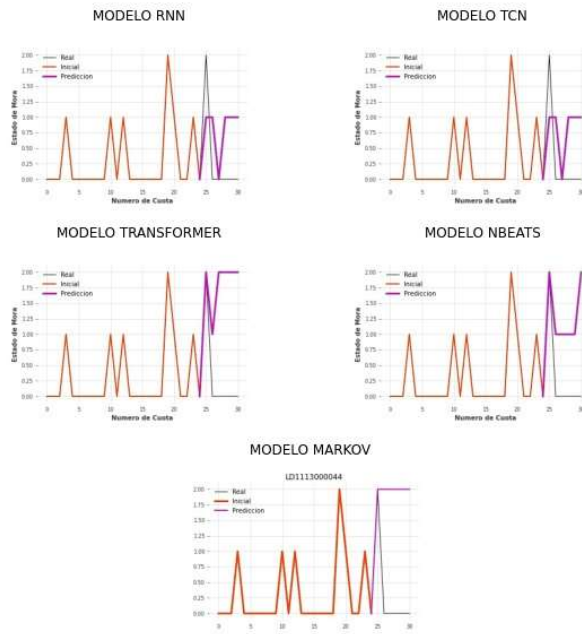
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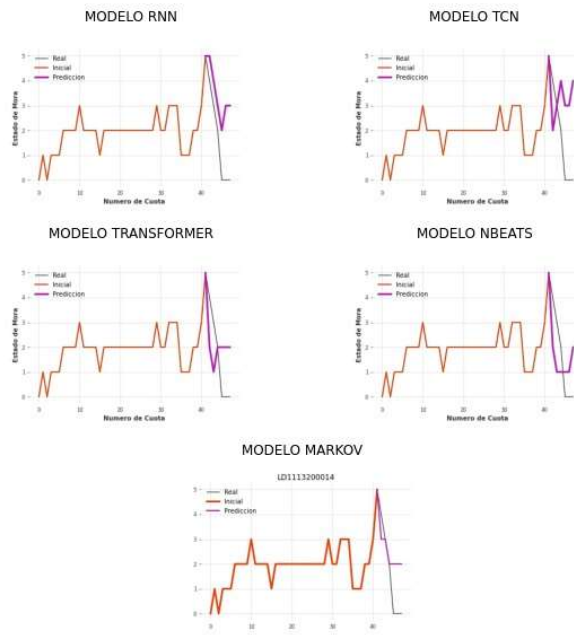


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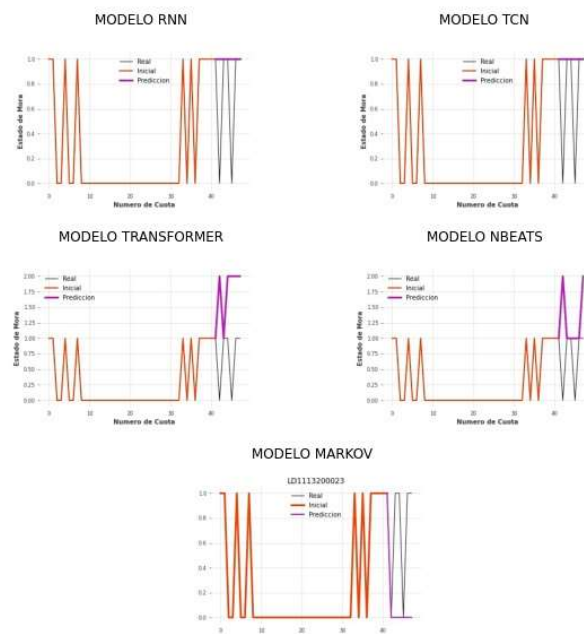




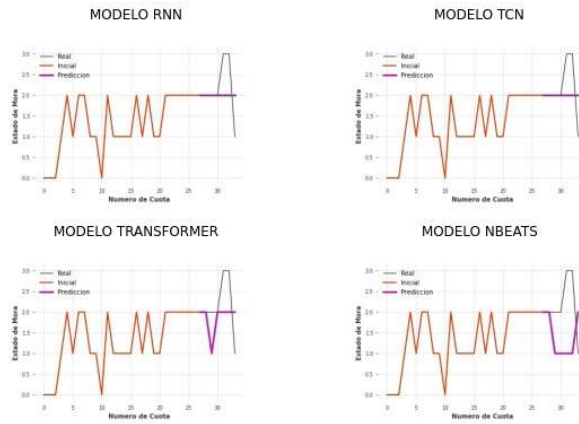
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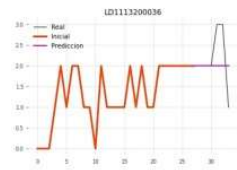
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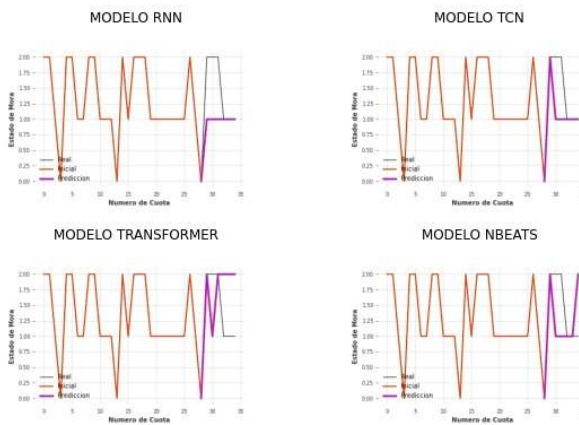
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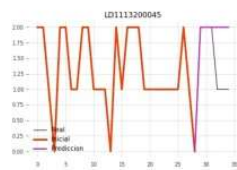
MODELO MARKOV



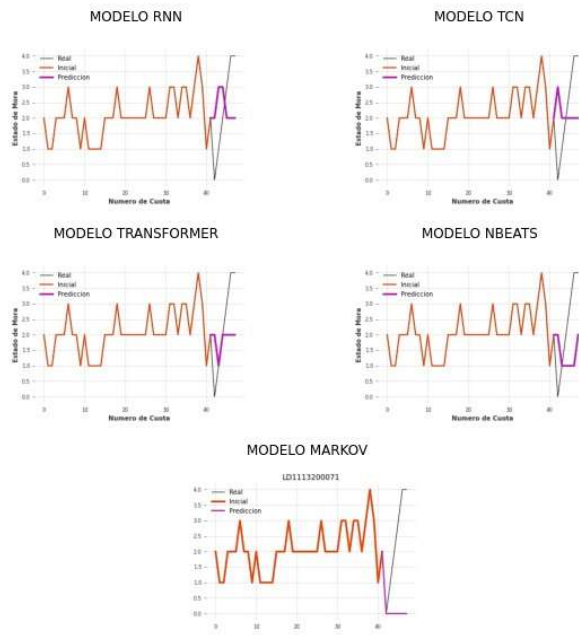
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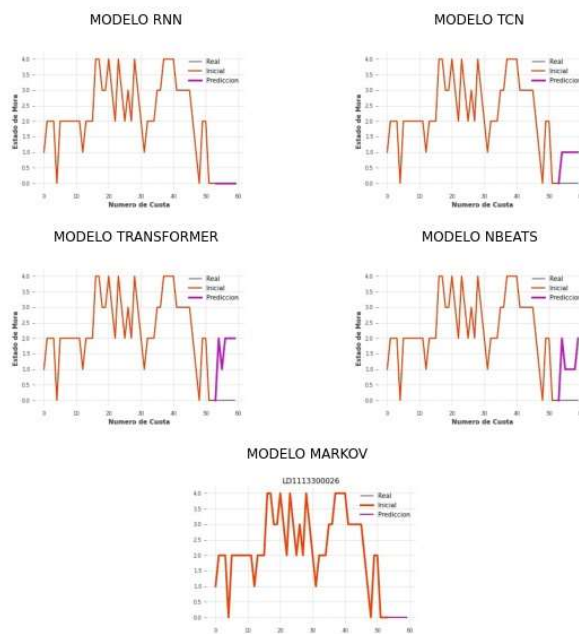
MODELO MARKOV



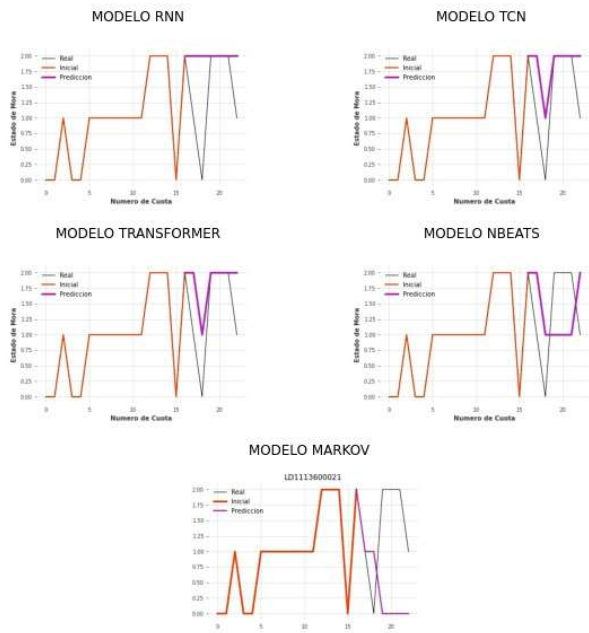
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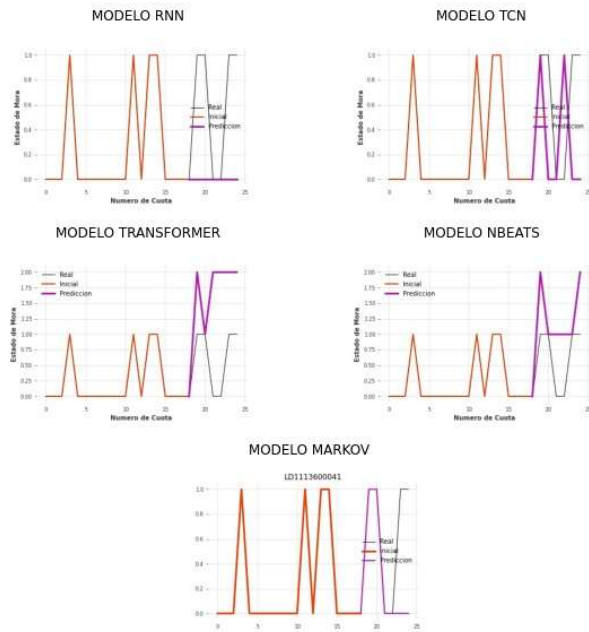
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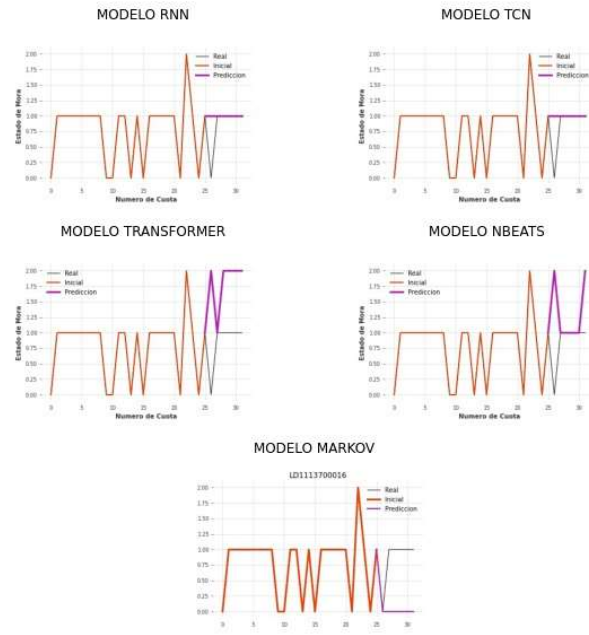
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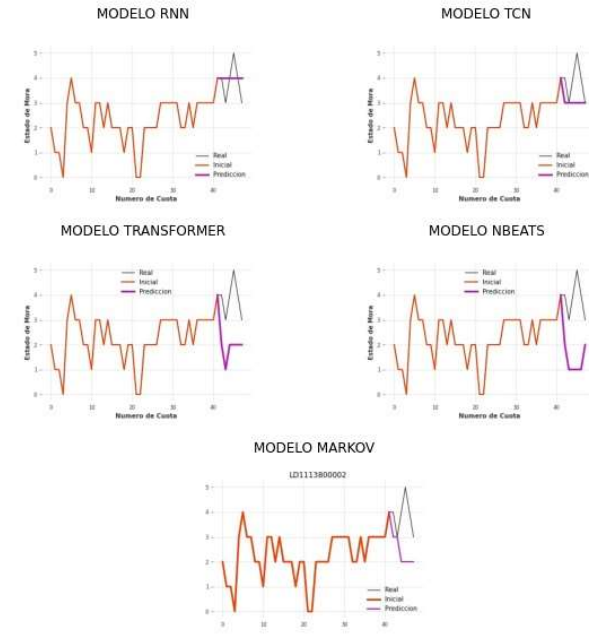
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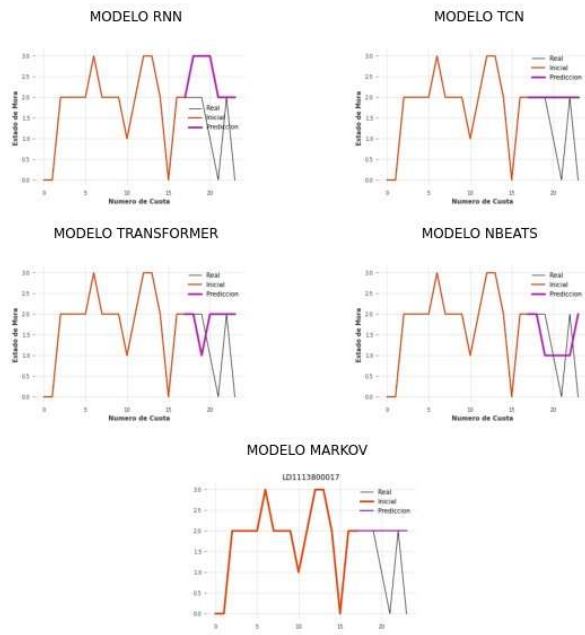
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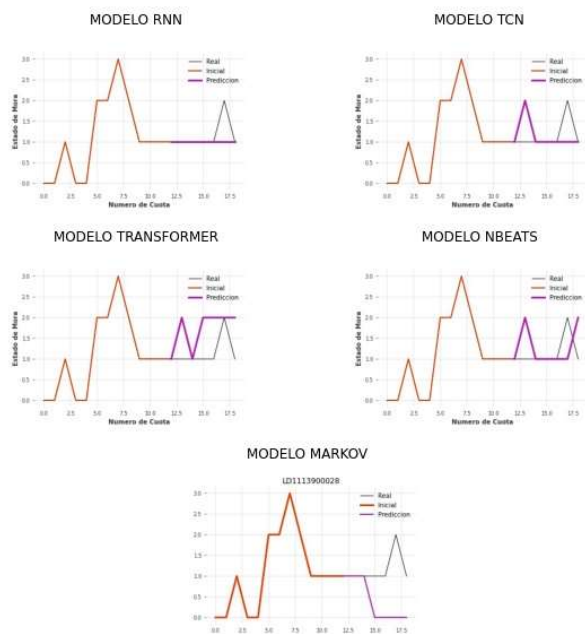
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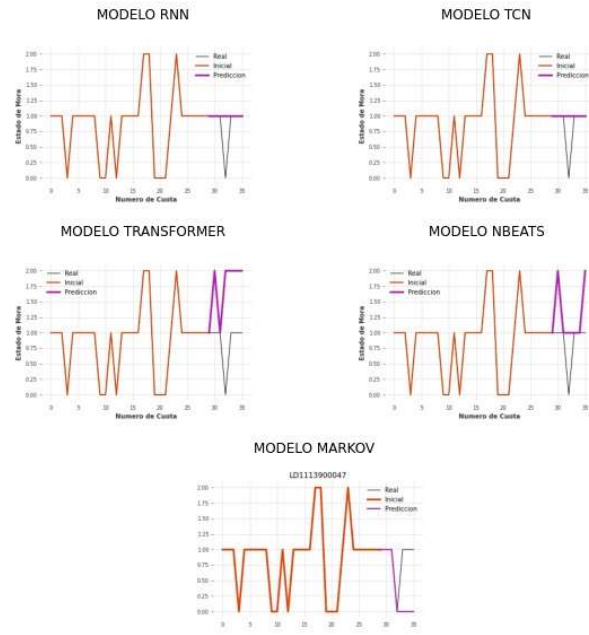
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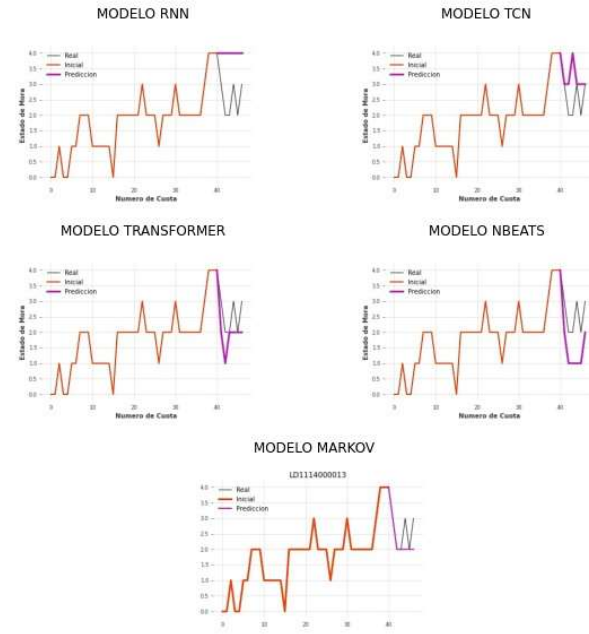
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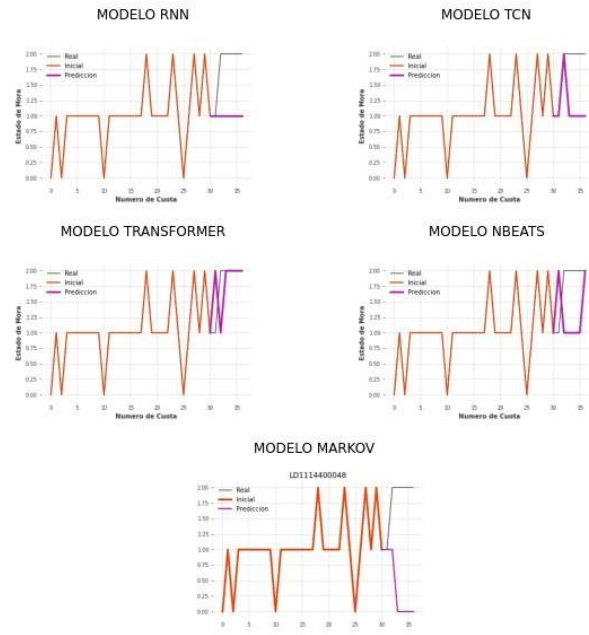
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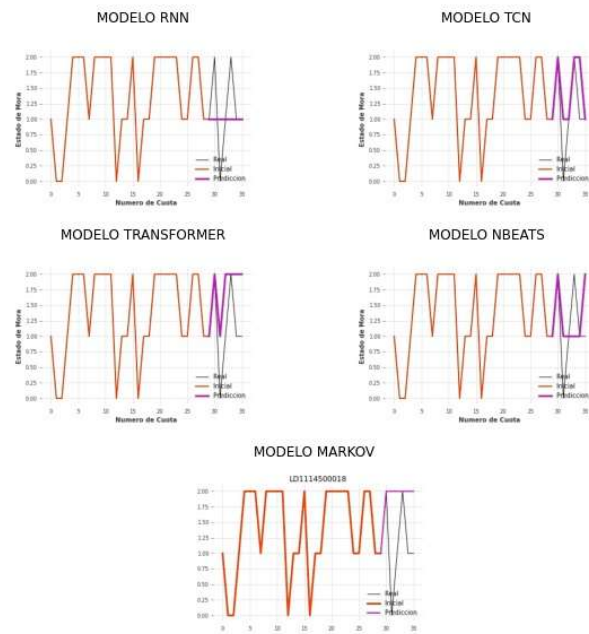
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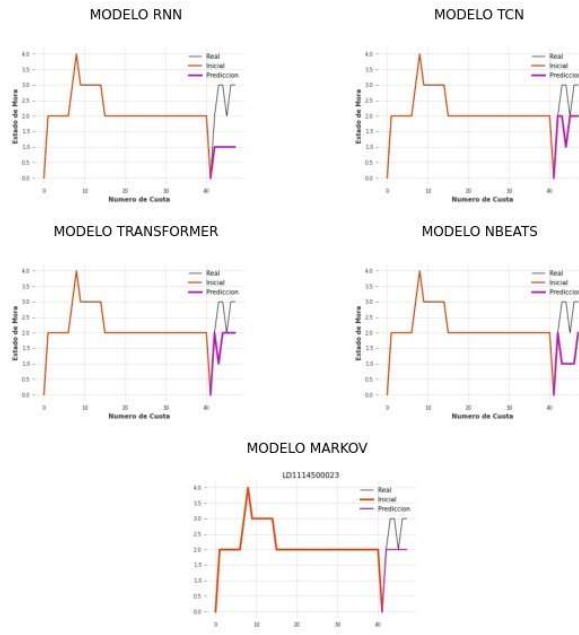


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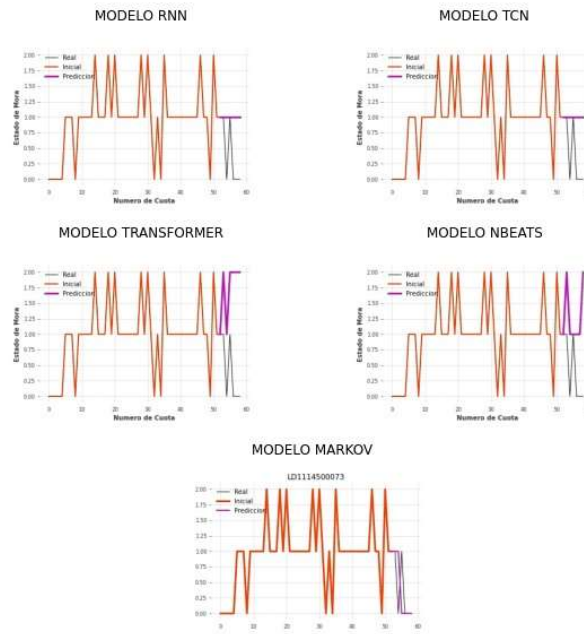




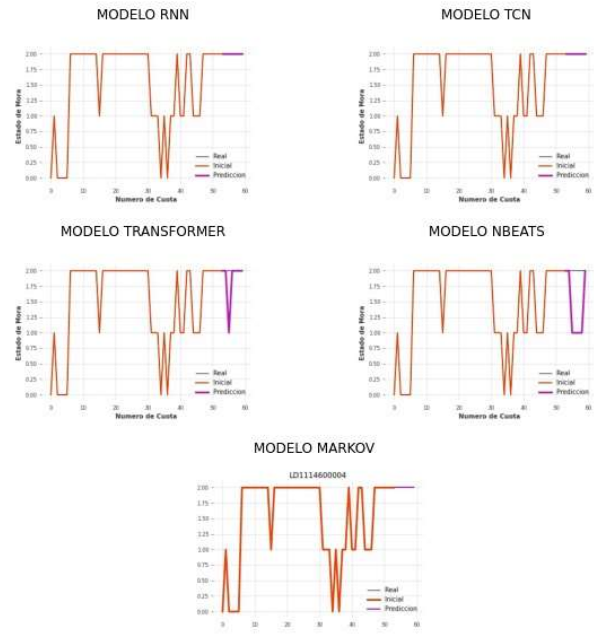
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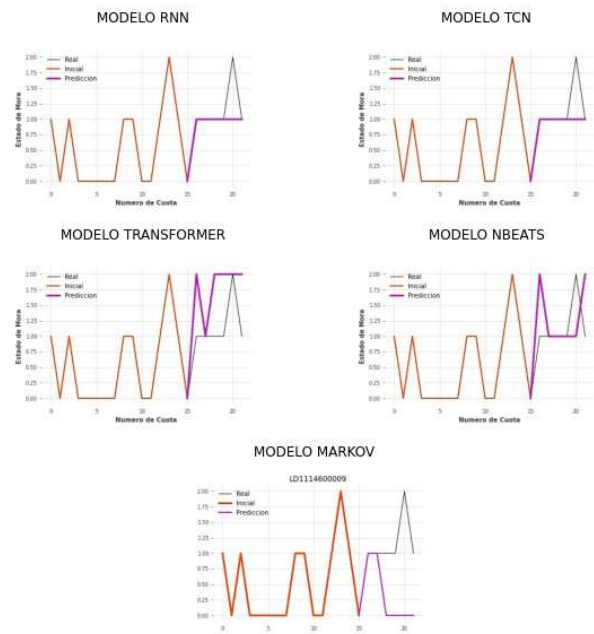
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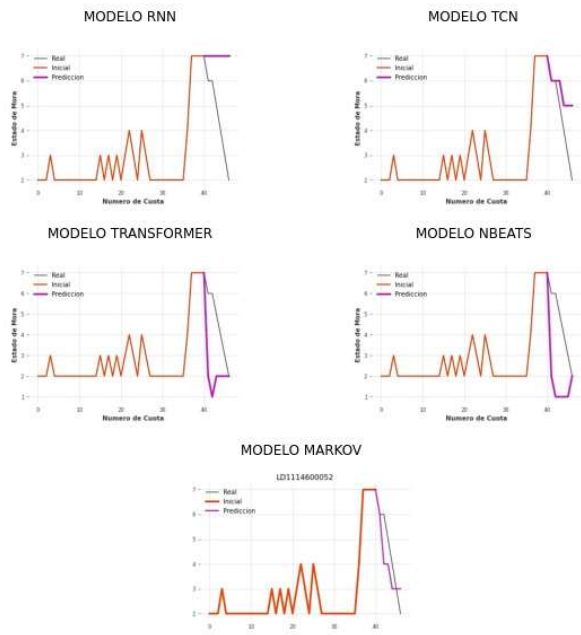
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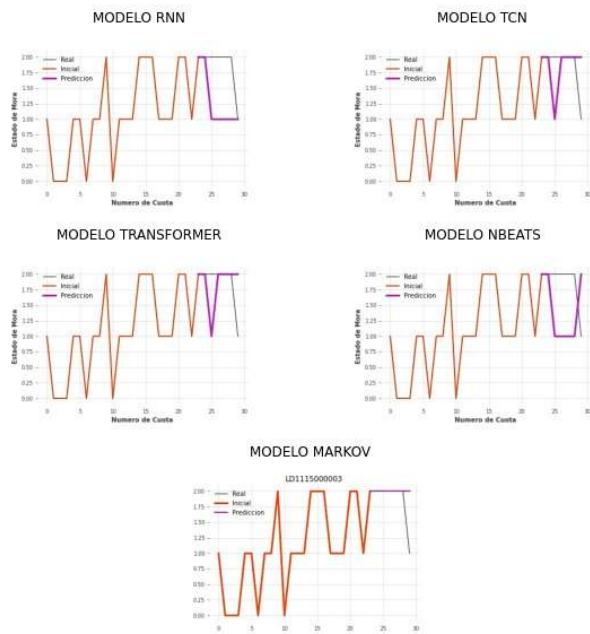
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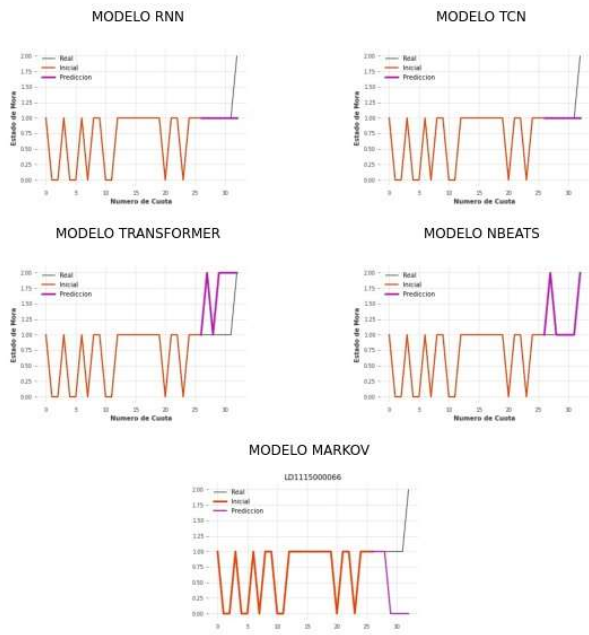
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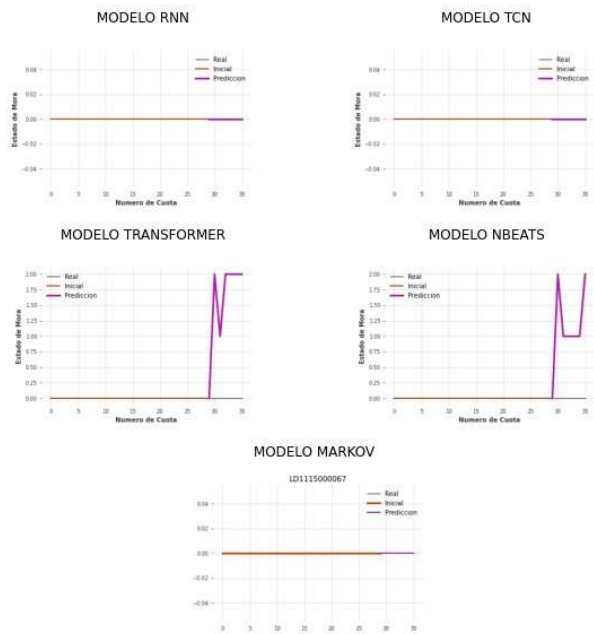
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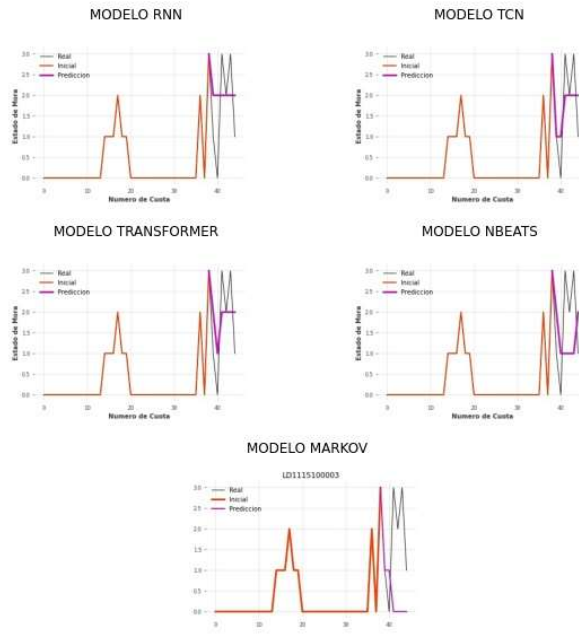
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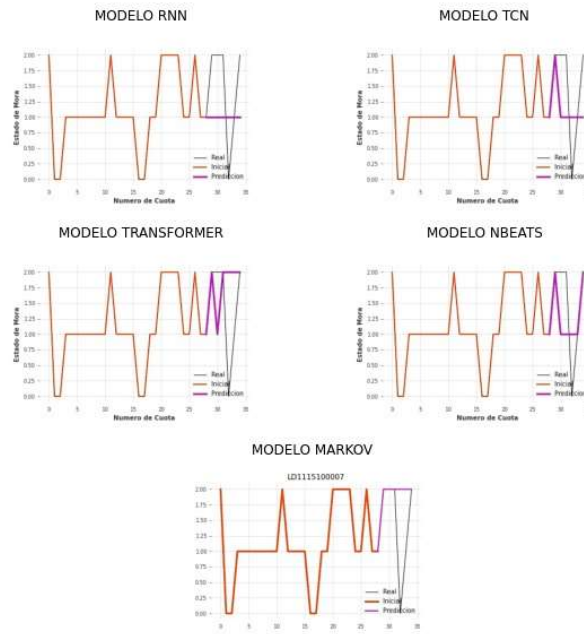
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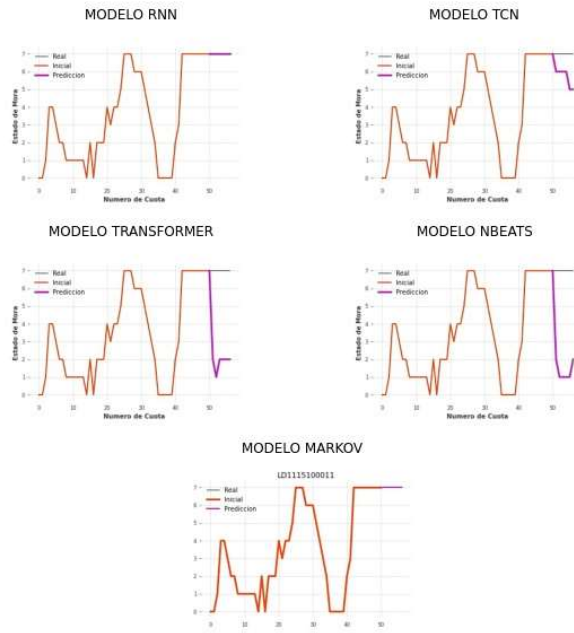
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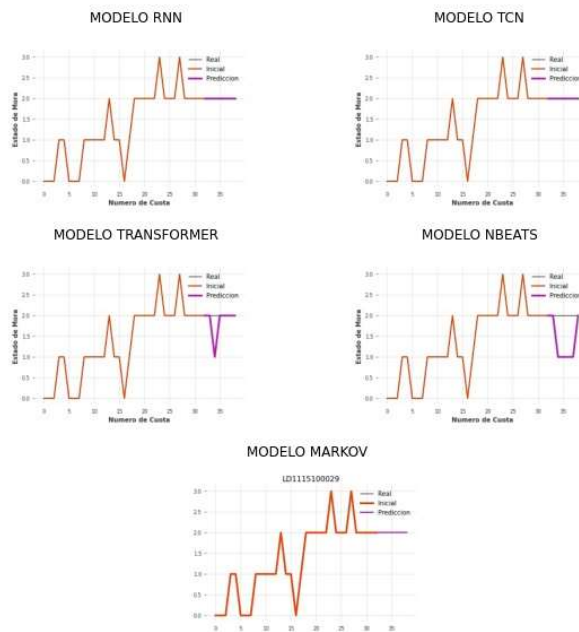
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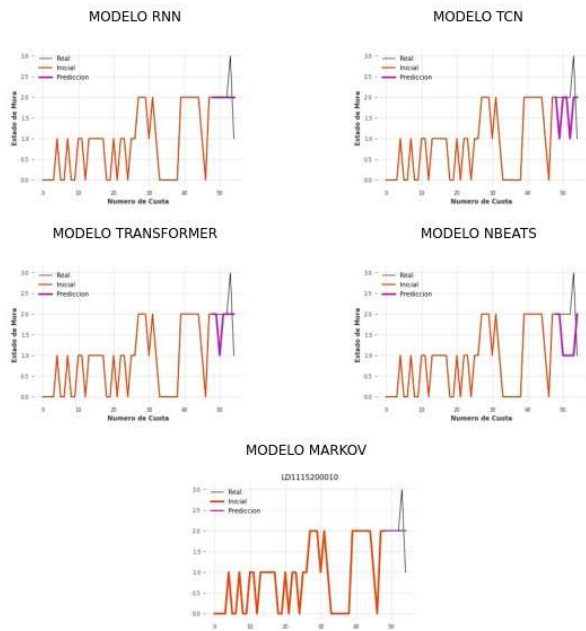
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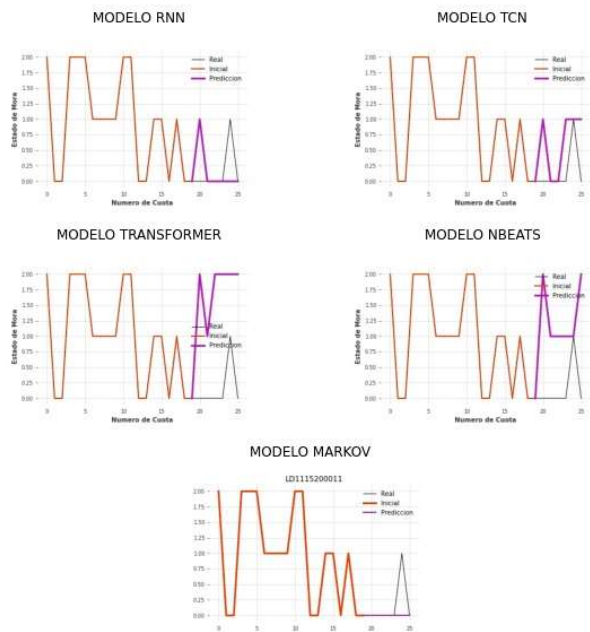
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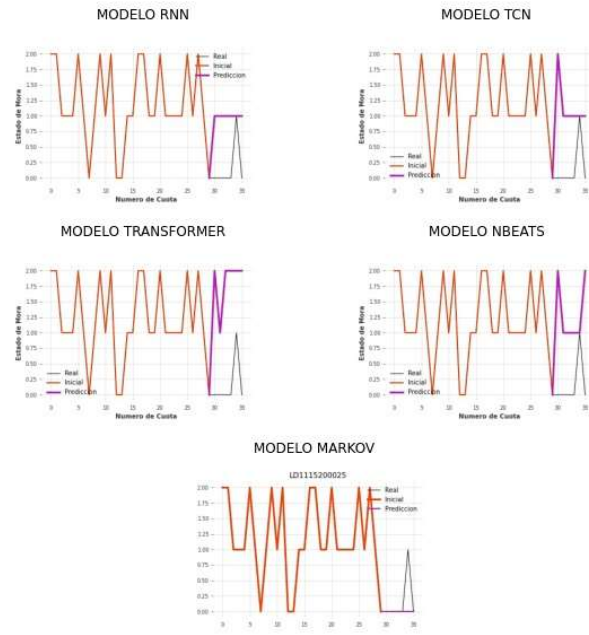
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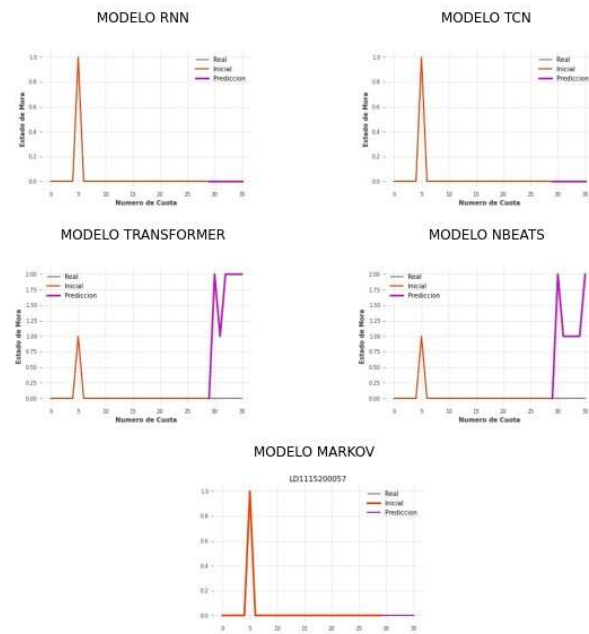
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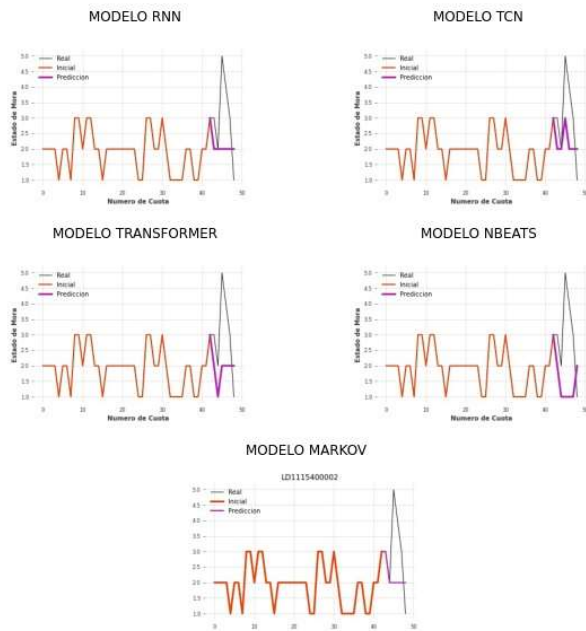


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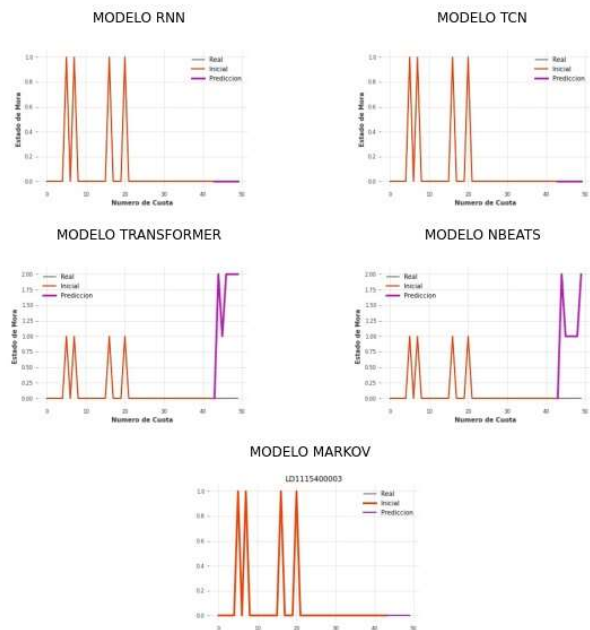




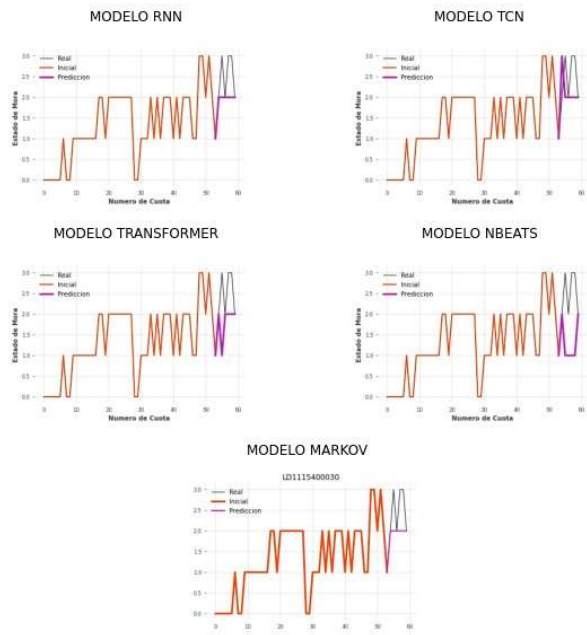
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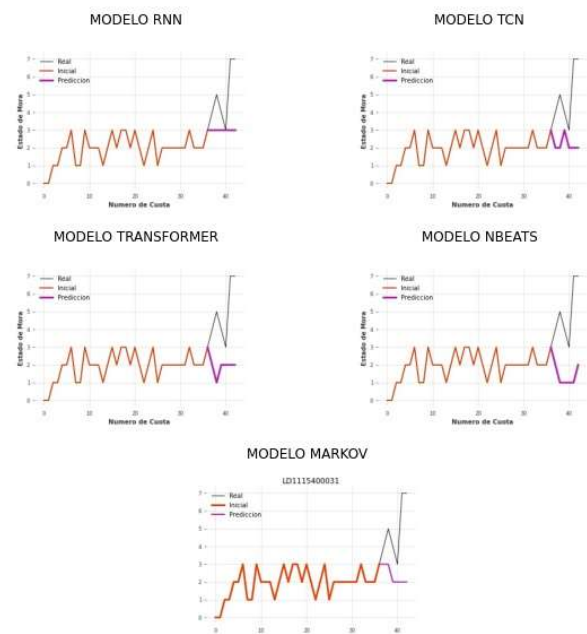
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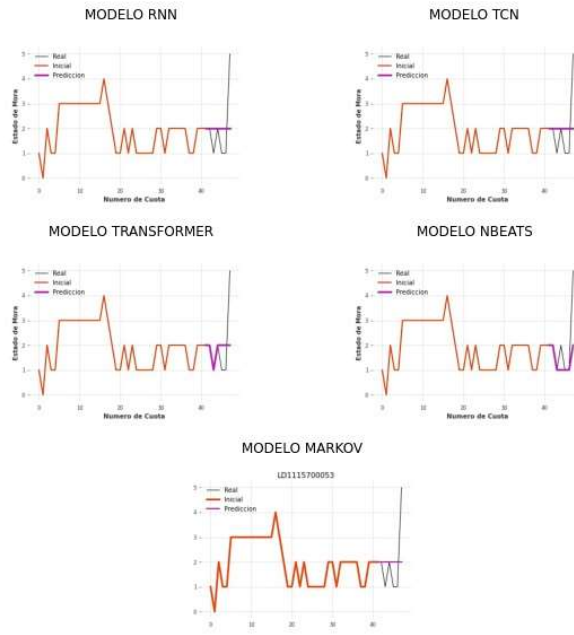
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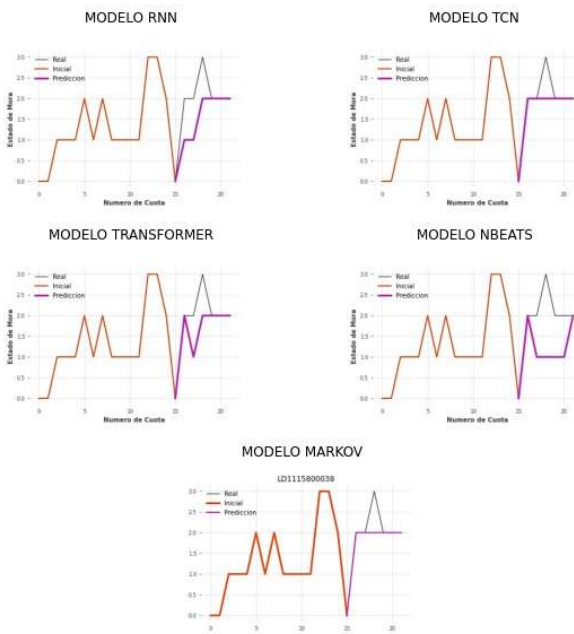
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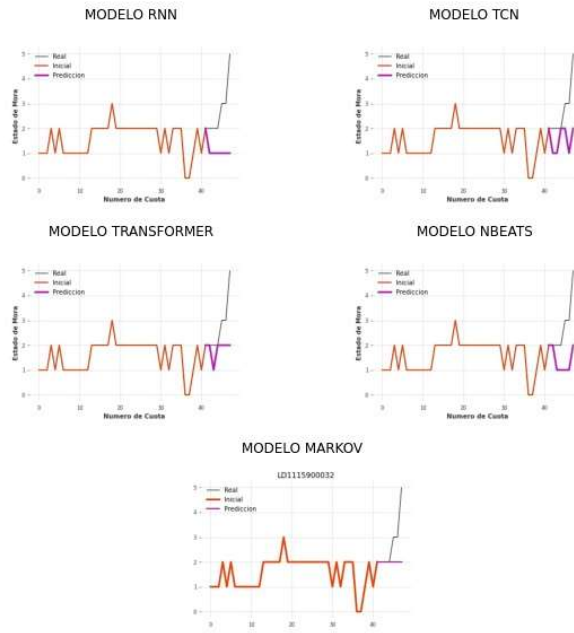
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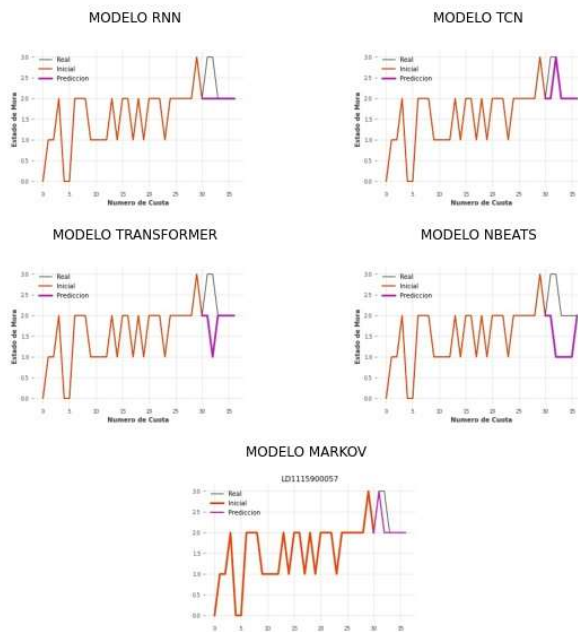
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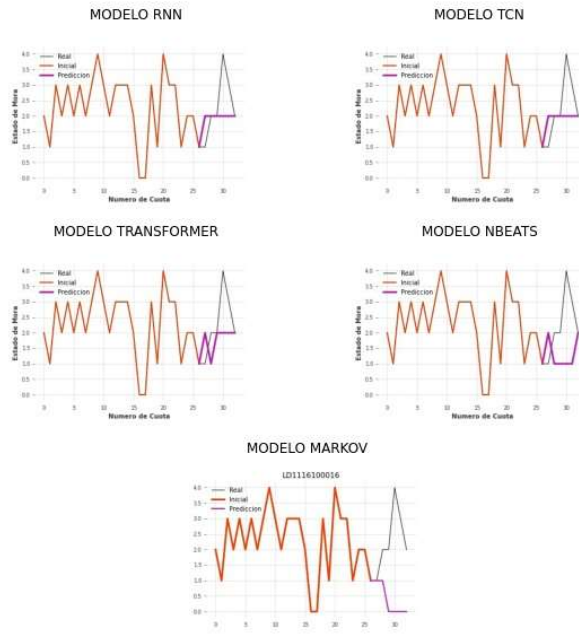
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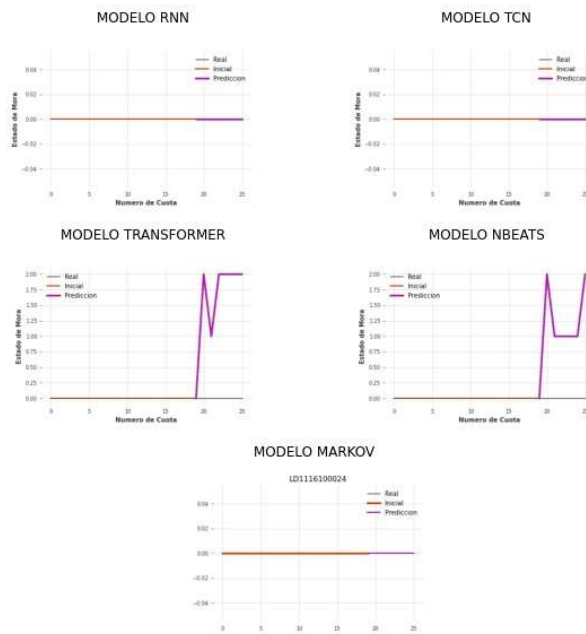
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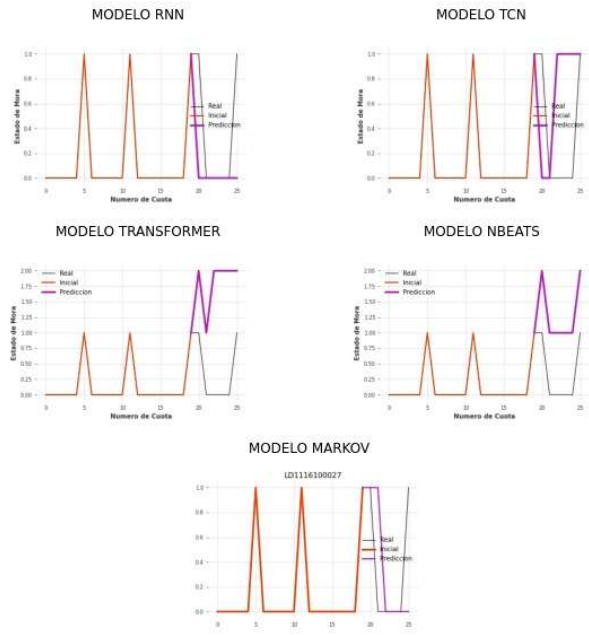
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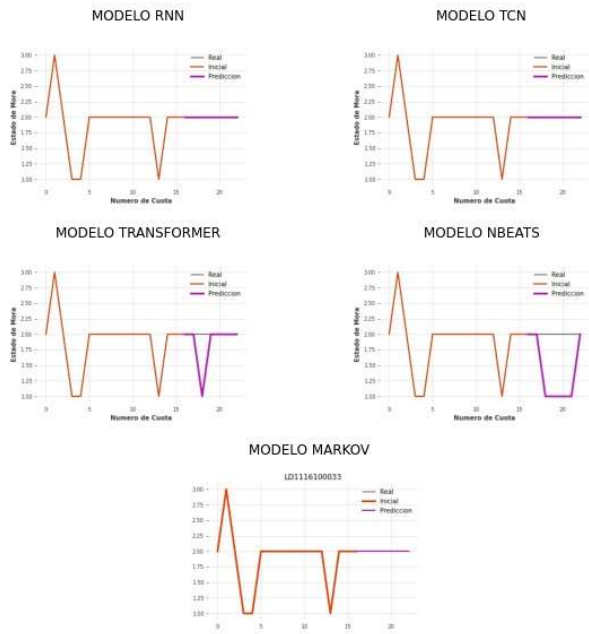
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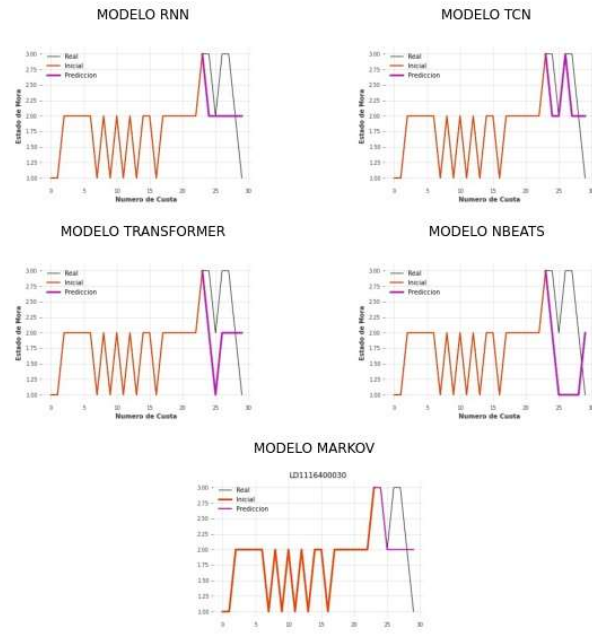
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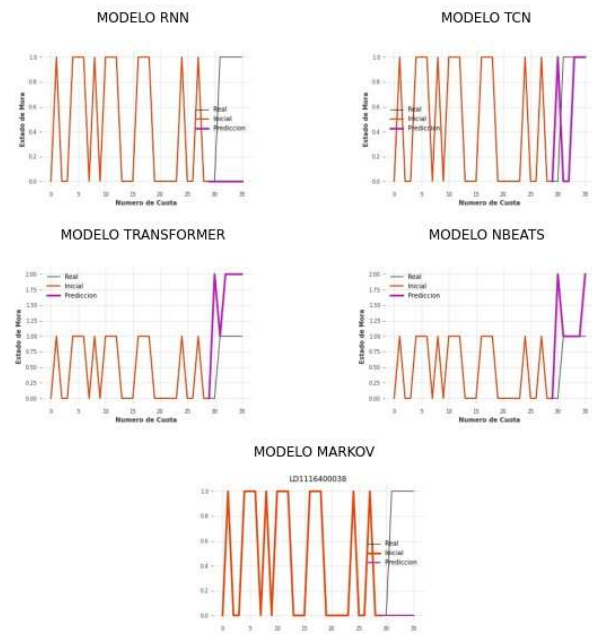
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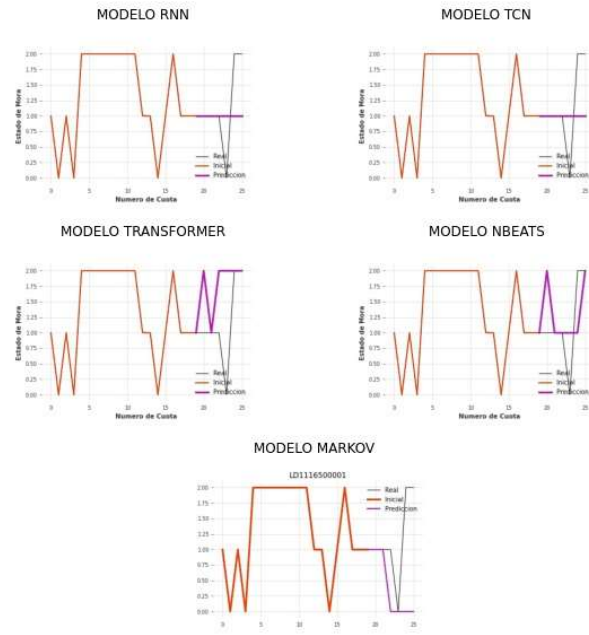


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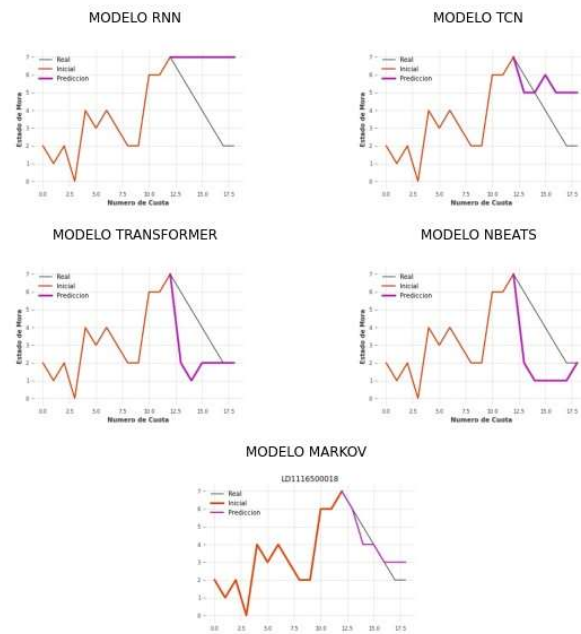




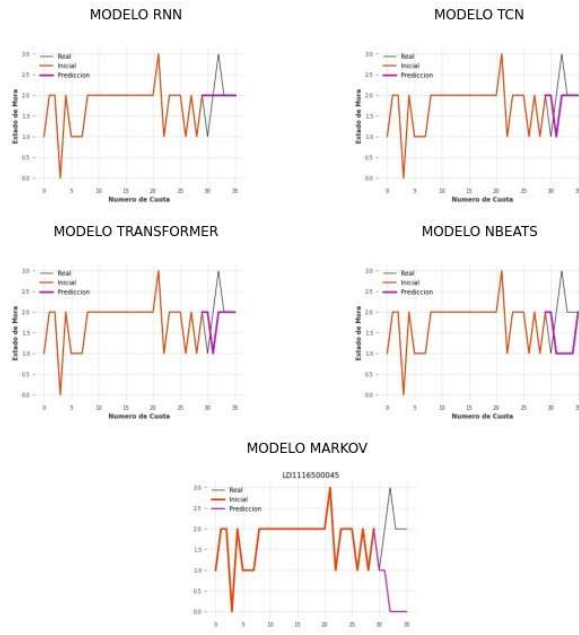
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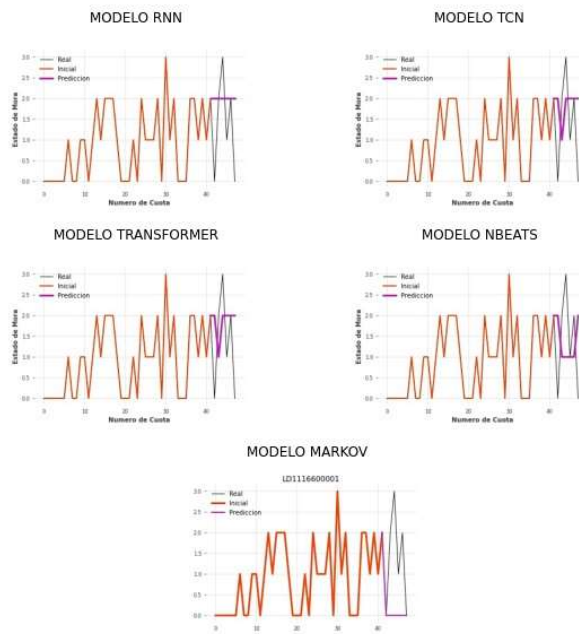
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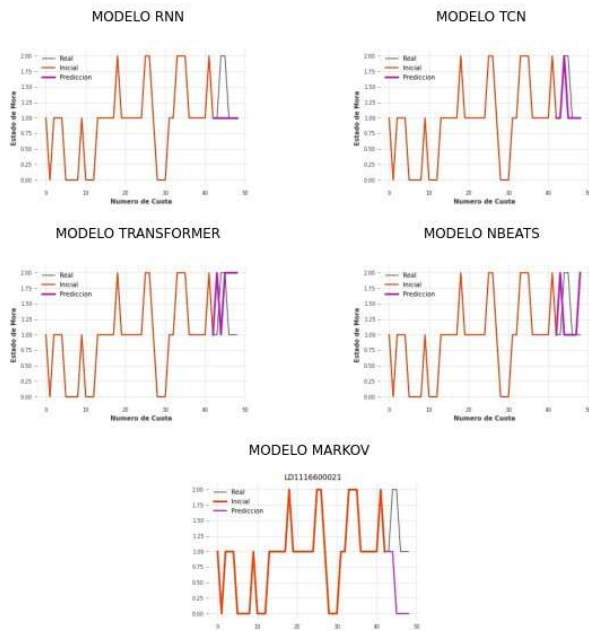
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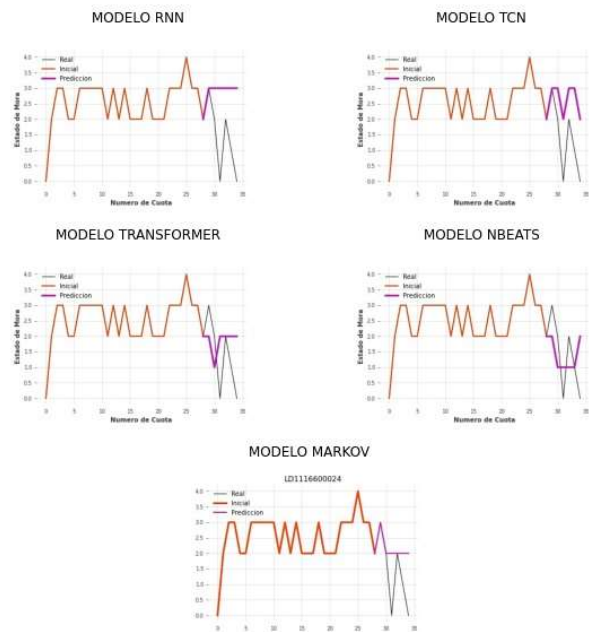
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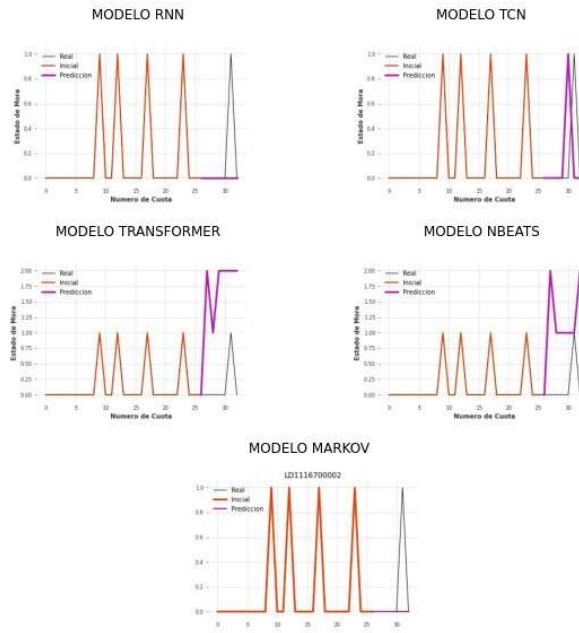
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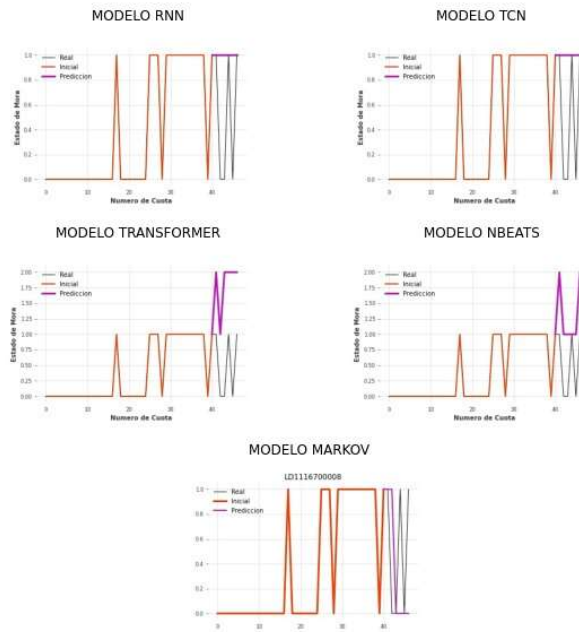
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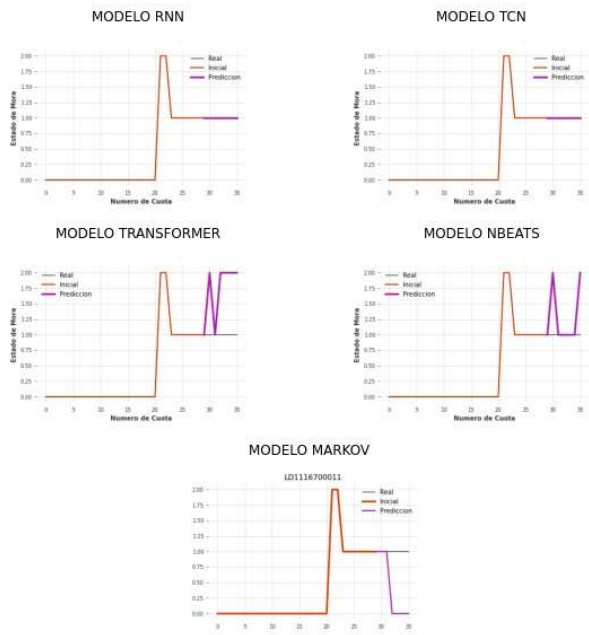
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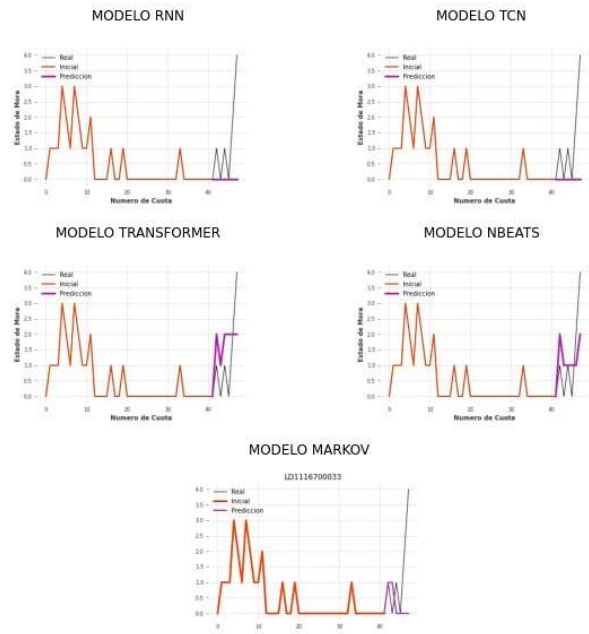
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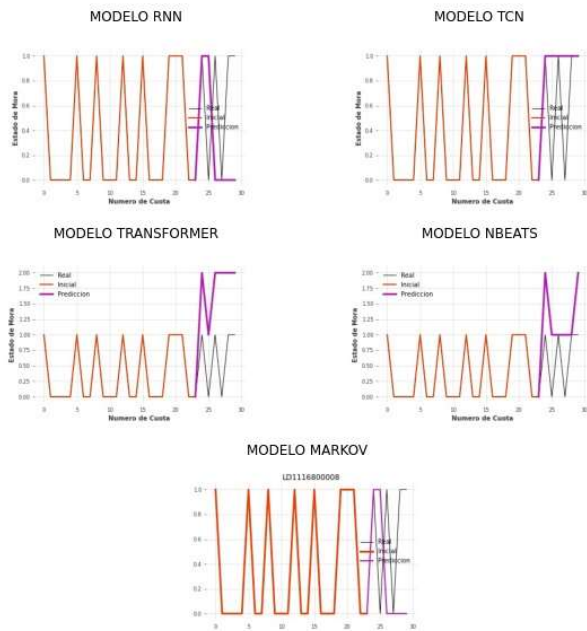
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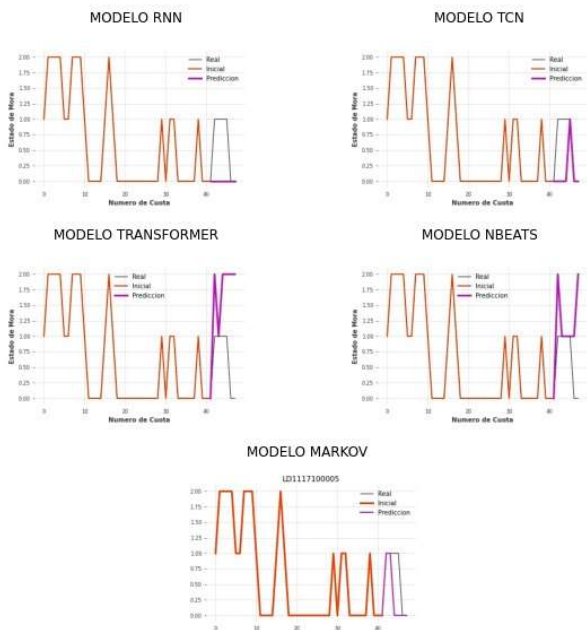
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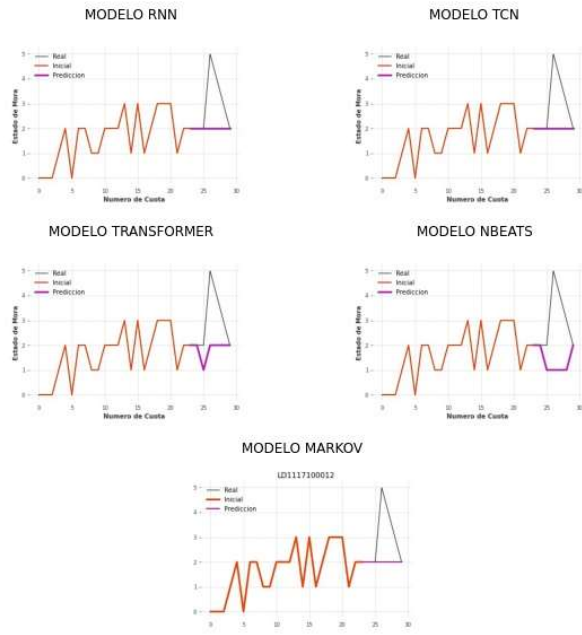
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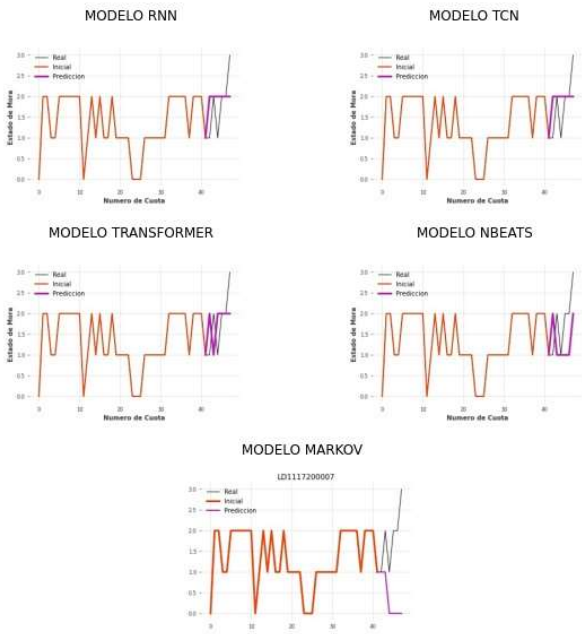
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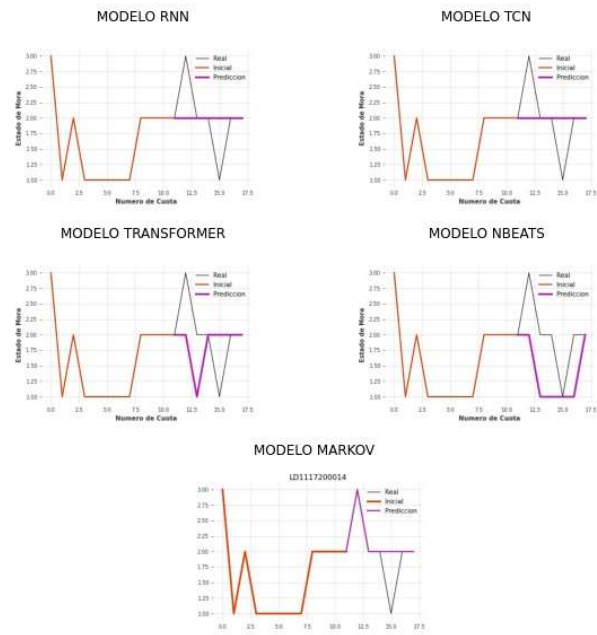
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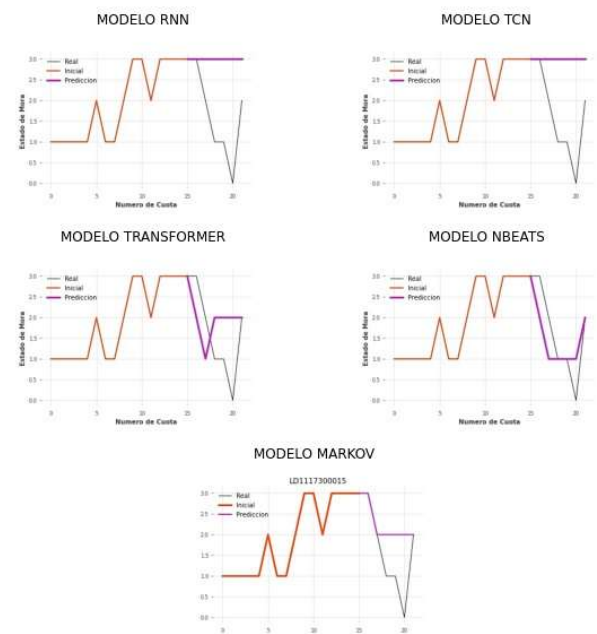
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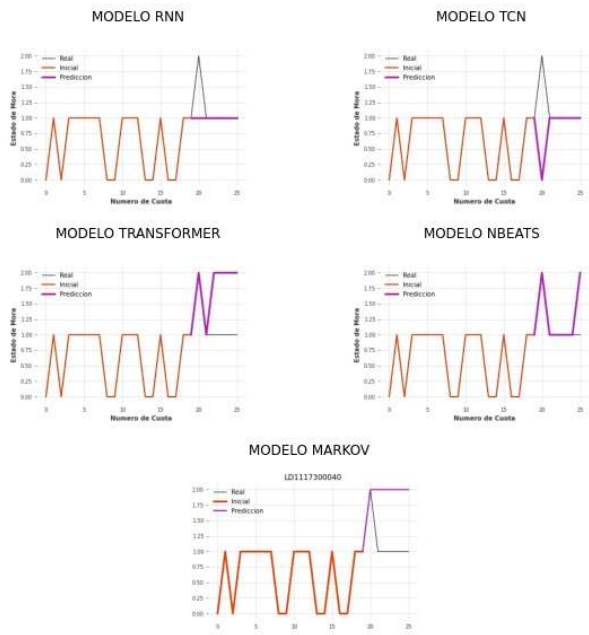


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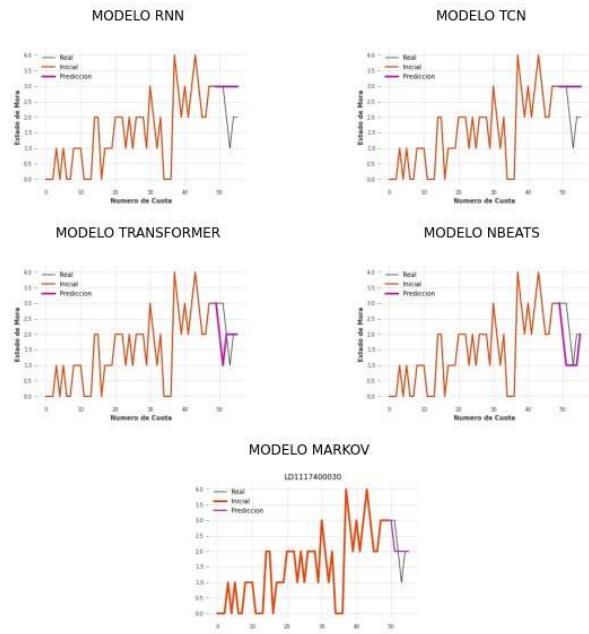




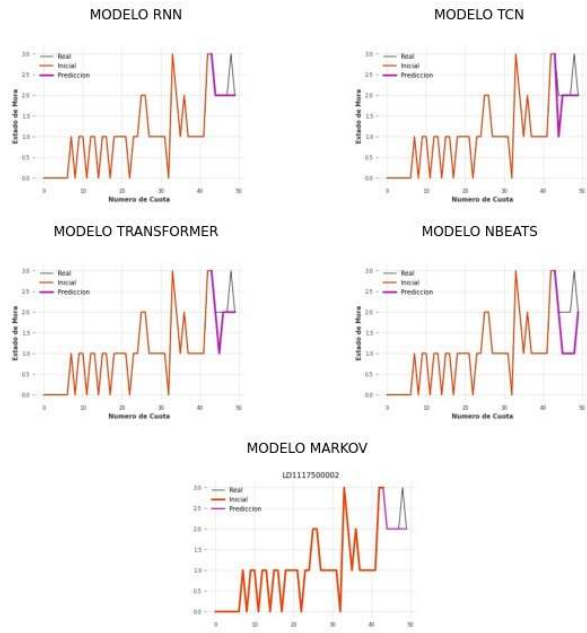
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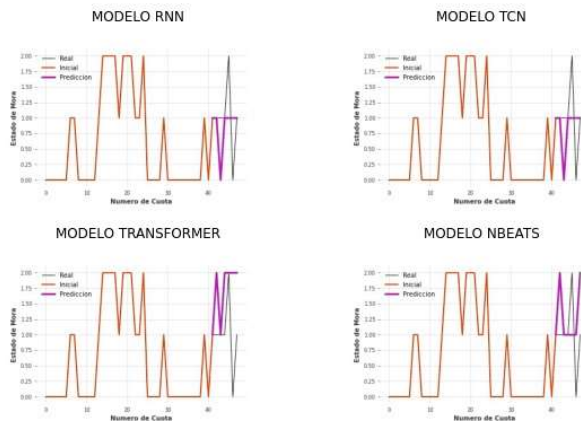
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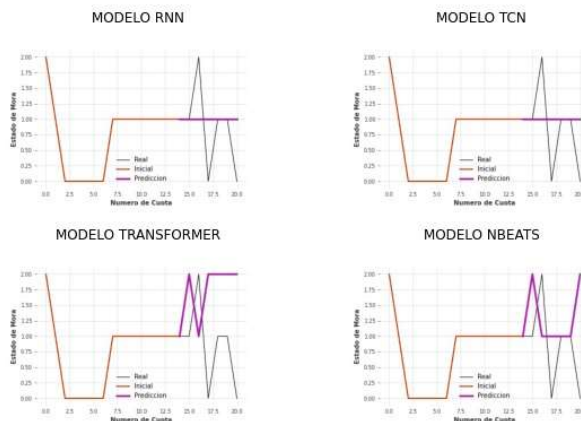
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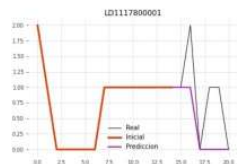
MODELO MARKOV



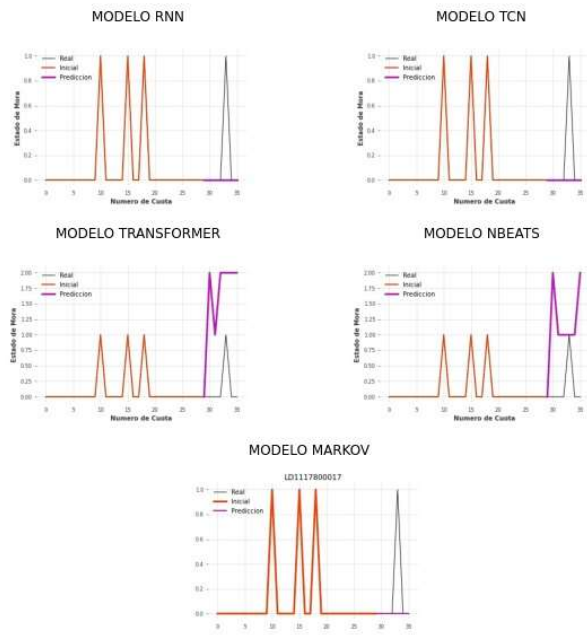
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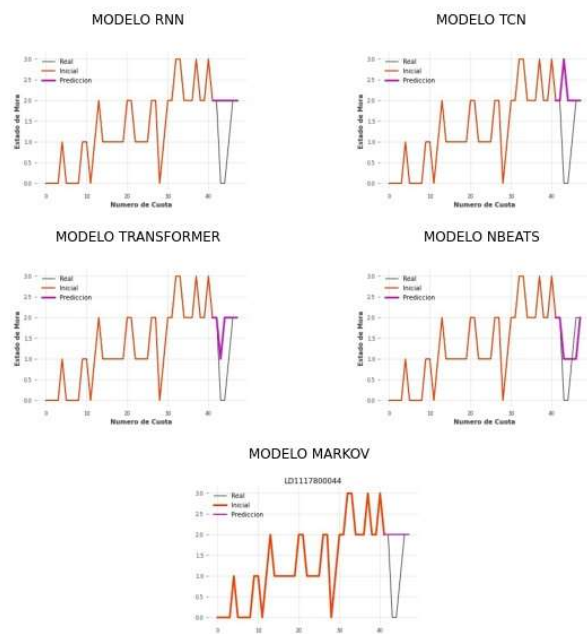
MODELO MARKOV



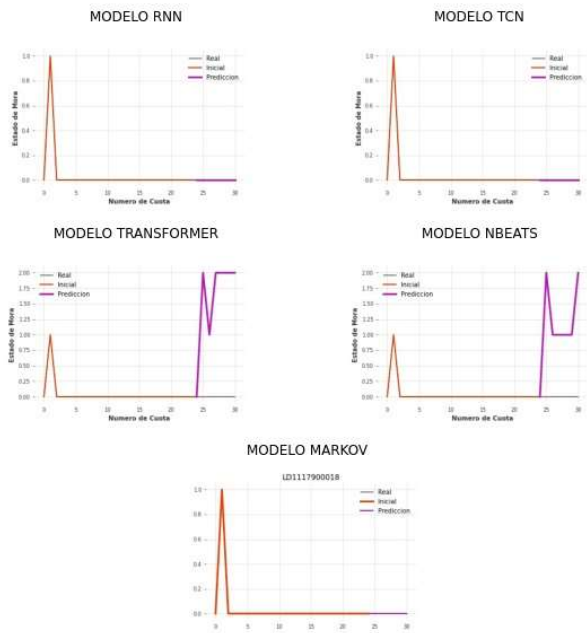
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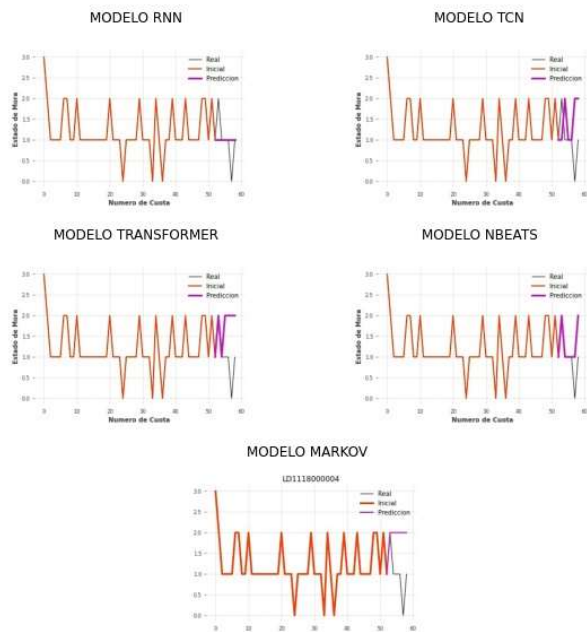
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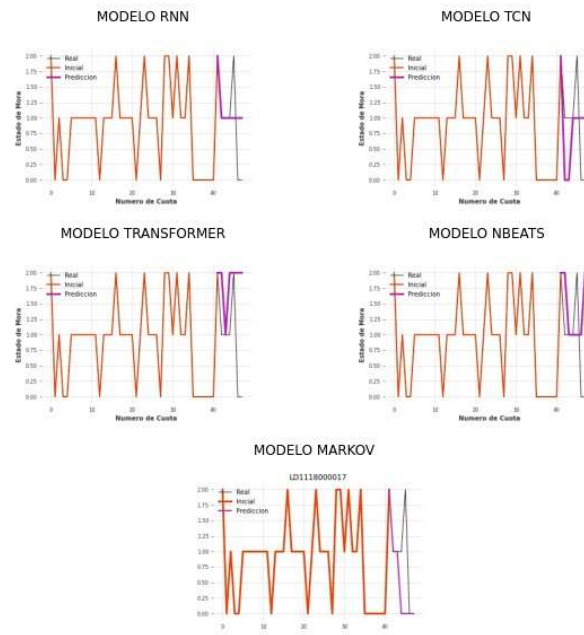
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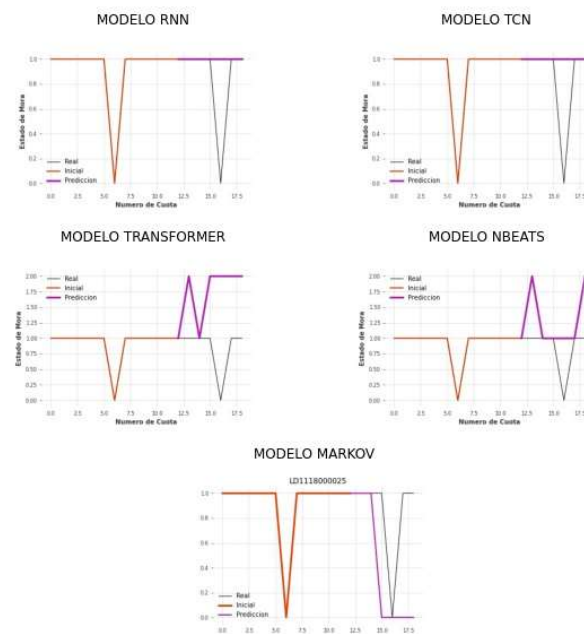
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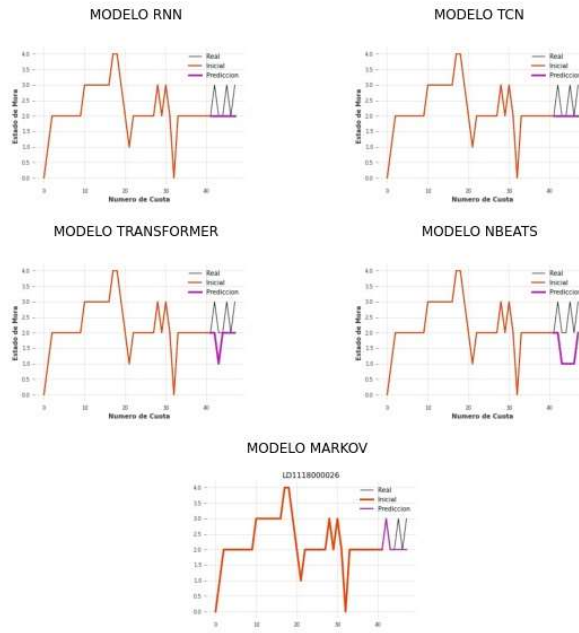
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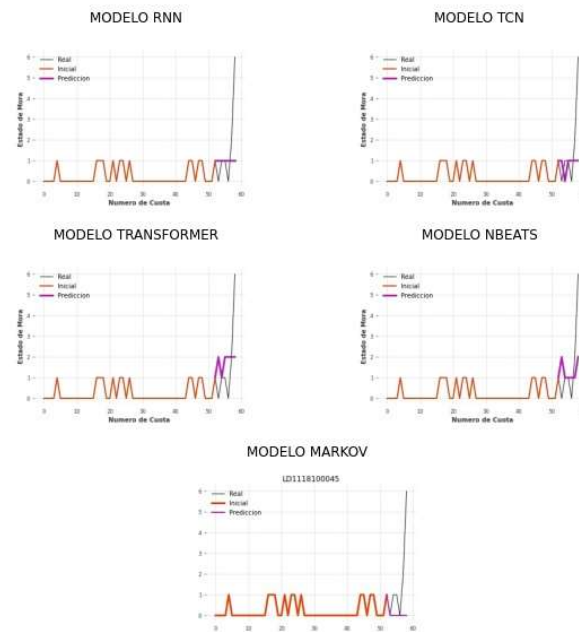
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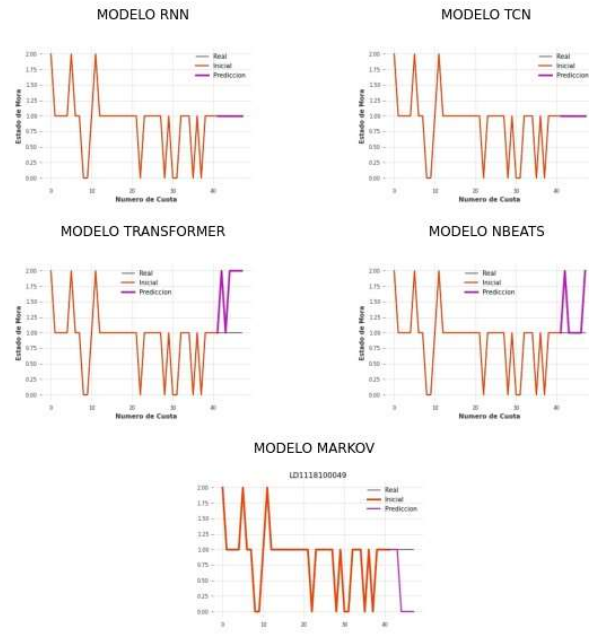
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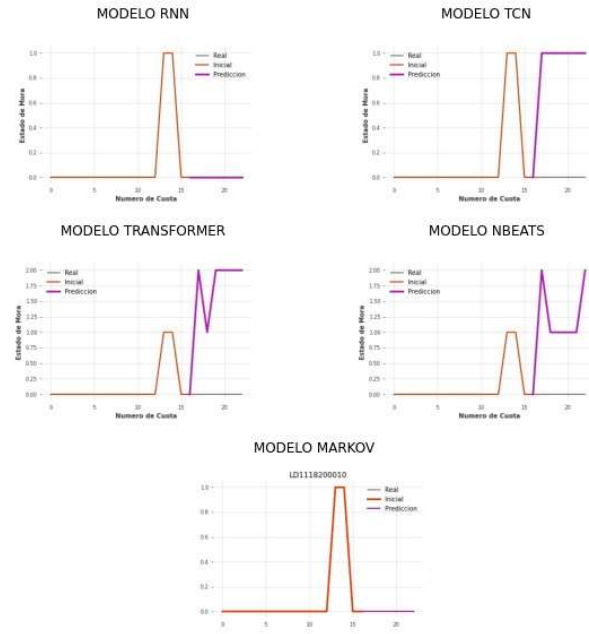
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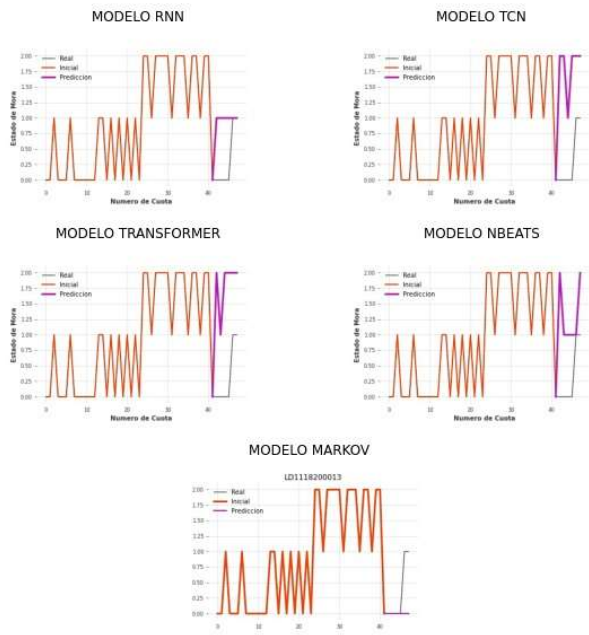


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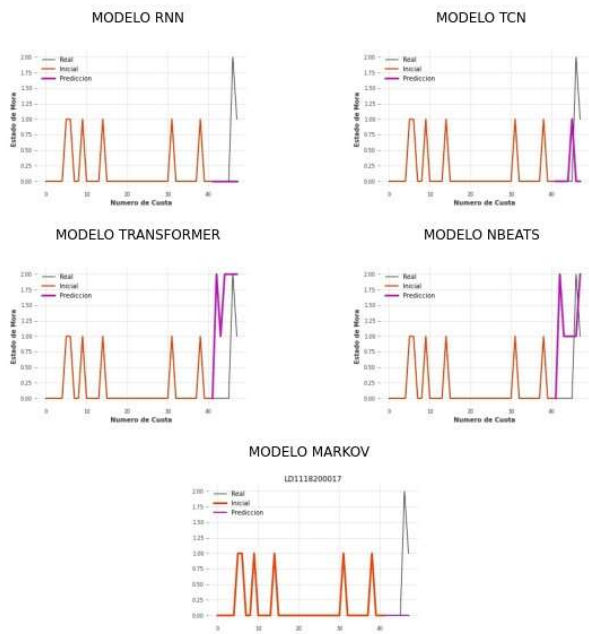




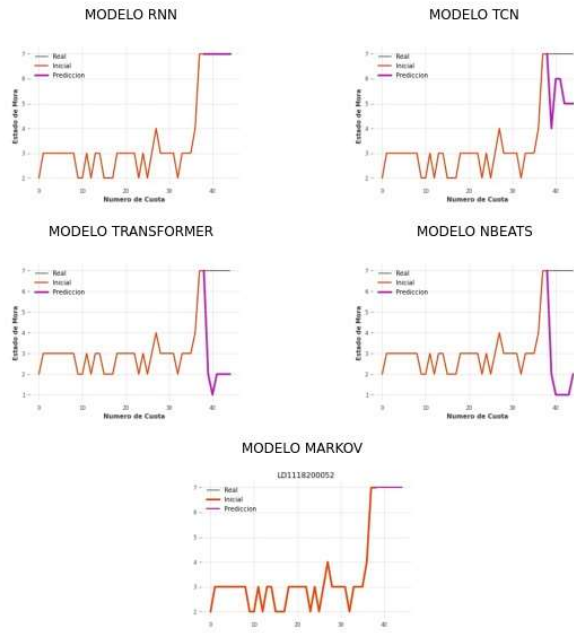
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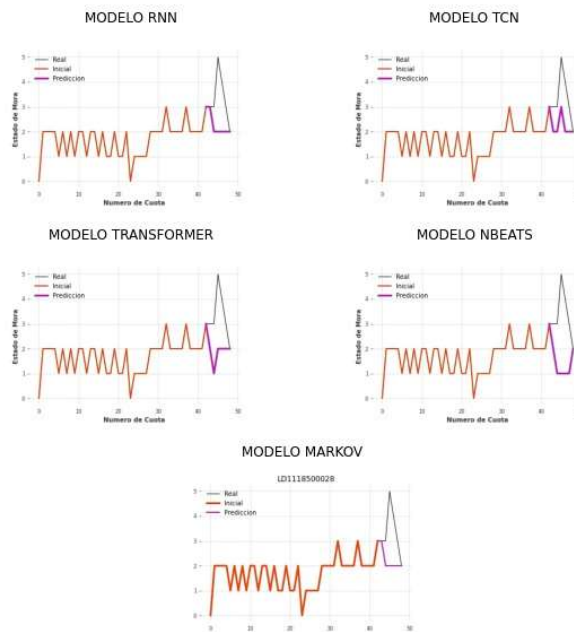
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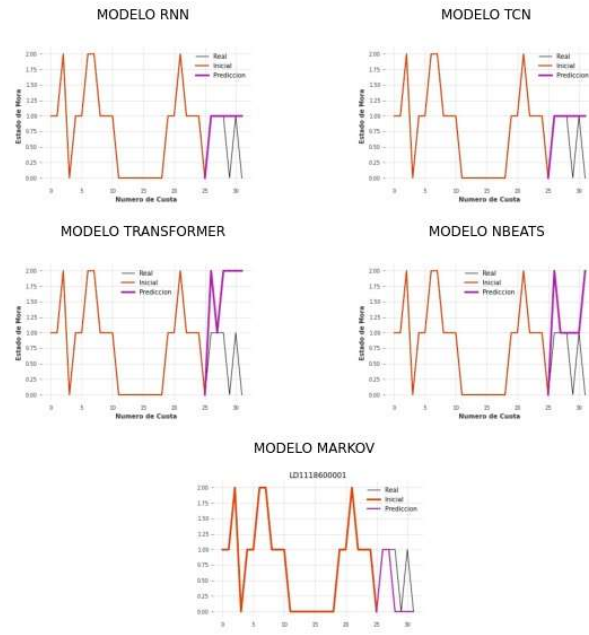
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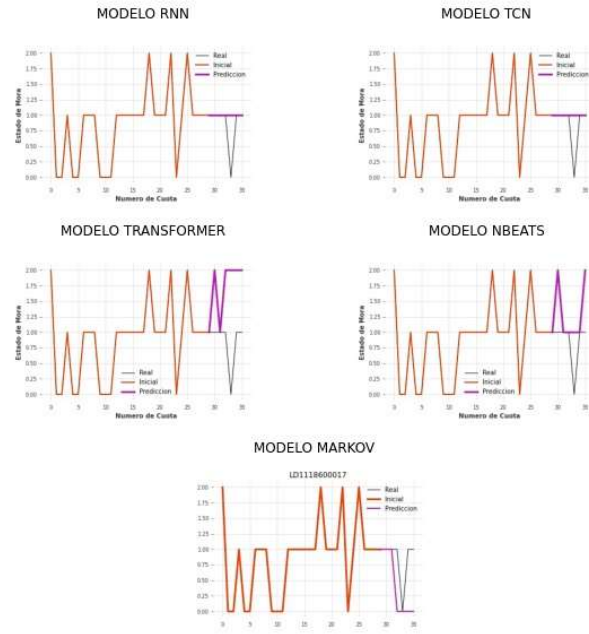
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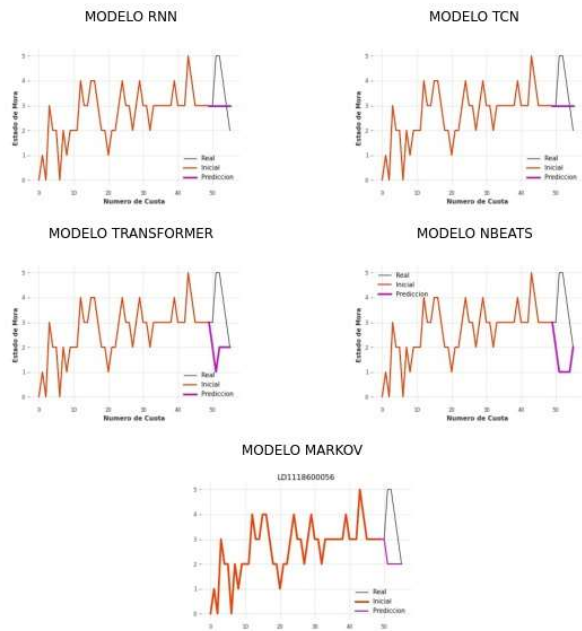
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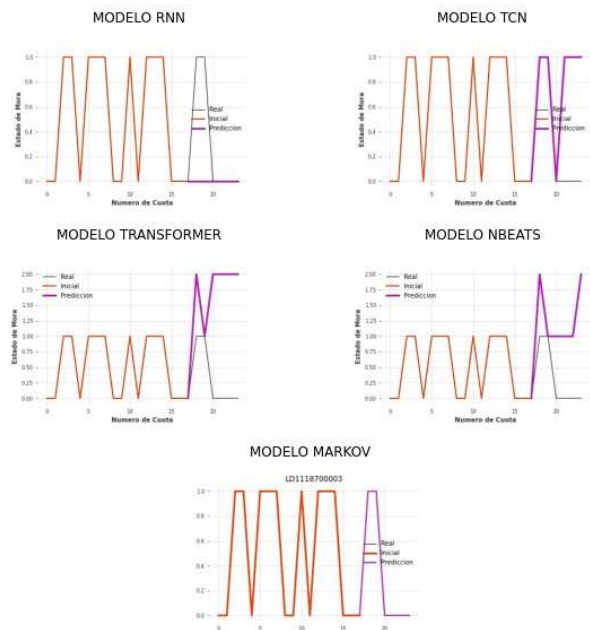
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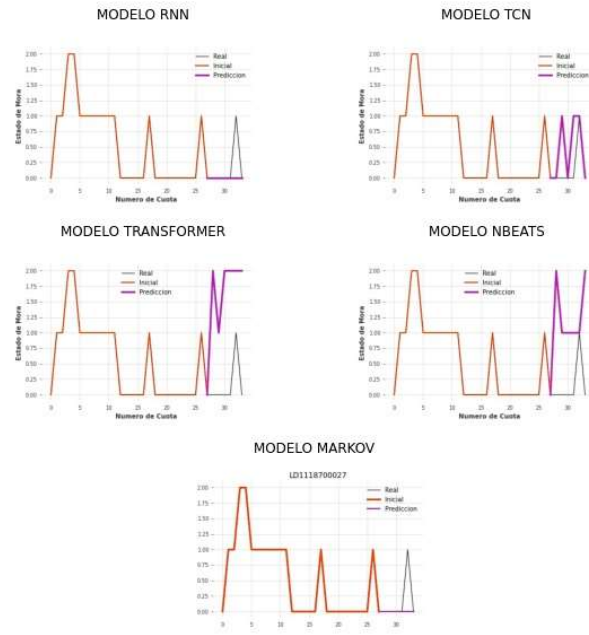
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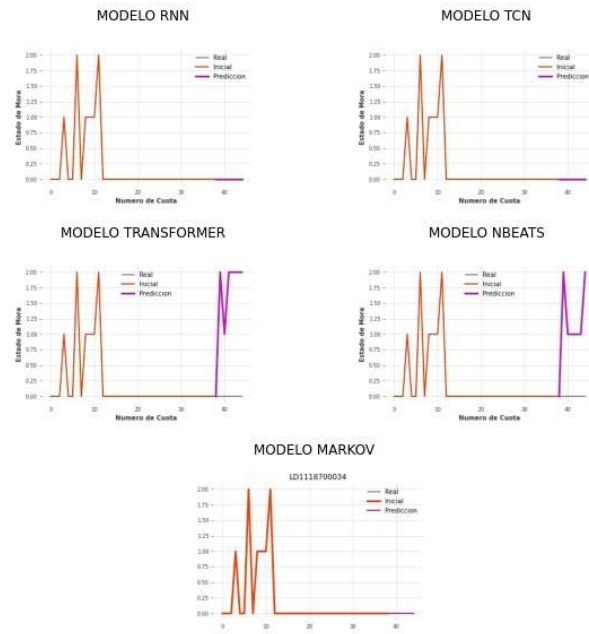
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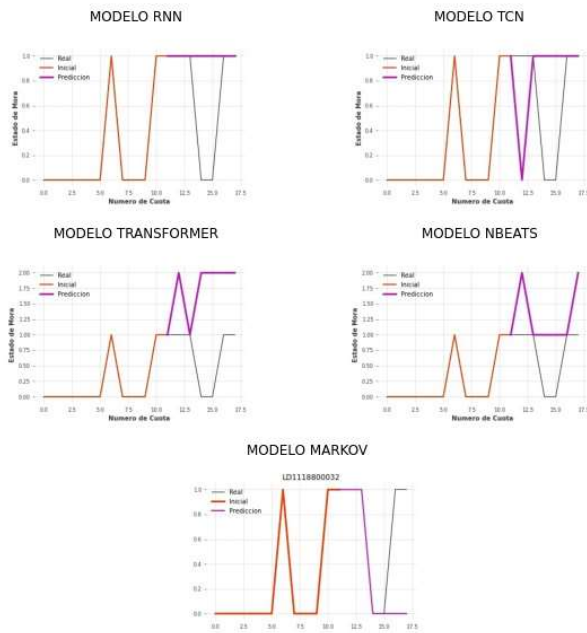
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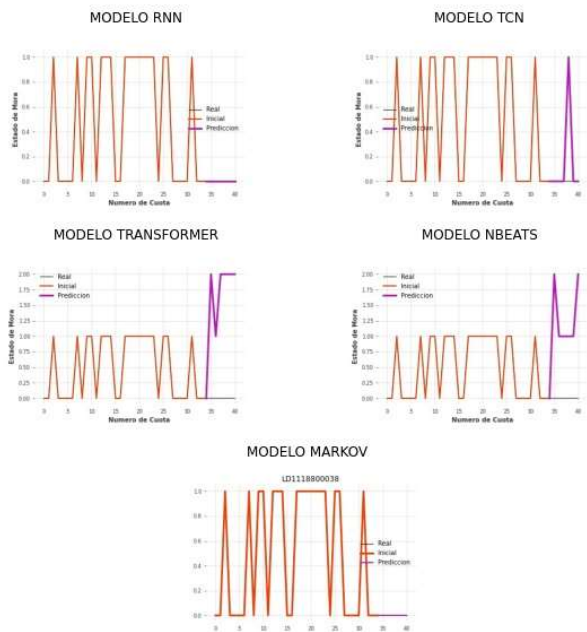
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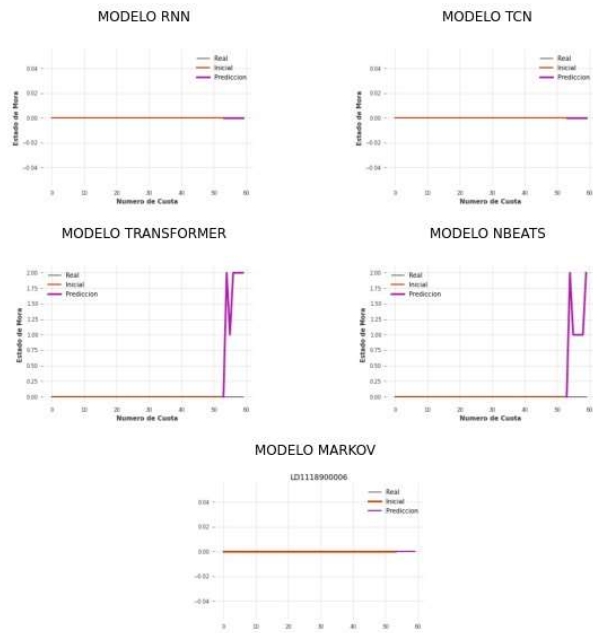
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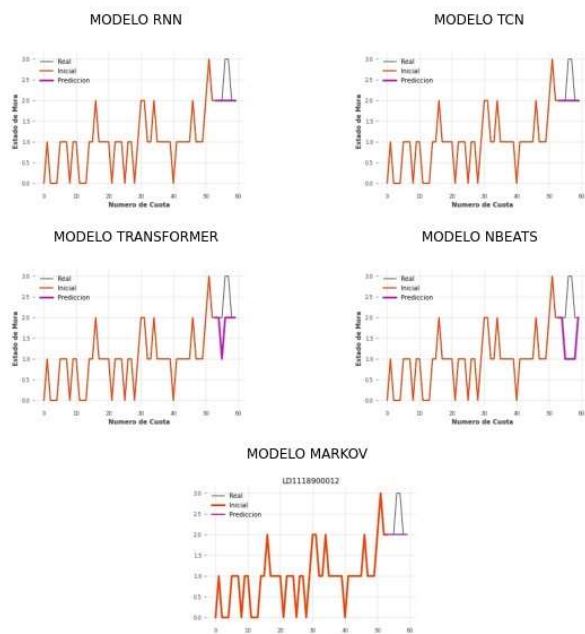
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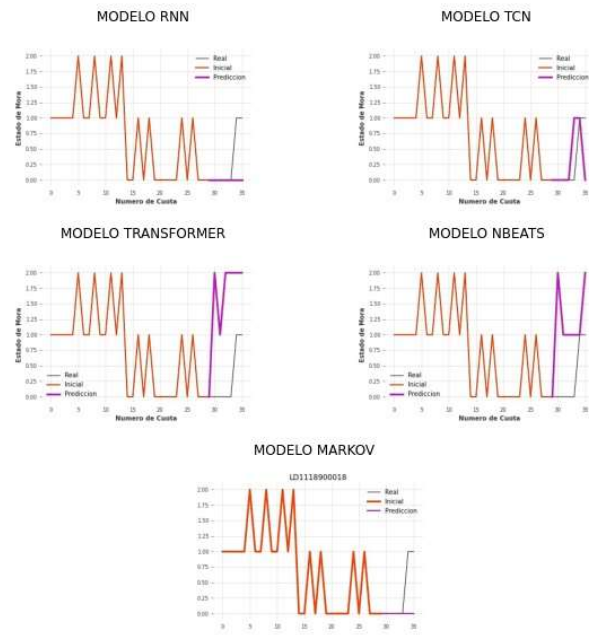
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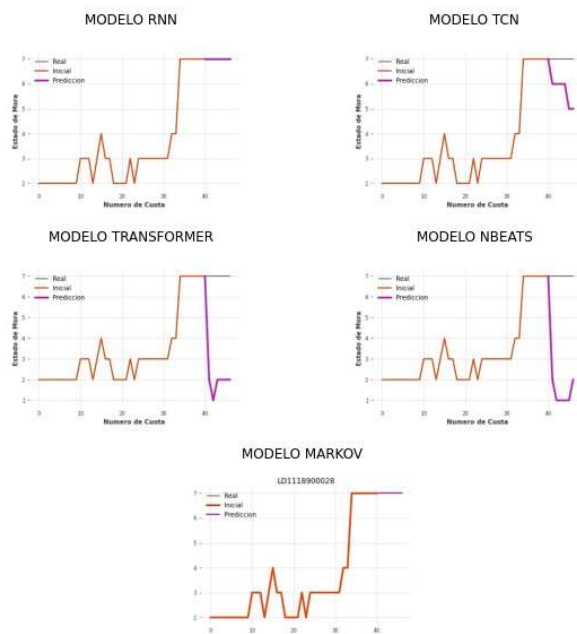
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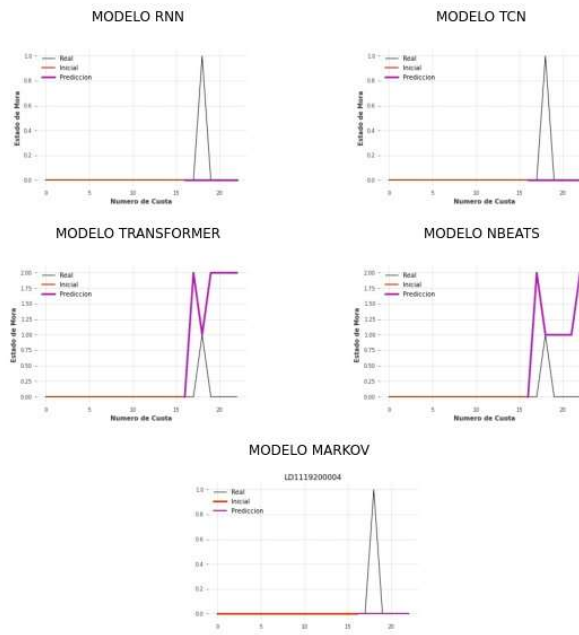


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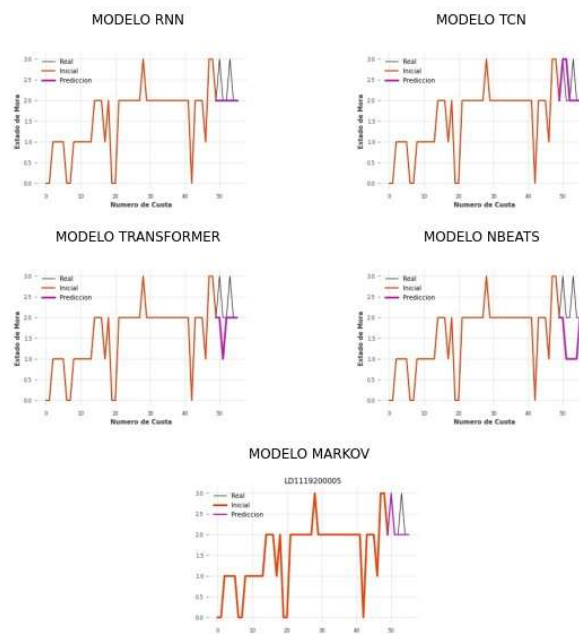




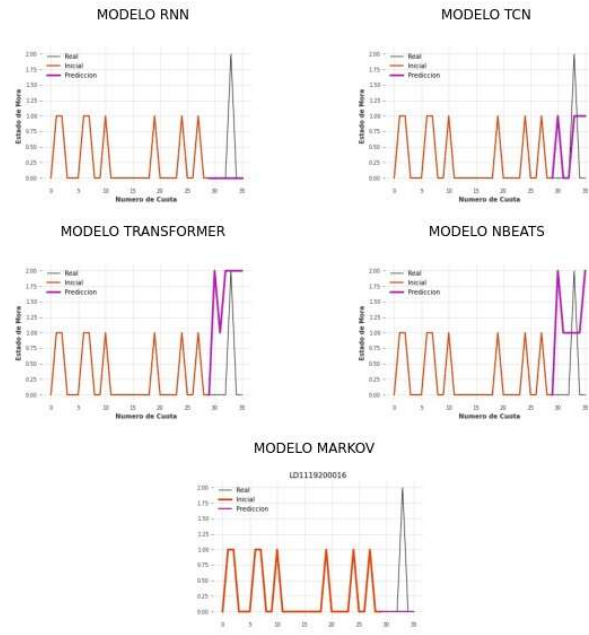
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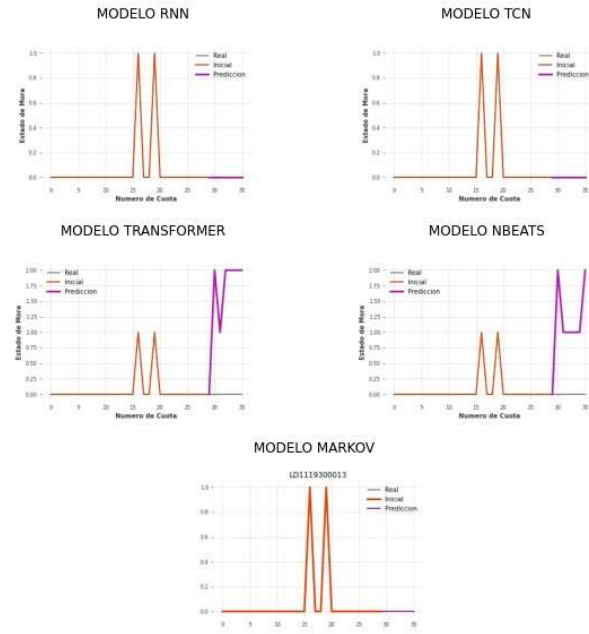
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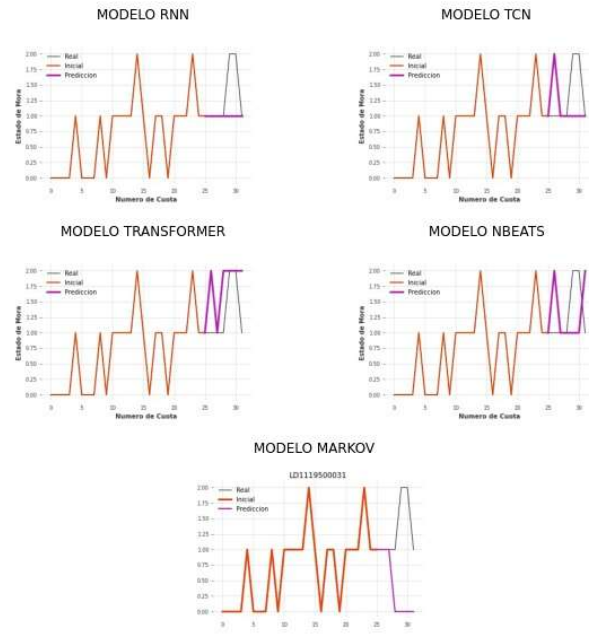
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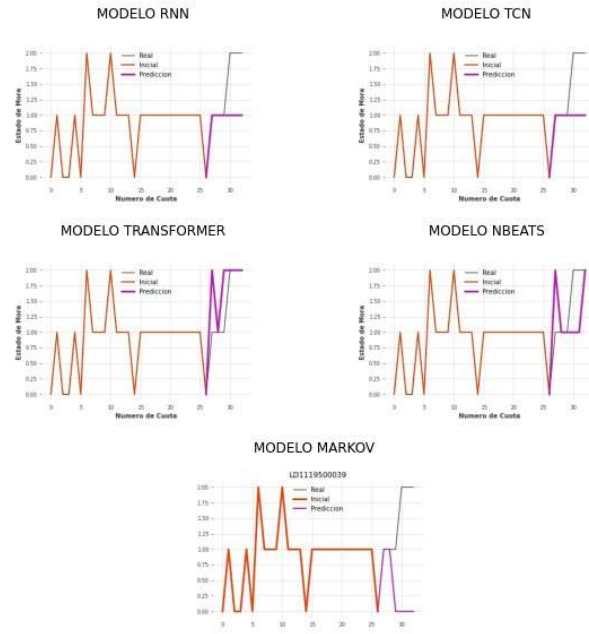
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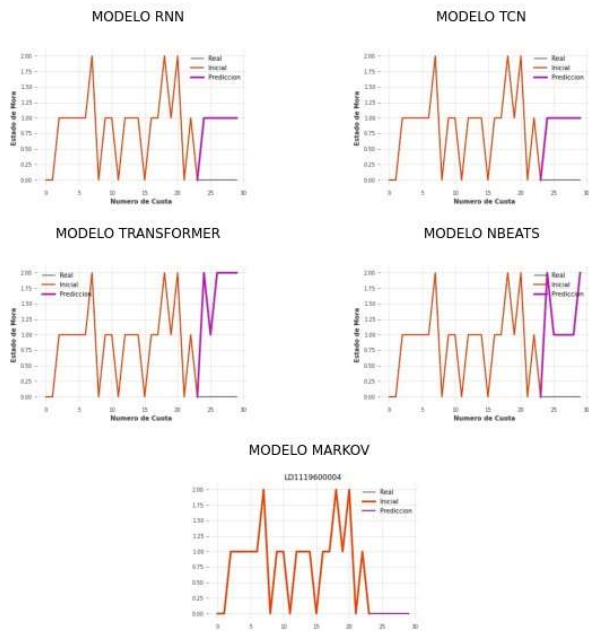
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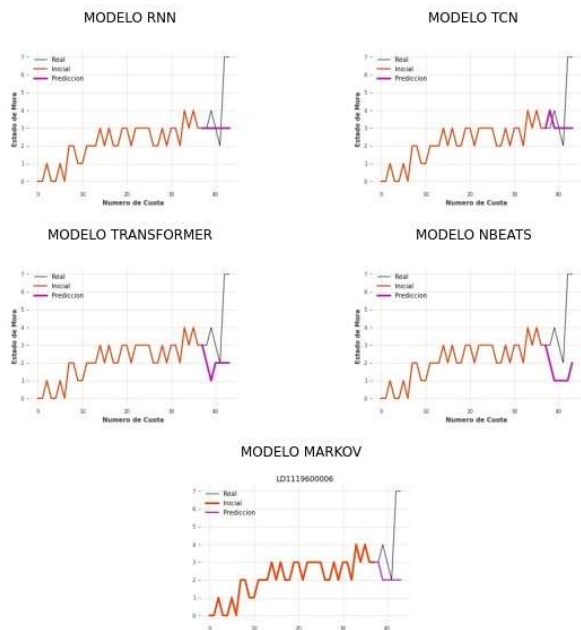
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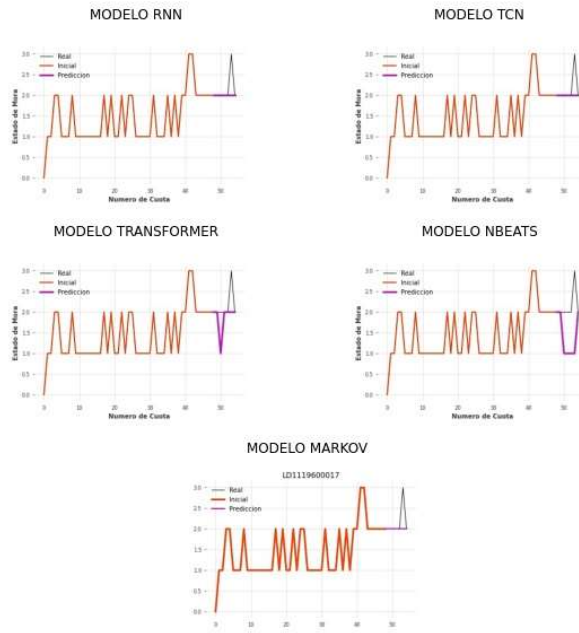
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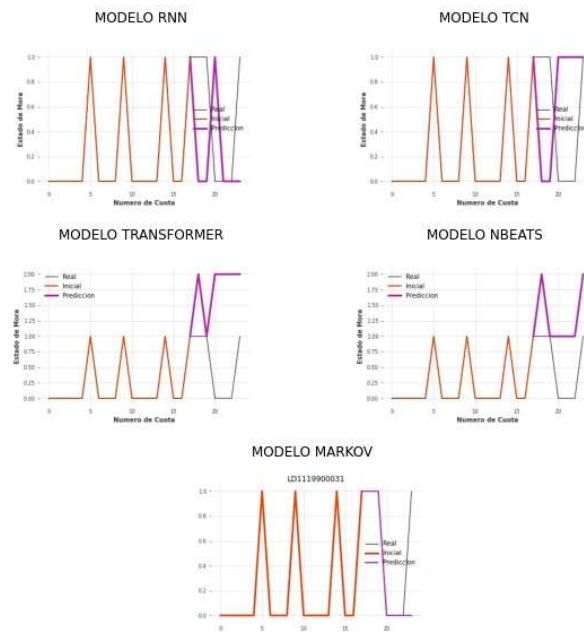
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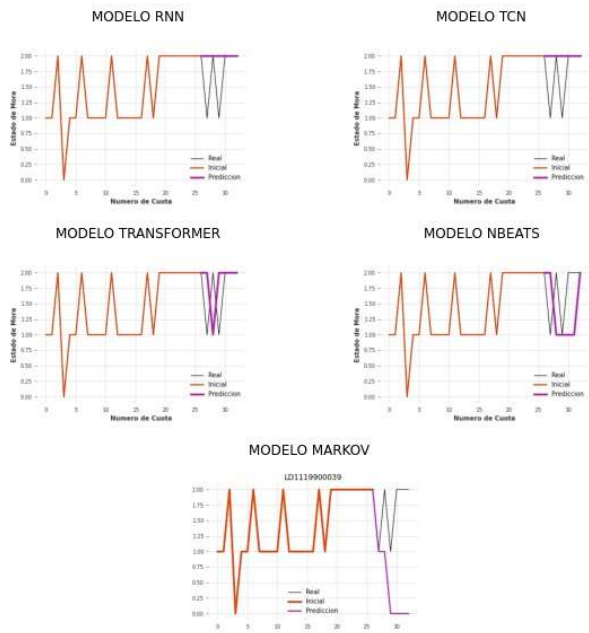
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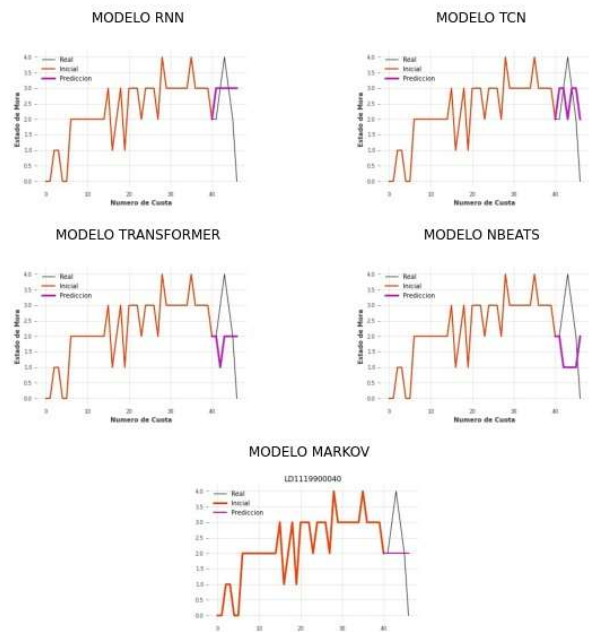
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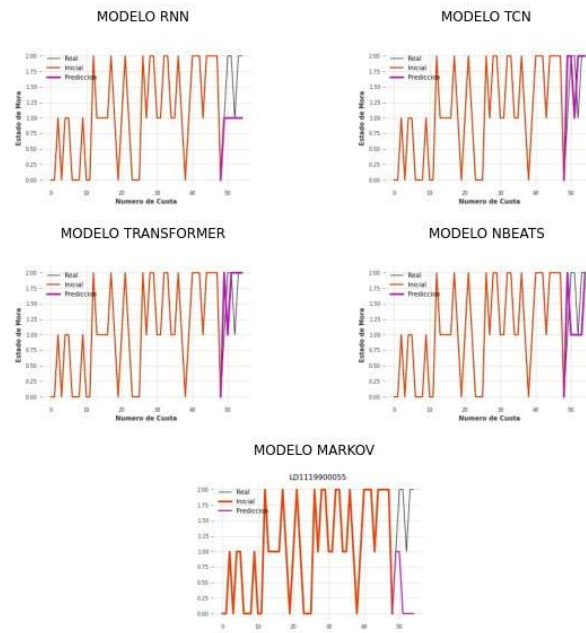
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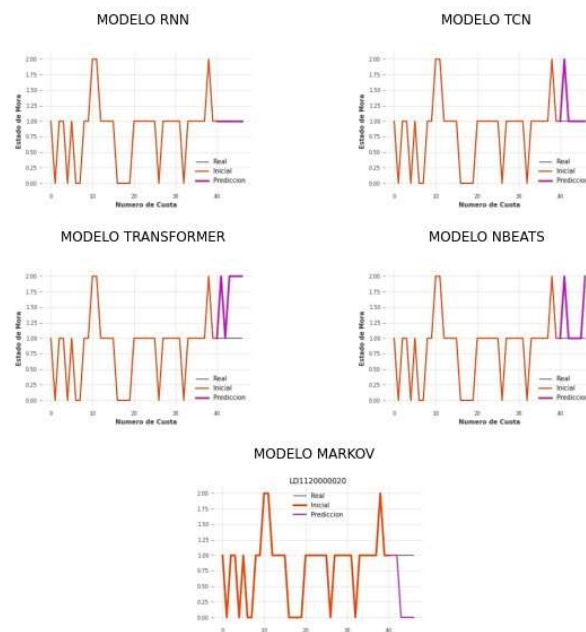
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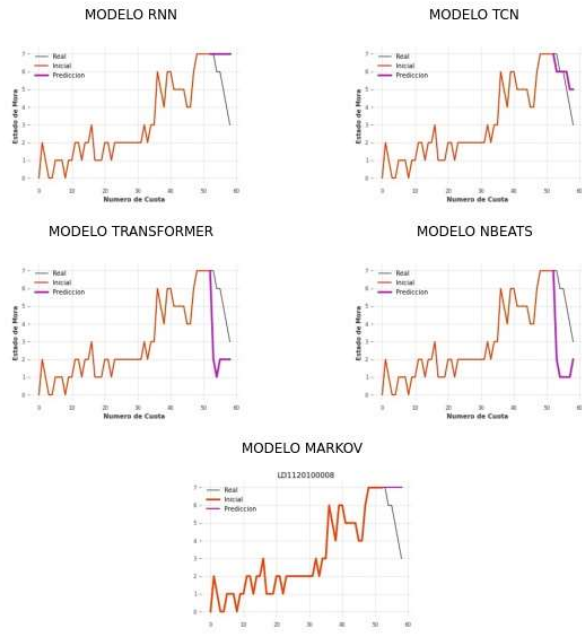
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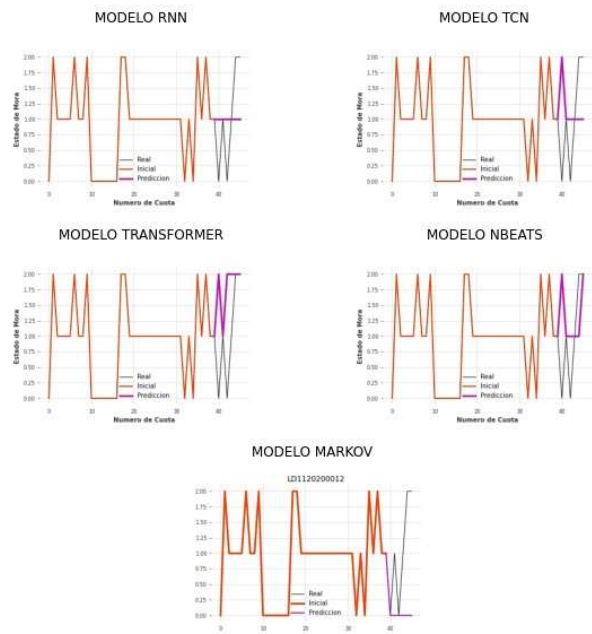
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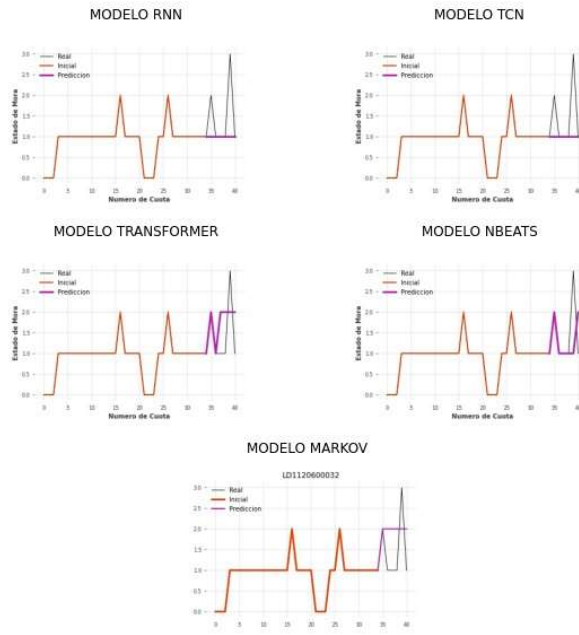


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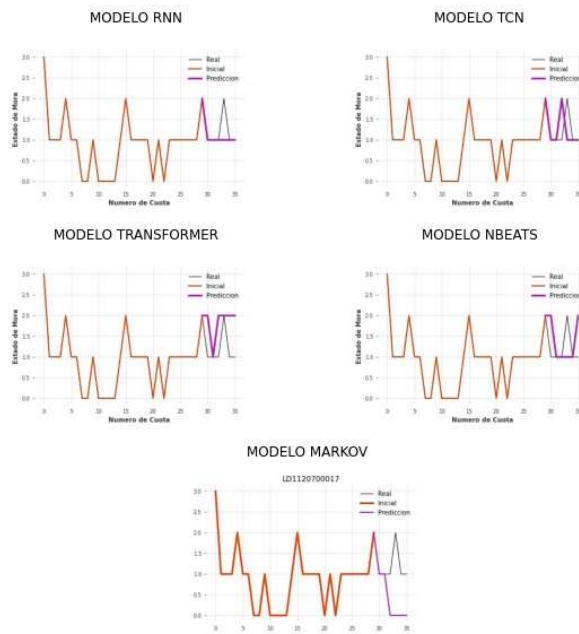




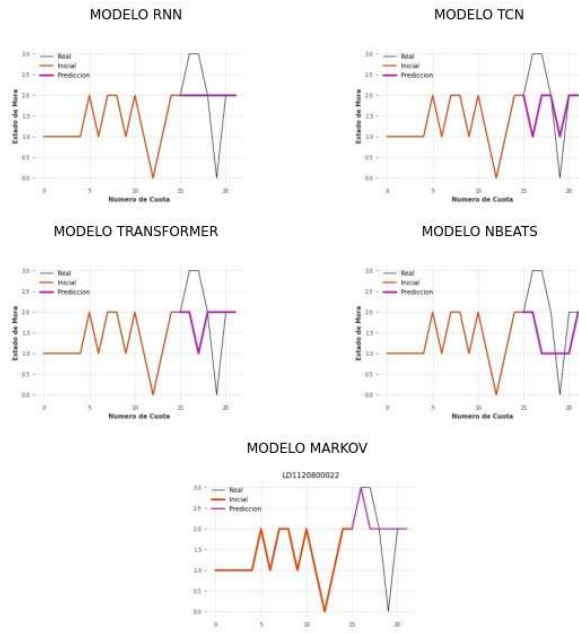
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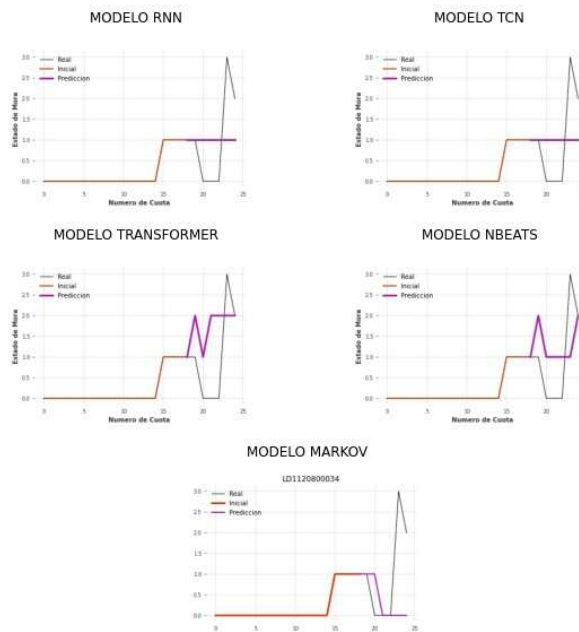
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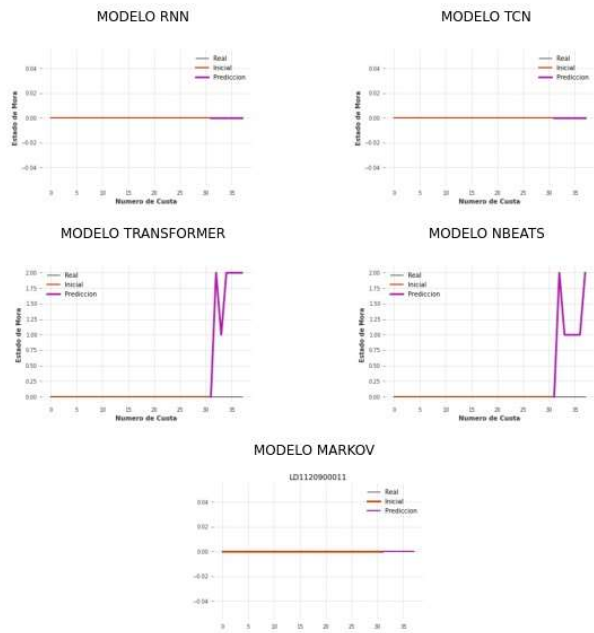
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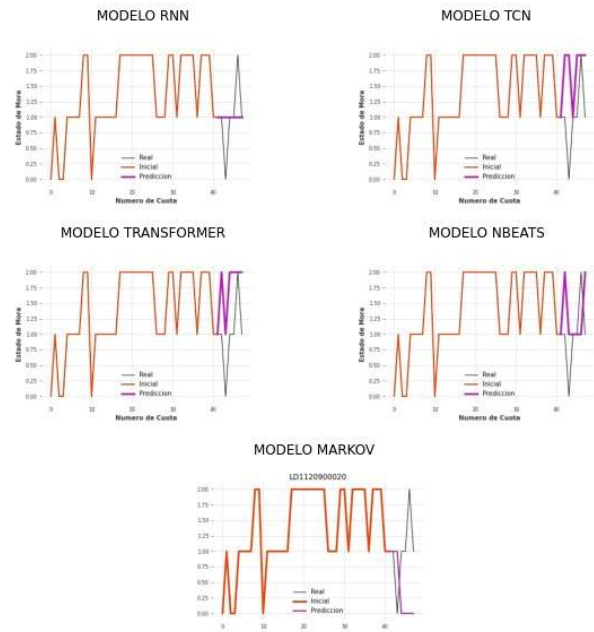
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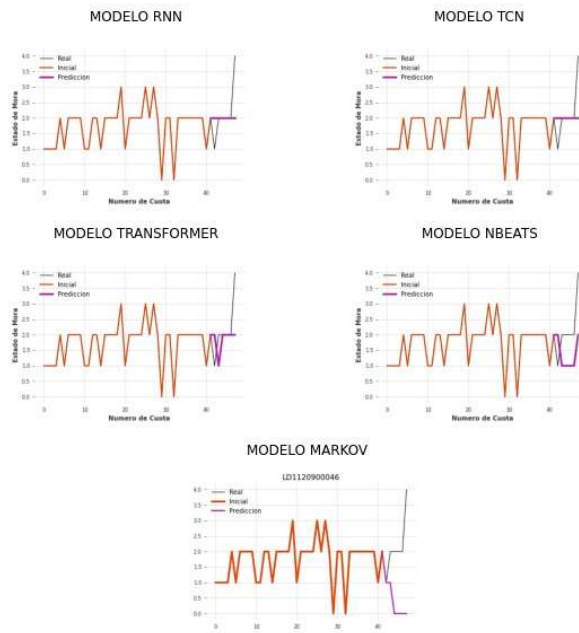
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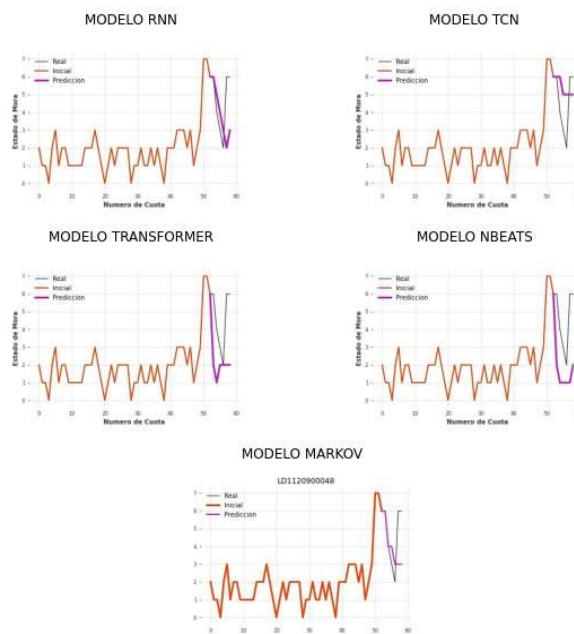
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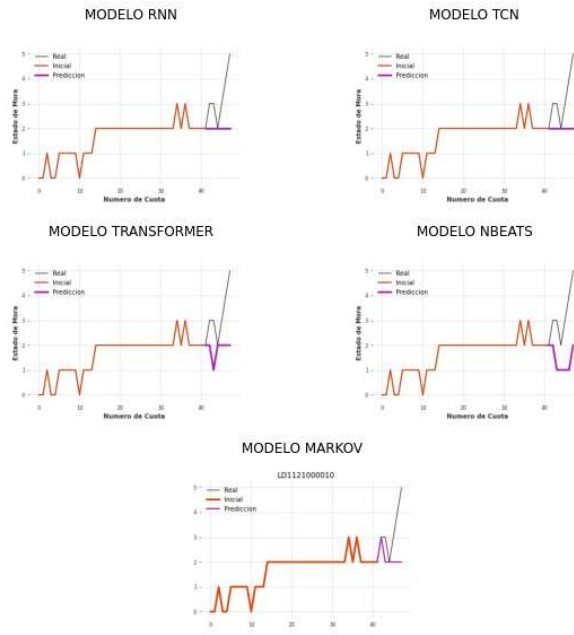
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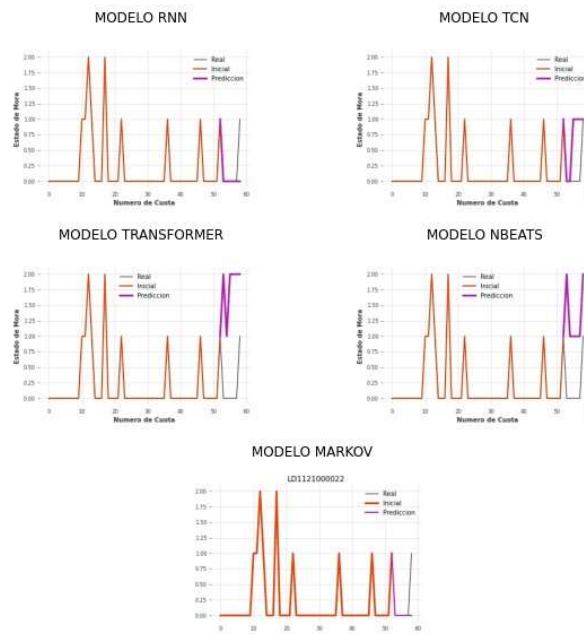
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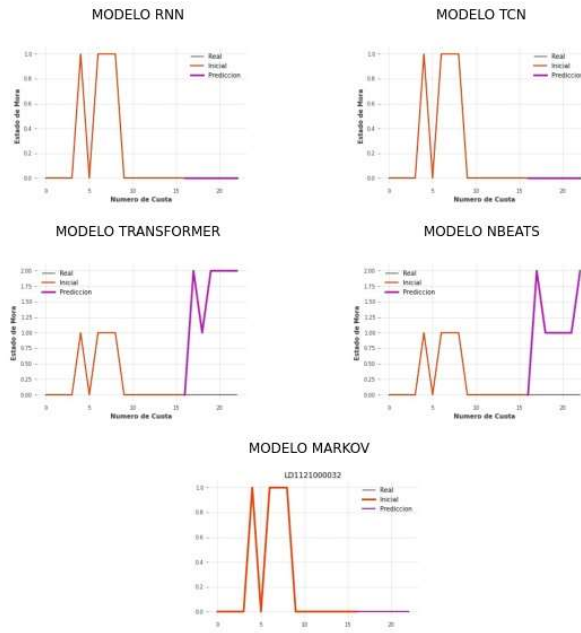
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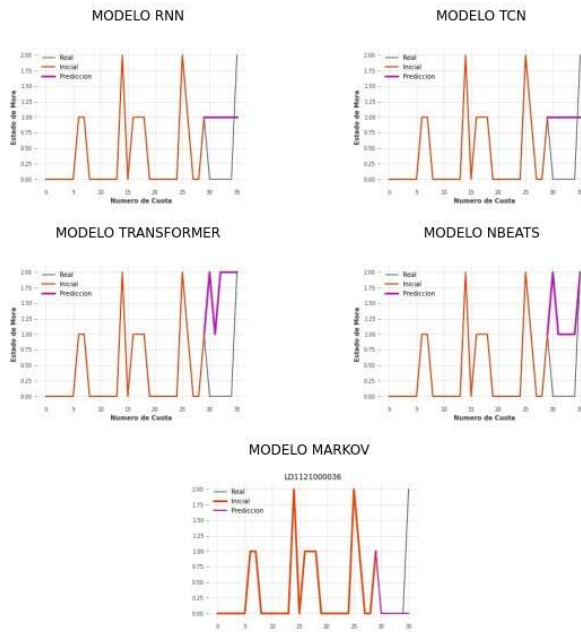
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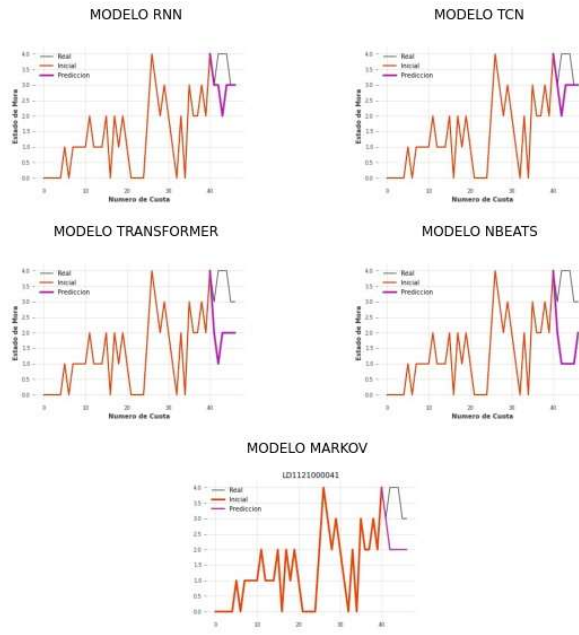
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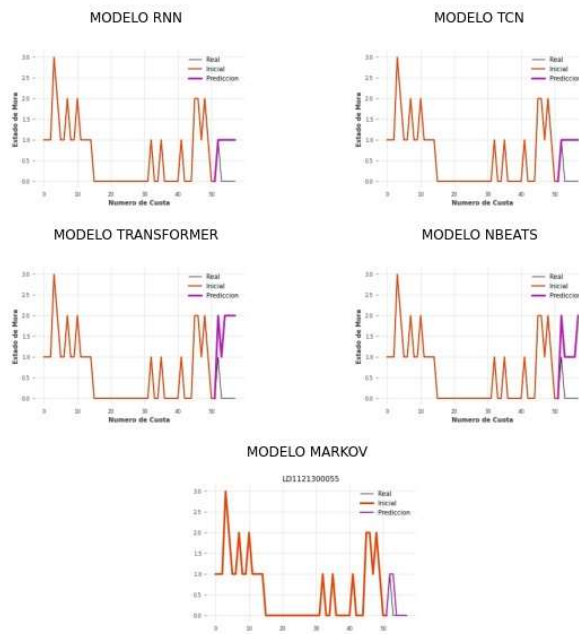
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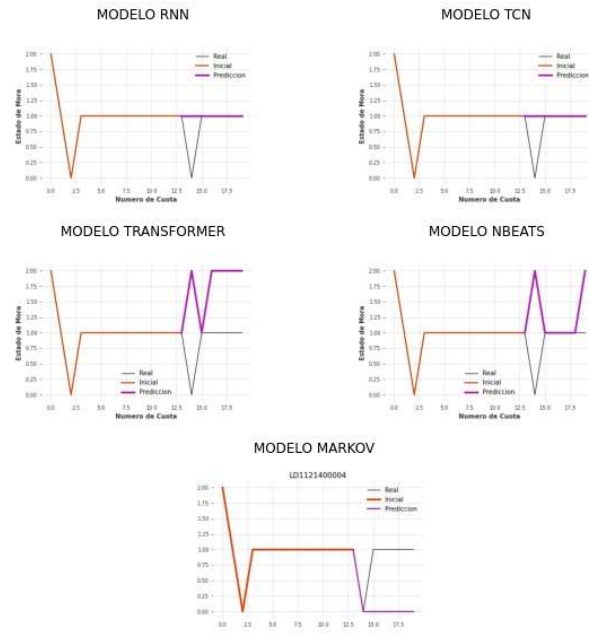
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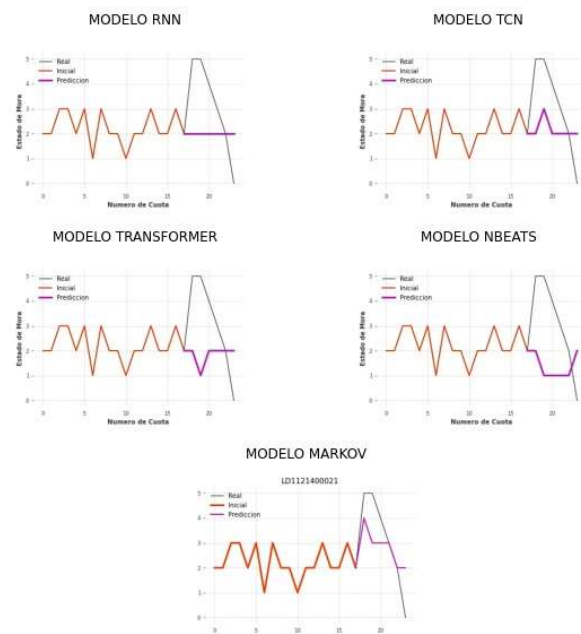
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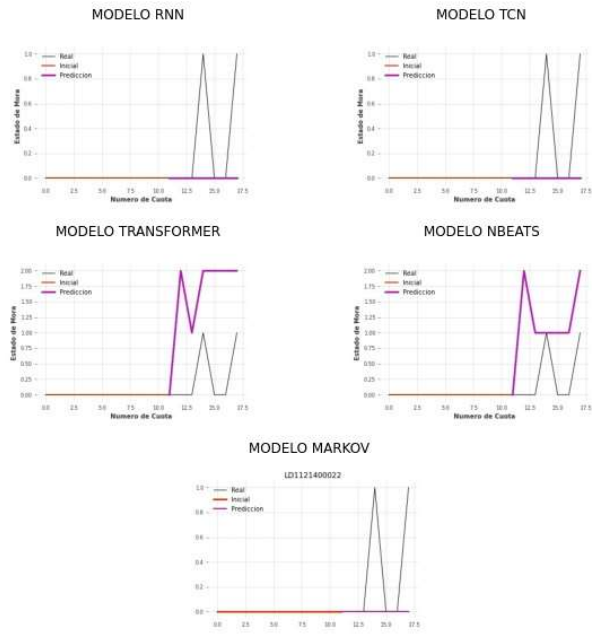


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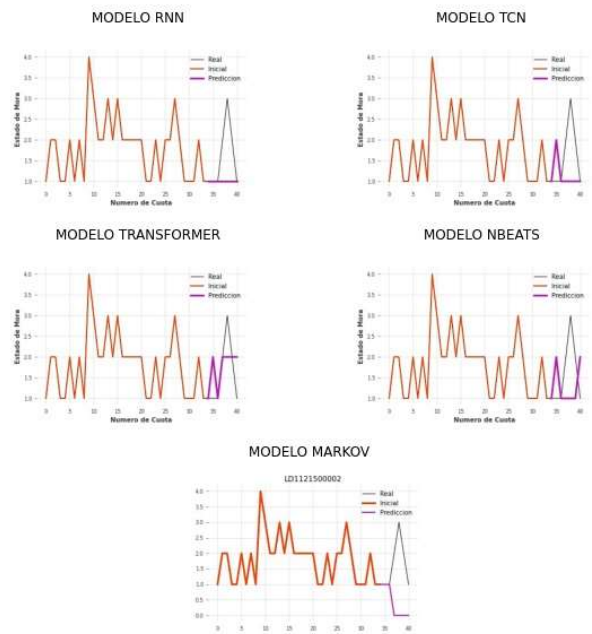




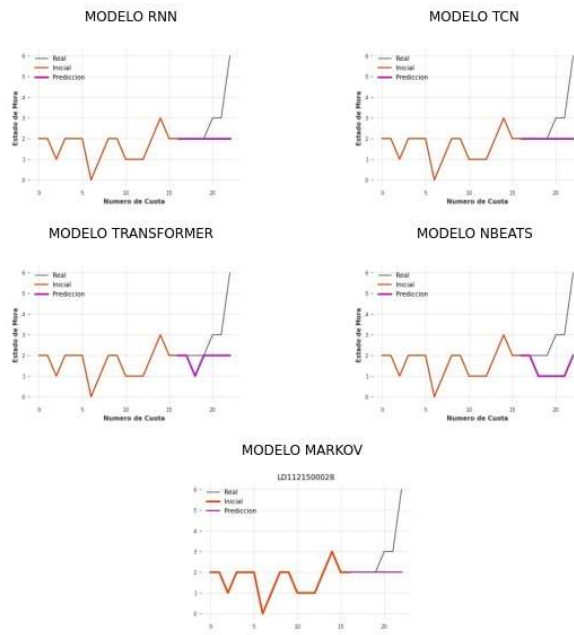
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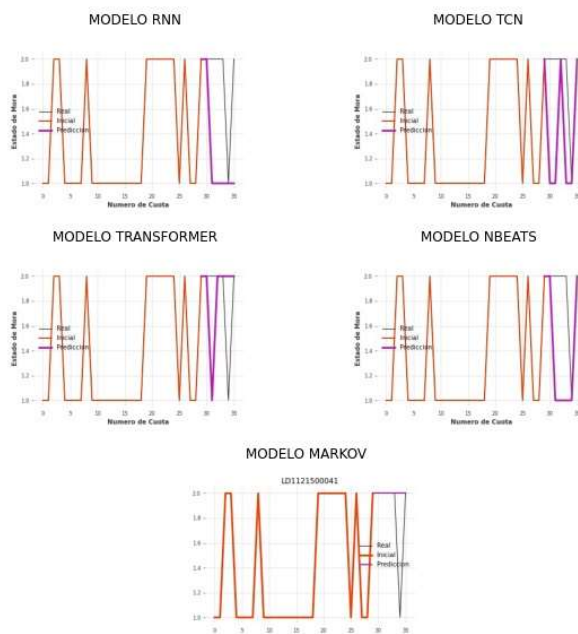
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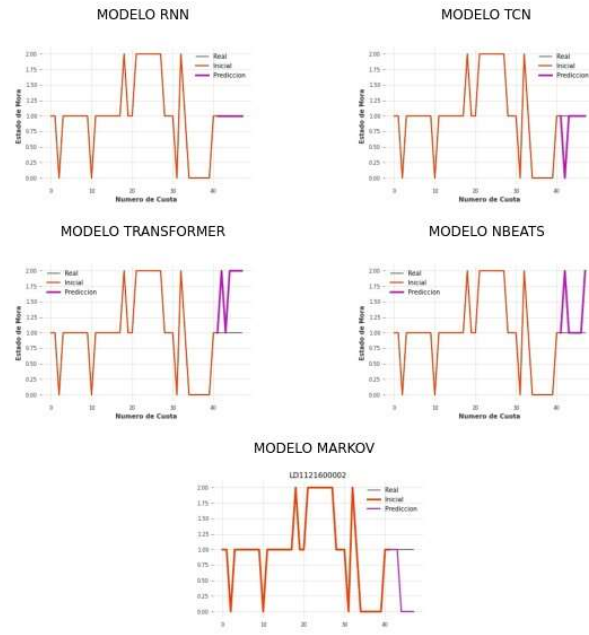
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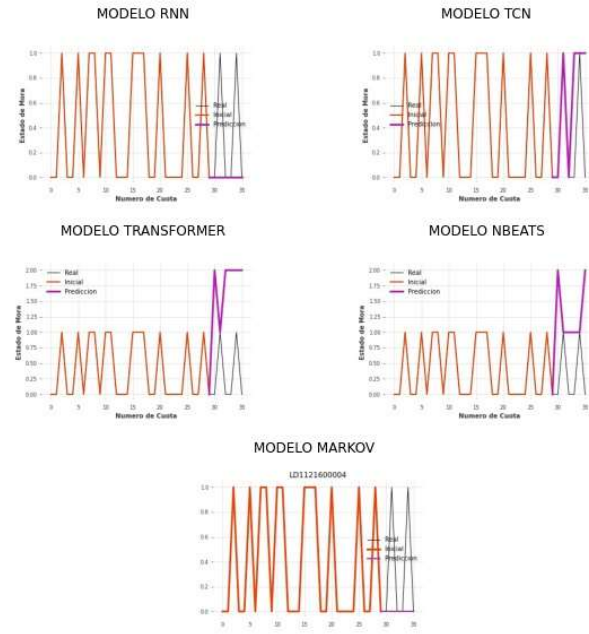
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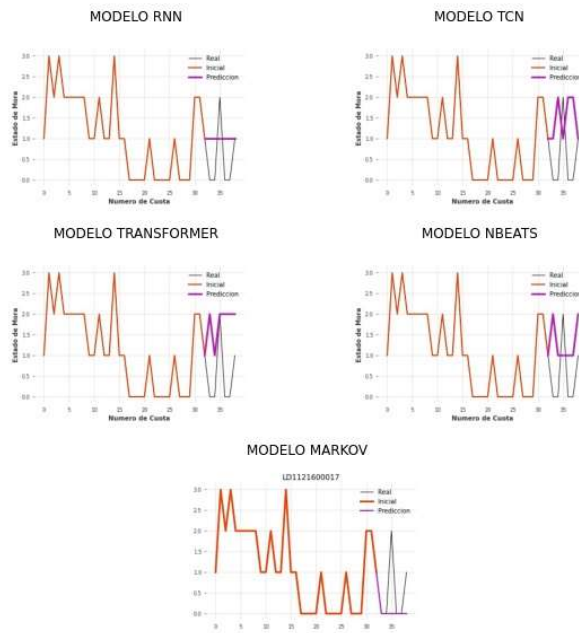
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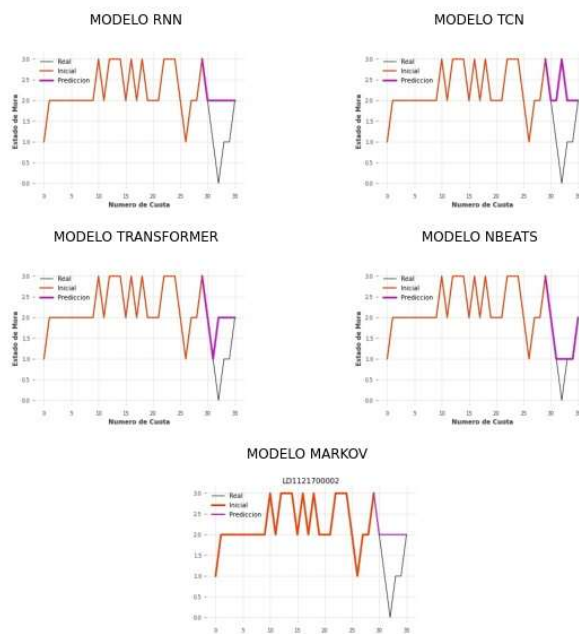
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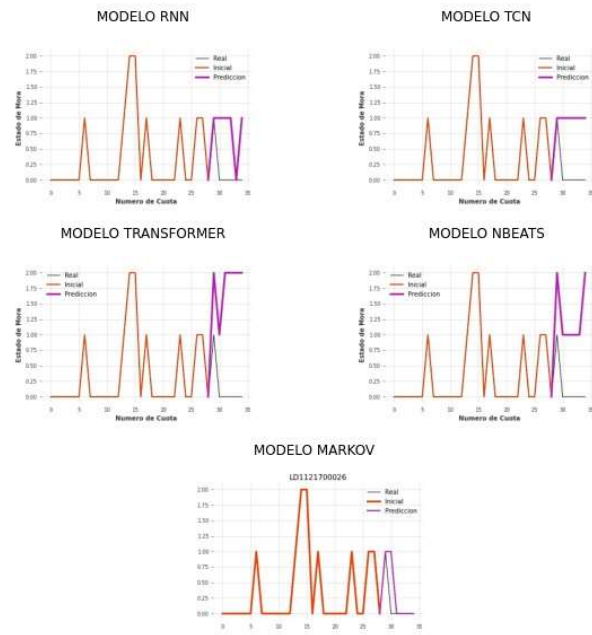
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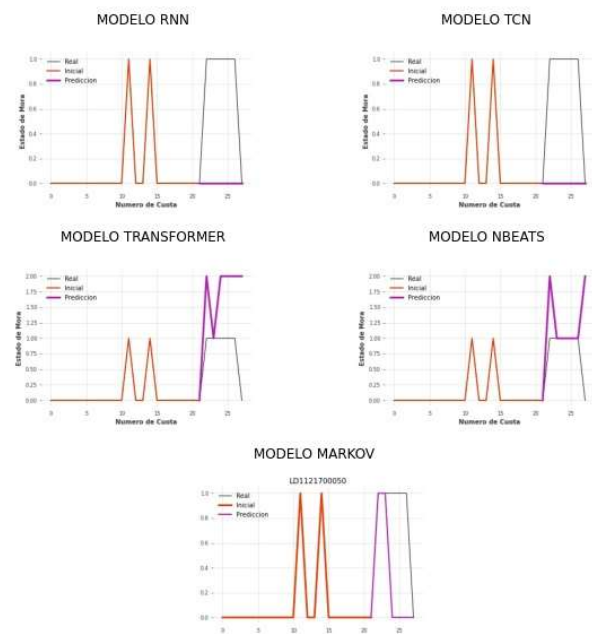
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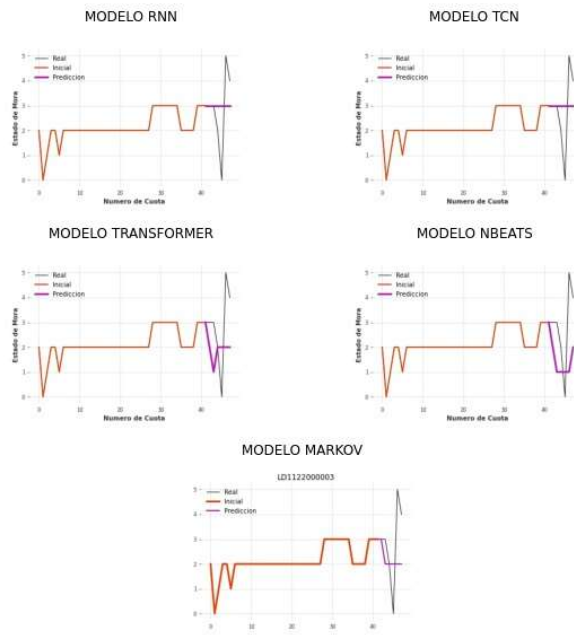
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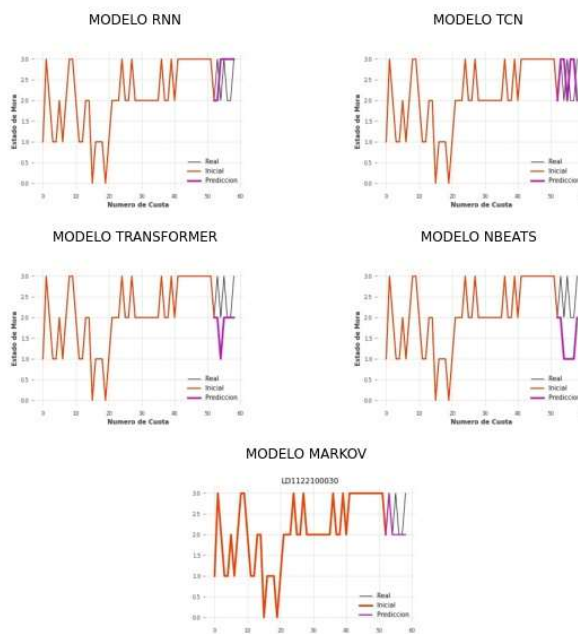
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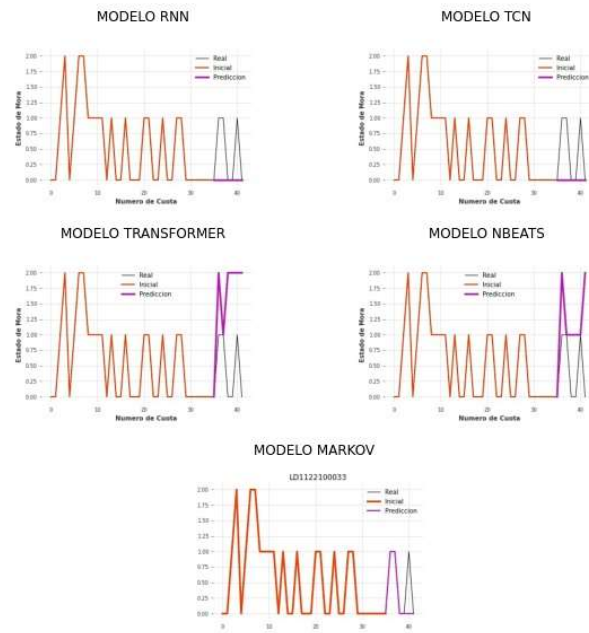
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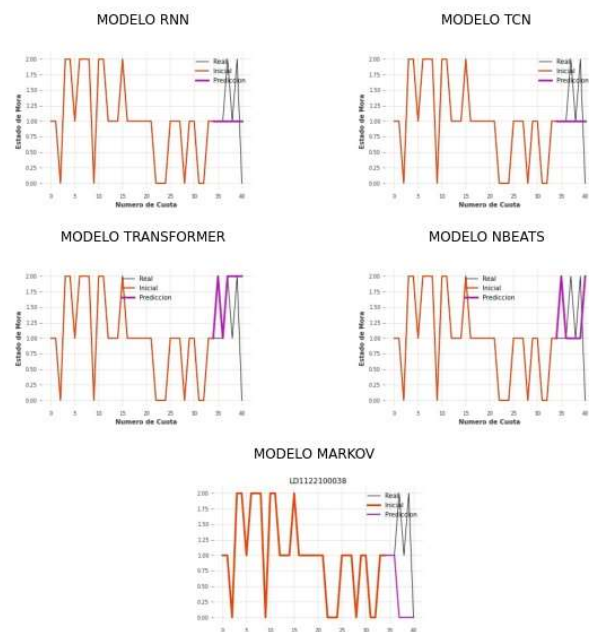
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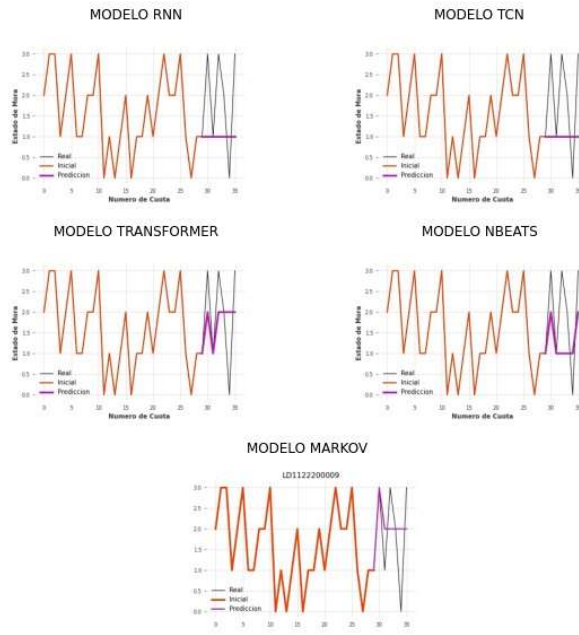
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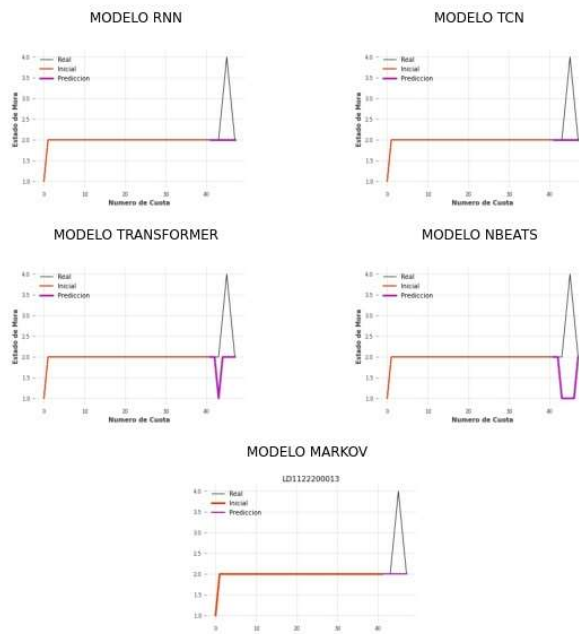
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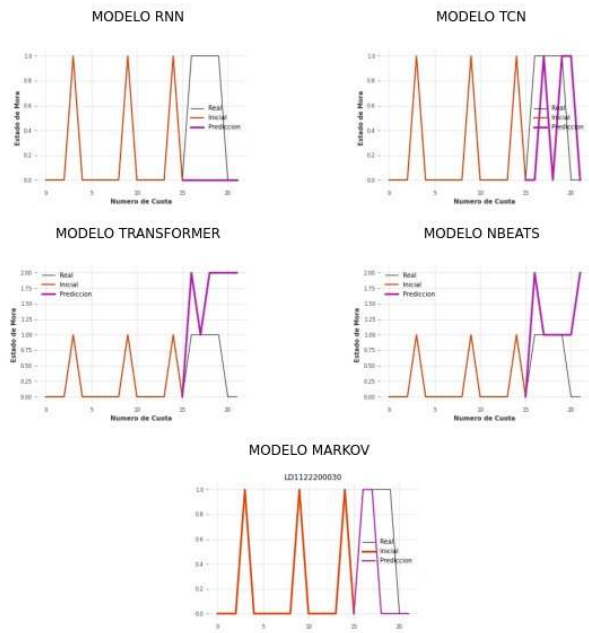


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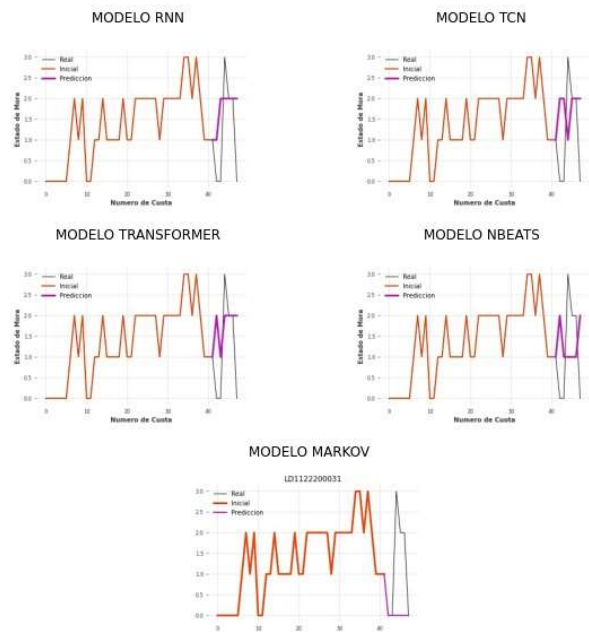




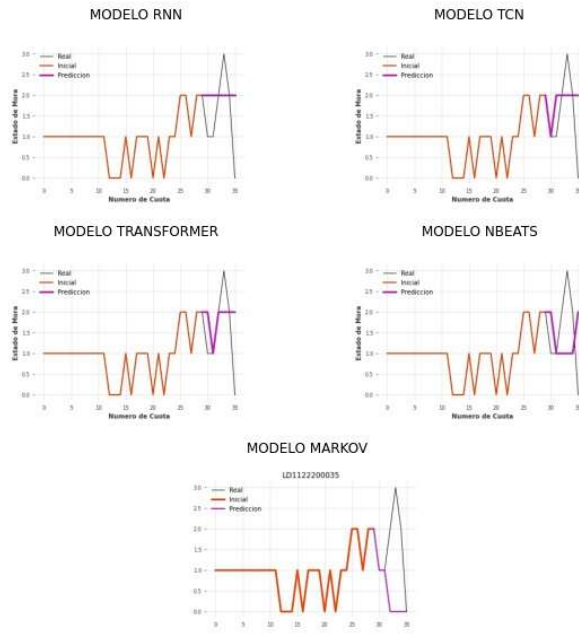
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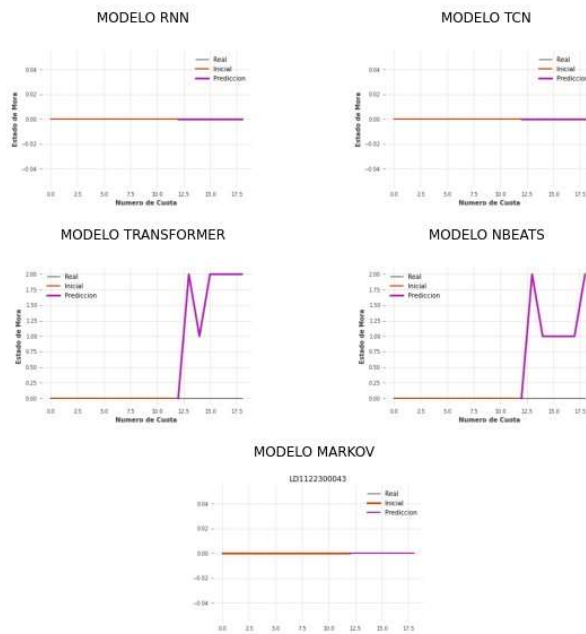
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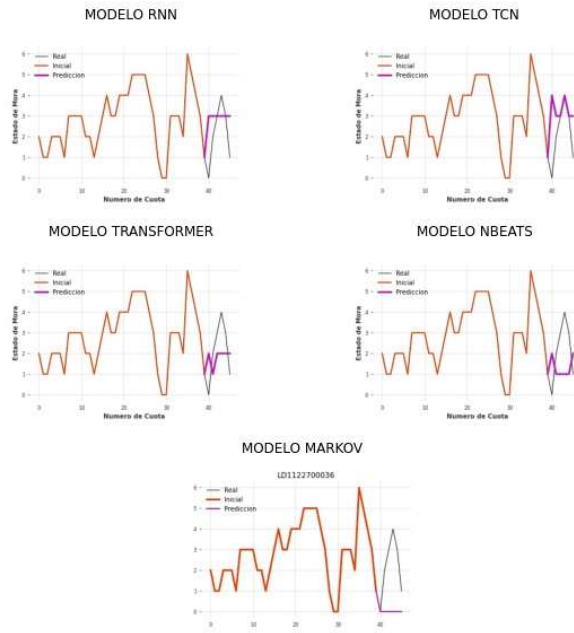
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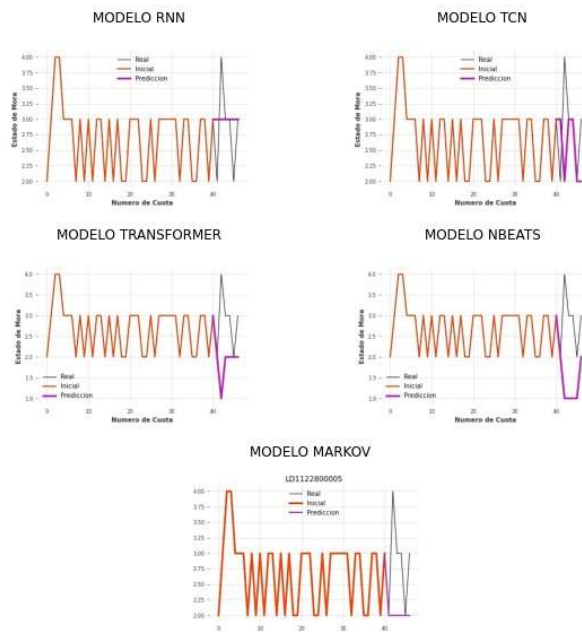
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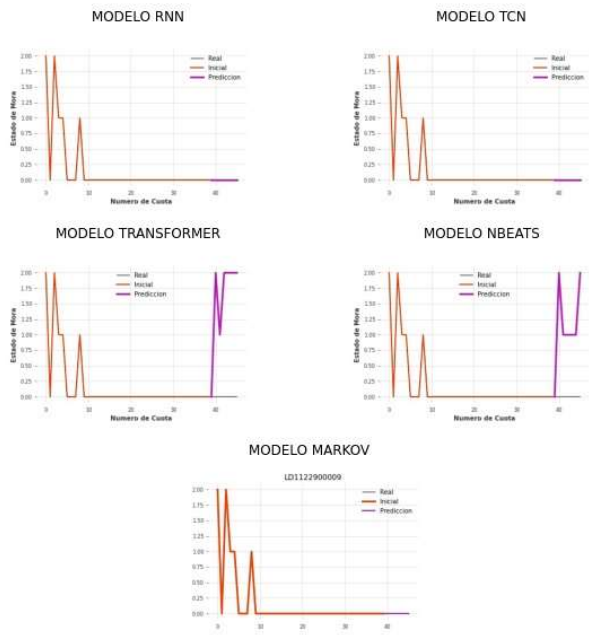
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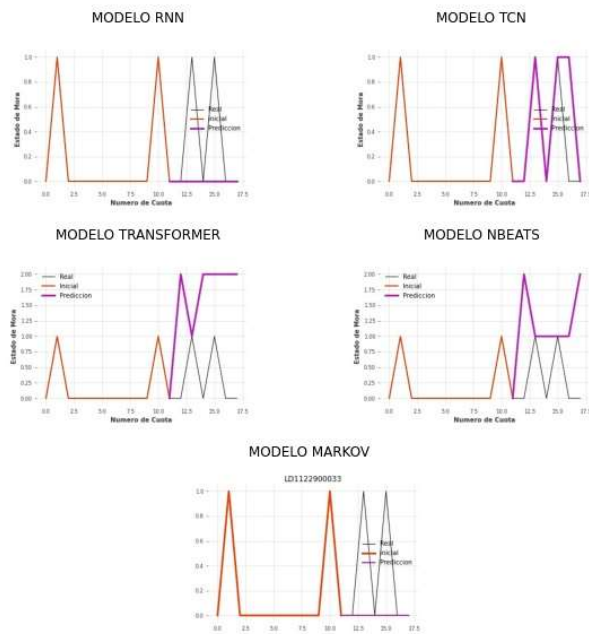
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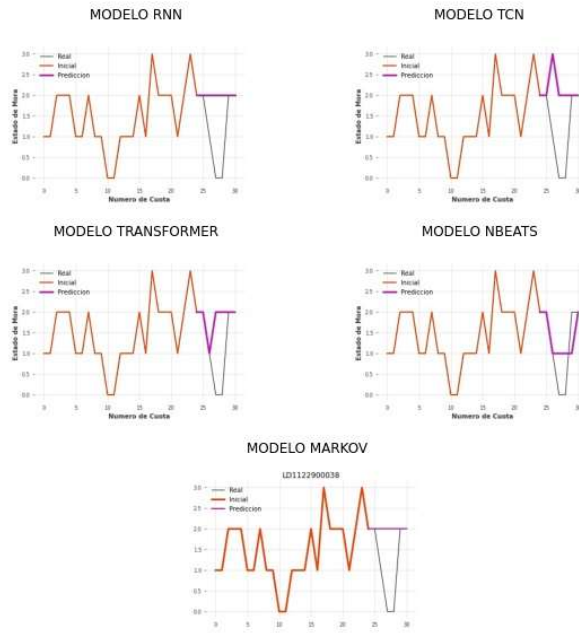
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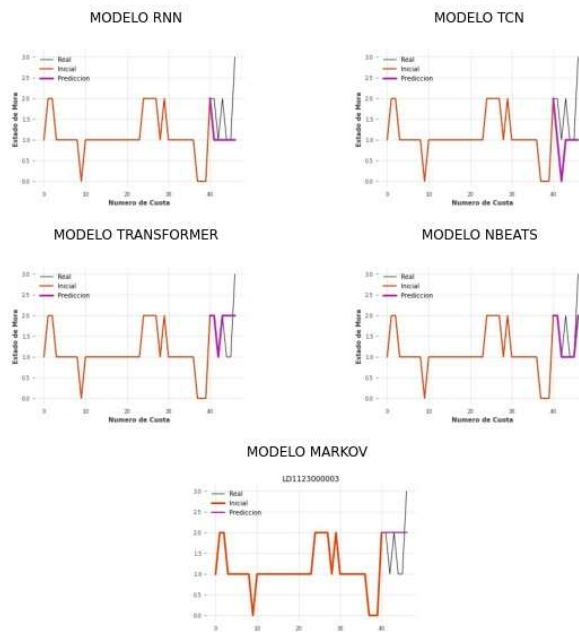
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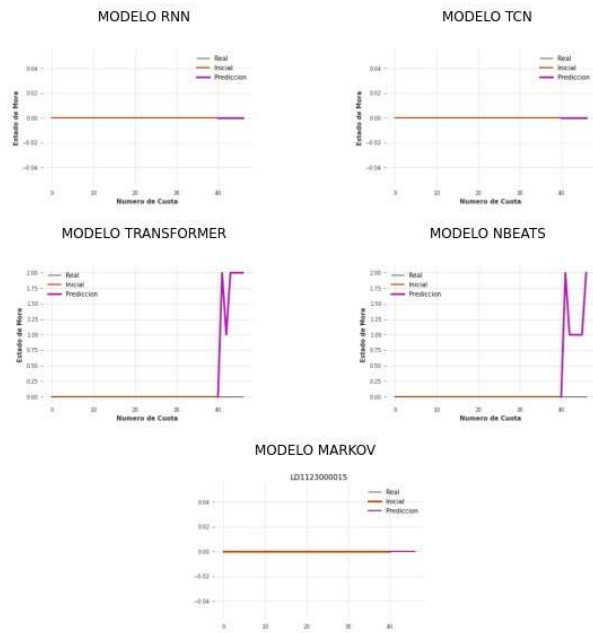
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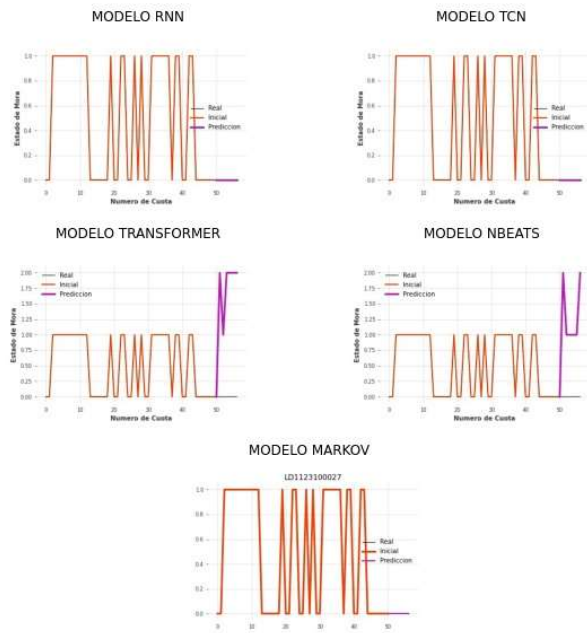
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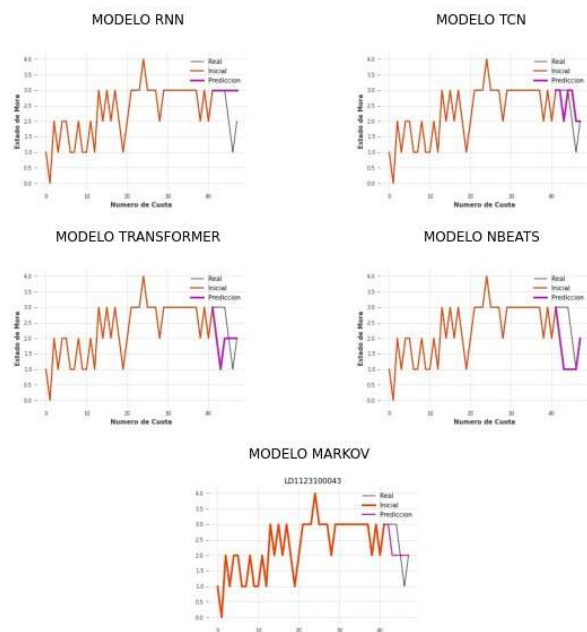
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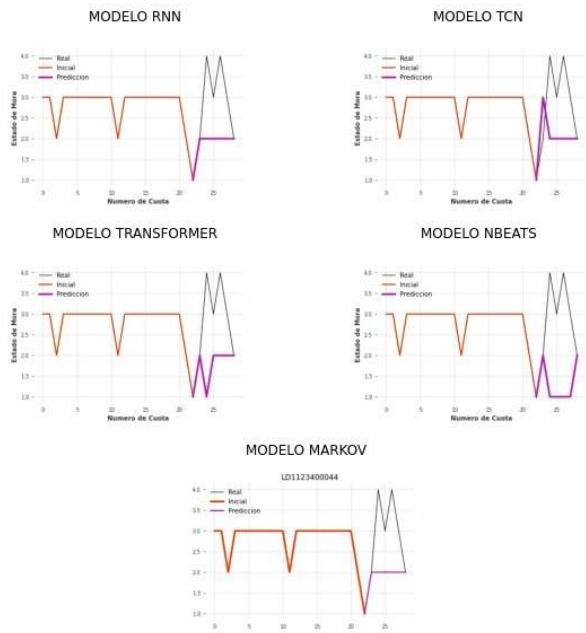
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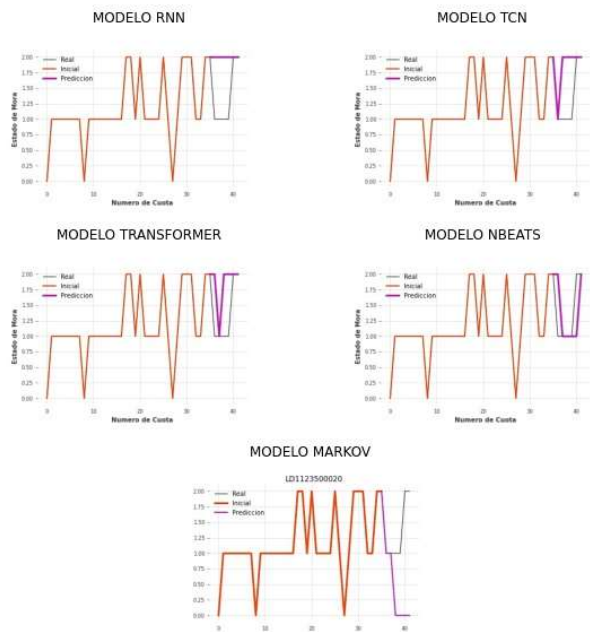
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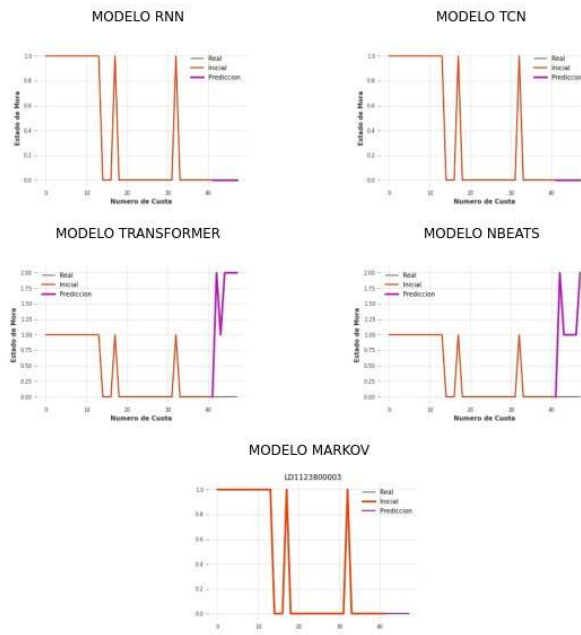


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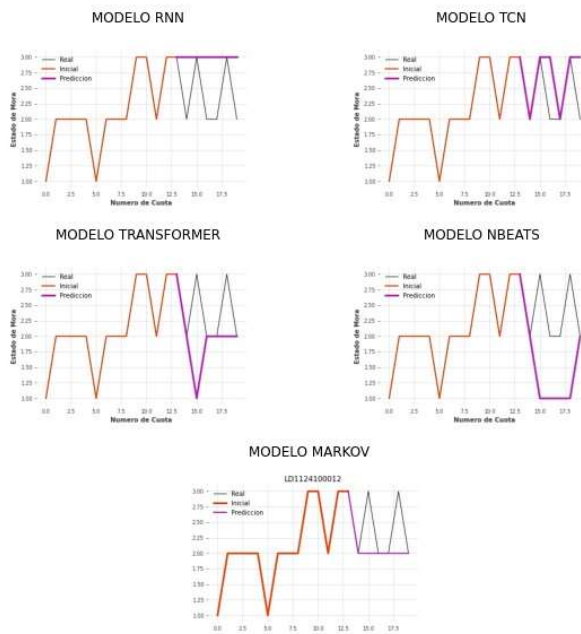




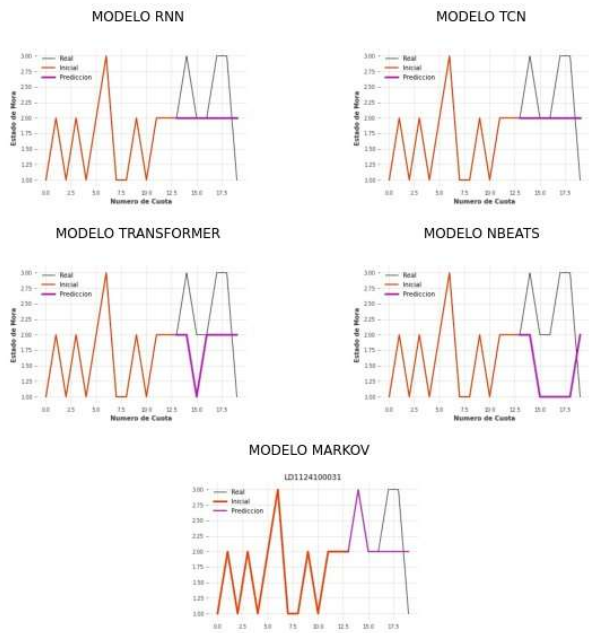
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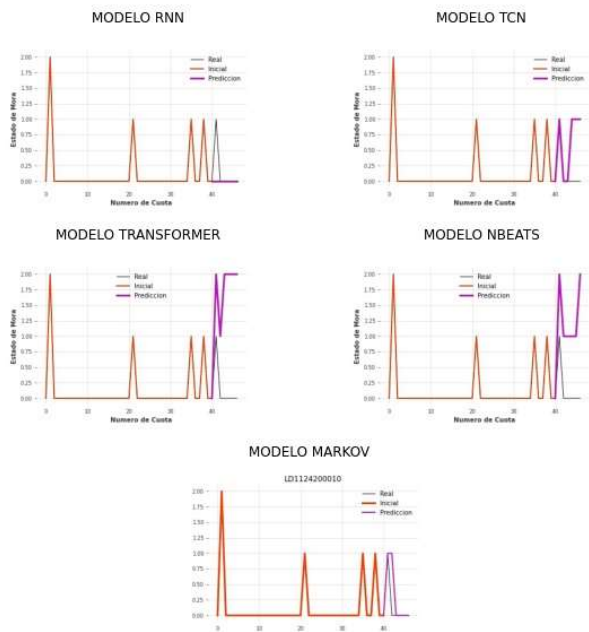
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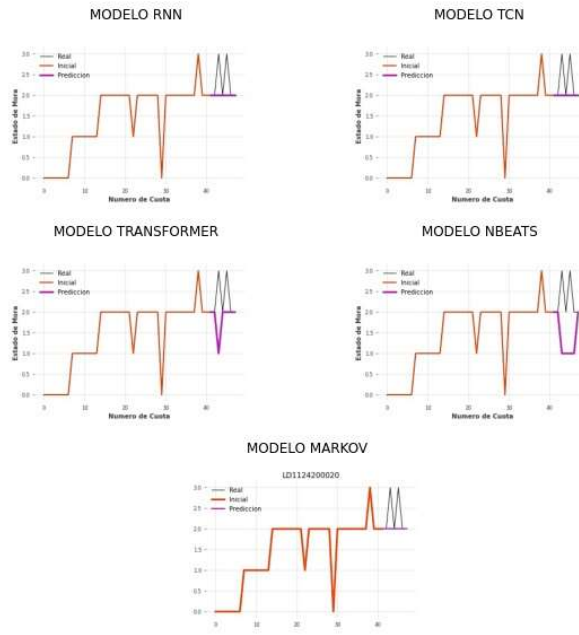
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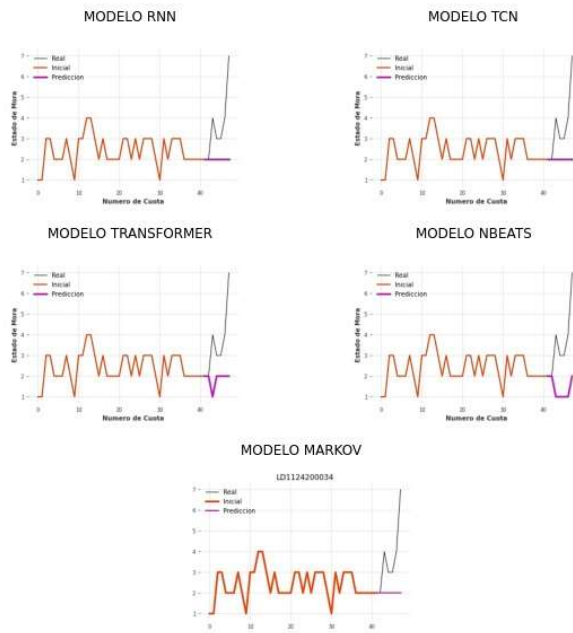
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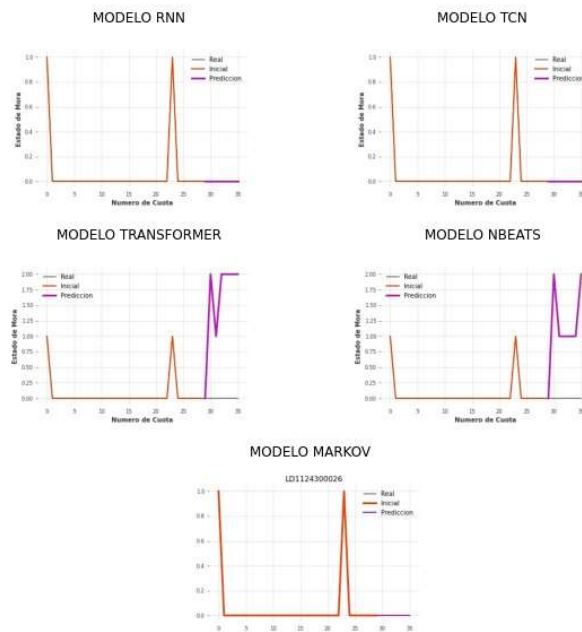
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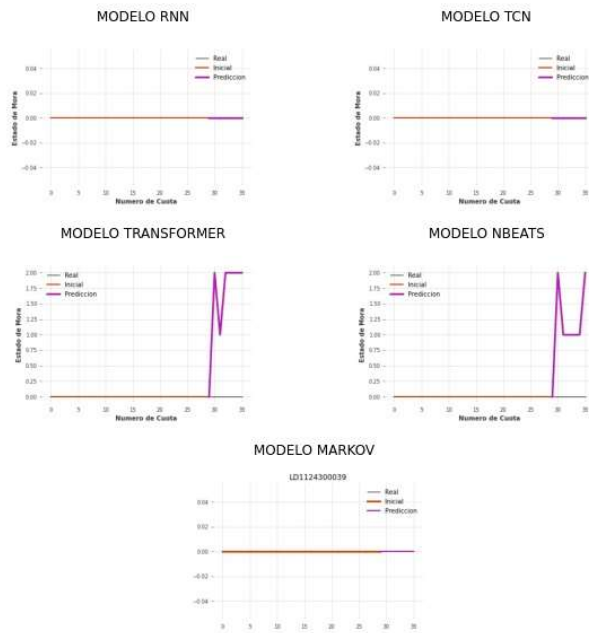
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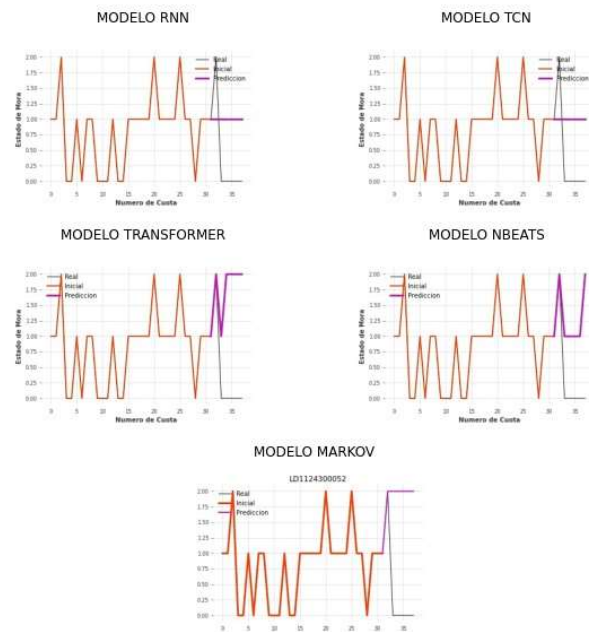
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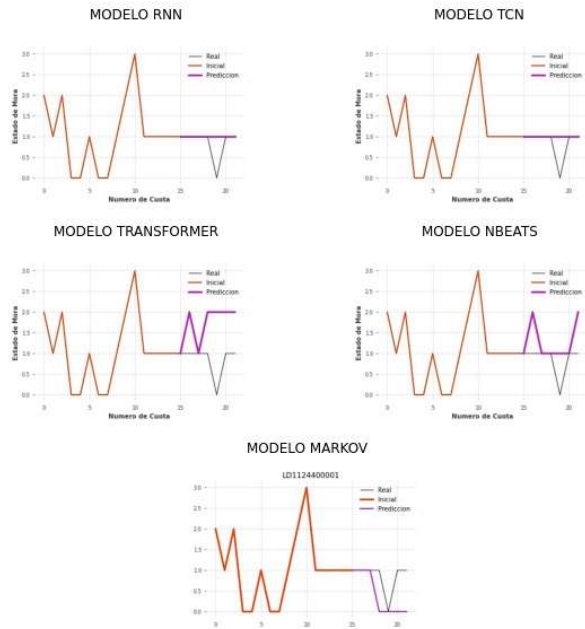
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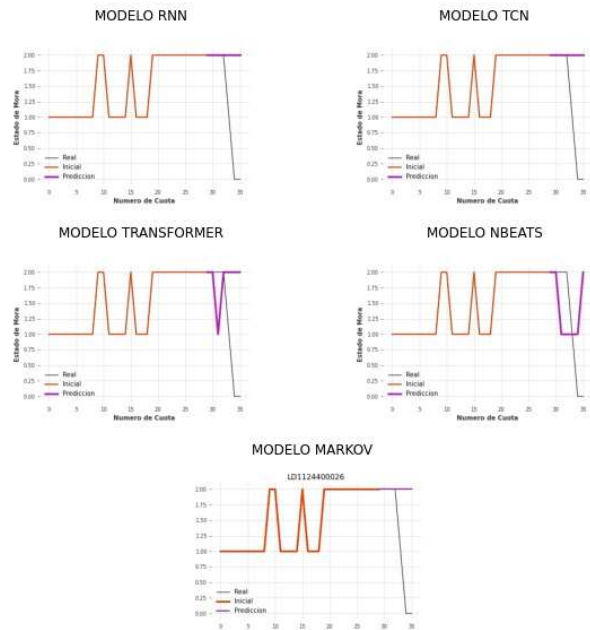
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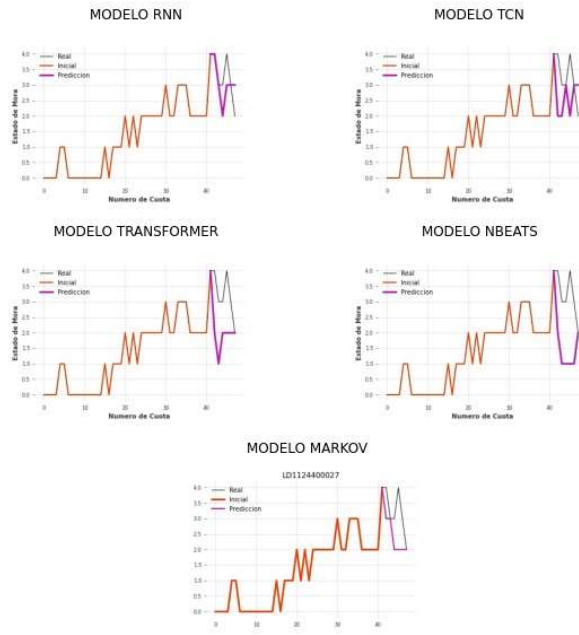
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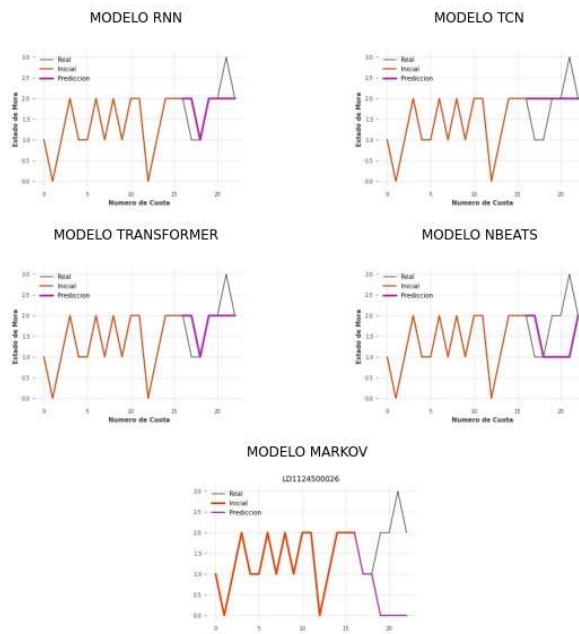
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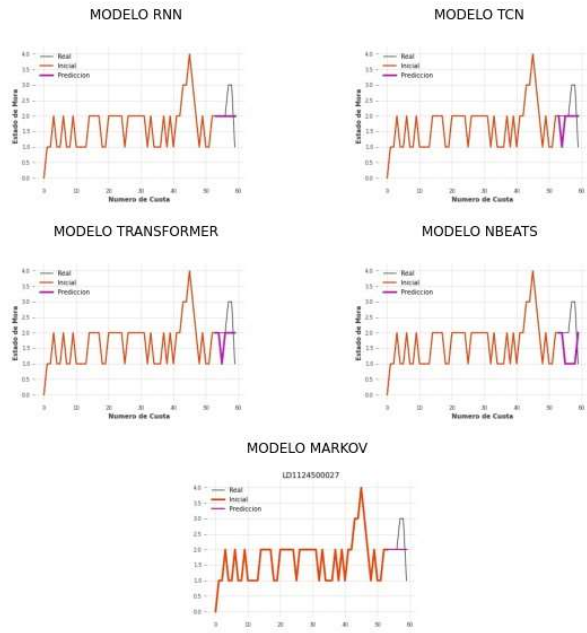
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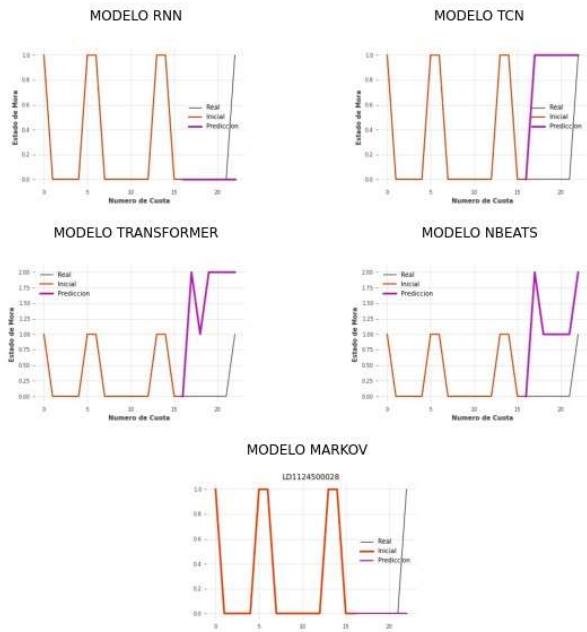
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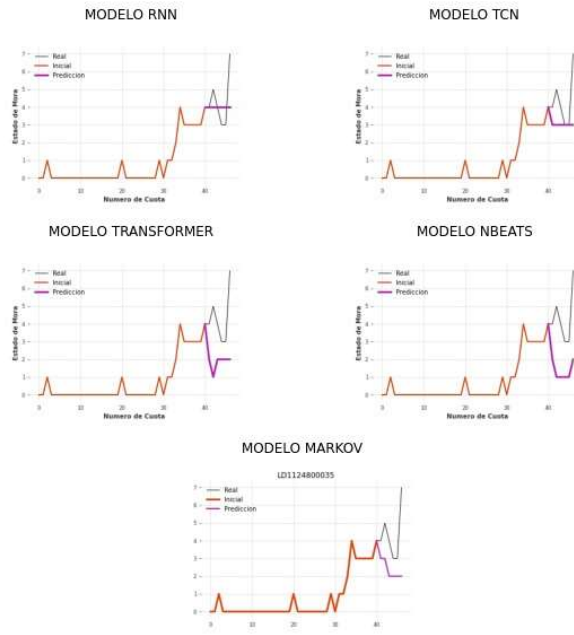


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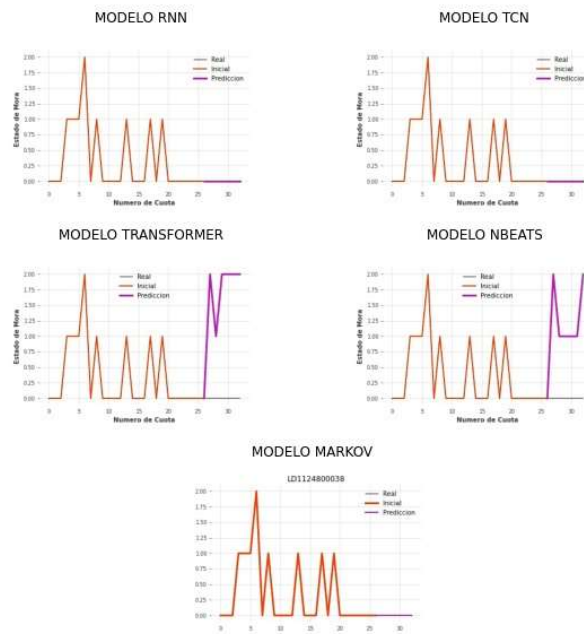




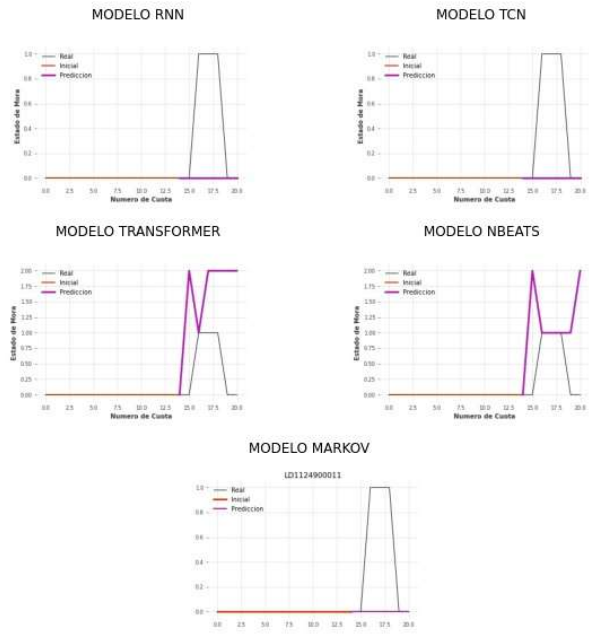
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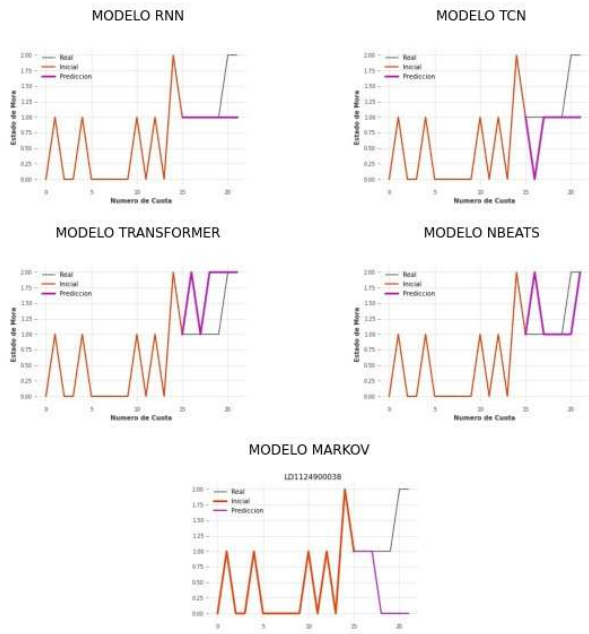
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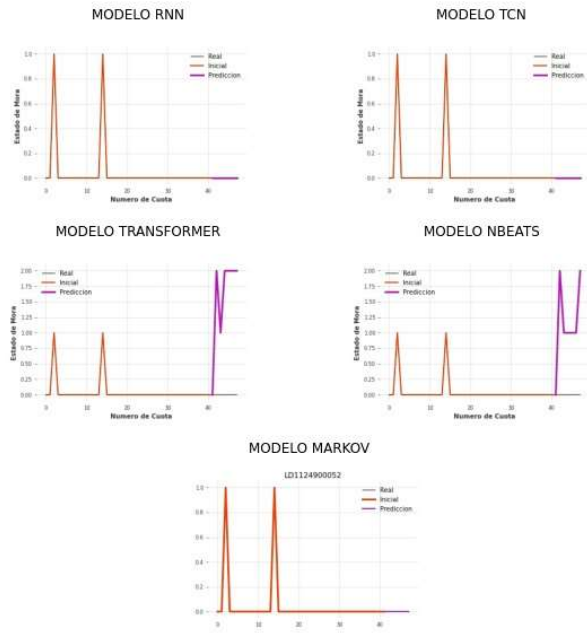
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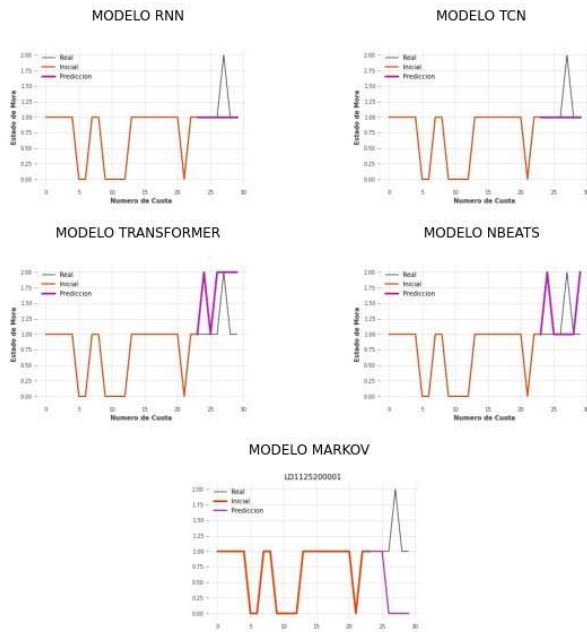
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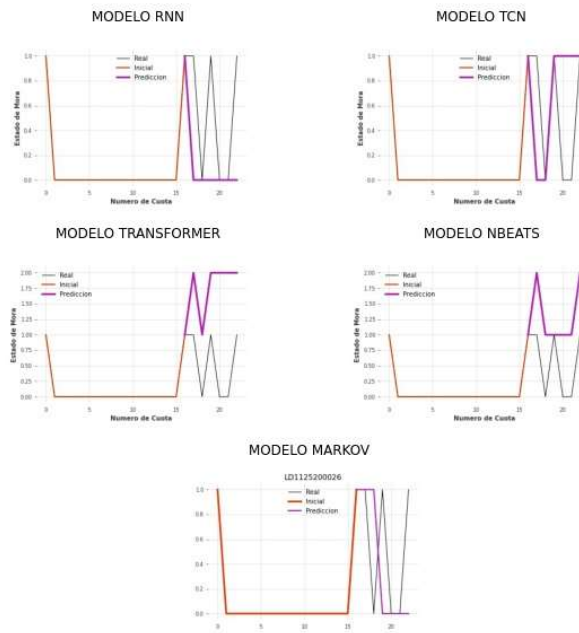
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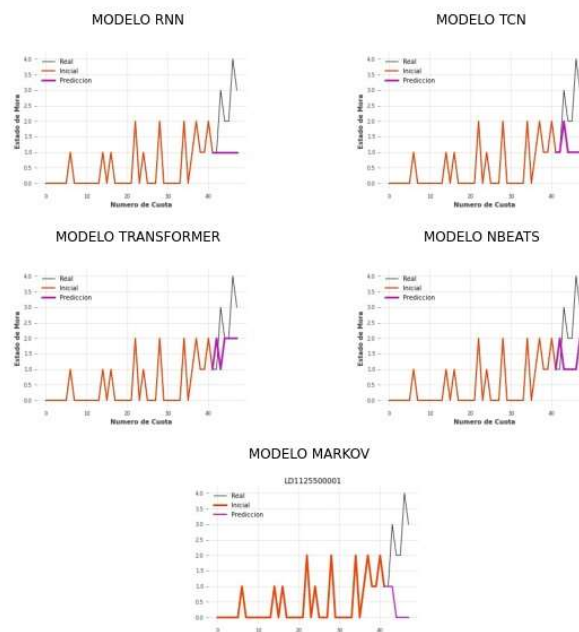
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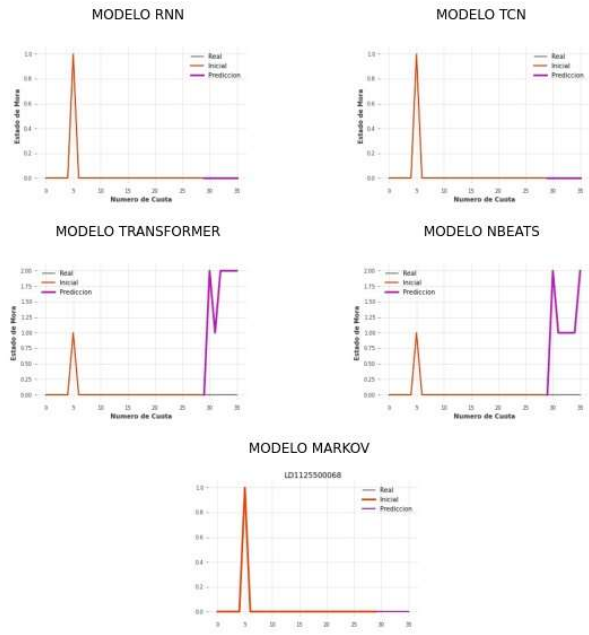
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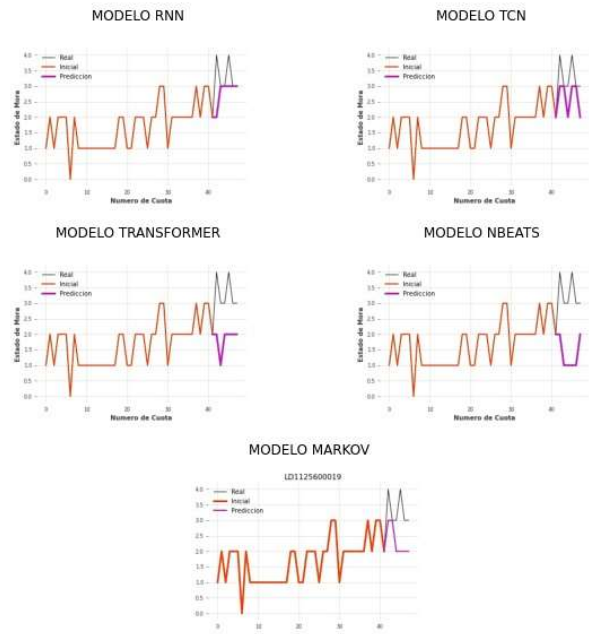
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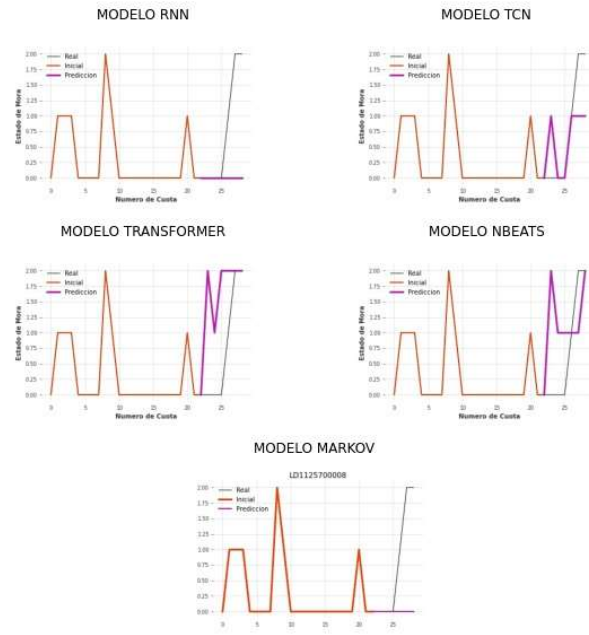
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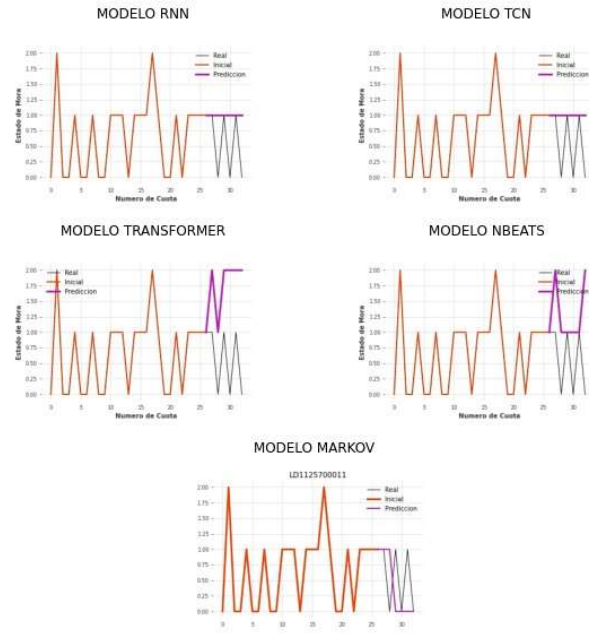
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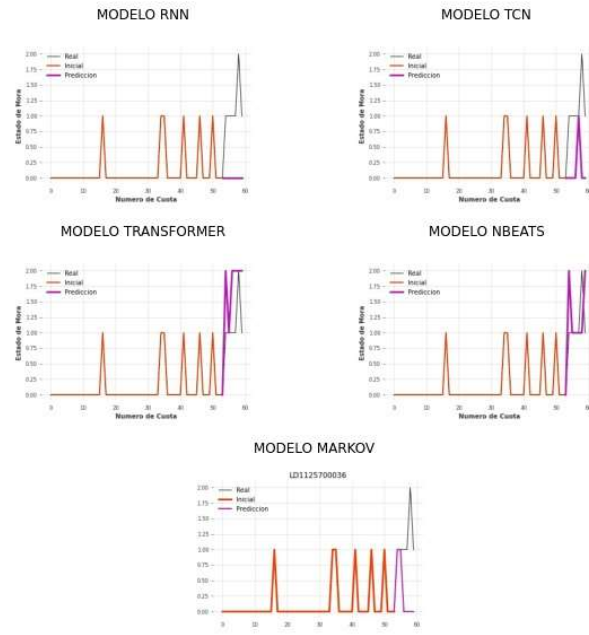
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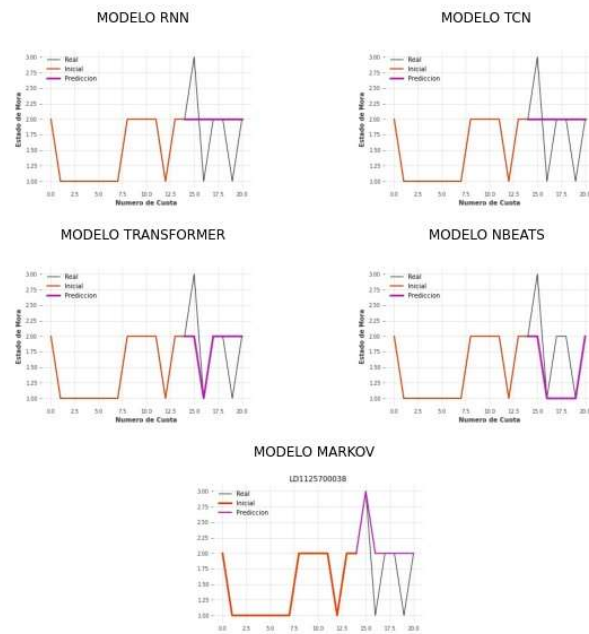
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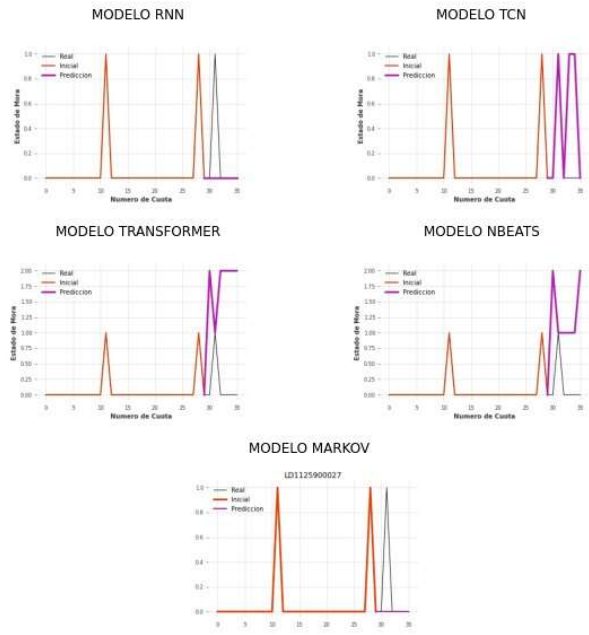
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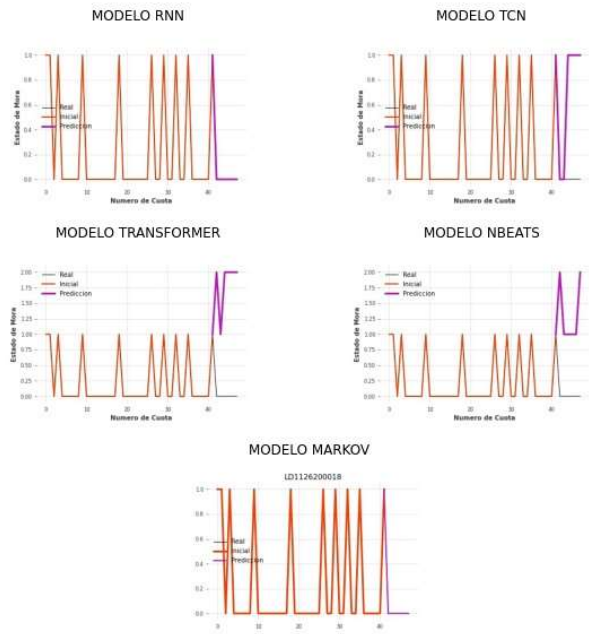
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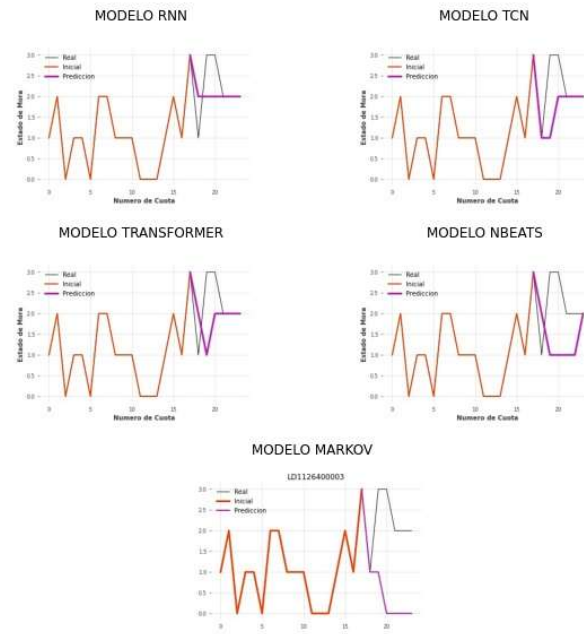




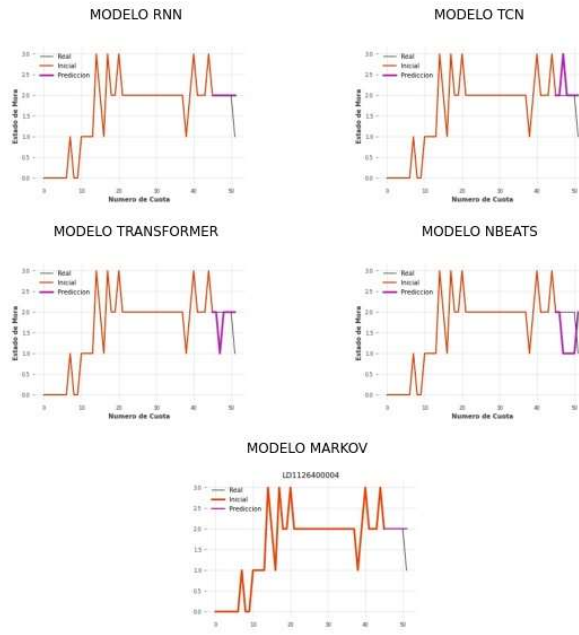
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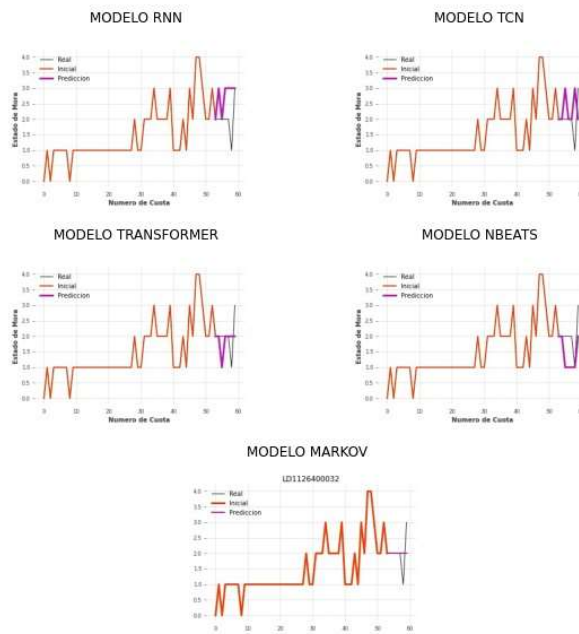
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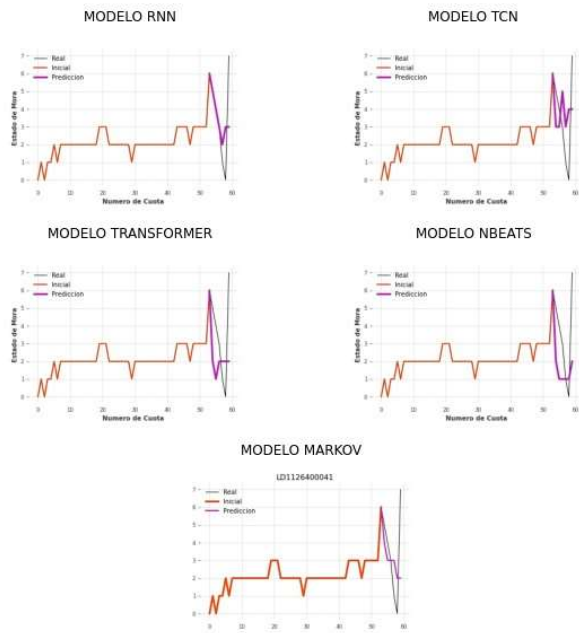
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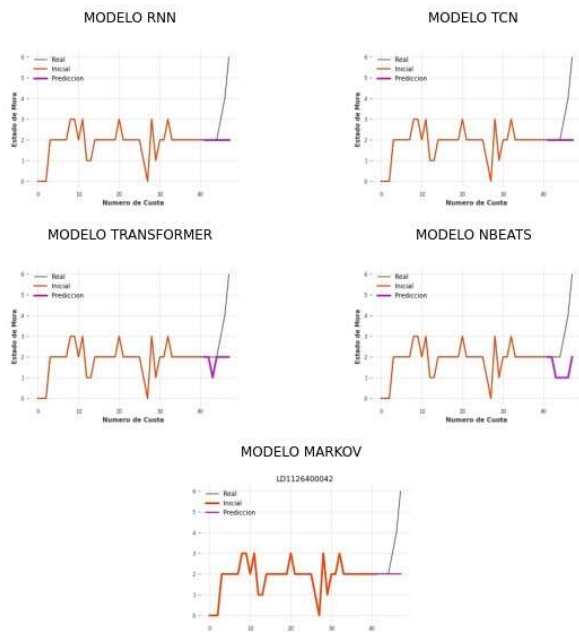
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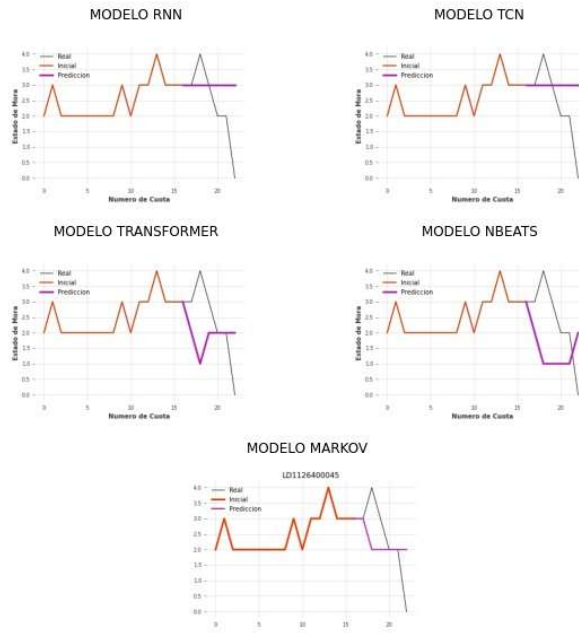
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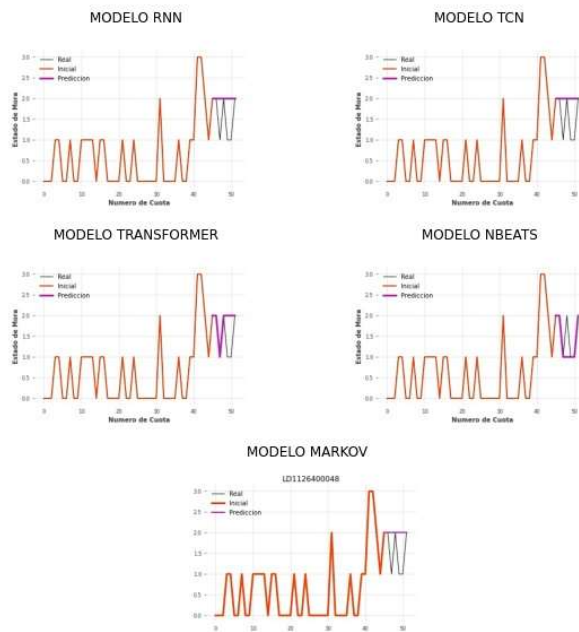
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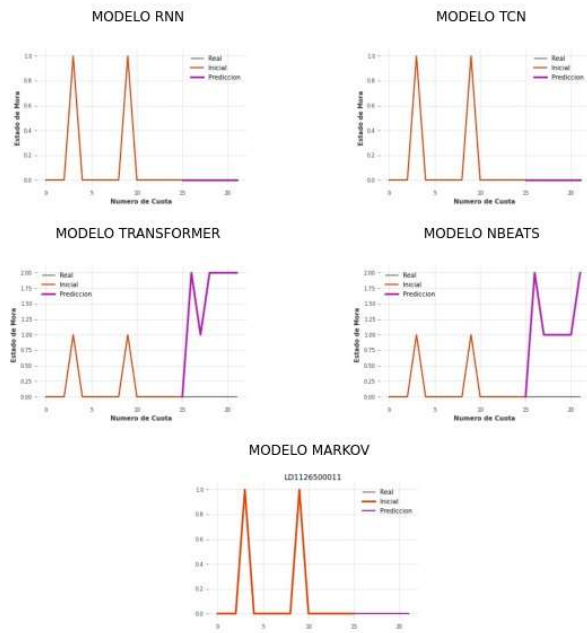
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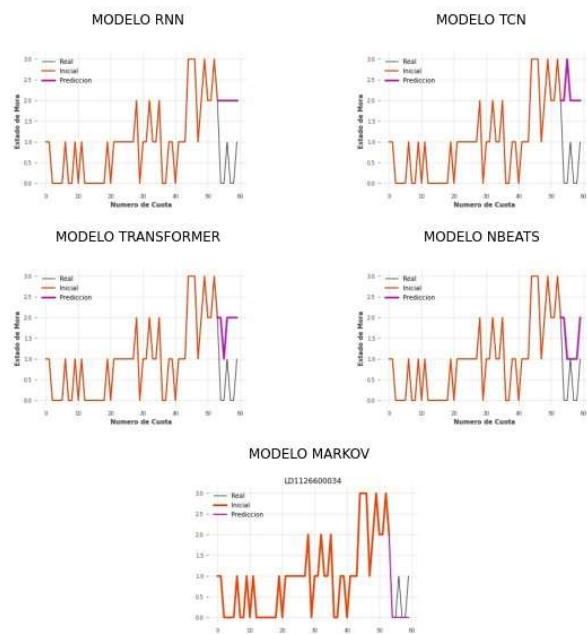
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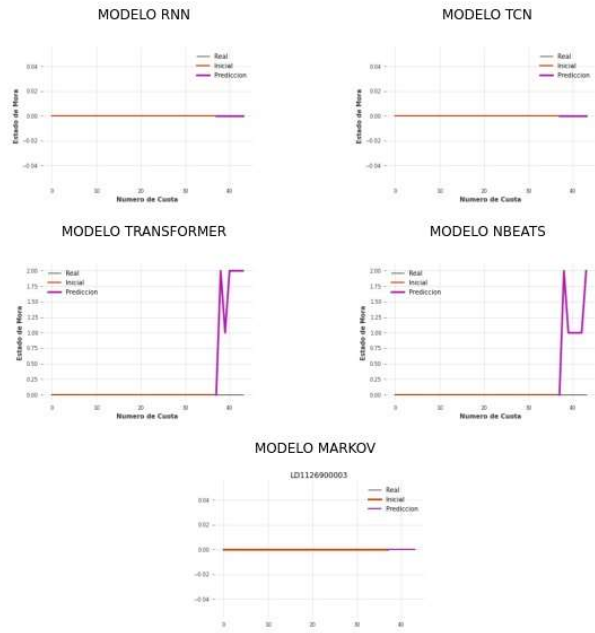
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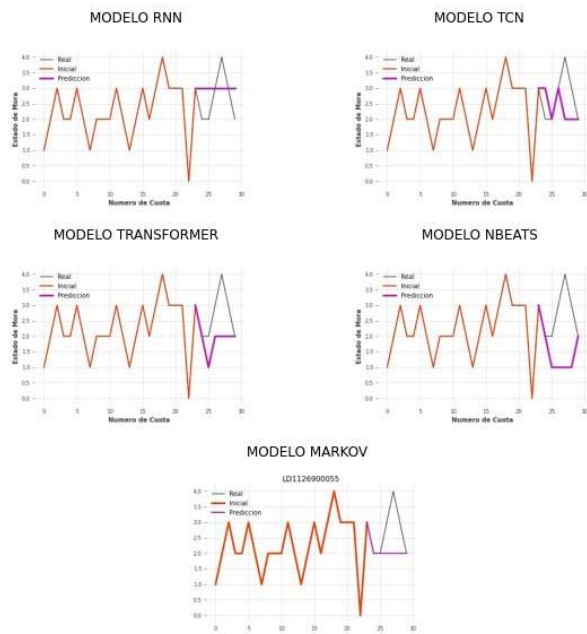
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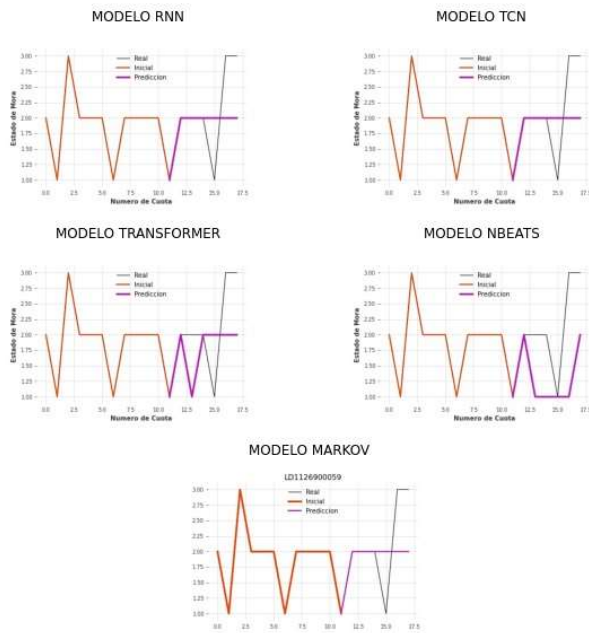
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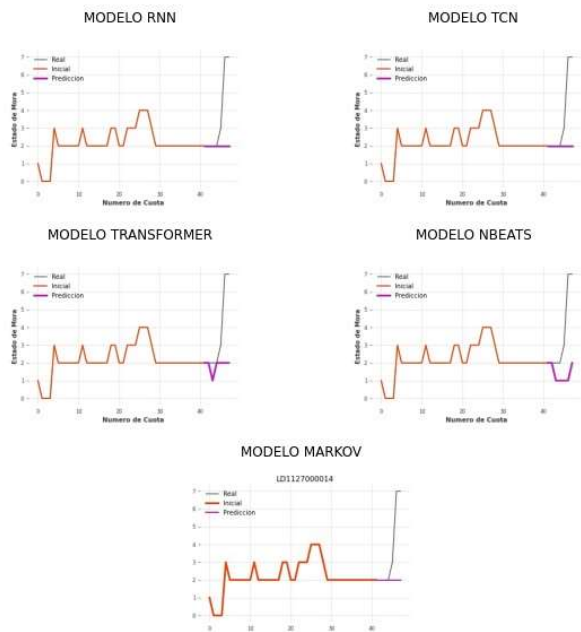
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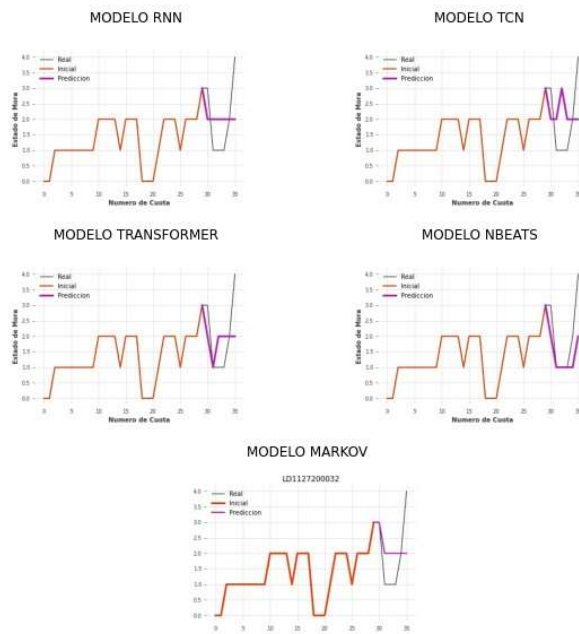
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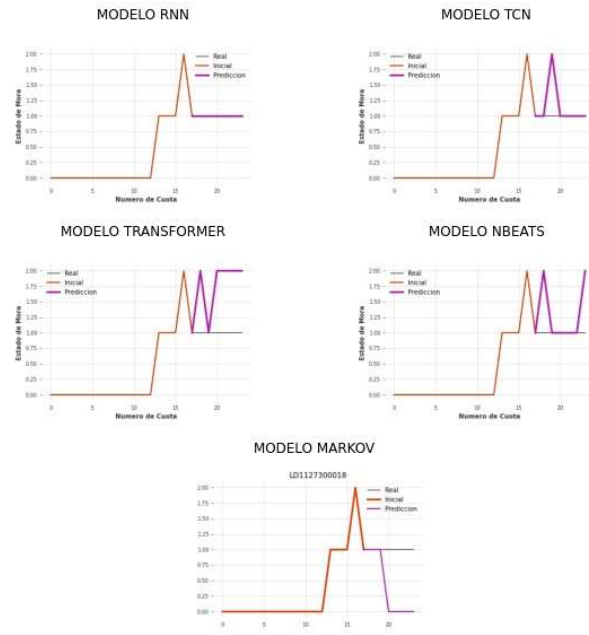


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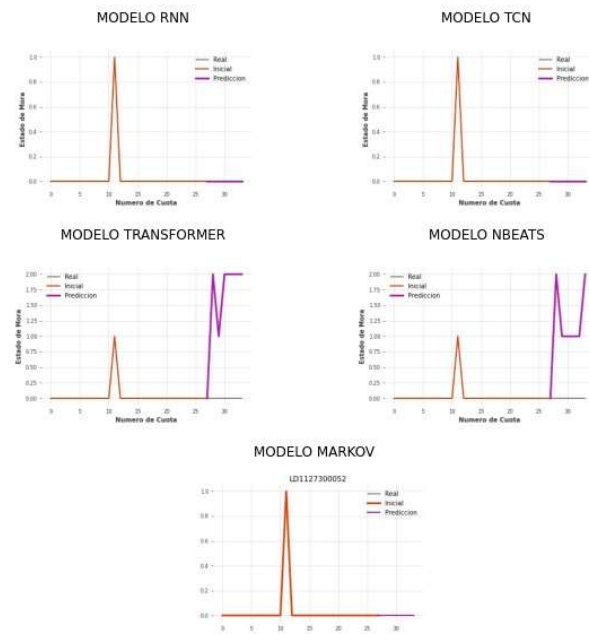




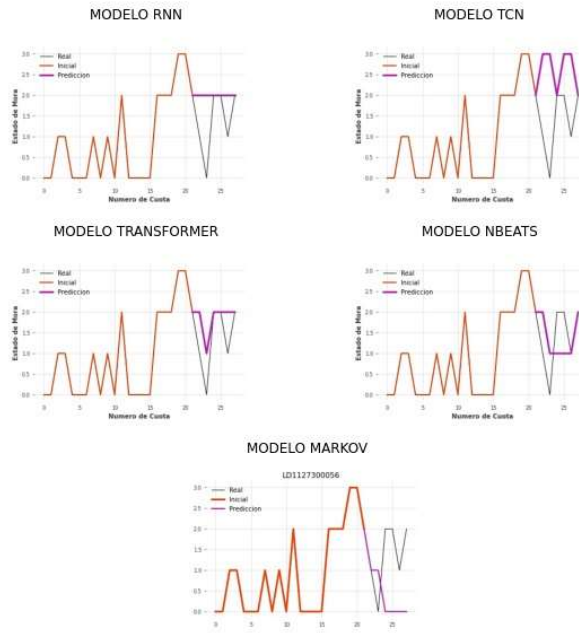
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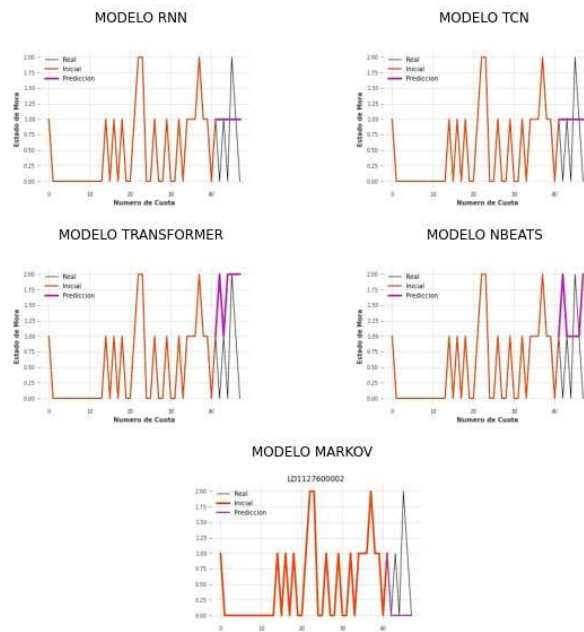
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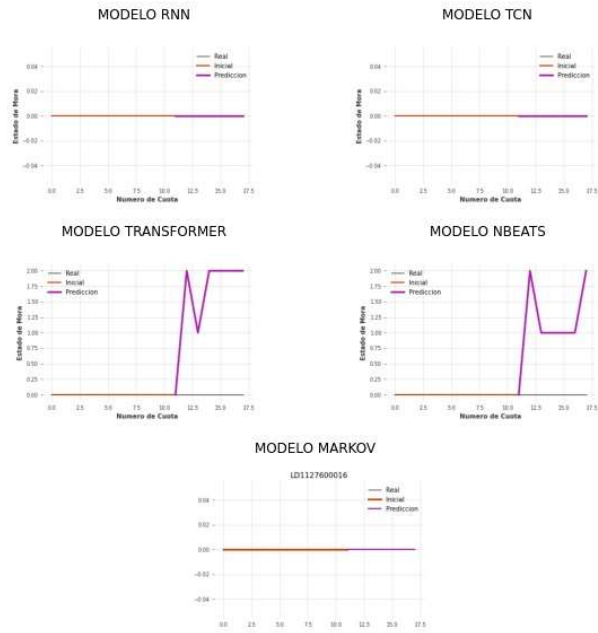
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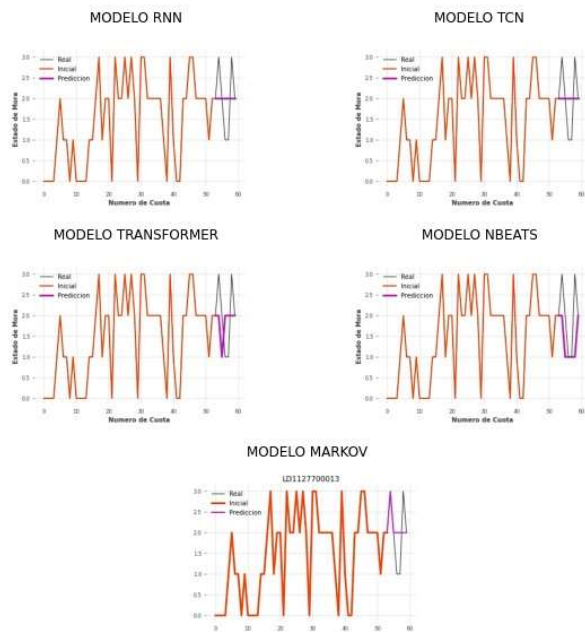
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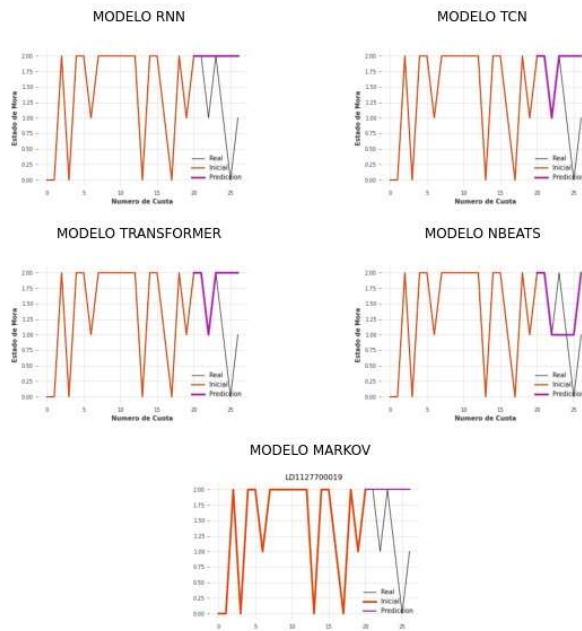
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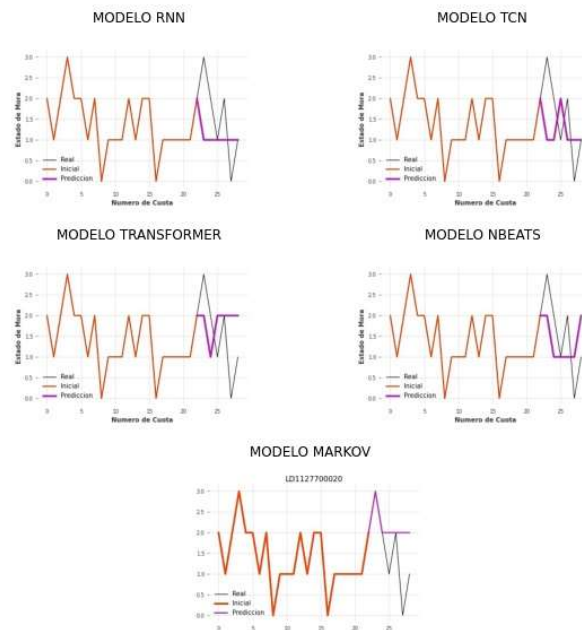
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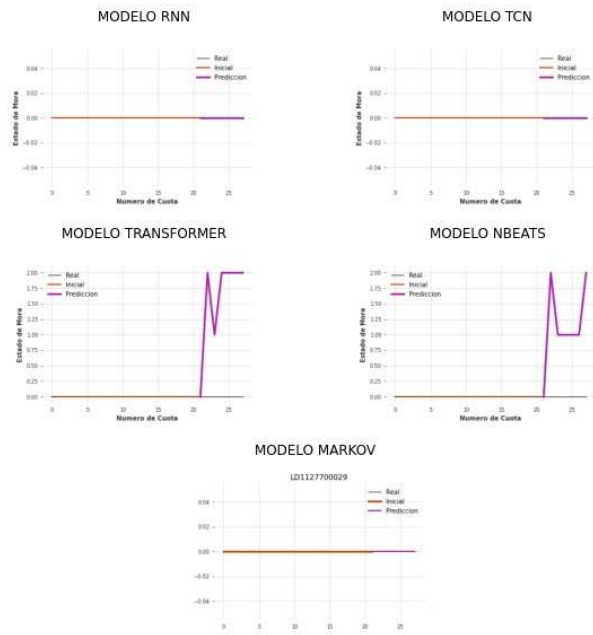
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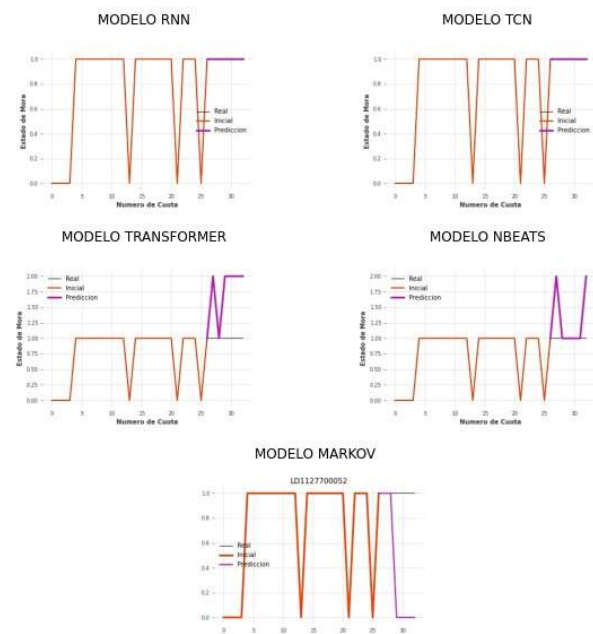
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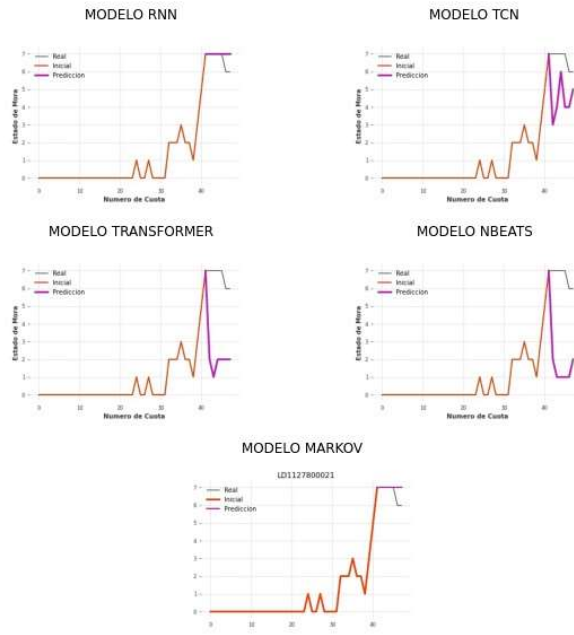
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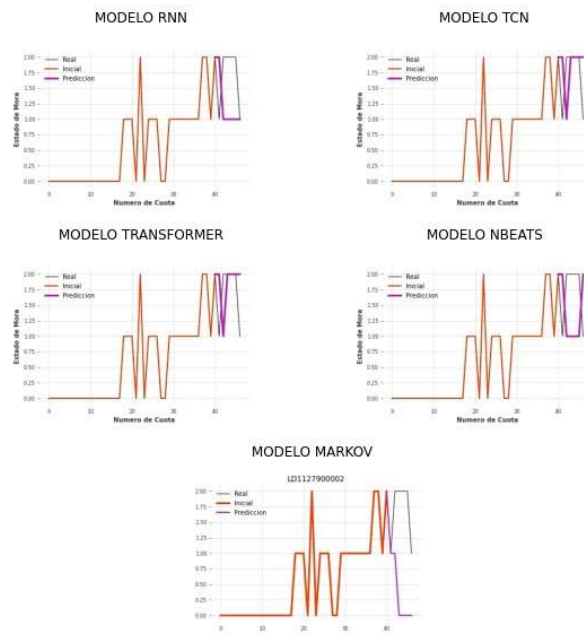
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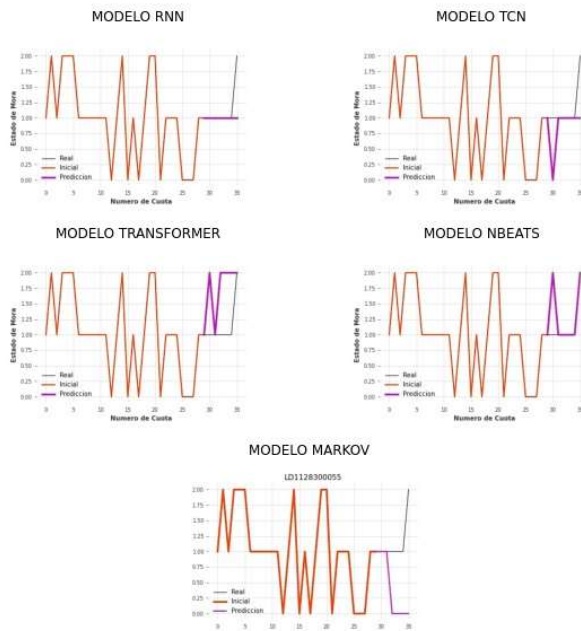


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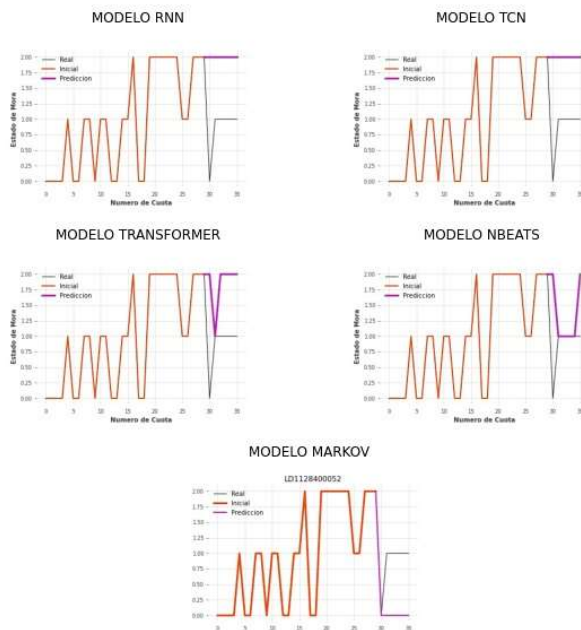




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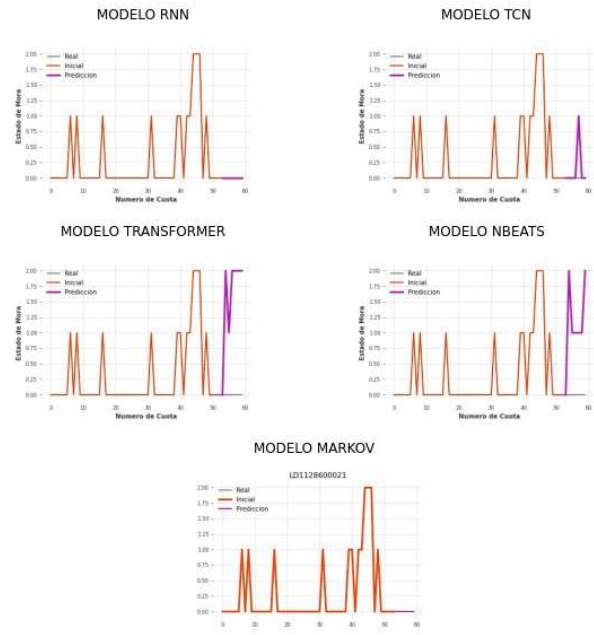


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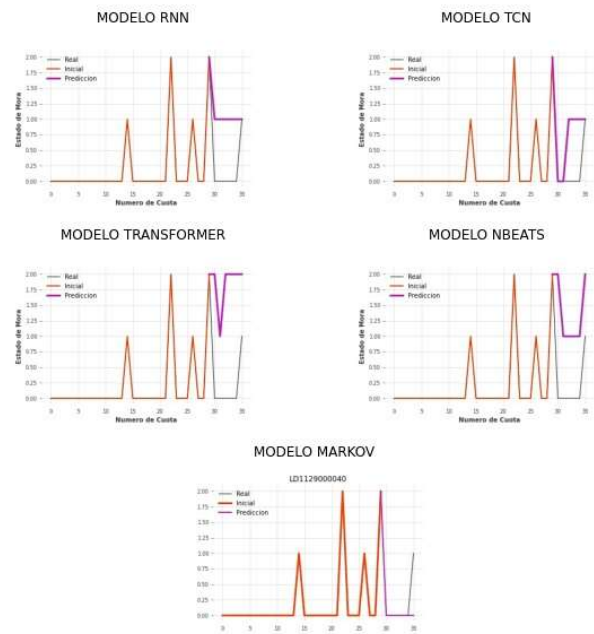




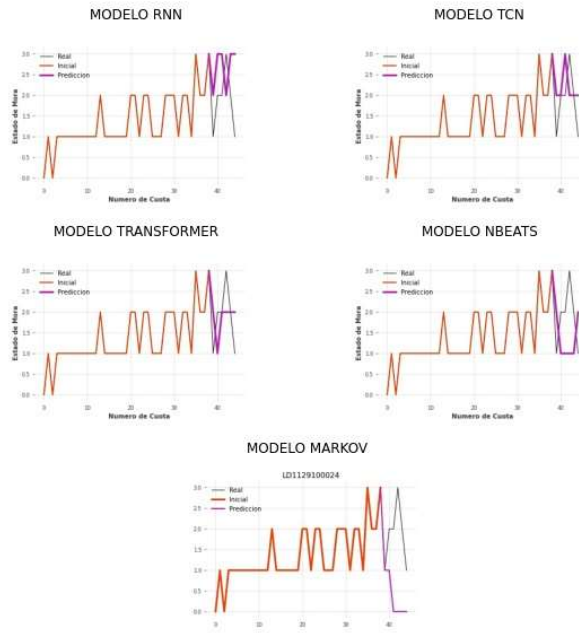
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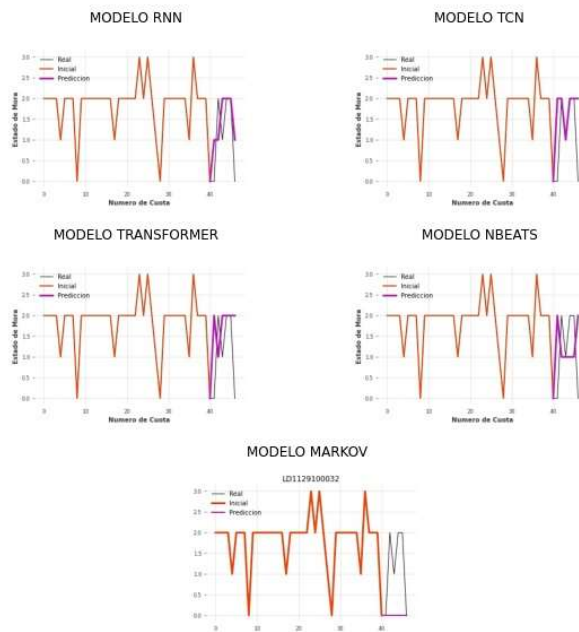
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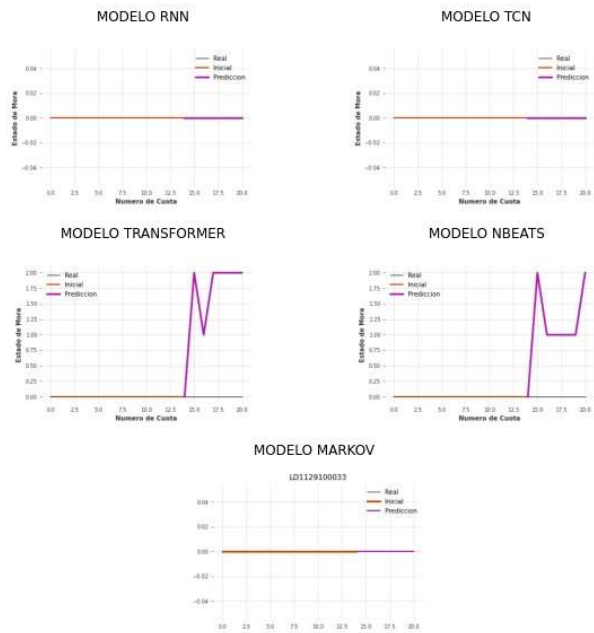
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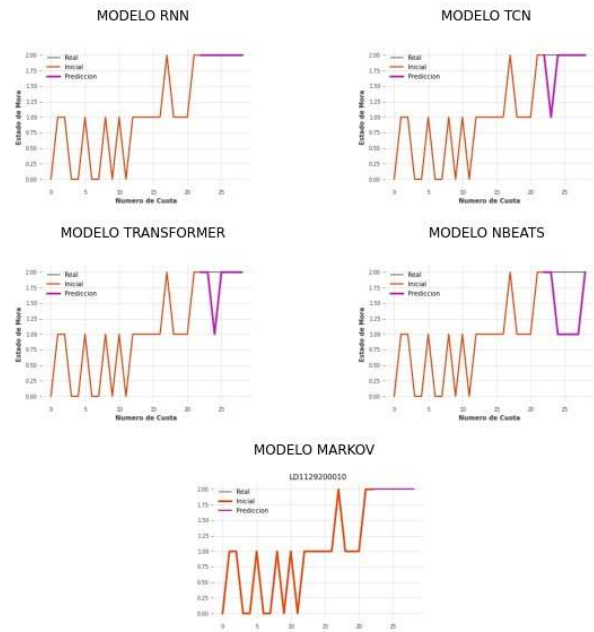
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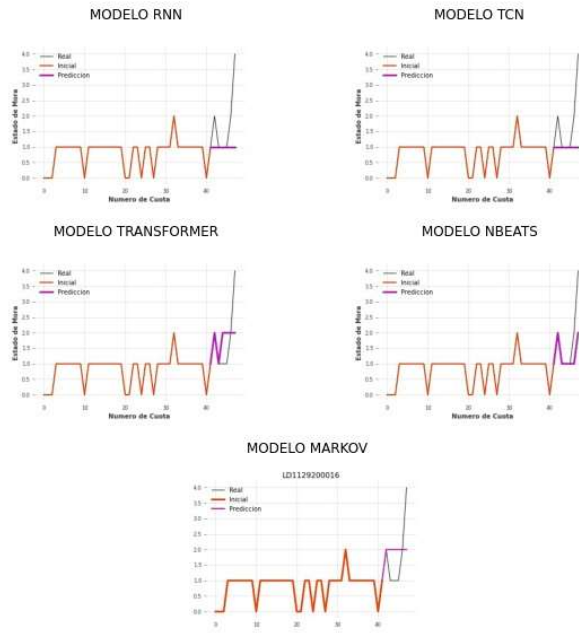
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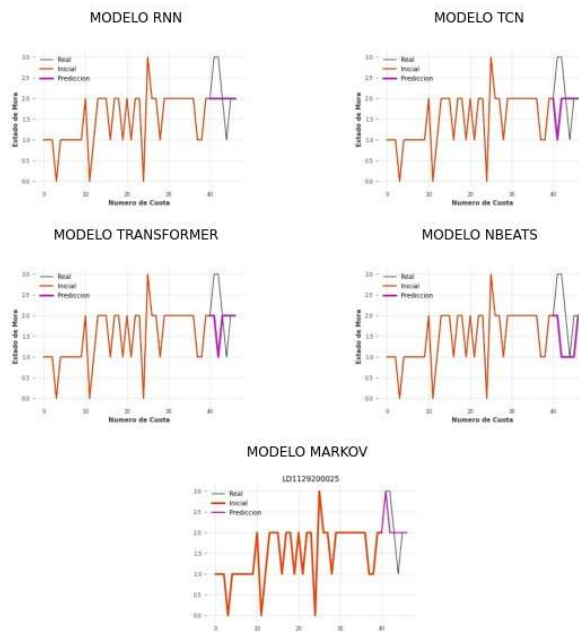
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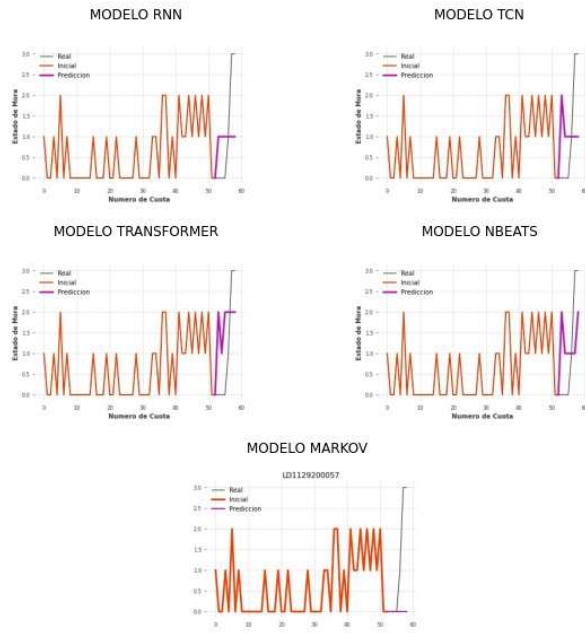
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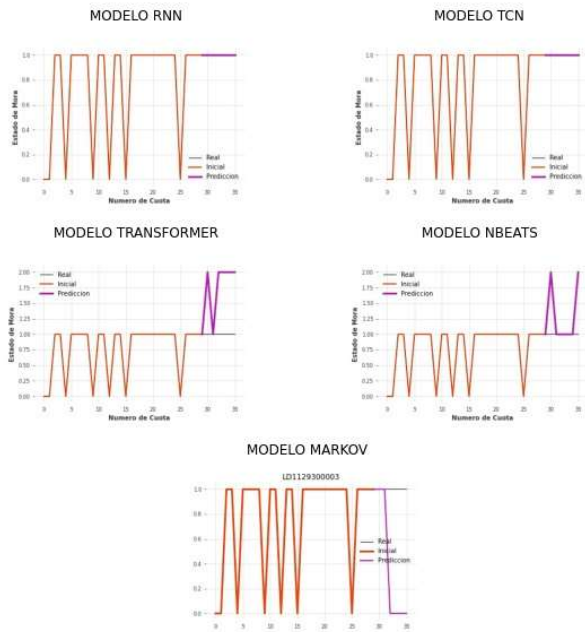
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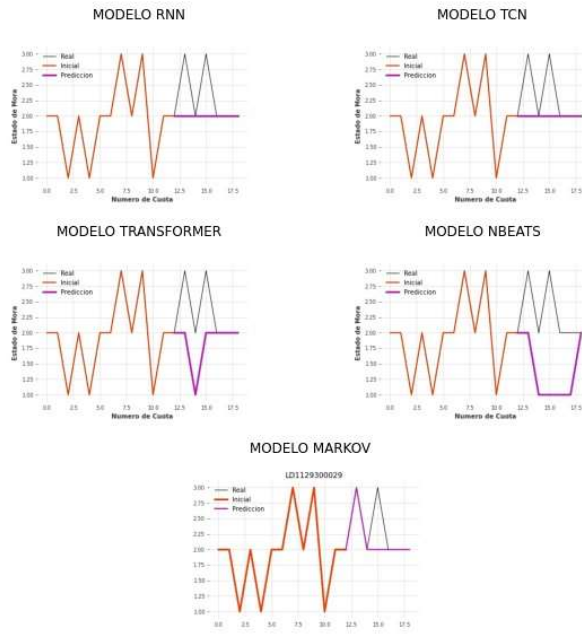
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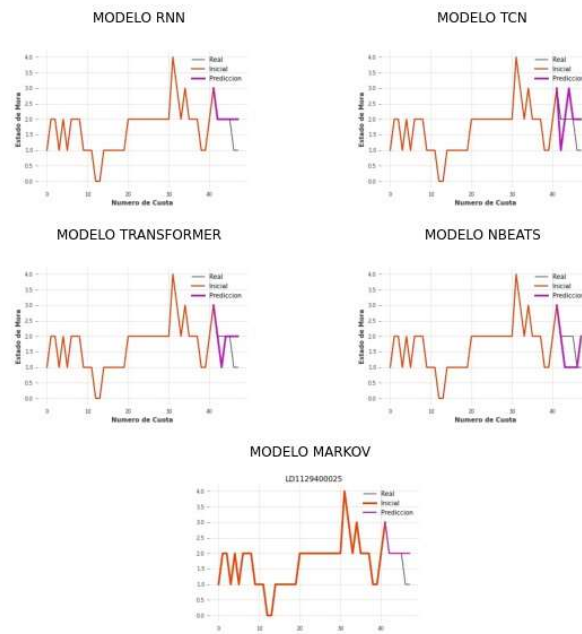
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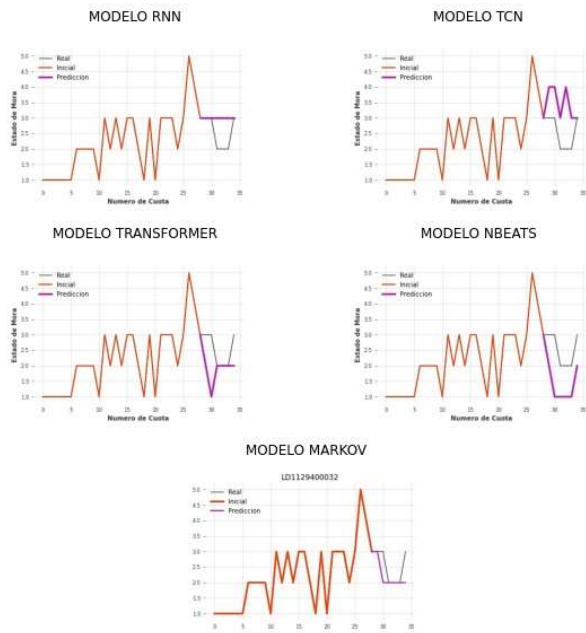
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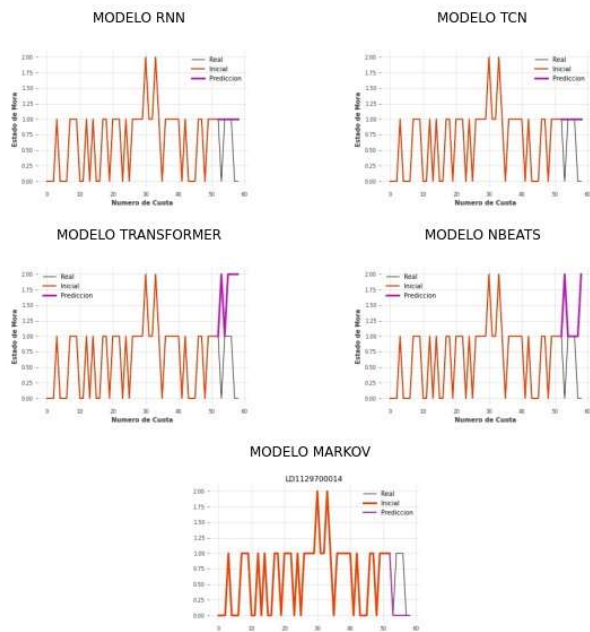
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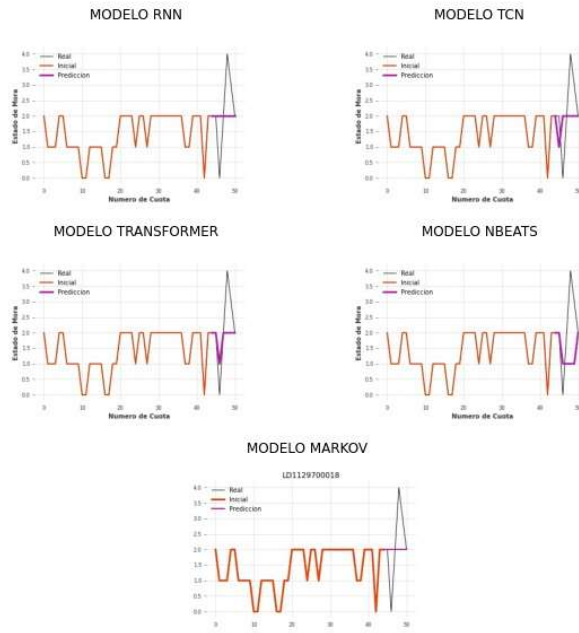
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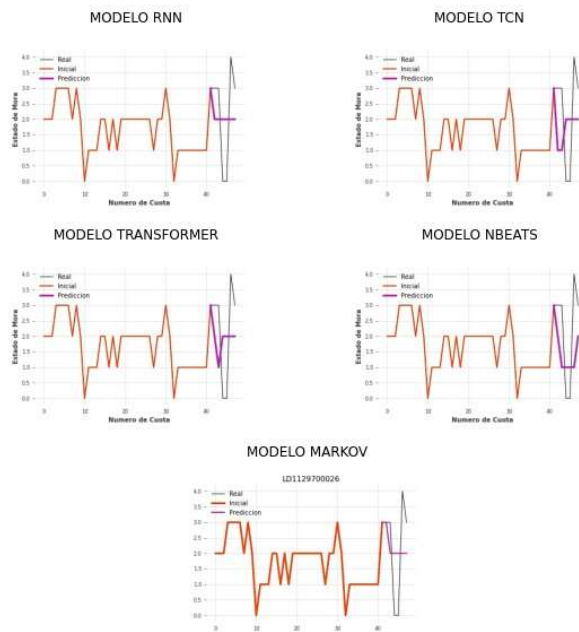
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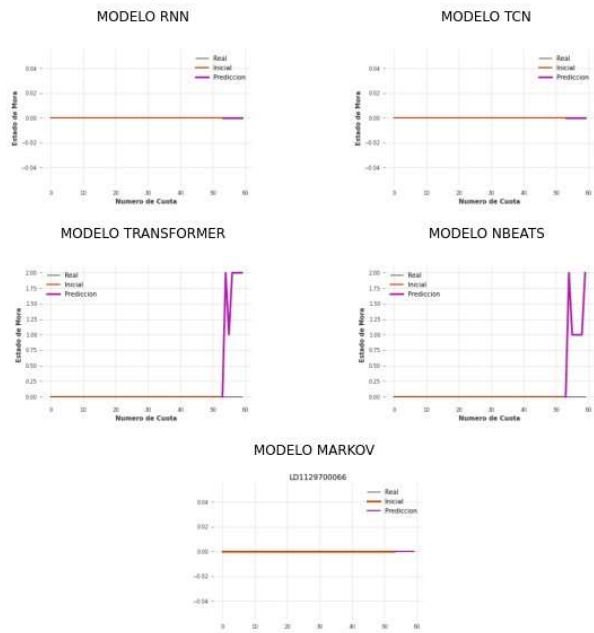


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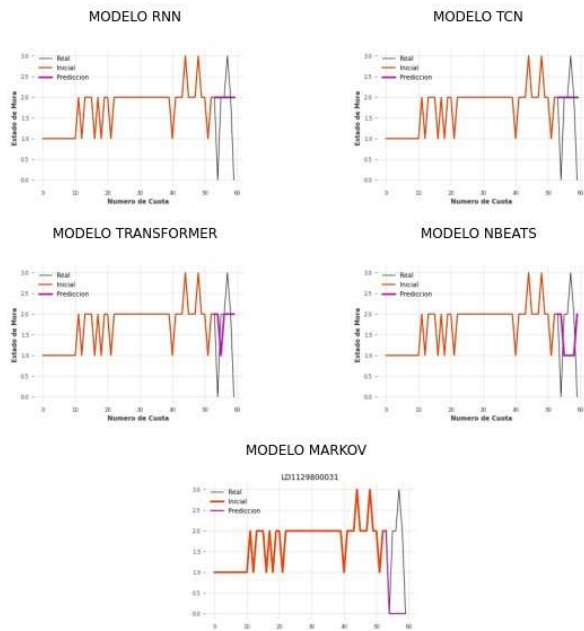
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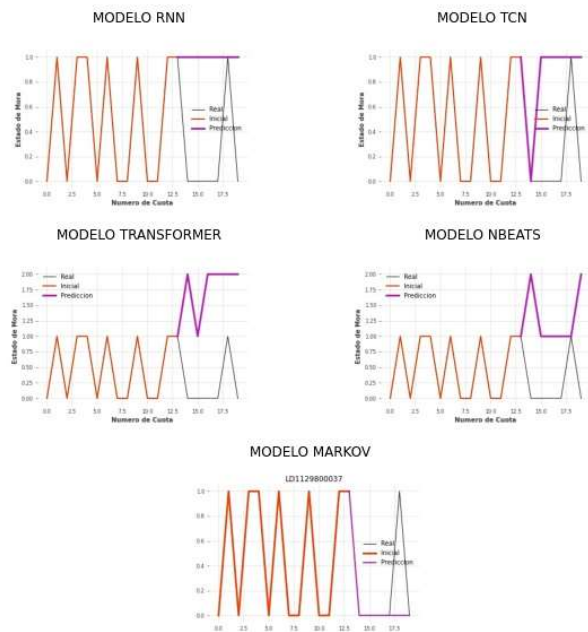
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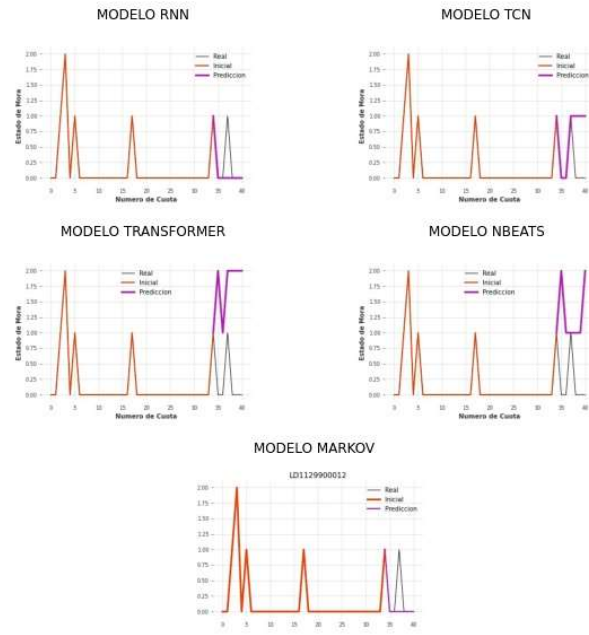
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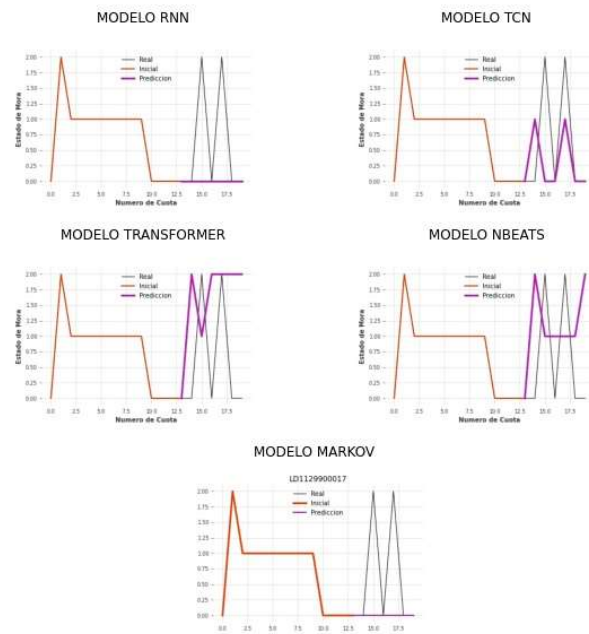
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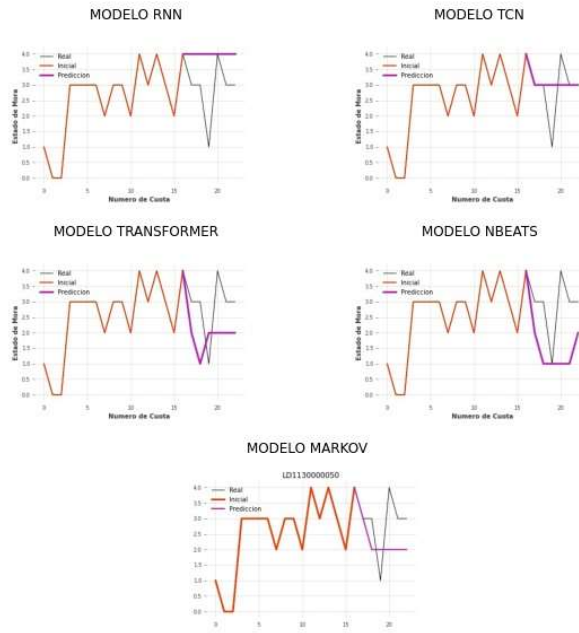
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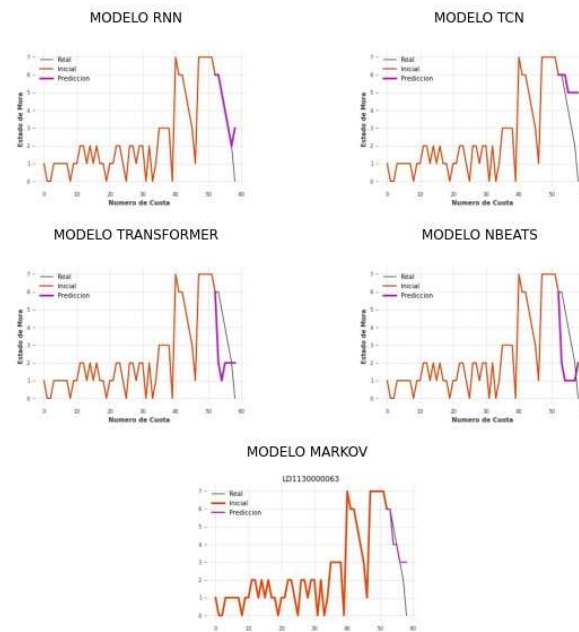
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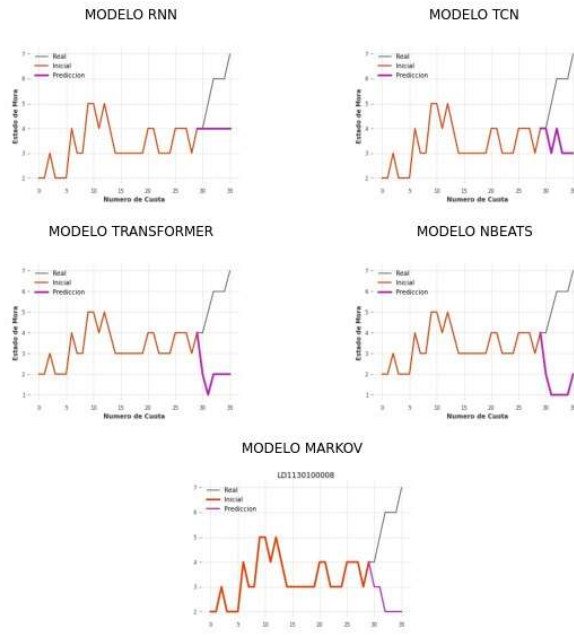
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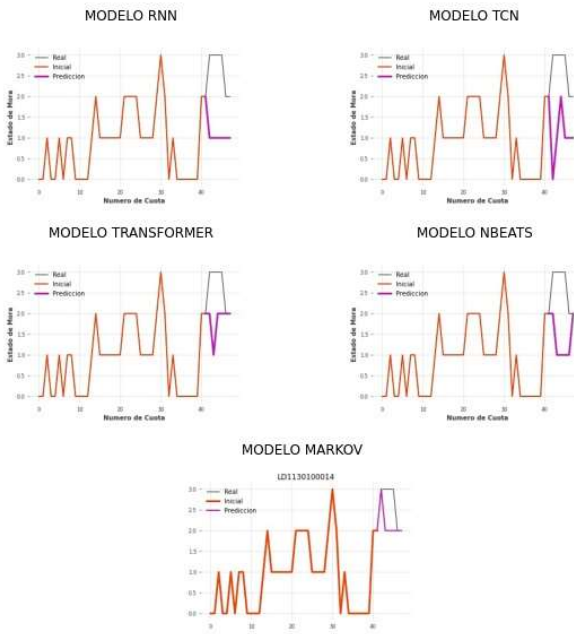
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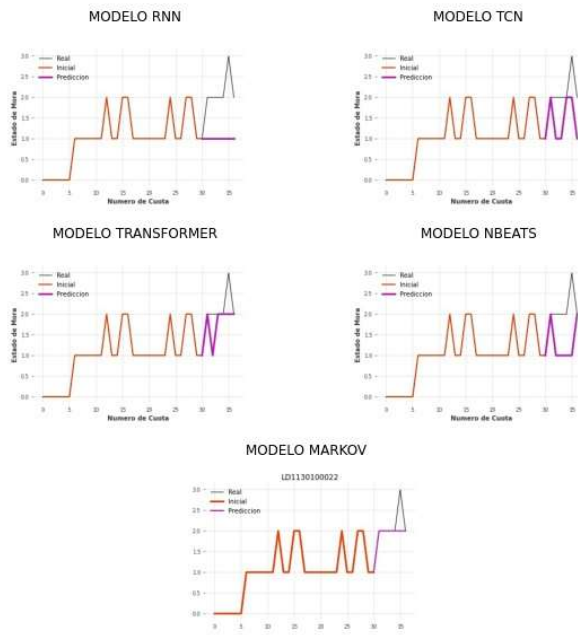
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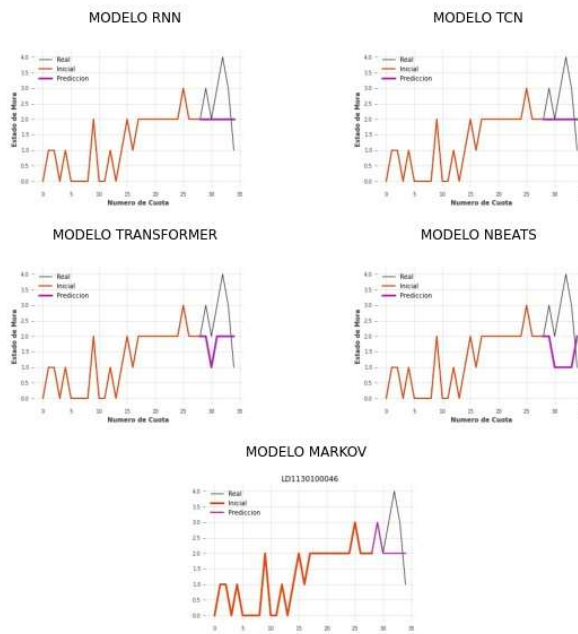
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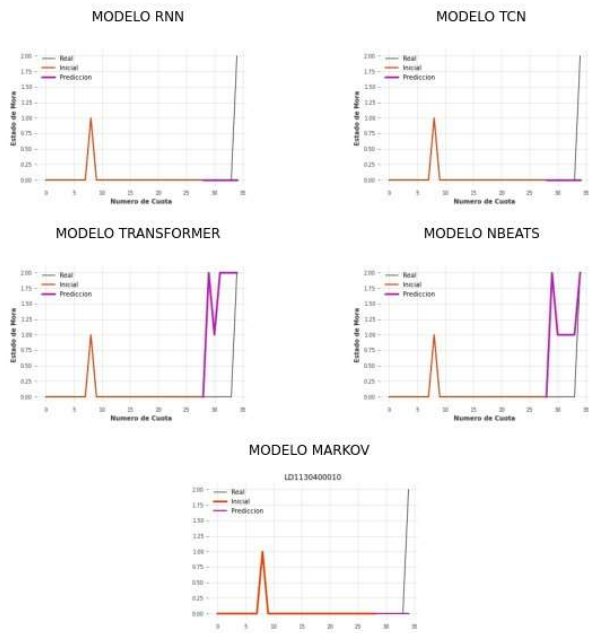
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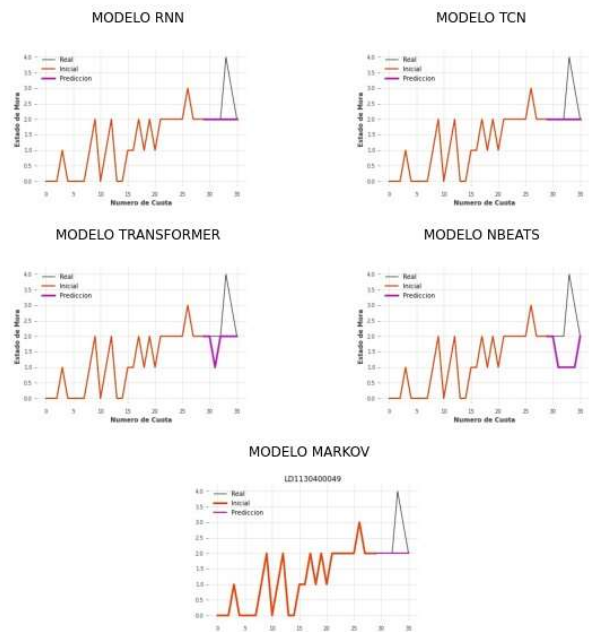
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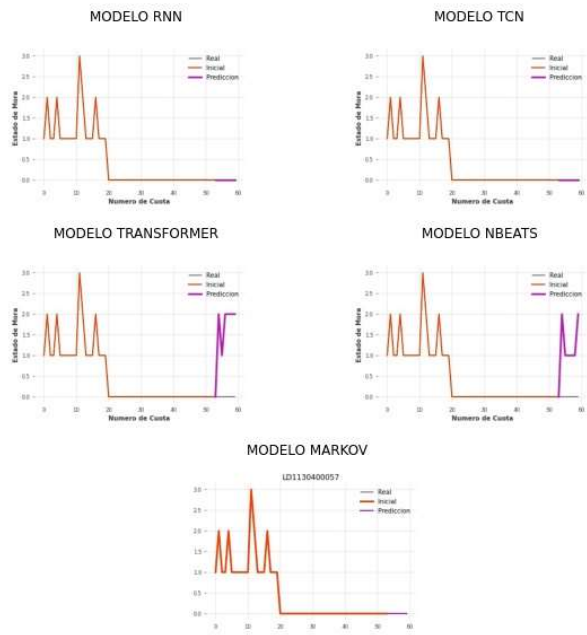
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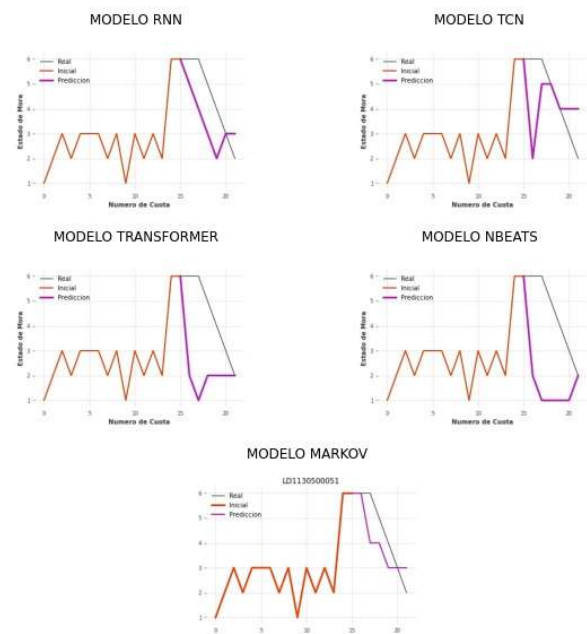
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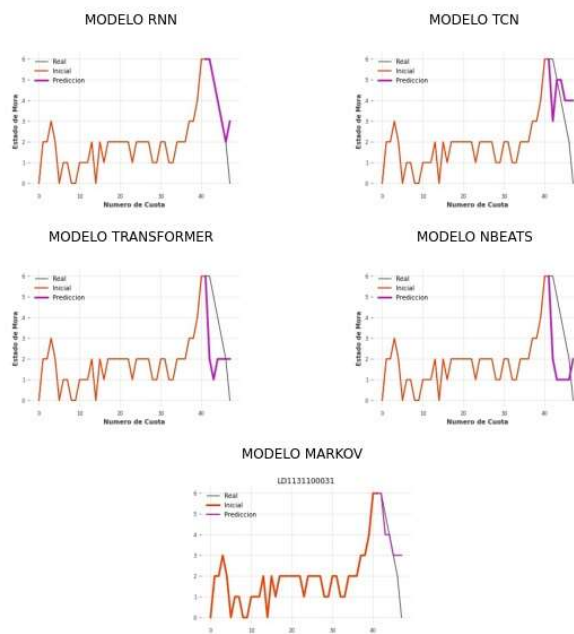




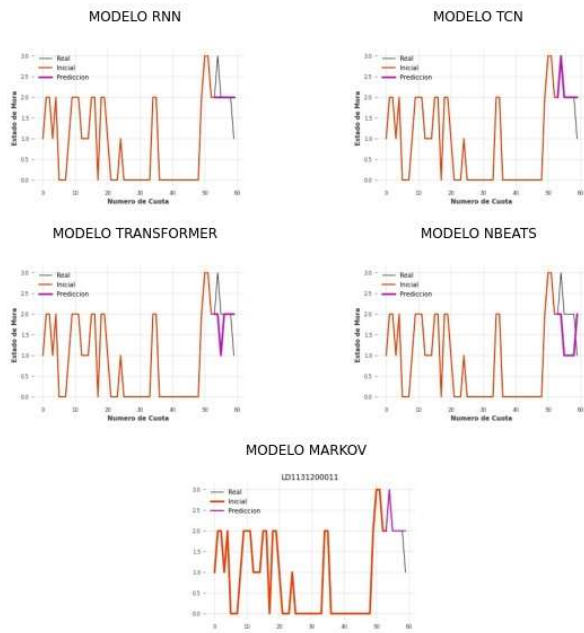
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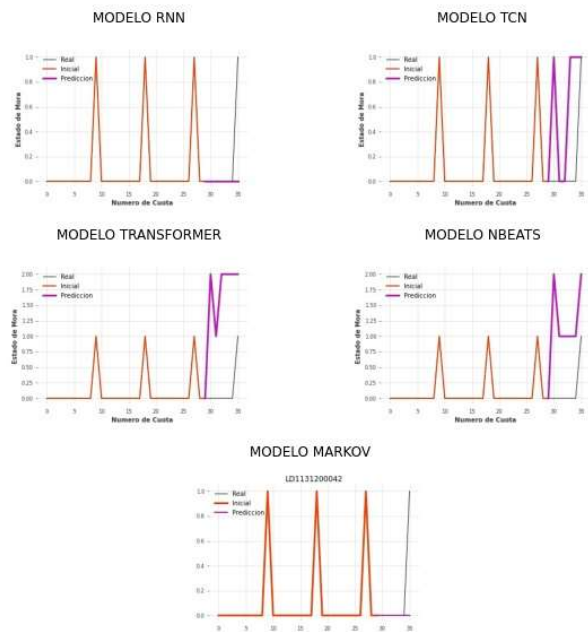
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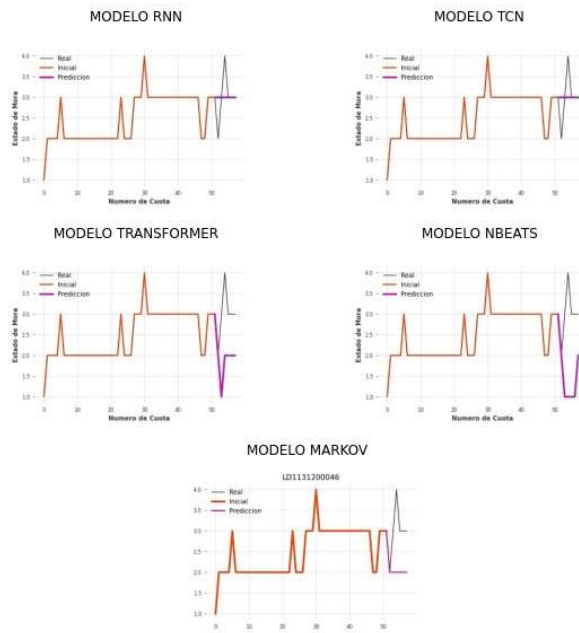
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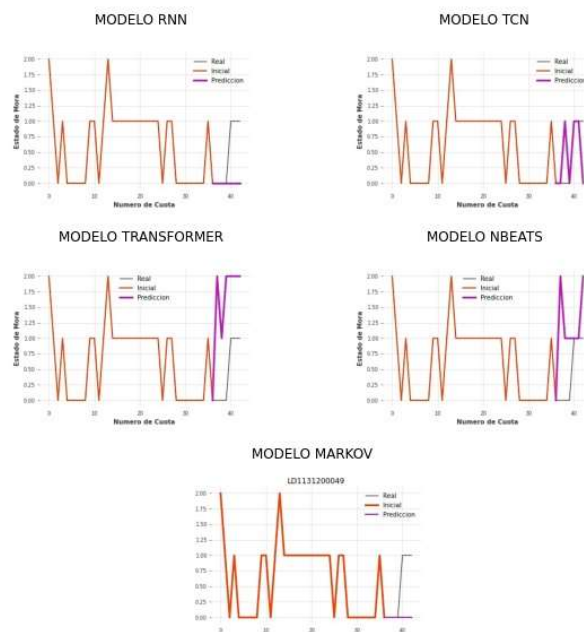
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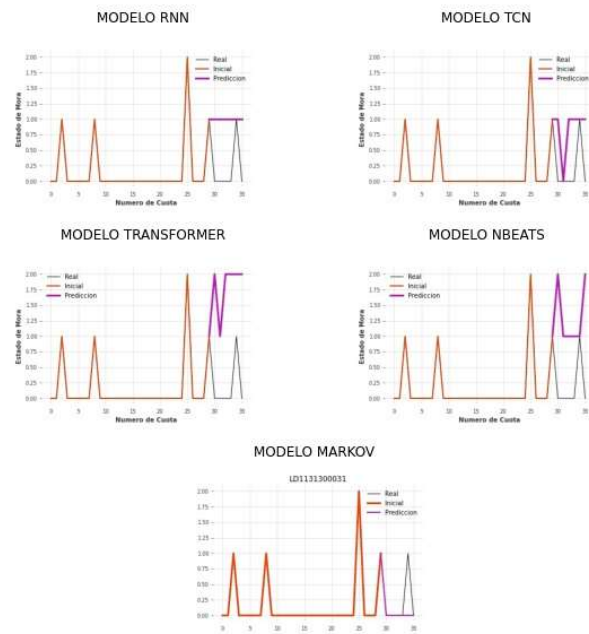
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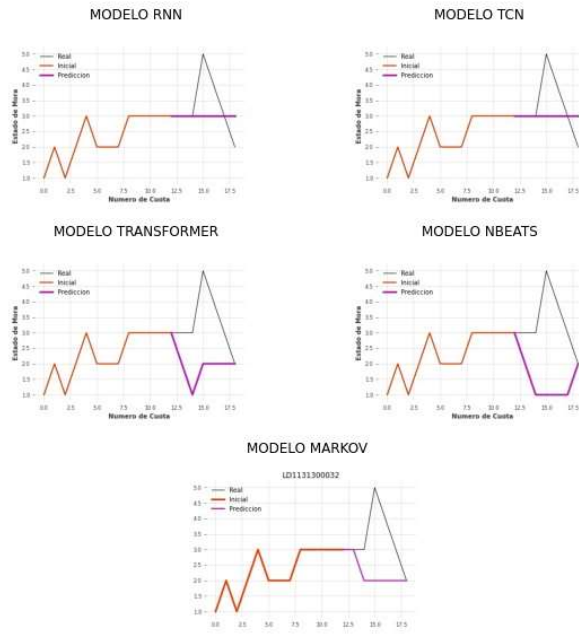
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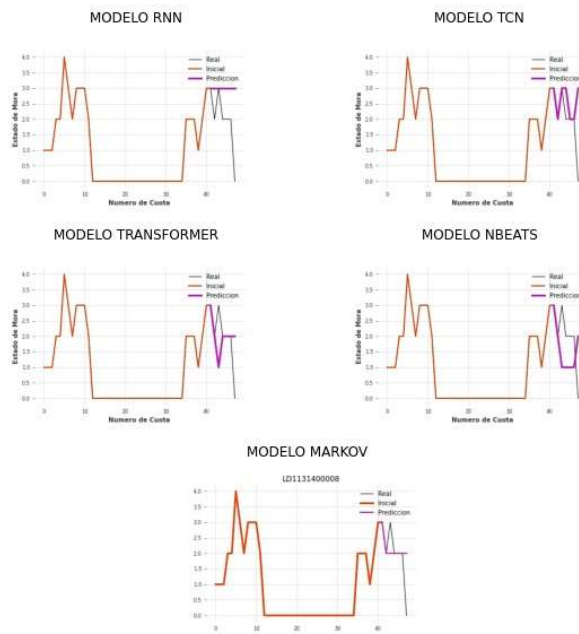
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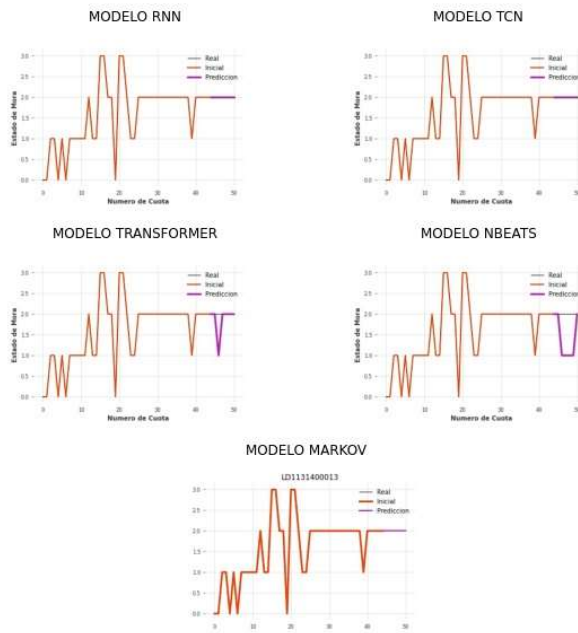
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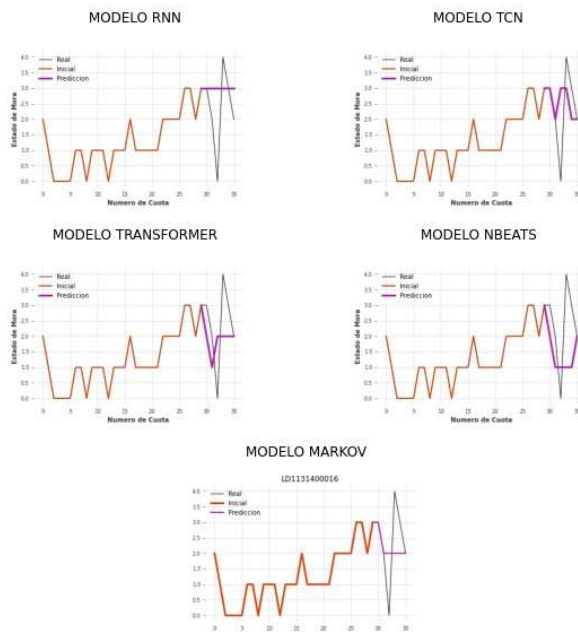
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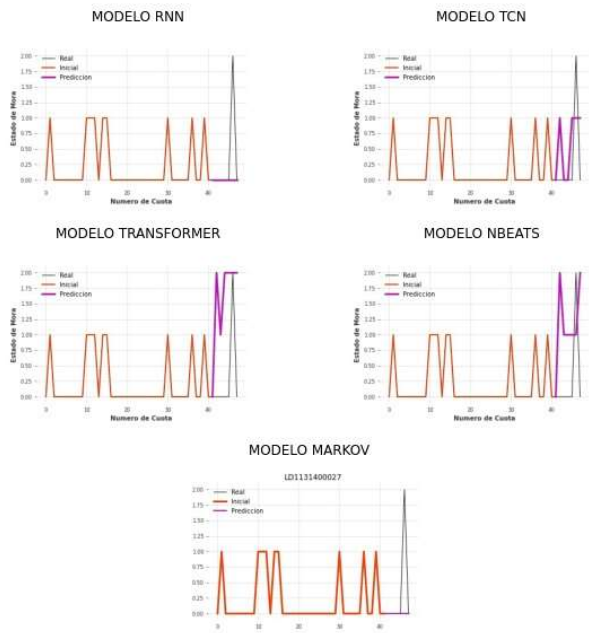
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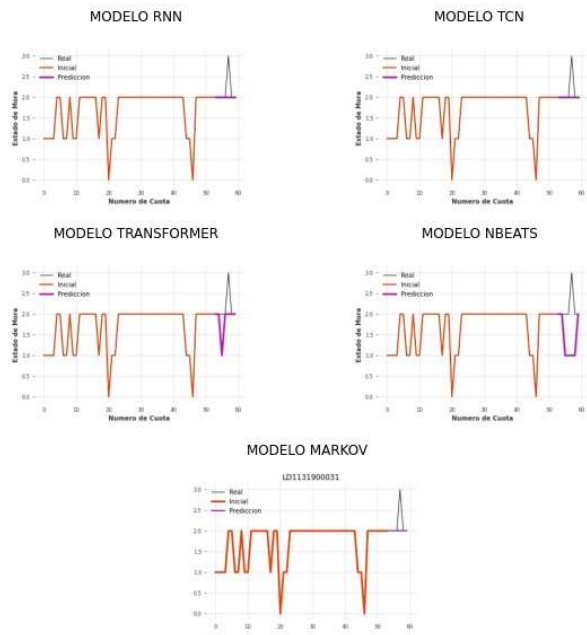
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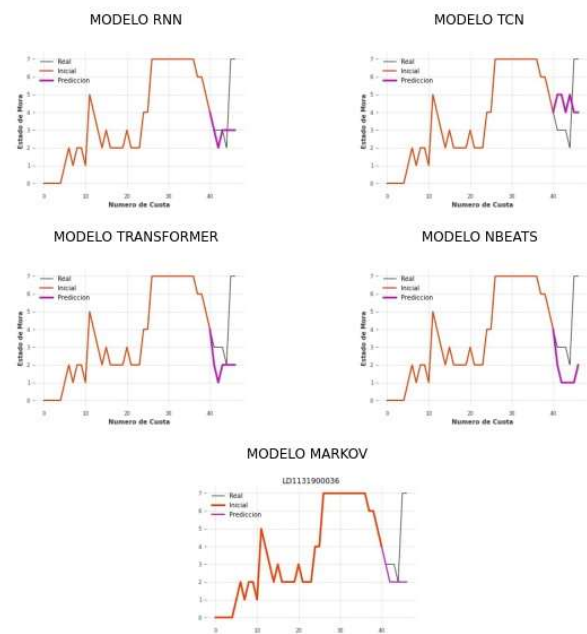
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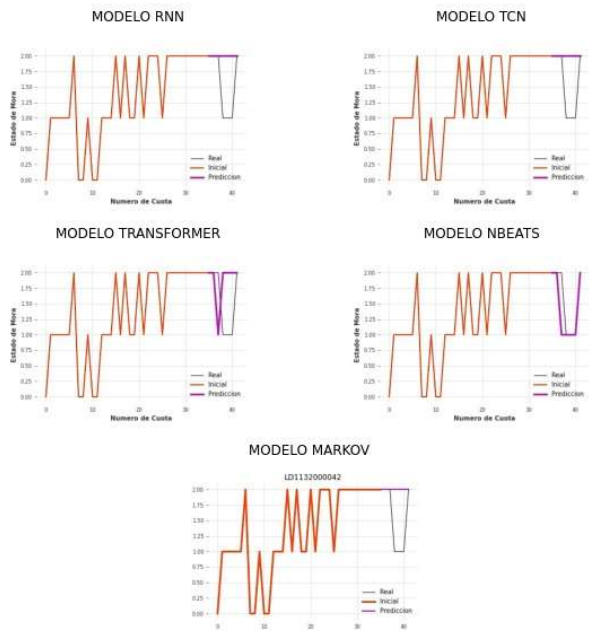


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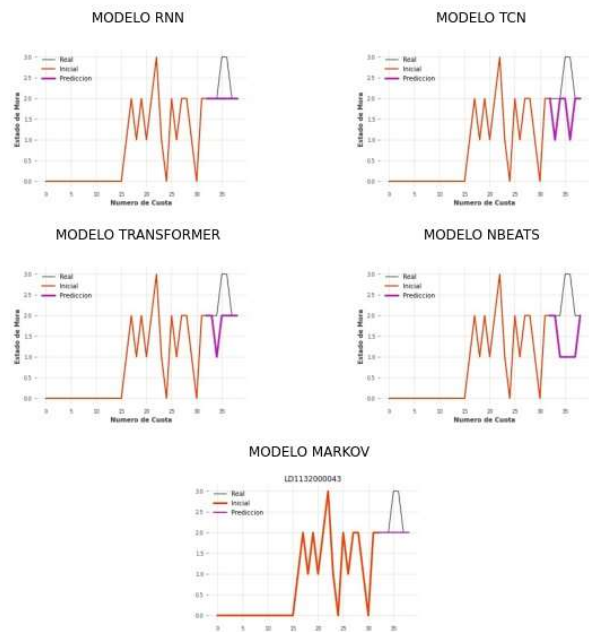




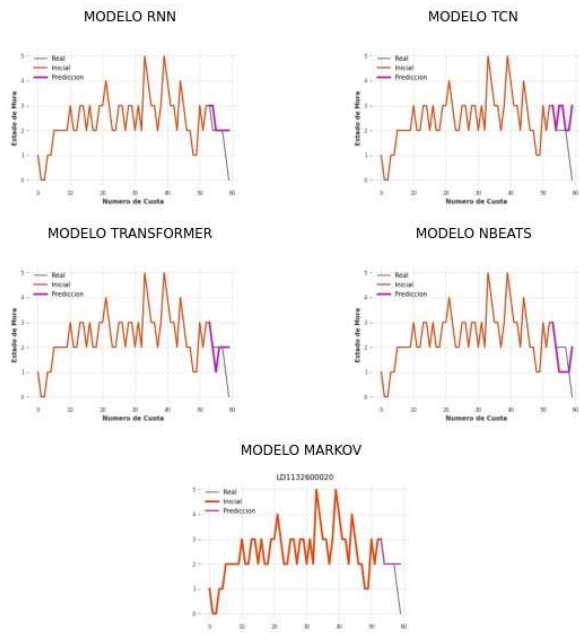
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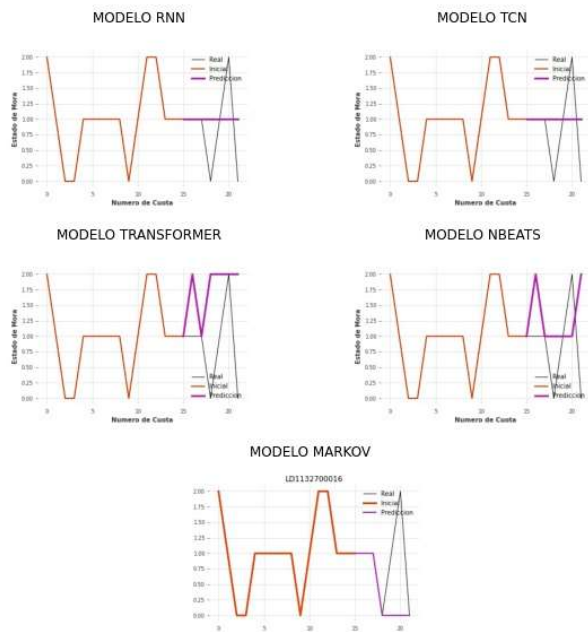
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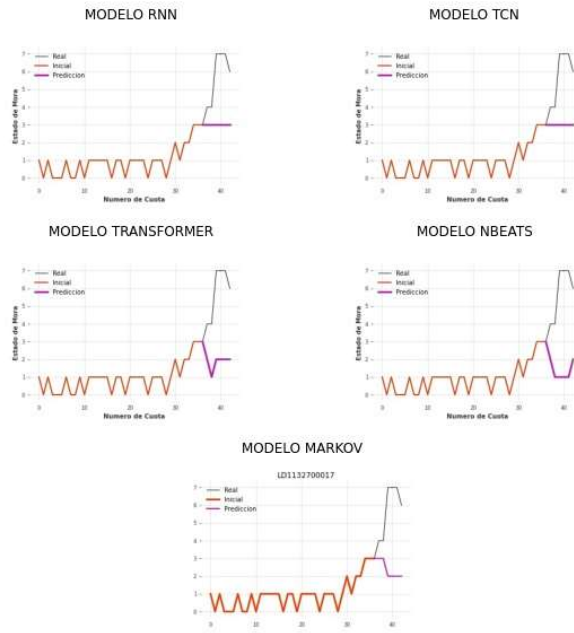
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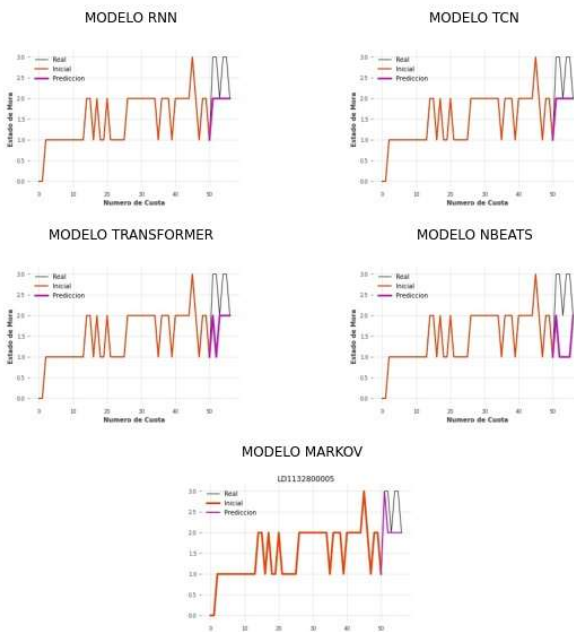
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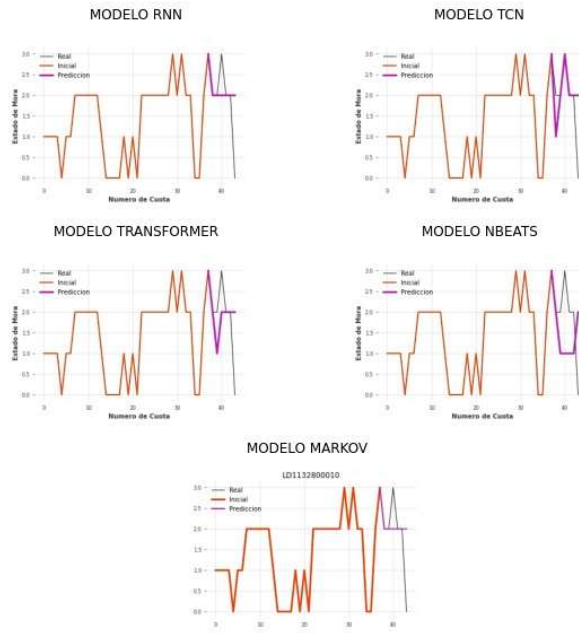
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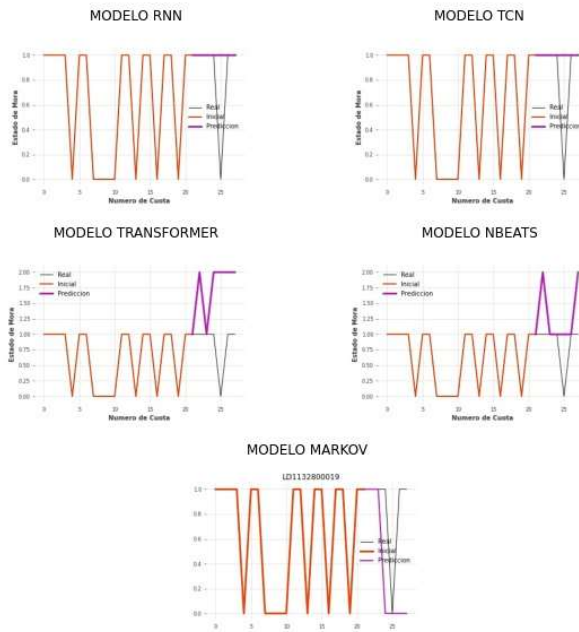
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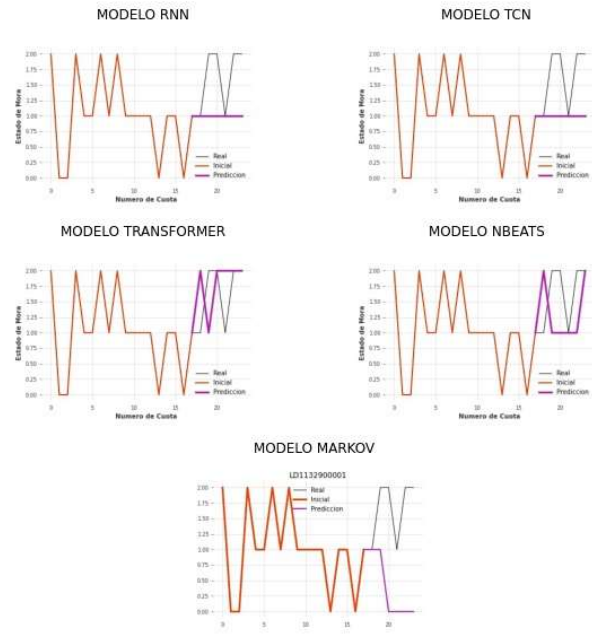
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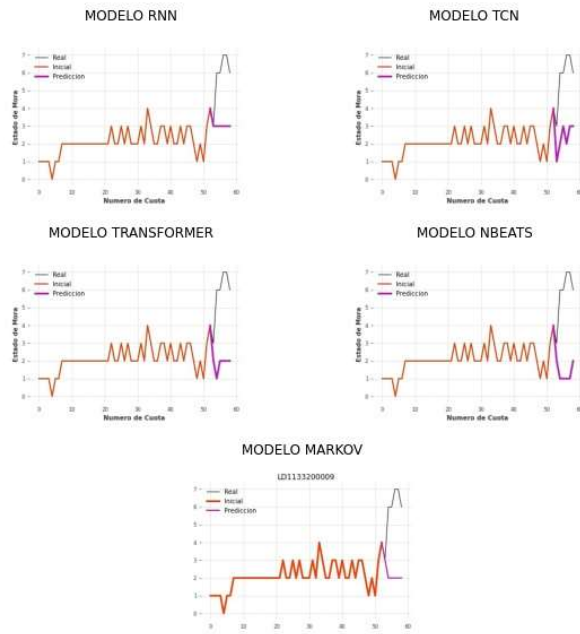
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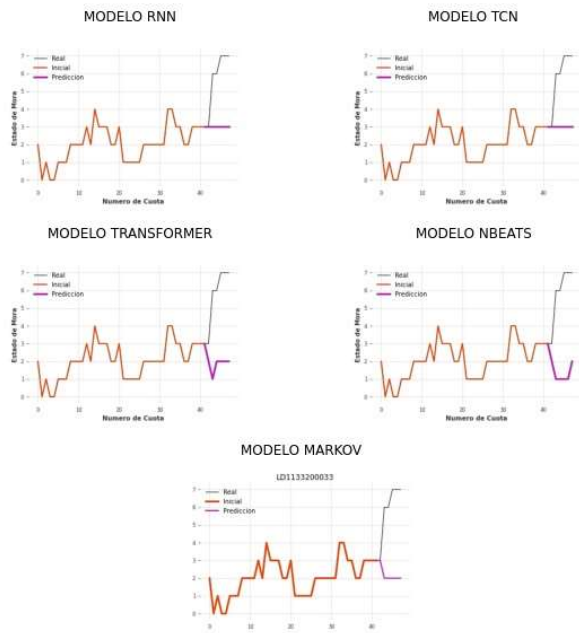
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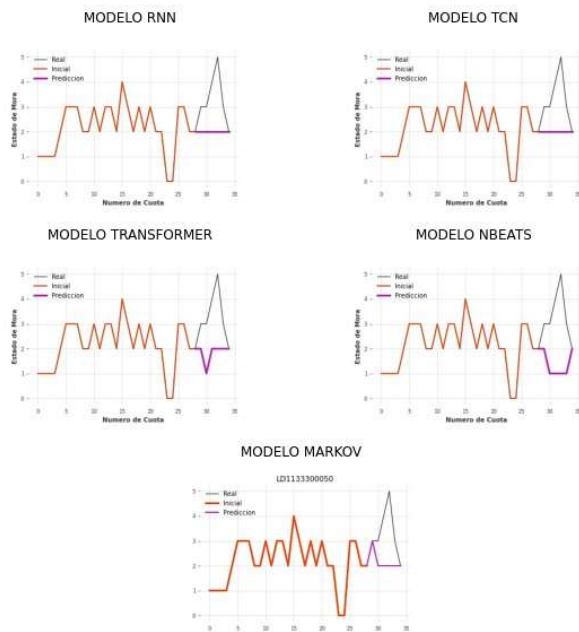
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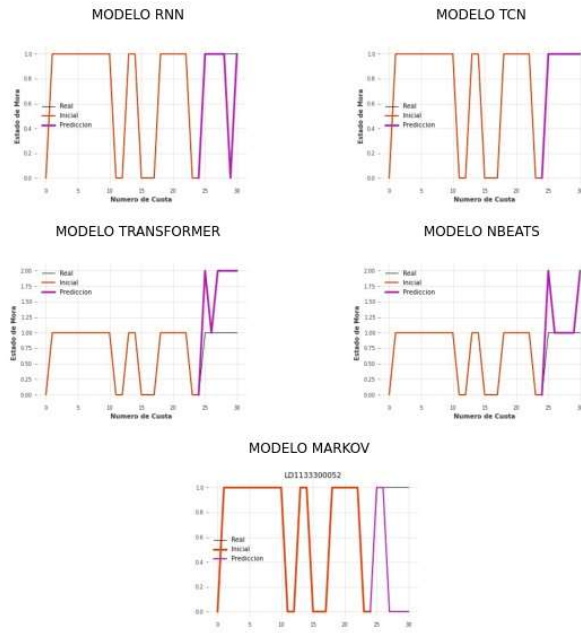
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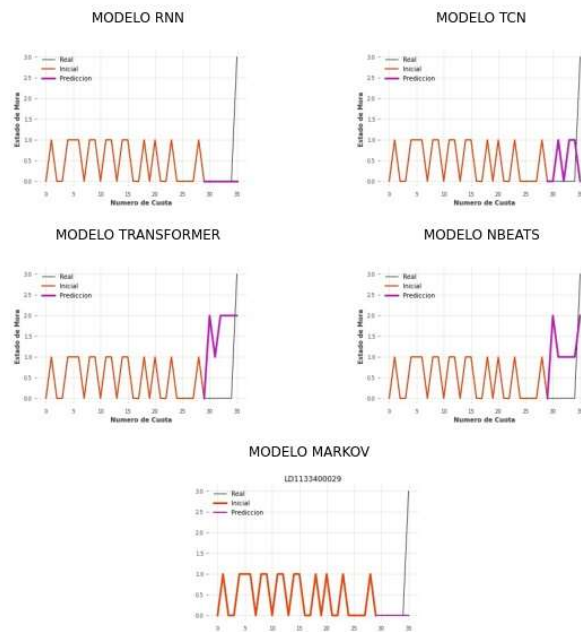
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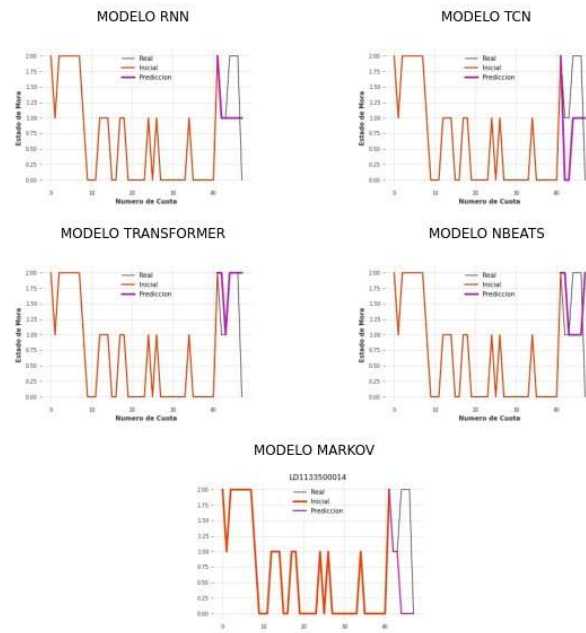
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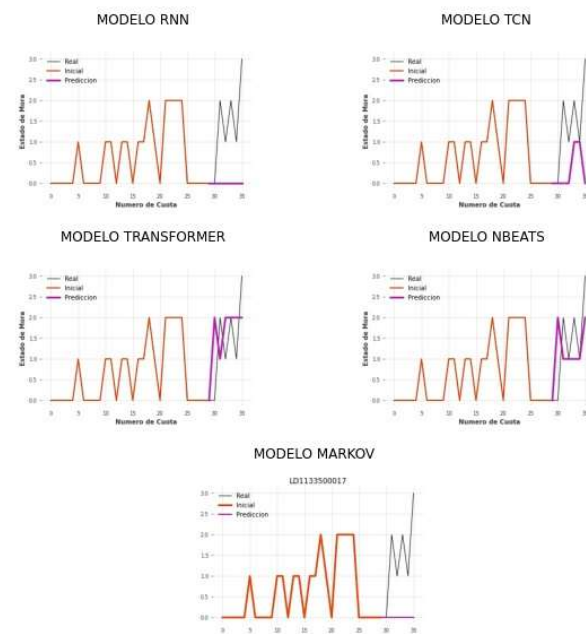
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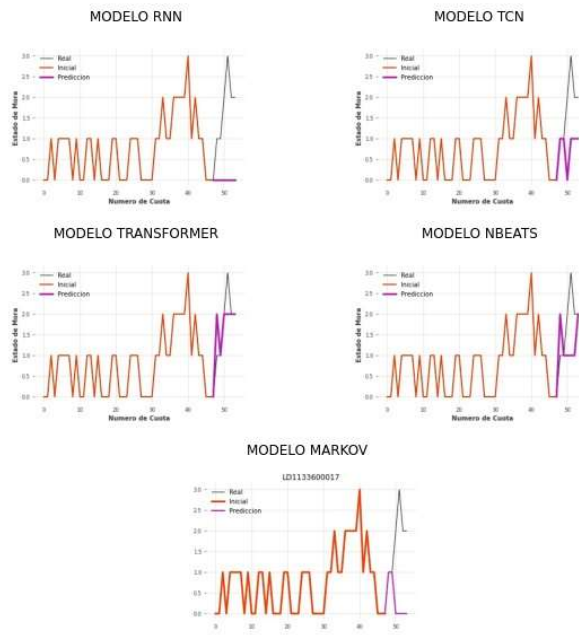
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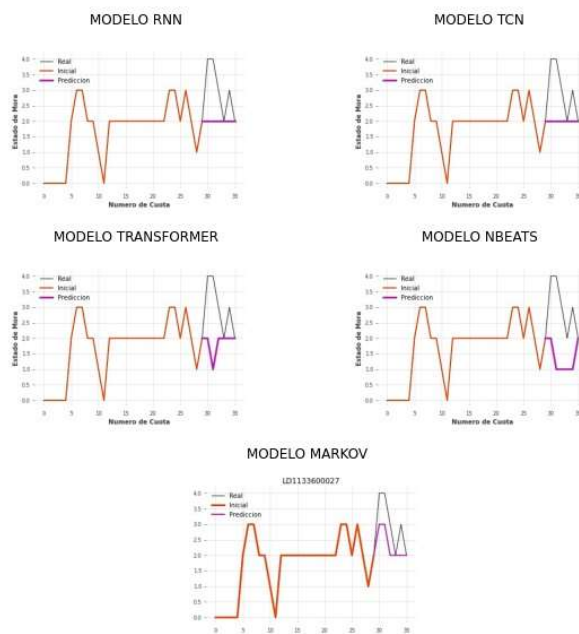
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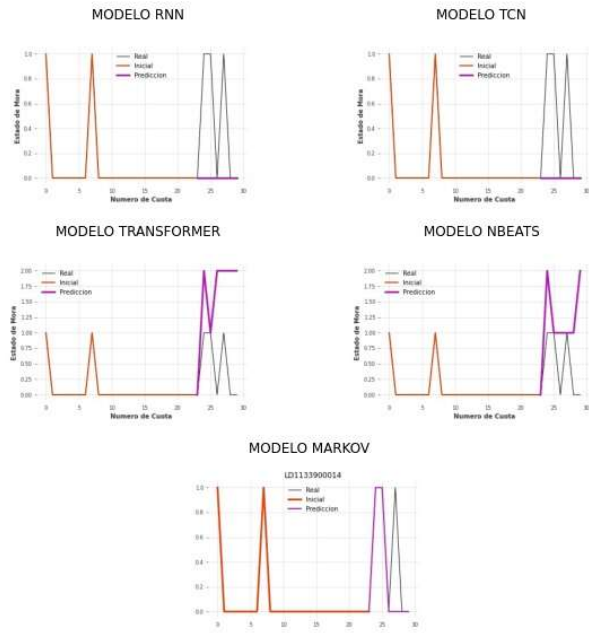
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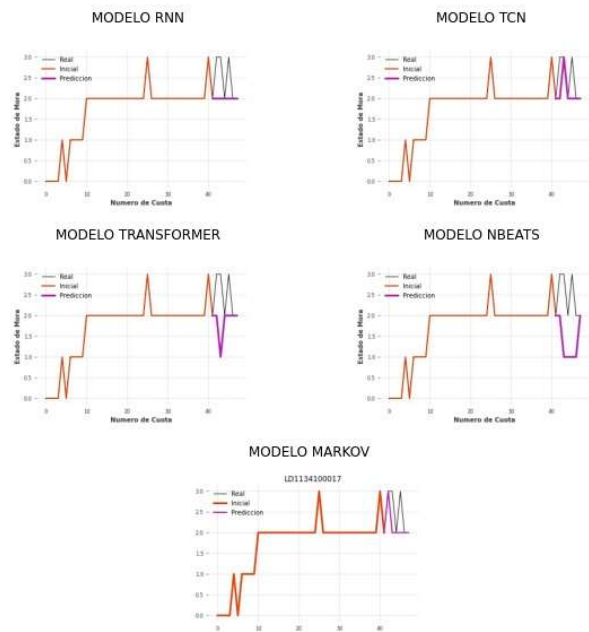
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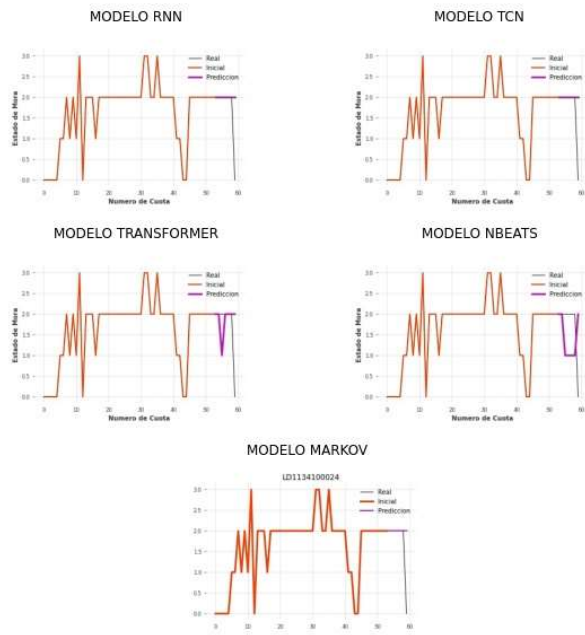
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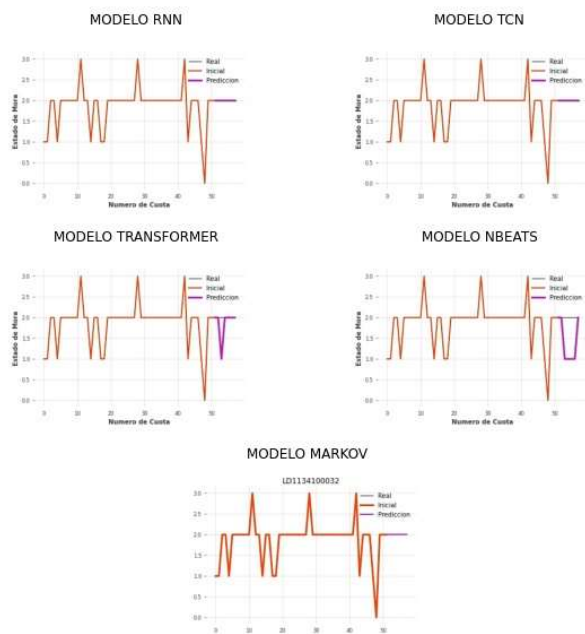
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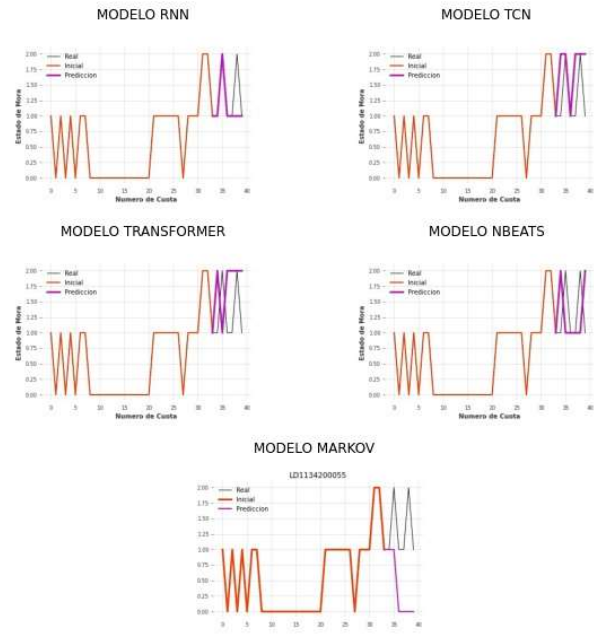
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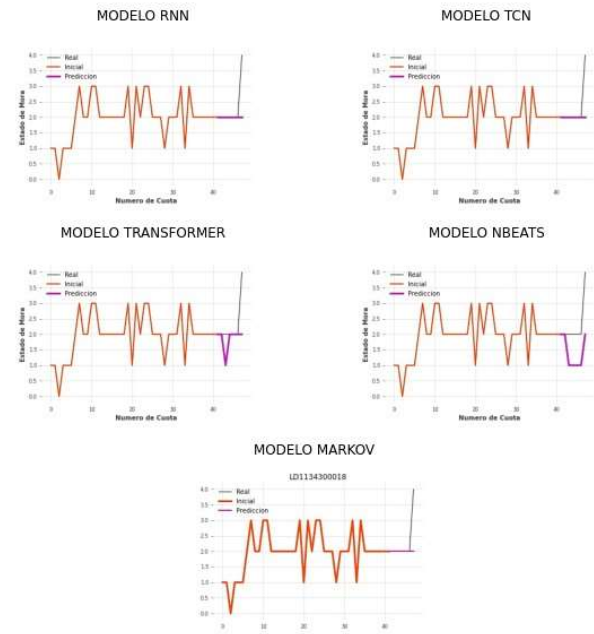
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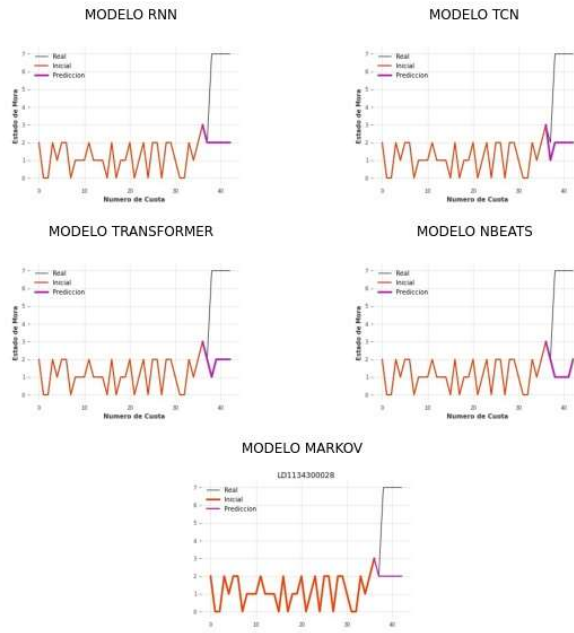
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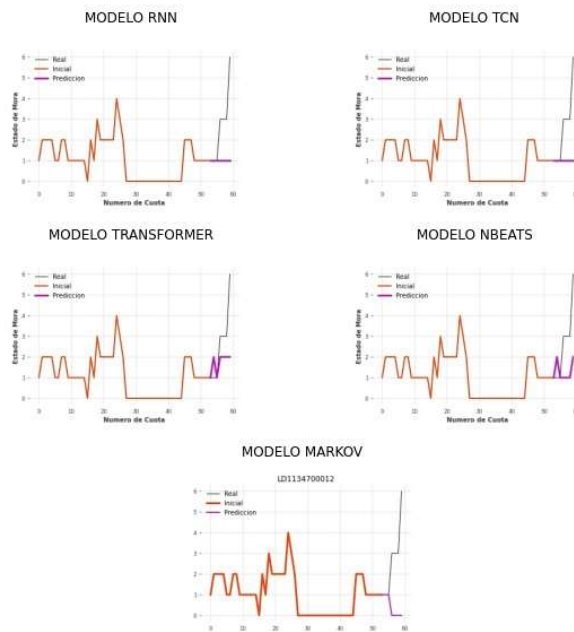
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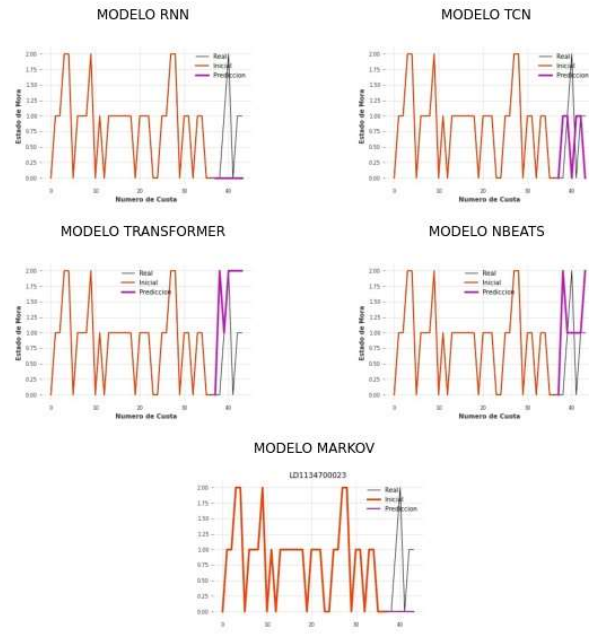
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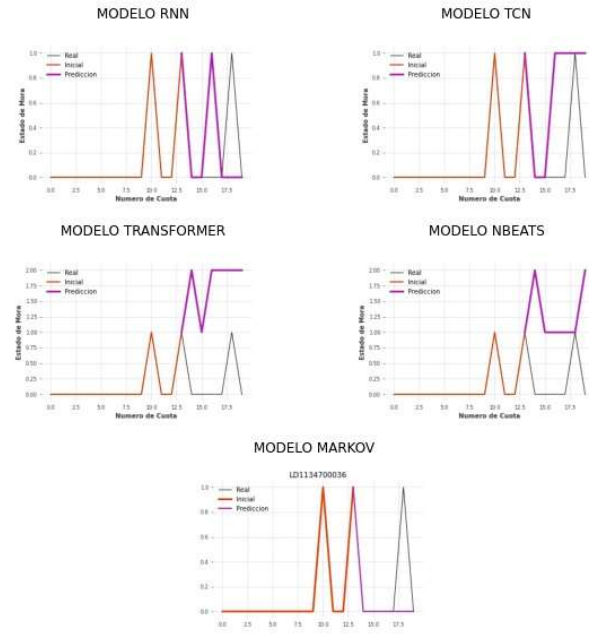
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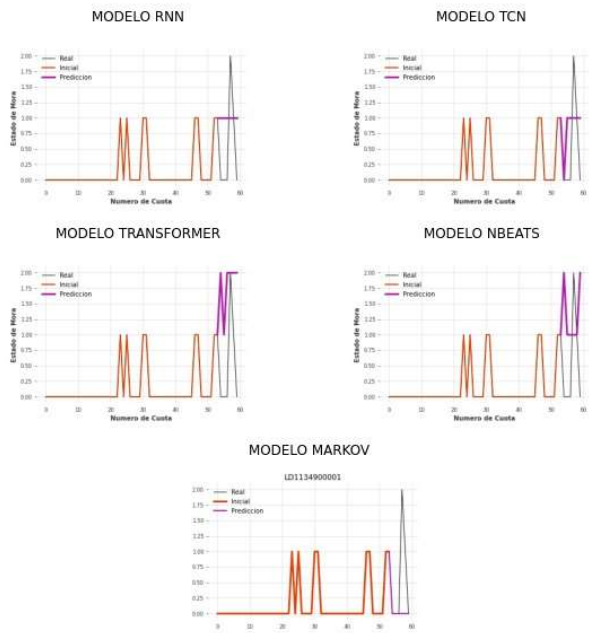
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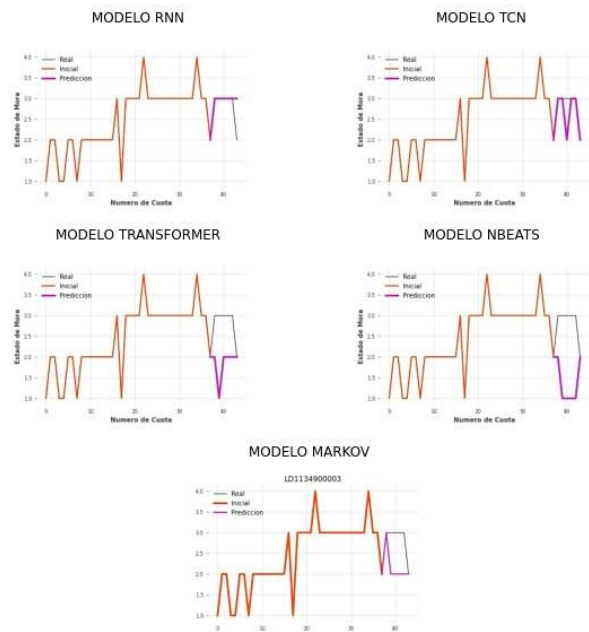
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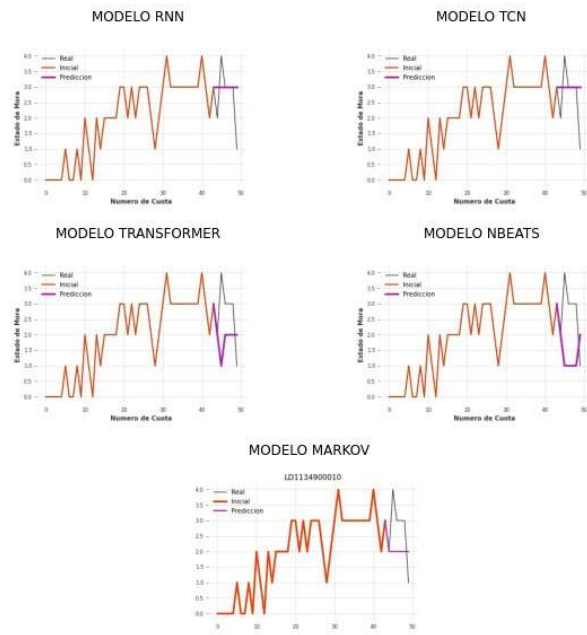


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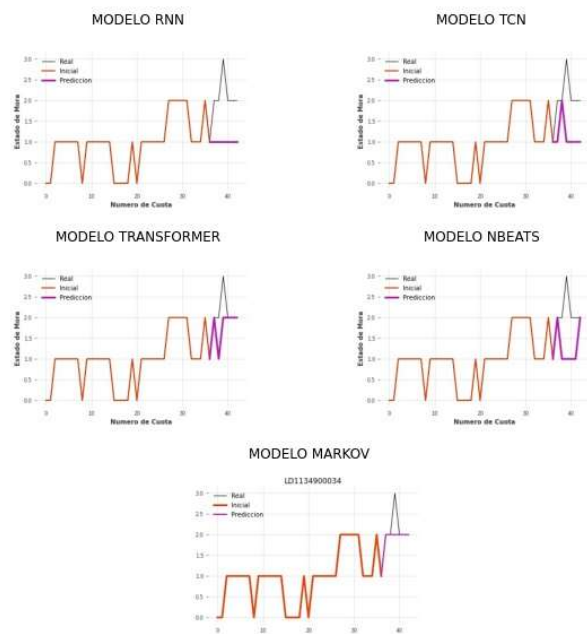




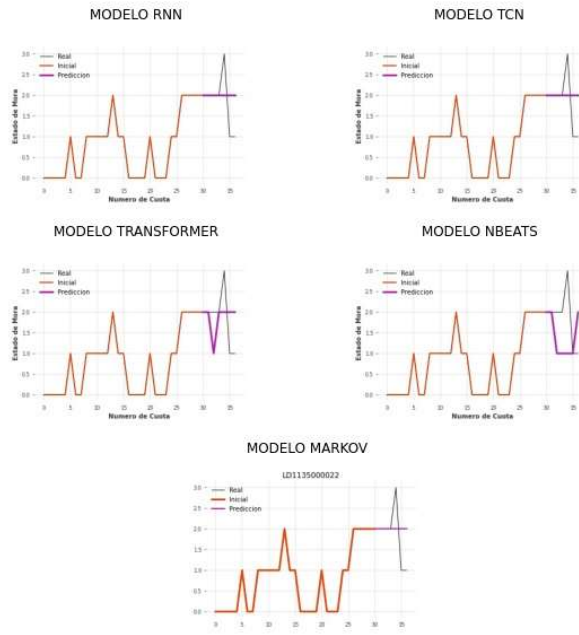
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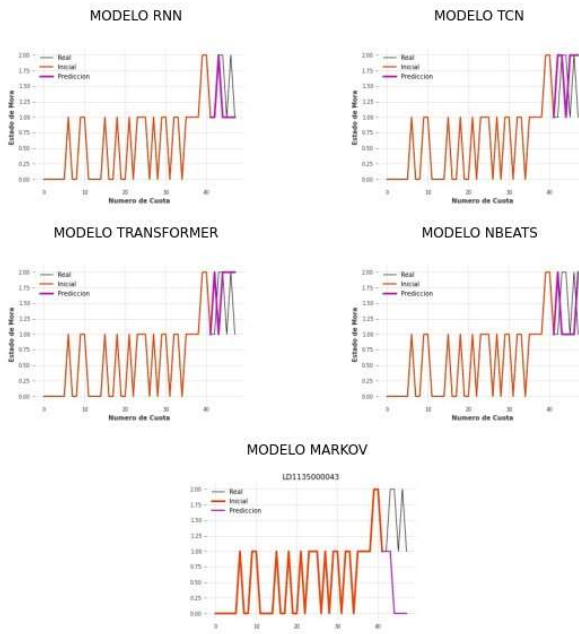
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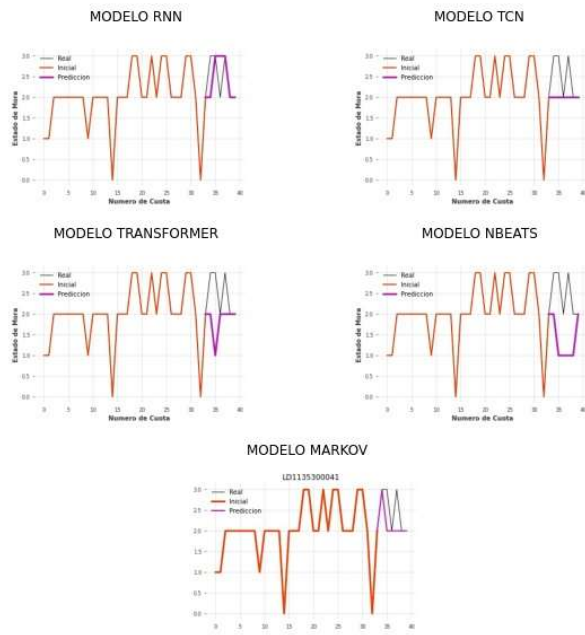
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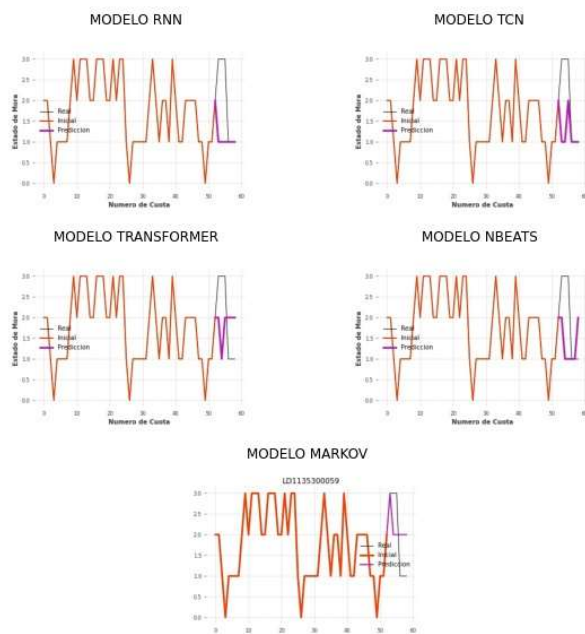
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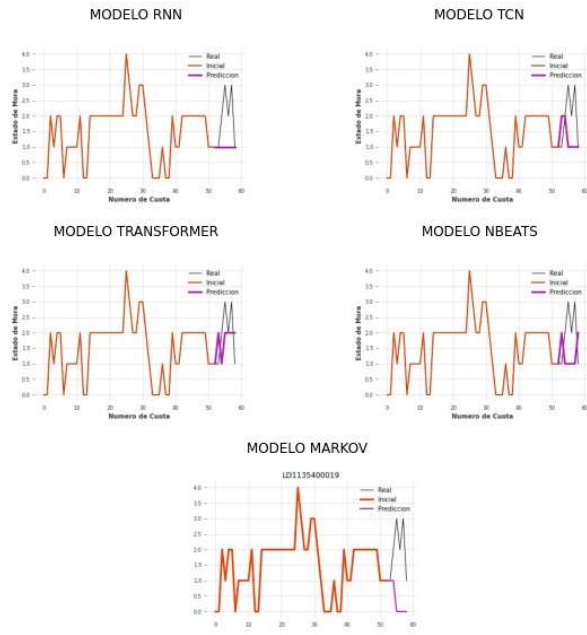
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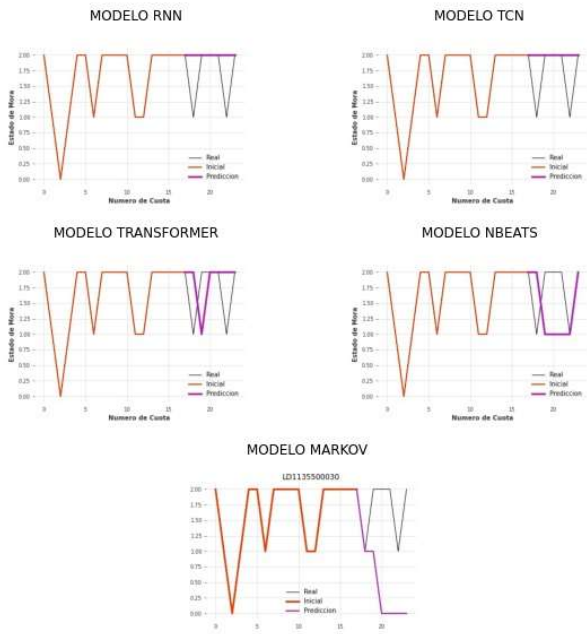
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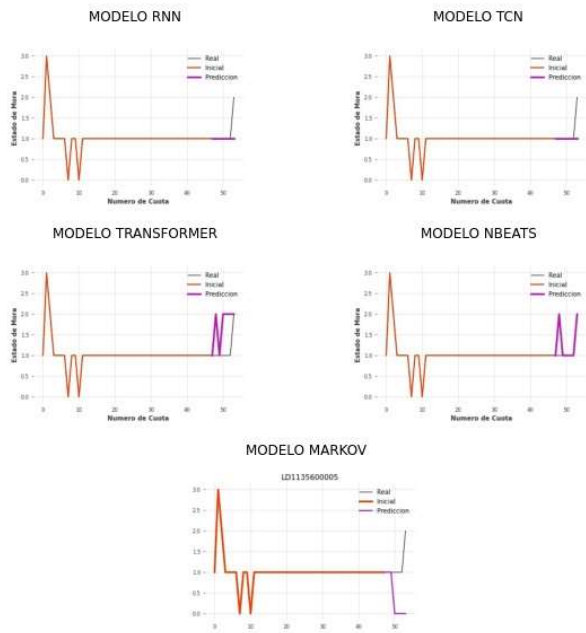
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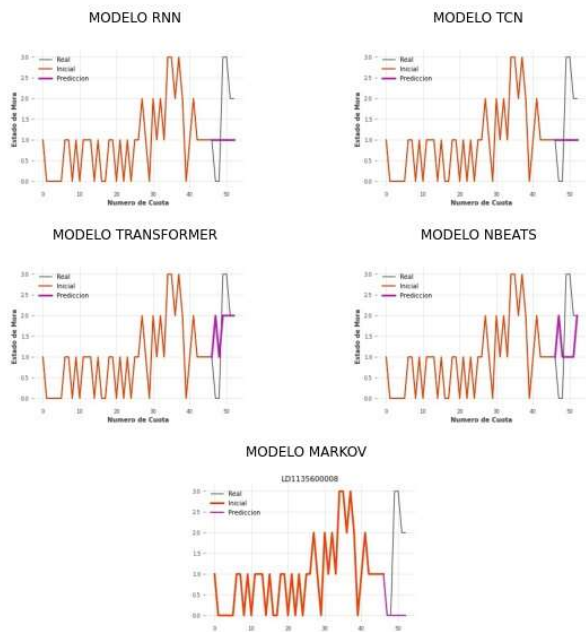
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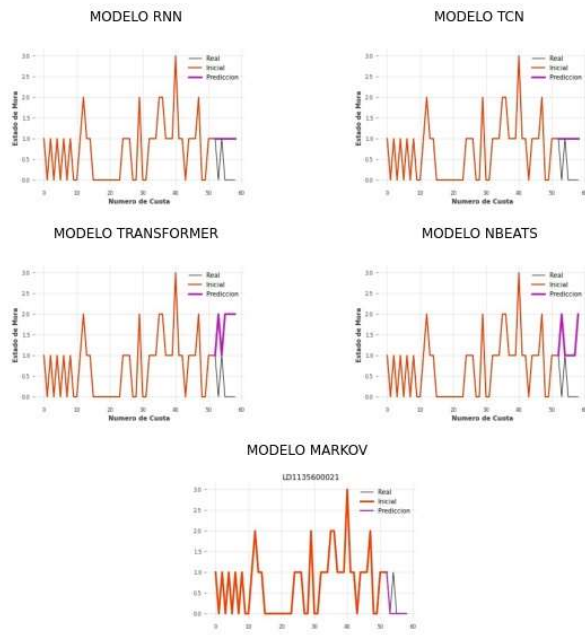
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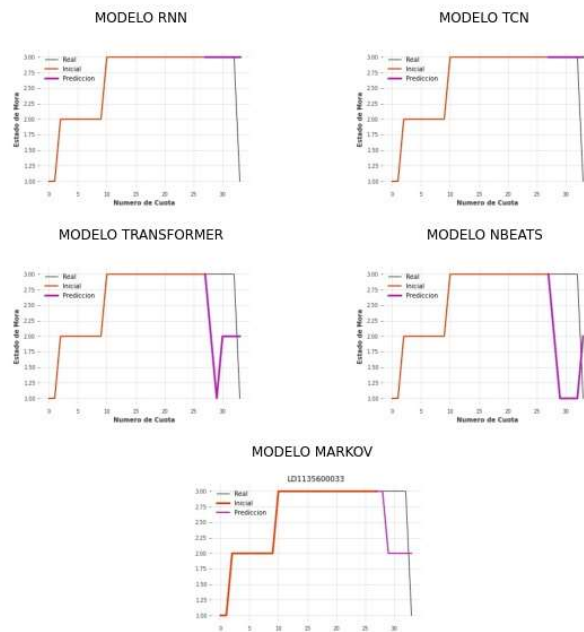
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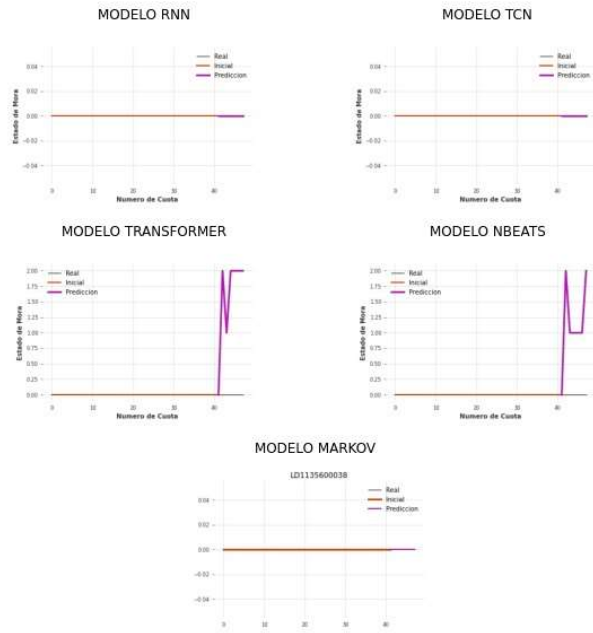
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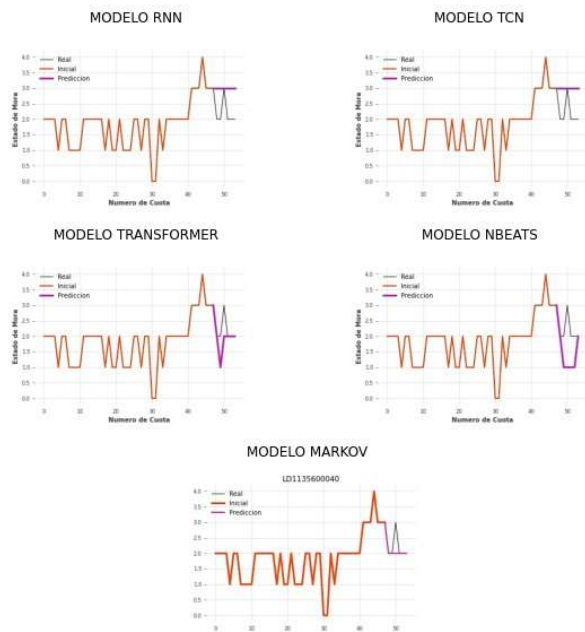
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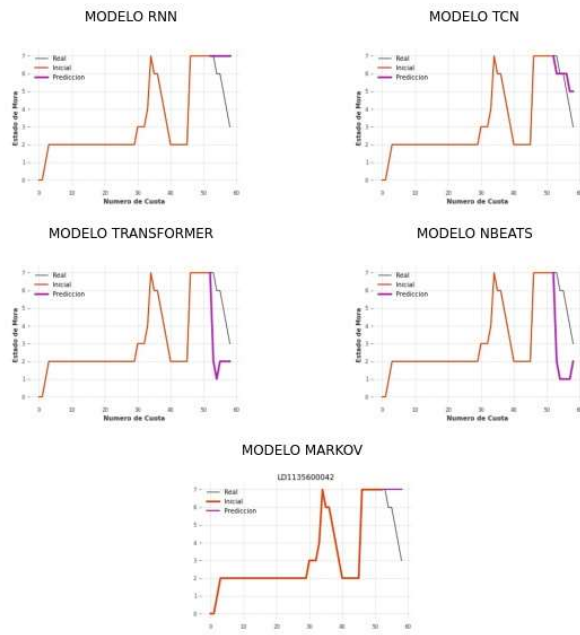
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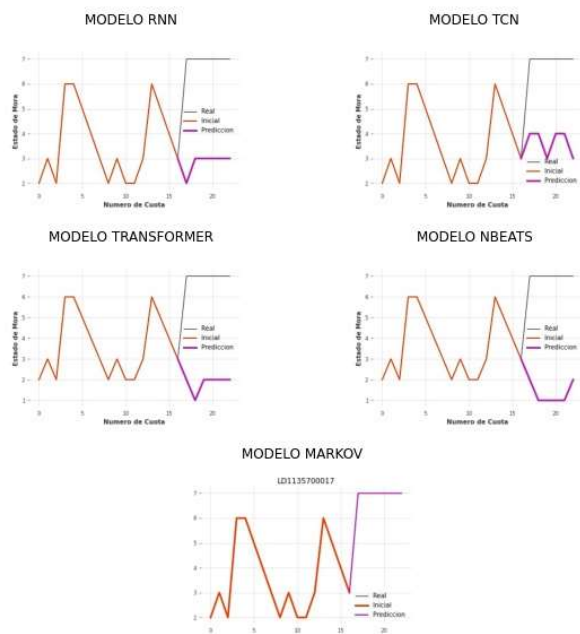
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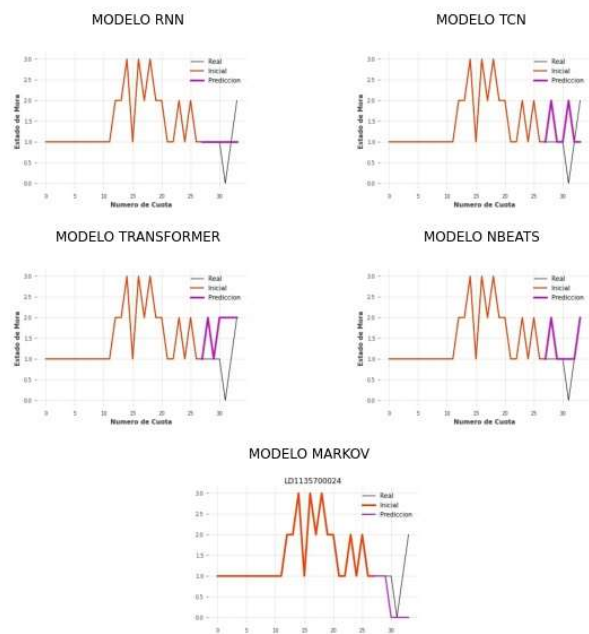




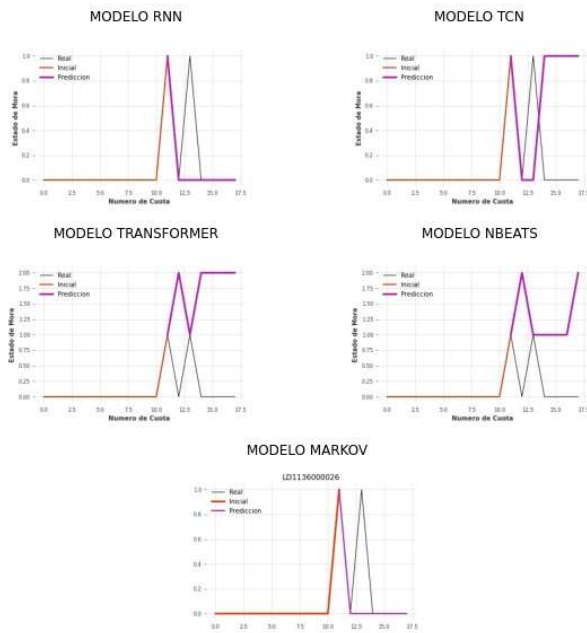
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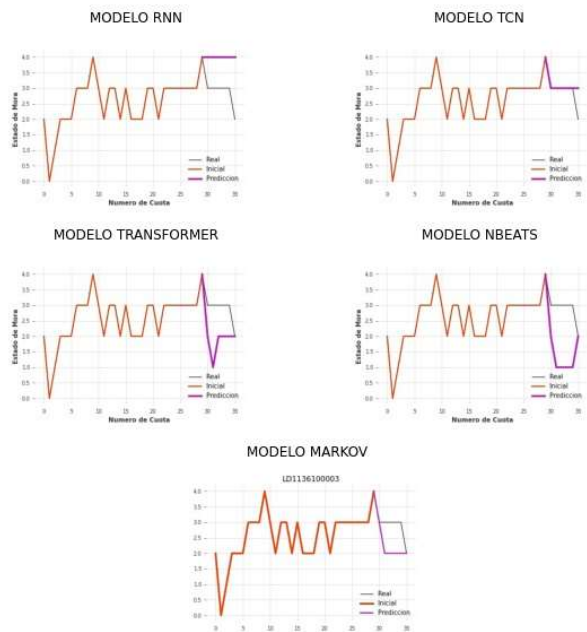
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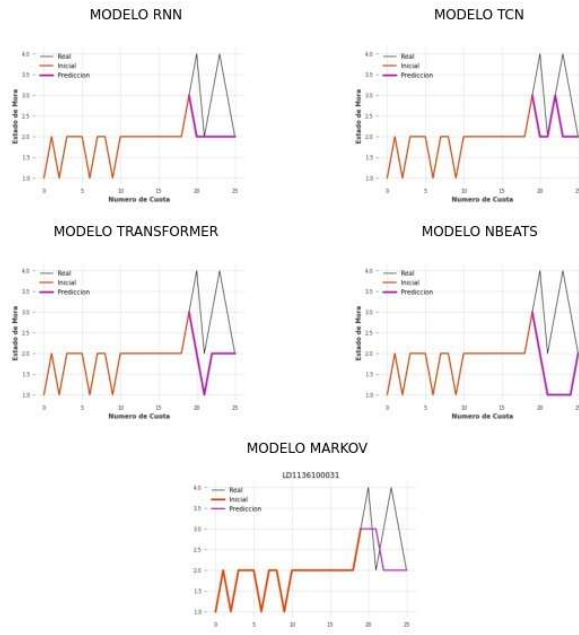
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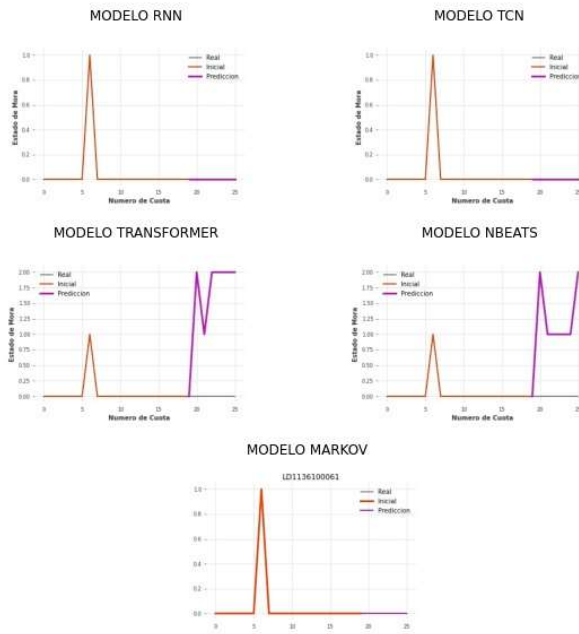
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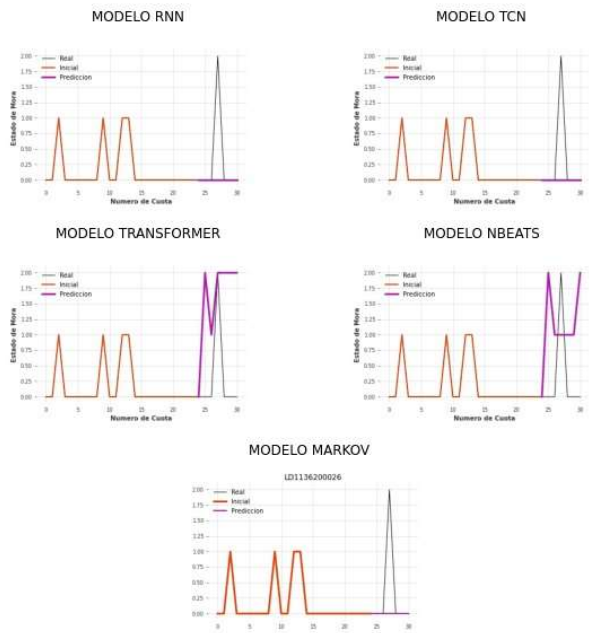
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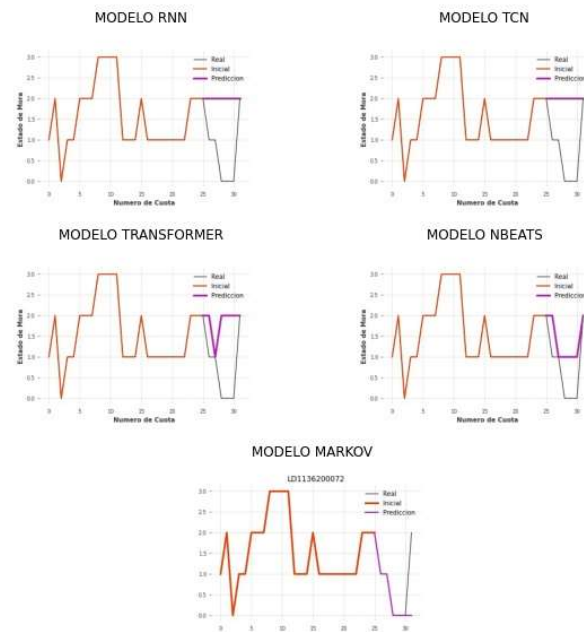
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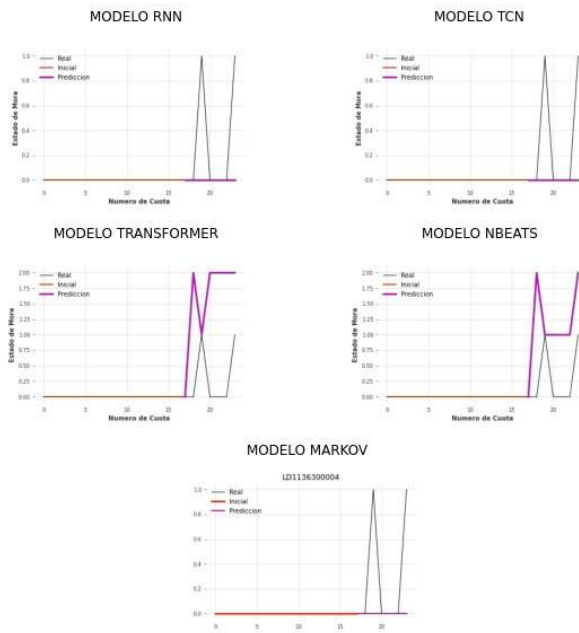
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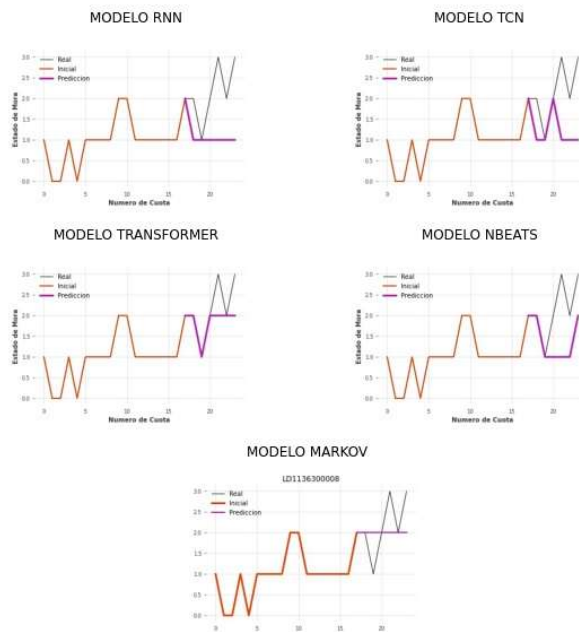
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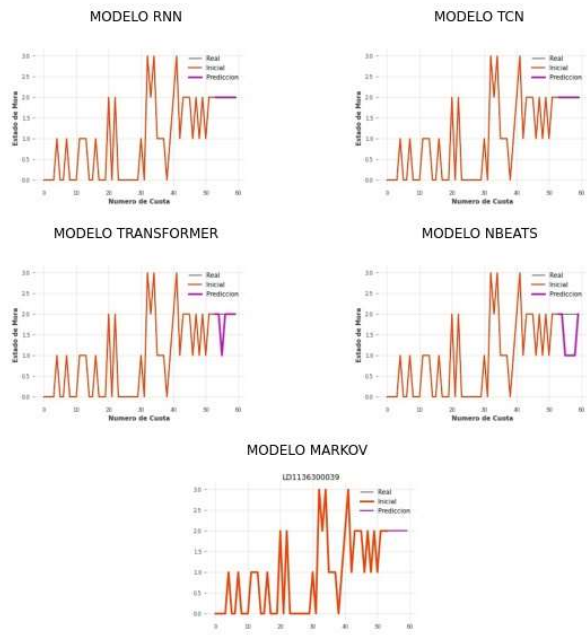
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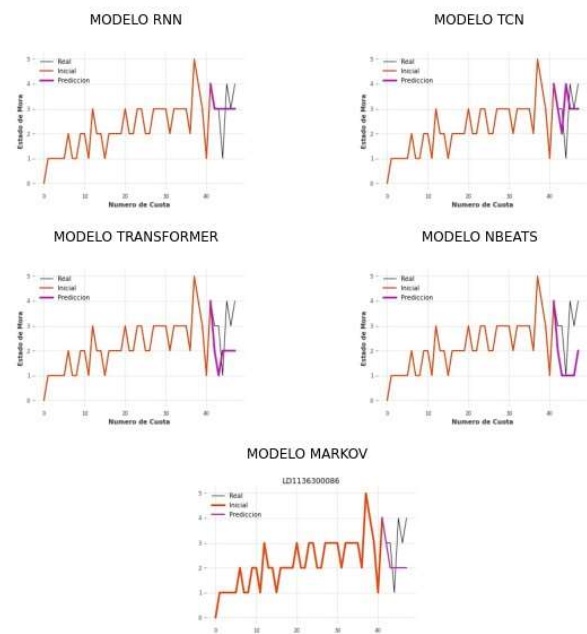
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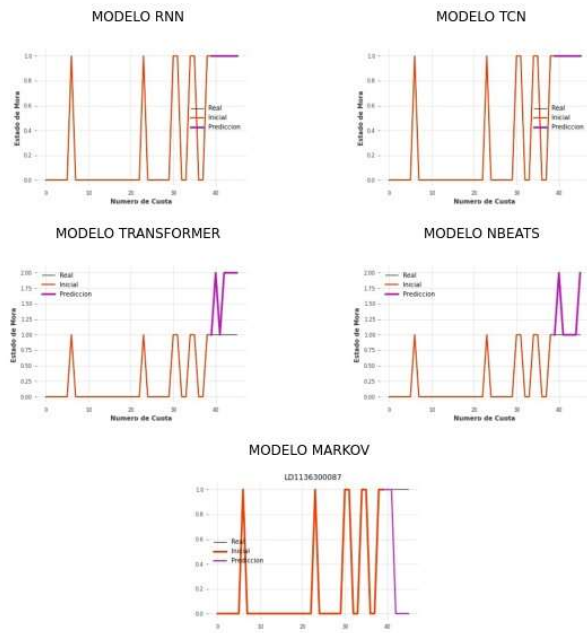
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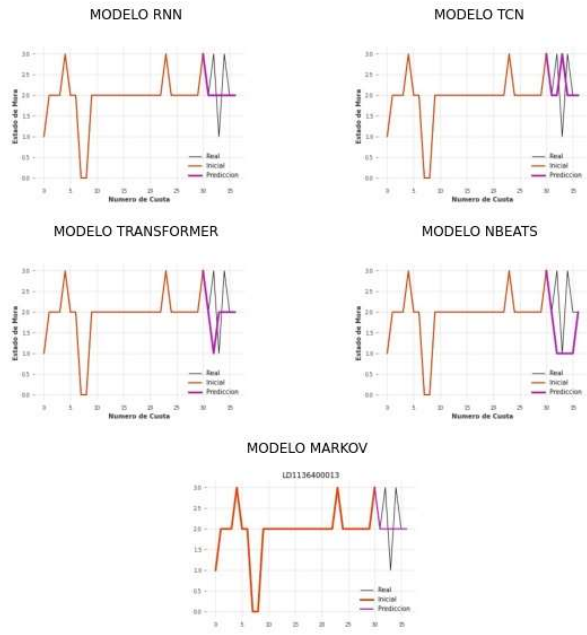


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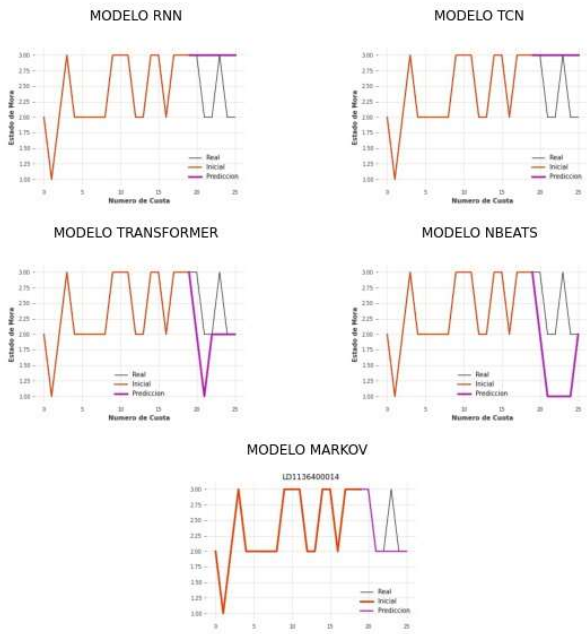




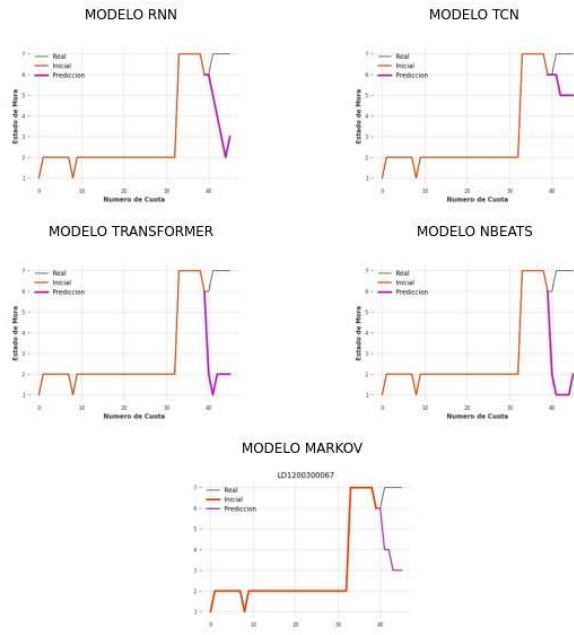
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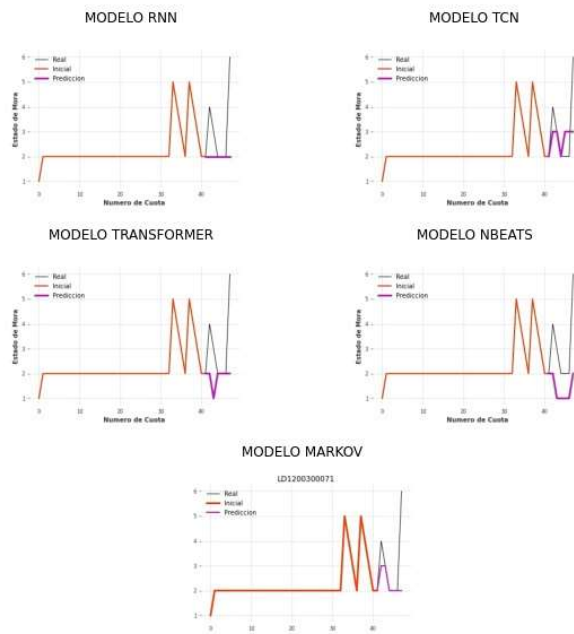
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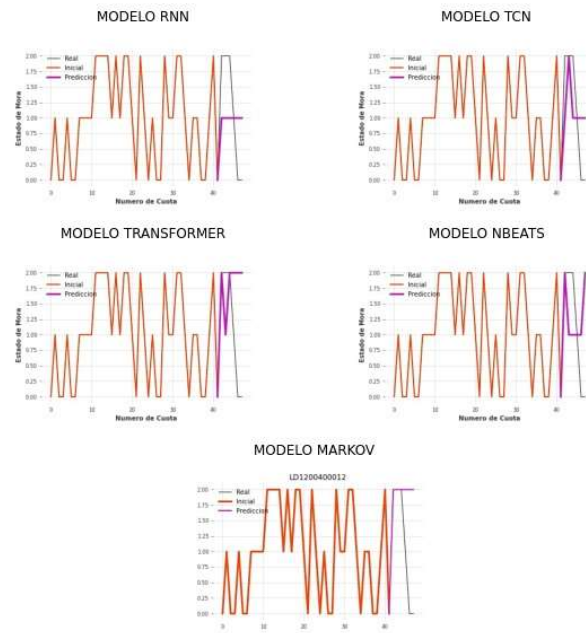
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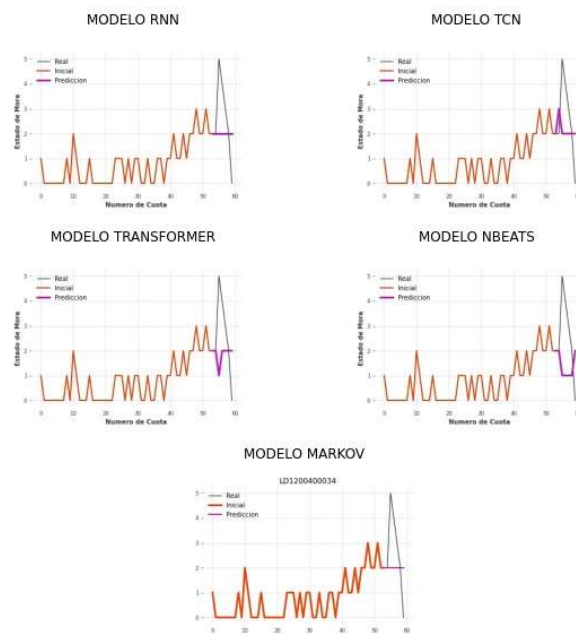
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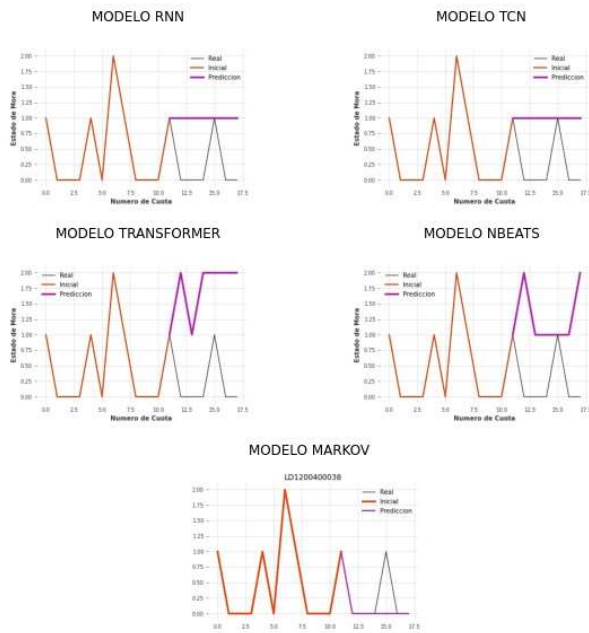
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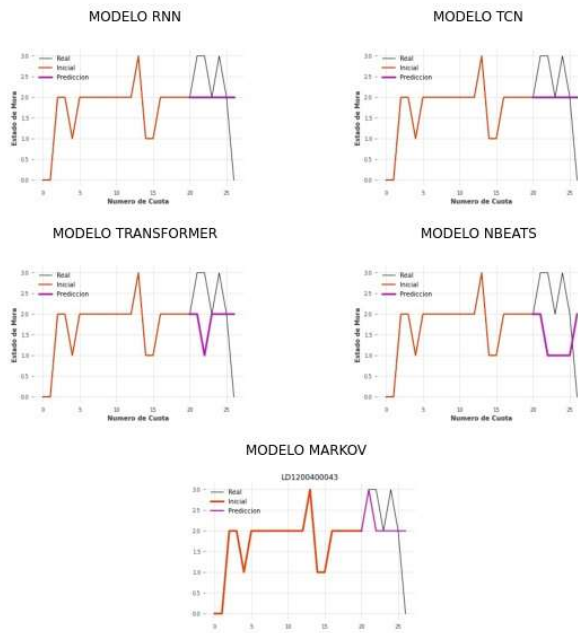
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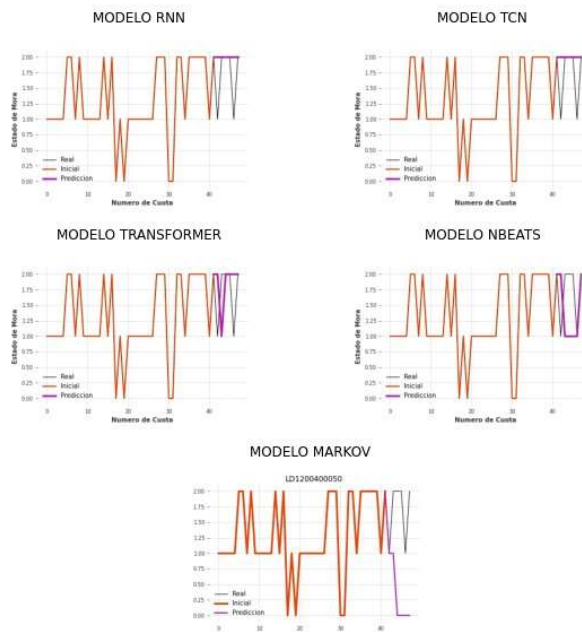
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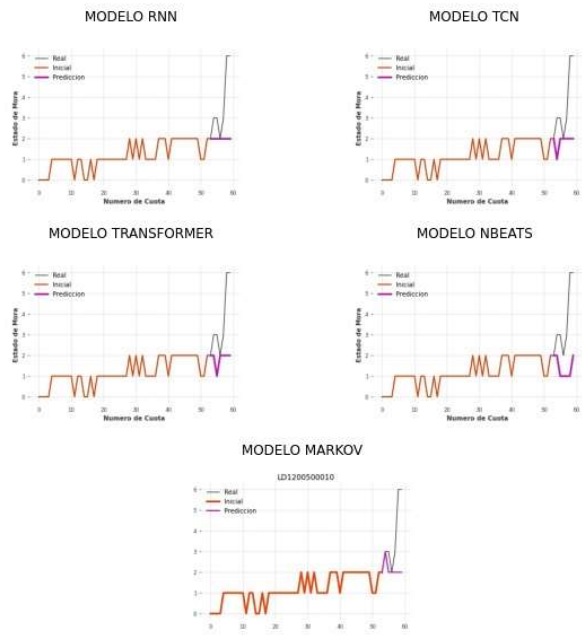
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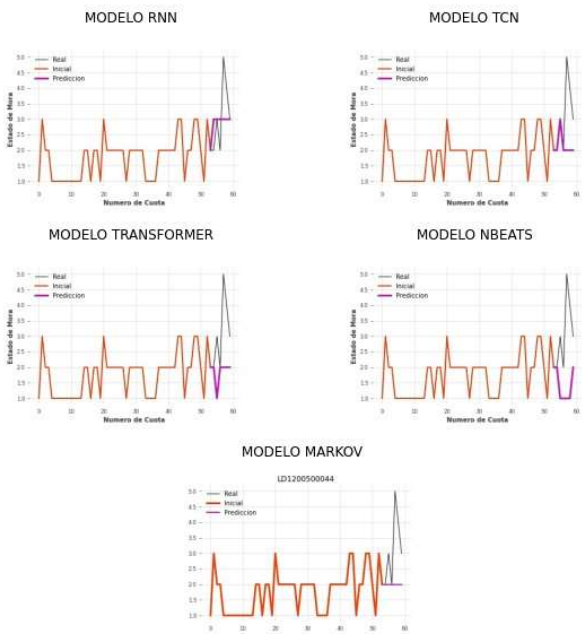
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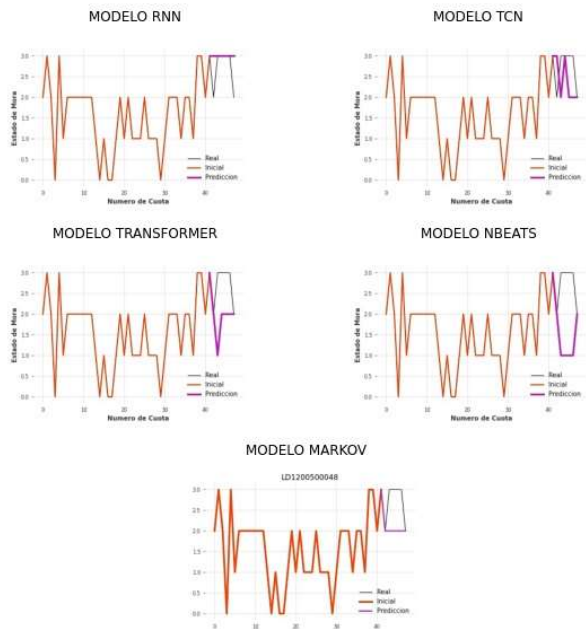
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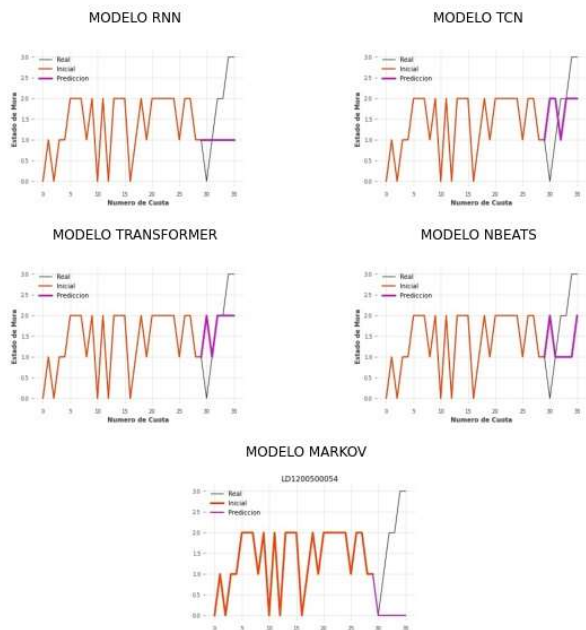
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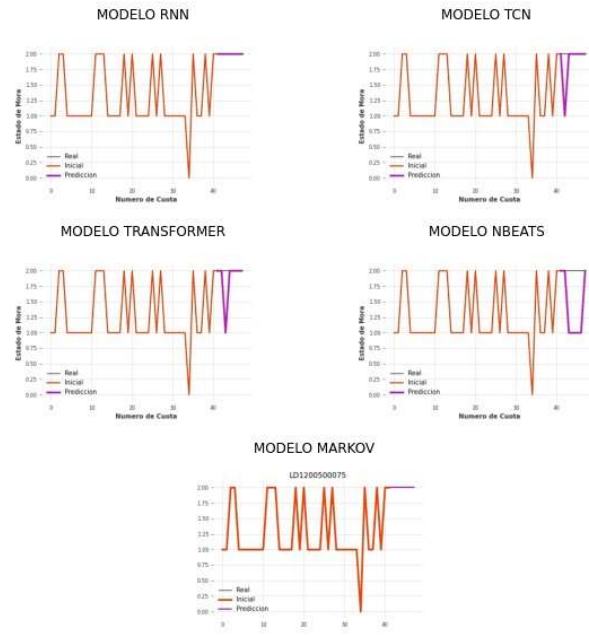
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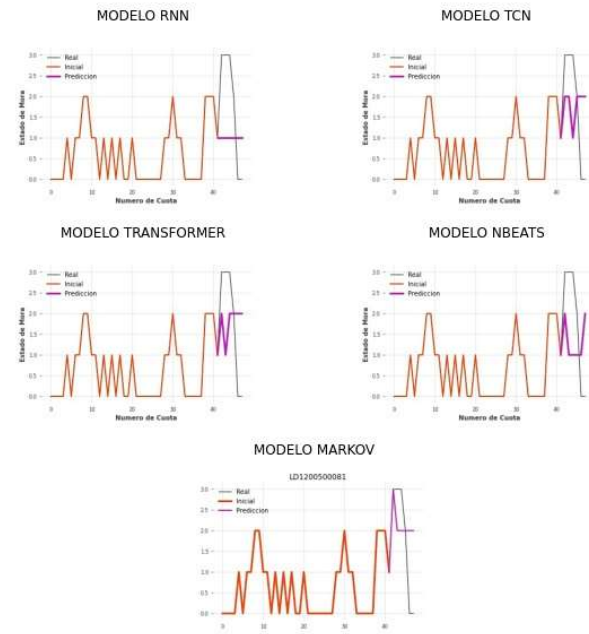
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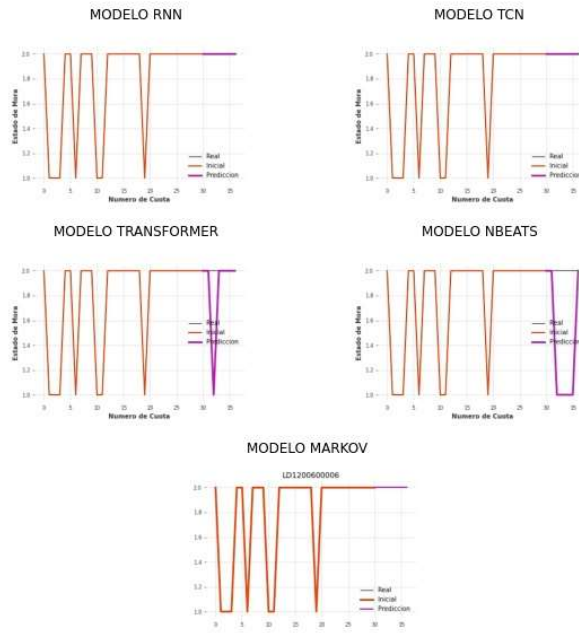


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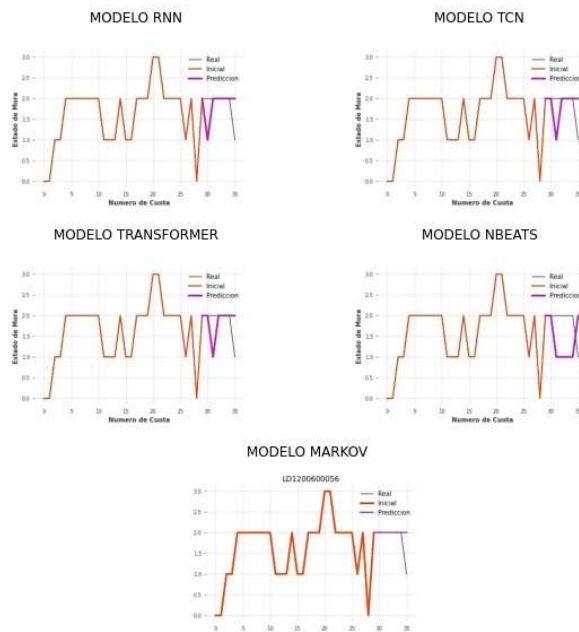




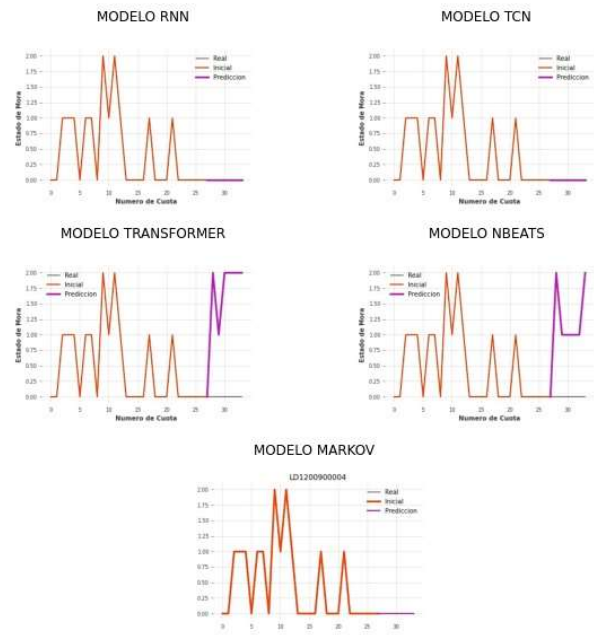
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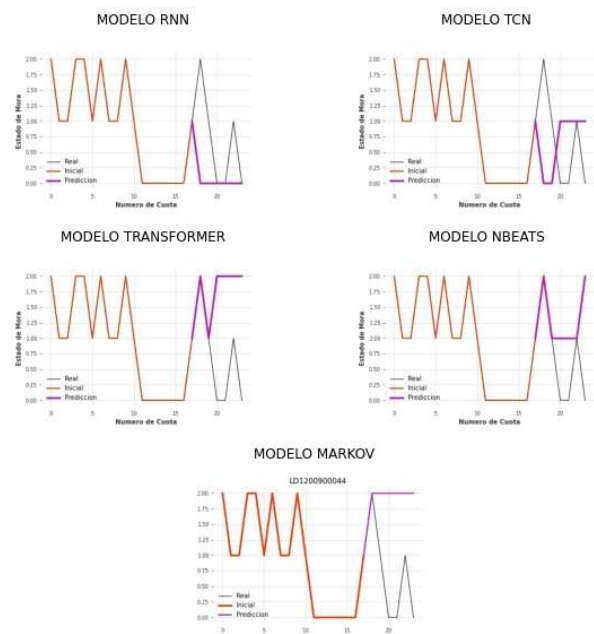
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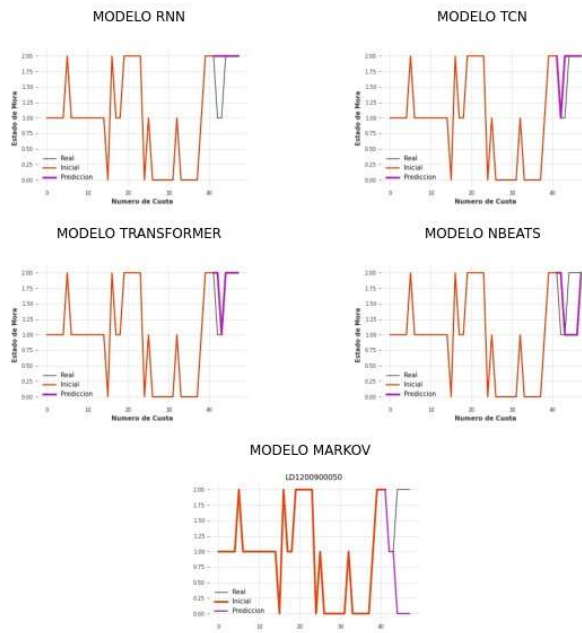
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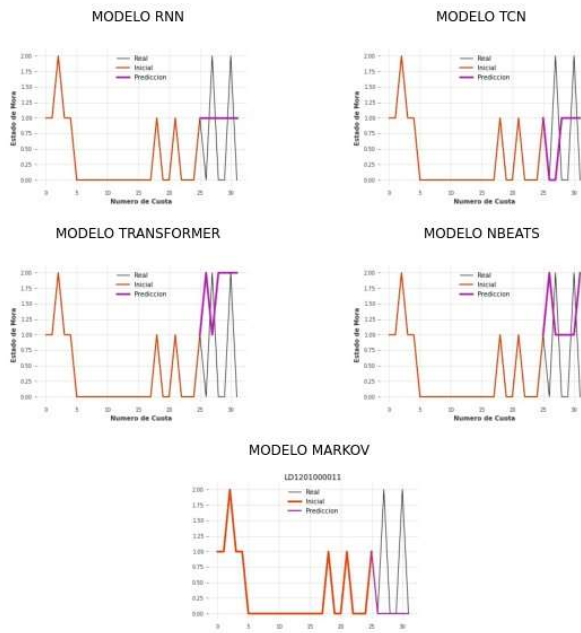
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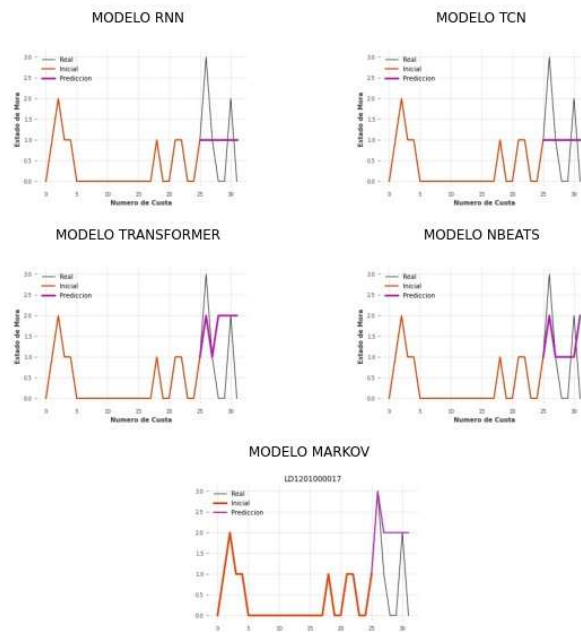
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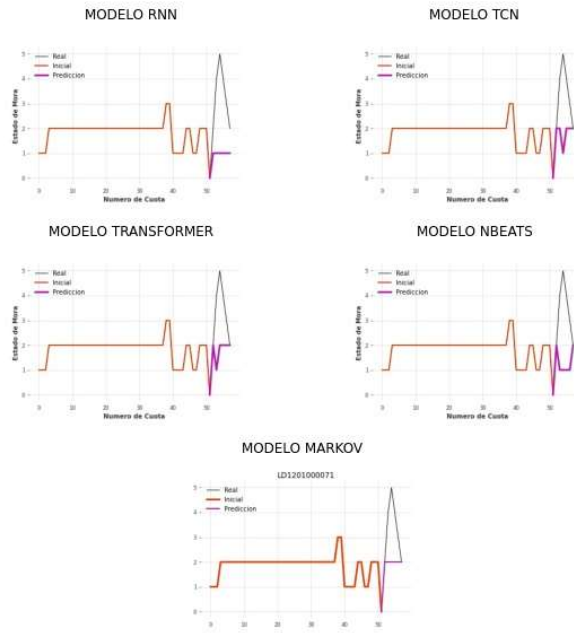
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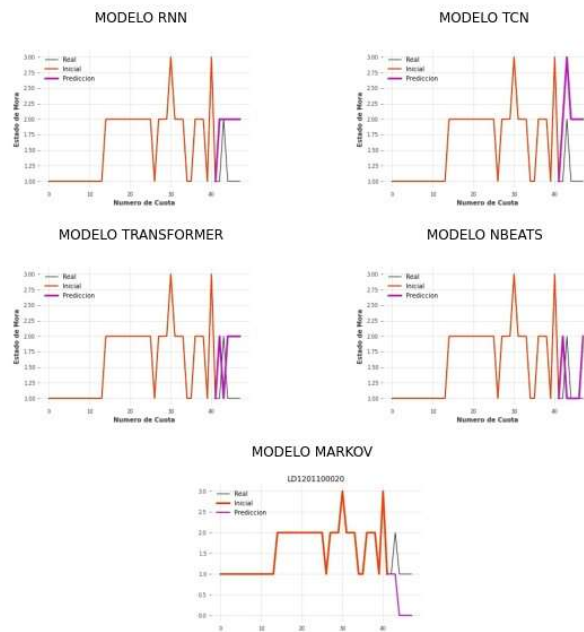
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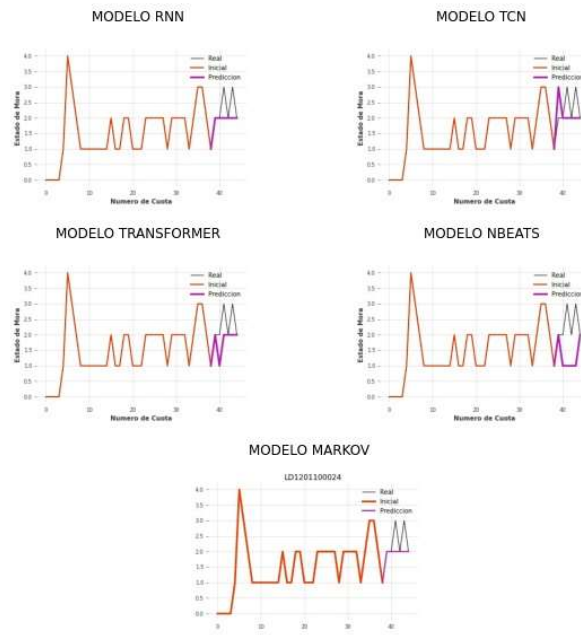
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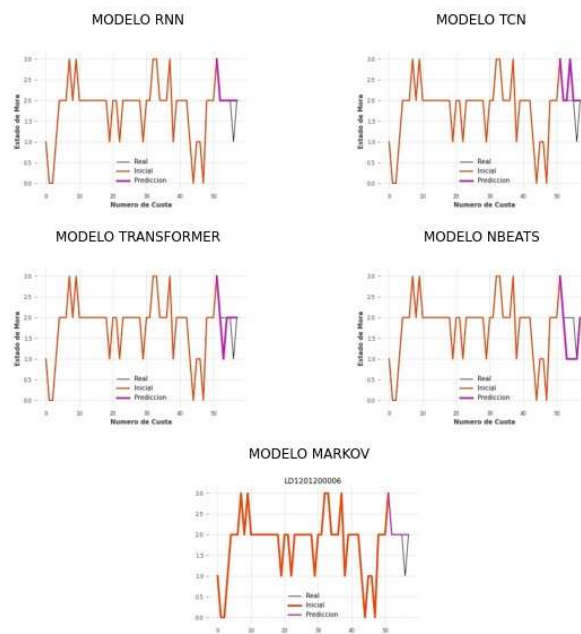
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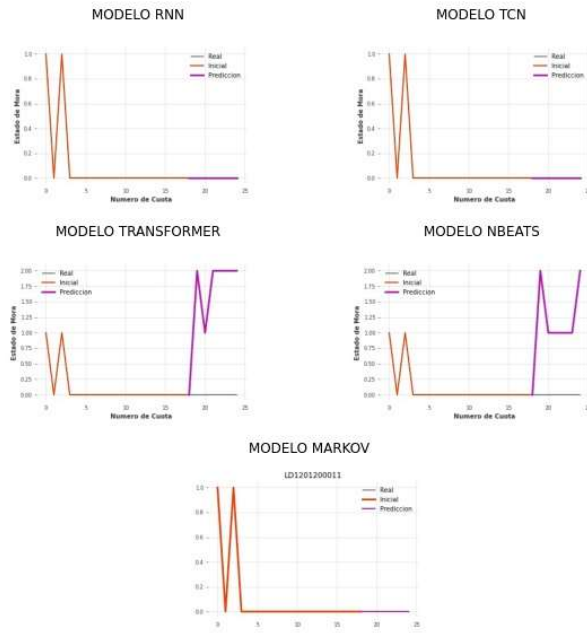
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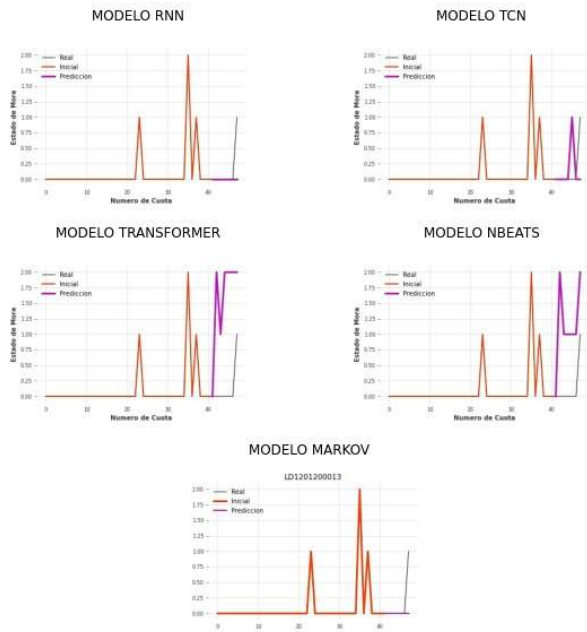
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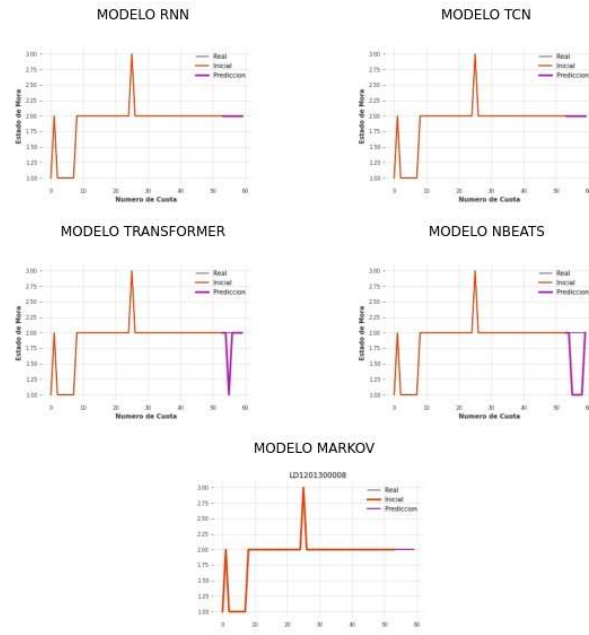
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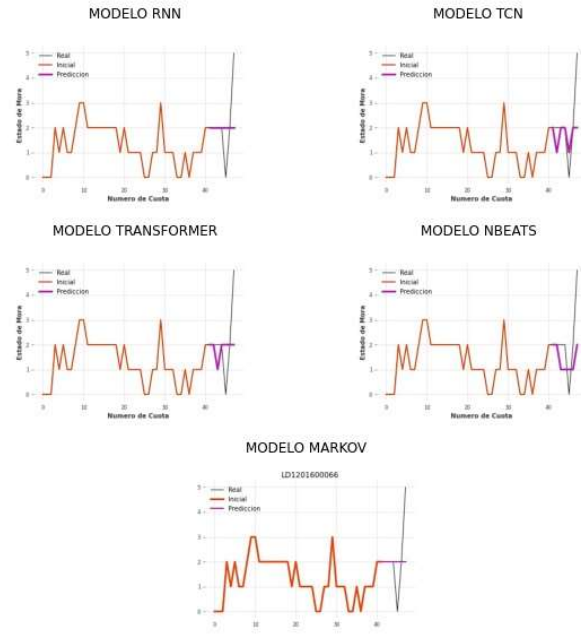
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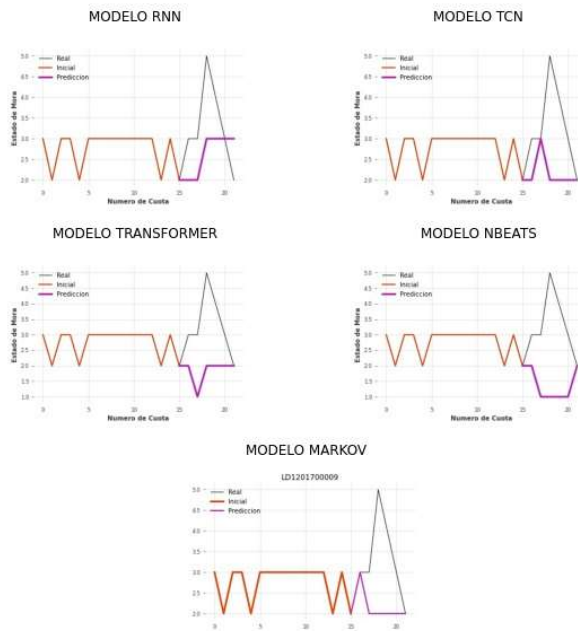


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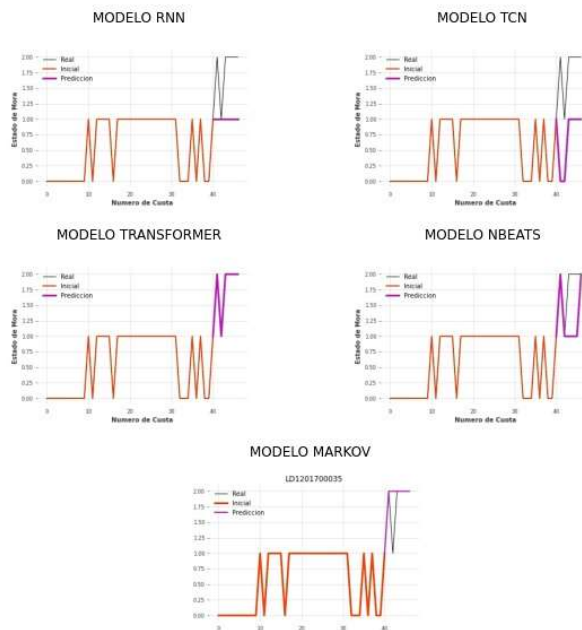




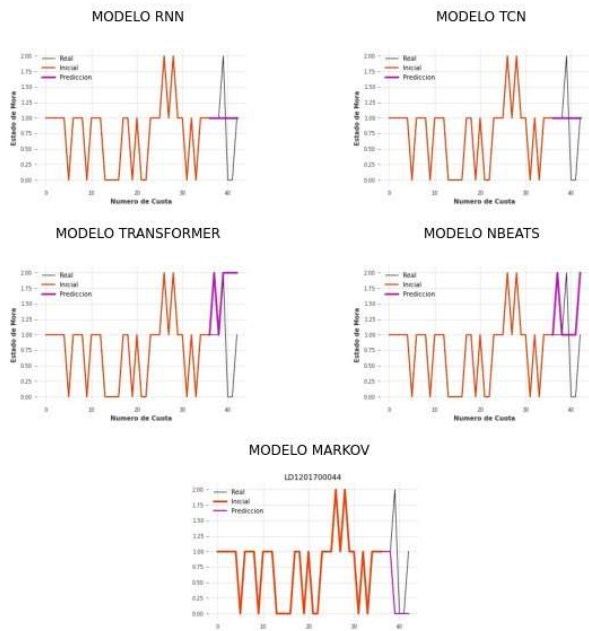
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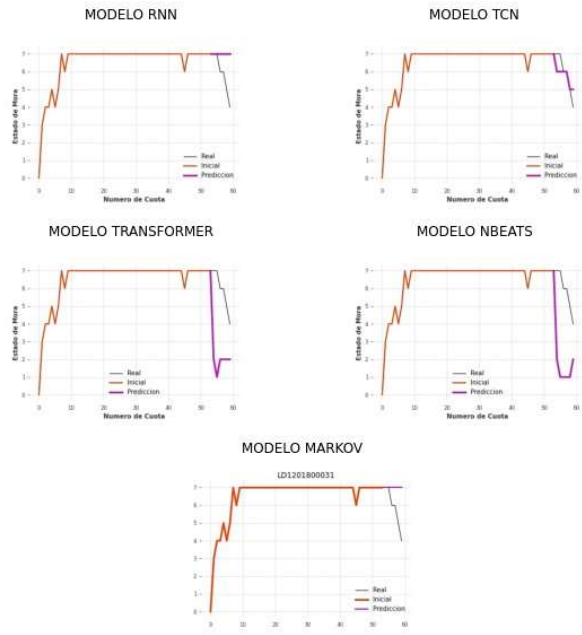
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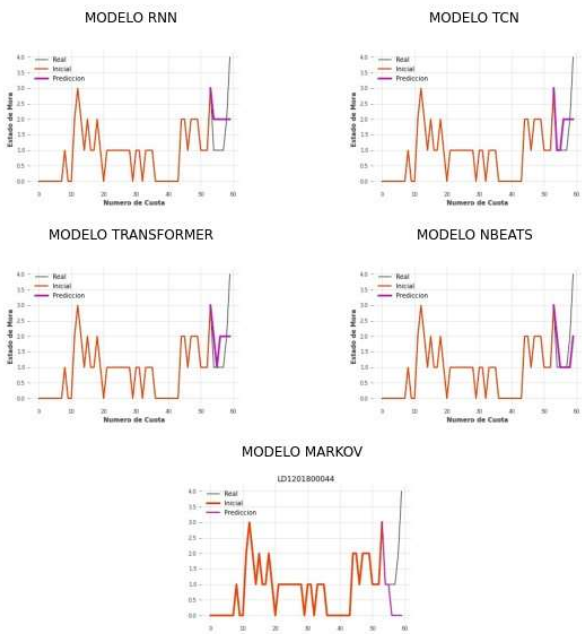
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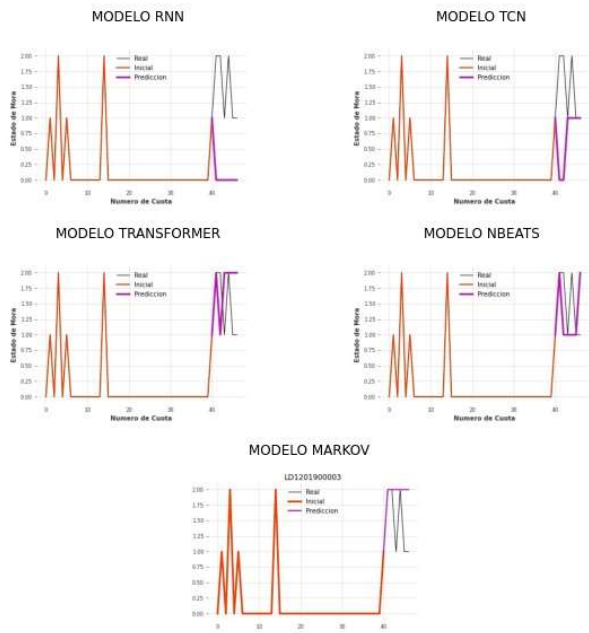
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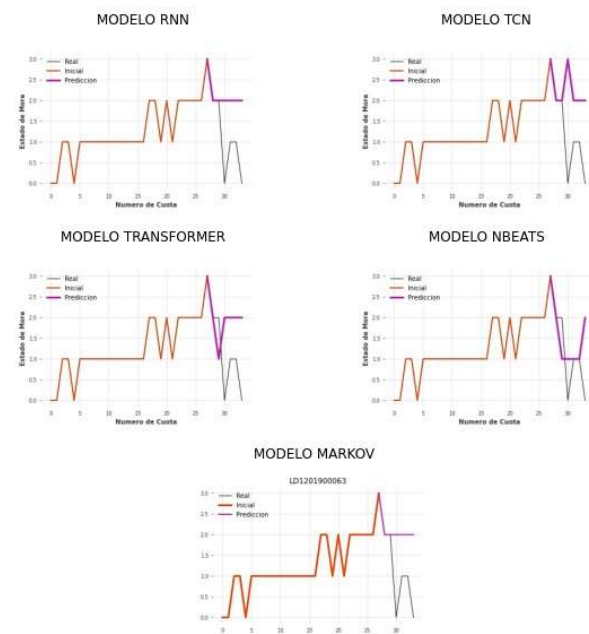
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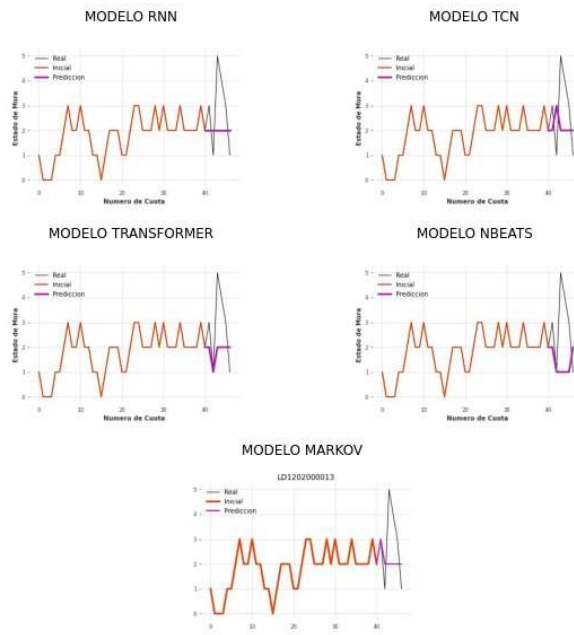
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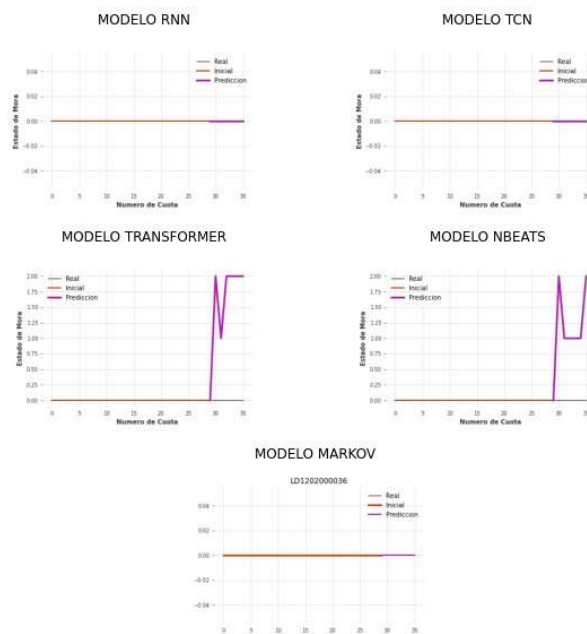
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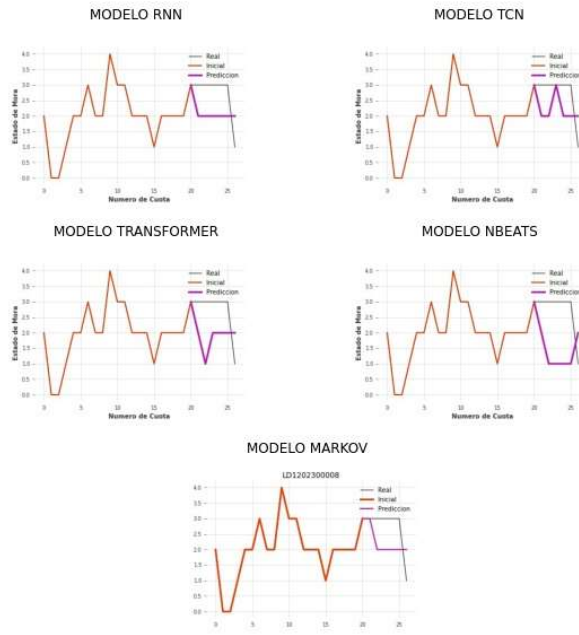
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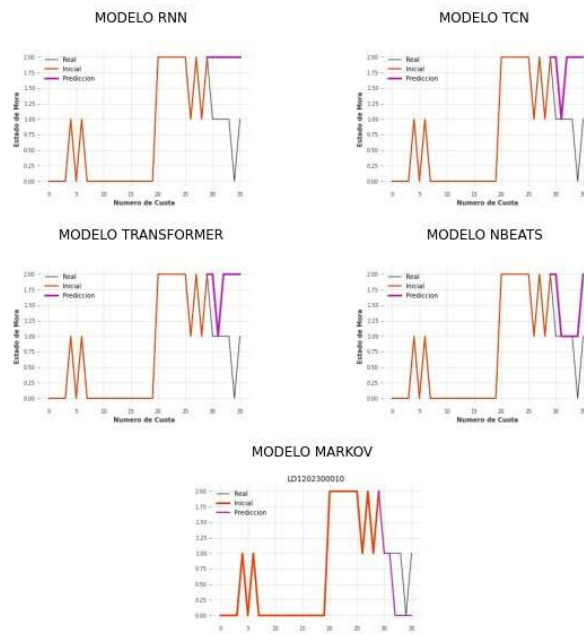
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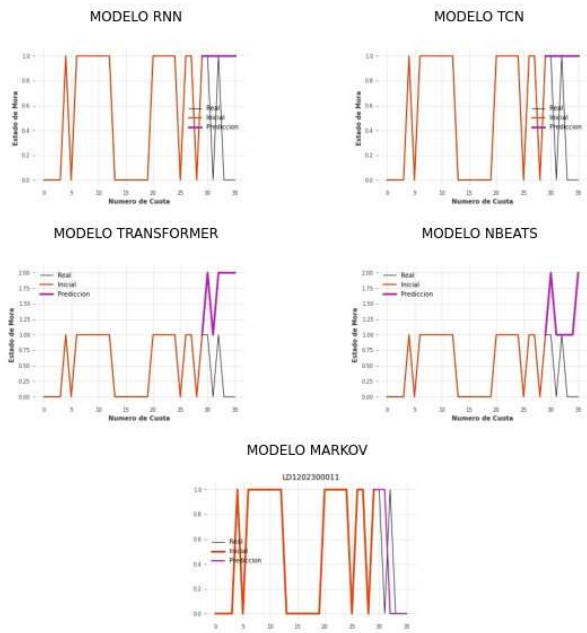


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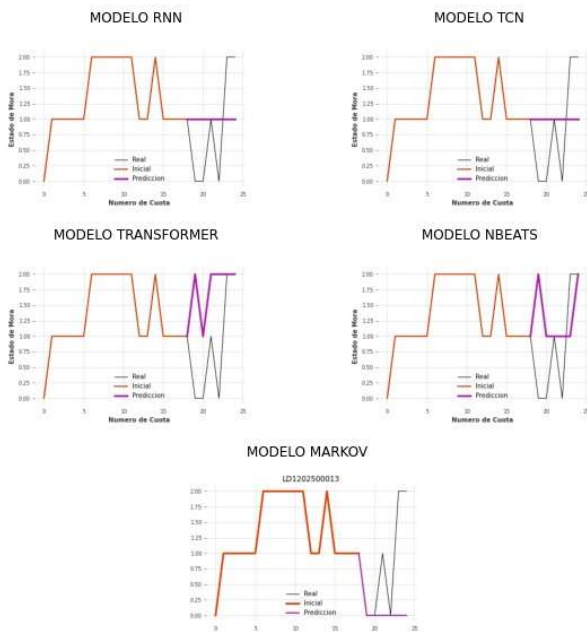




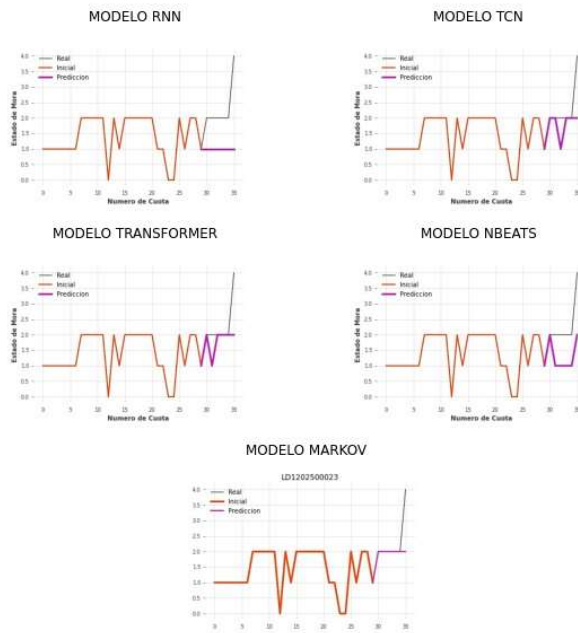
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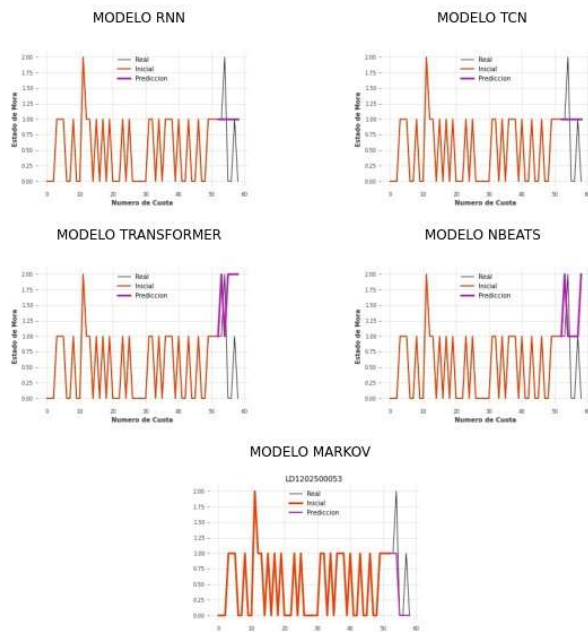
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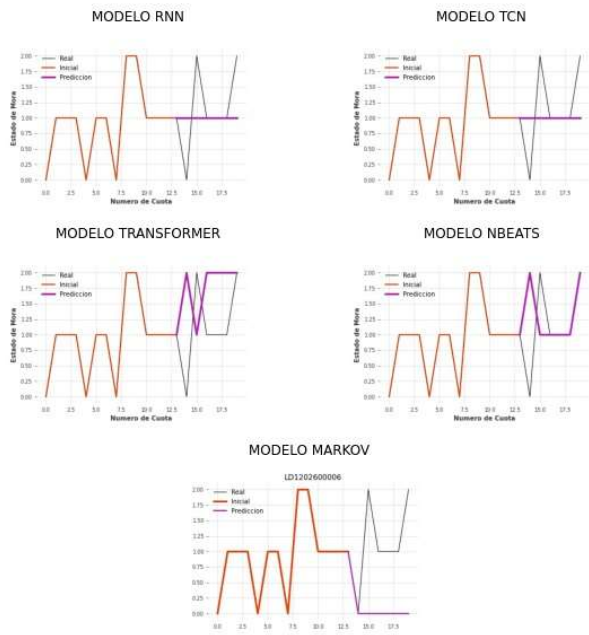
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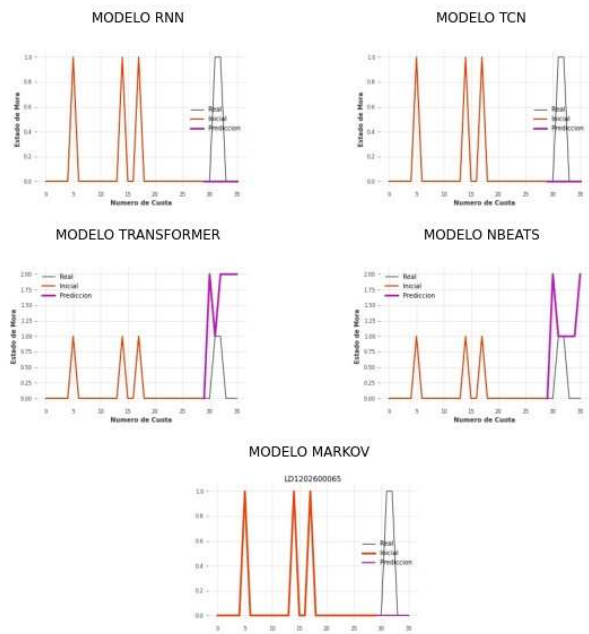
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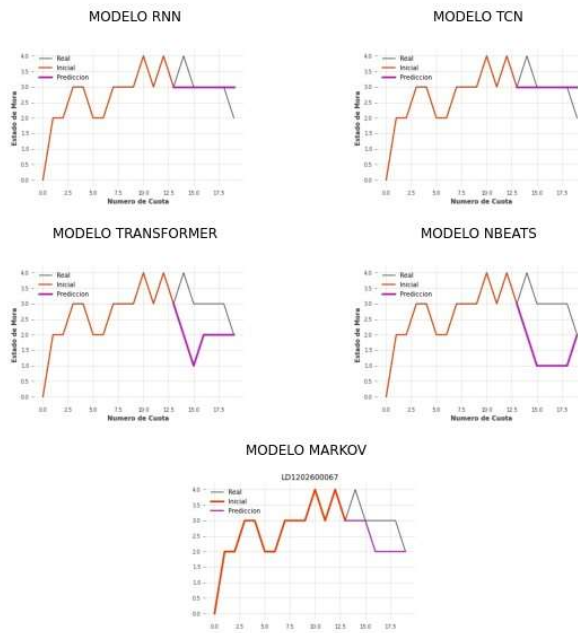
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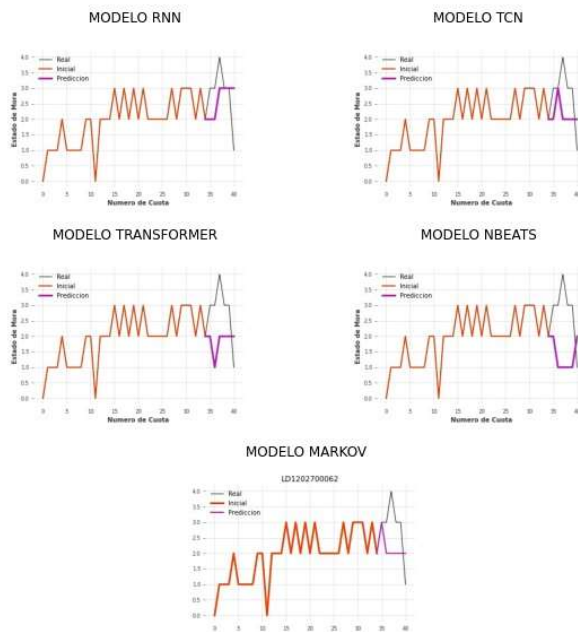
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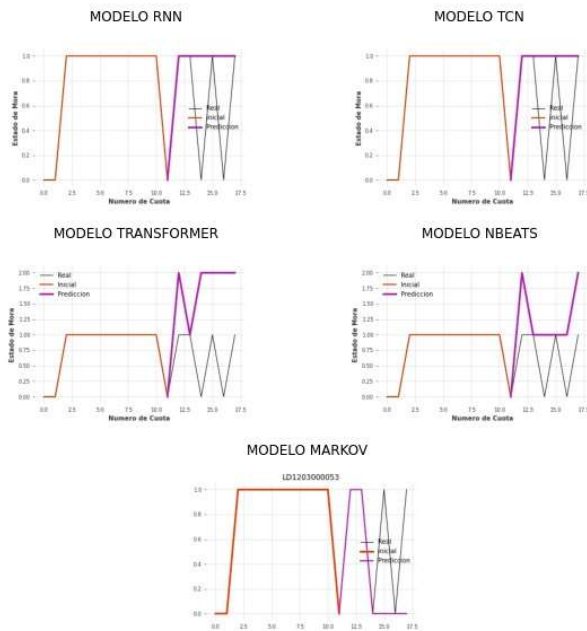
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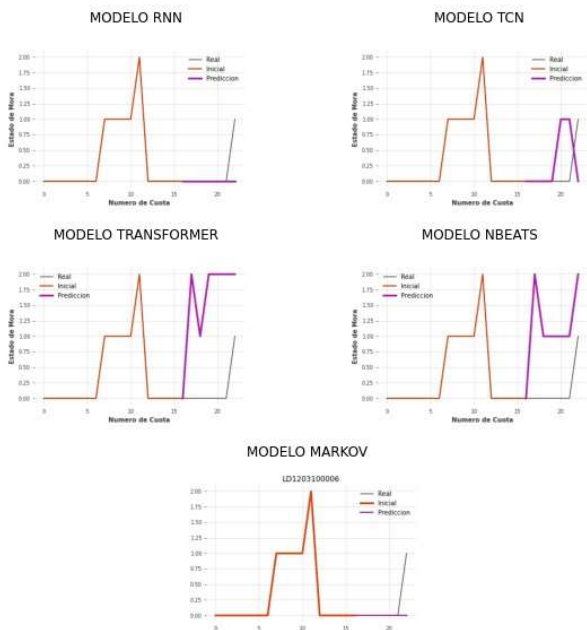
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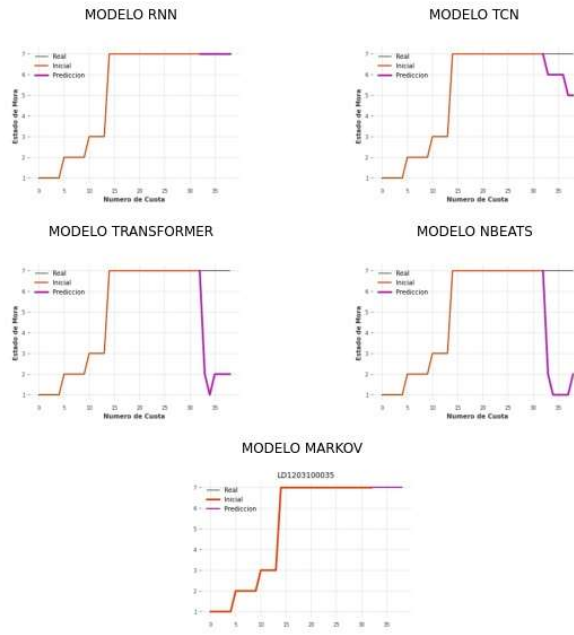
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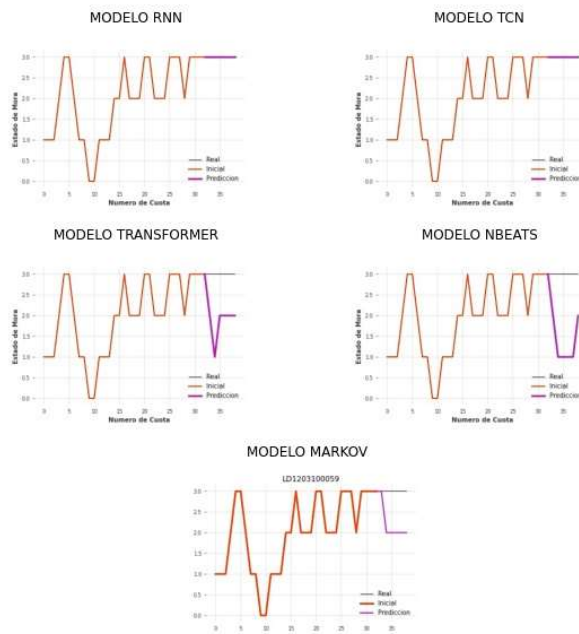
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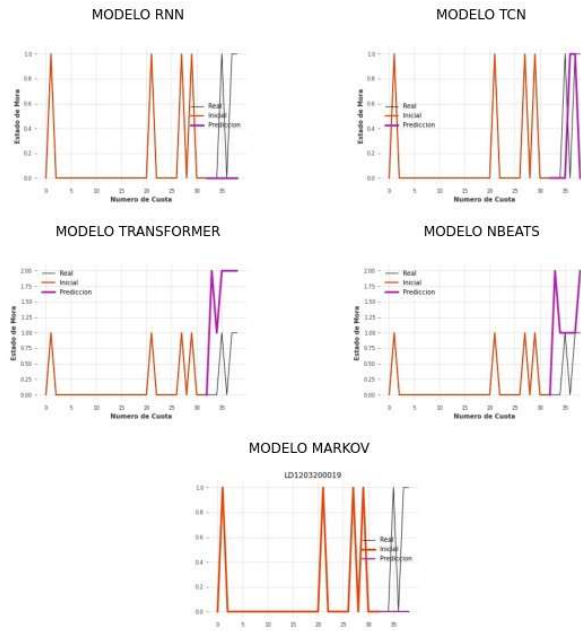
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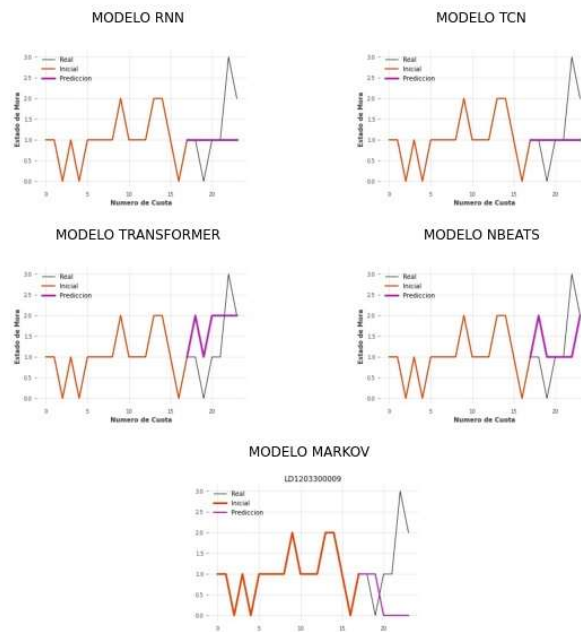
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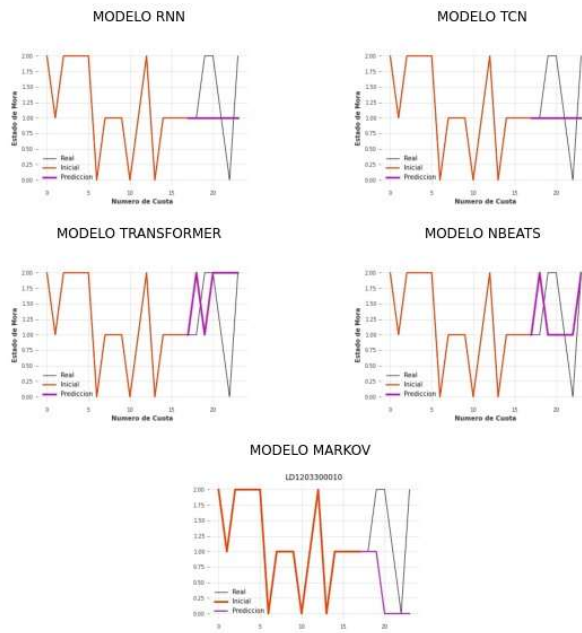
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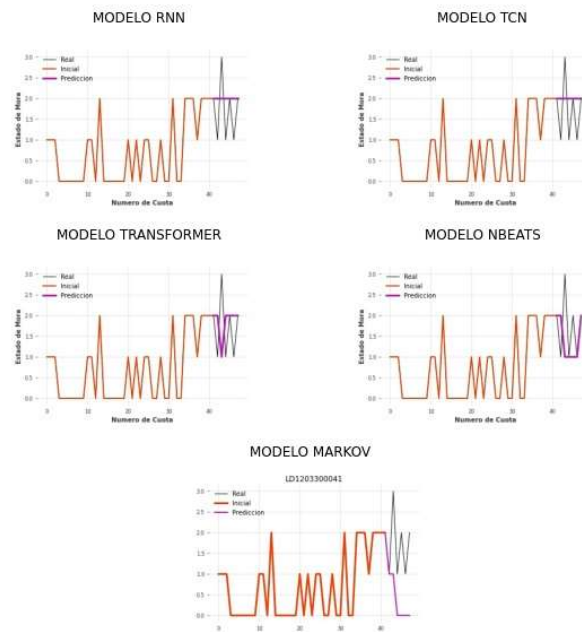
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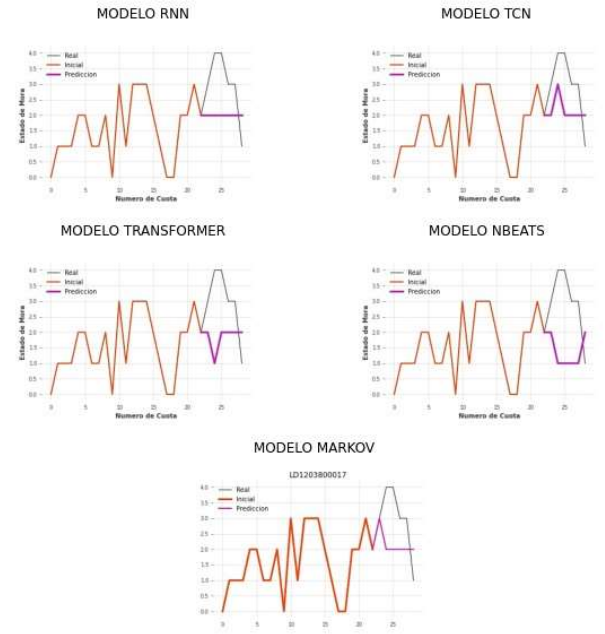




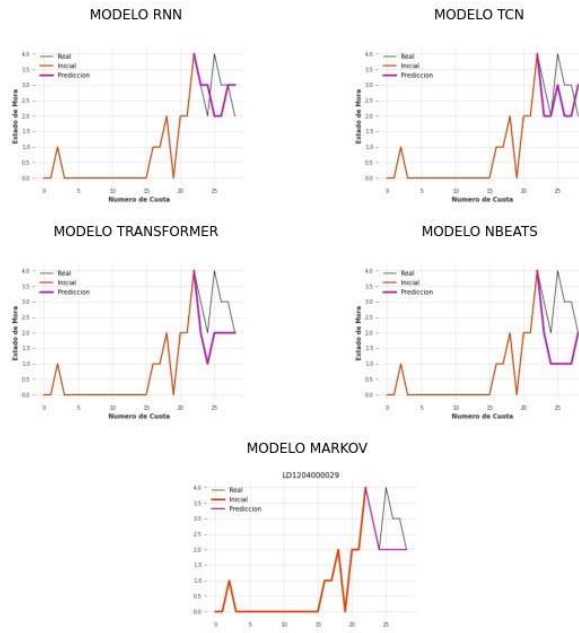
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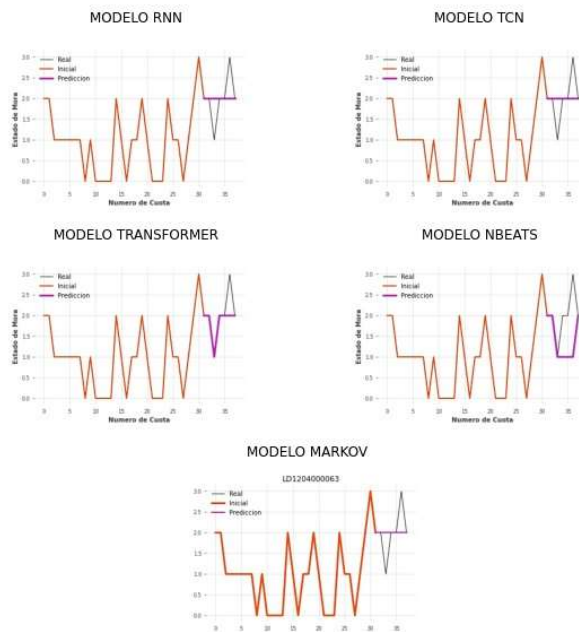
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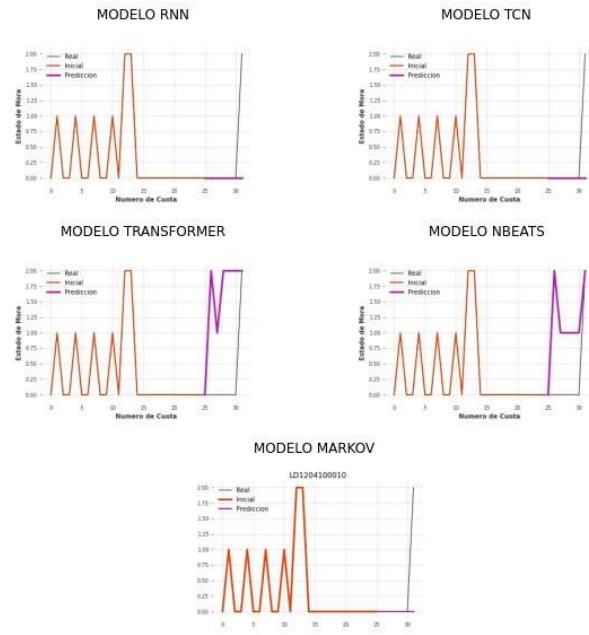
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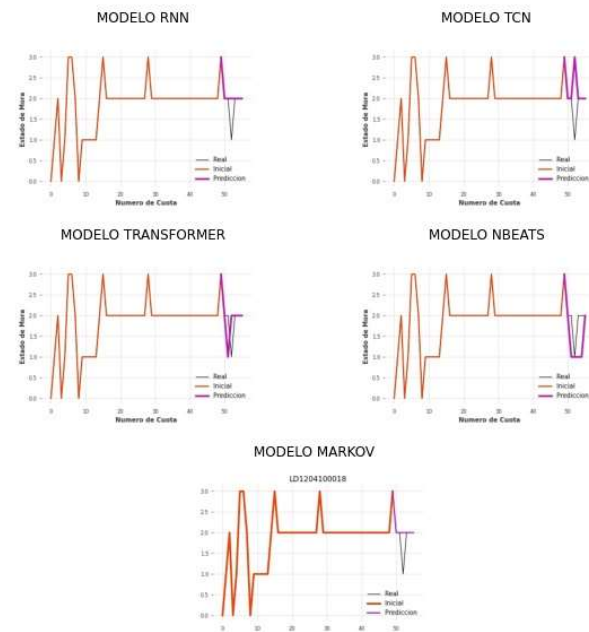
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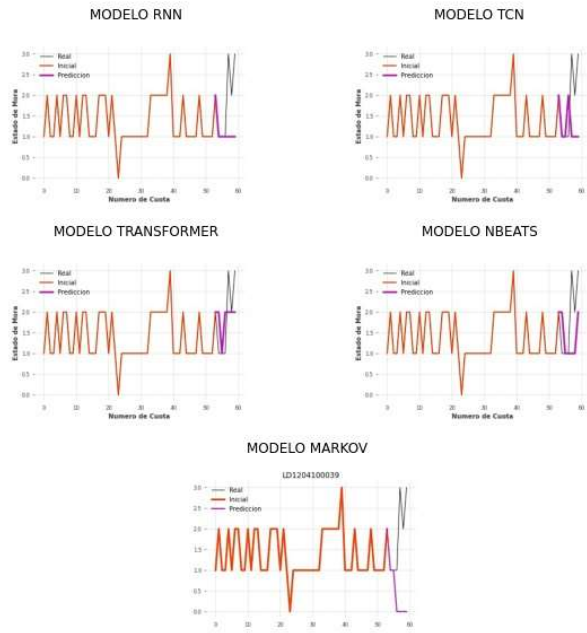
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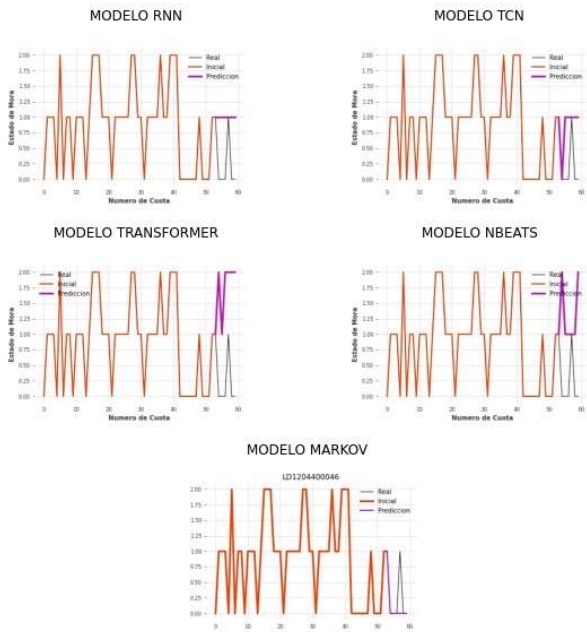
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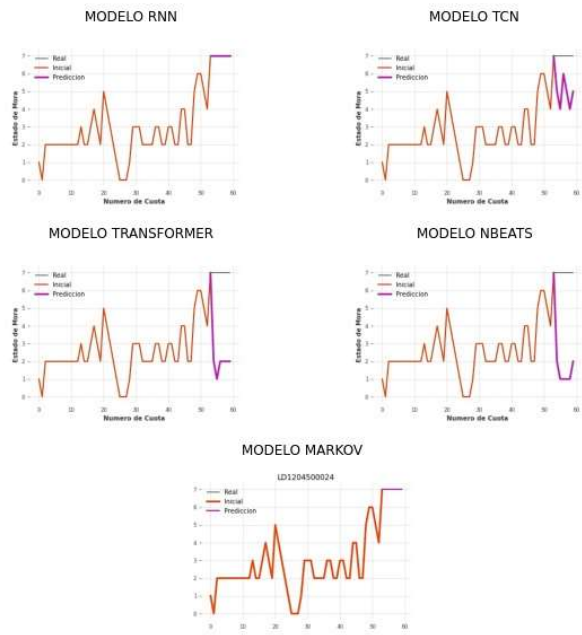
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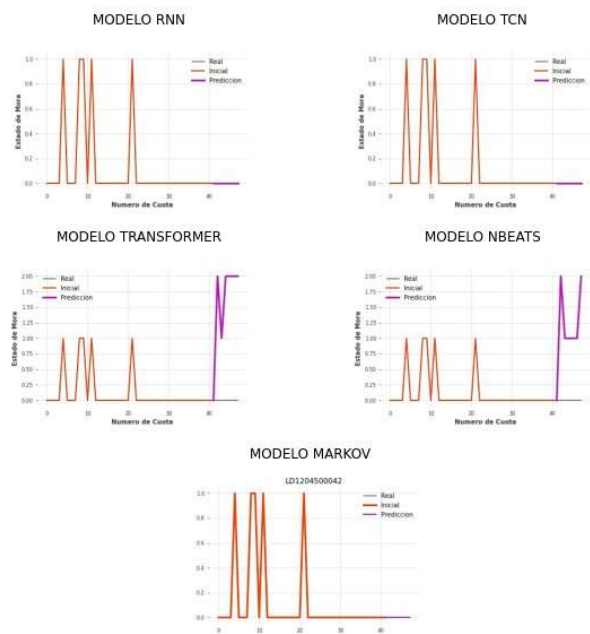
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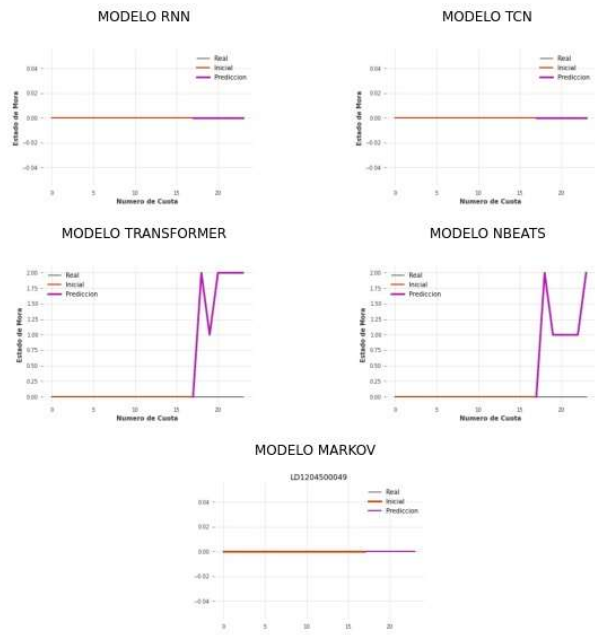
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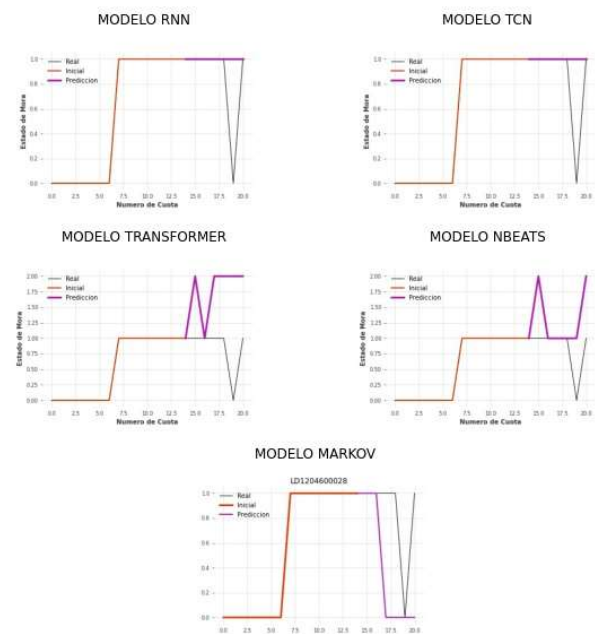
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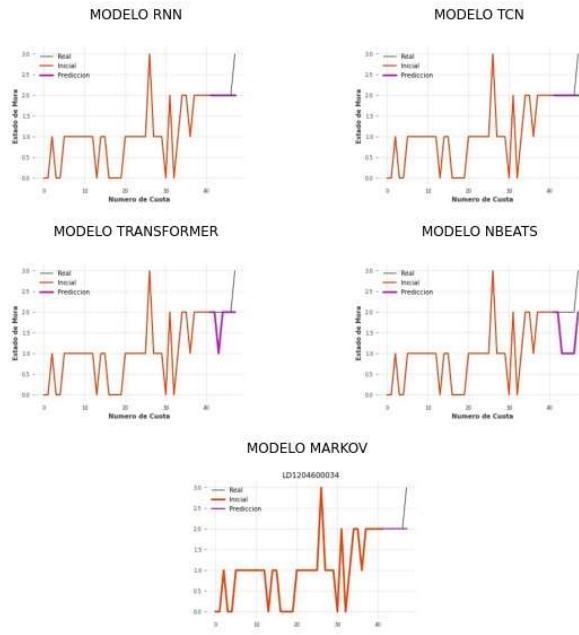
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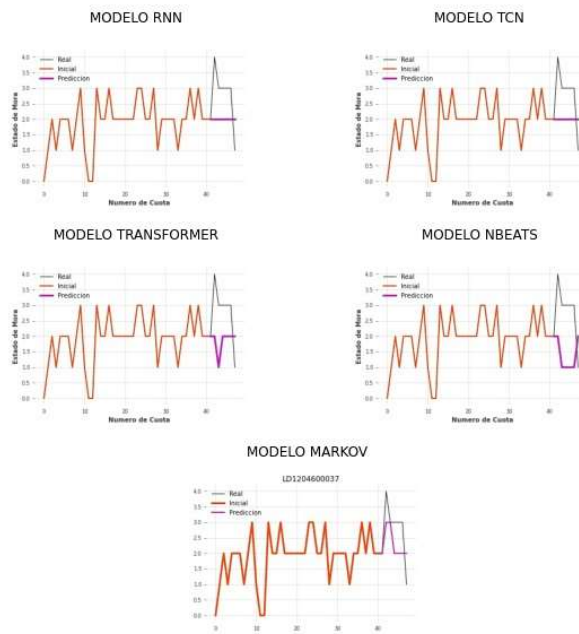
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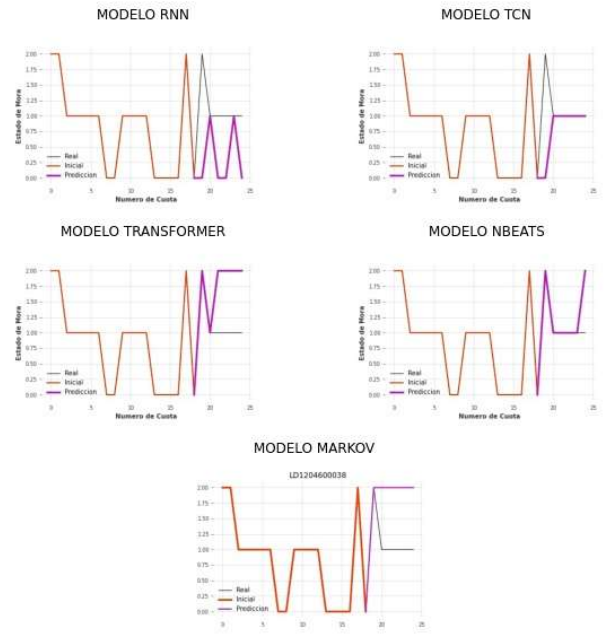
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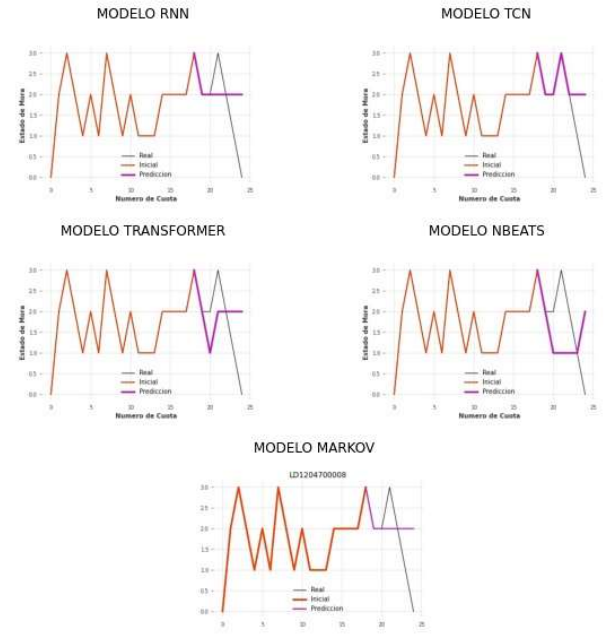
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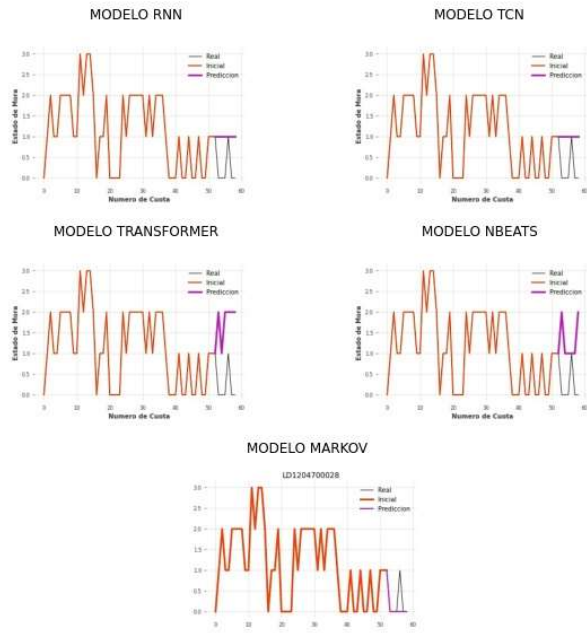


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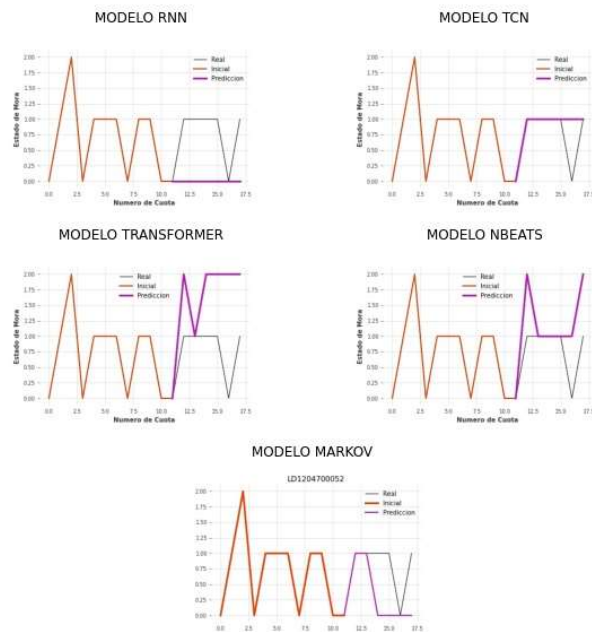




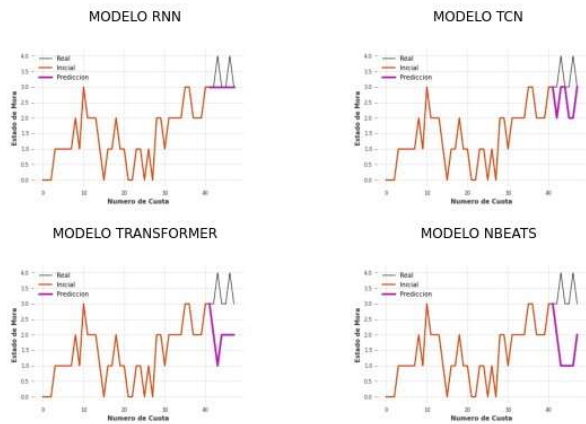
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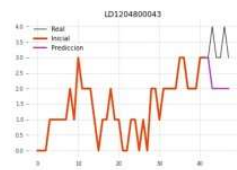
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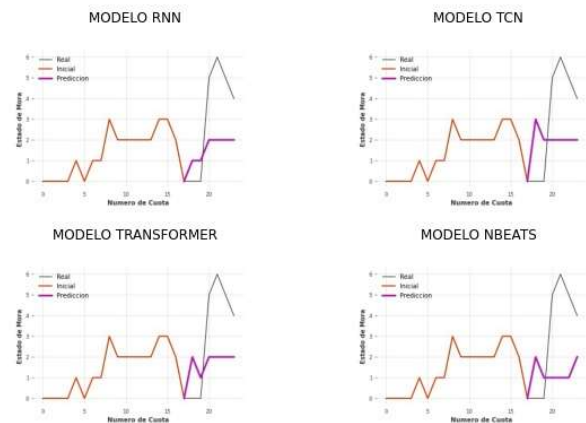
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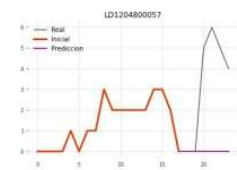
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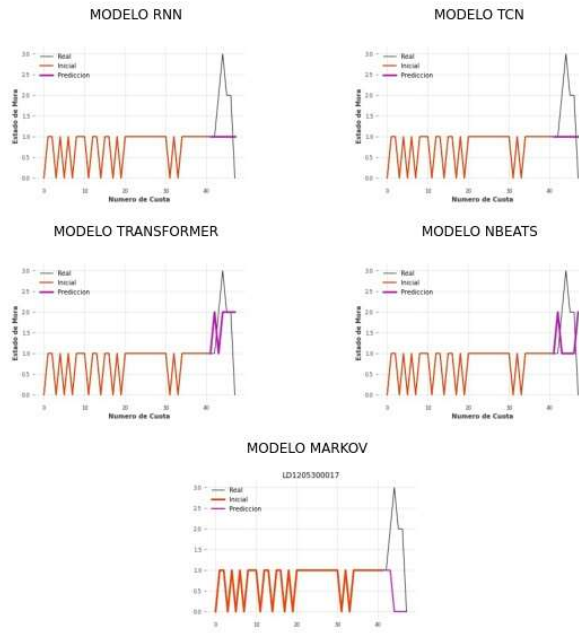
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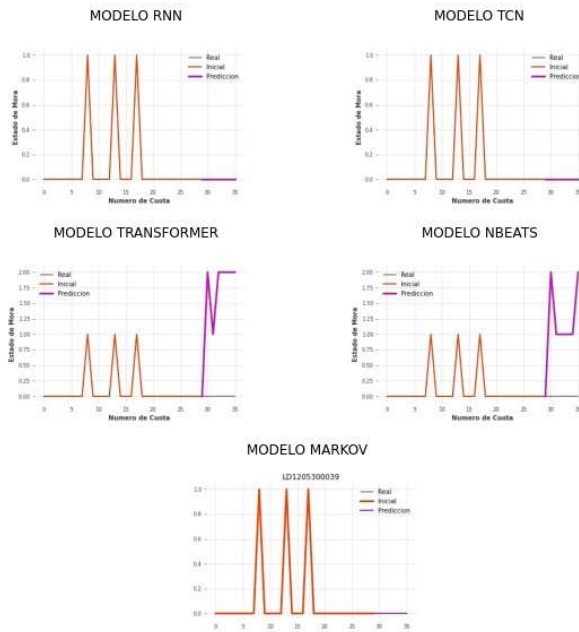
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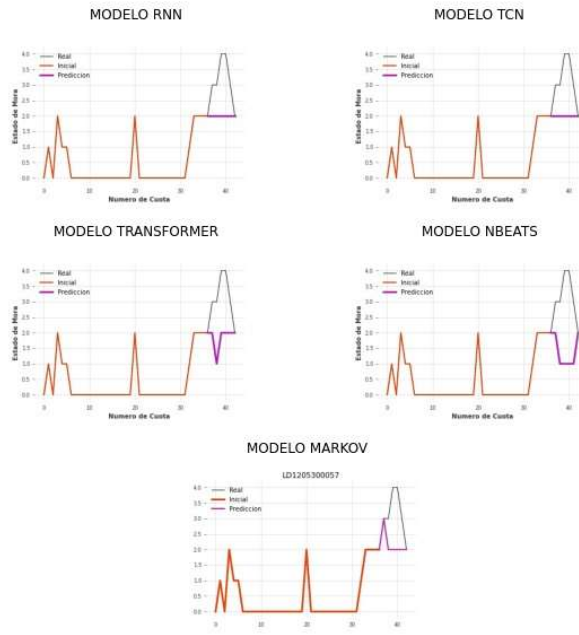
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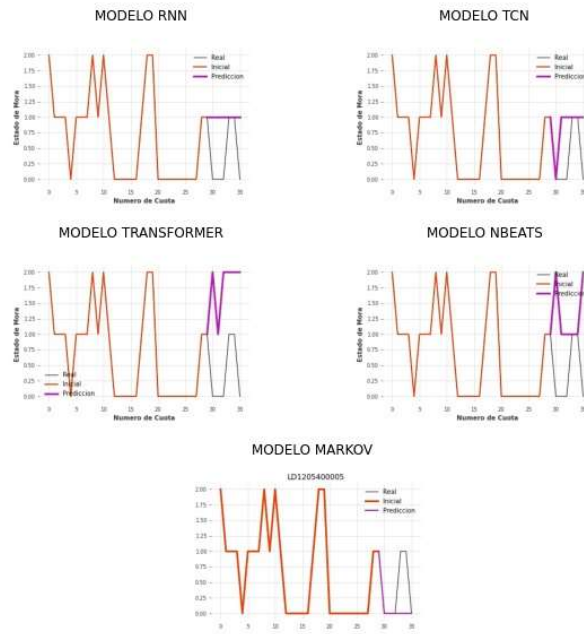
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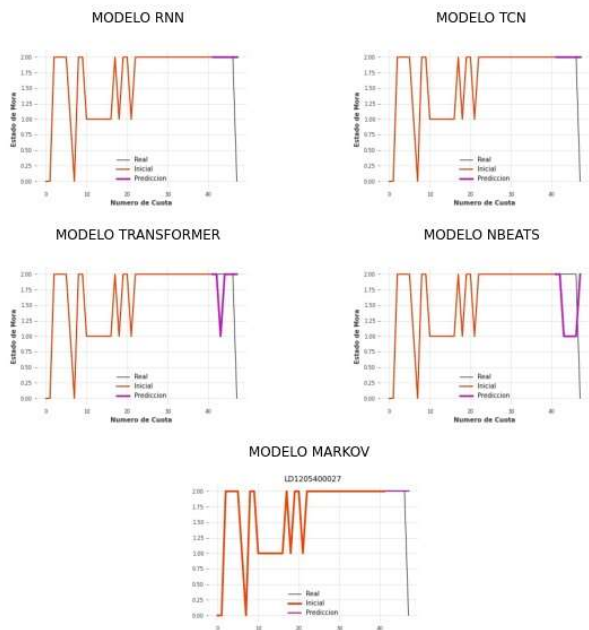
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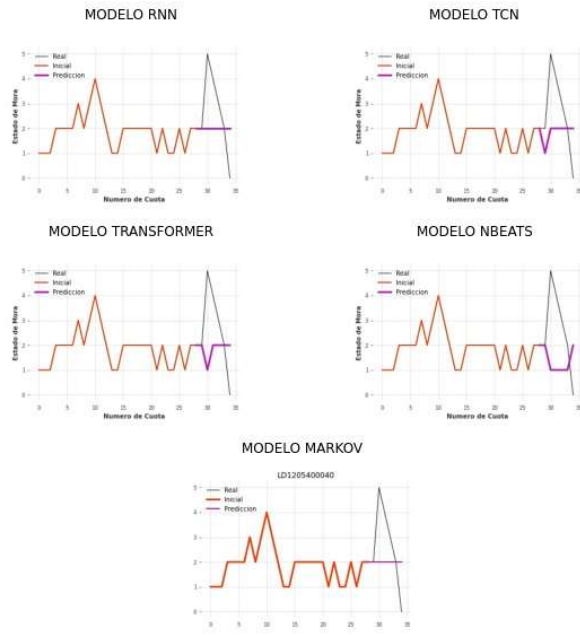
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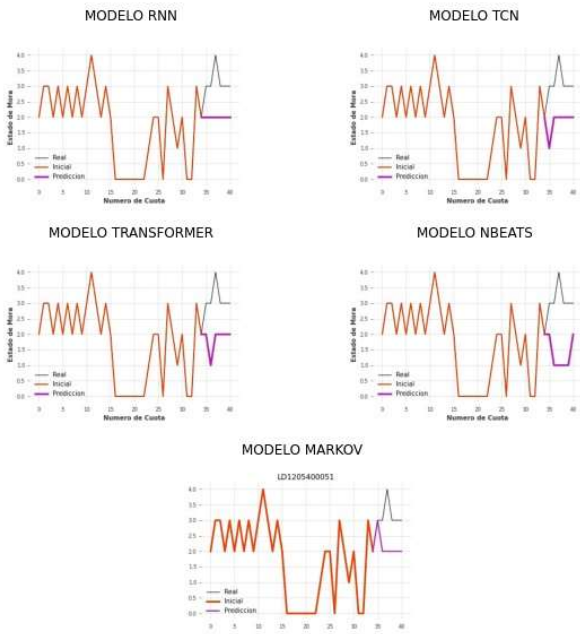
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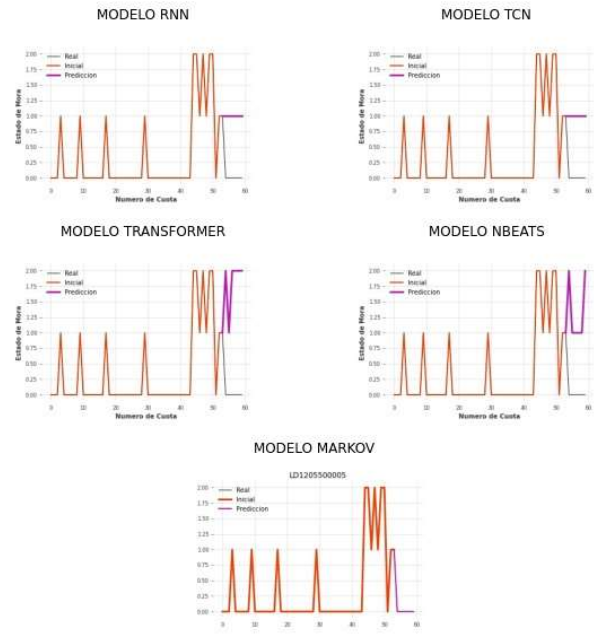
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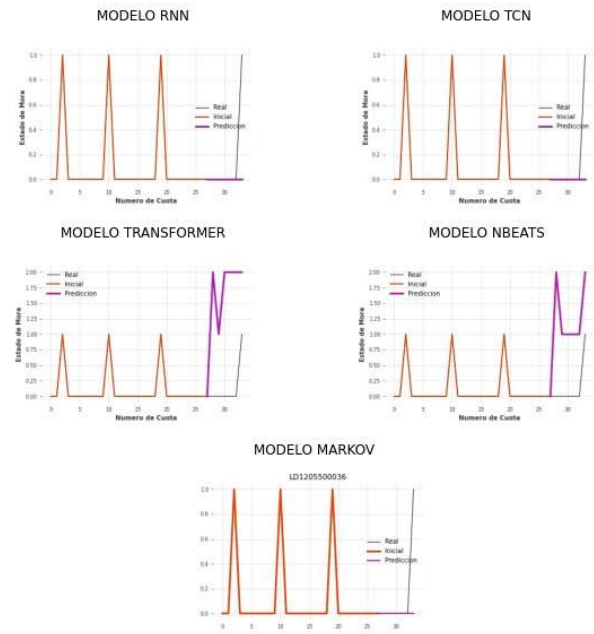
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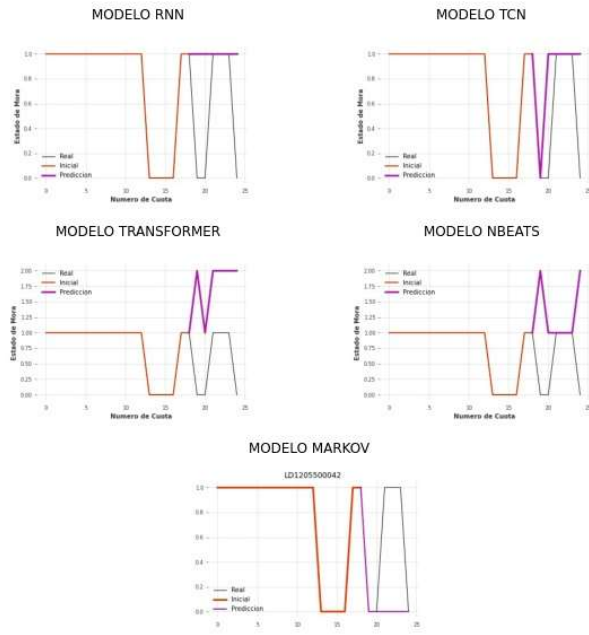
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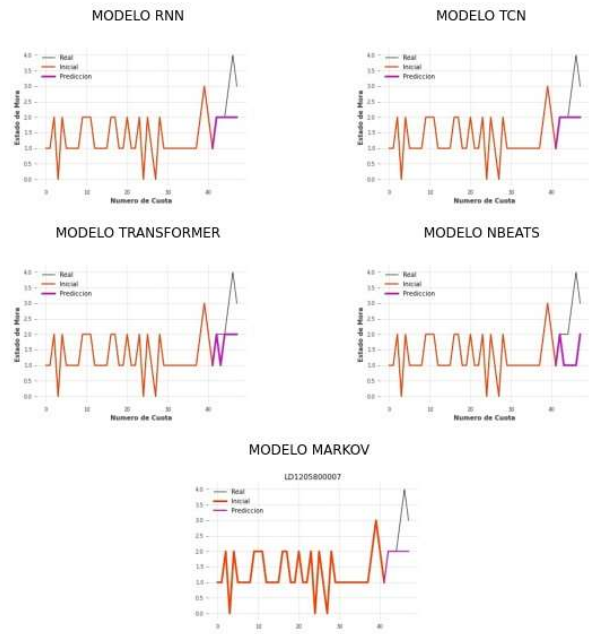
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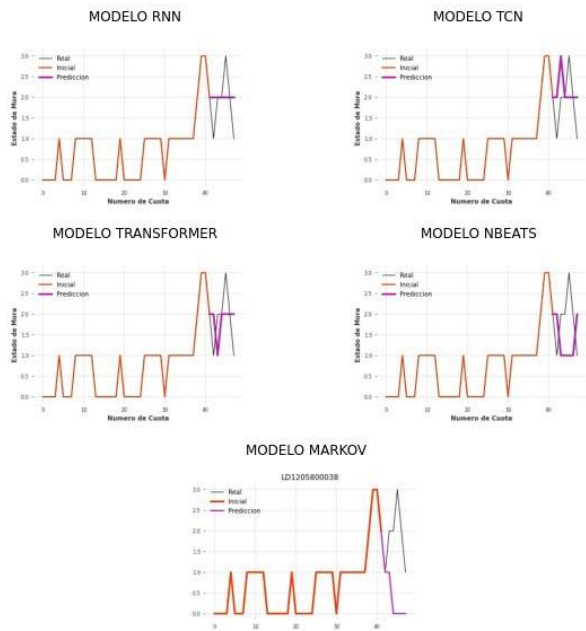


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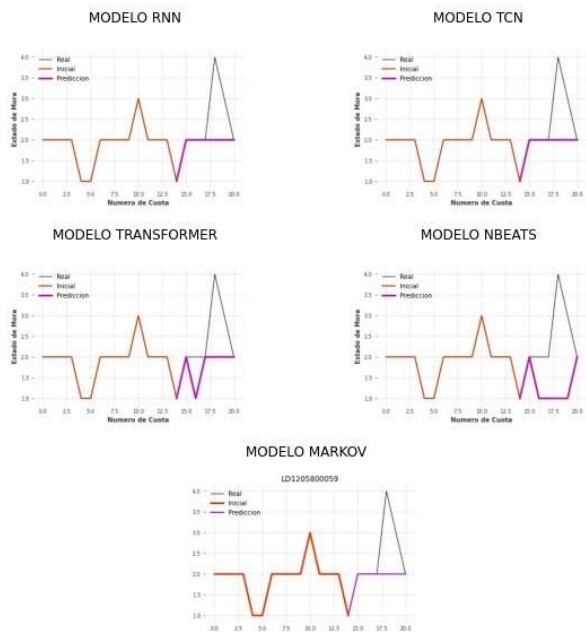




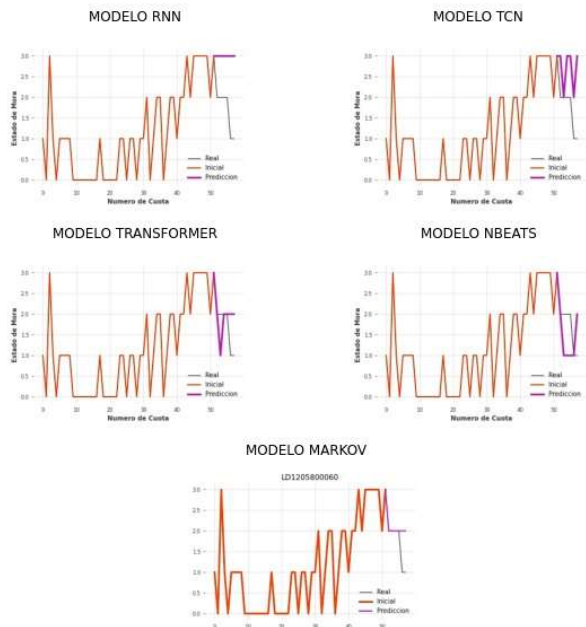
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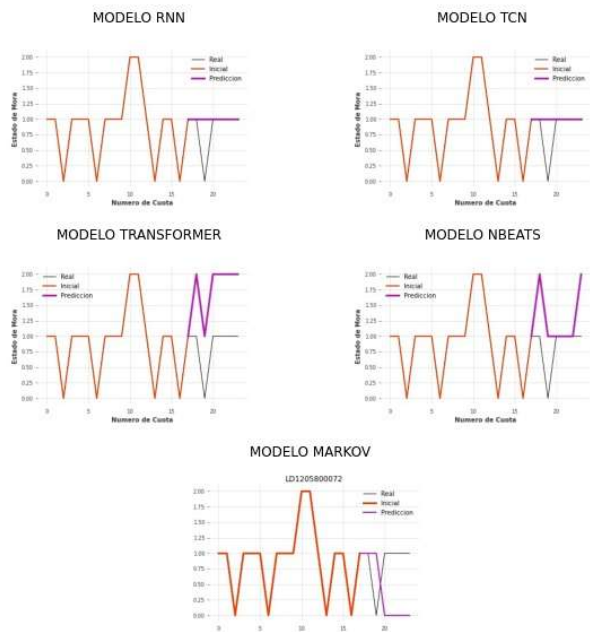
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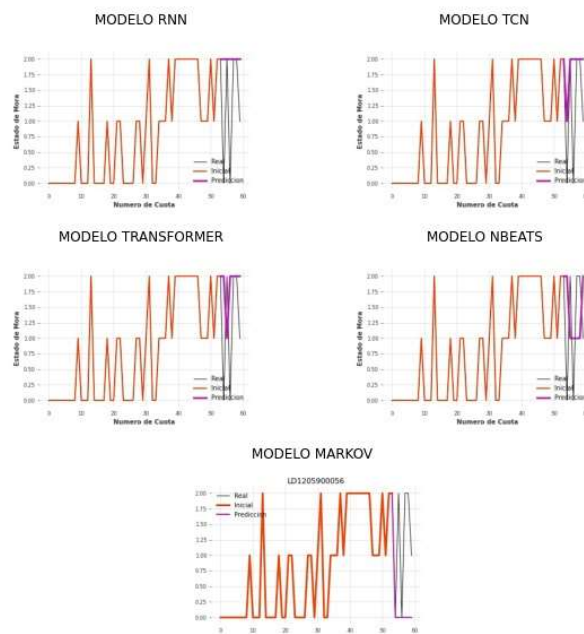
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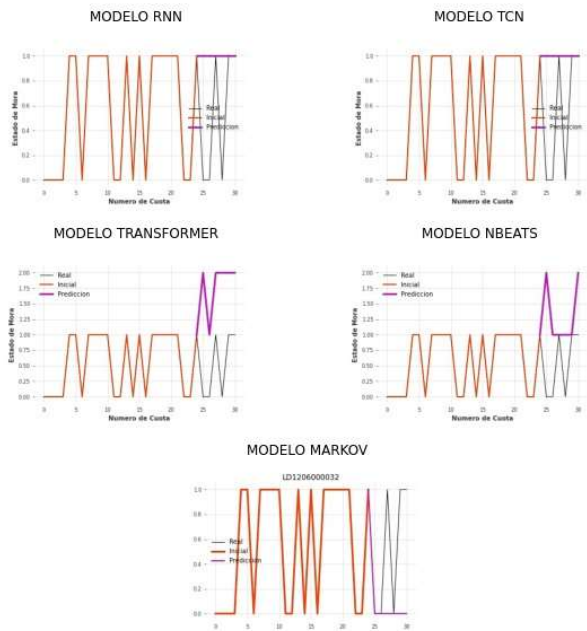
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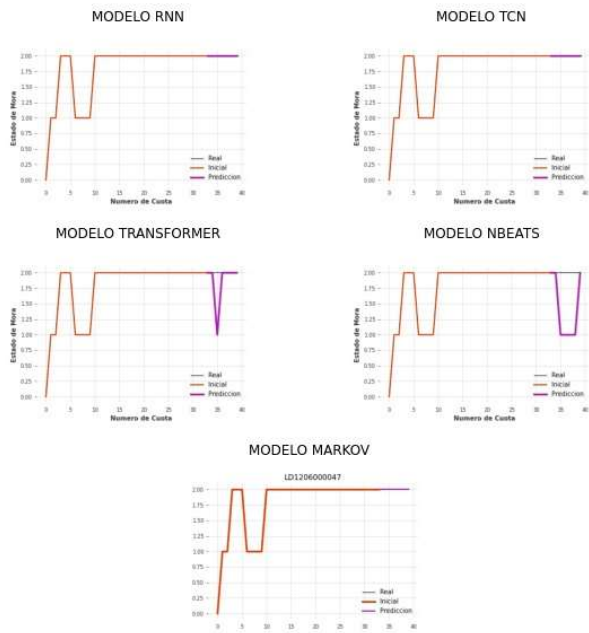
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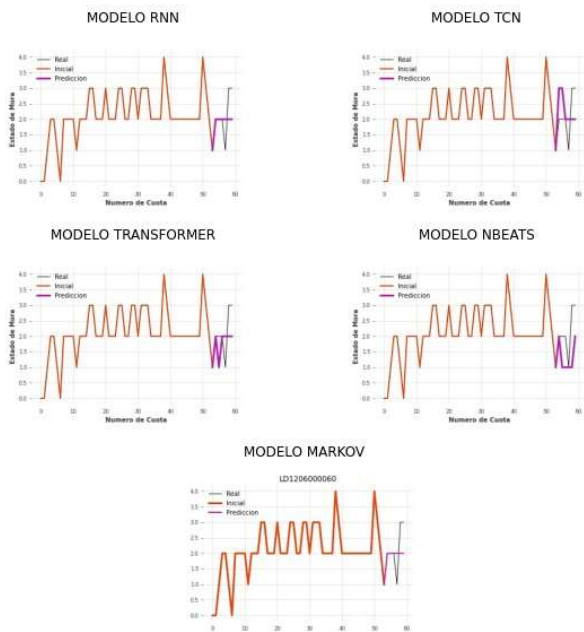
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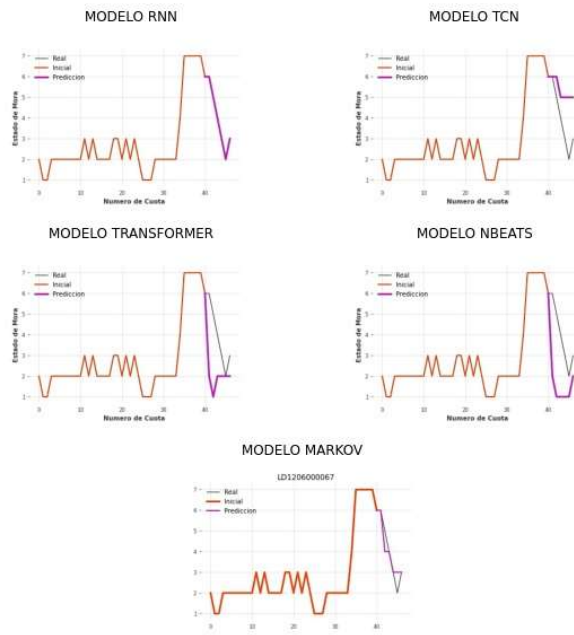
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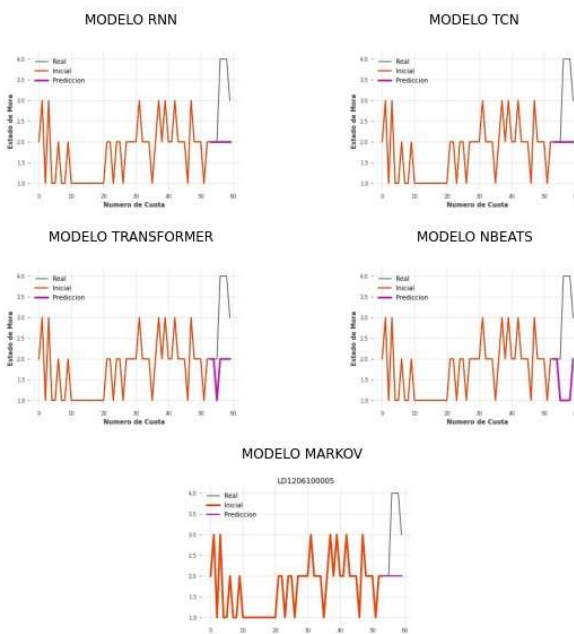
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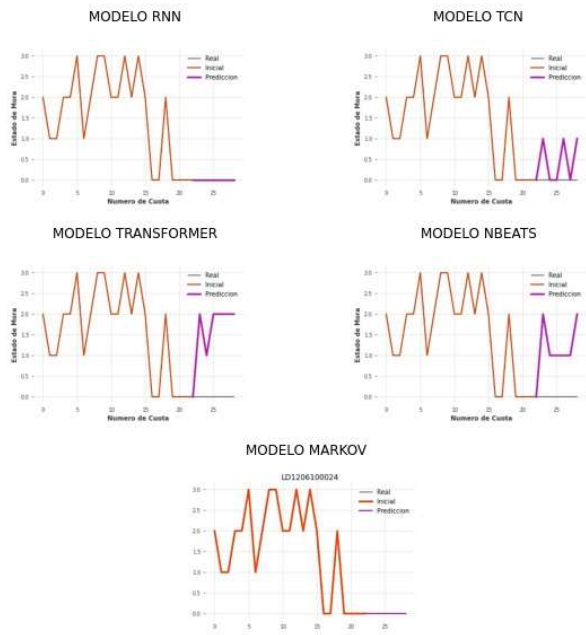
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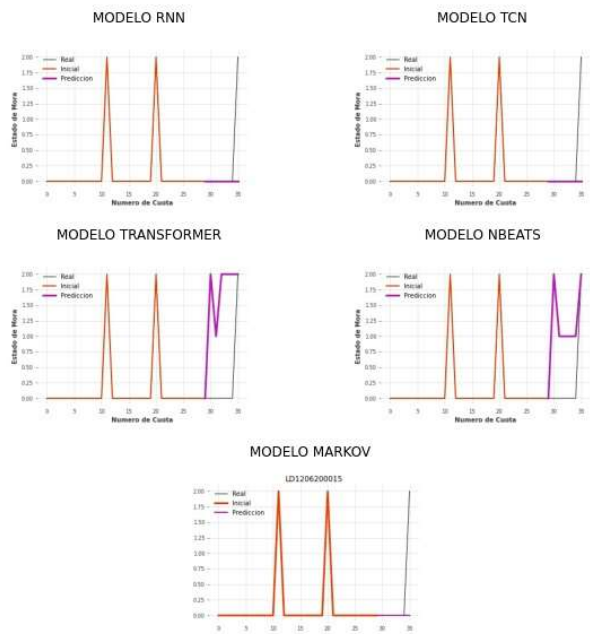
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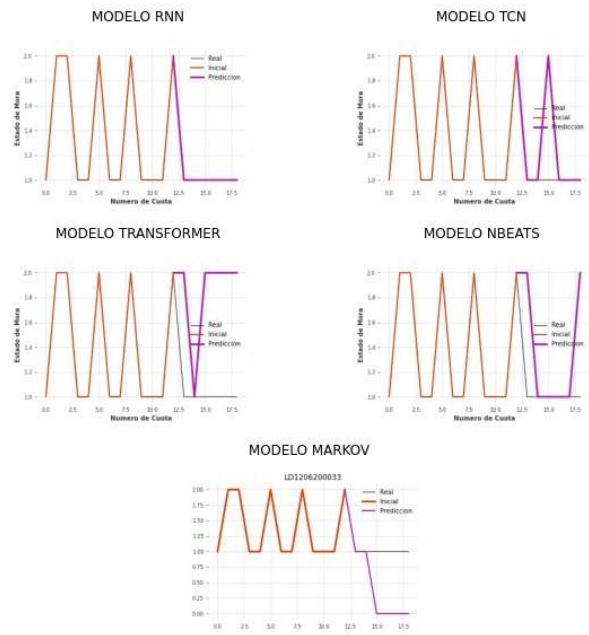
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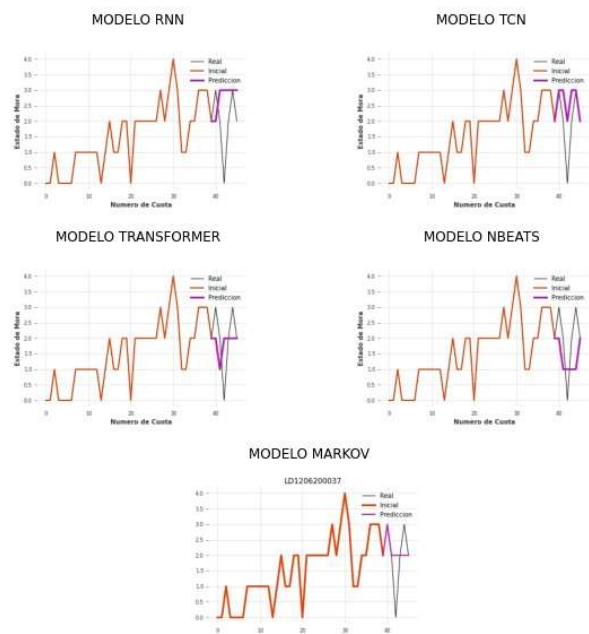
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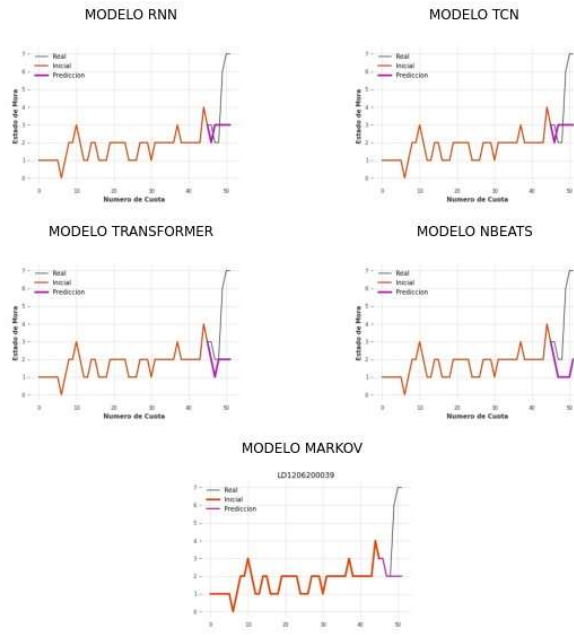


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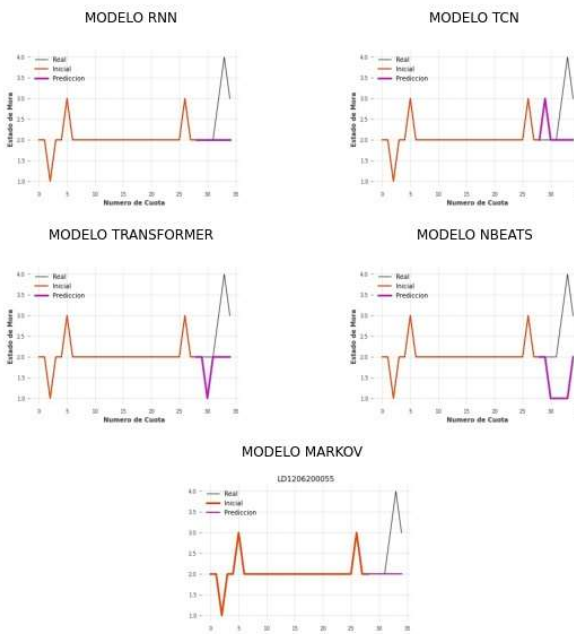




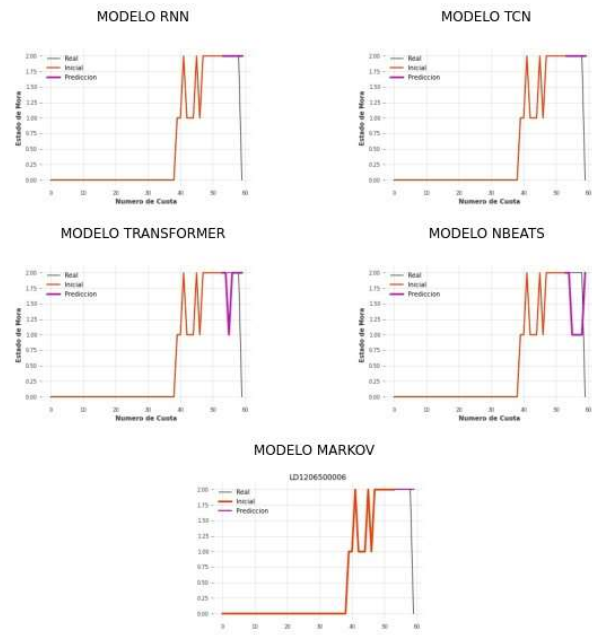
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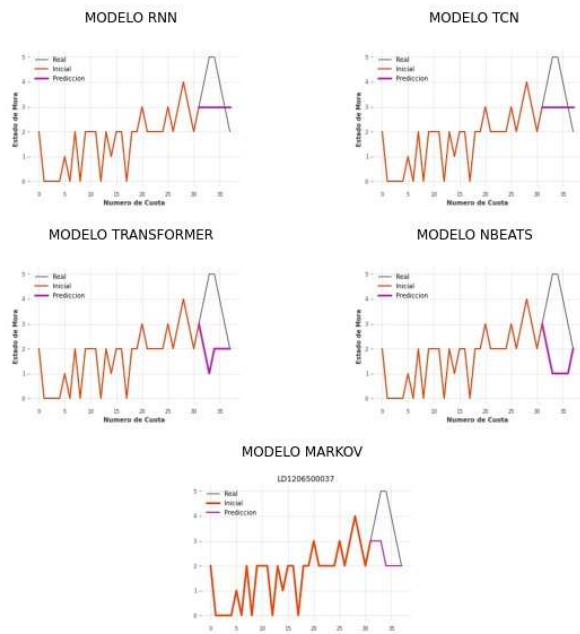
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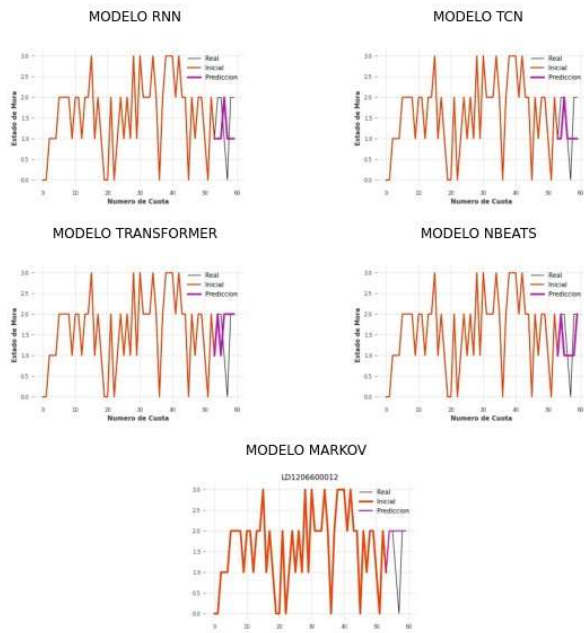
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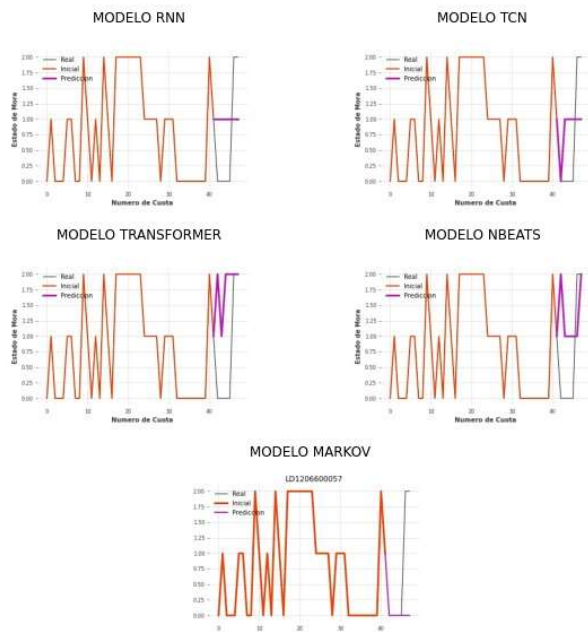
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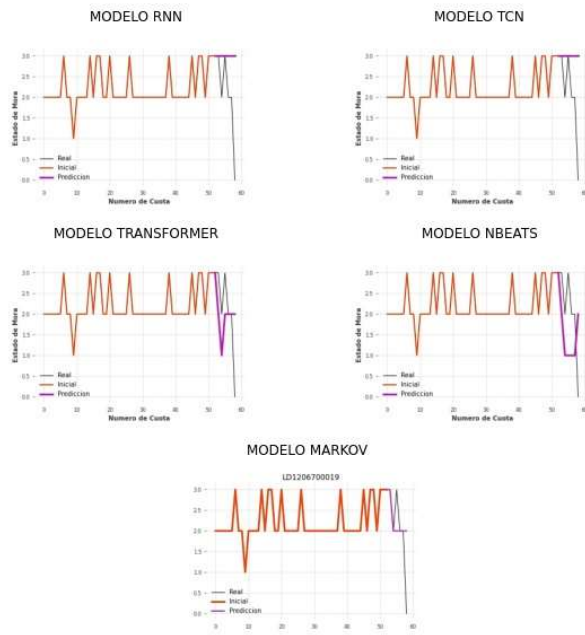
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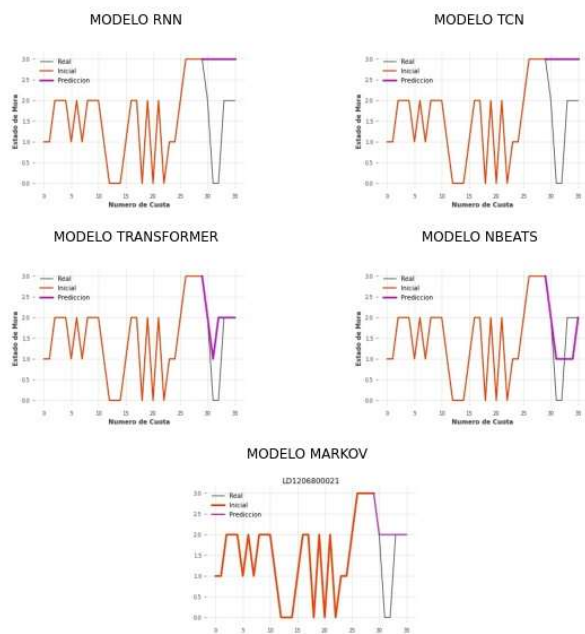
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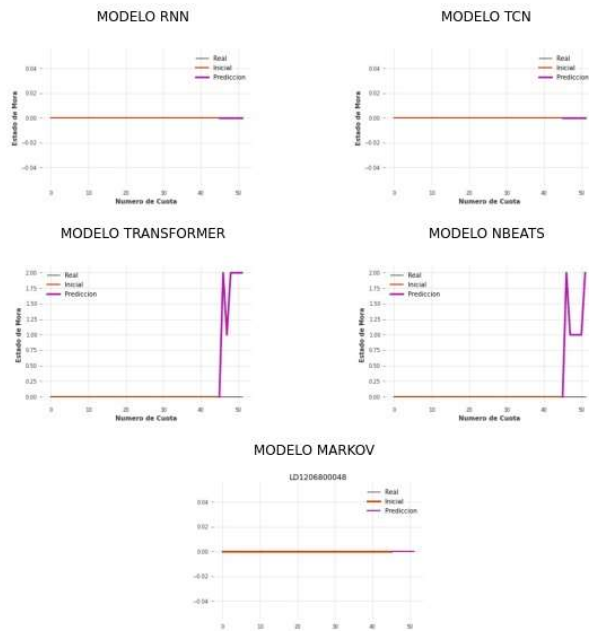
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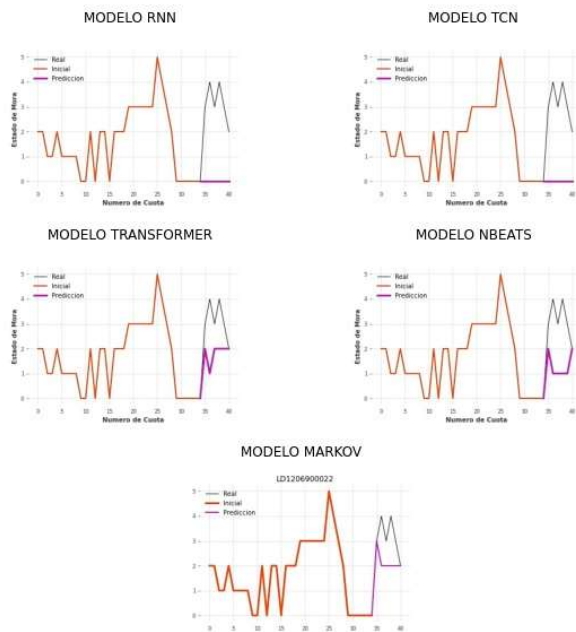
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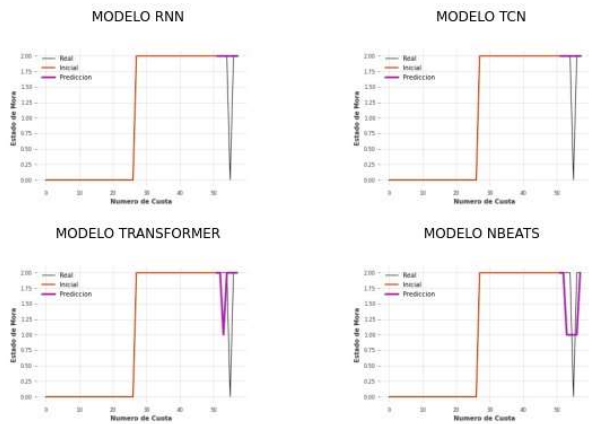
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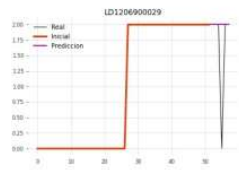
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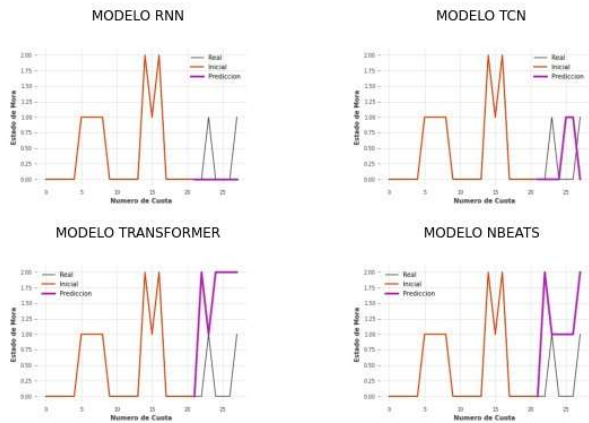
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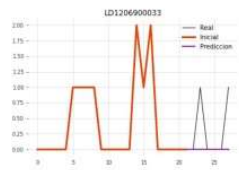
MODELO MARKOV



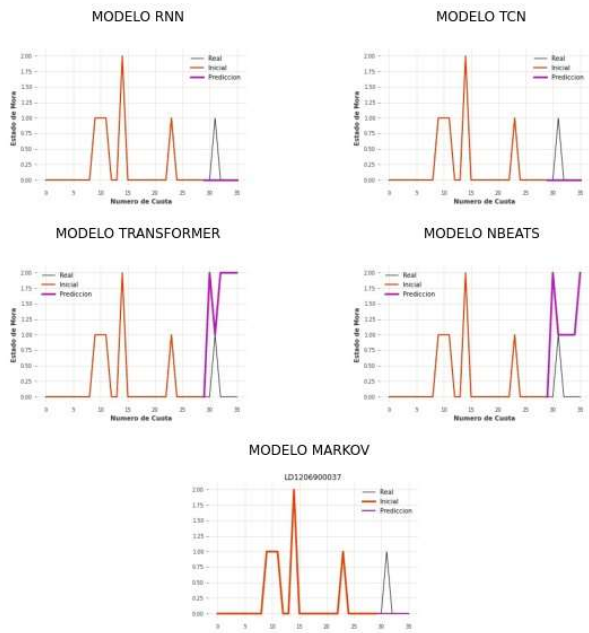
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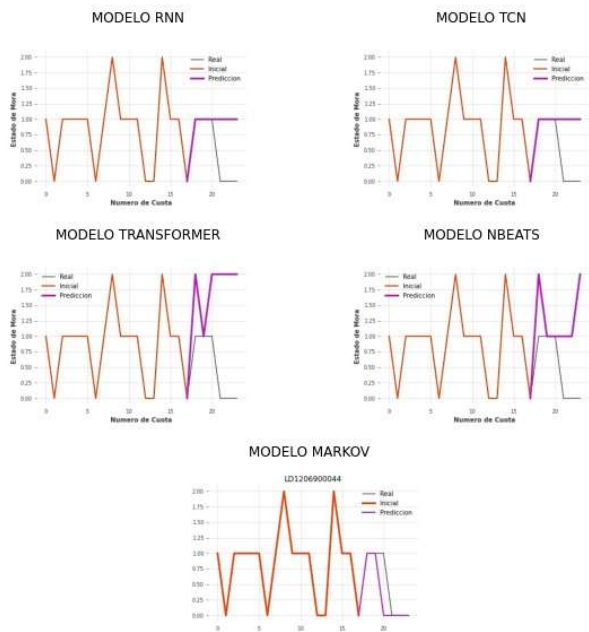
MODELO MARKOV



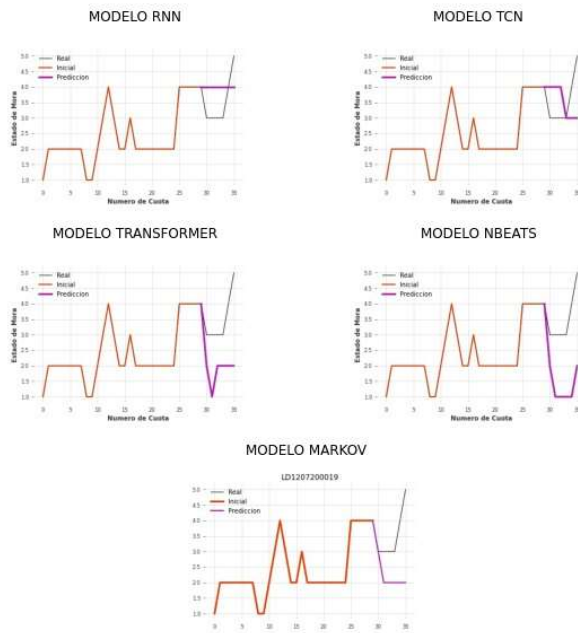
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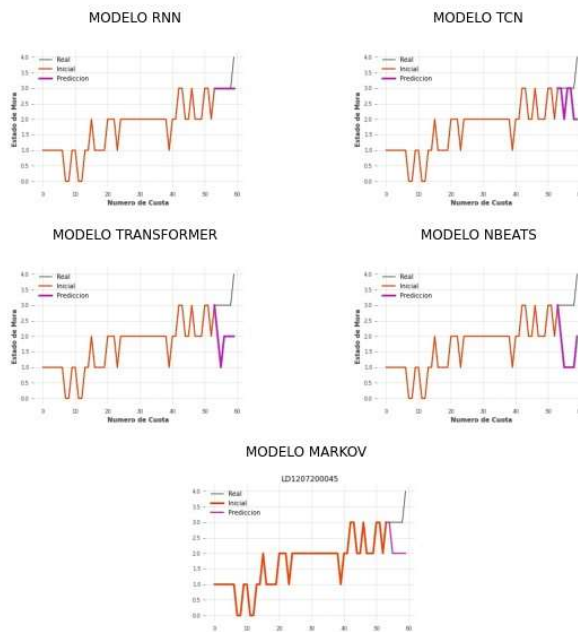
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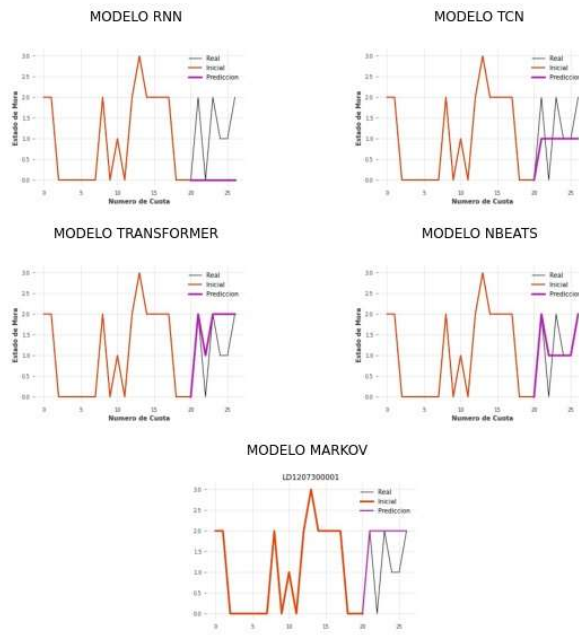


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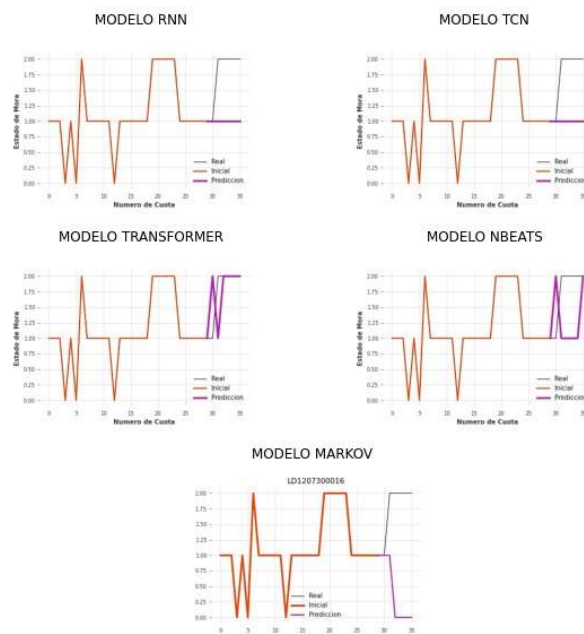




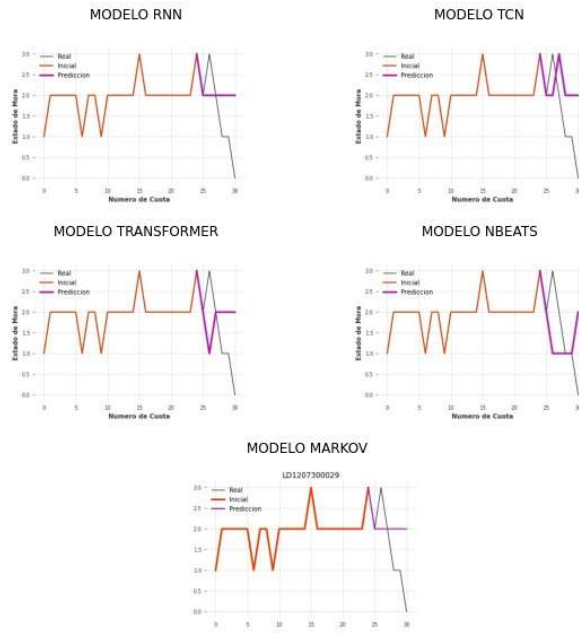
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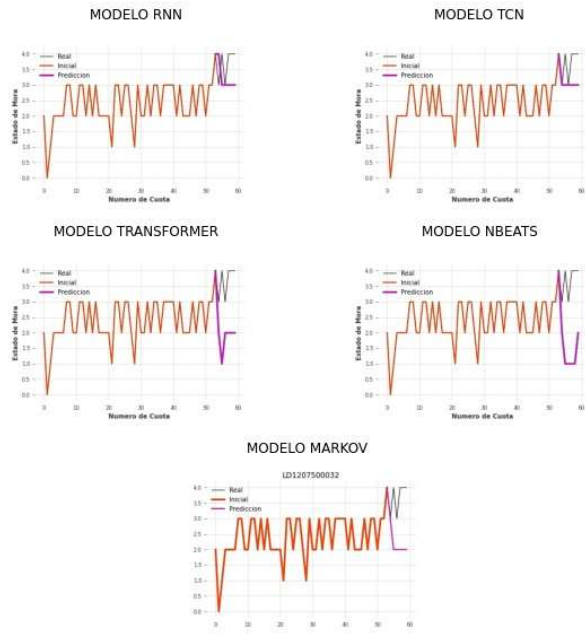
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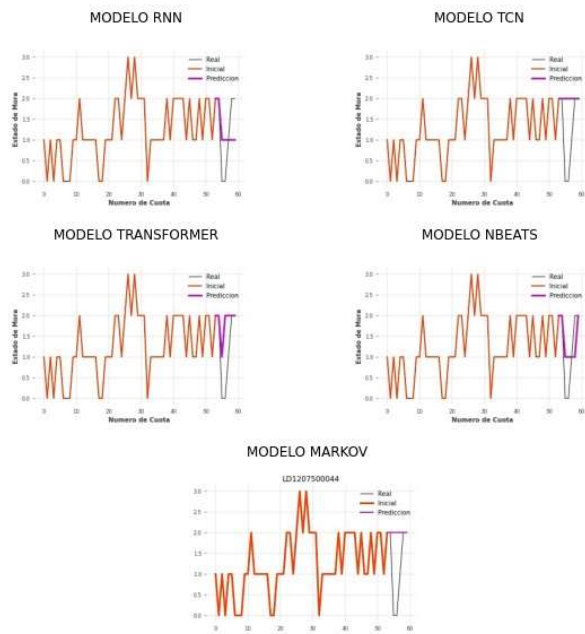
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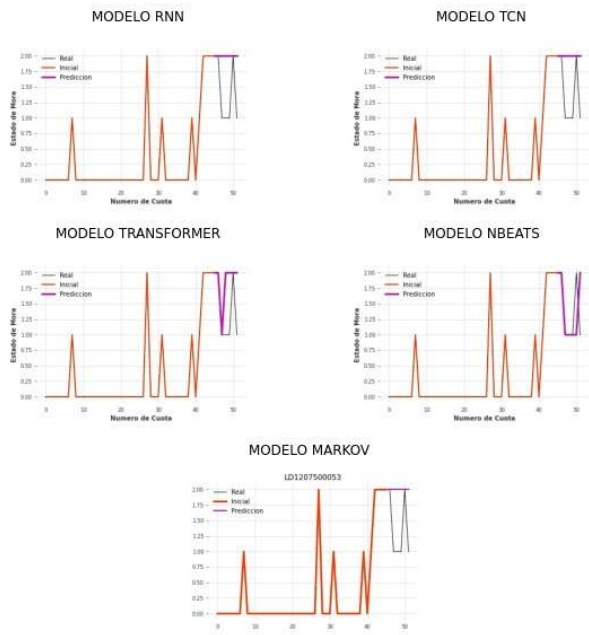
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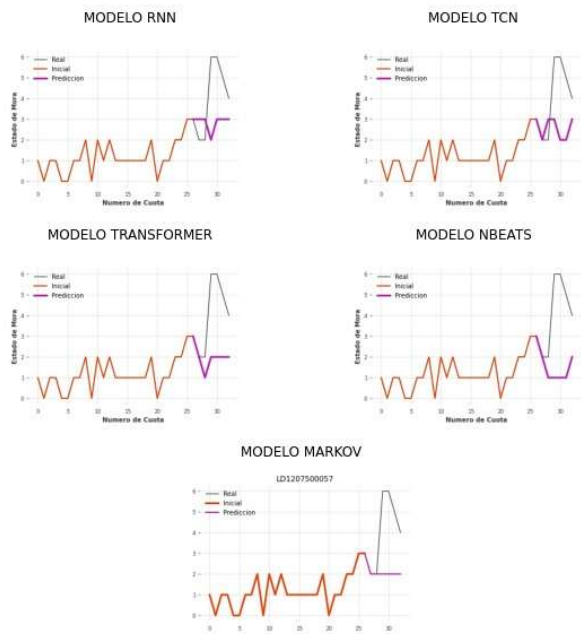
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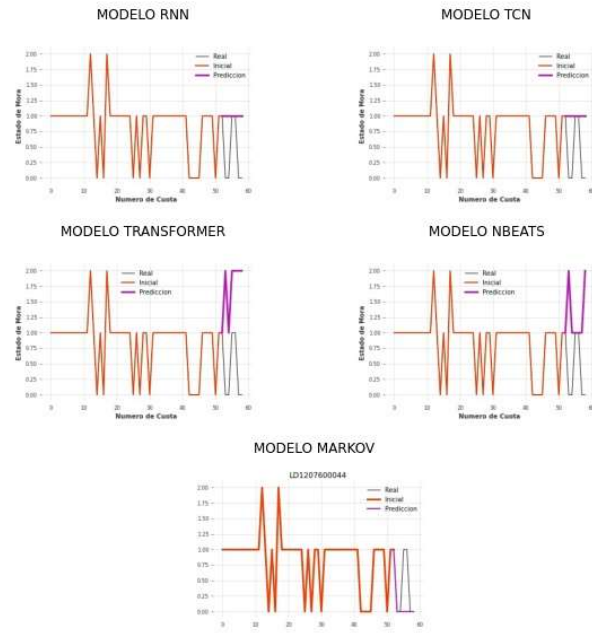
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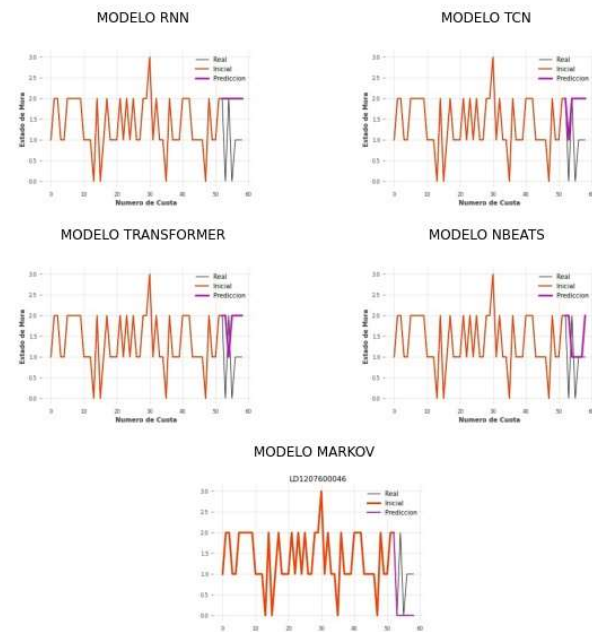
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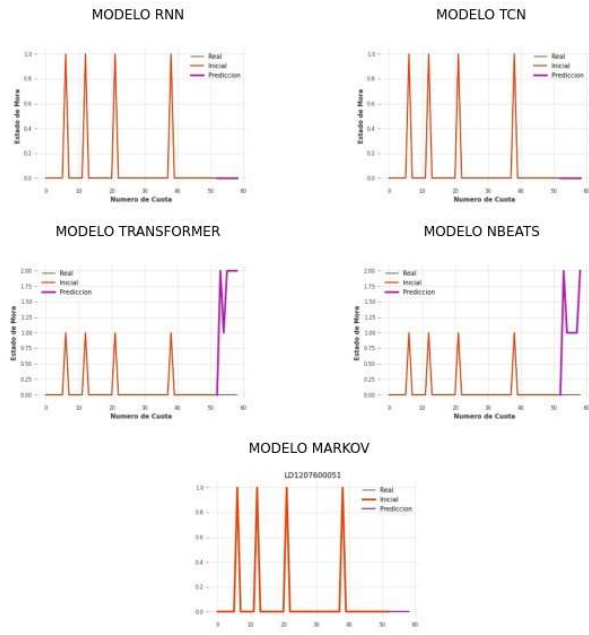
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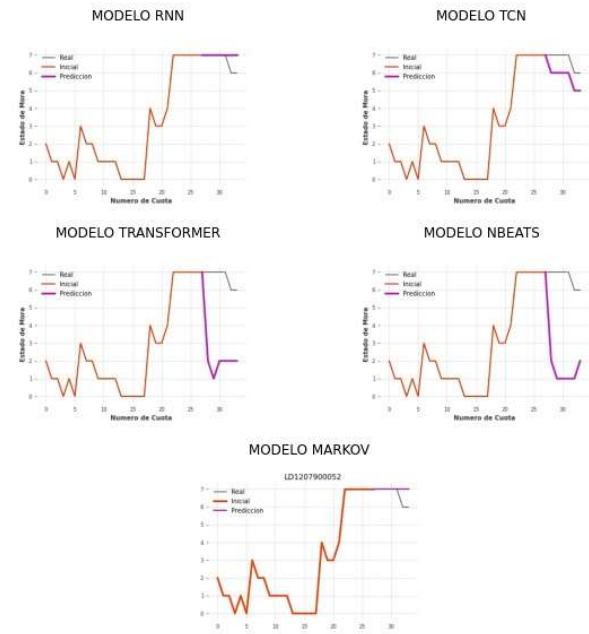
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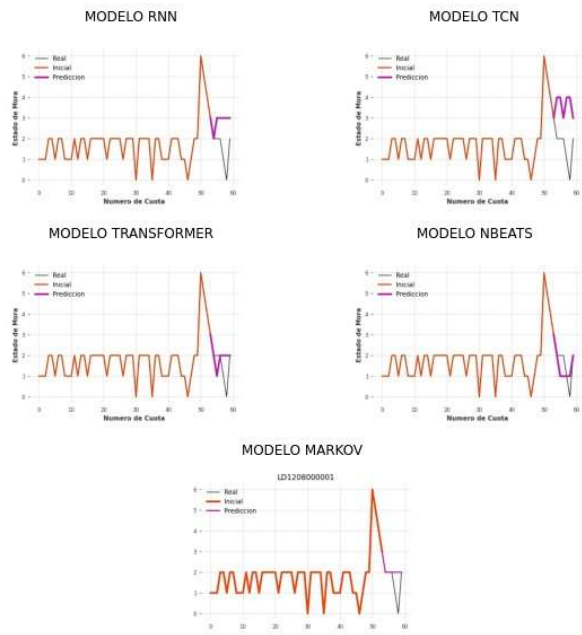
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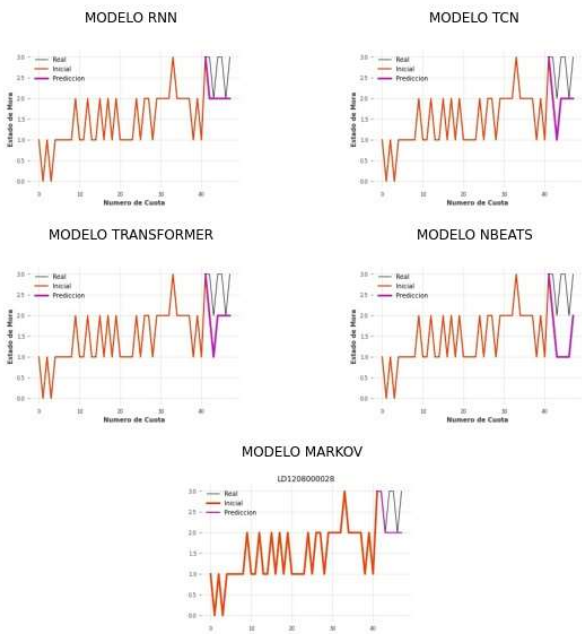
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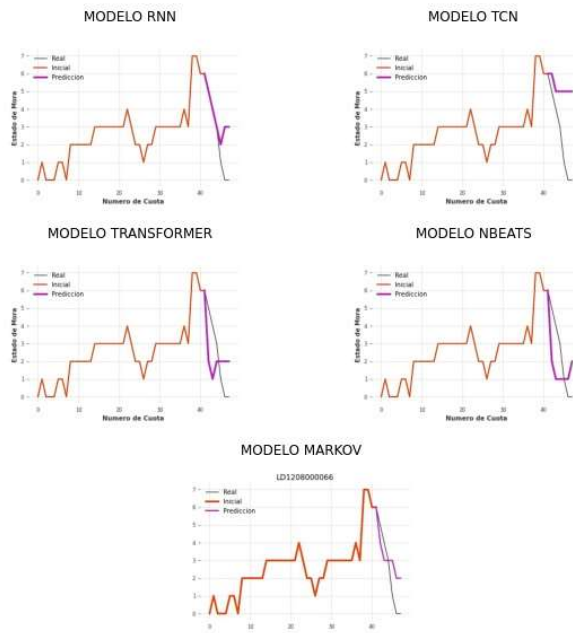
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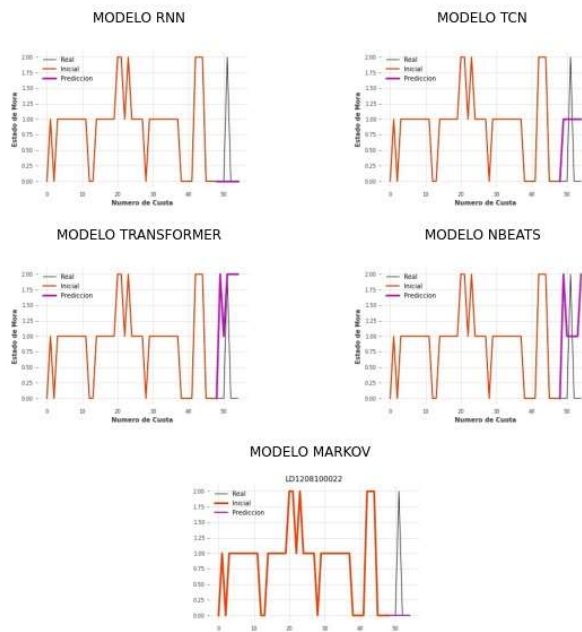
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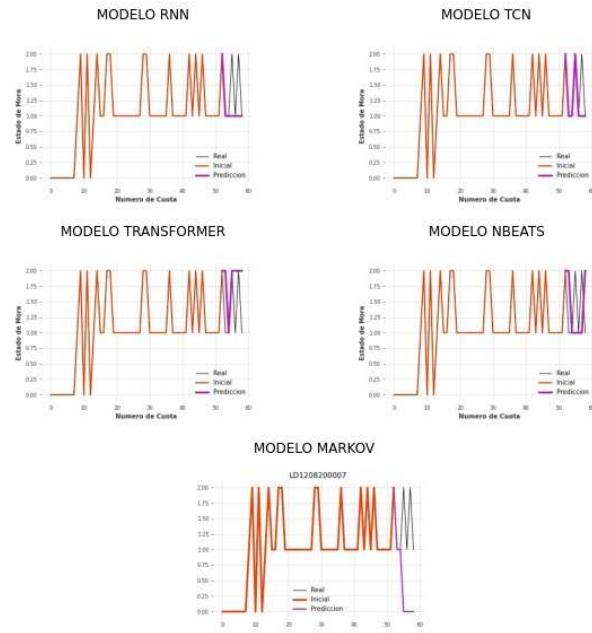


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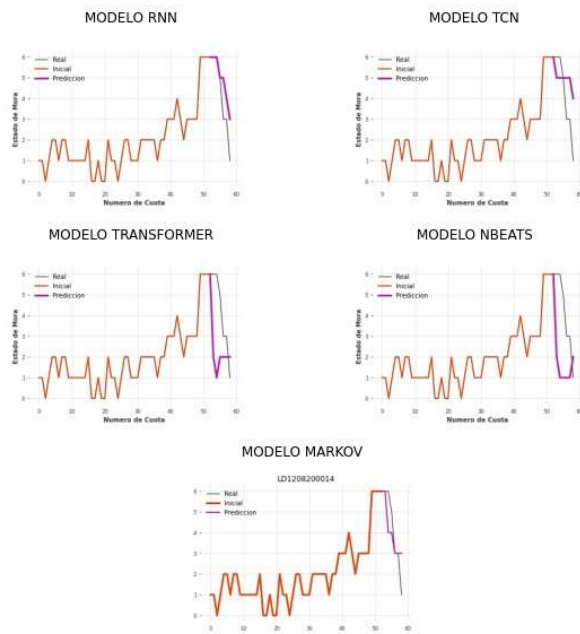




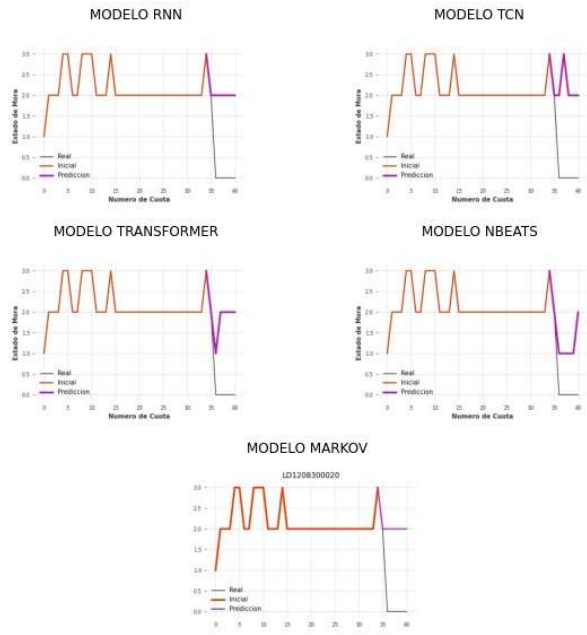
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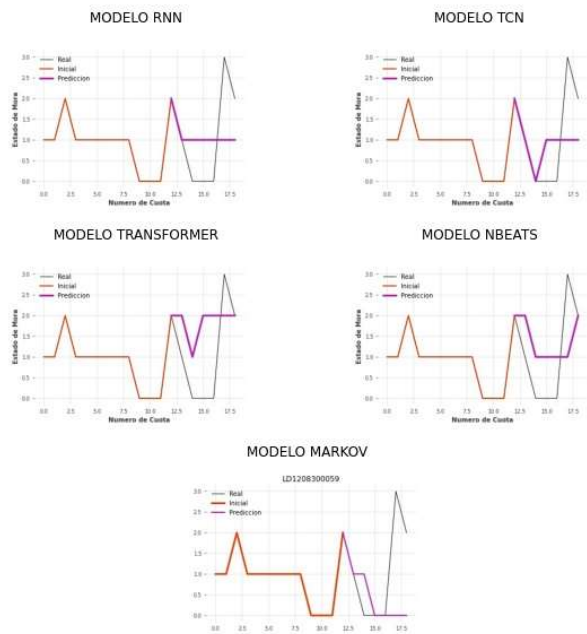
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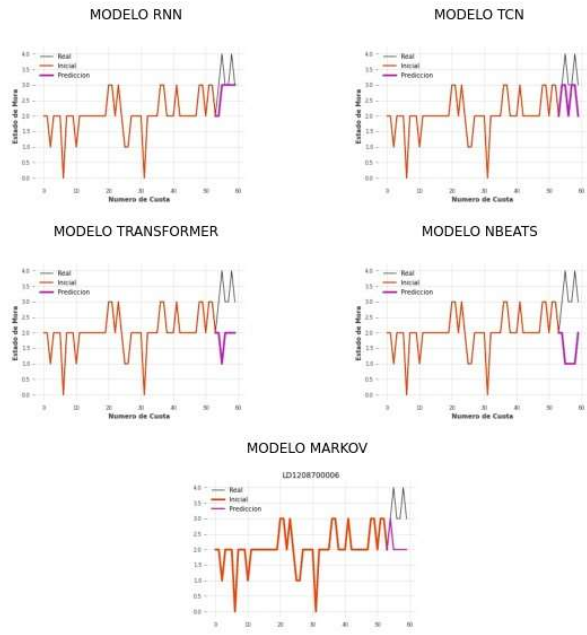
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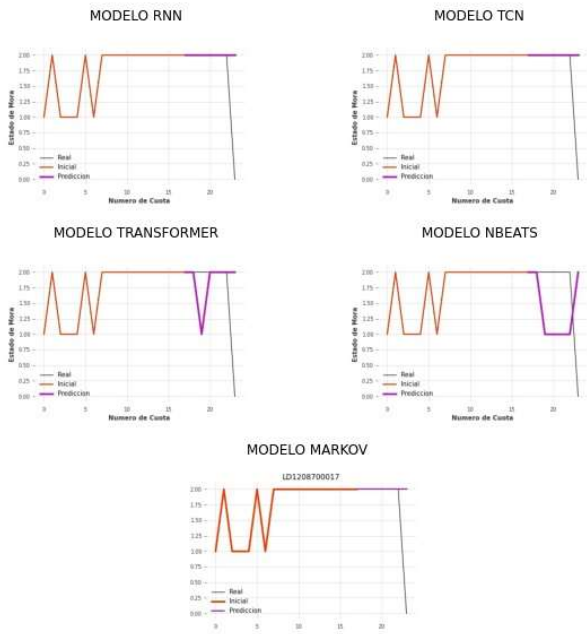
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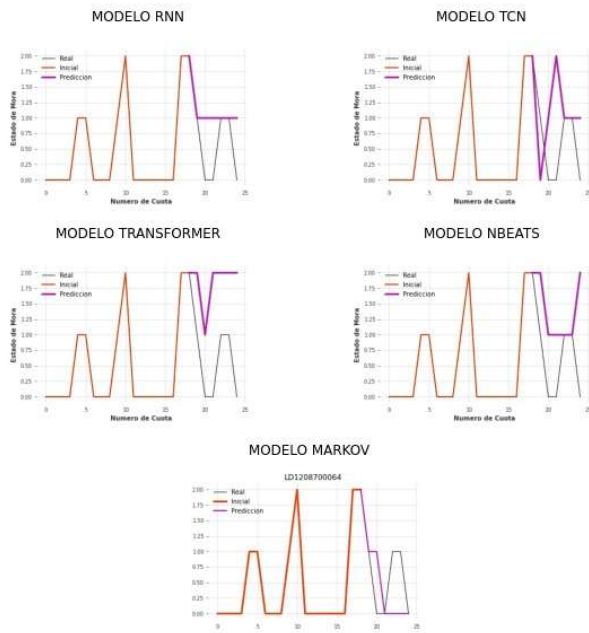
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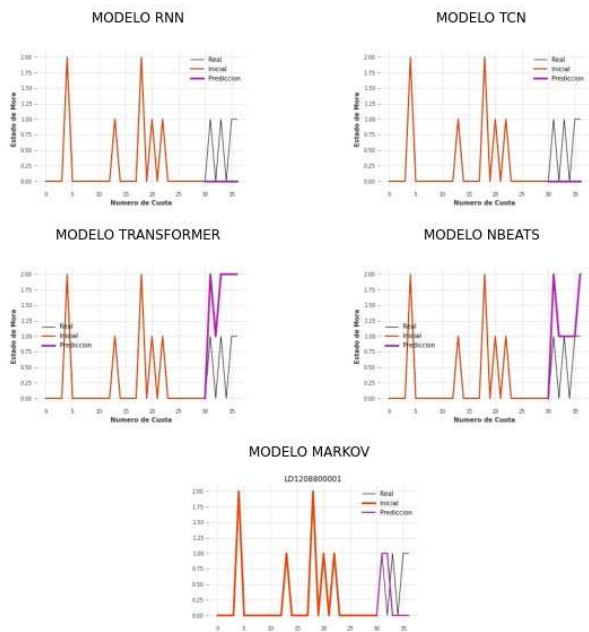
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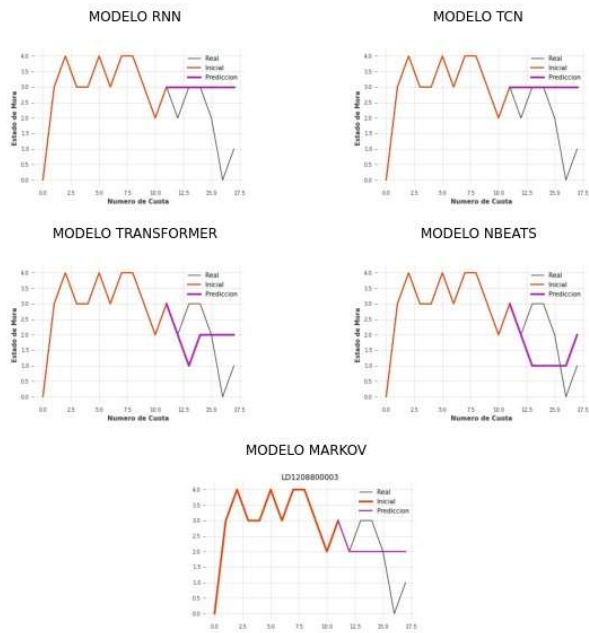
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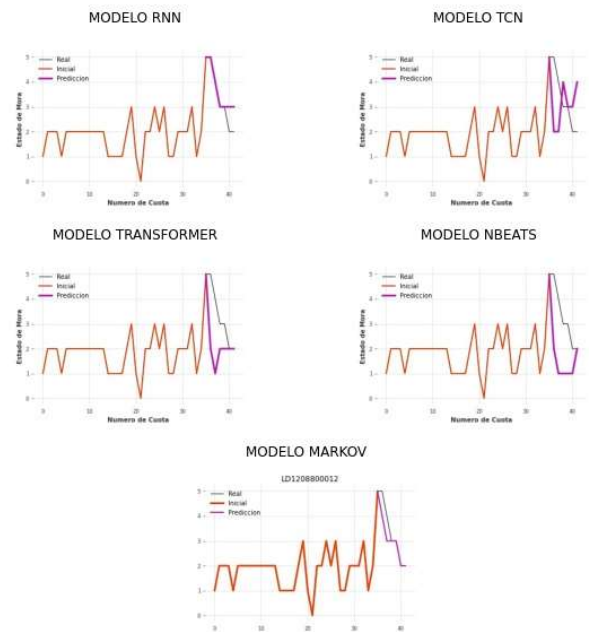
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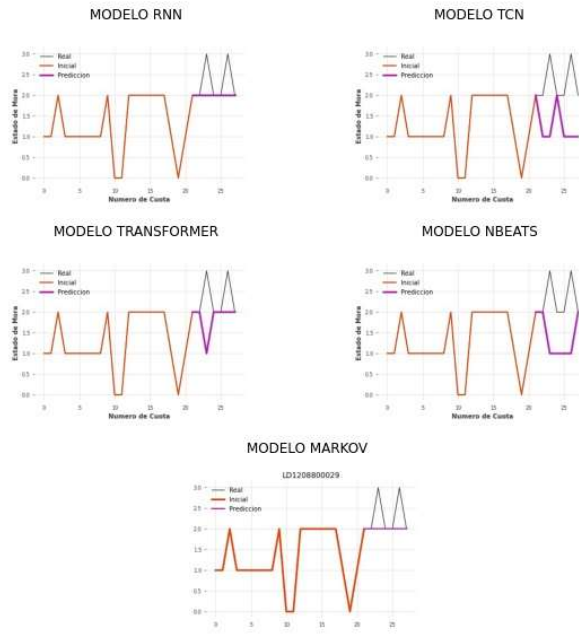
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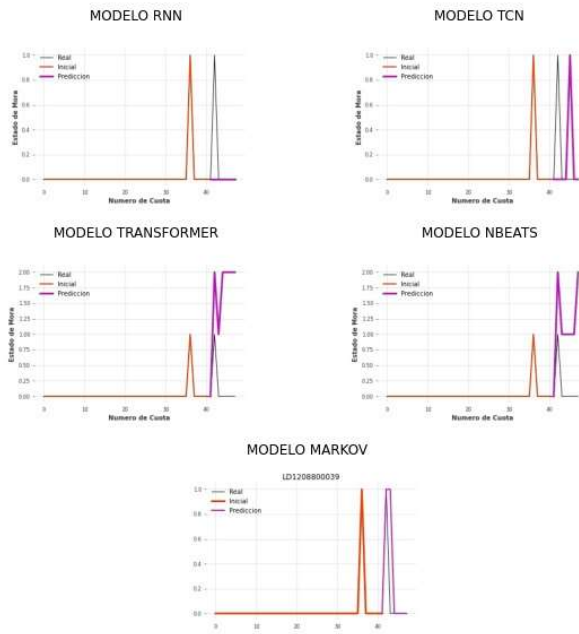
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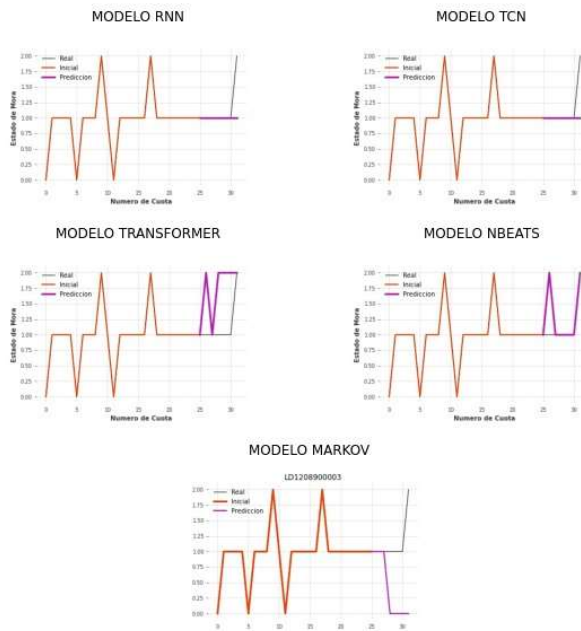
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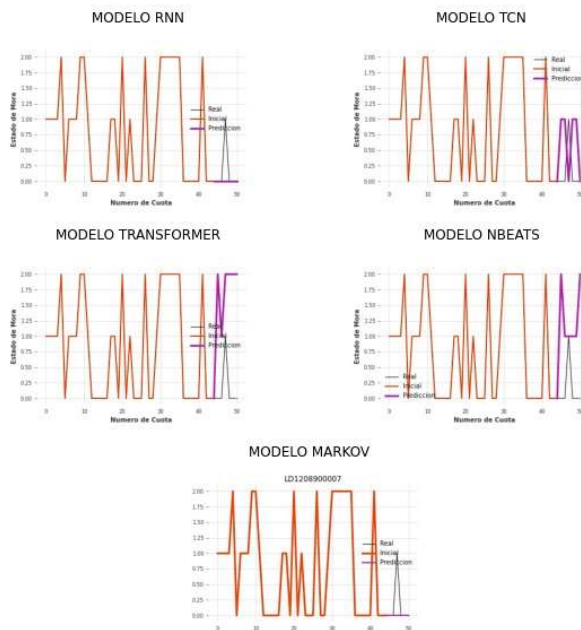
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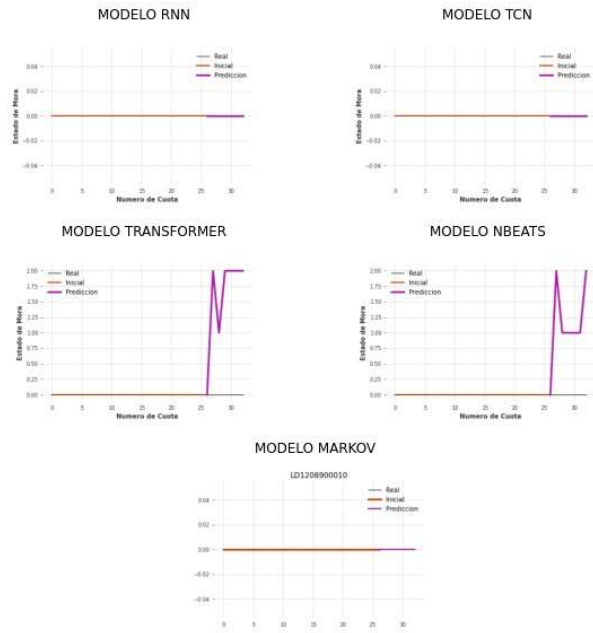
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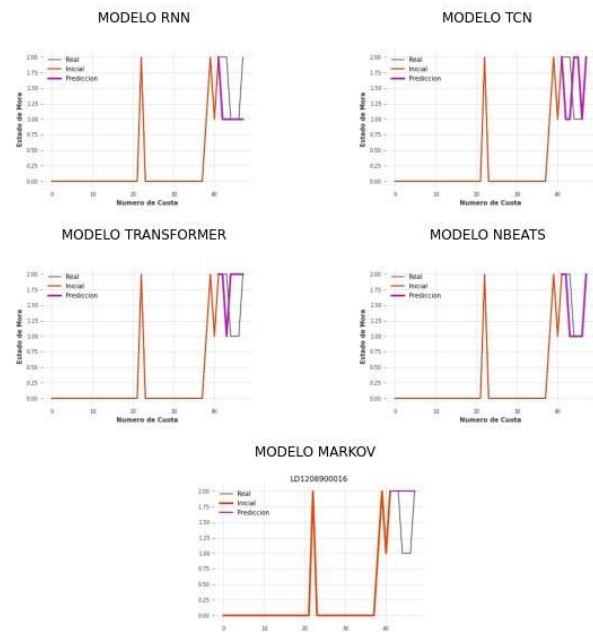
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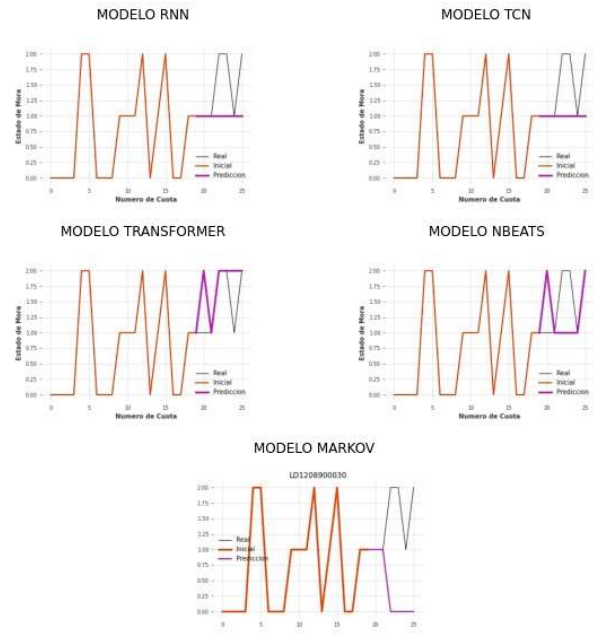


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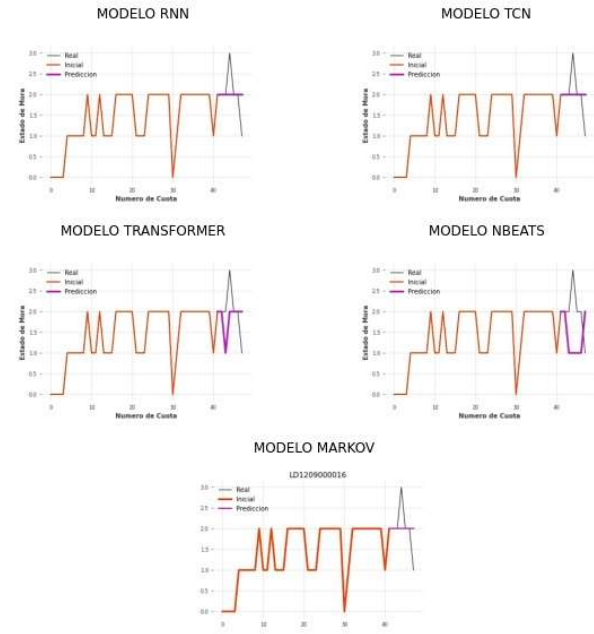




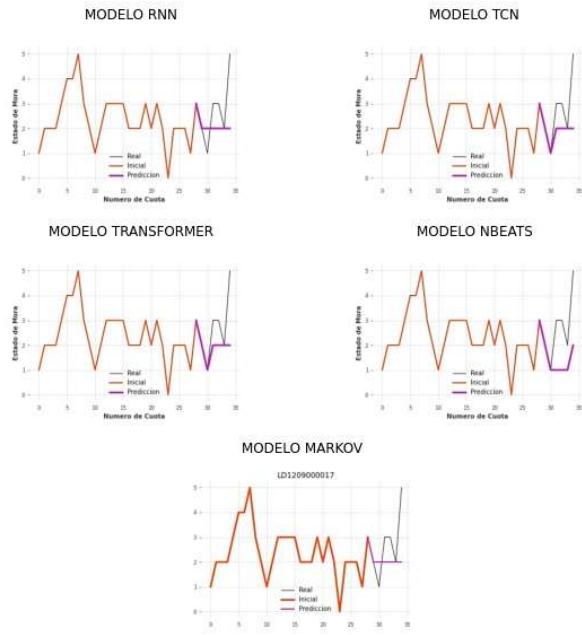
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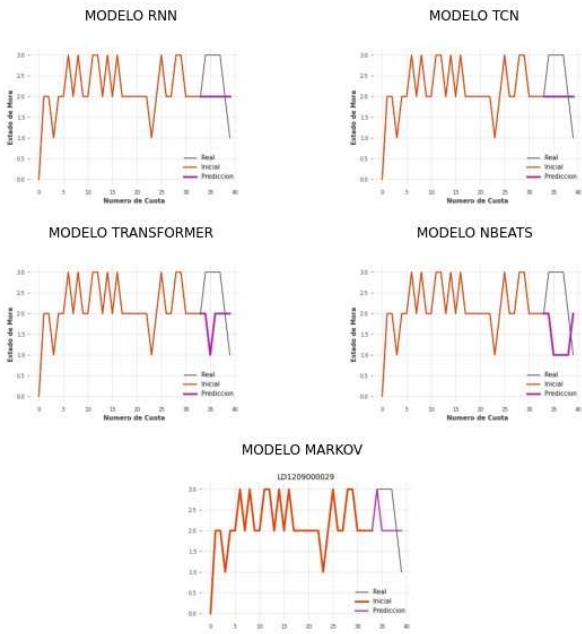
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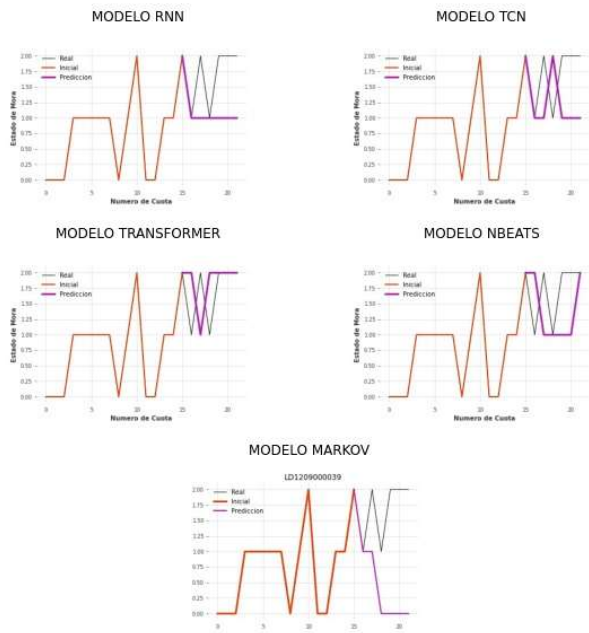
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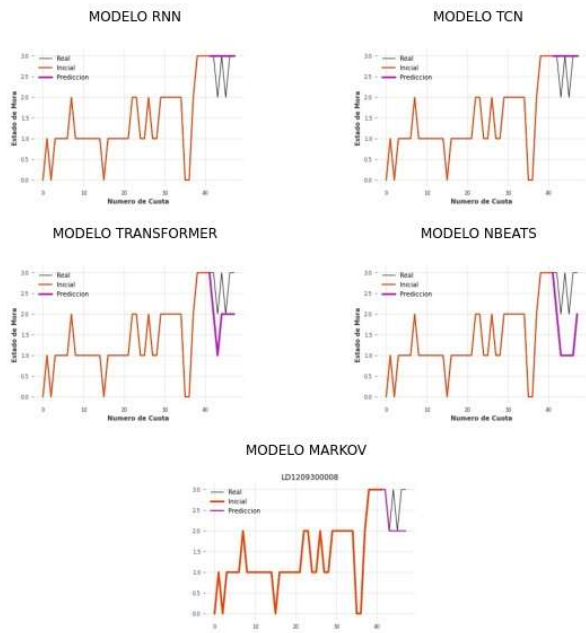
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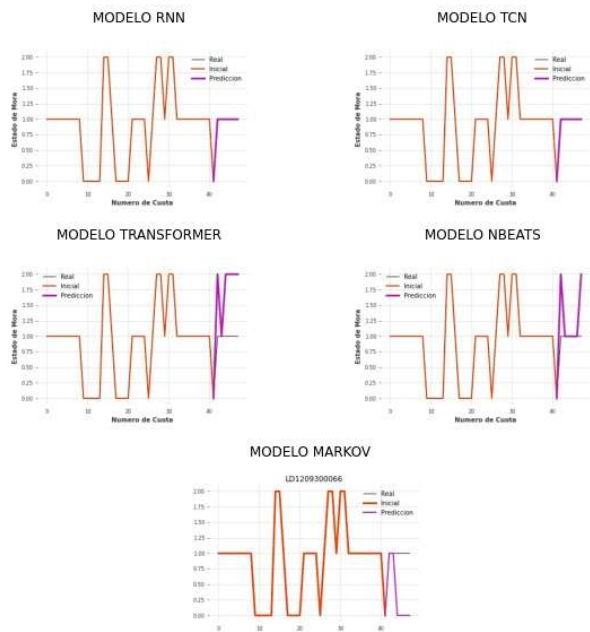
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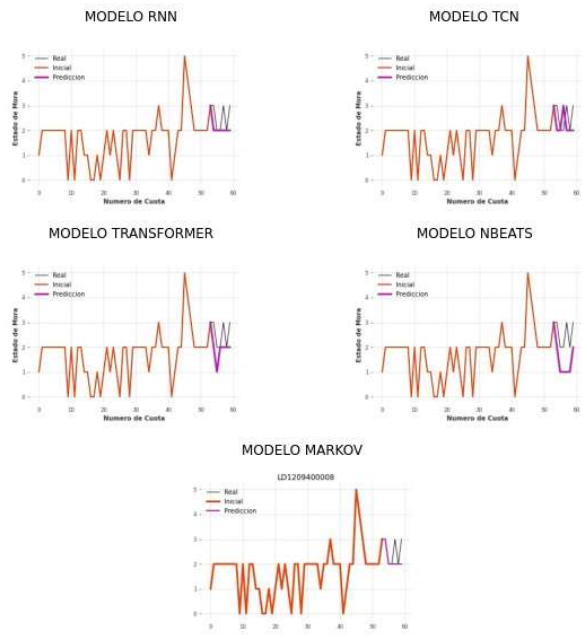
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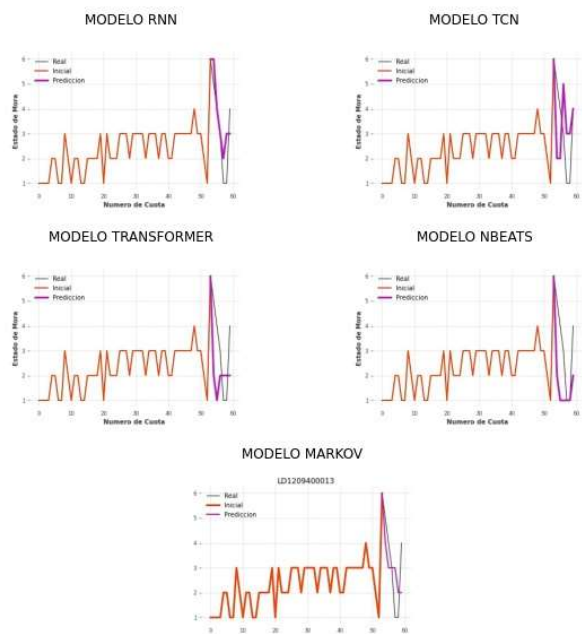
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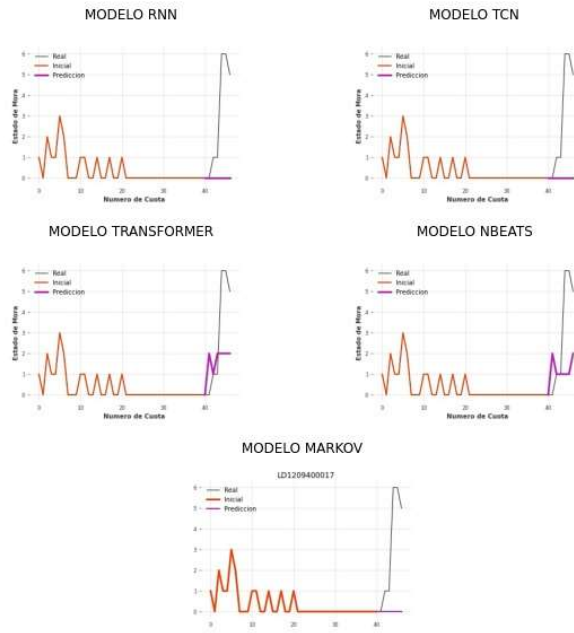
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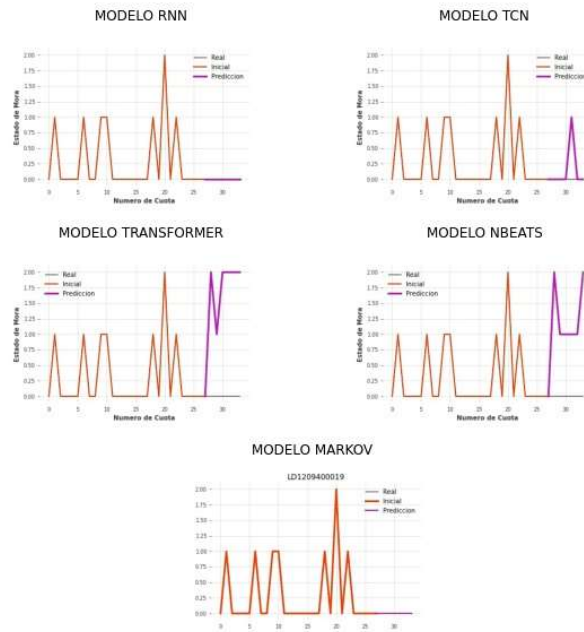
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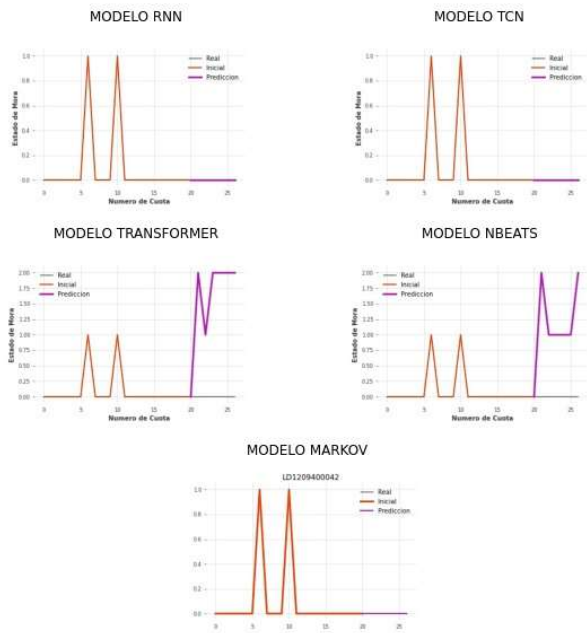
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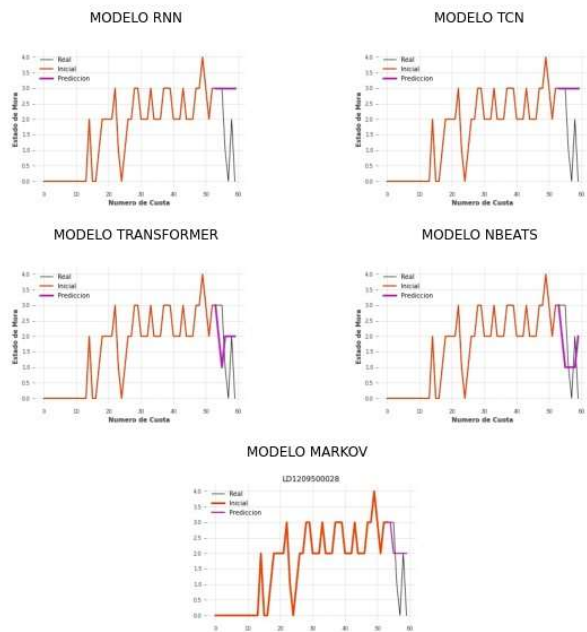
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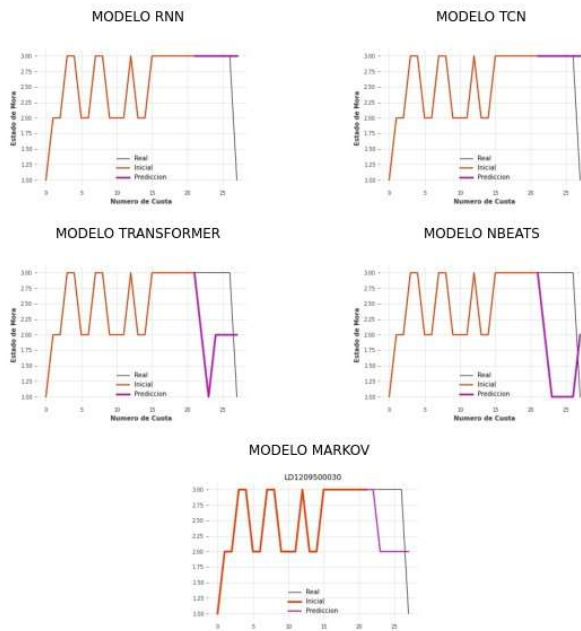
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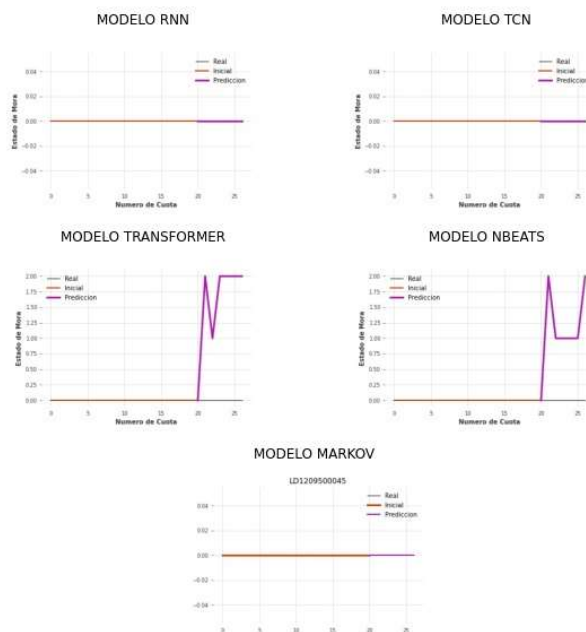
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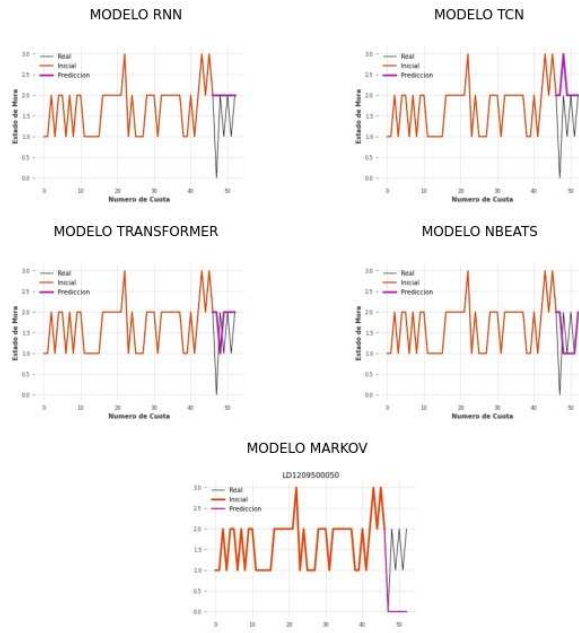


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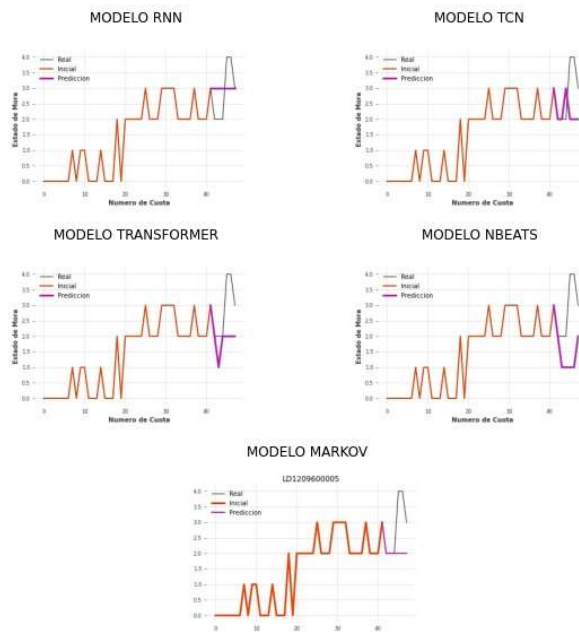




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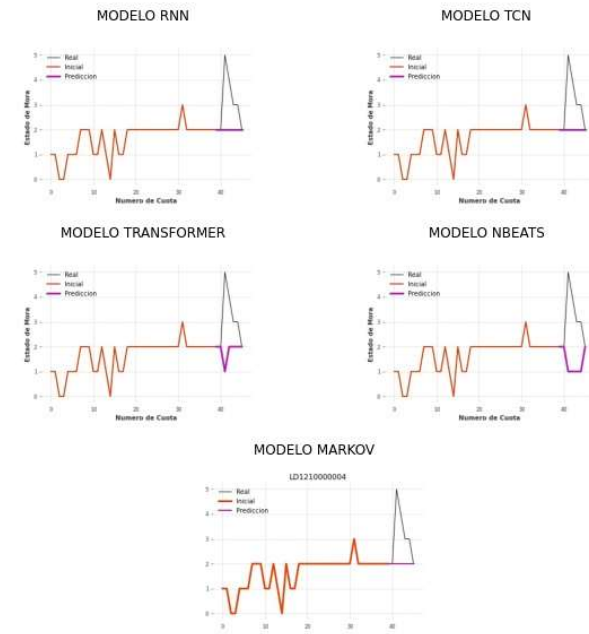
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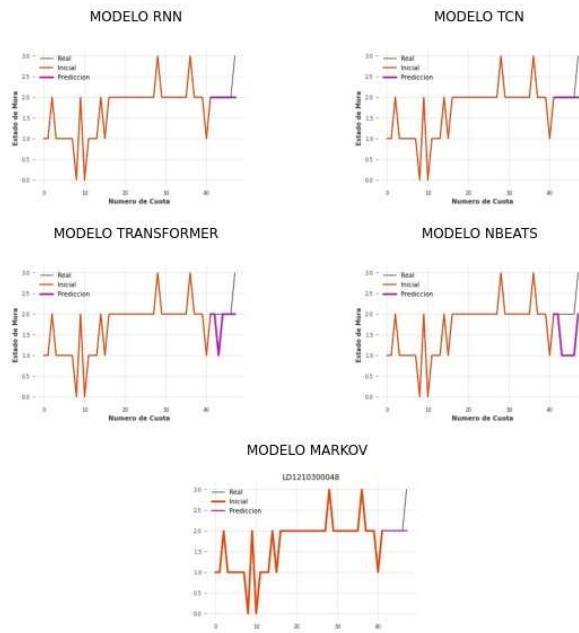


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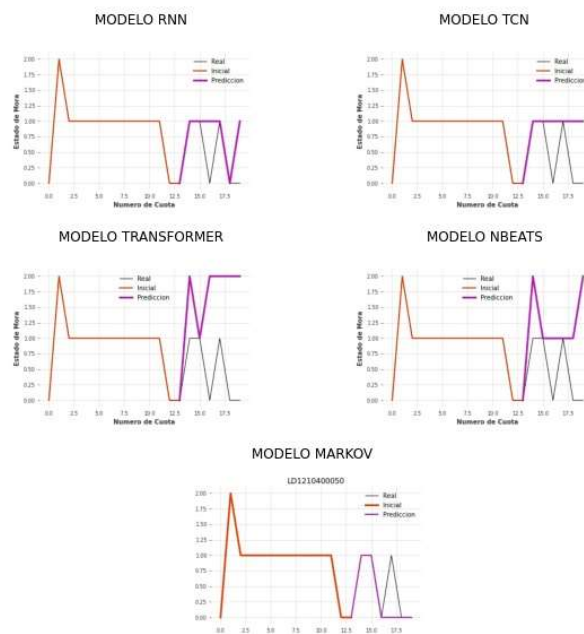




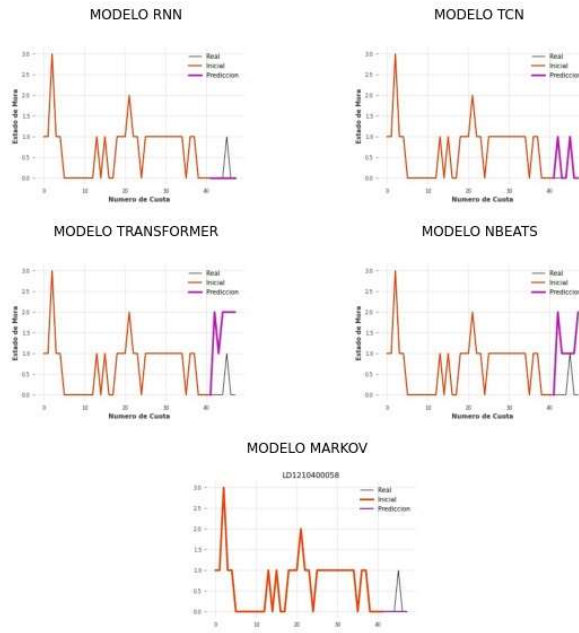
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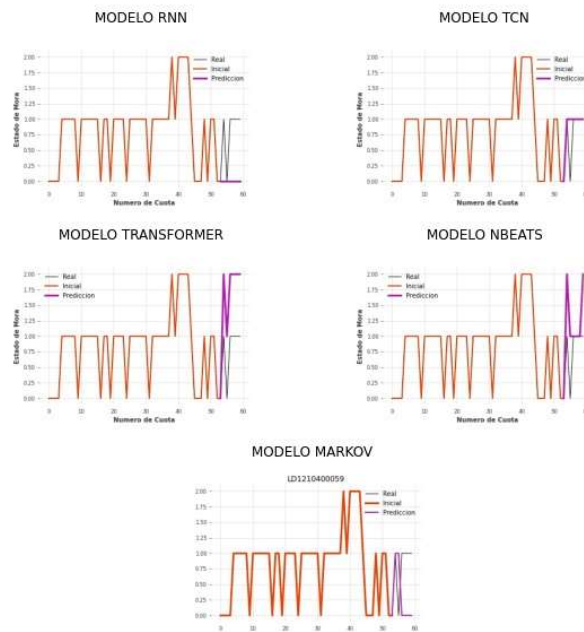
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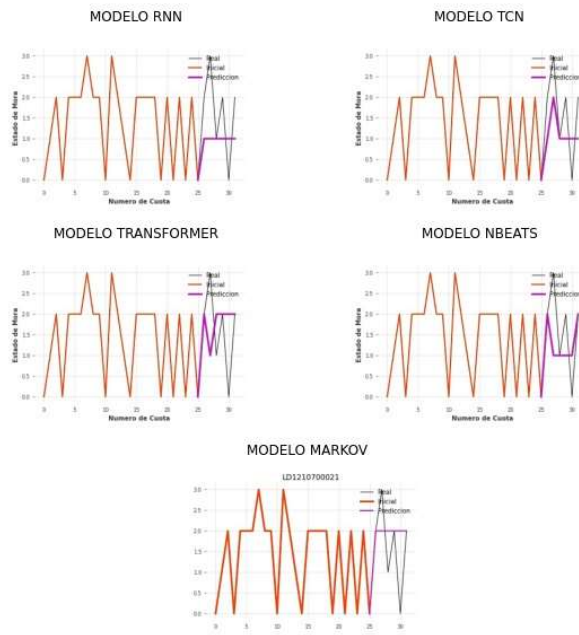
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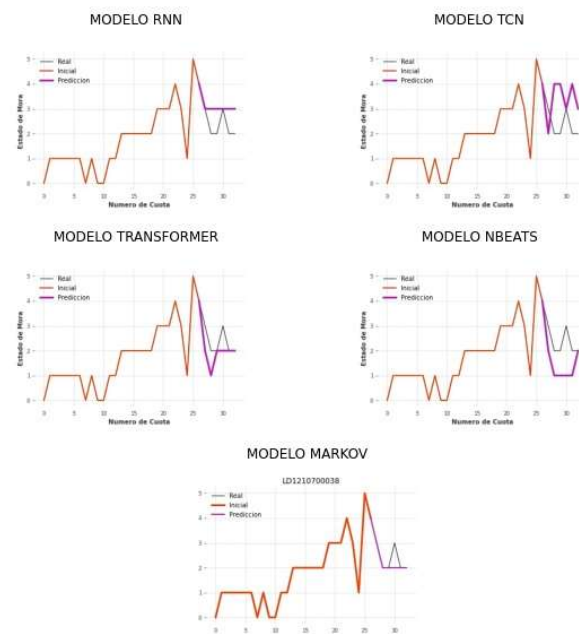
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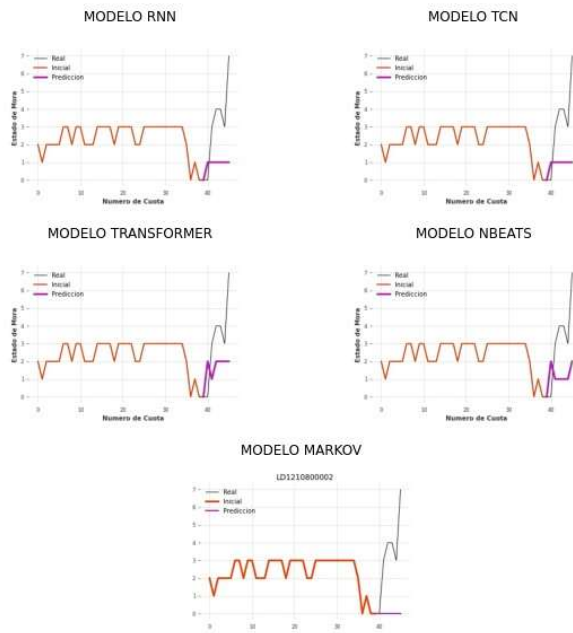
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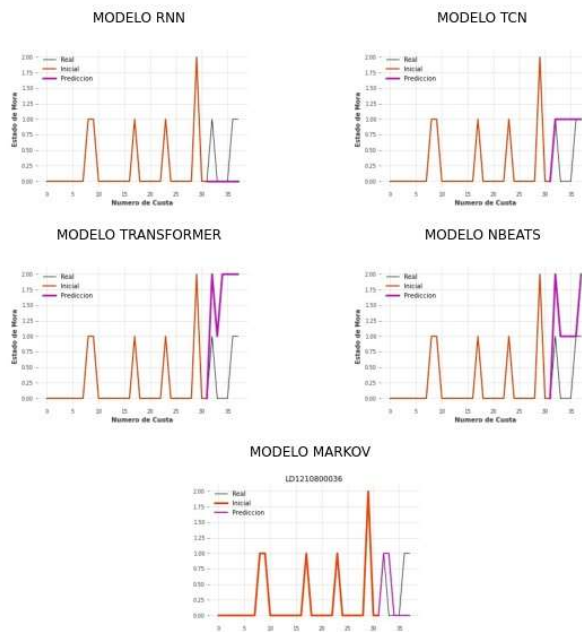
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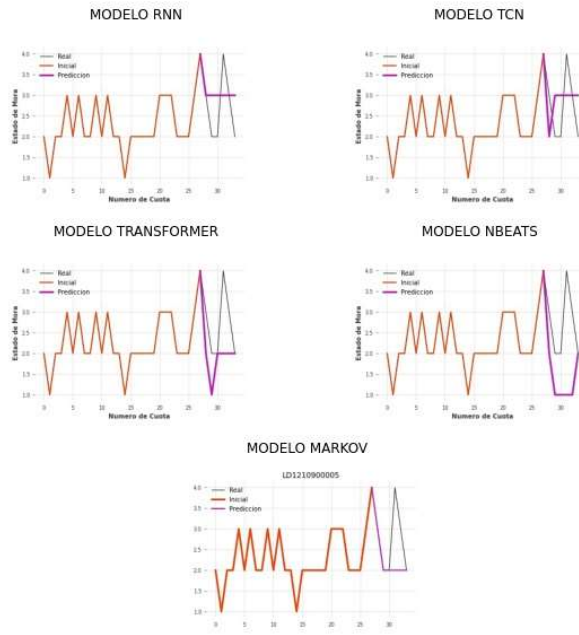
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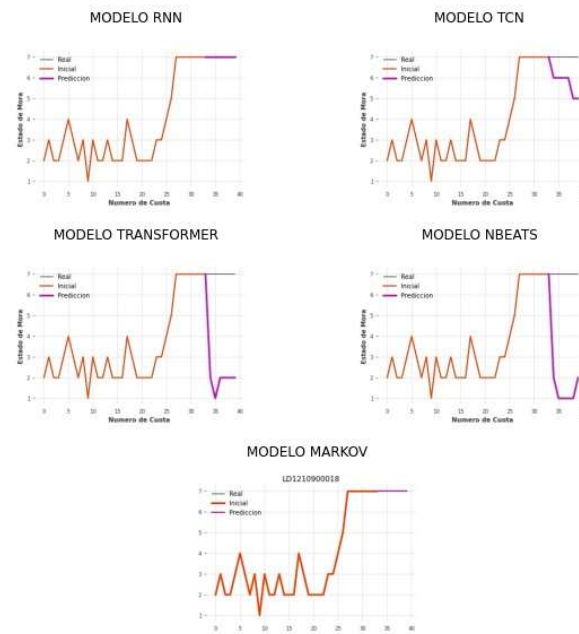
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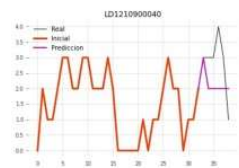




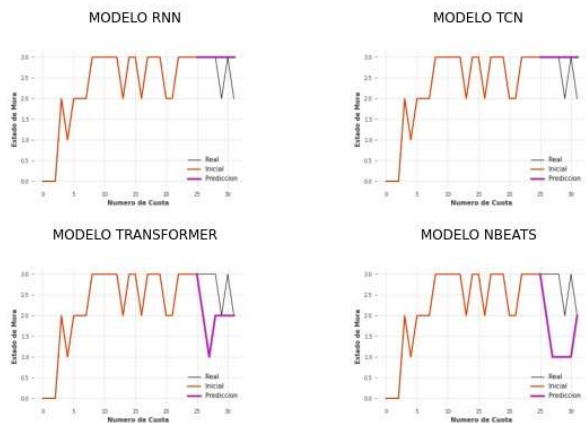
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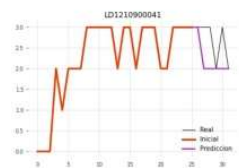
MODELO MARKOV



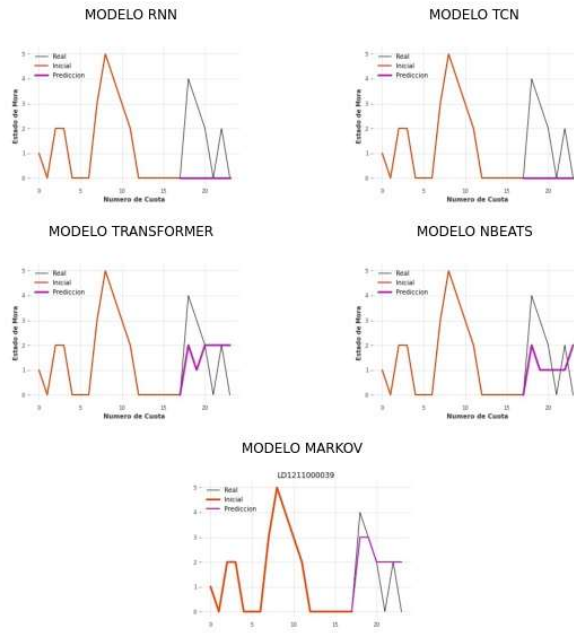
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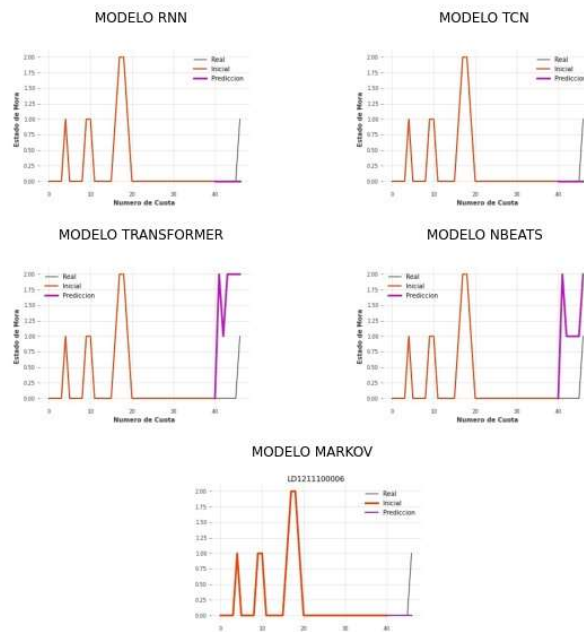
MODELO MARKOV



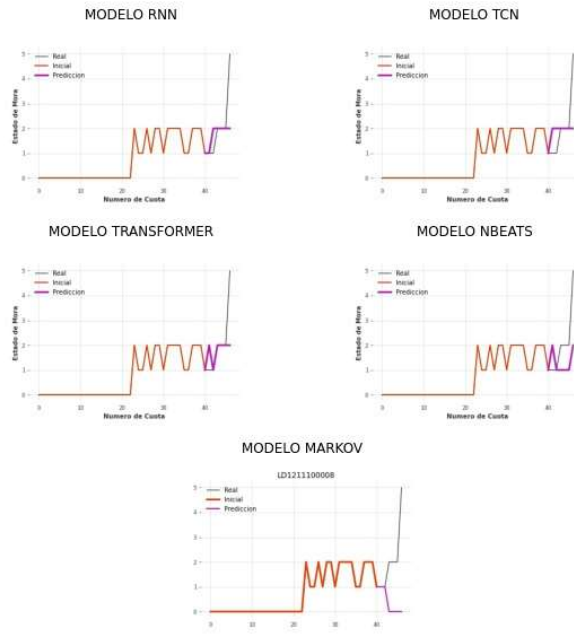
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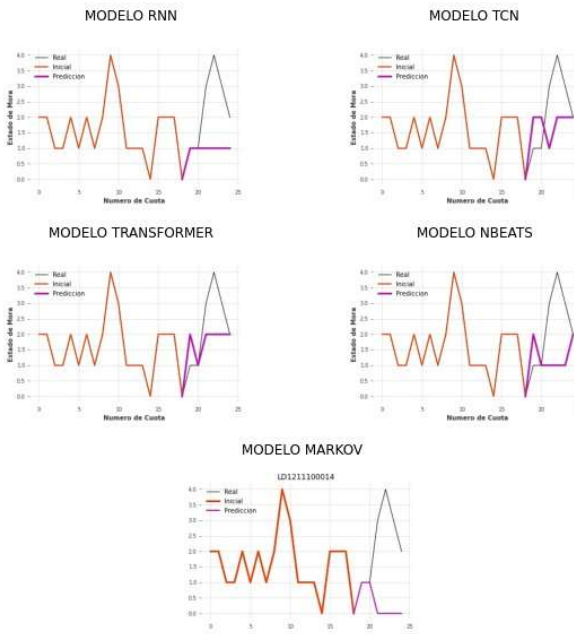
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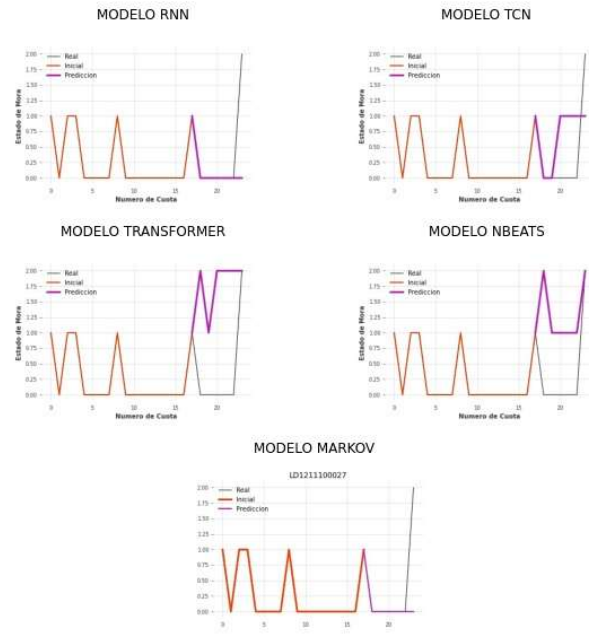
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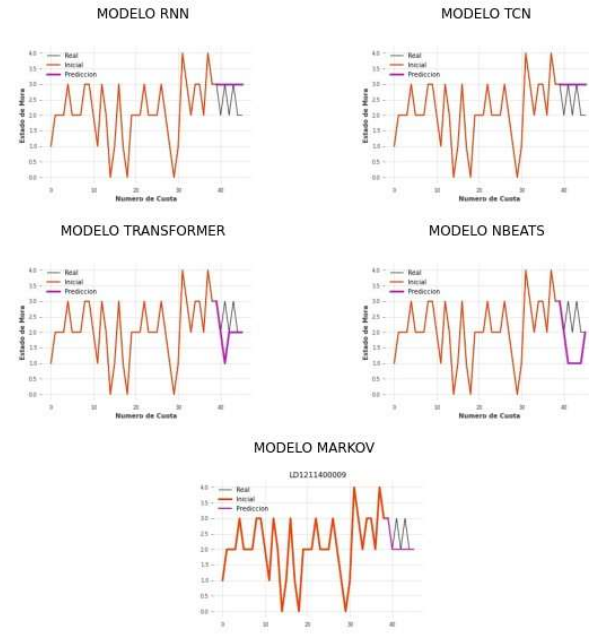
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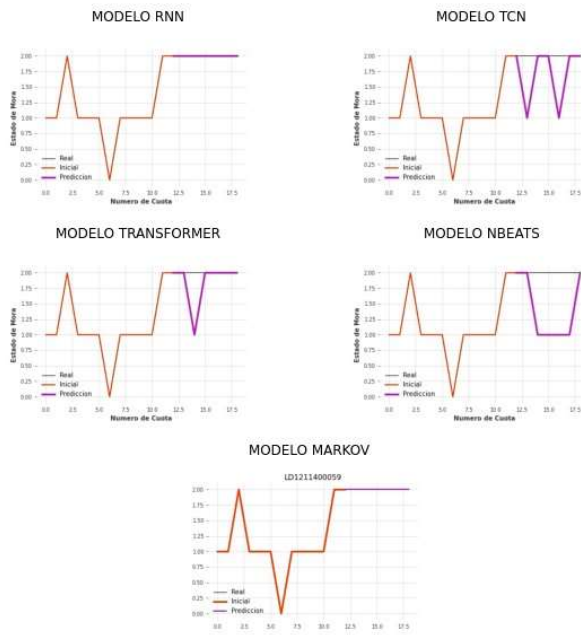
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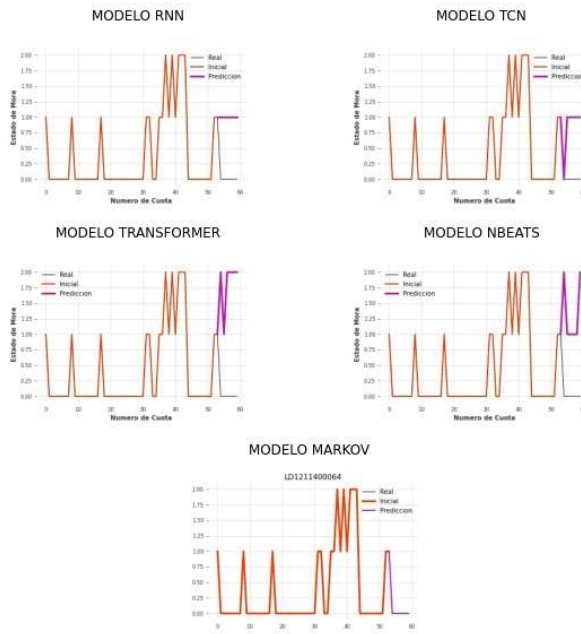
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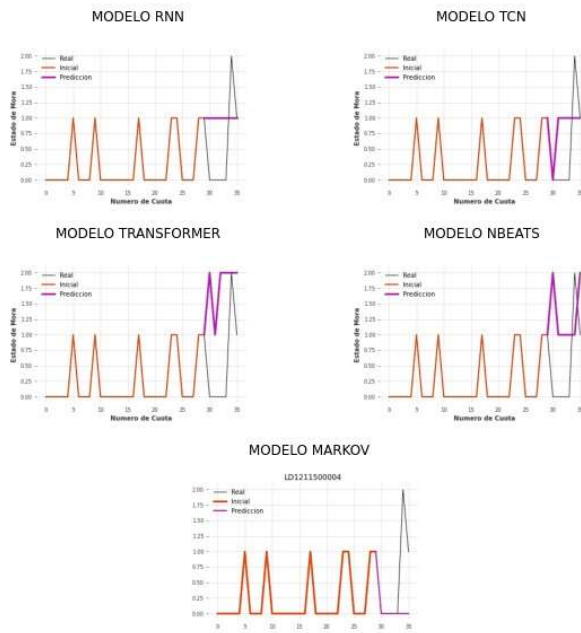
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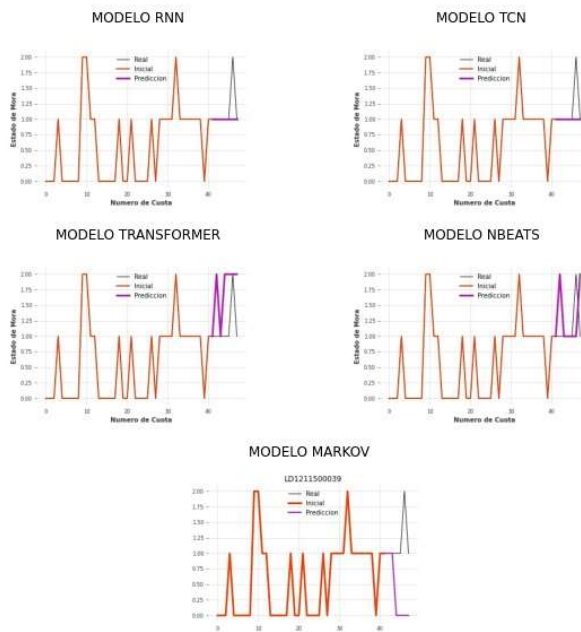
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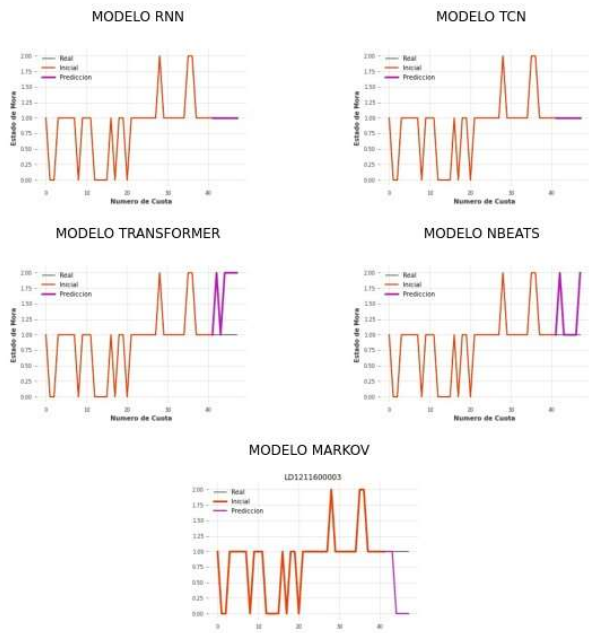
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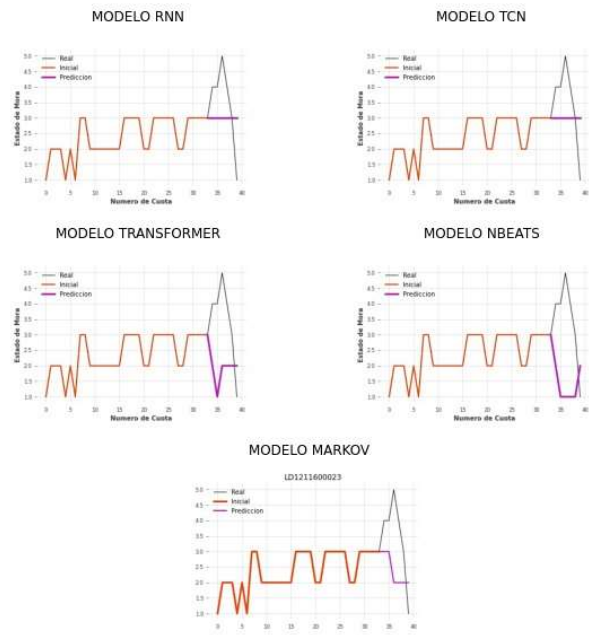
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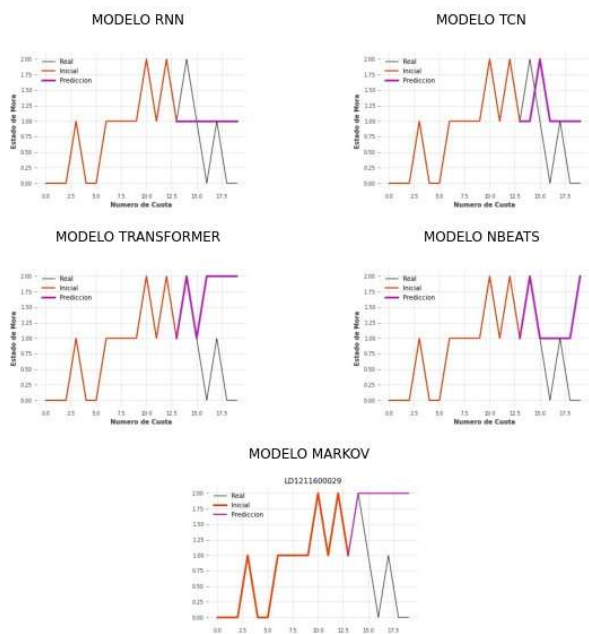
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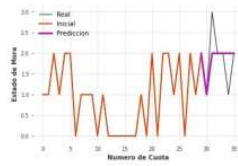
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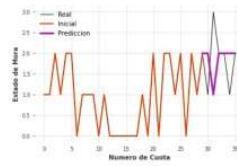


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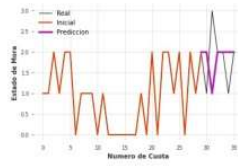
MODELO RNN



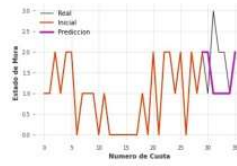
MODELO TCN



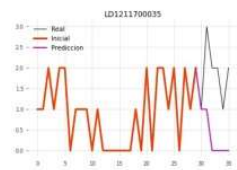
MODELO TRANSFORMER



MODELO NBEATS

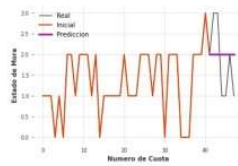


MODELO MARKOV

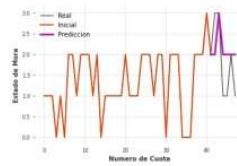


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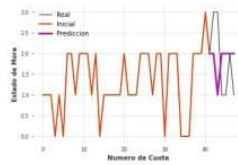
MODELO RNN



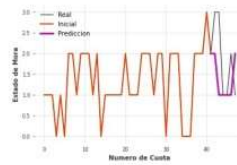
MODELO TCN



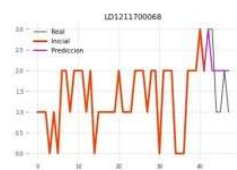
MODELO TRANSFORMER



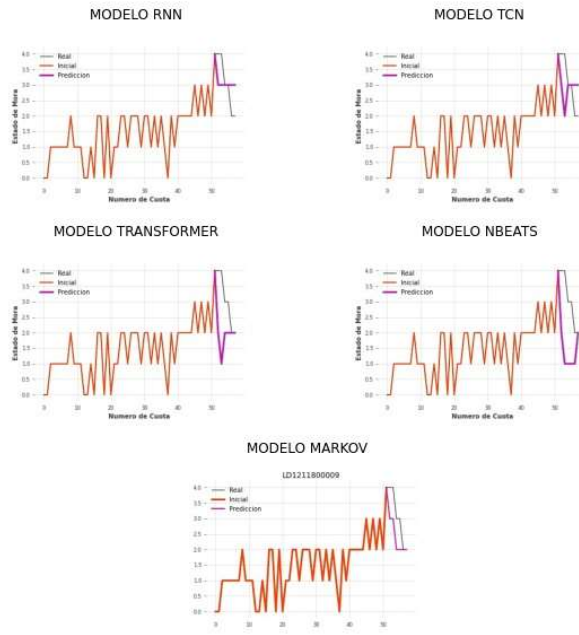
MODELO NBEATS



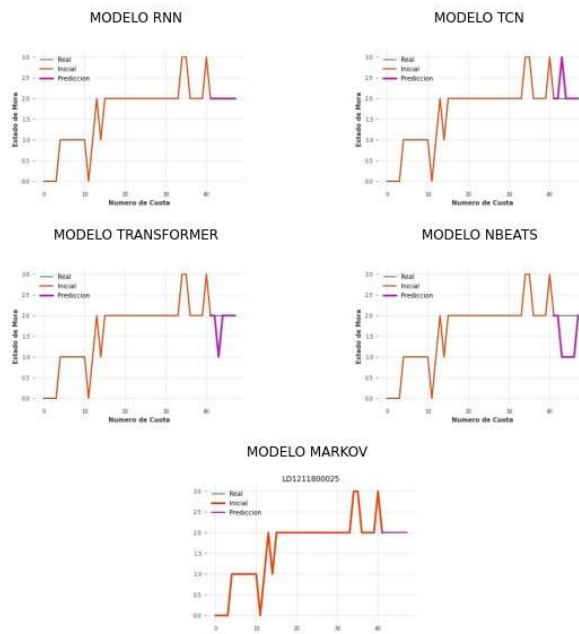
MODELO MARKOV



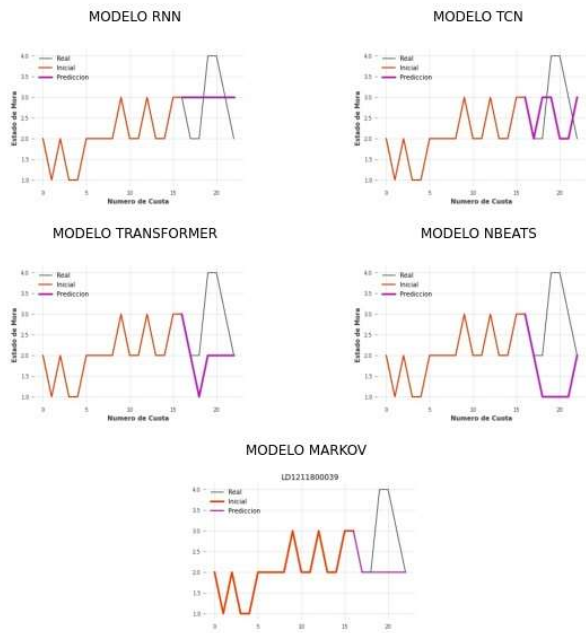
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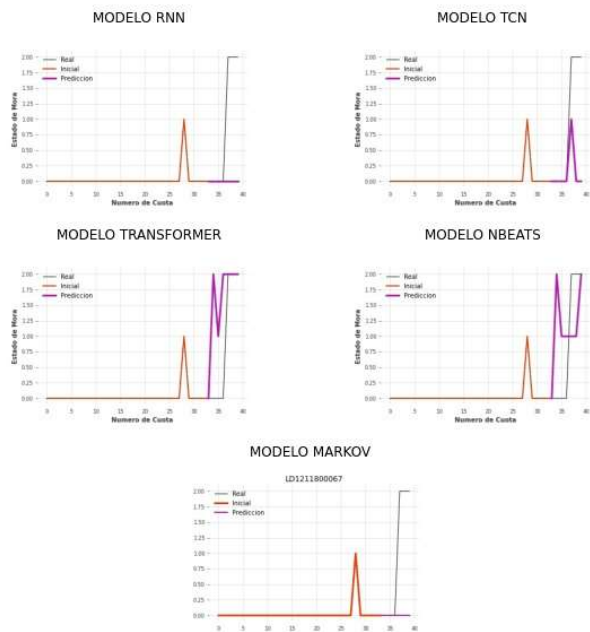
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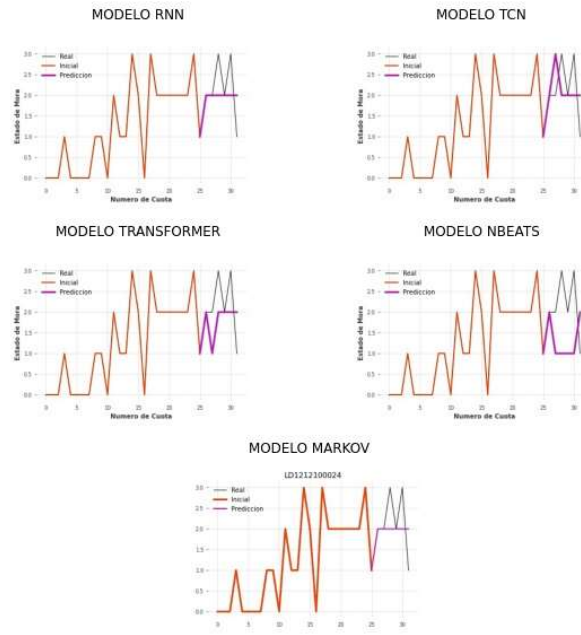
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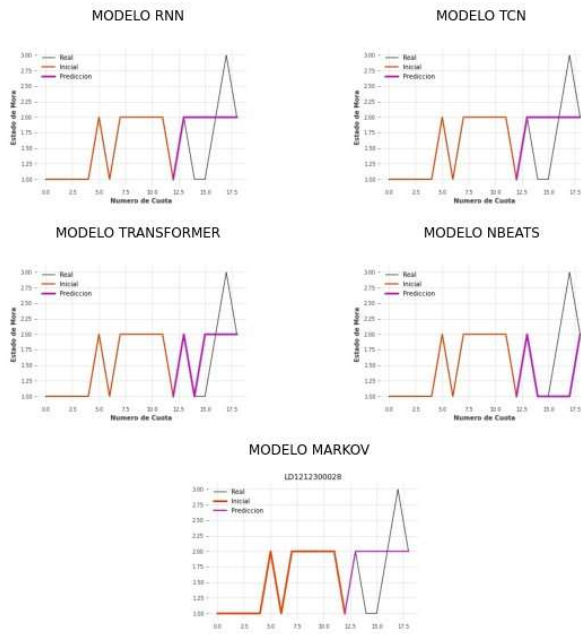
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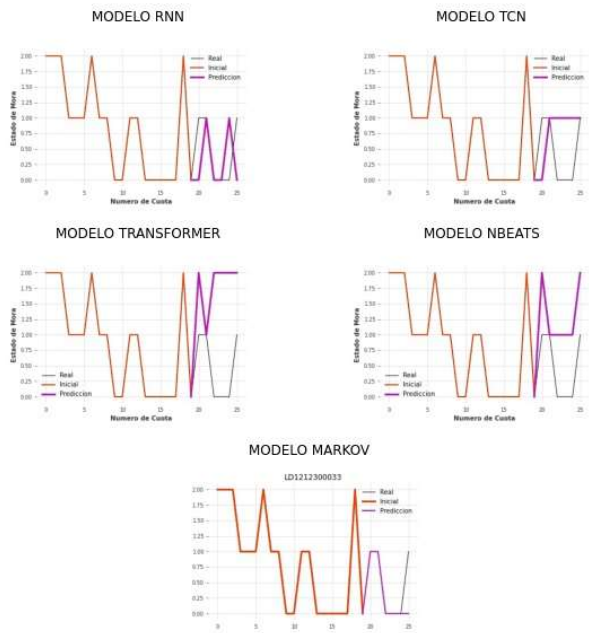
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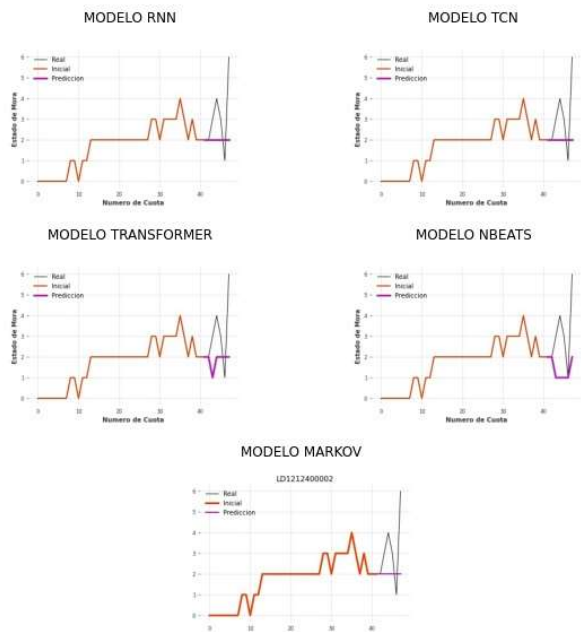
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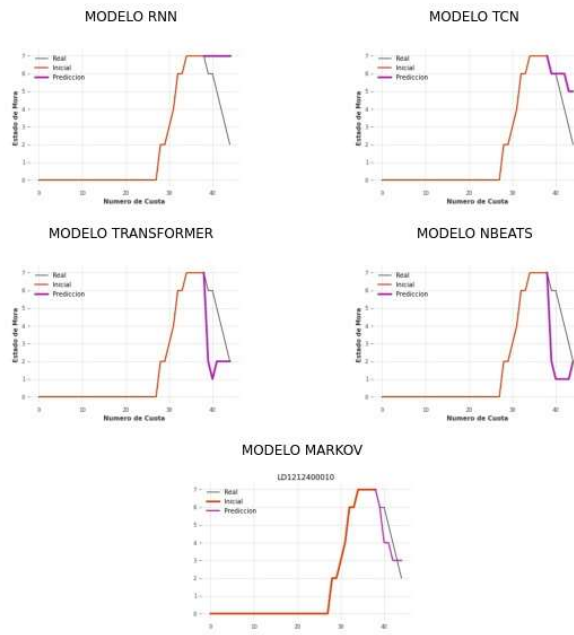
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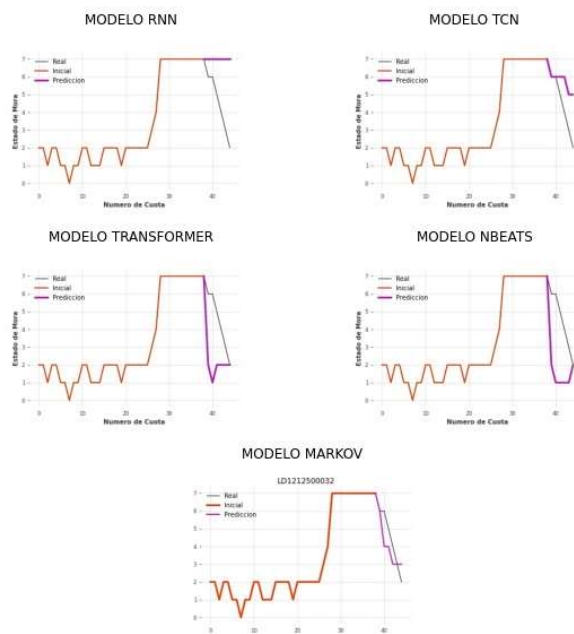
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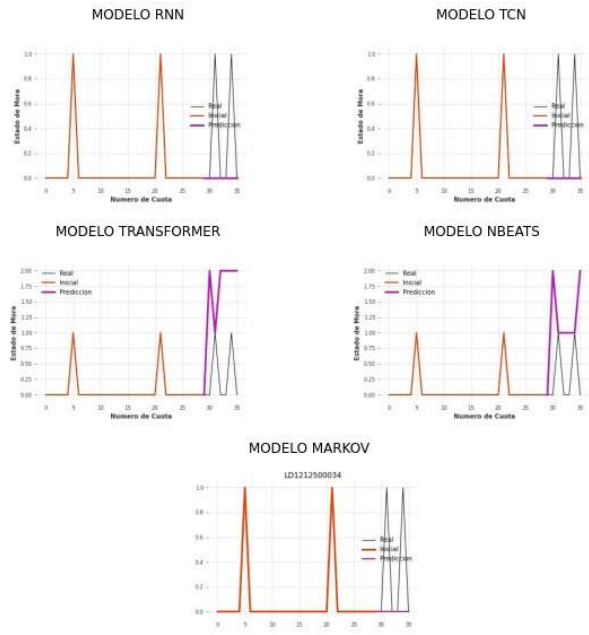
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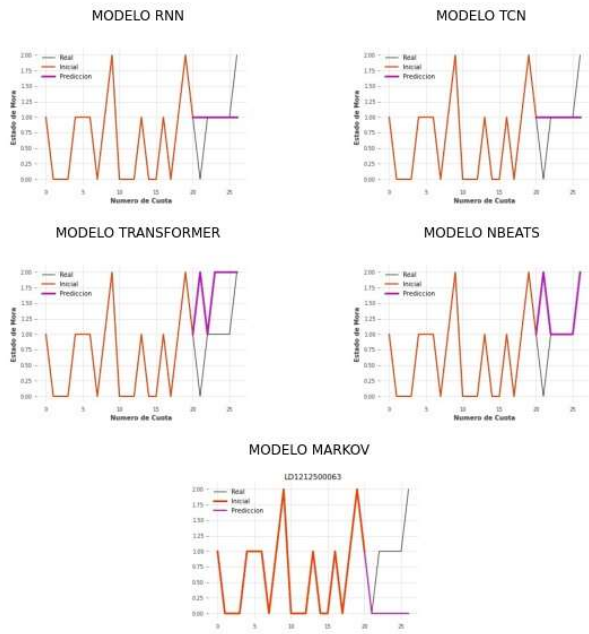
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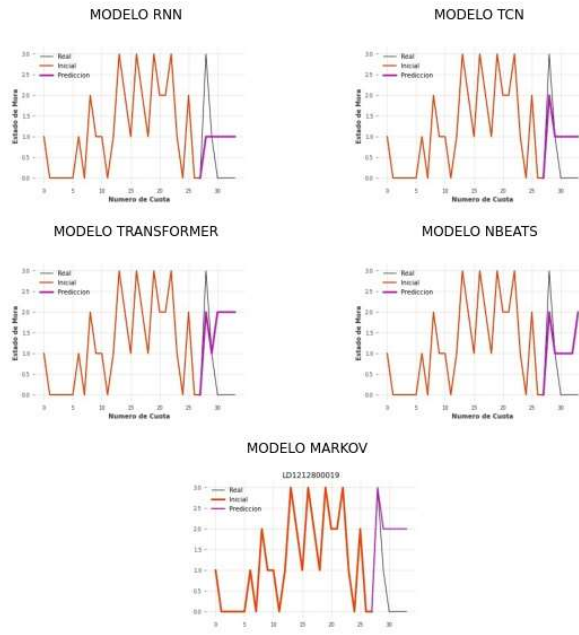
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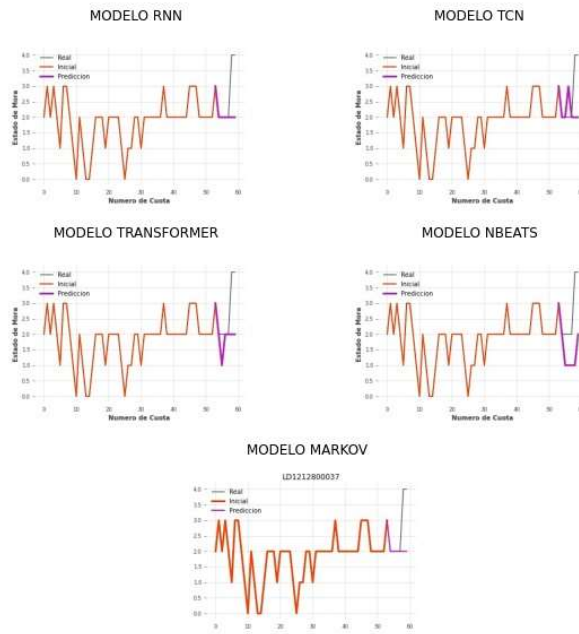
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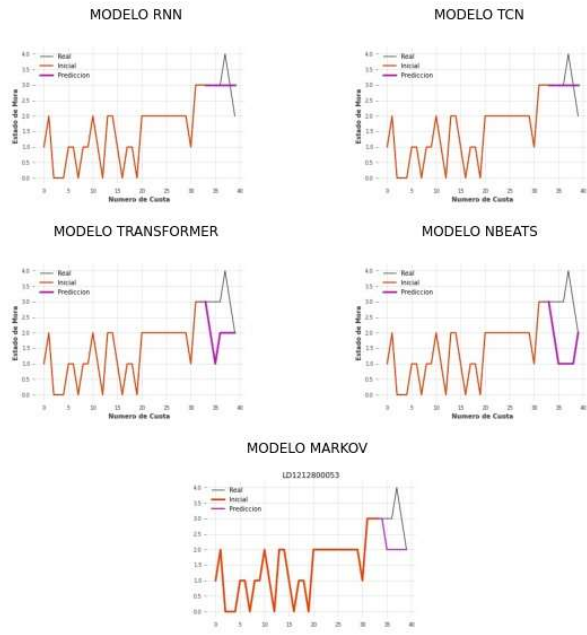


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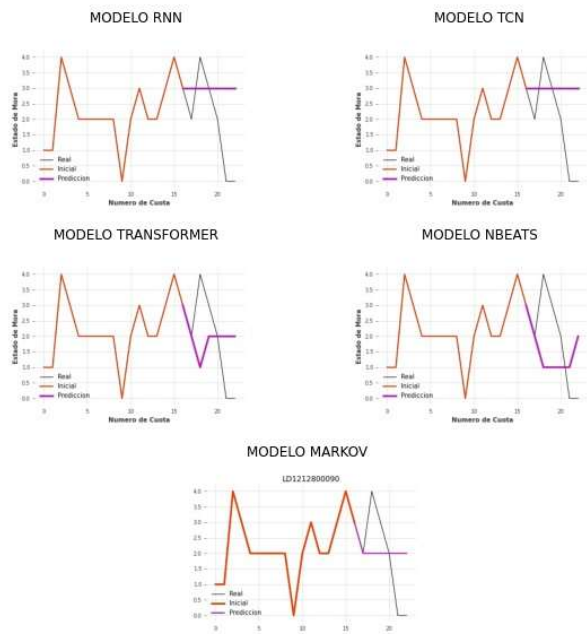




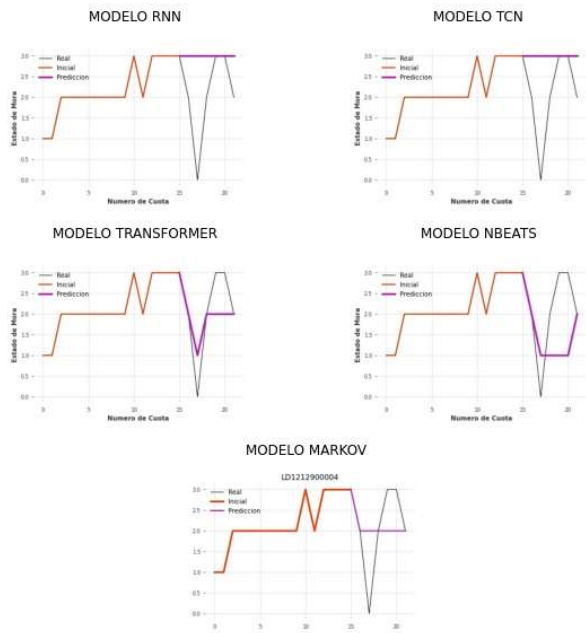
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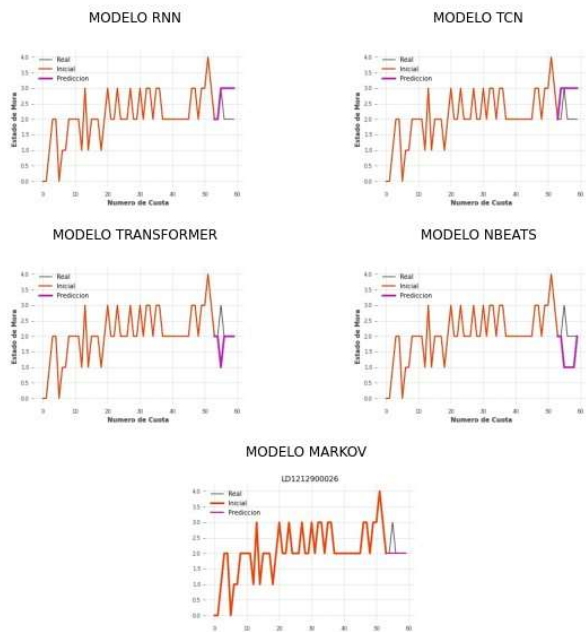
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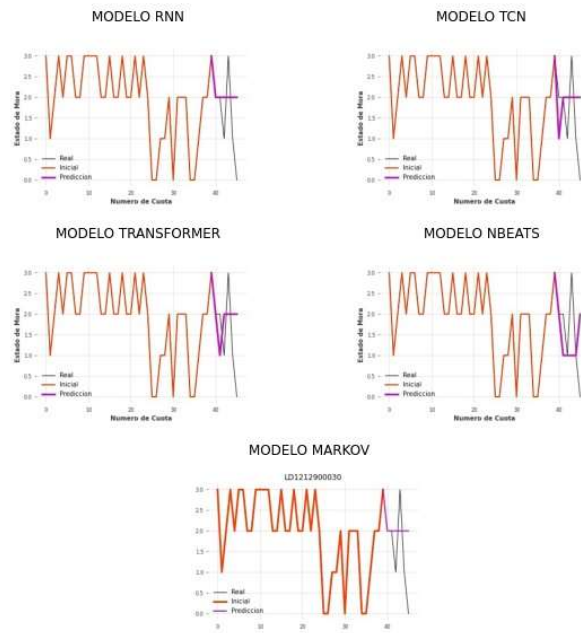
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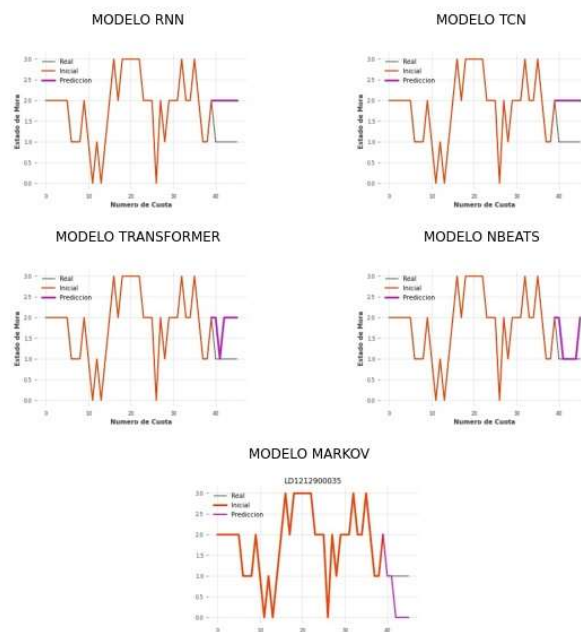
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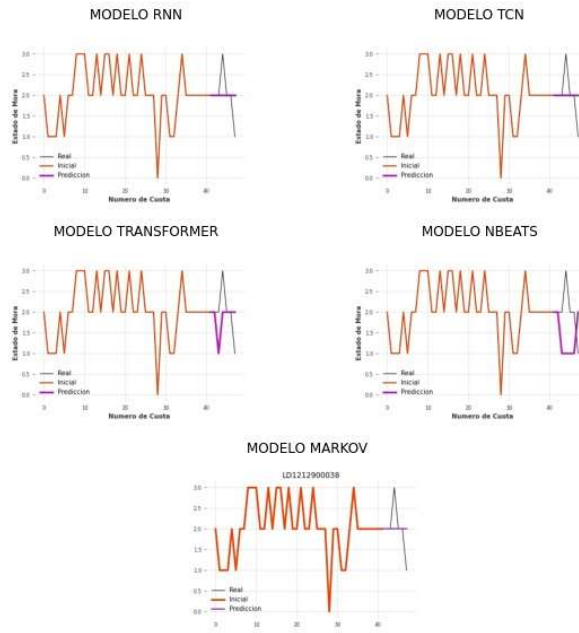
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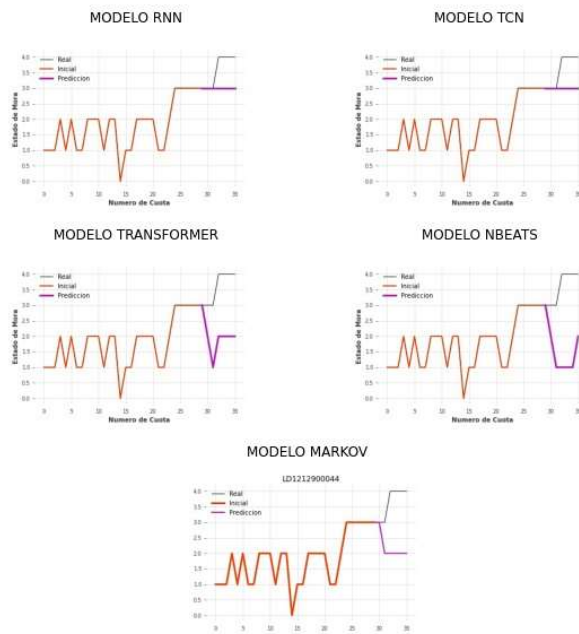
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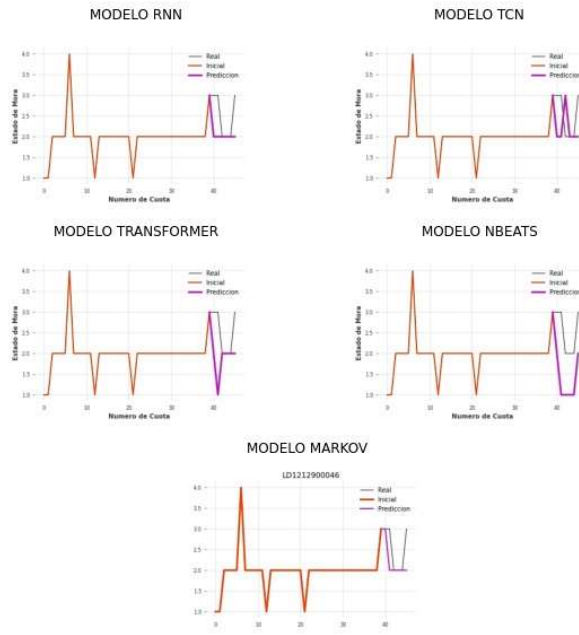
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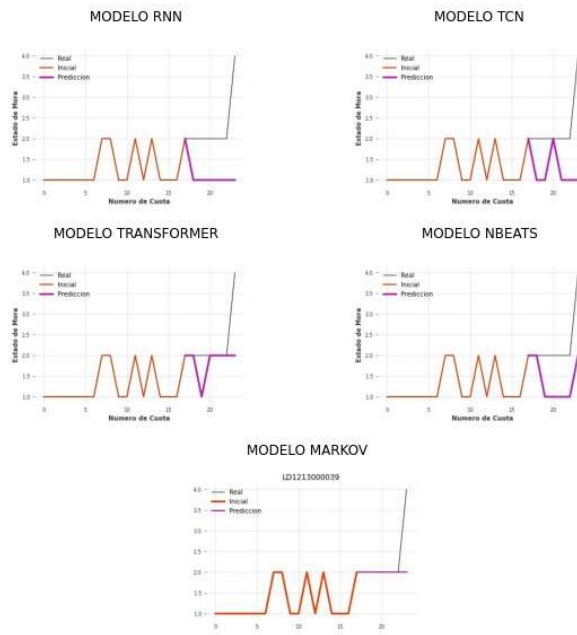
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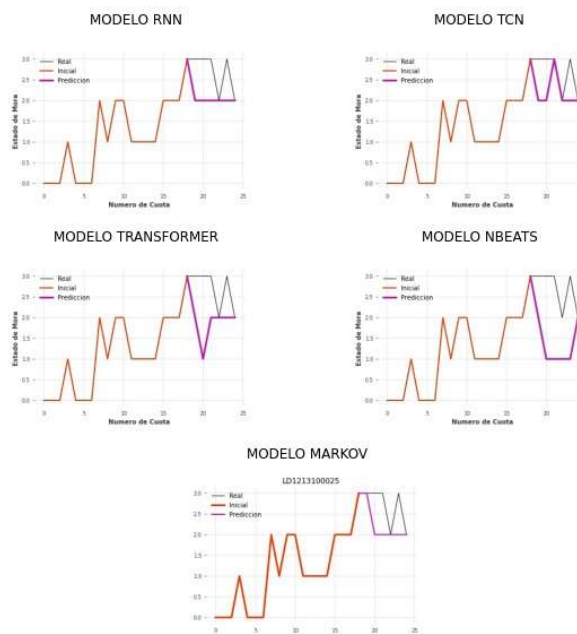
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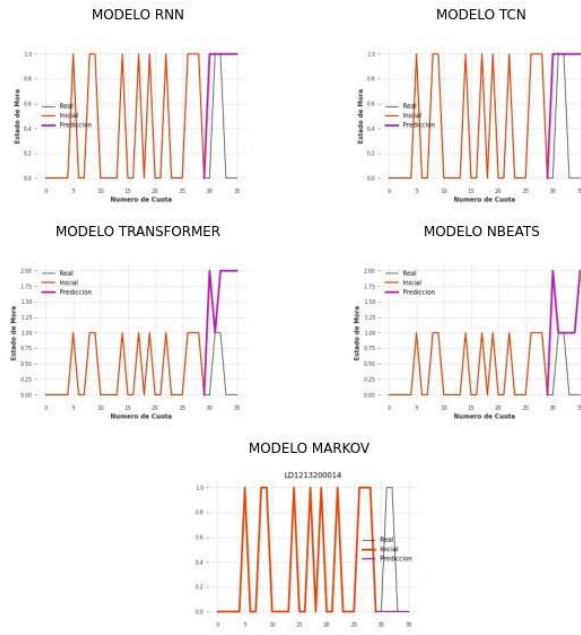
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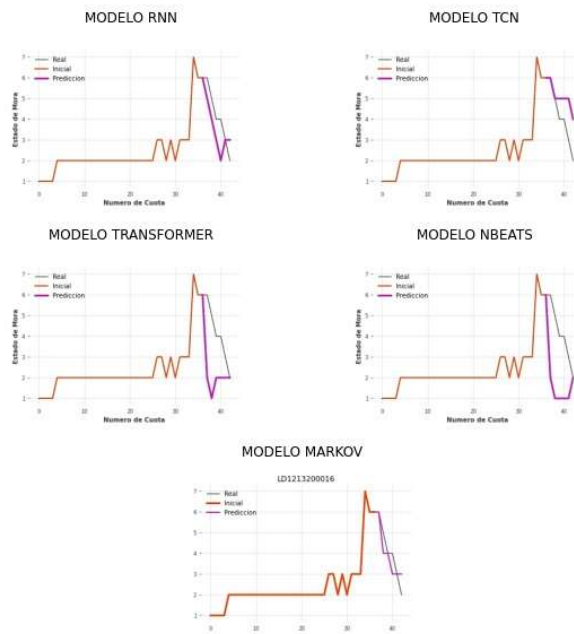
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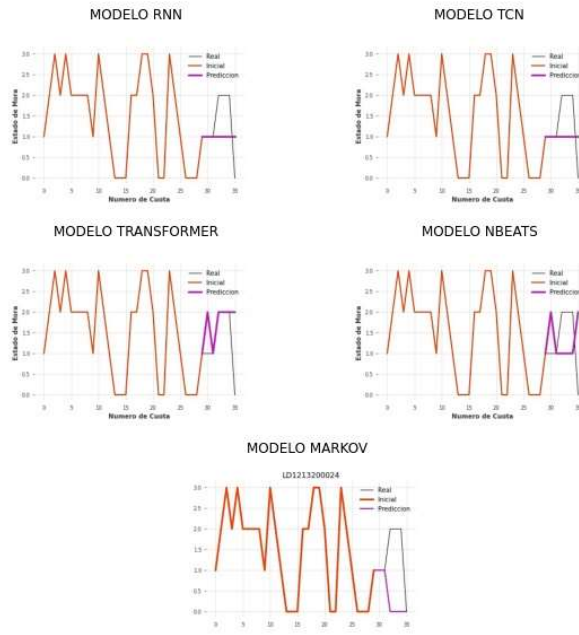
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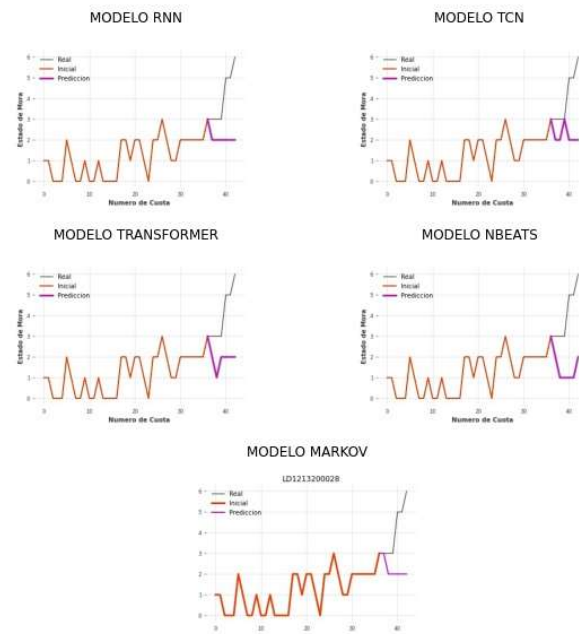
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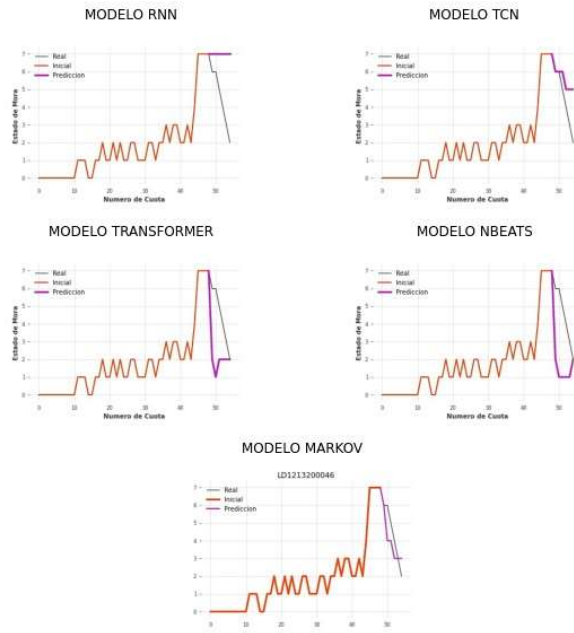


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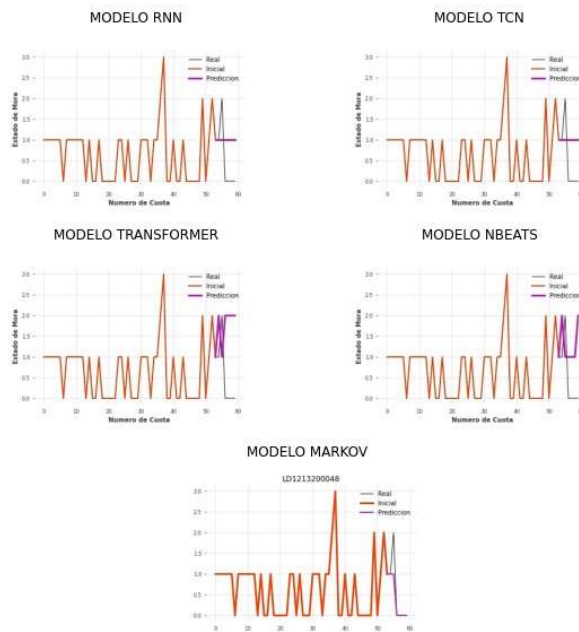




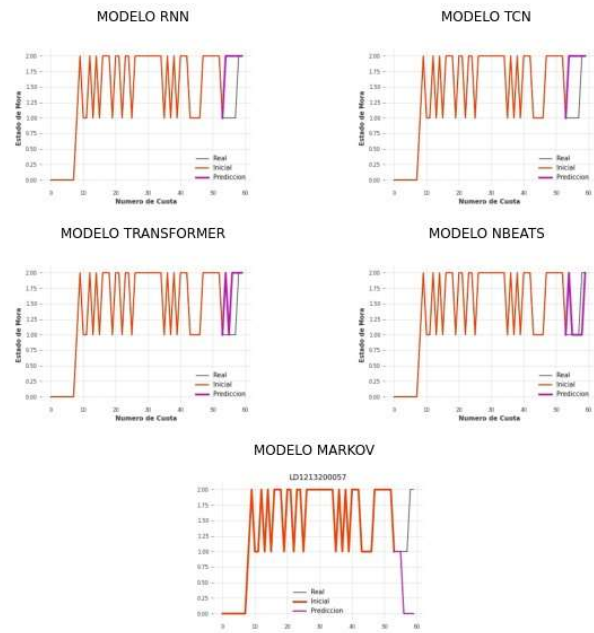
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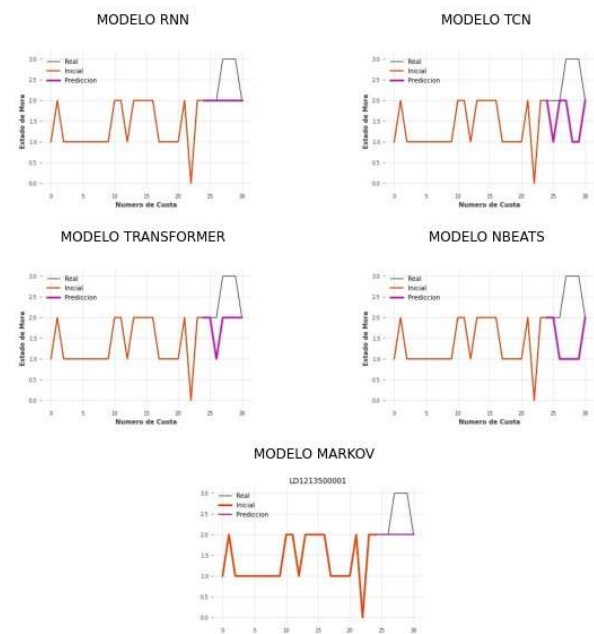
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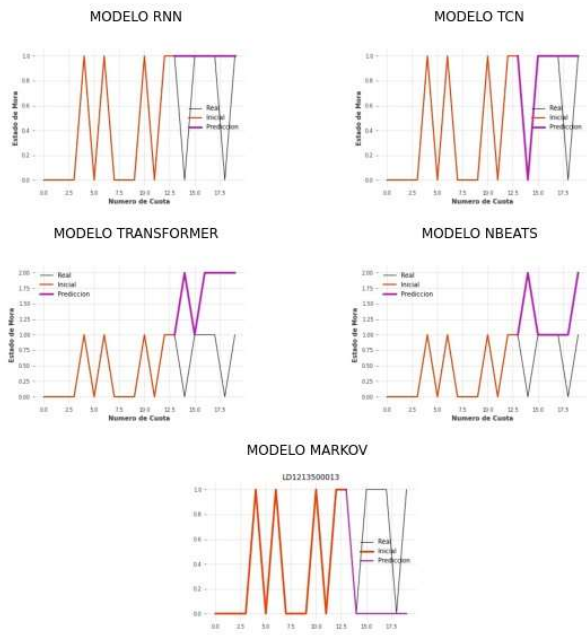
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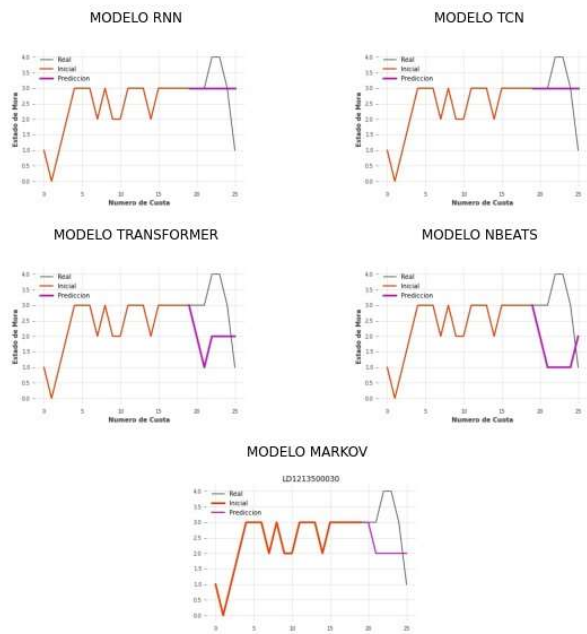
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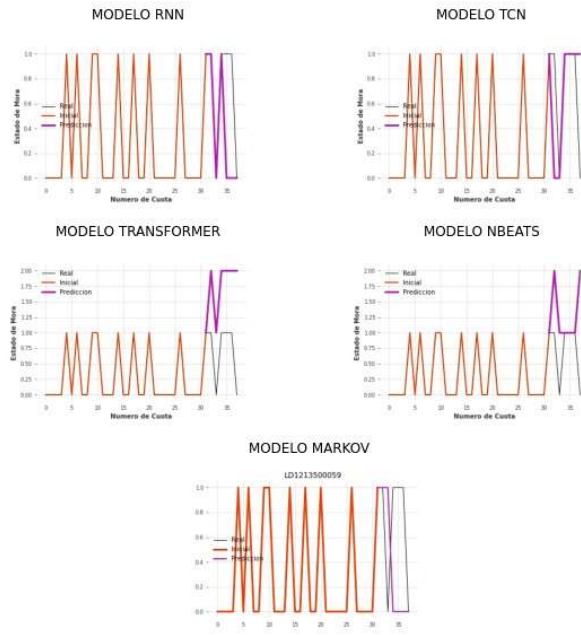
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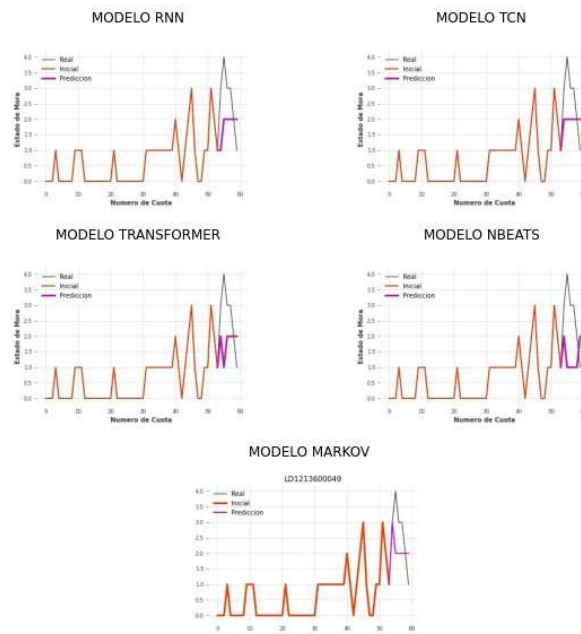
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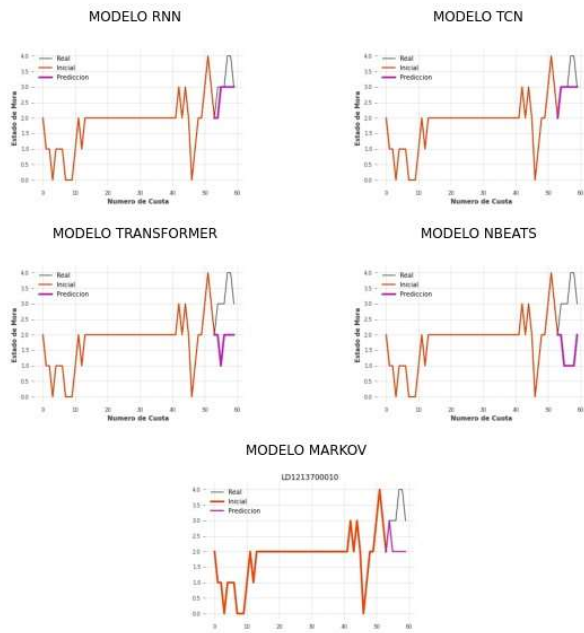
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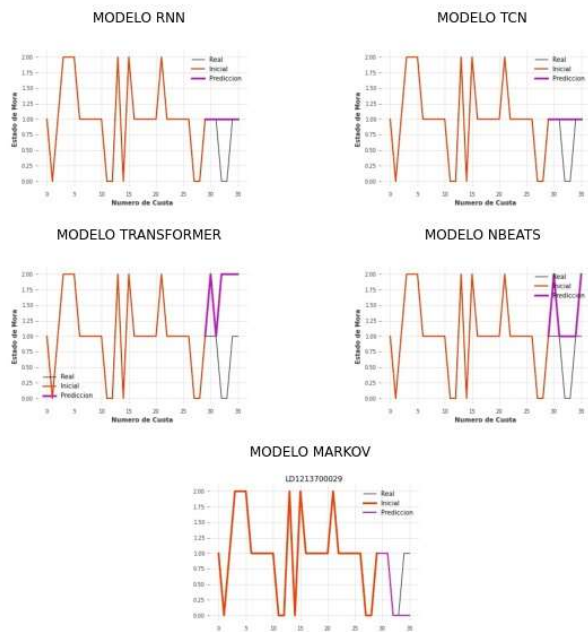
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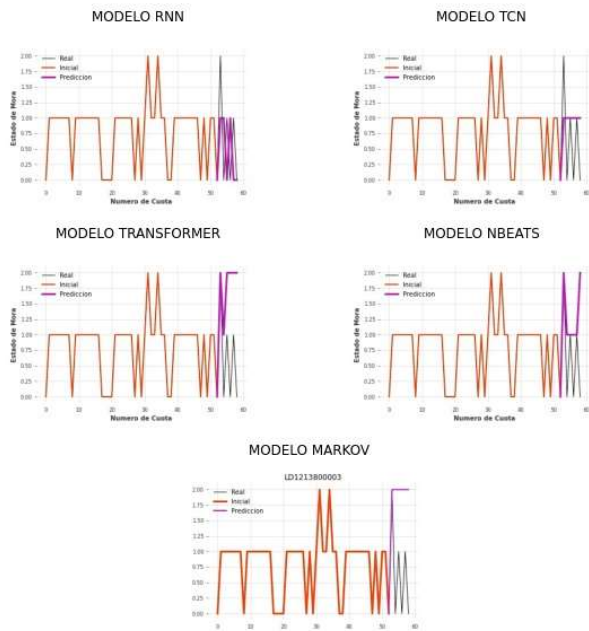
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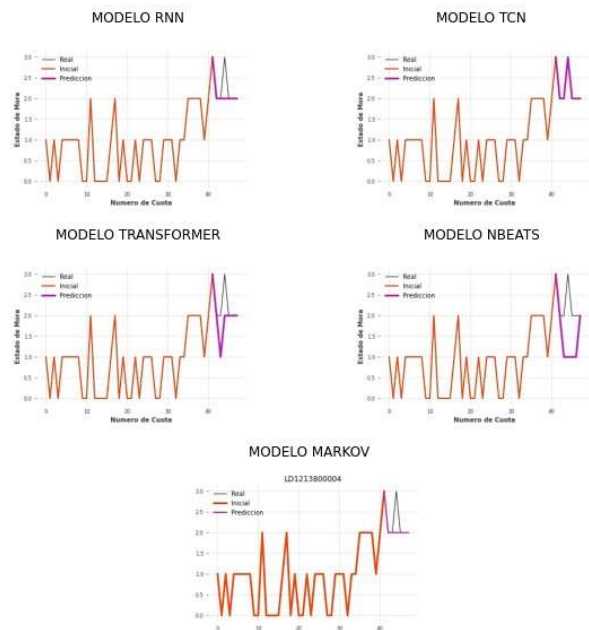
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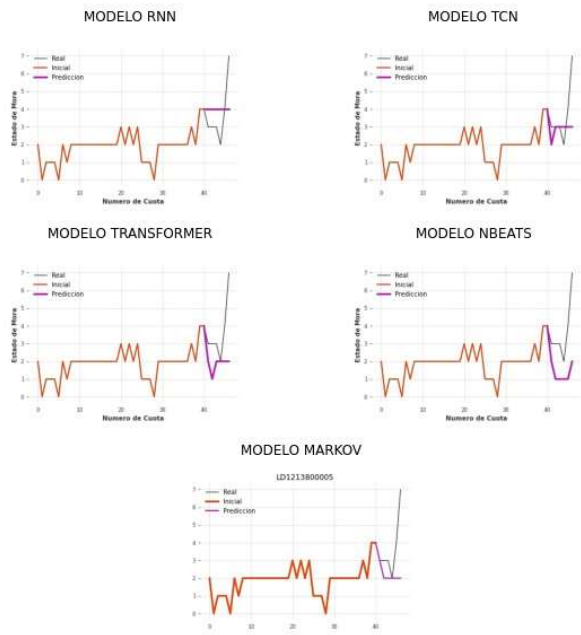
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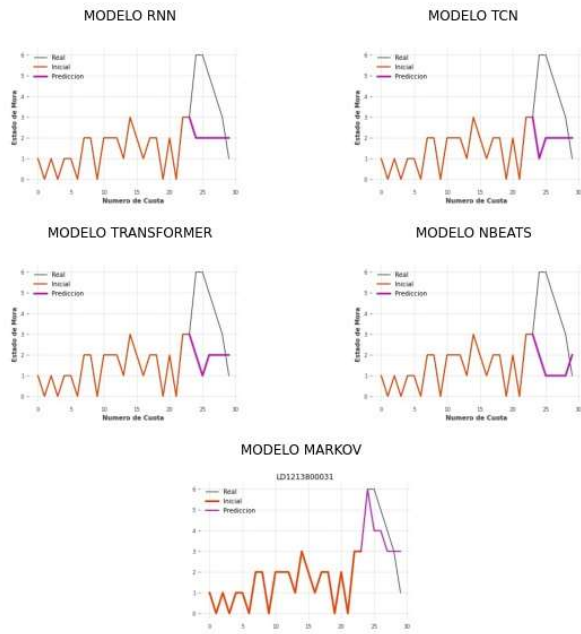
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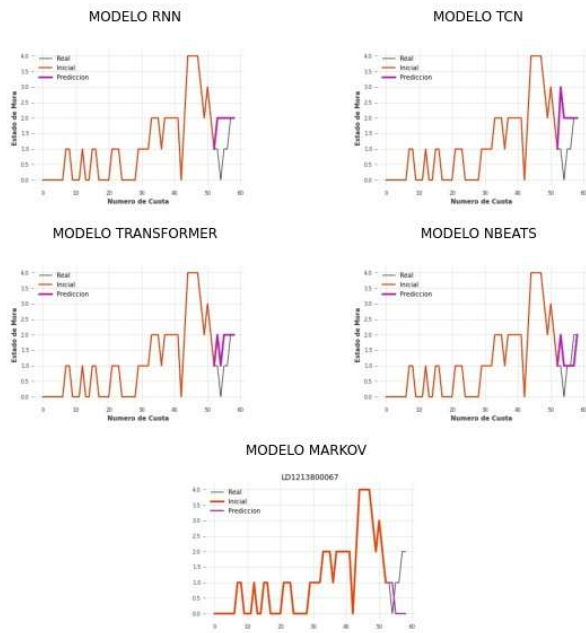
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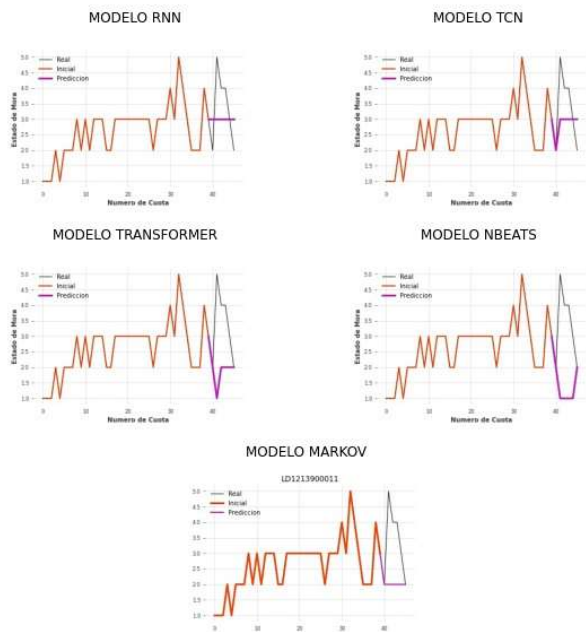
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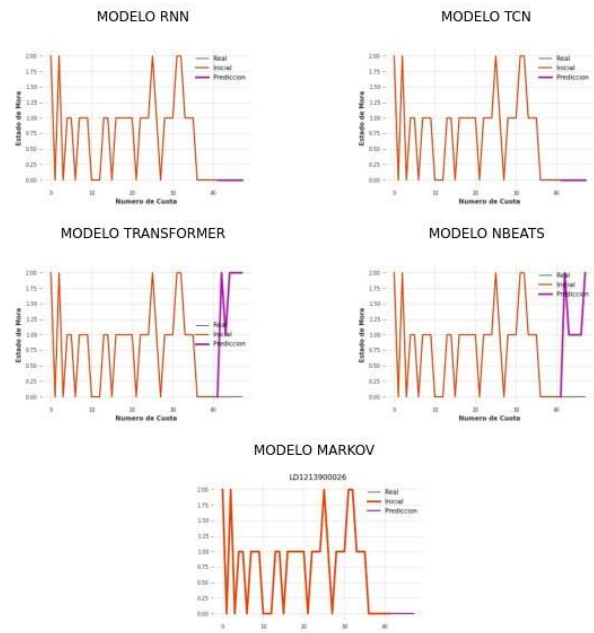


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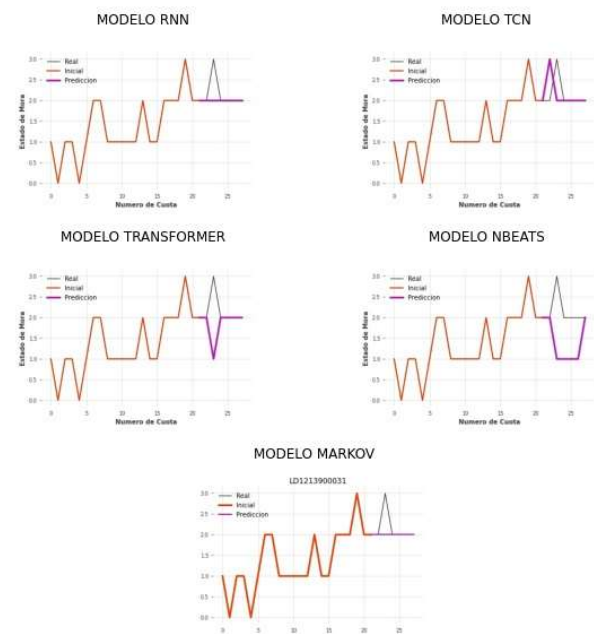




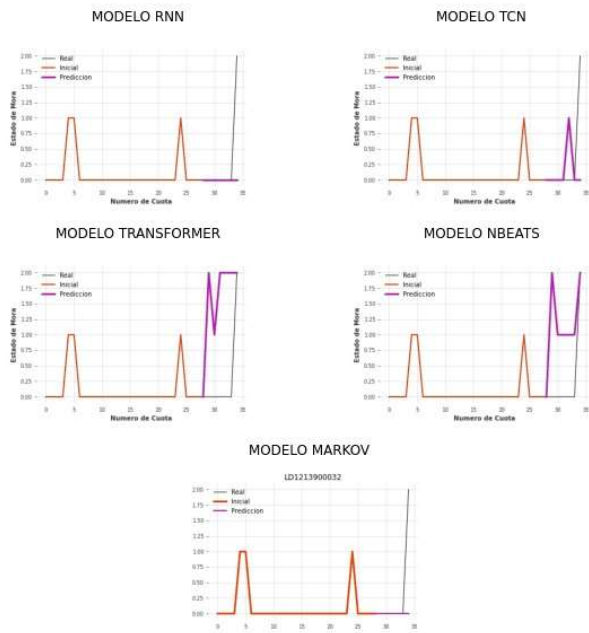
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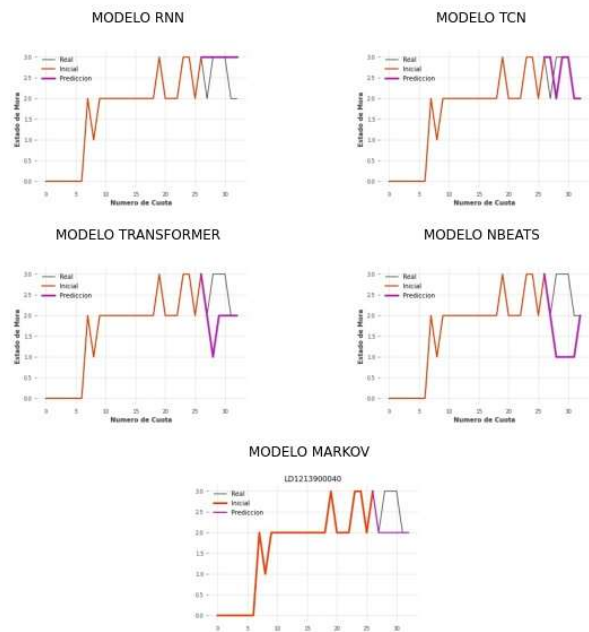
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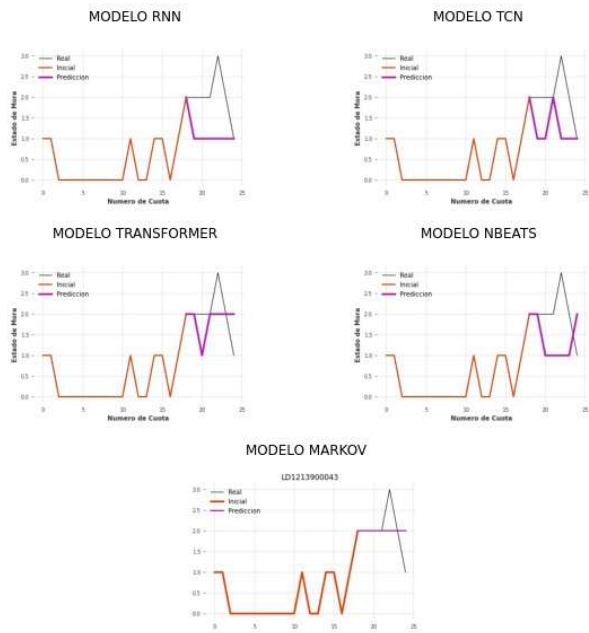
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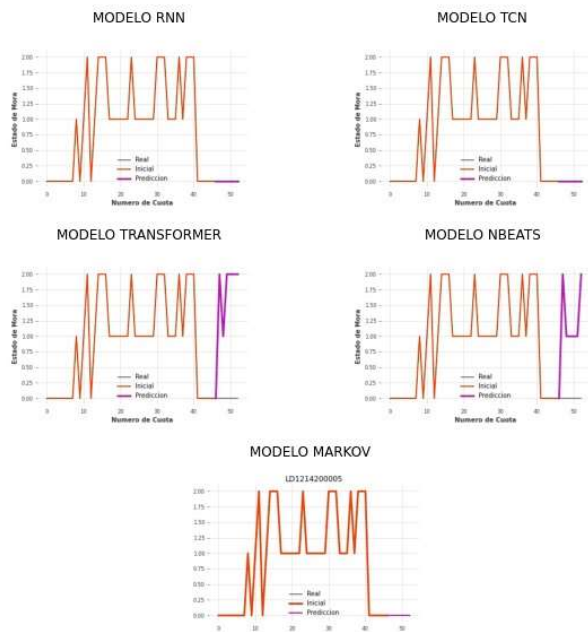
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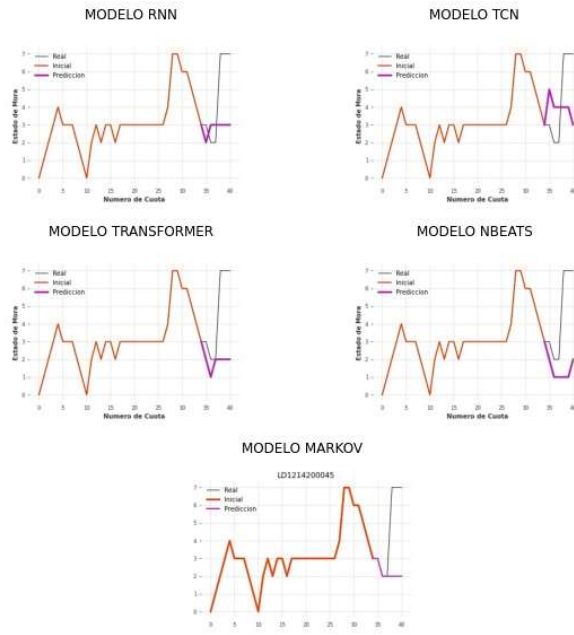
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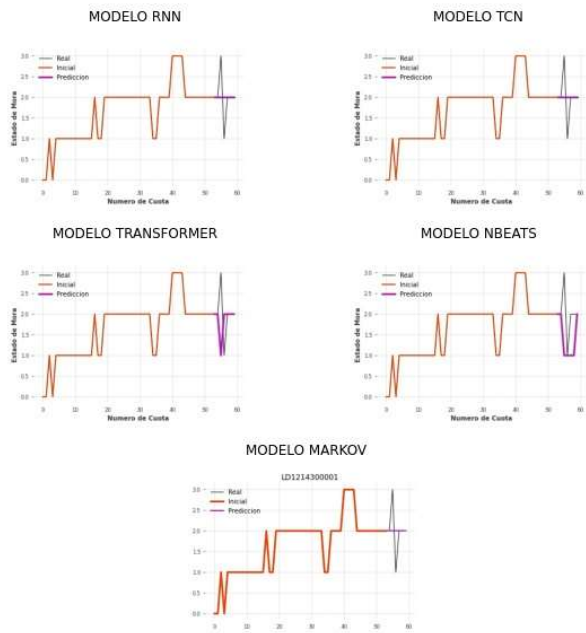
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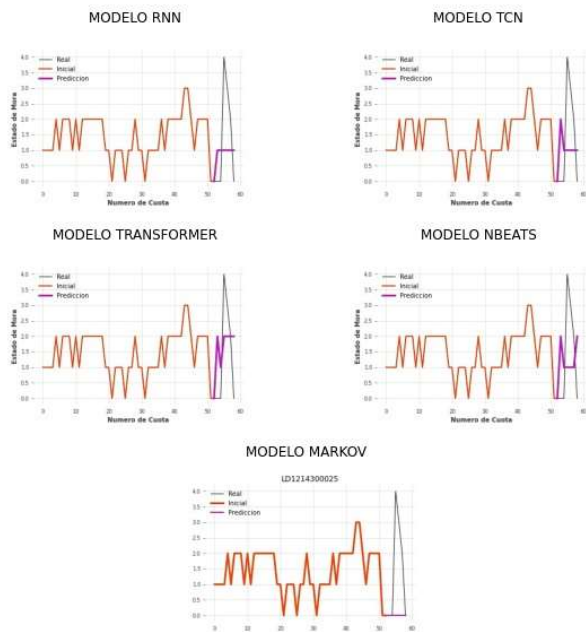
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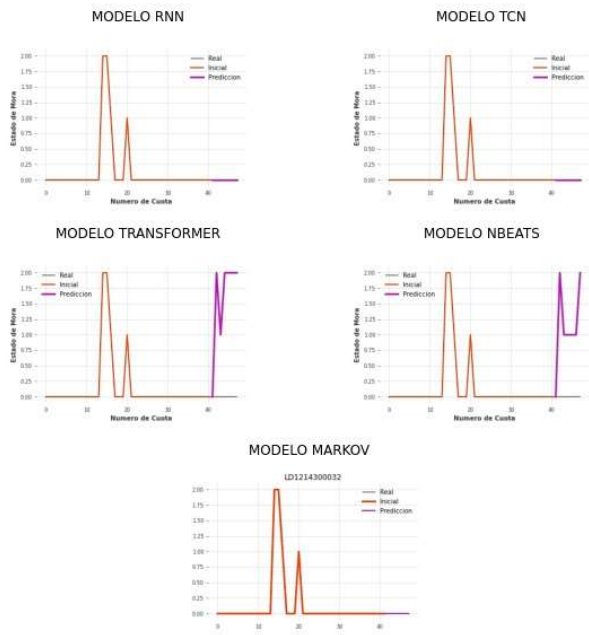
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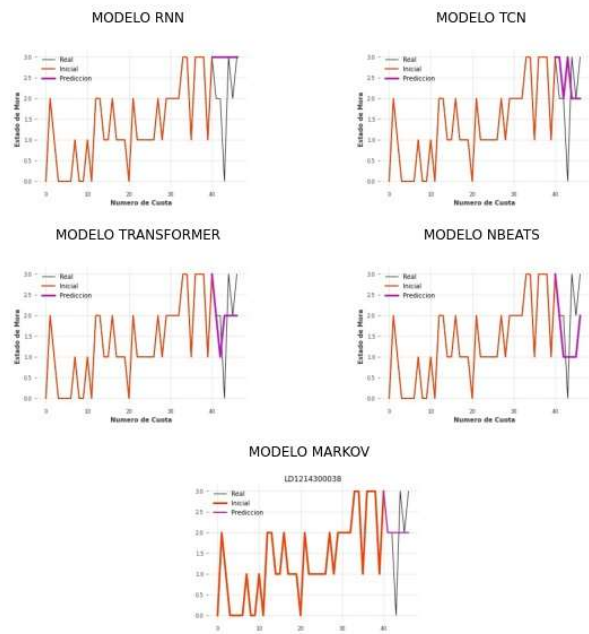
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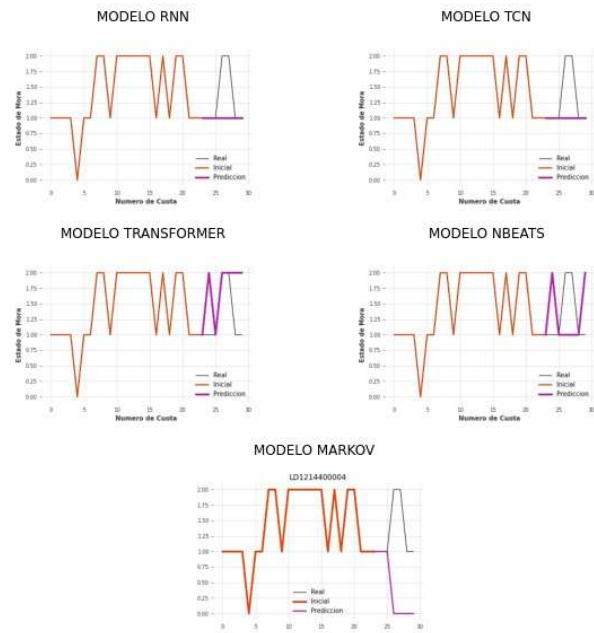
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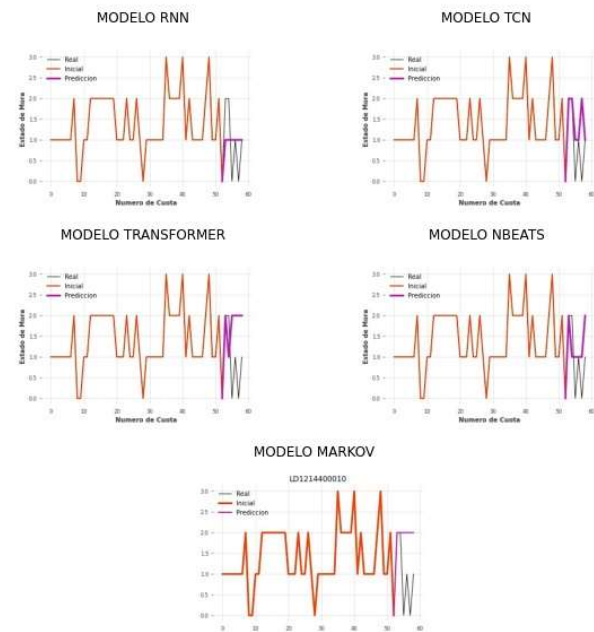
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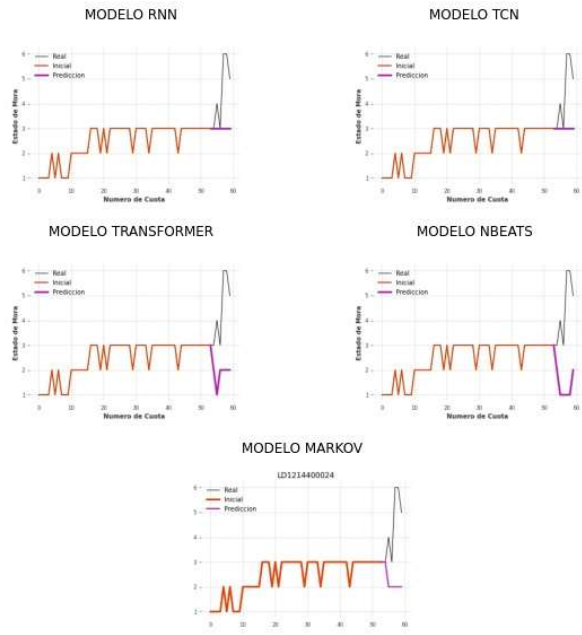
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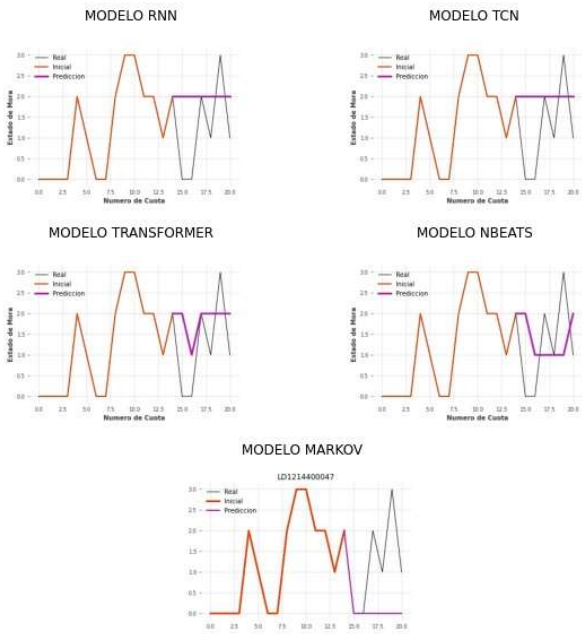
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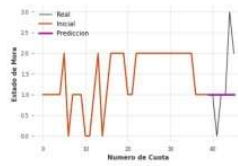
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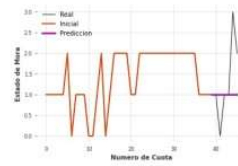


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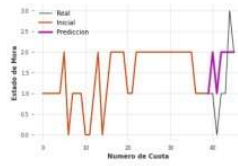
MODELO RNN



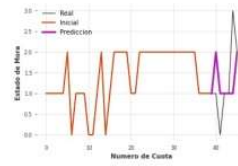
MODELO TCN



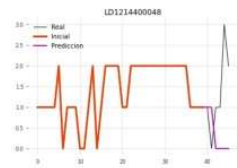
MODELO TRANSFORMER



MODELO NBEATS

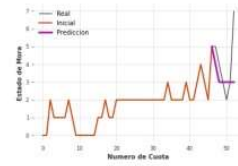


MODELO MARKOV

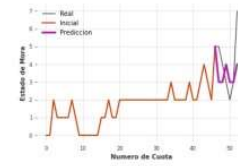


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MODELO RNN



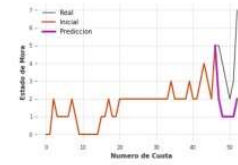
MODELO TCN



MODELO TRANSFORMER



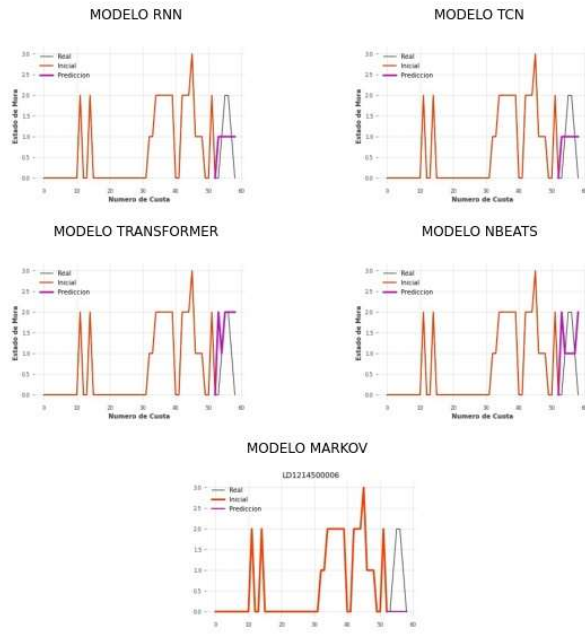
MODELO NBEATS



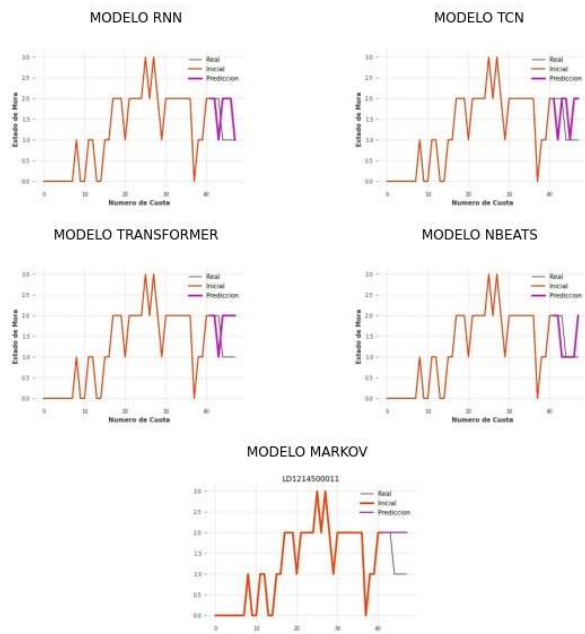
MODELO MARKOV



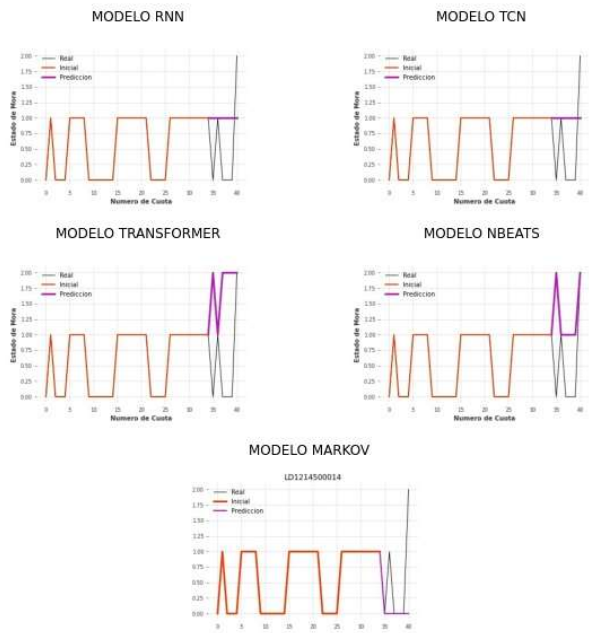
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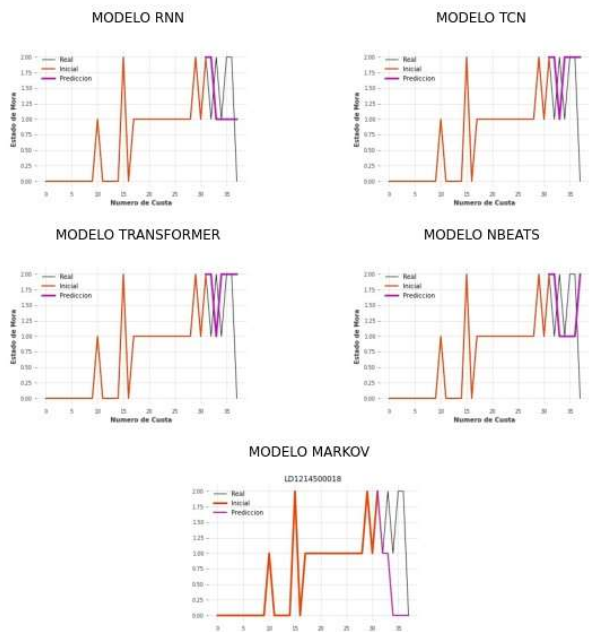
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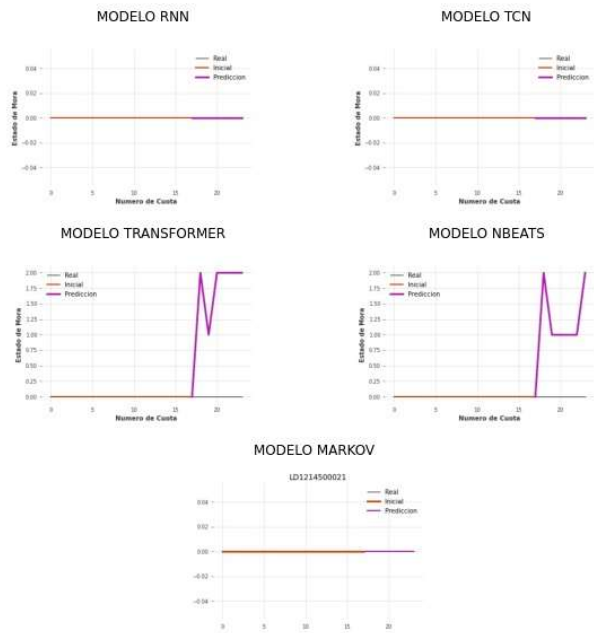
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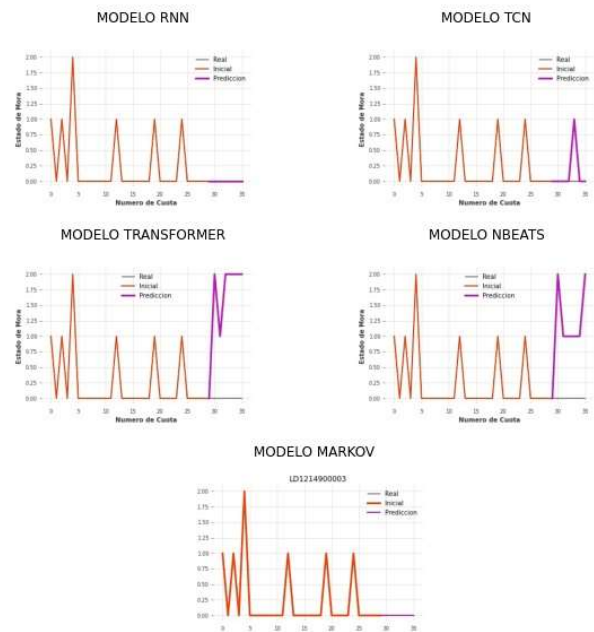
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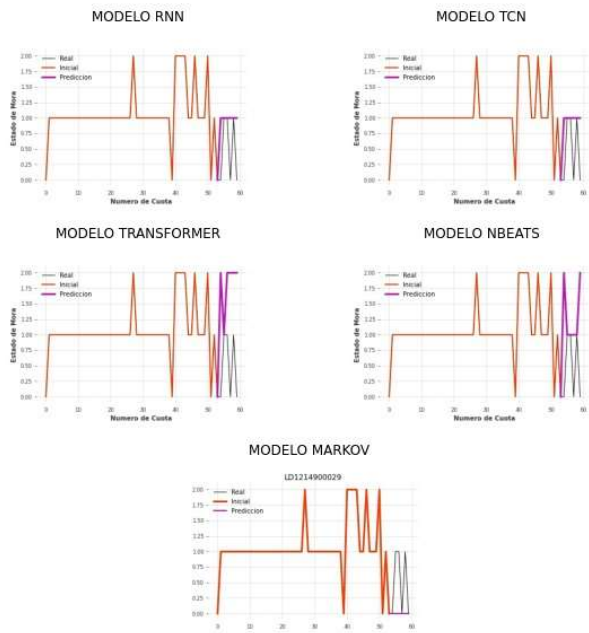
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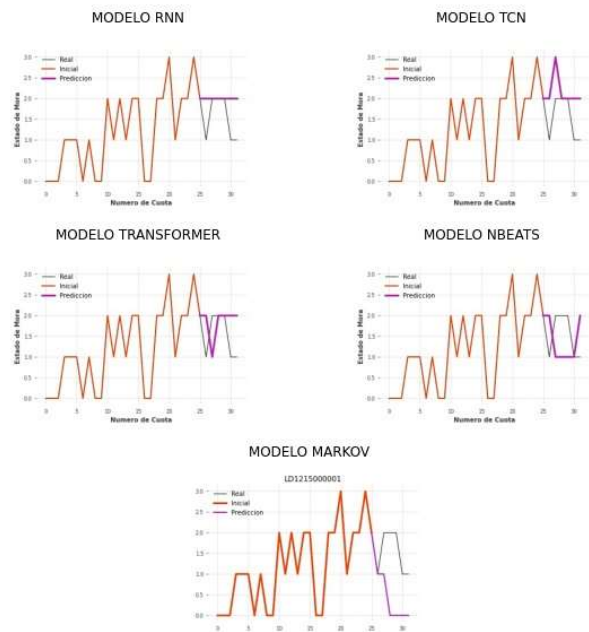
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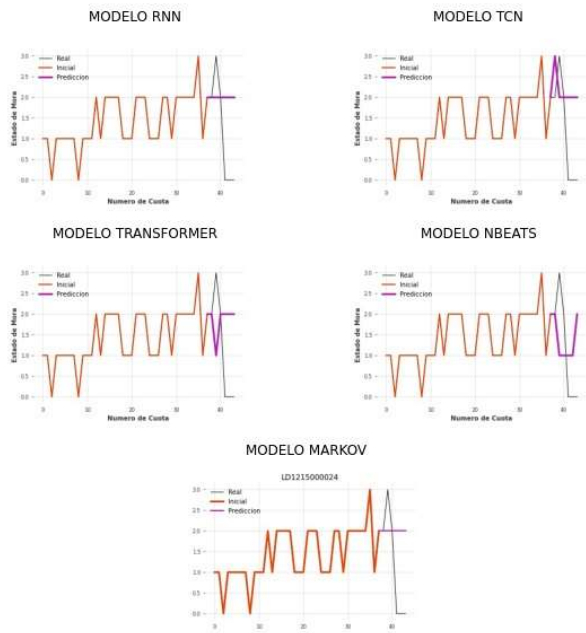
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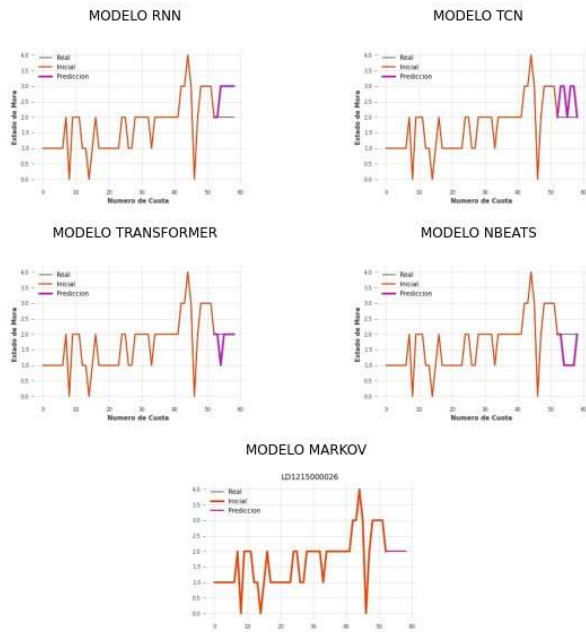
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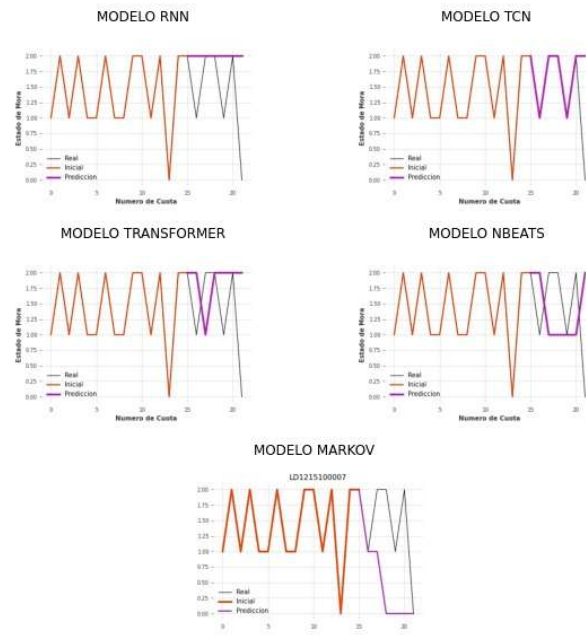
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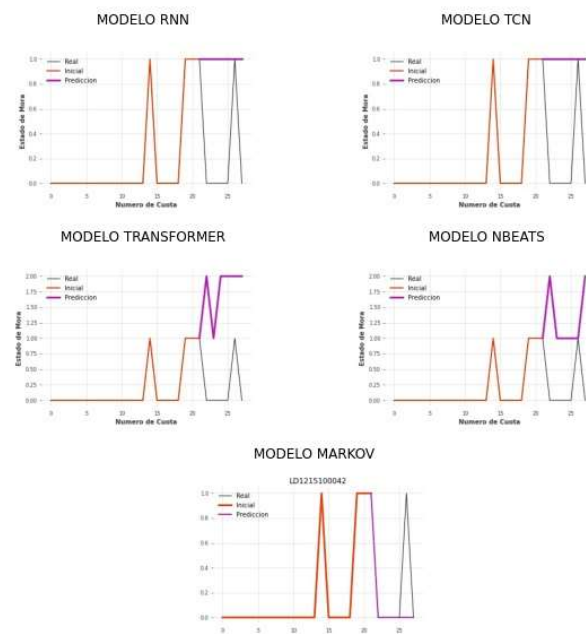
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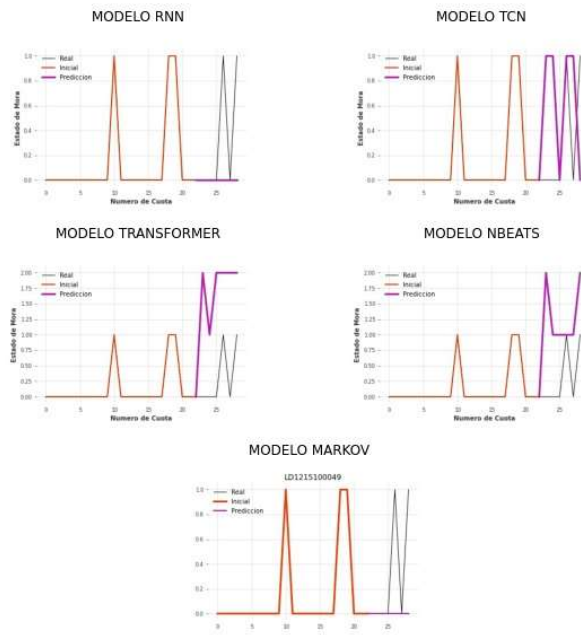
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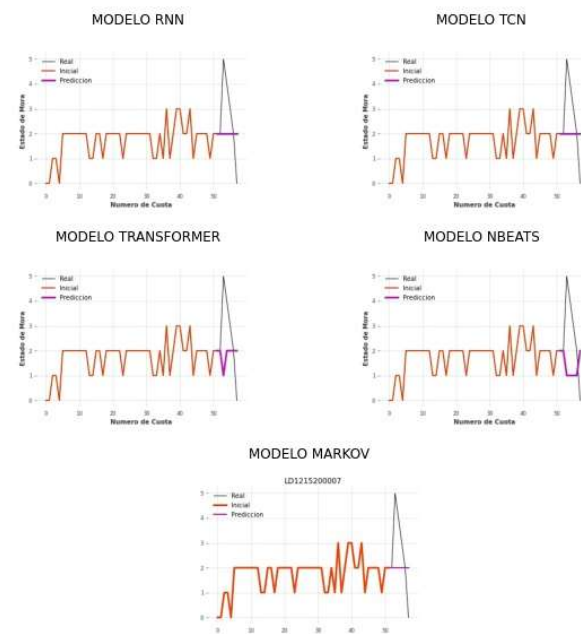




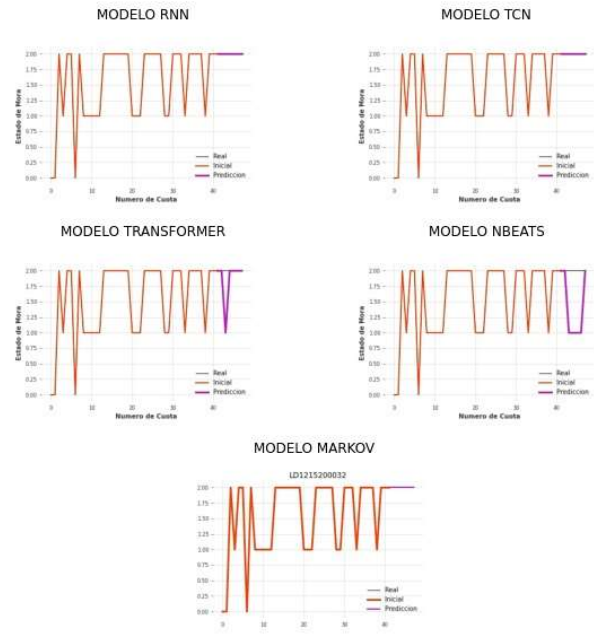
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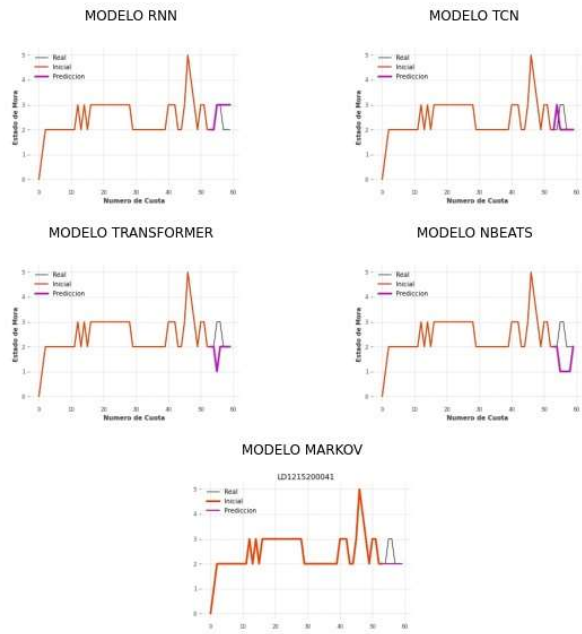
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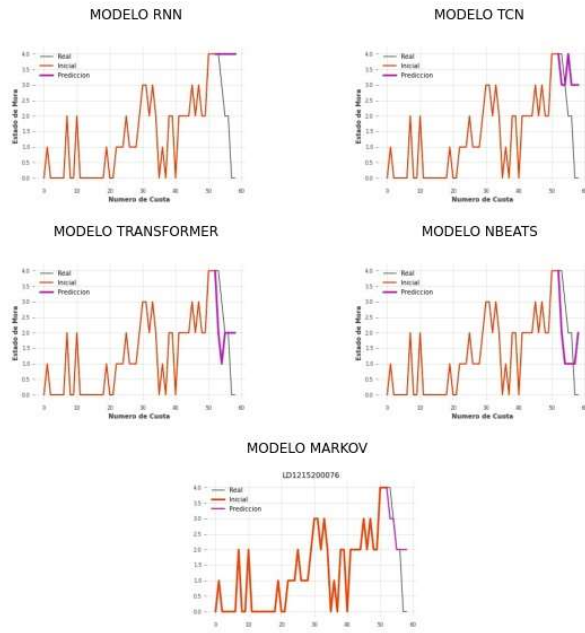
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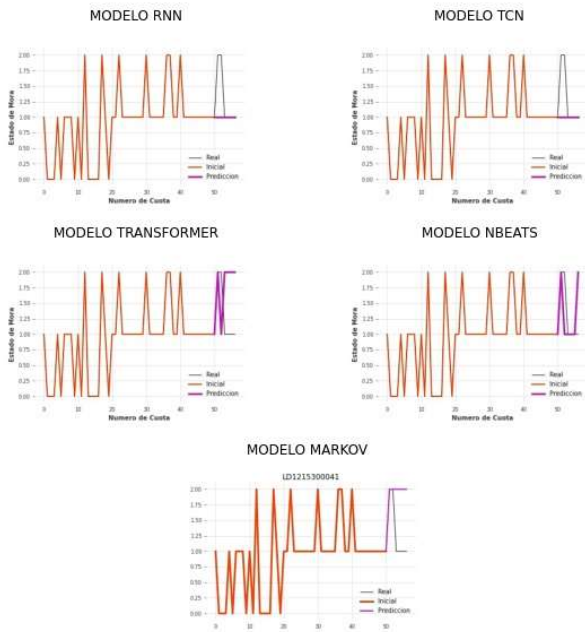
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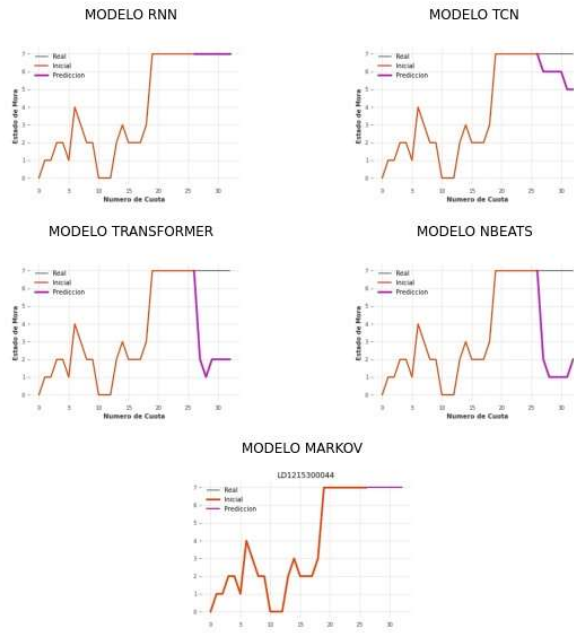
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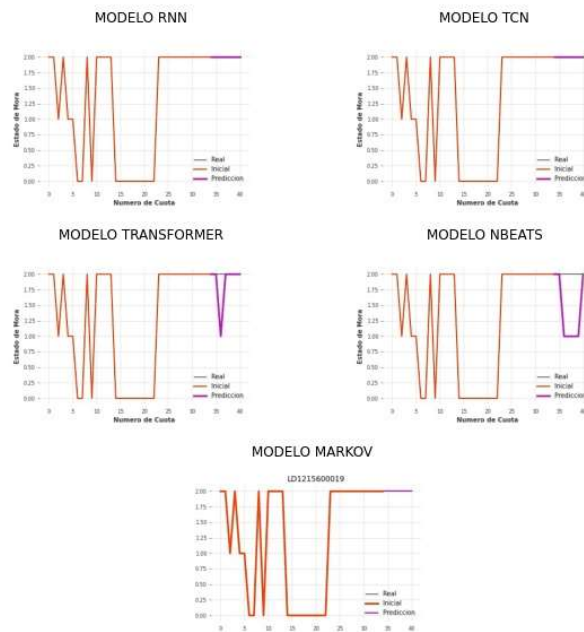
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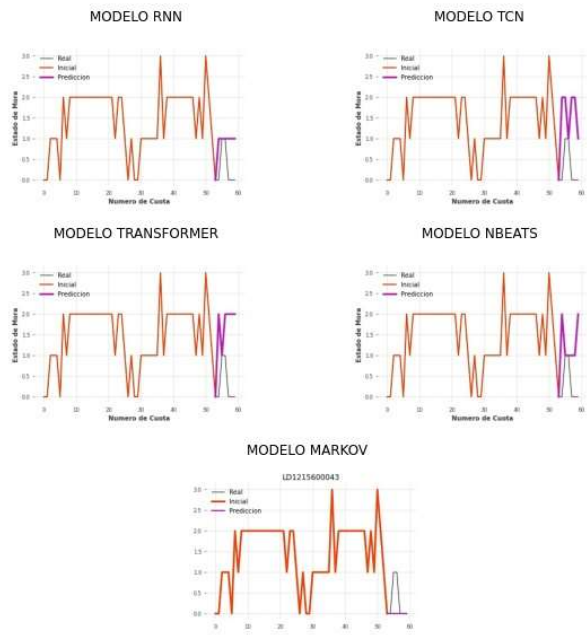
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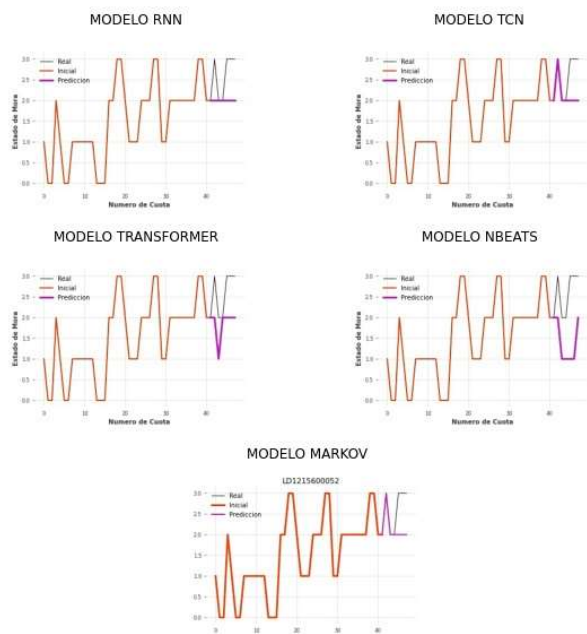
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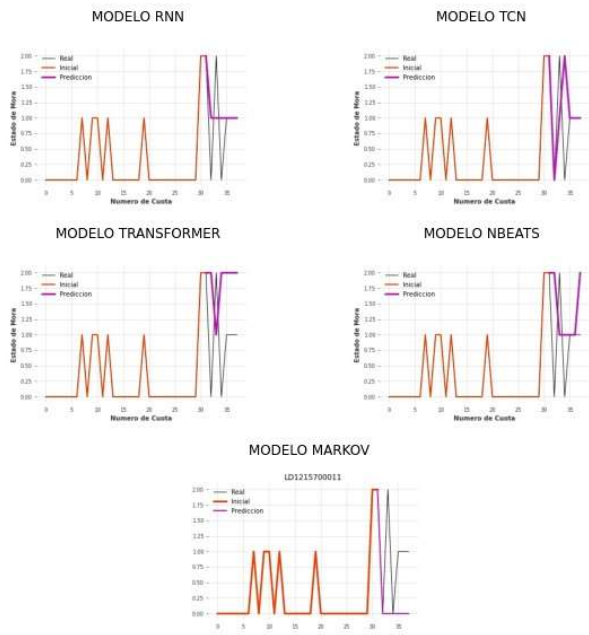
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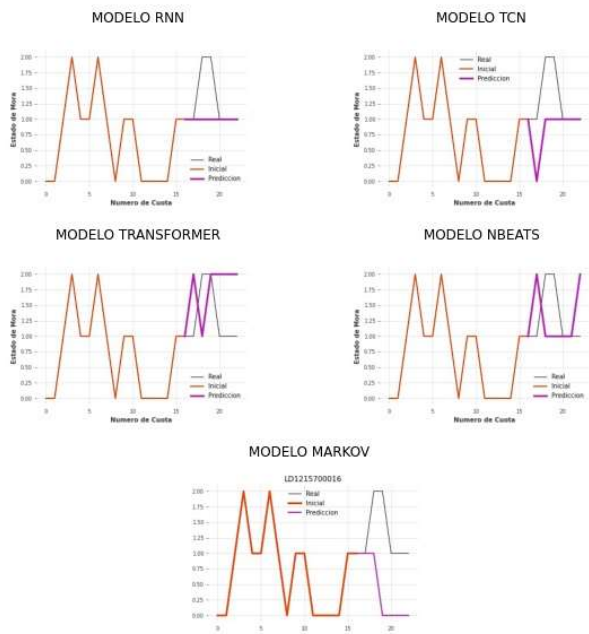
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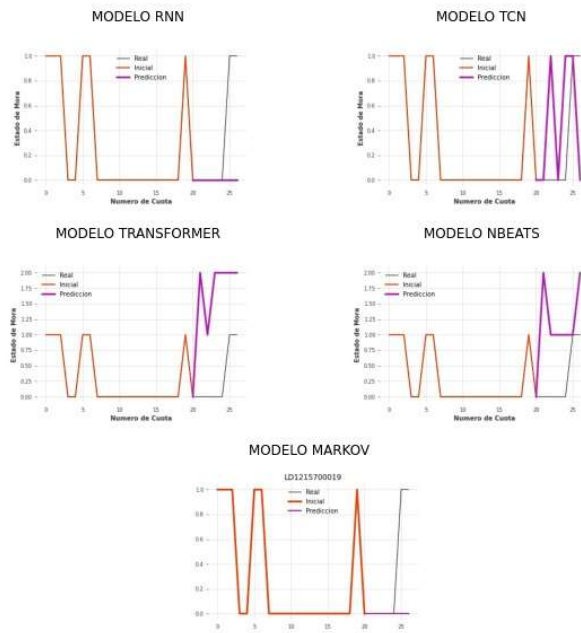
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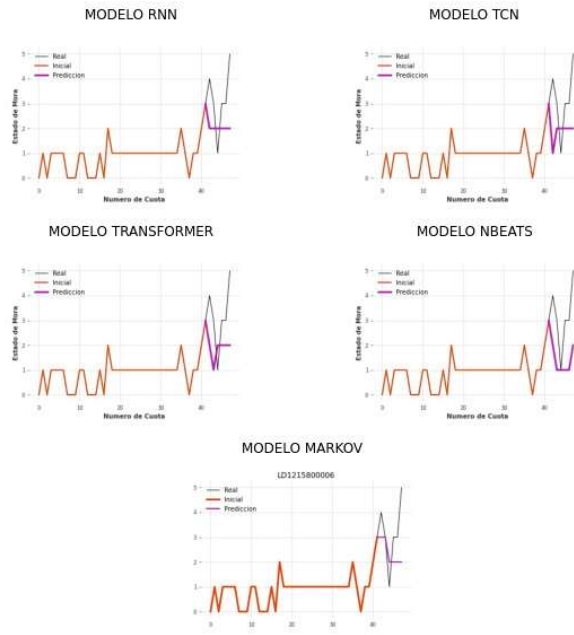
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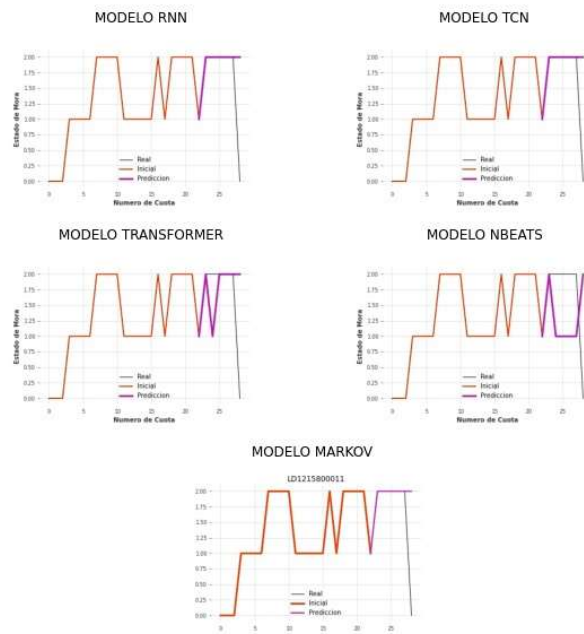
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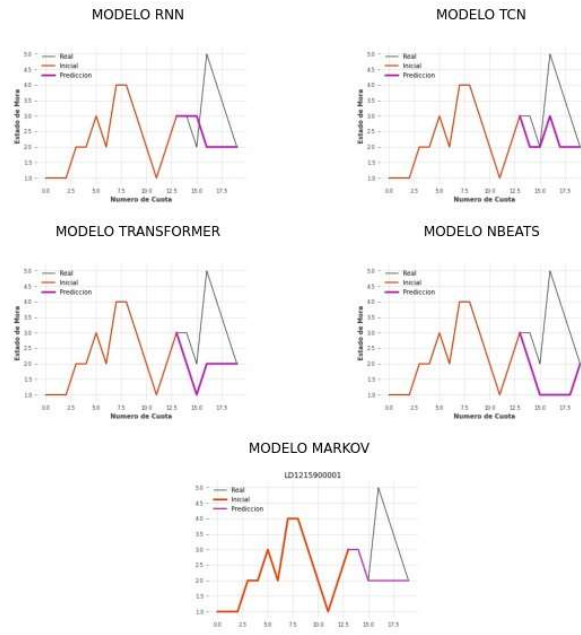


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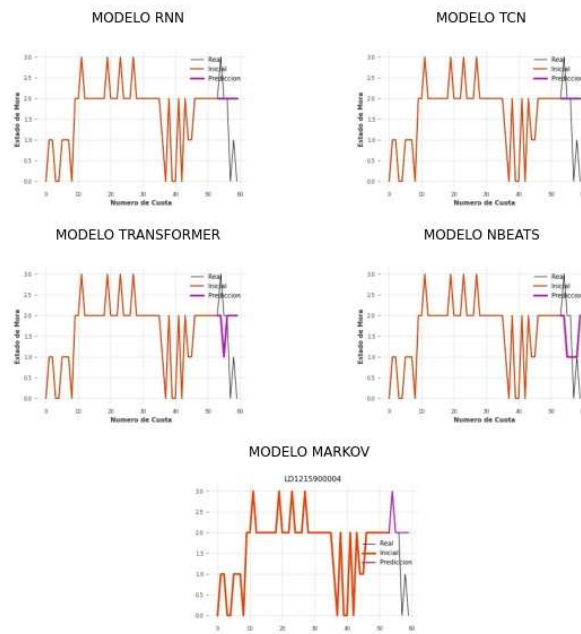




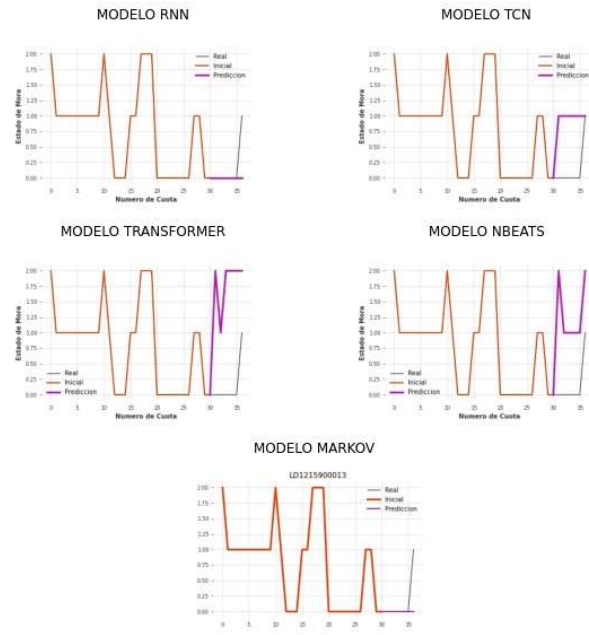
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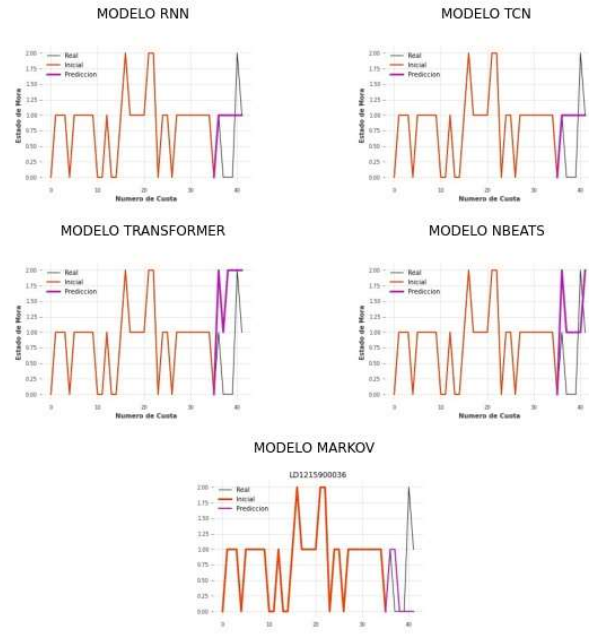
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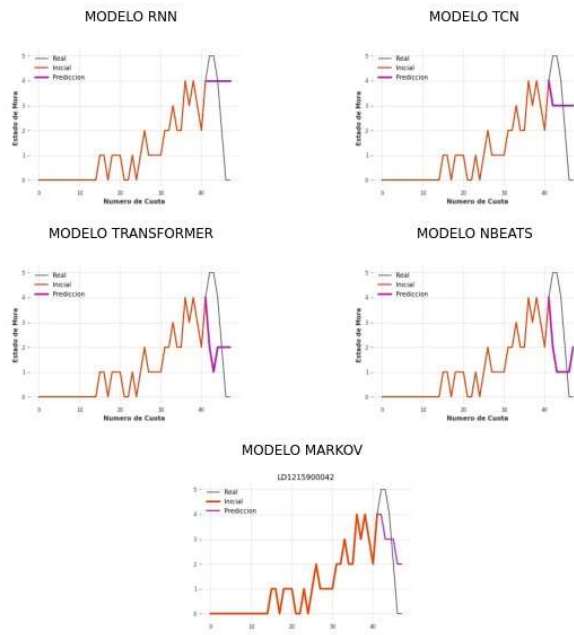
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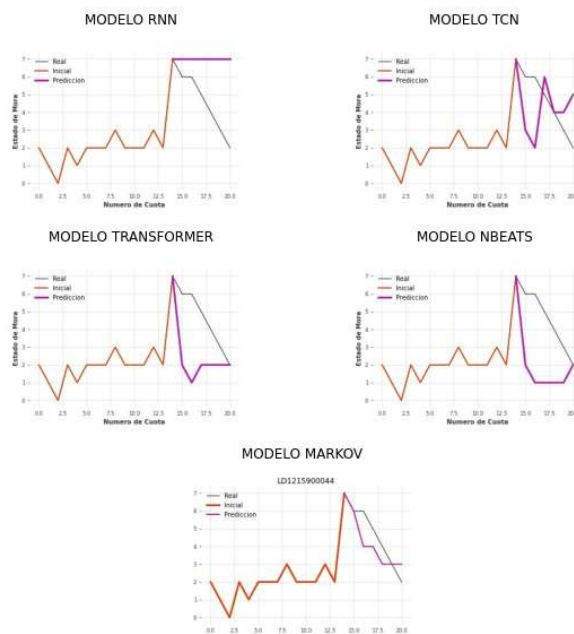
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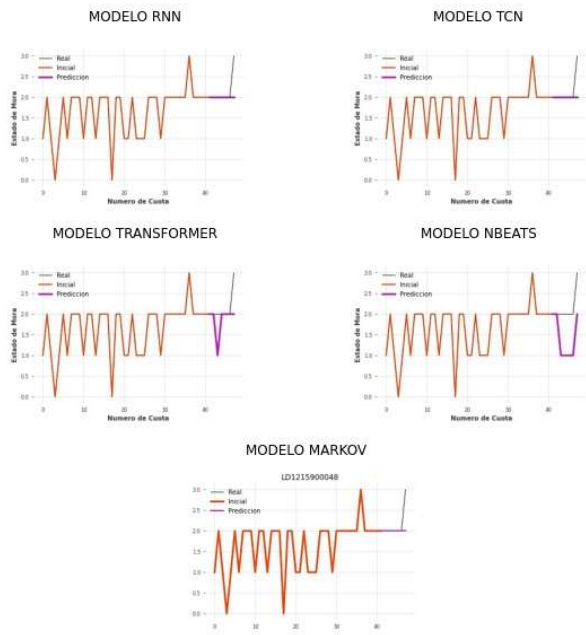
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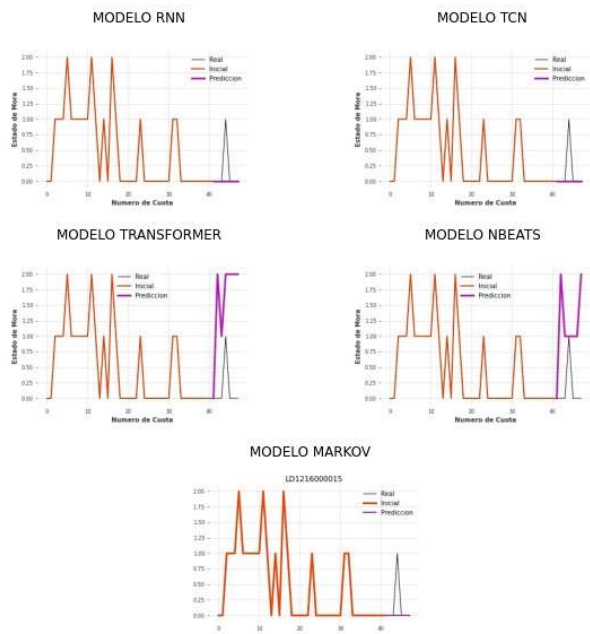
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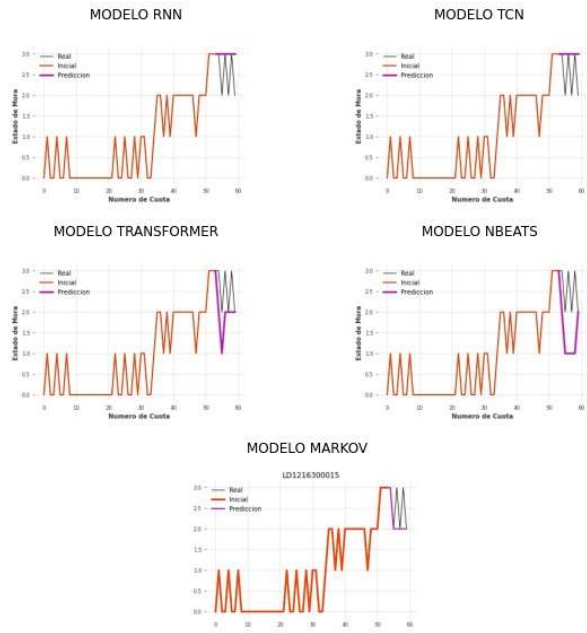
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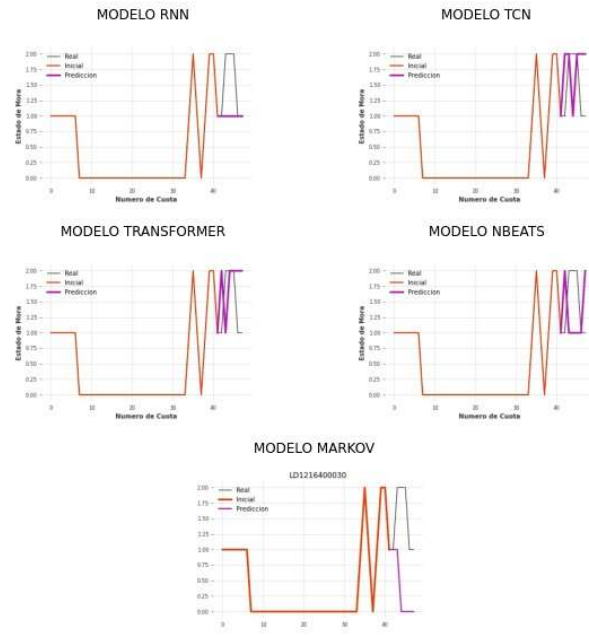
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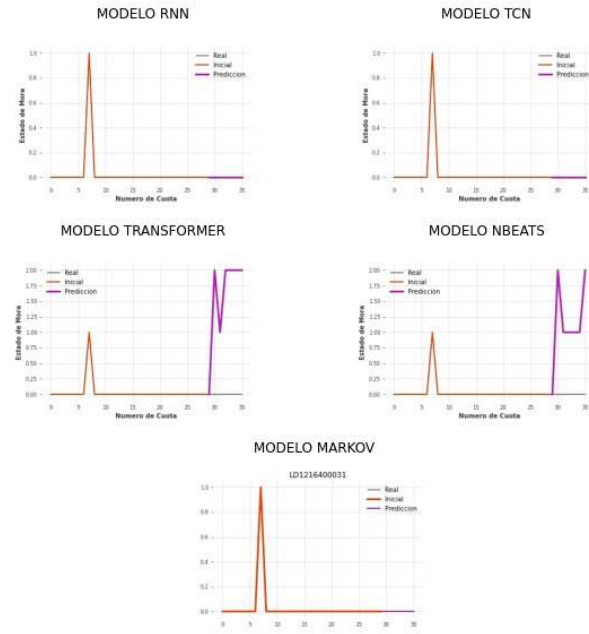
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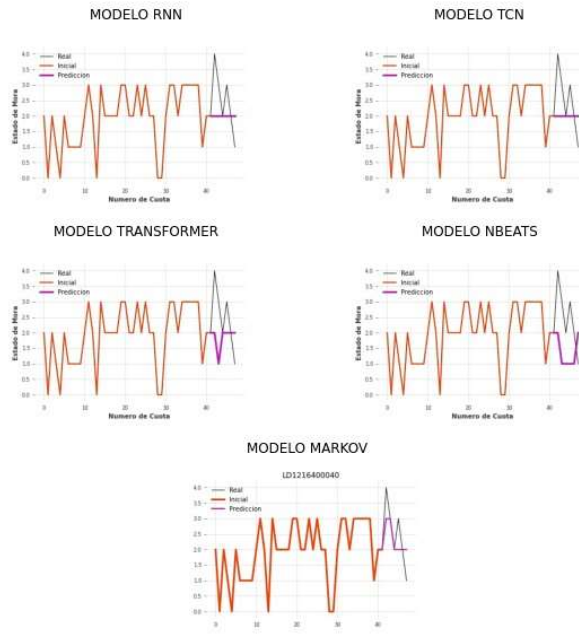
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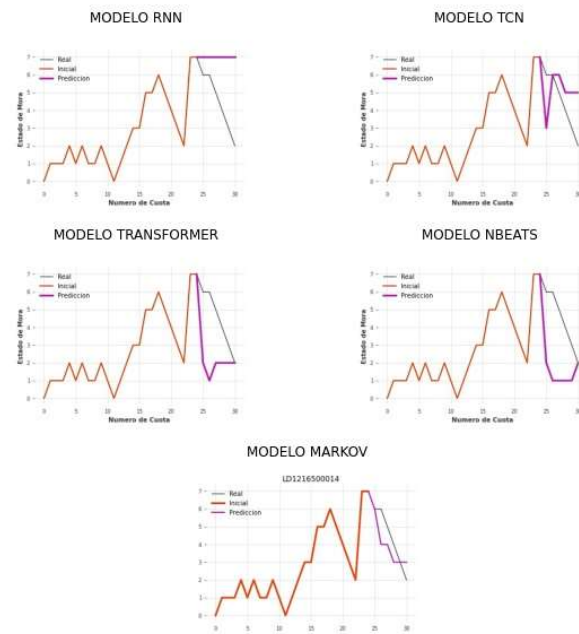
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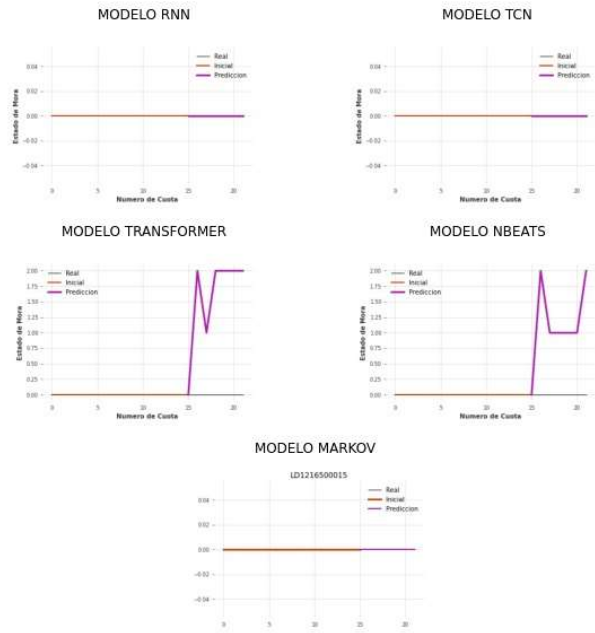
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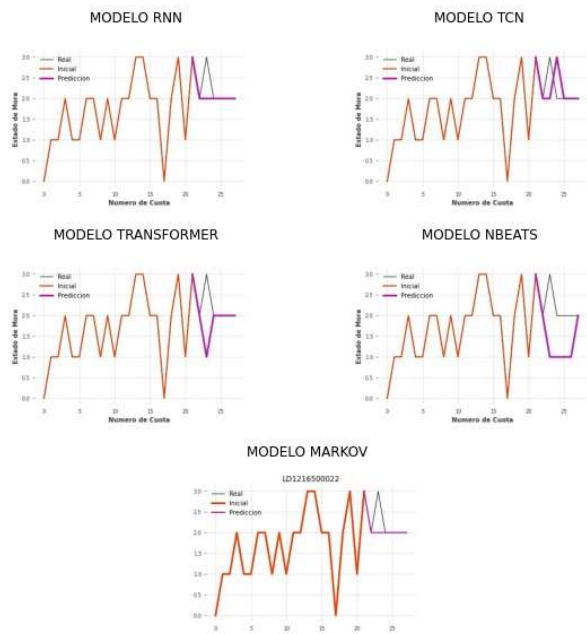
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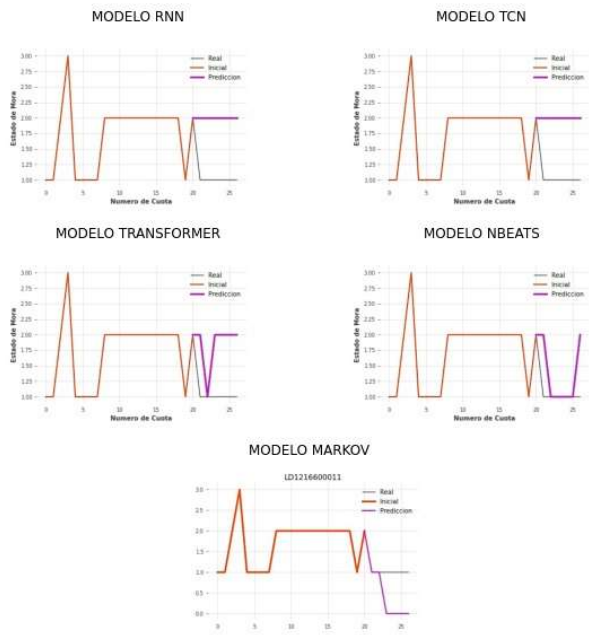


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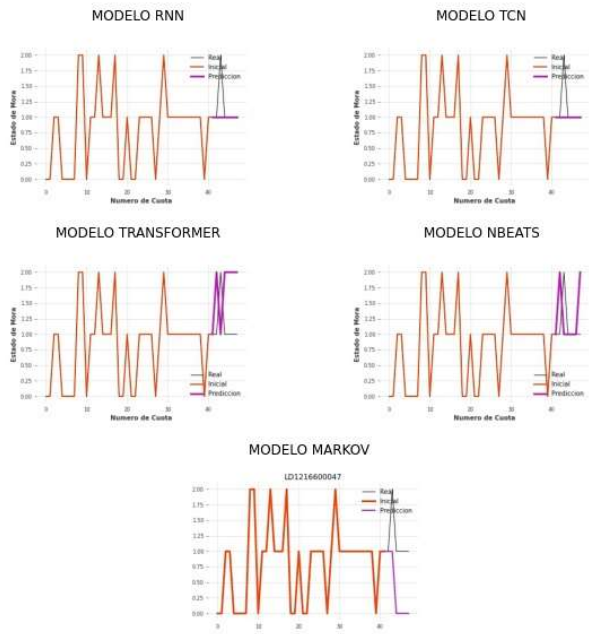




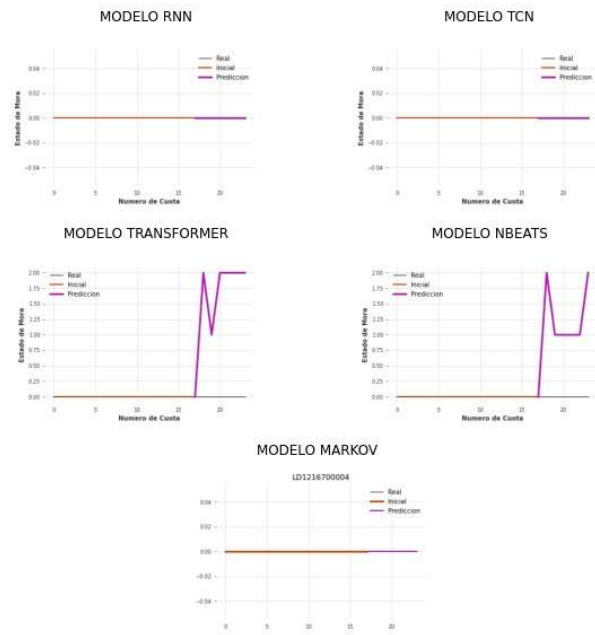
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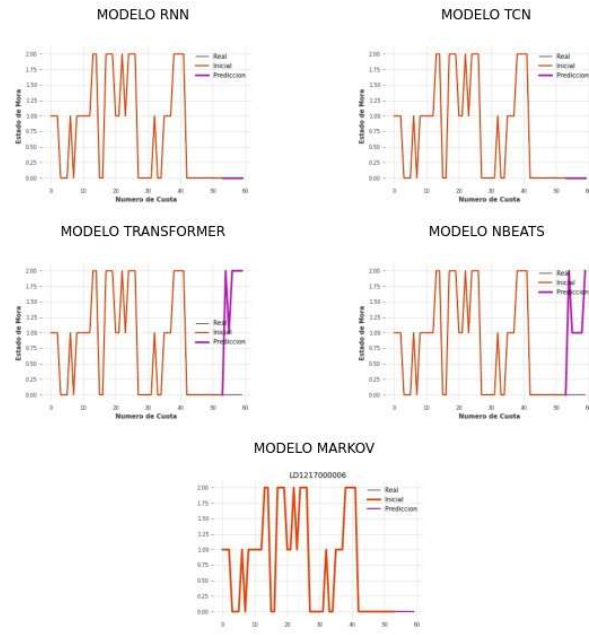
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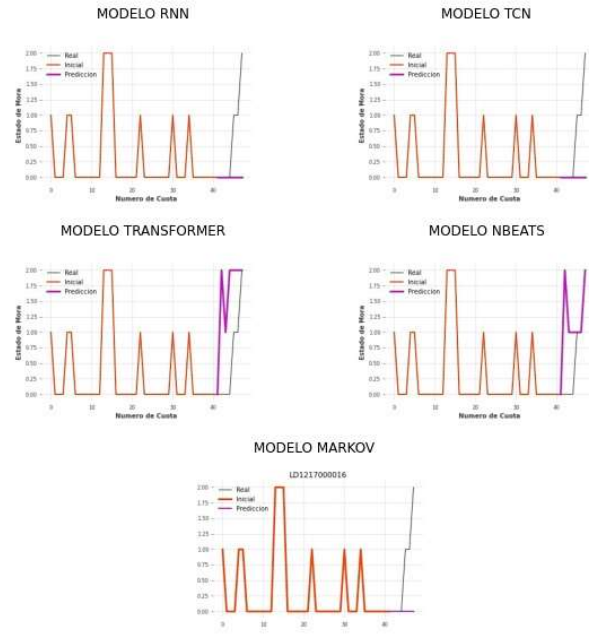
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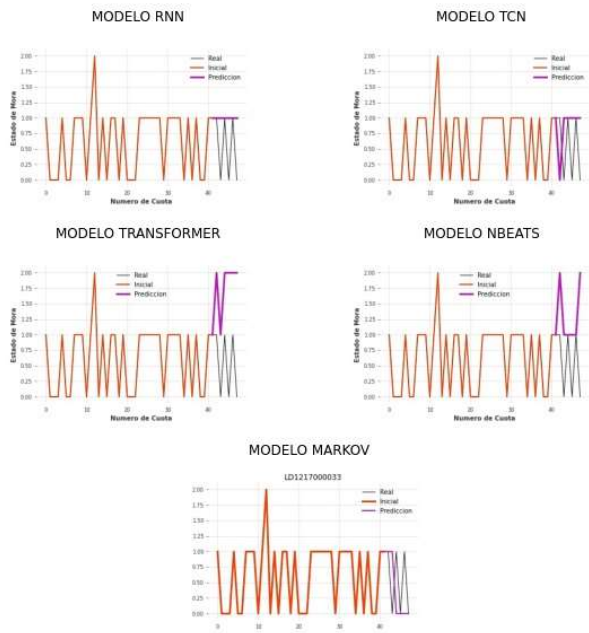
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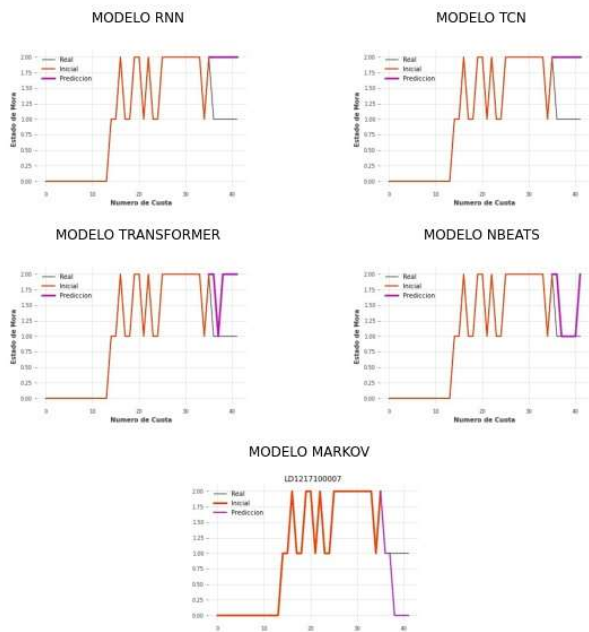
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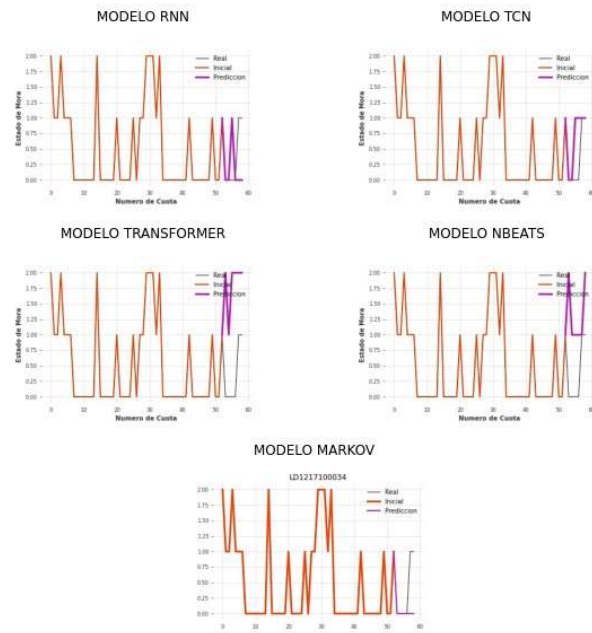
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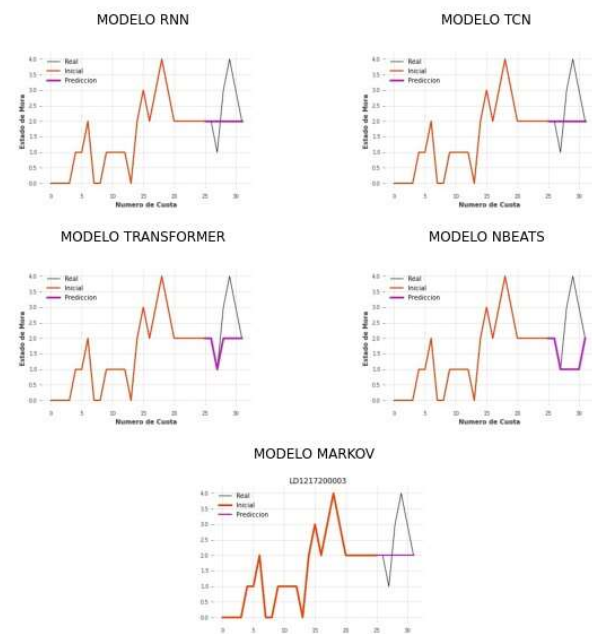
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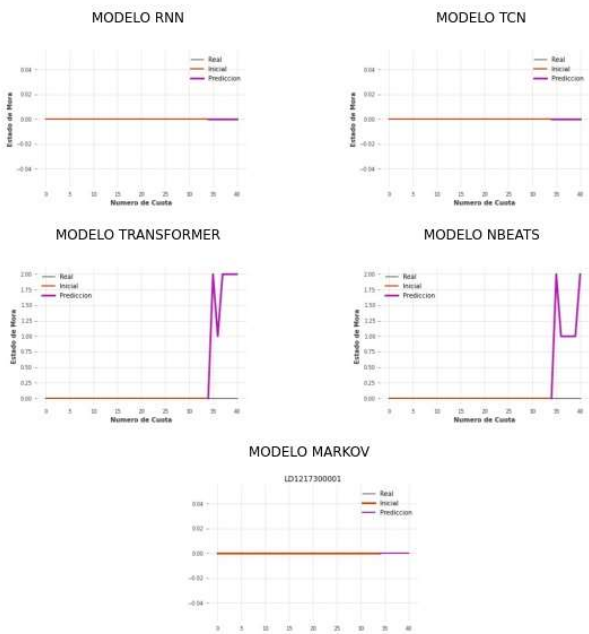
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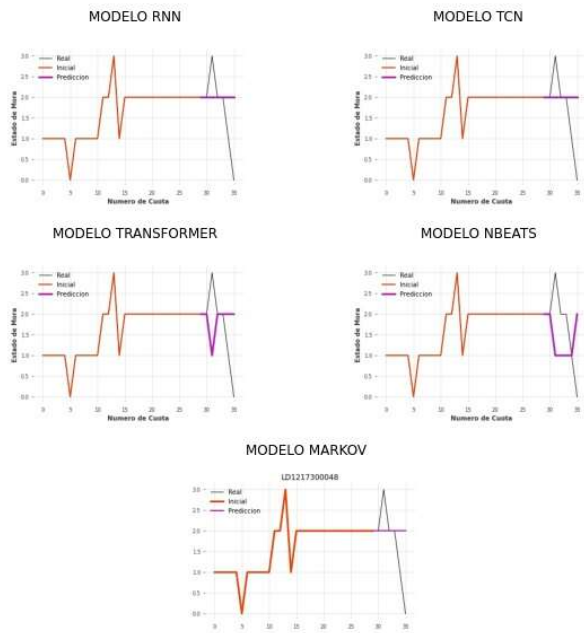
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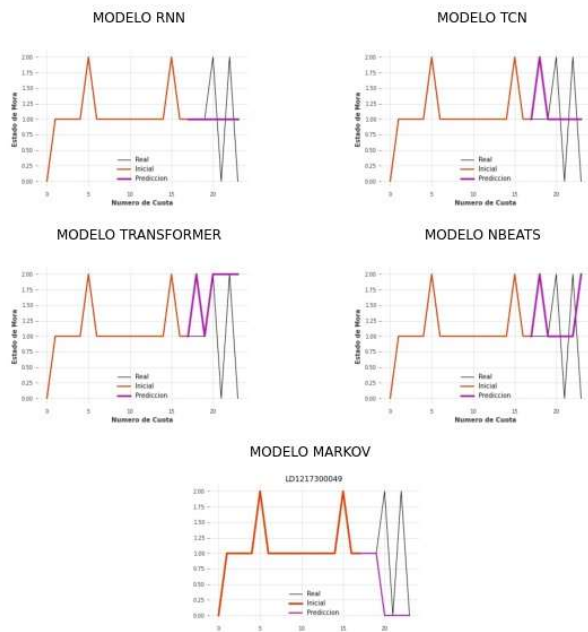
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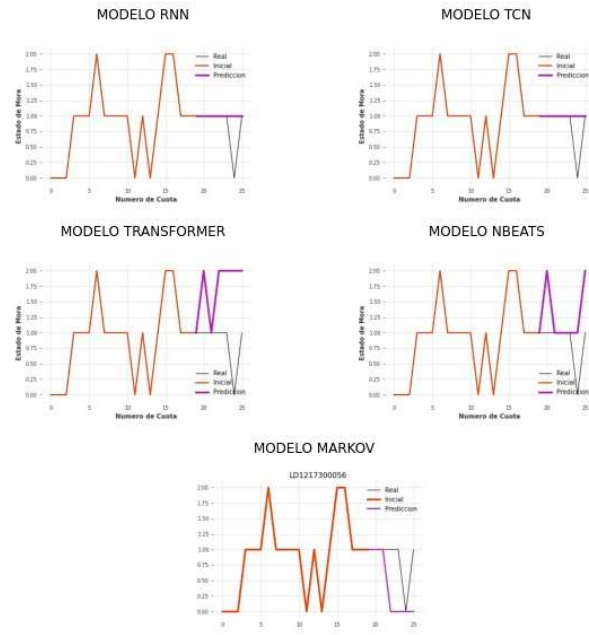
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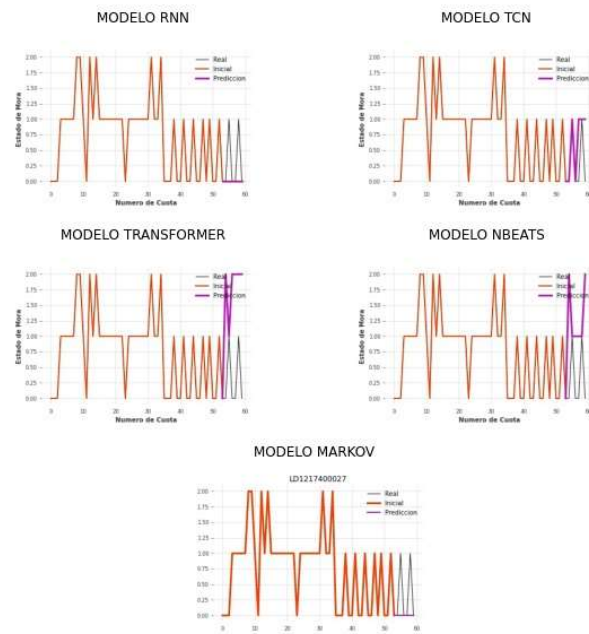
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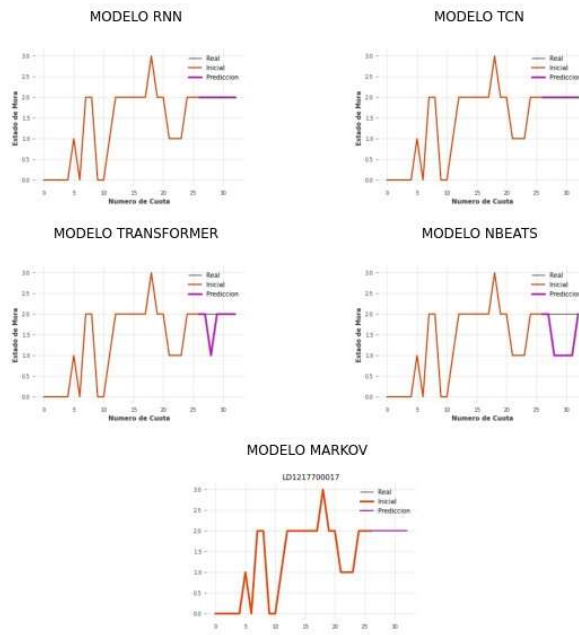


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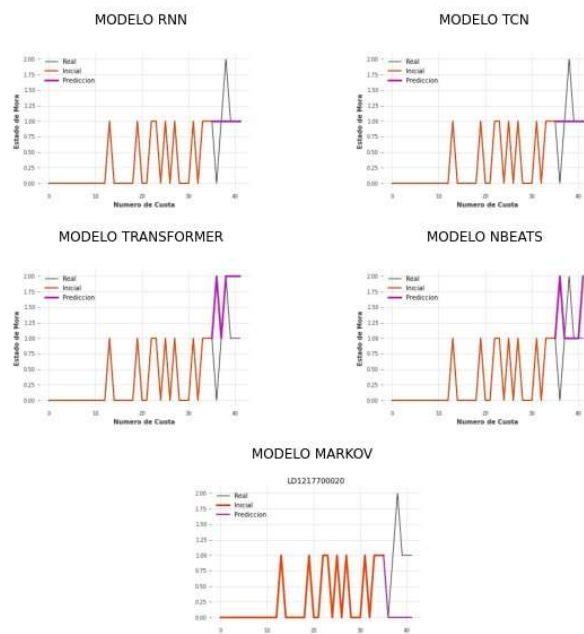




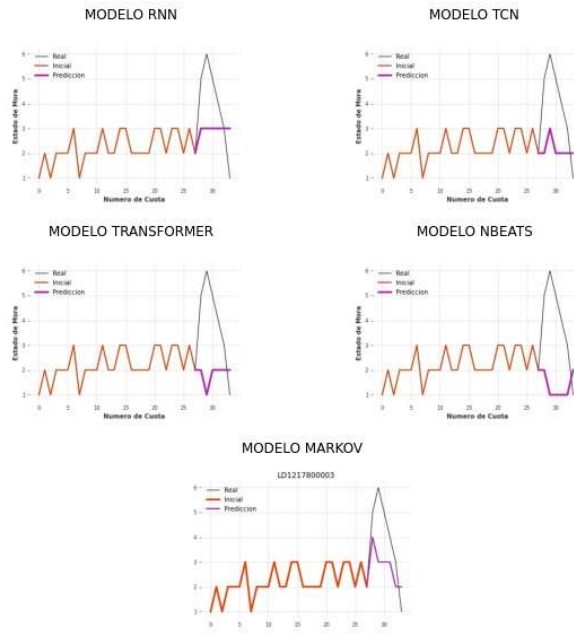
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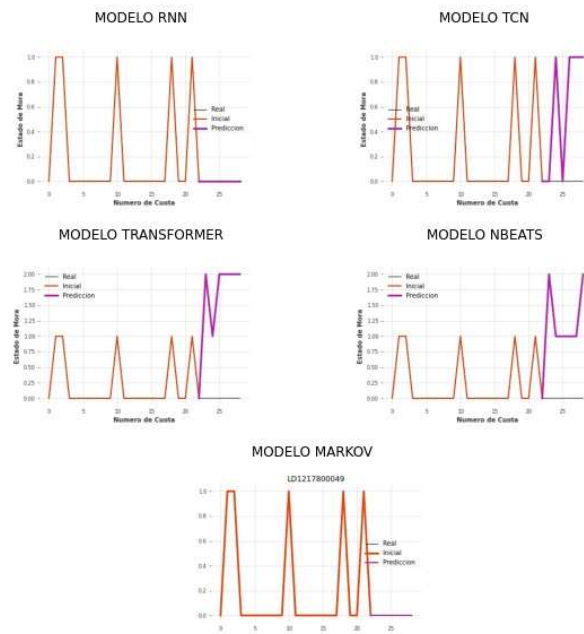
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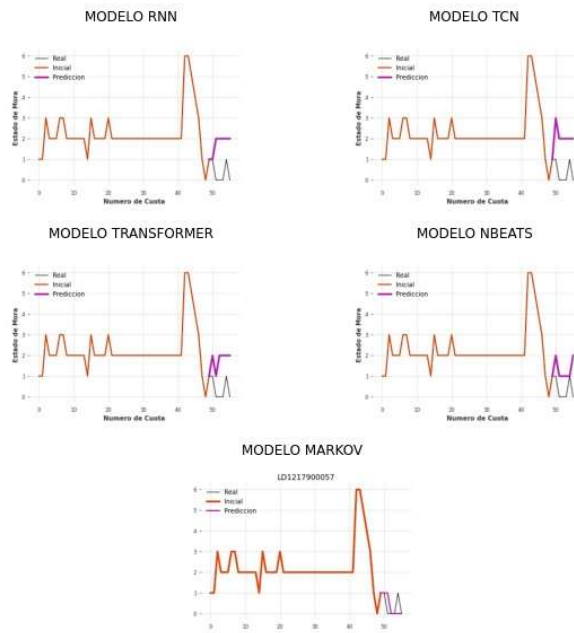
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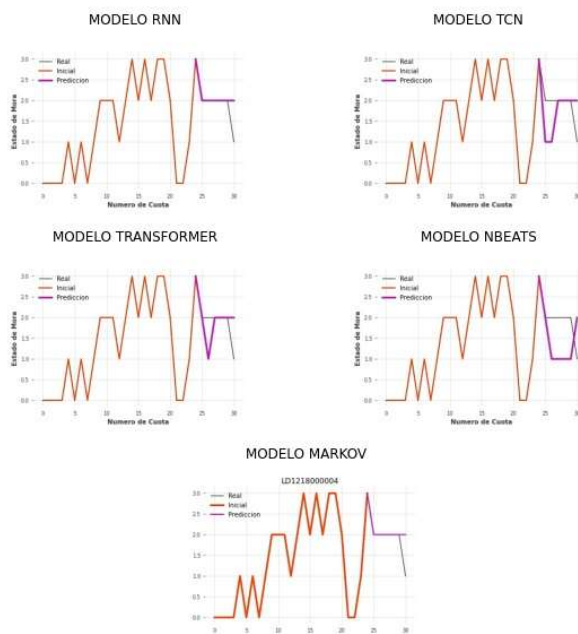
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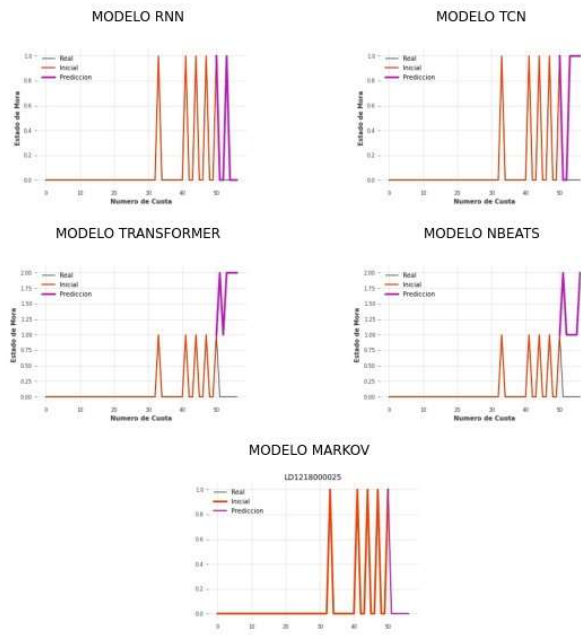
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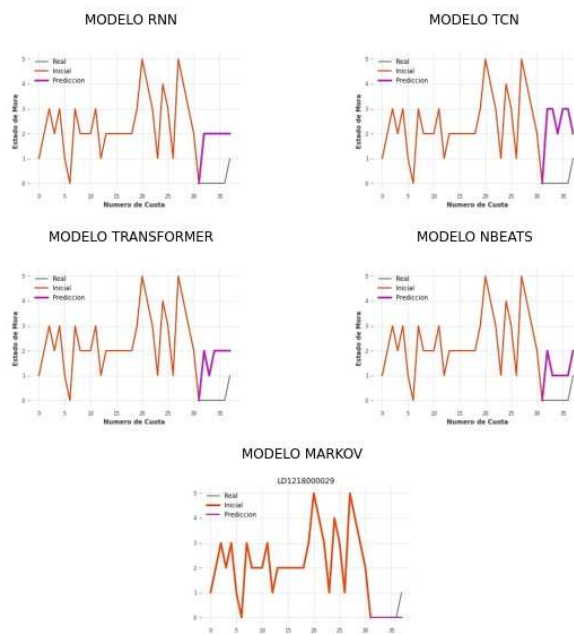
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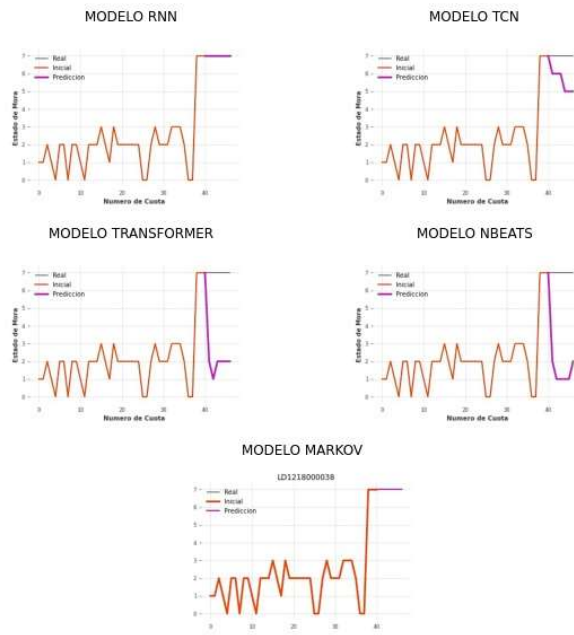
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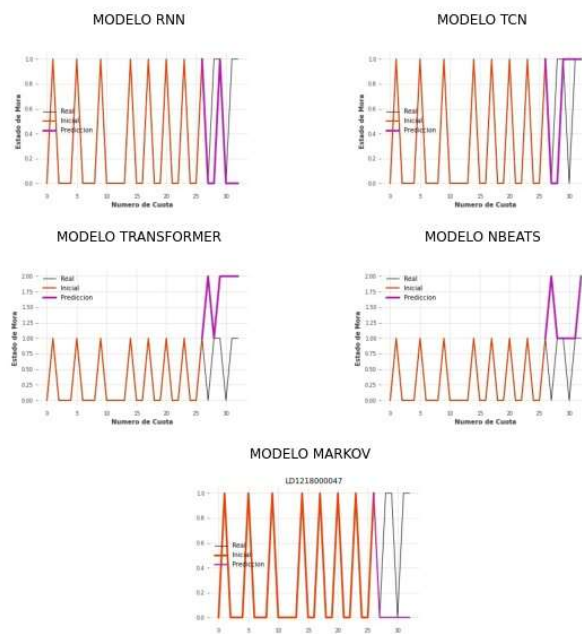
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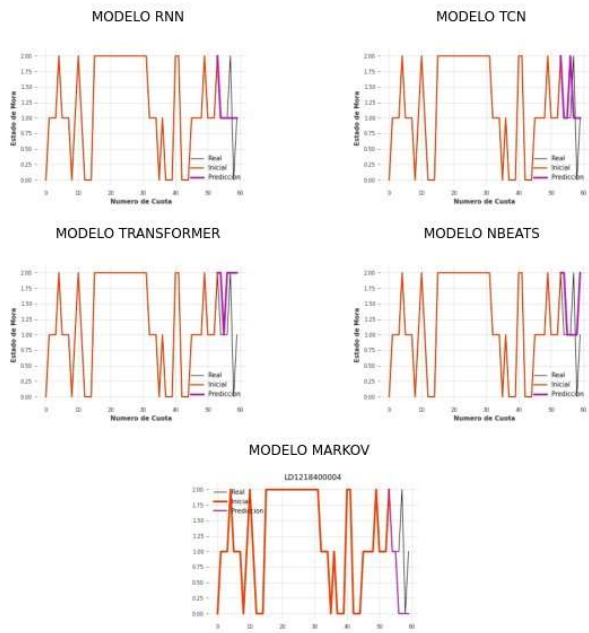
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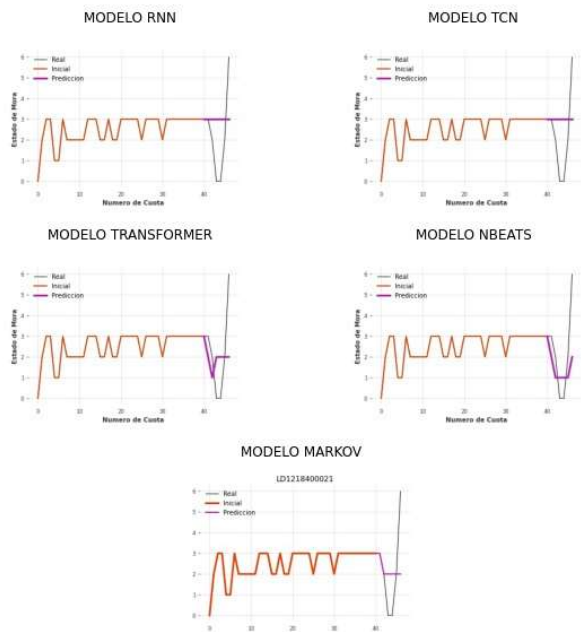
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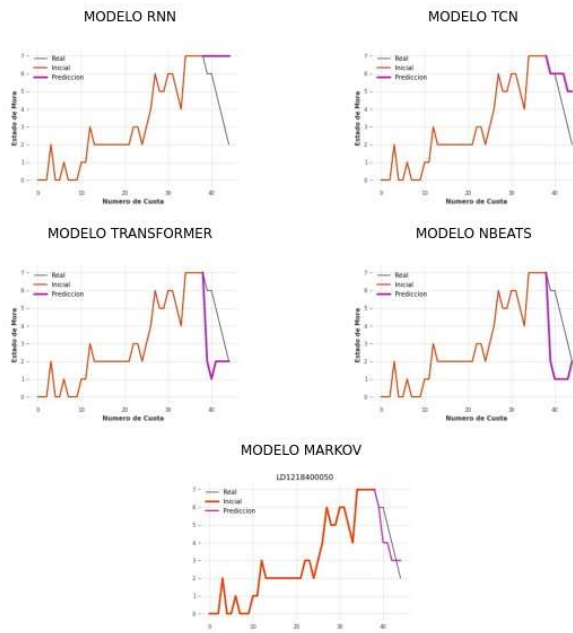
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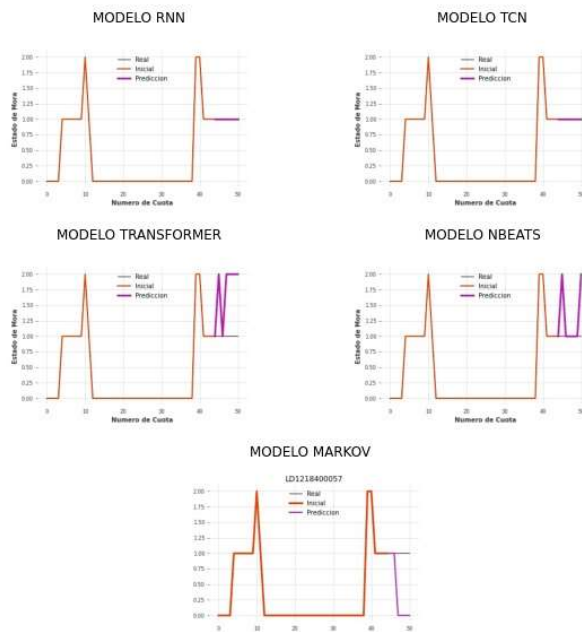
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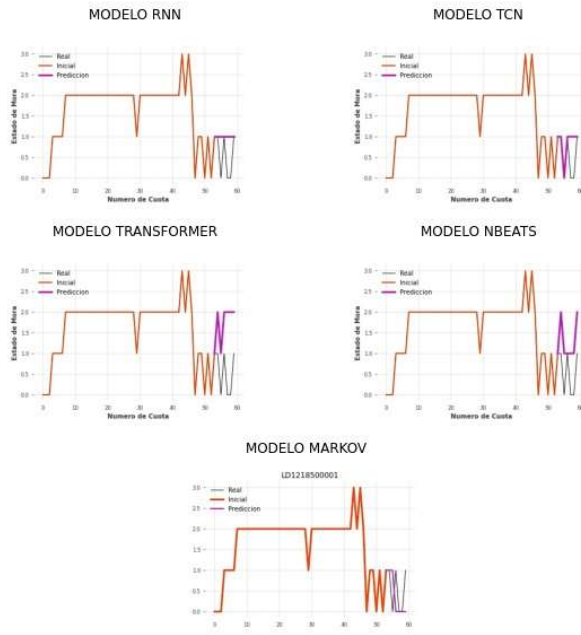
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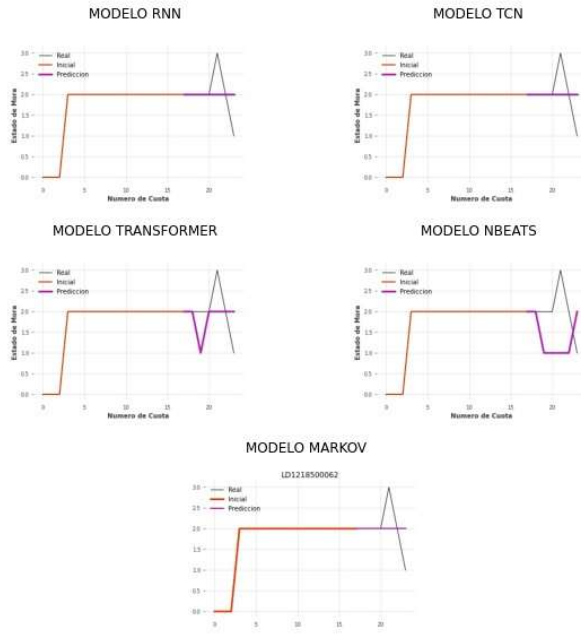
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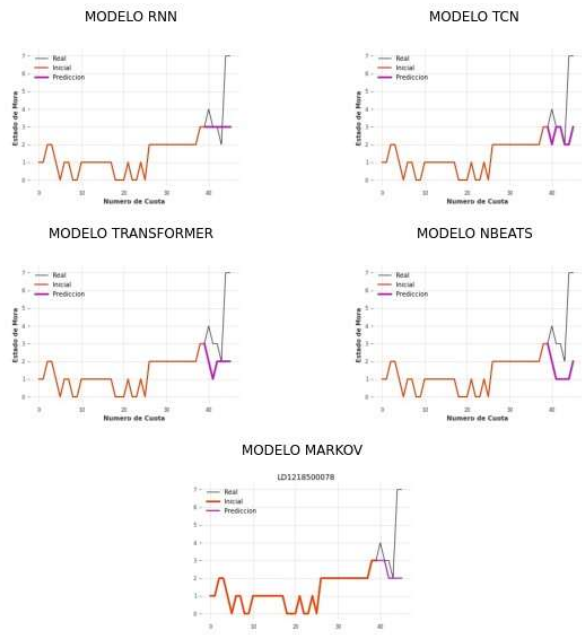


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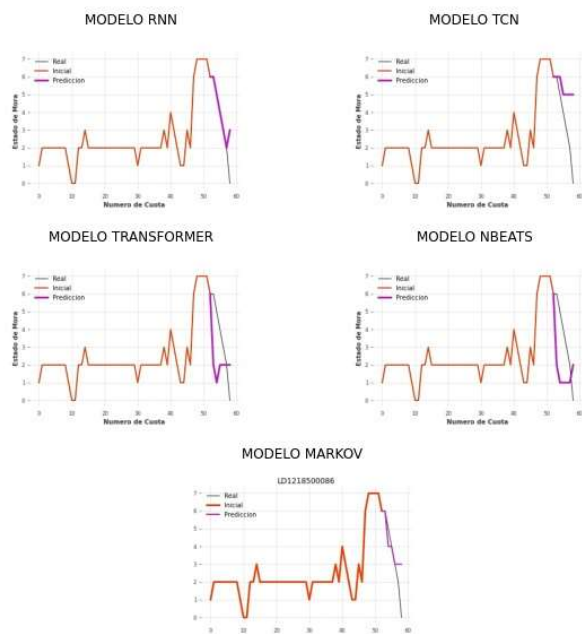




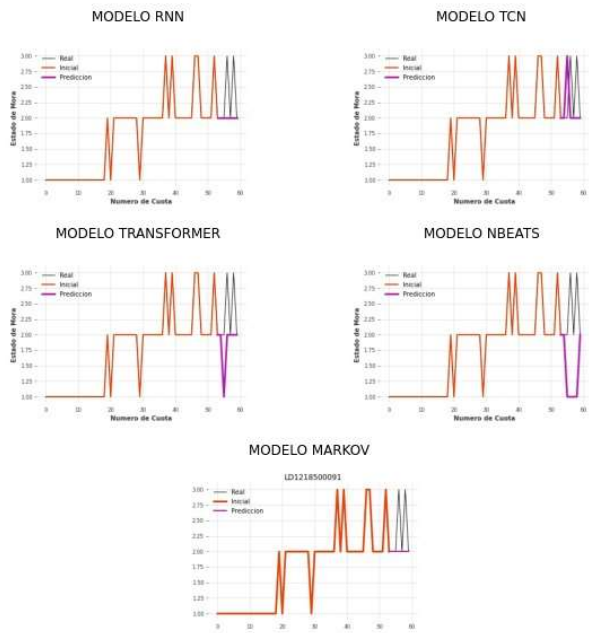
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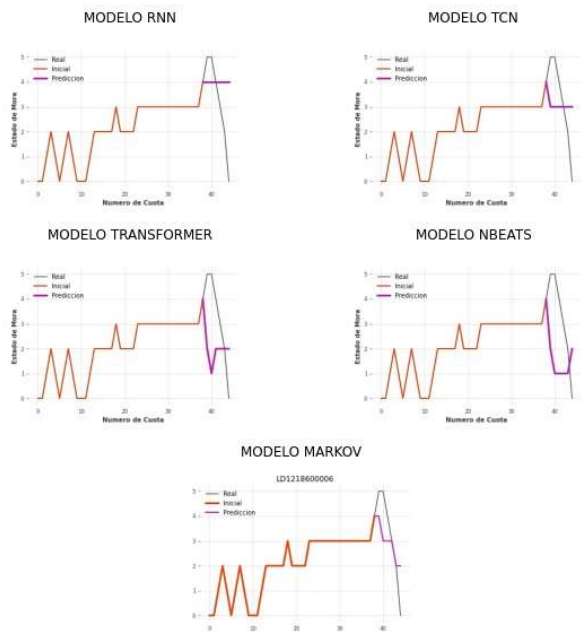
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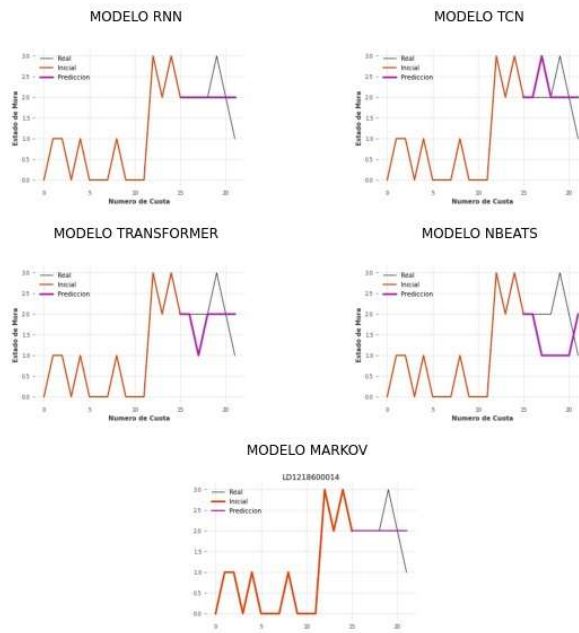
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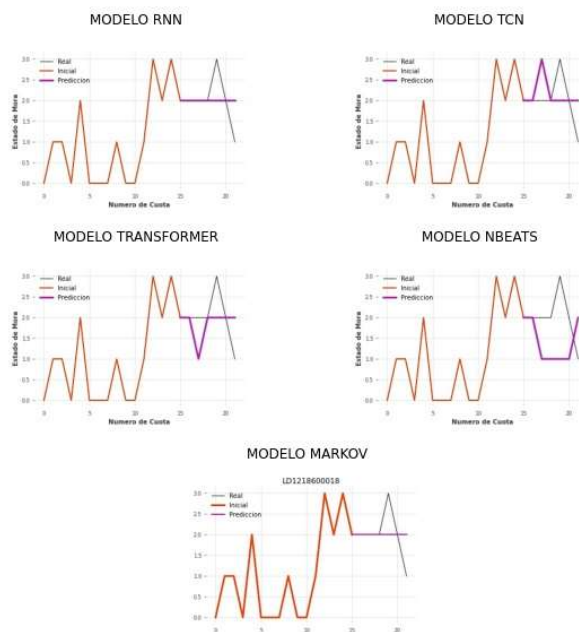
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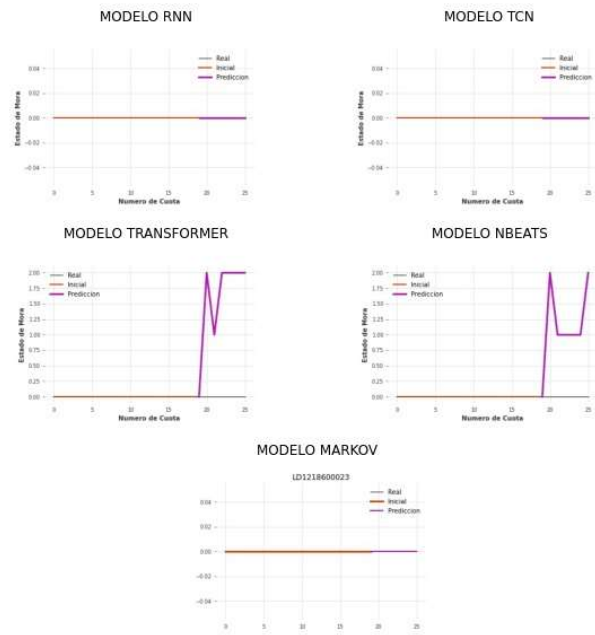
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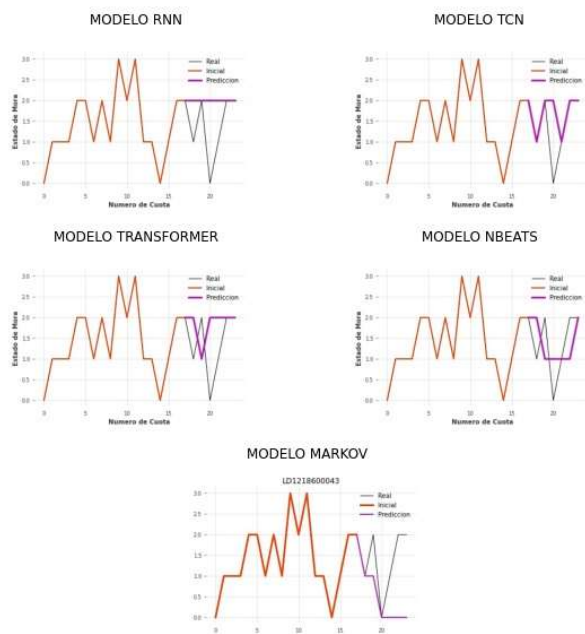
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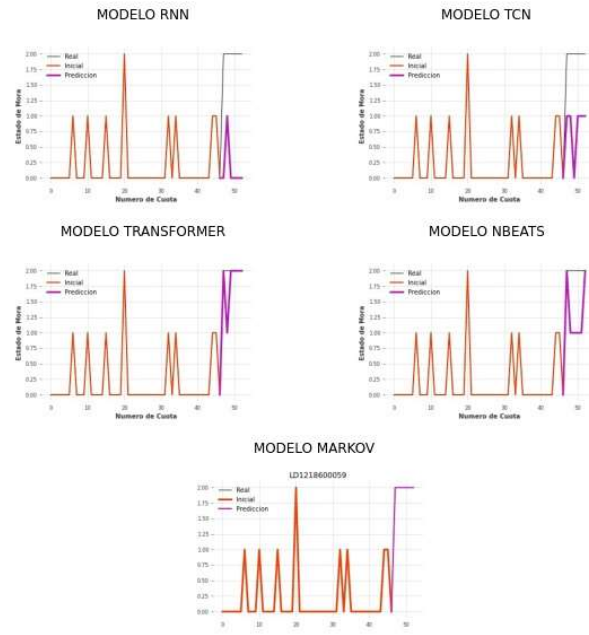
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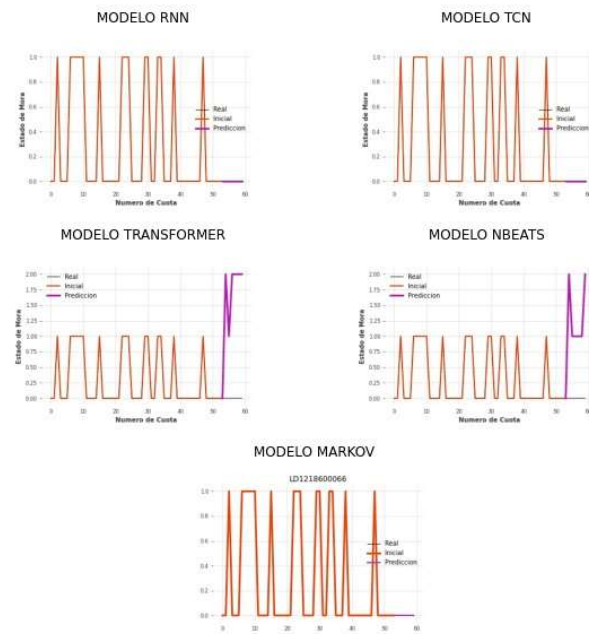
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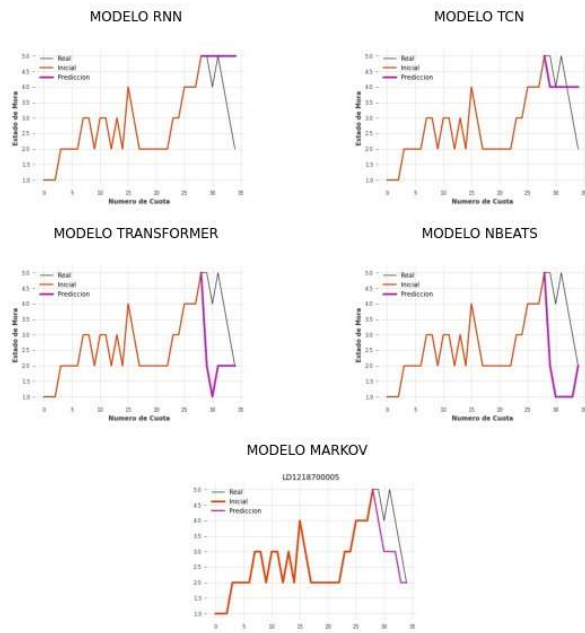
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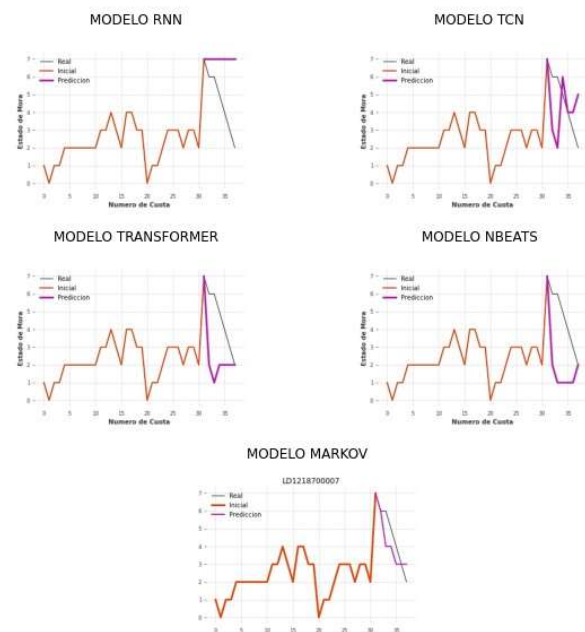
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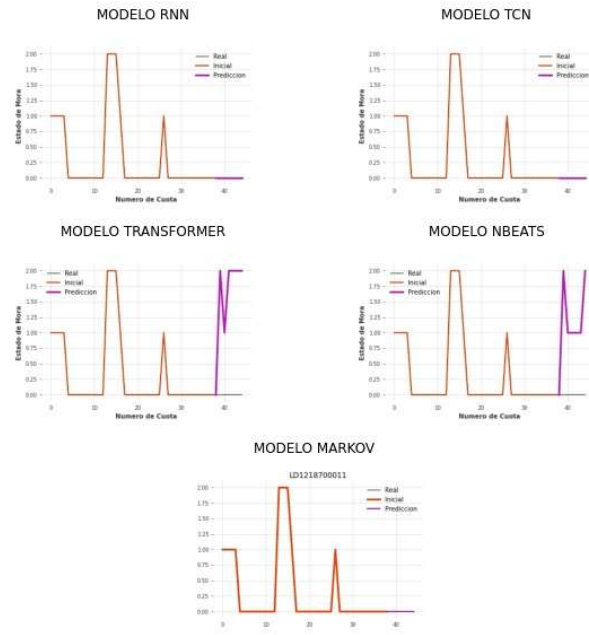
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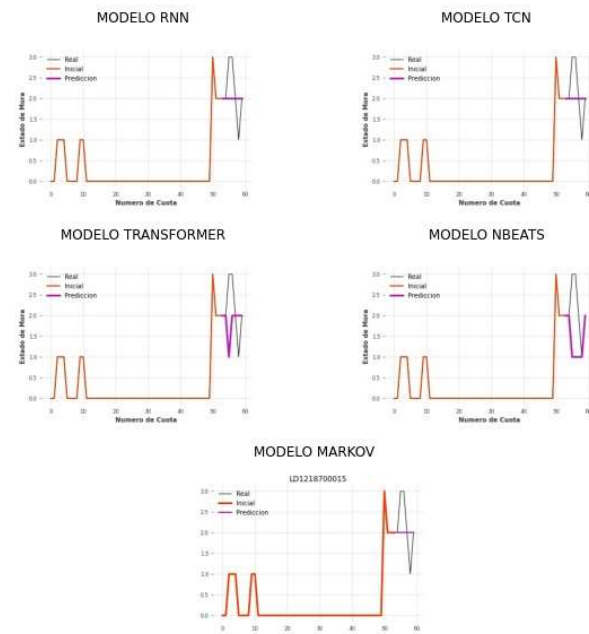
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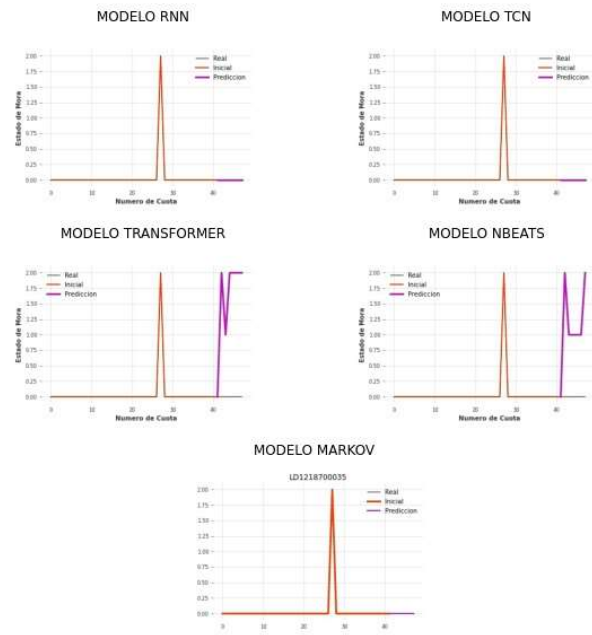
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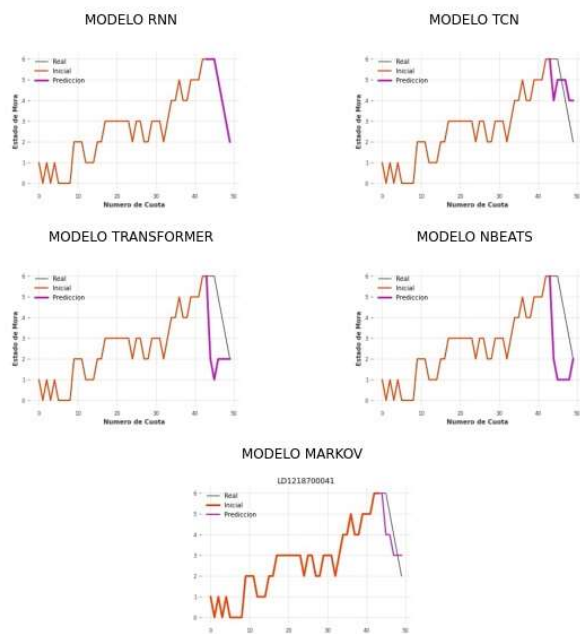
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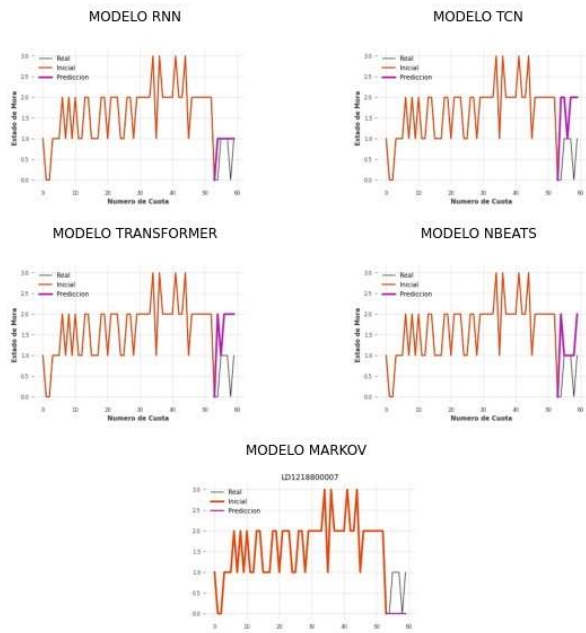


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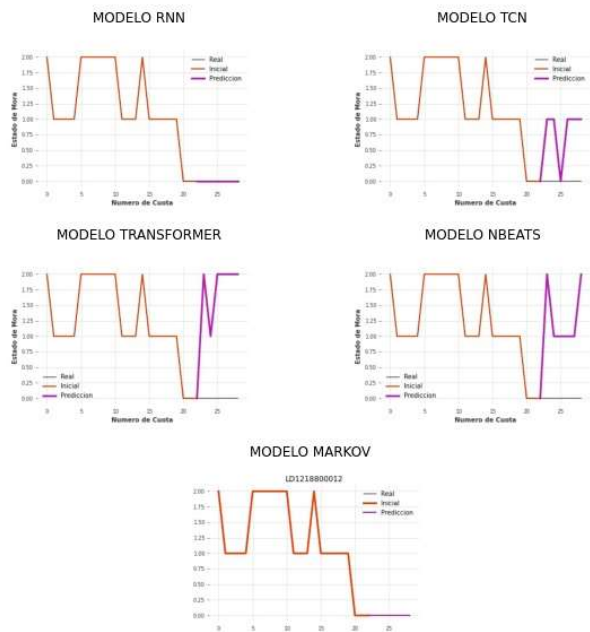




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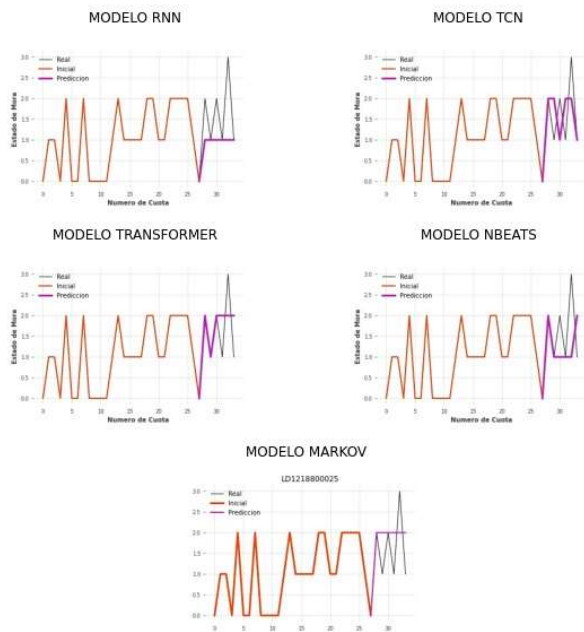
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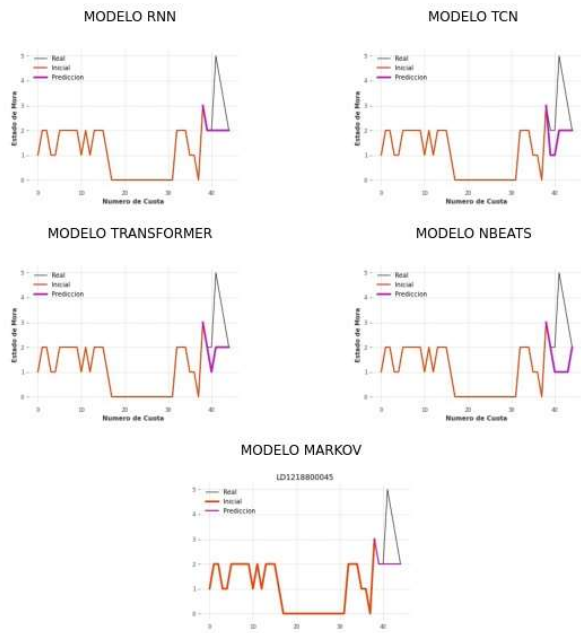
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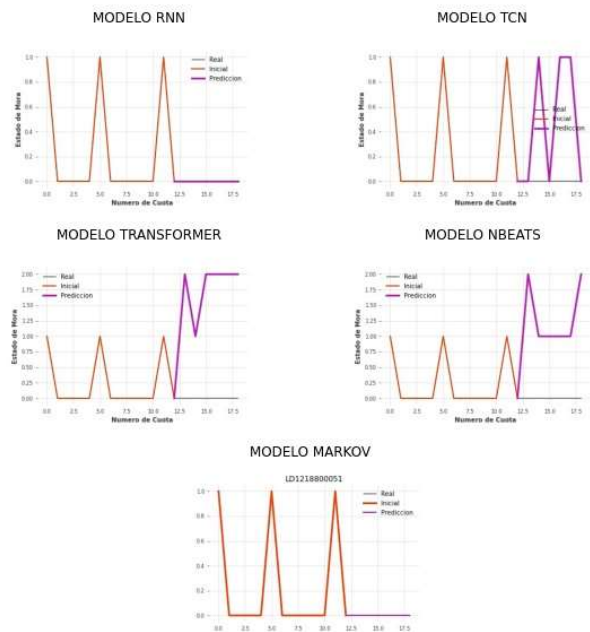
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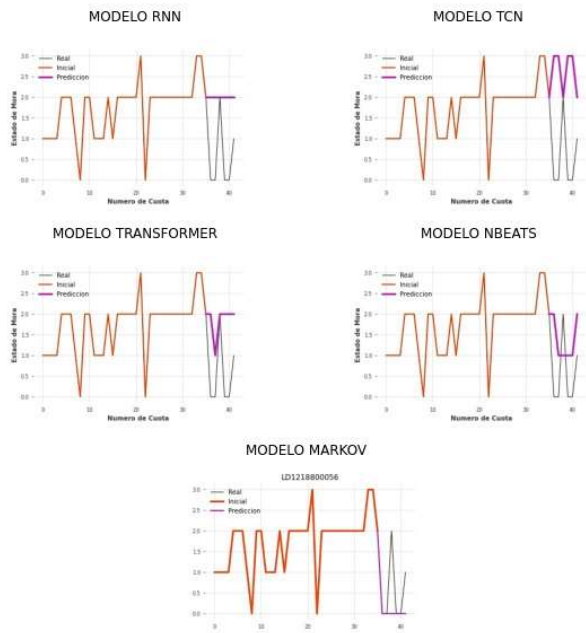
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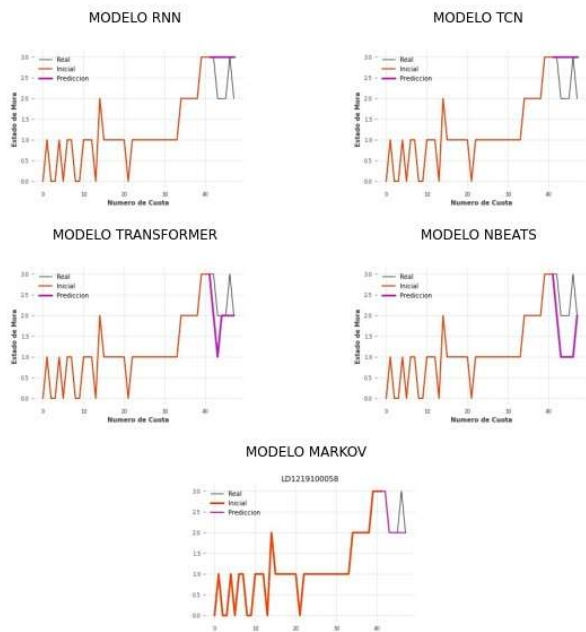
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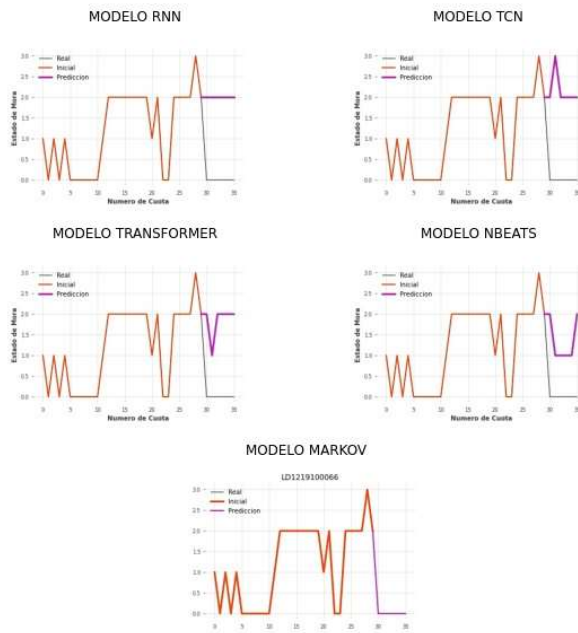
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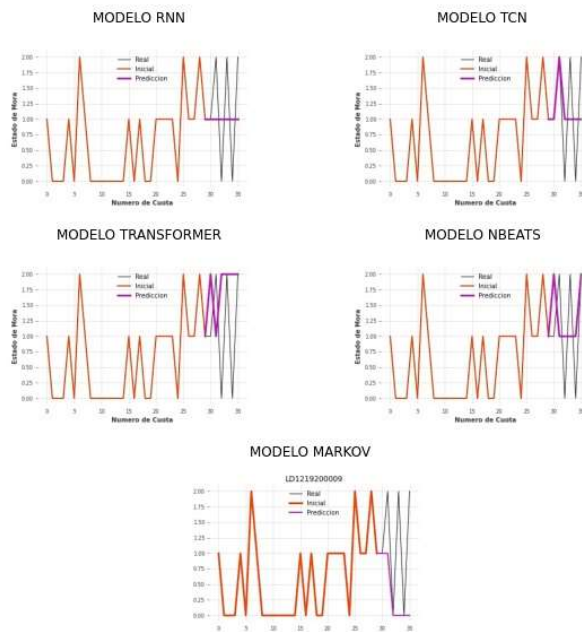
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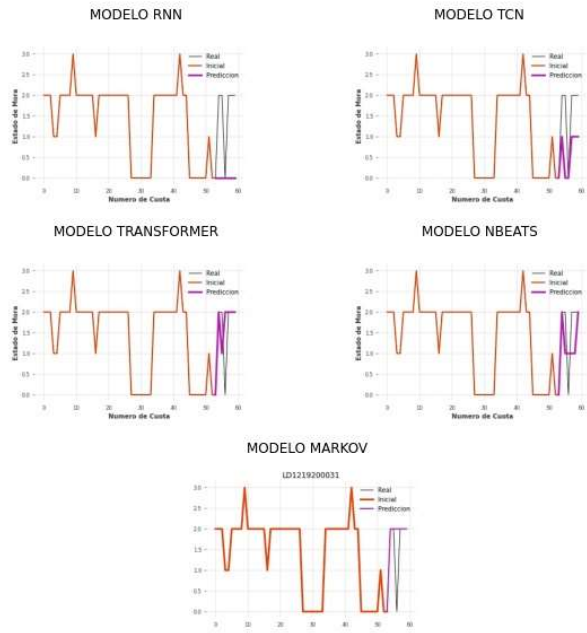
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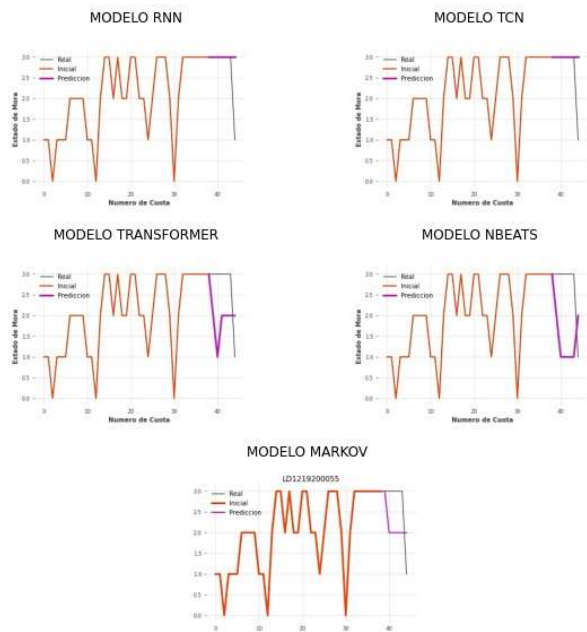
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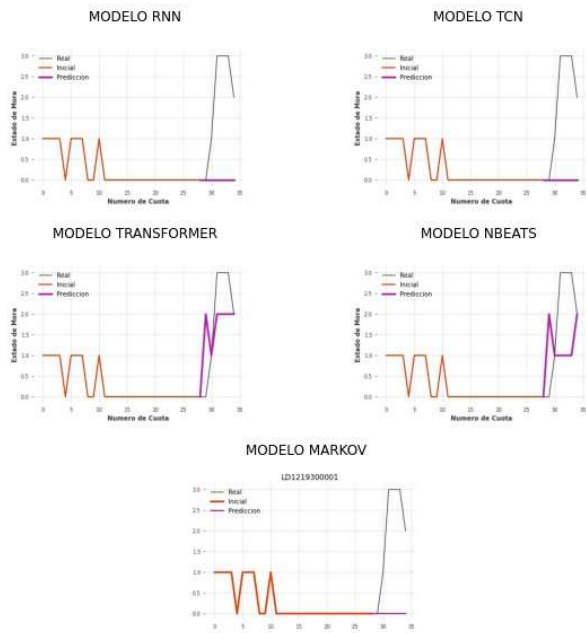
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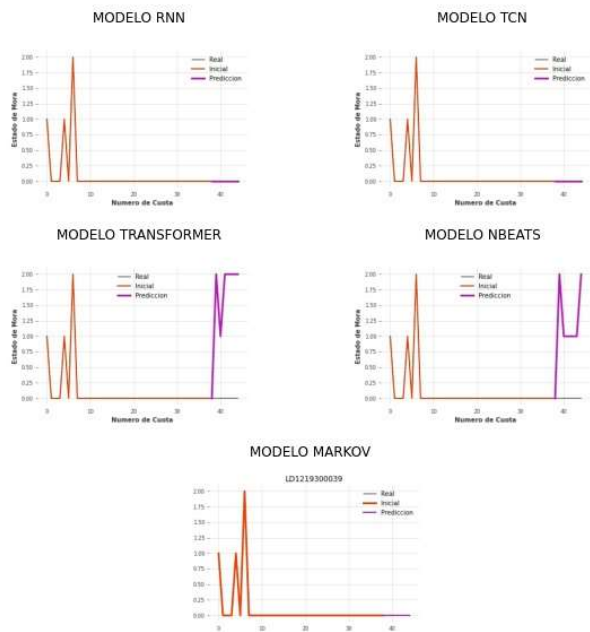
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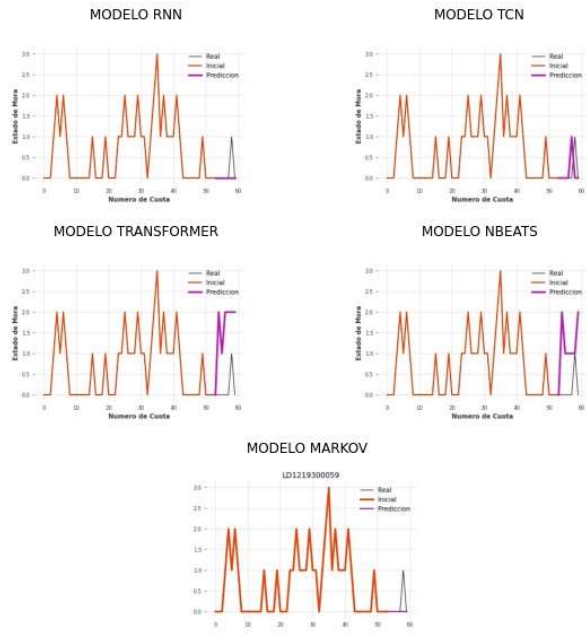
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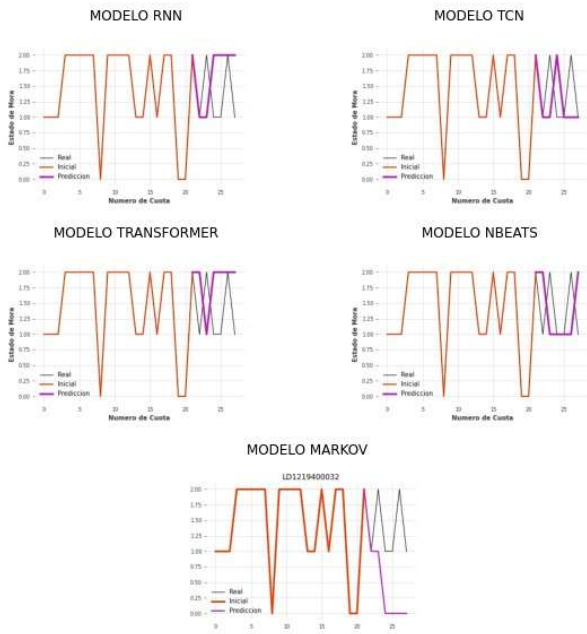
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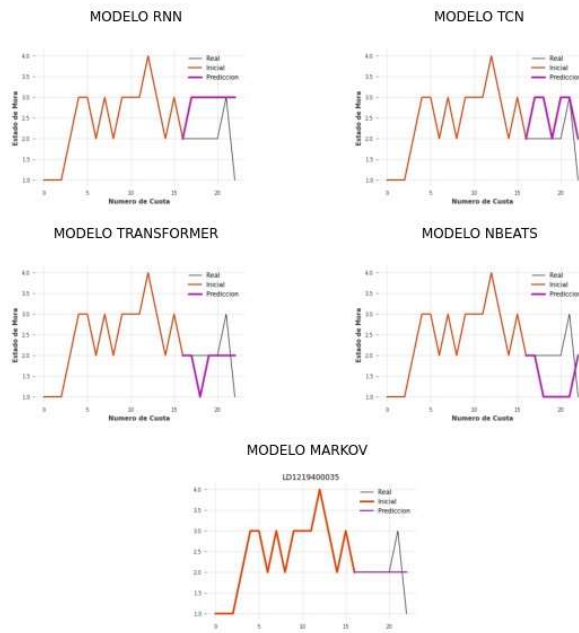


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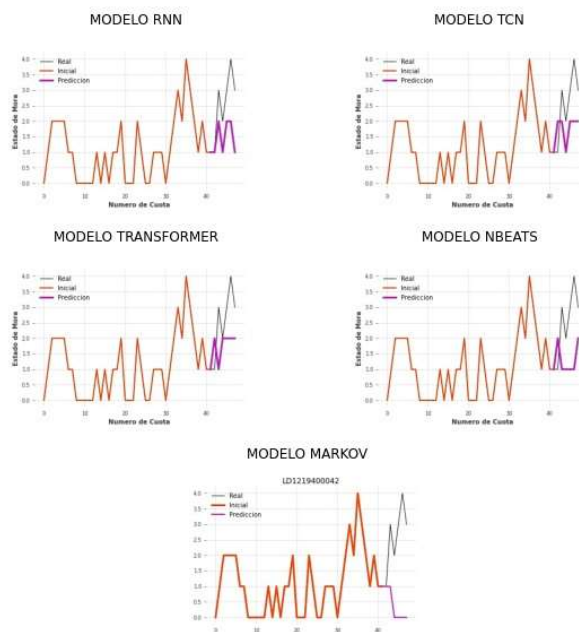




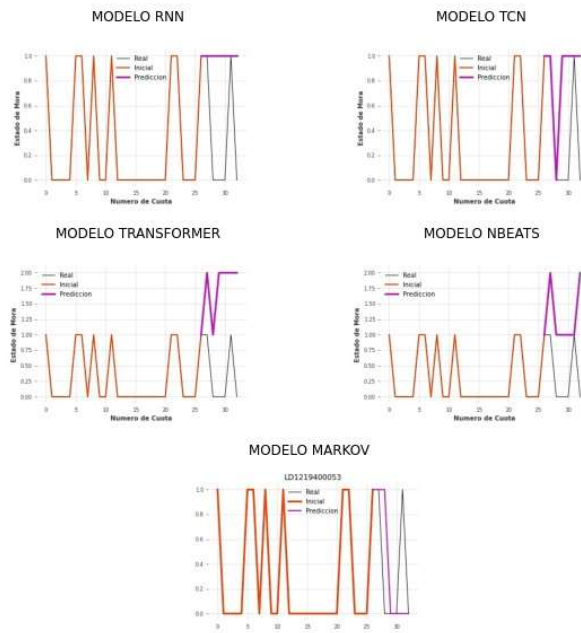
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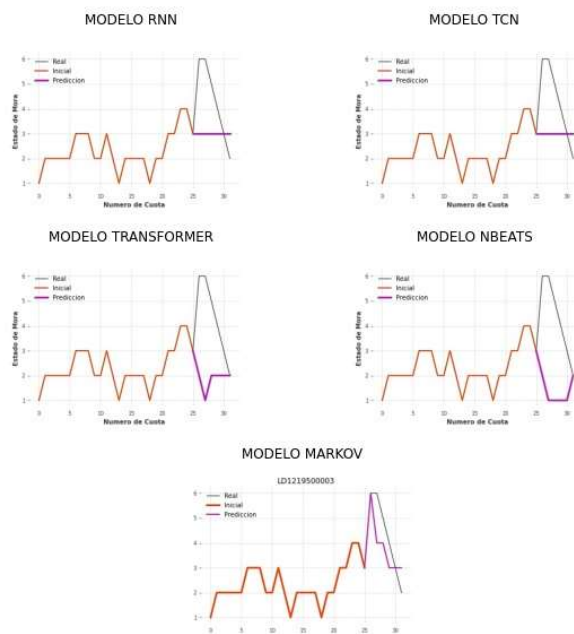
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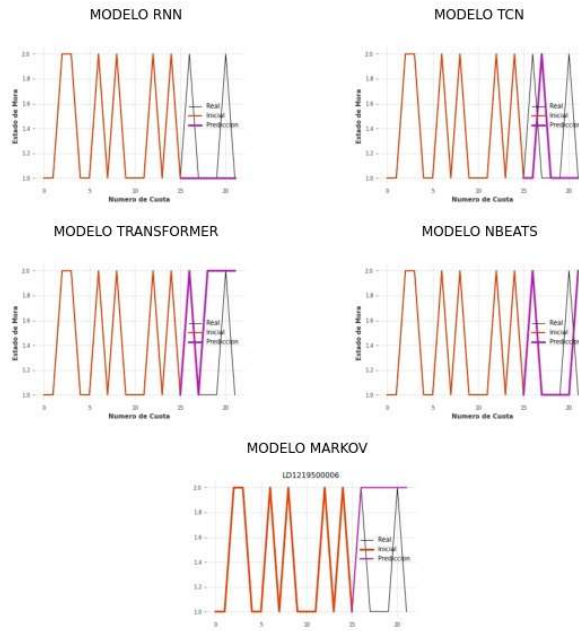
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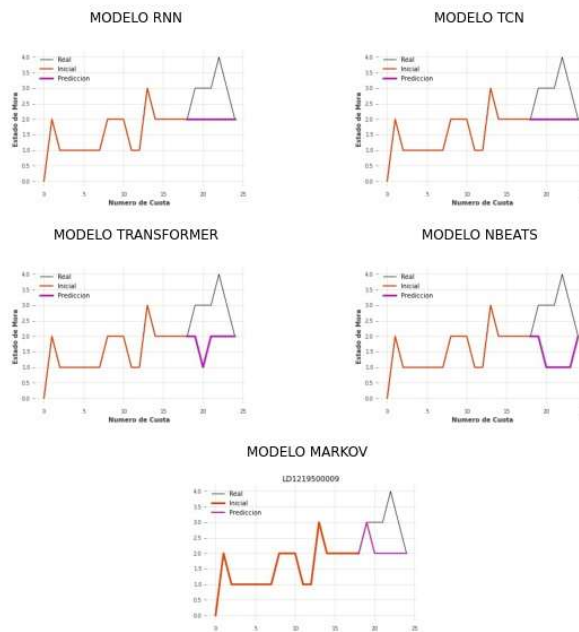
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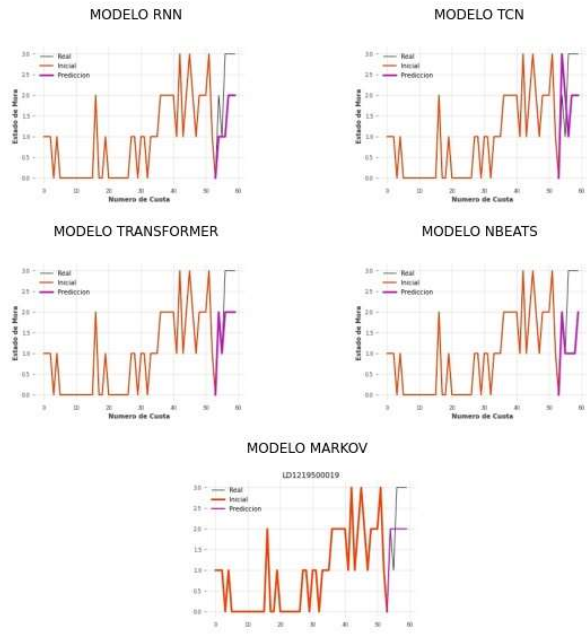
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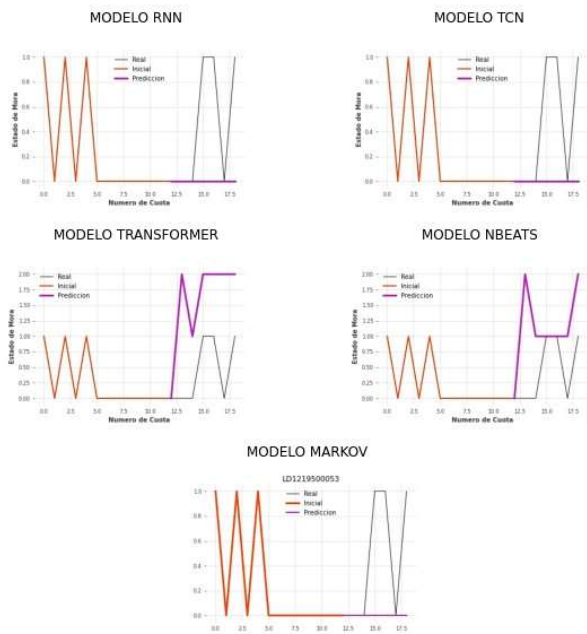
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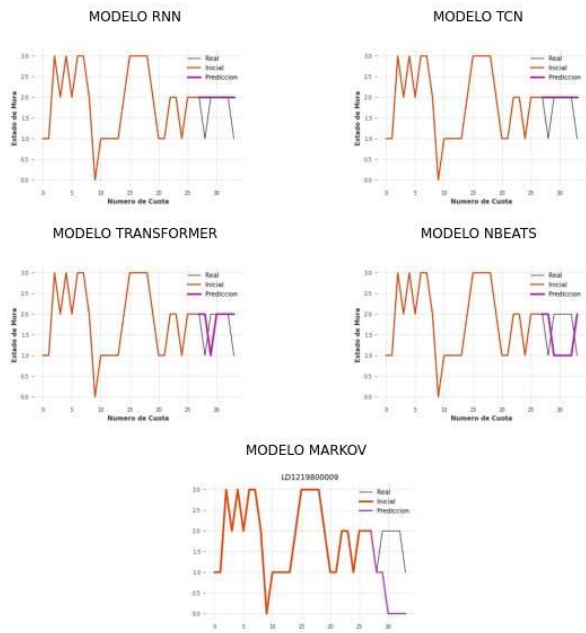
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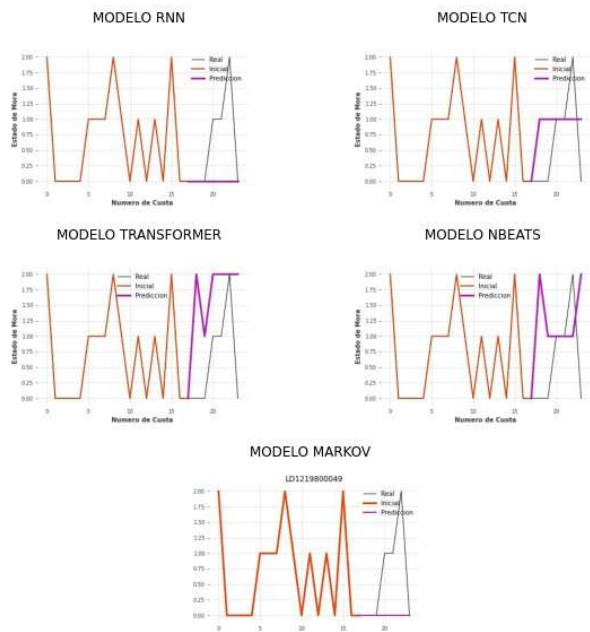
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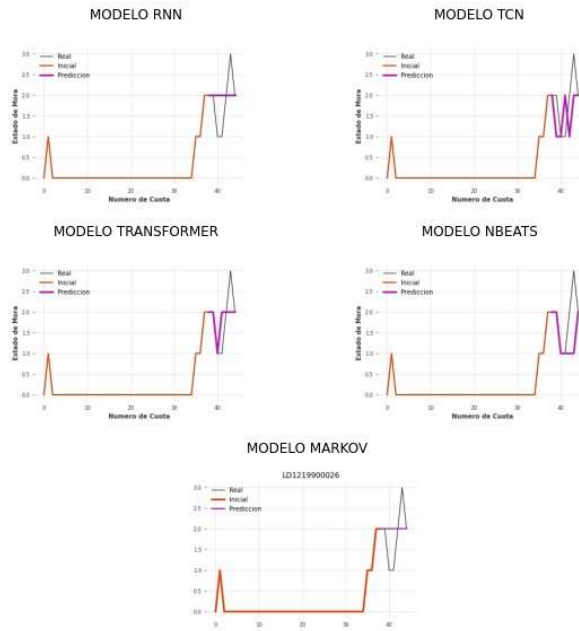
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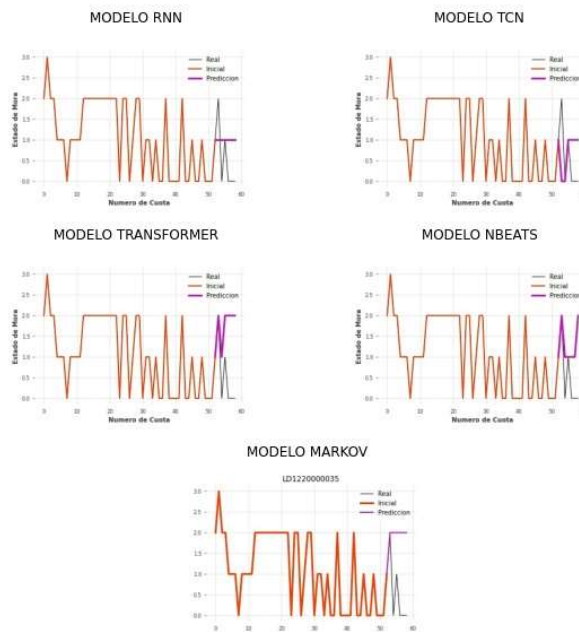
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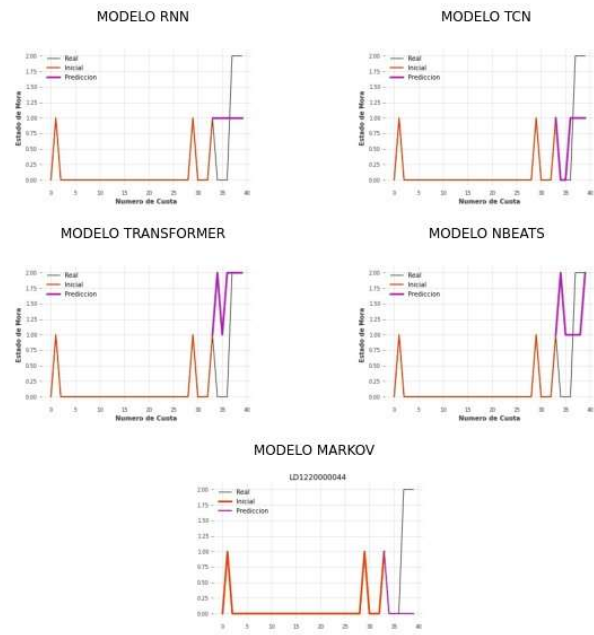
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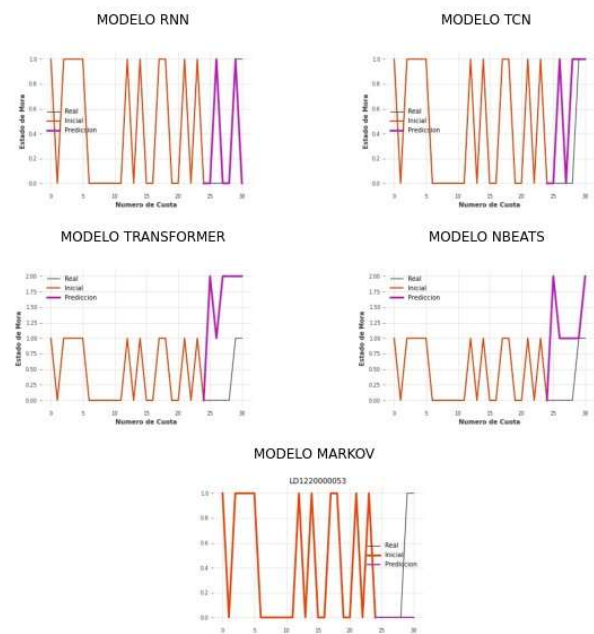
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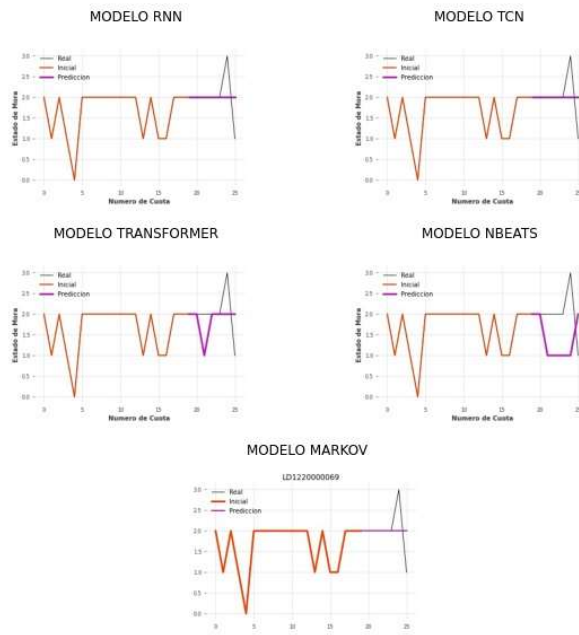
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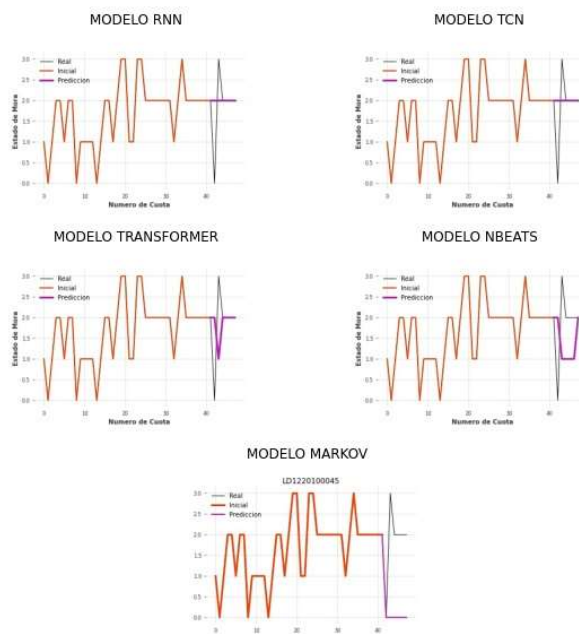
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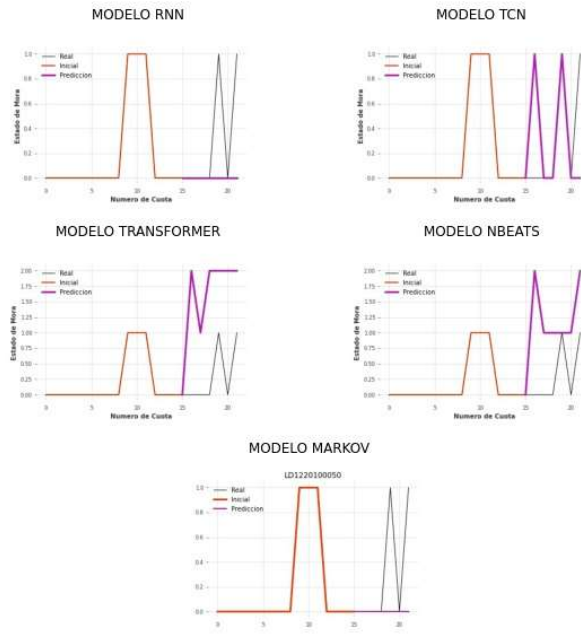


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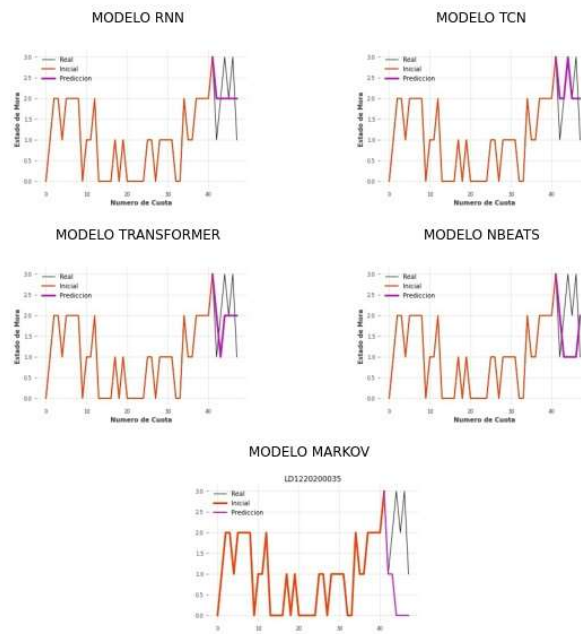




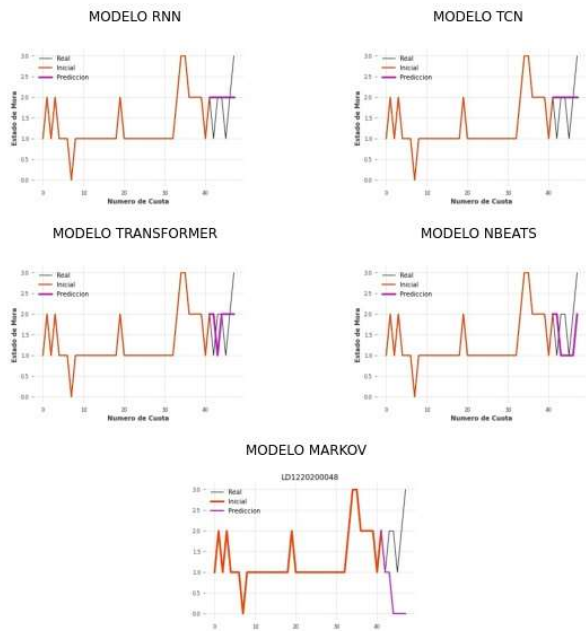
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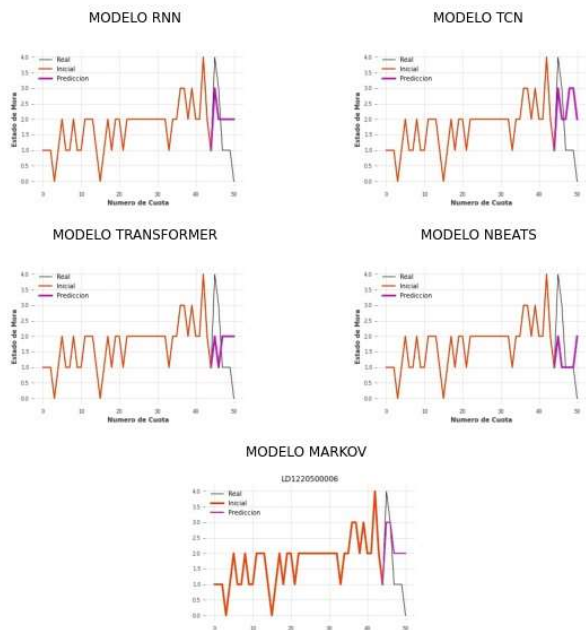
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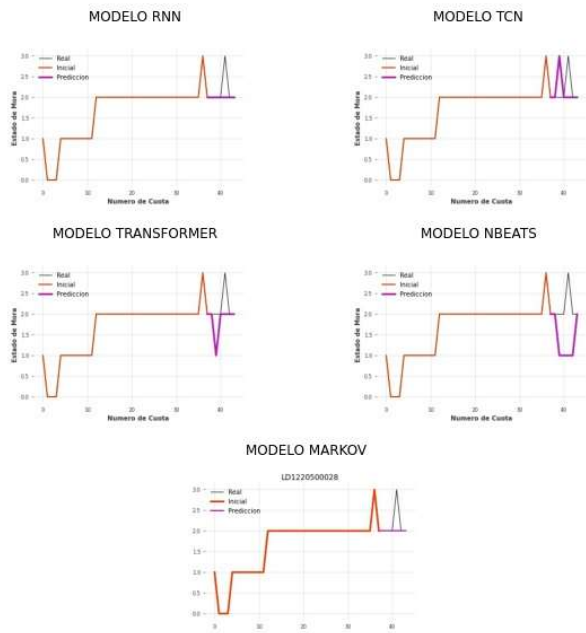
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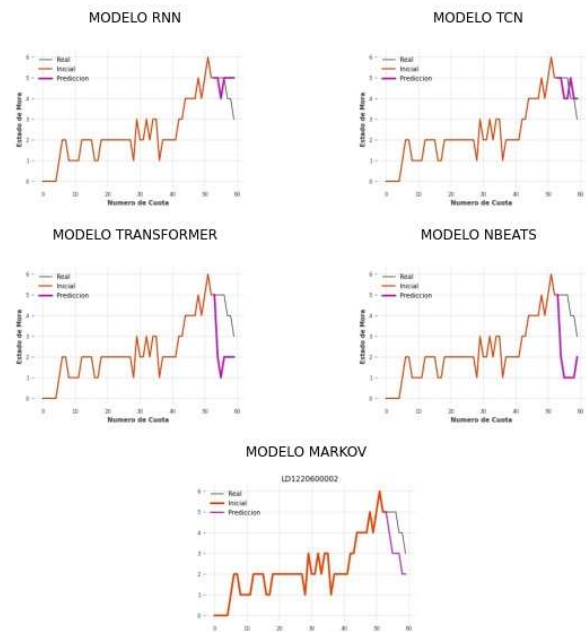
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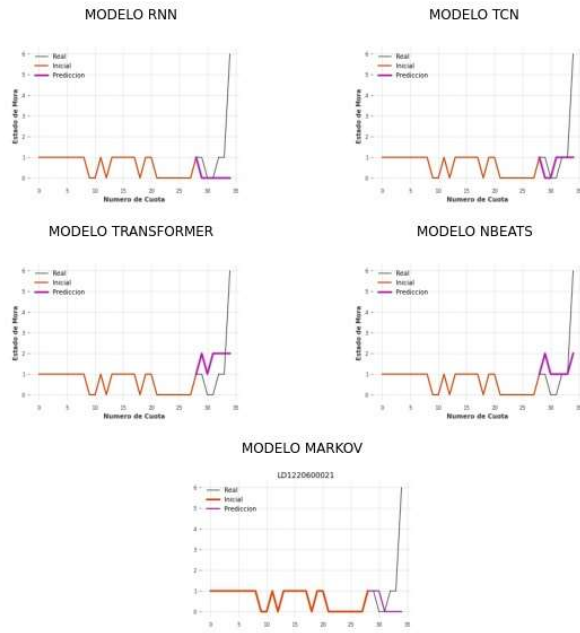
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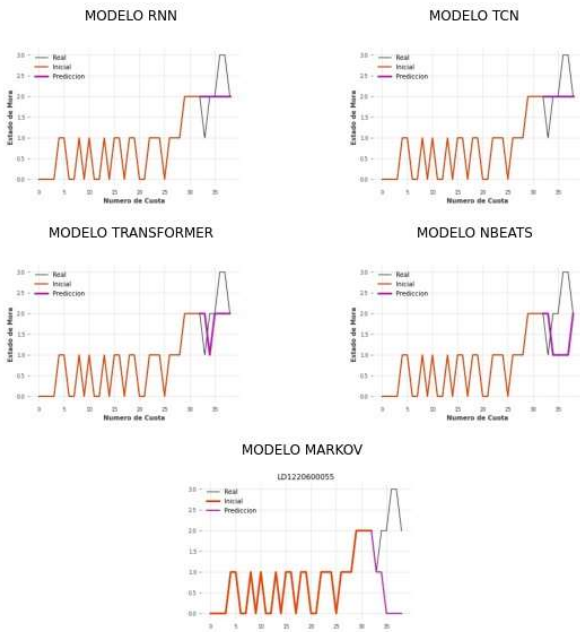
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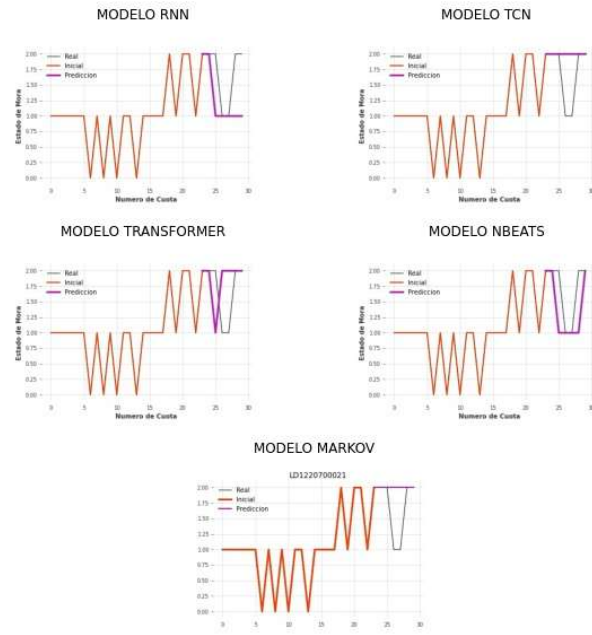
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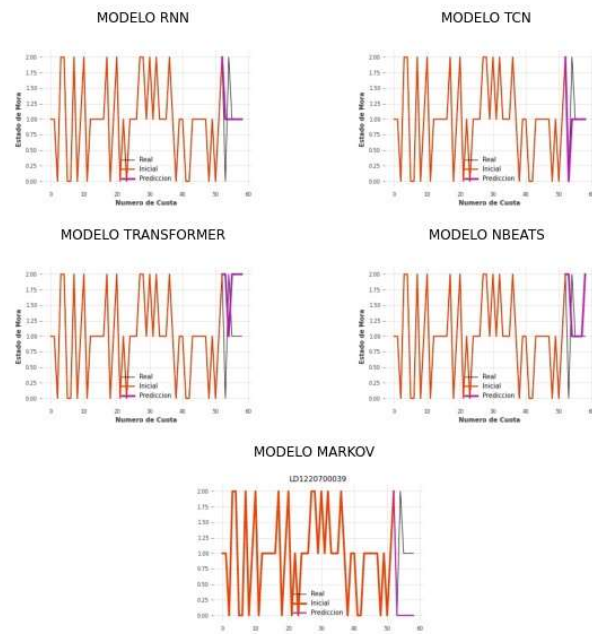
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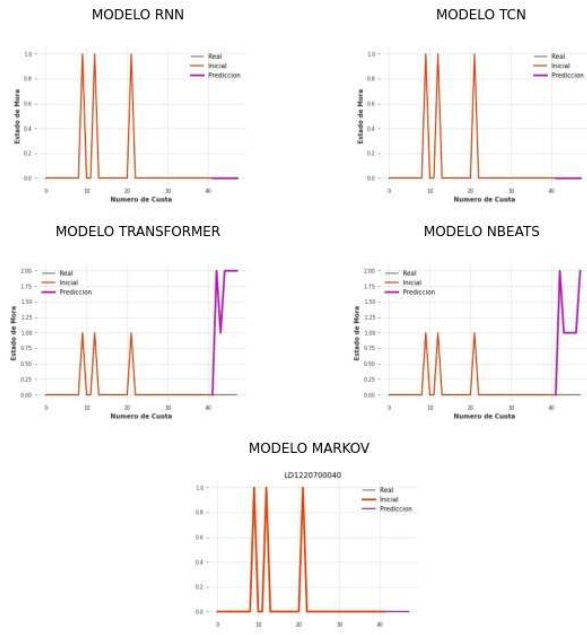
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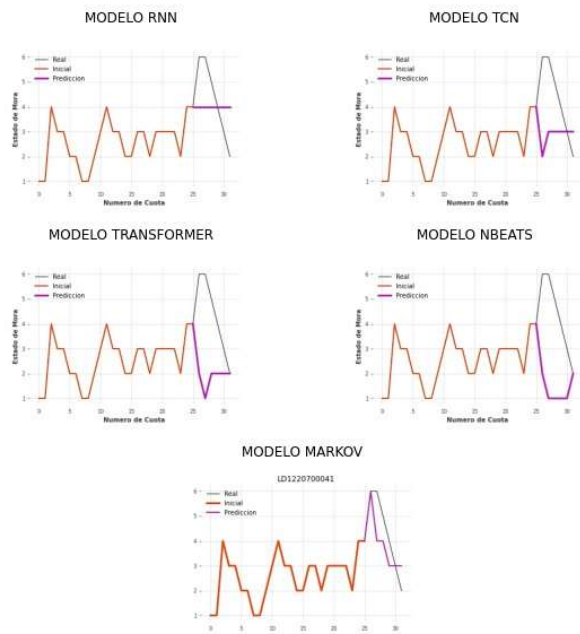
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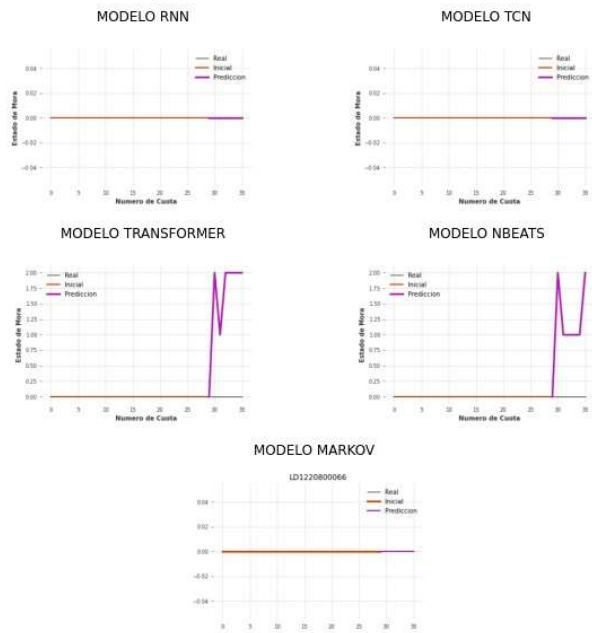
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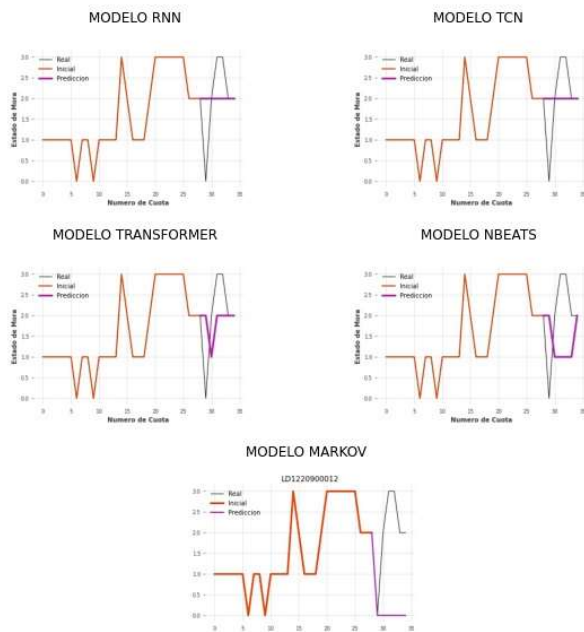
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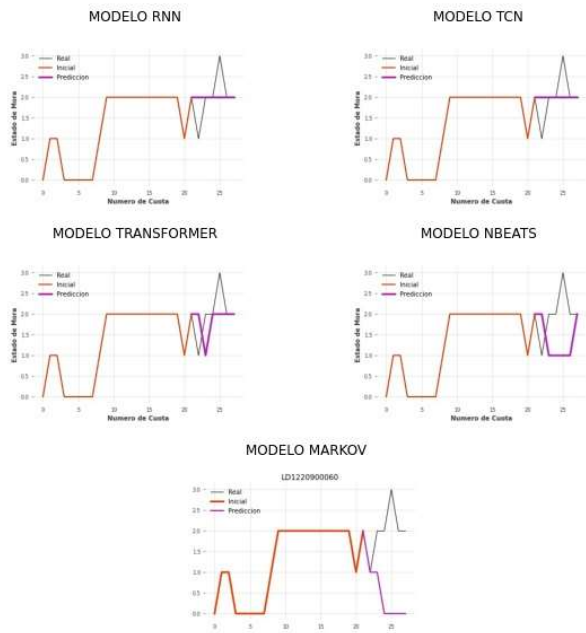
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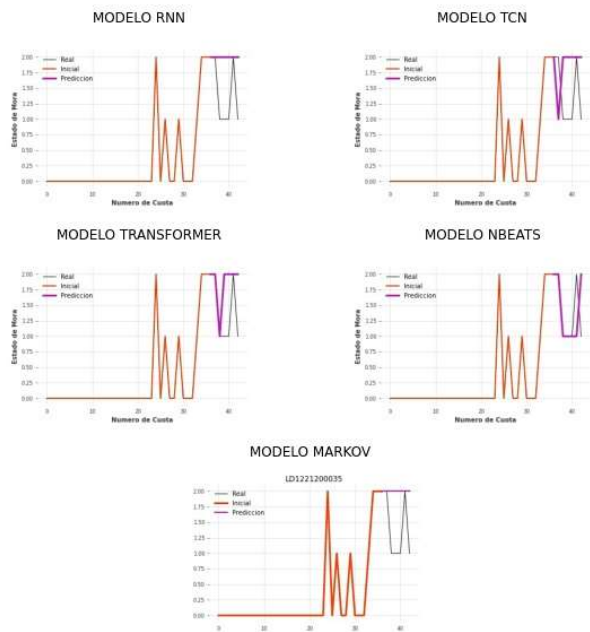
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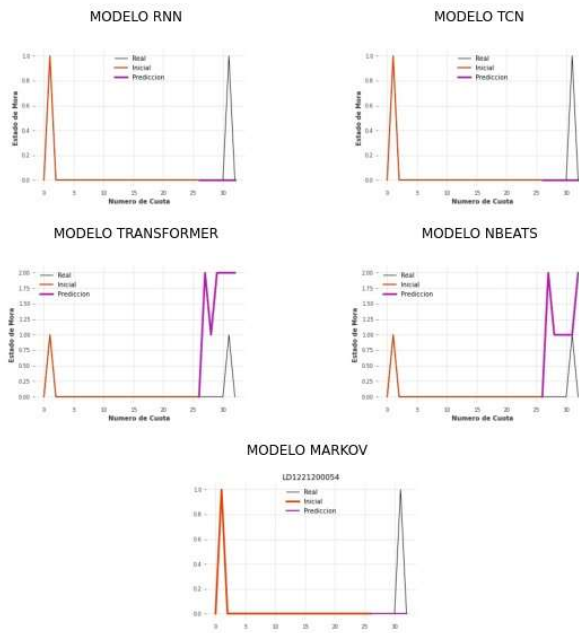


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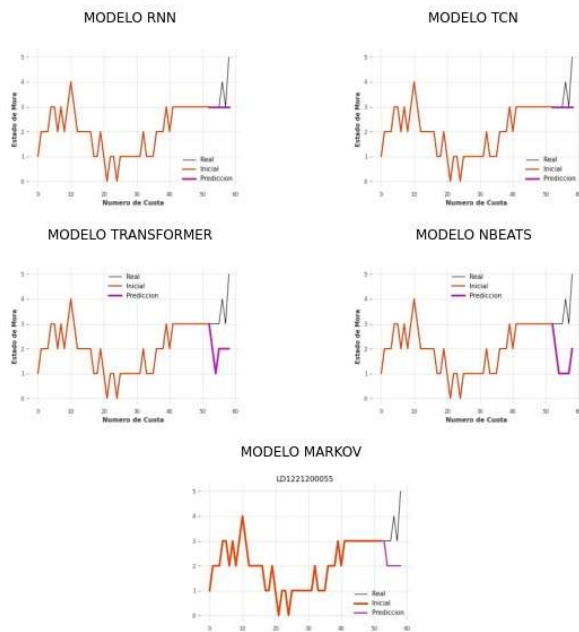




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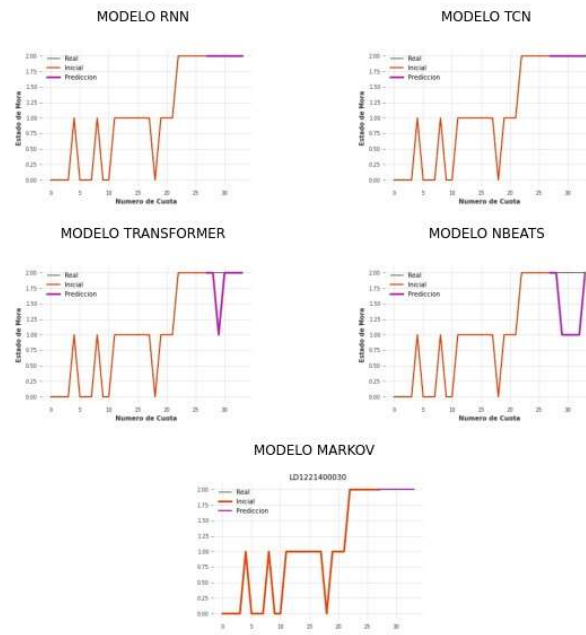


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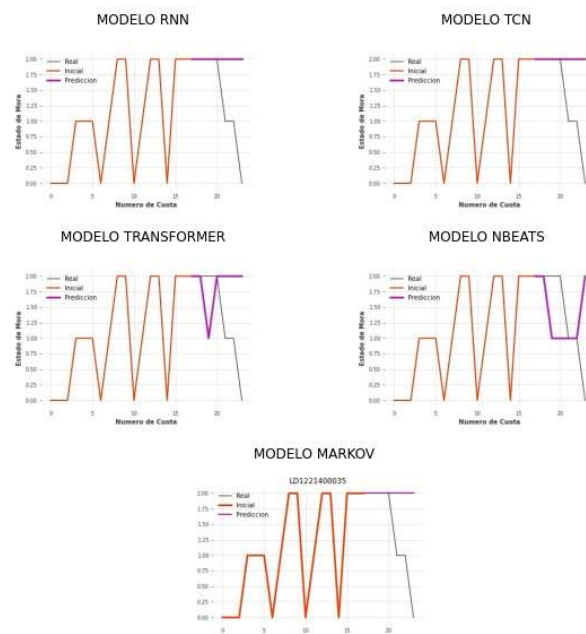




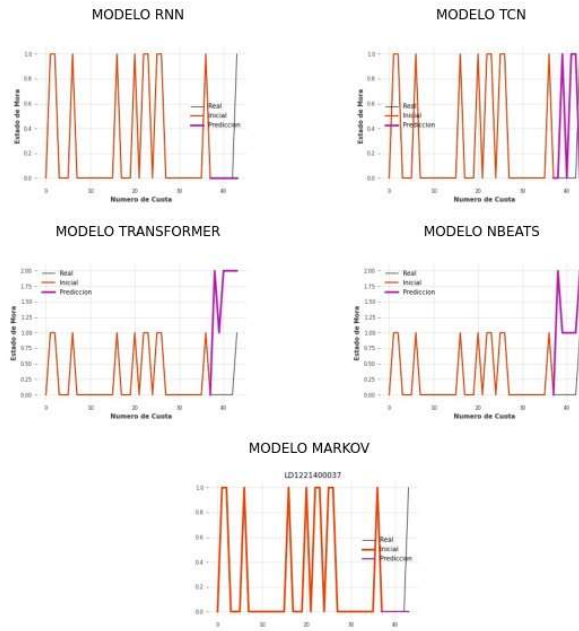
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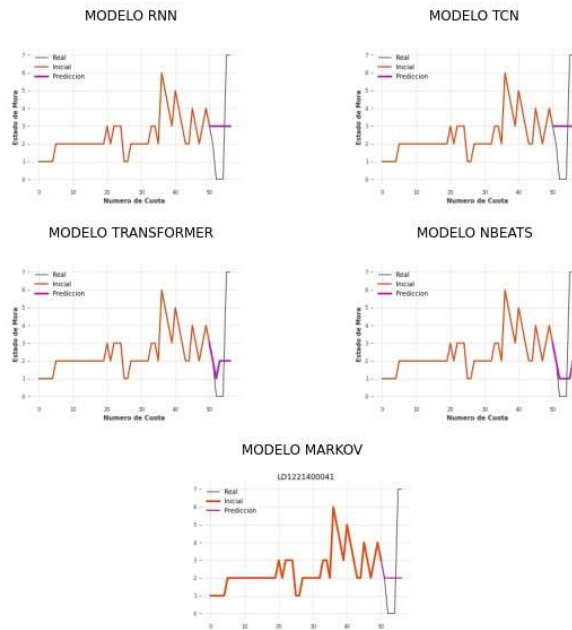
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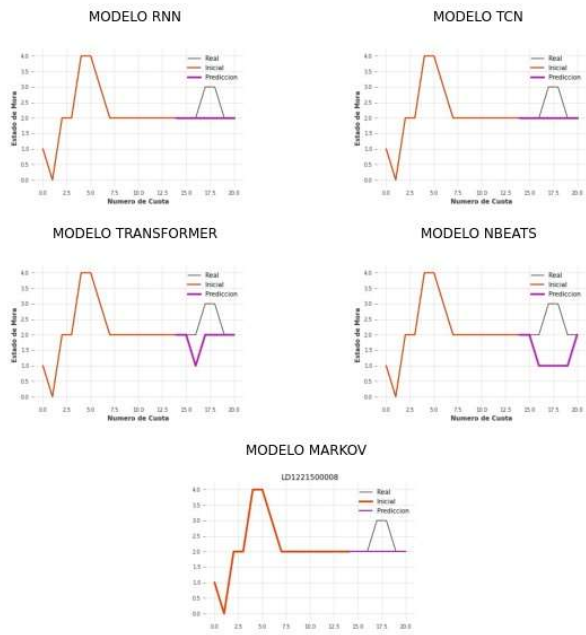
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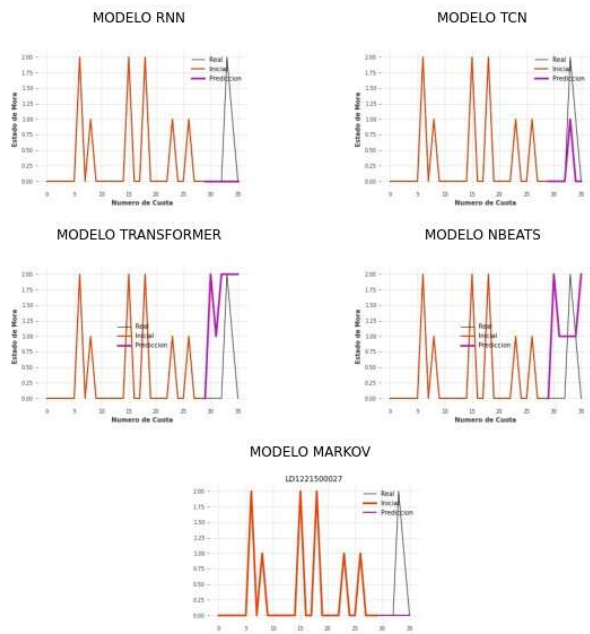
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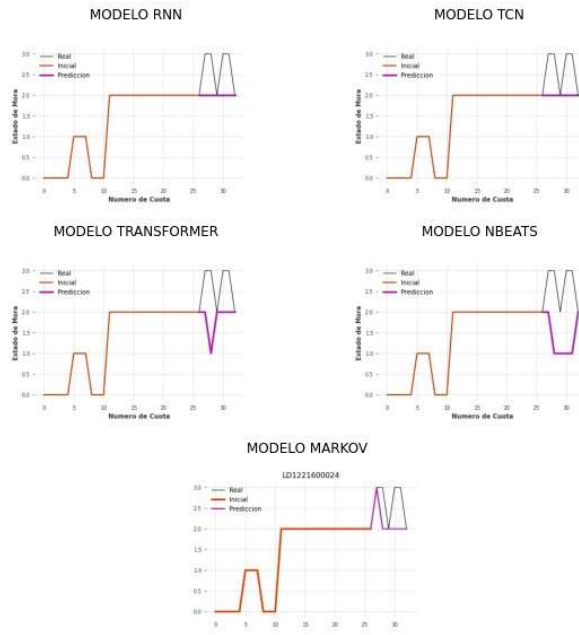
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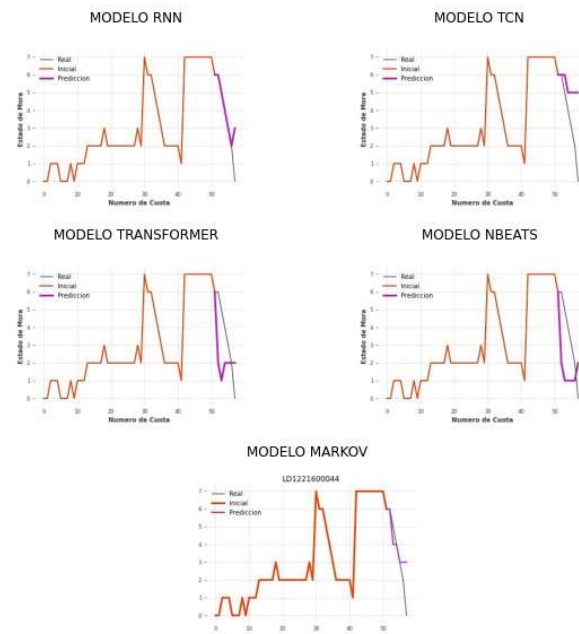
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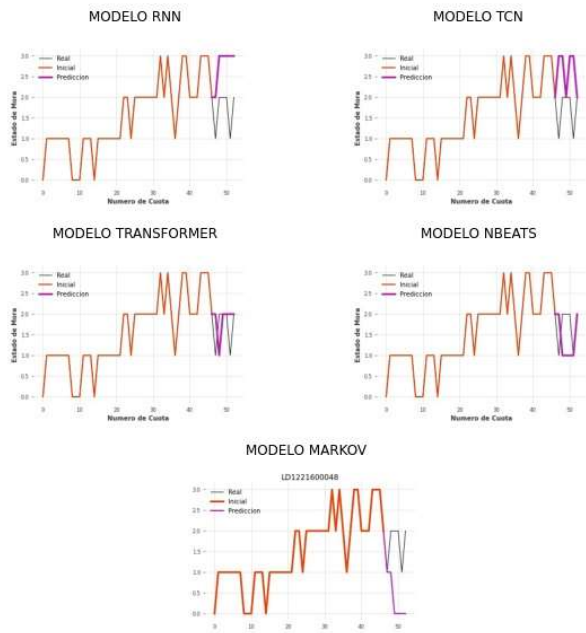
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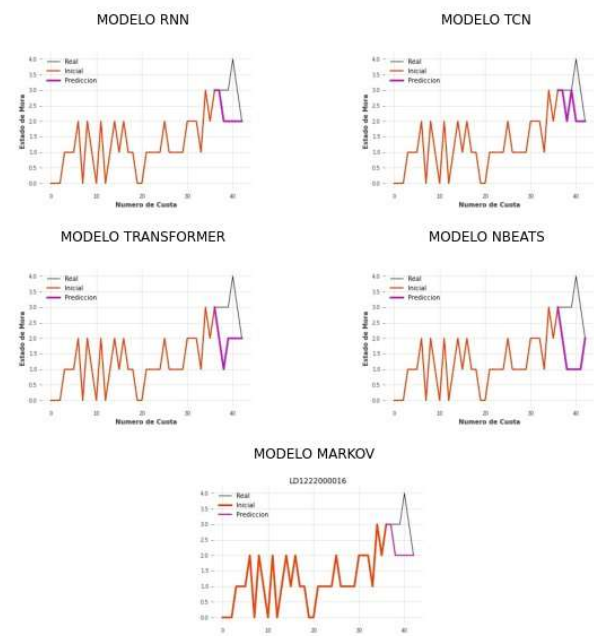
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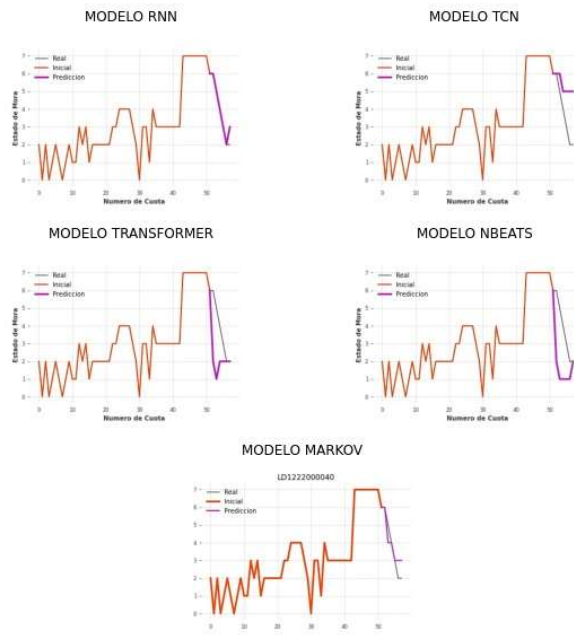


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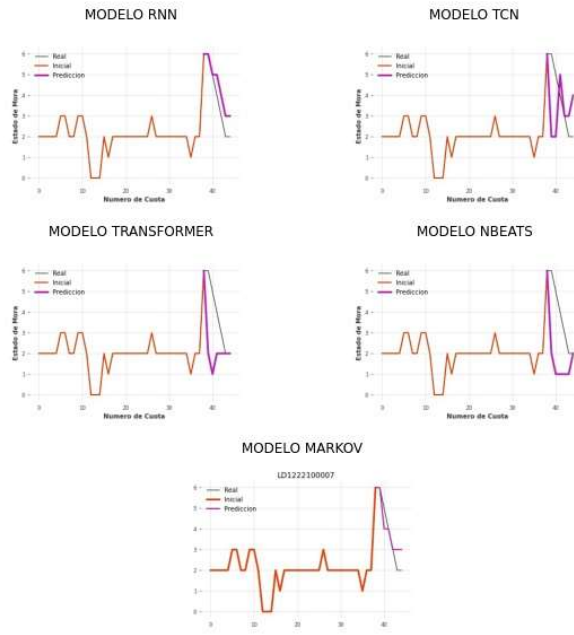
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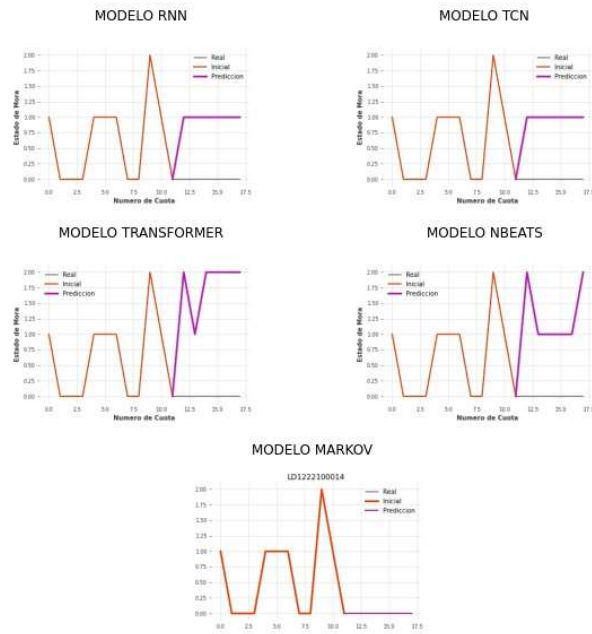
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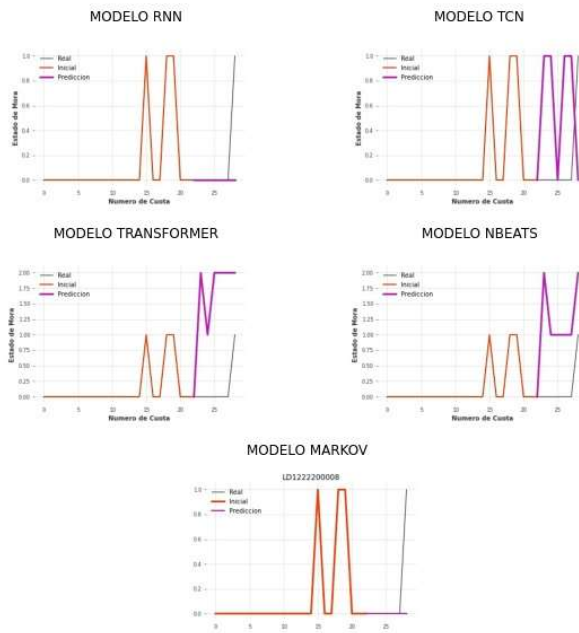
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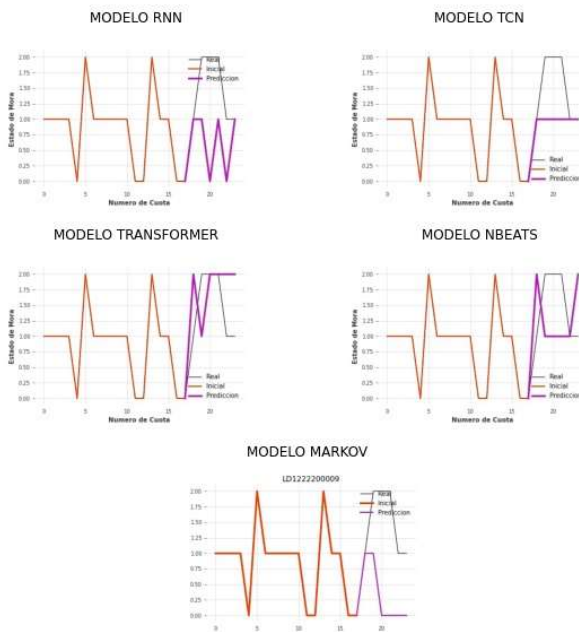
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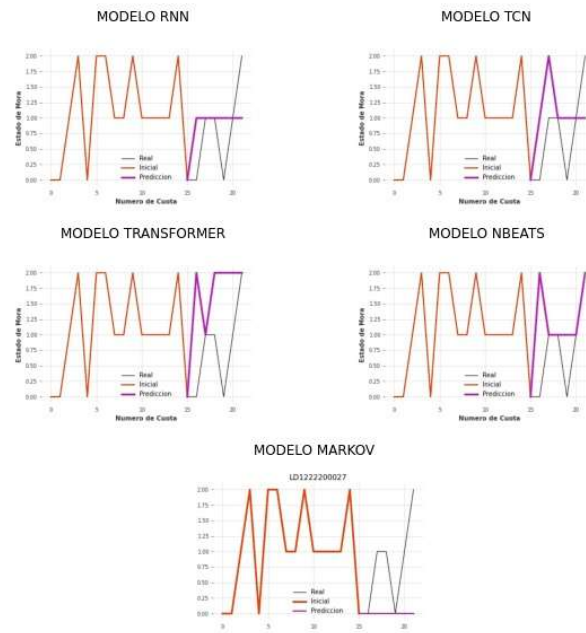
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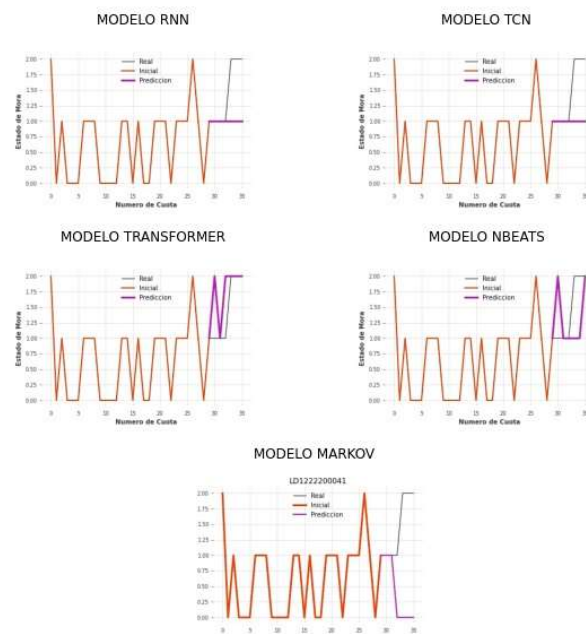
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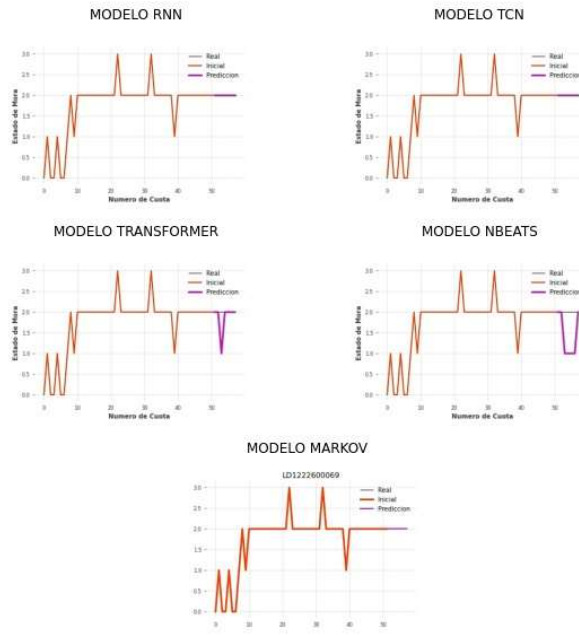
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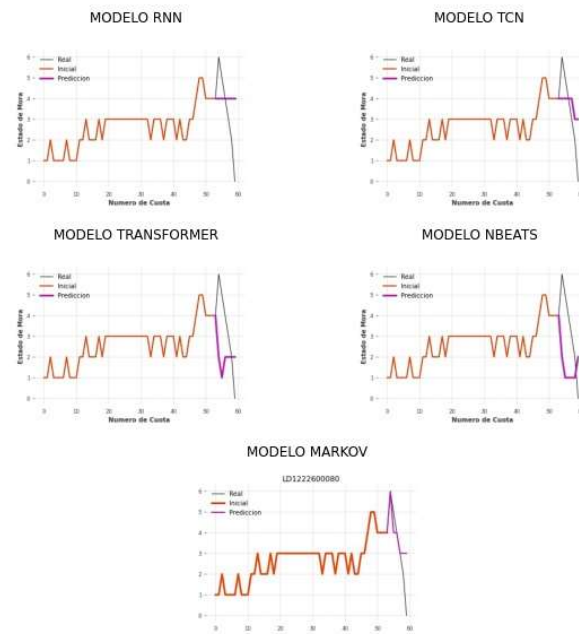
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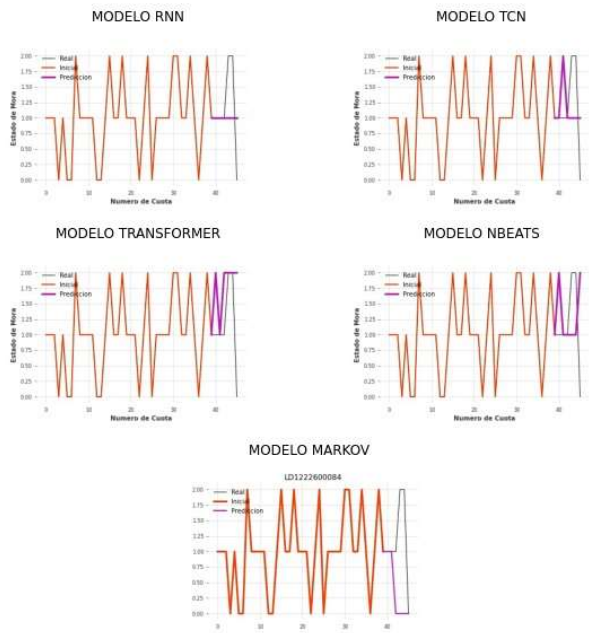
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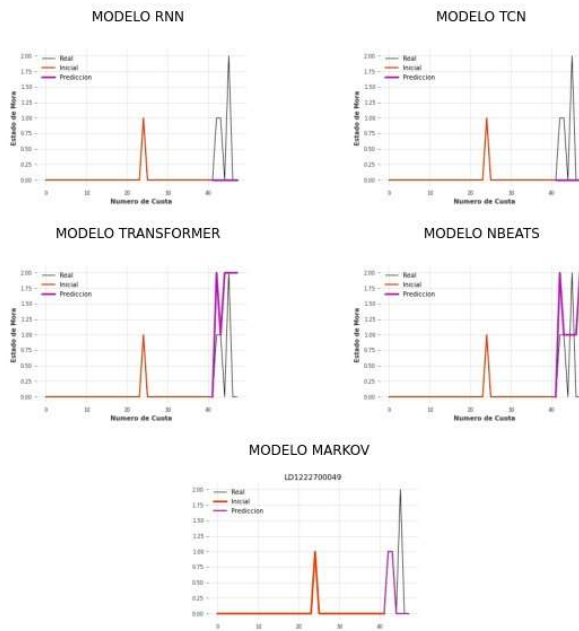
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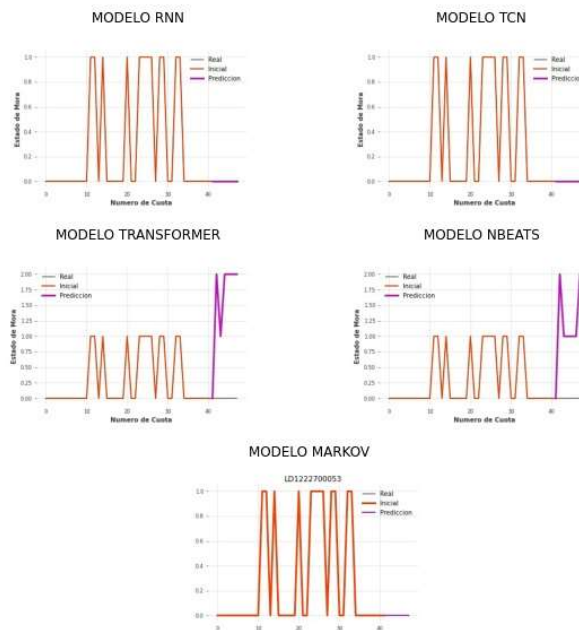
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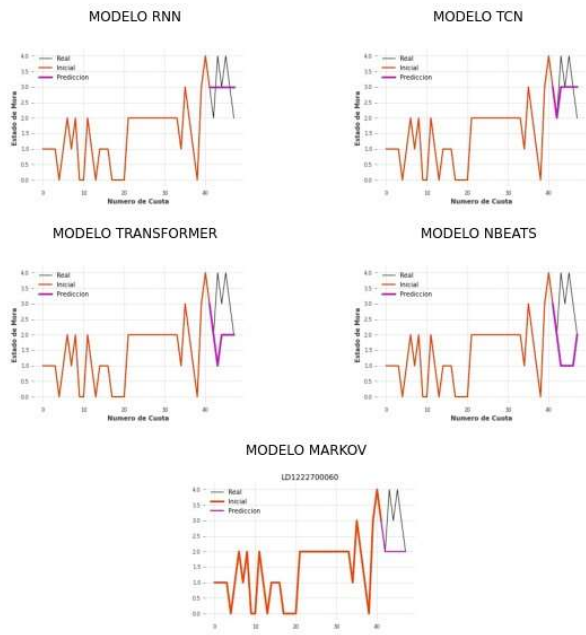
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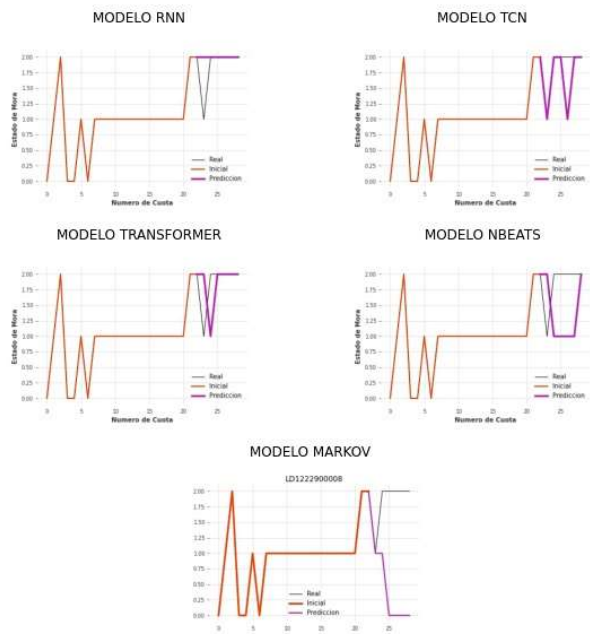
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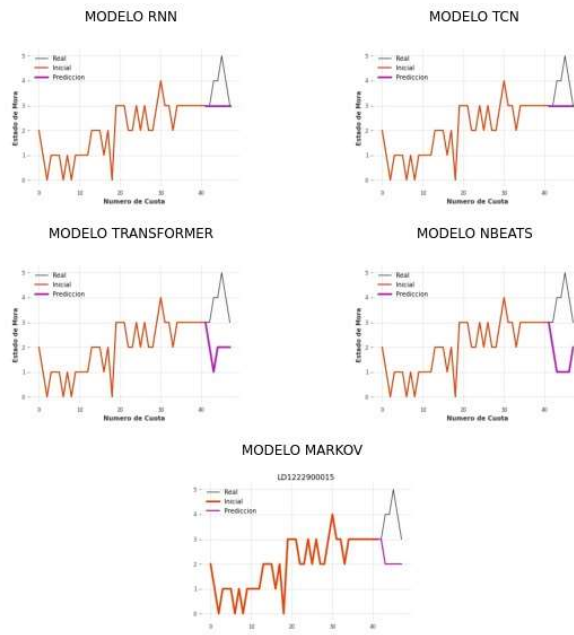


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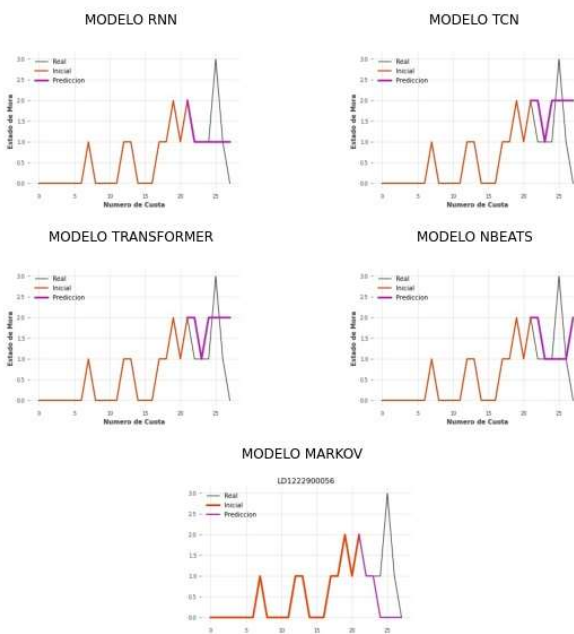




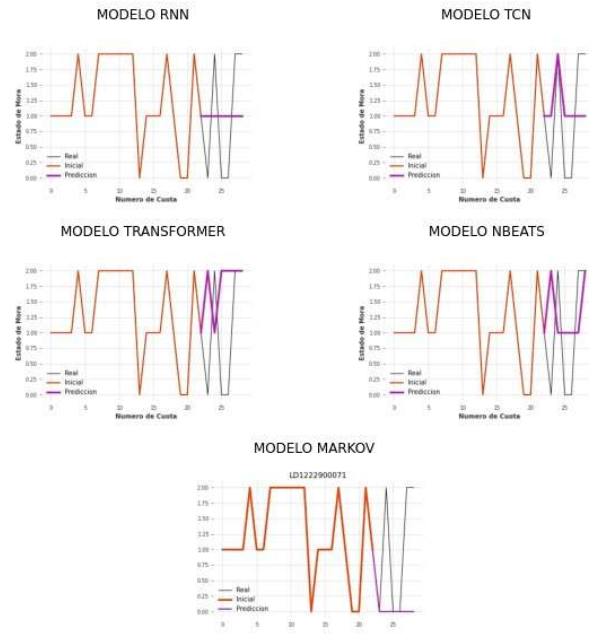
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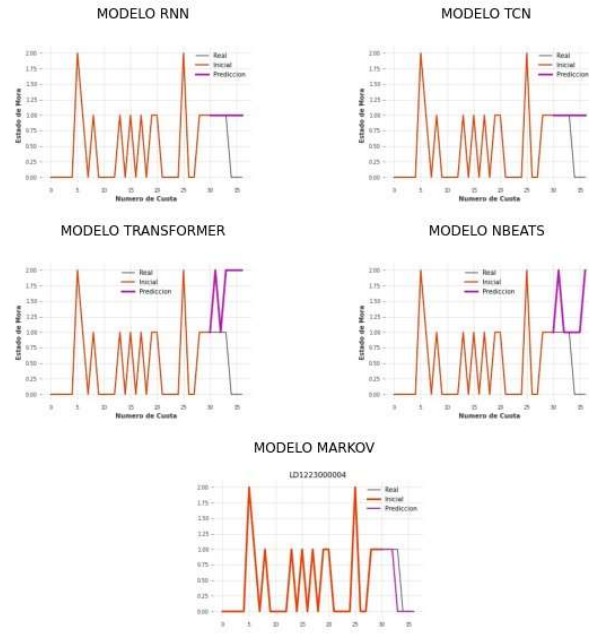
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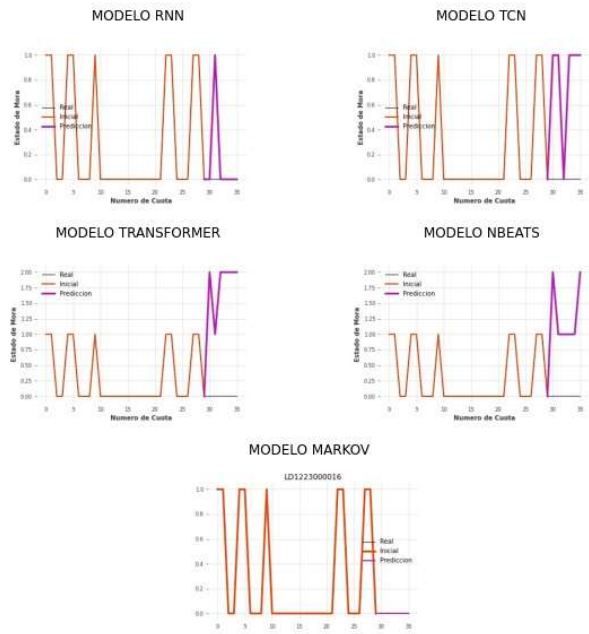
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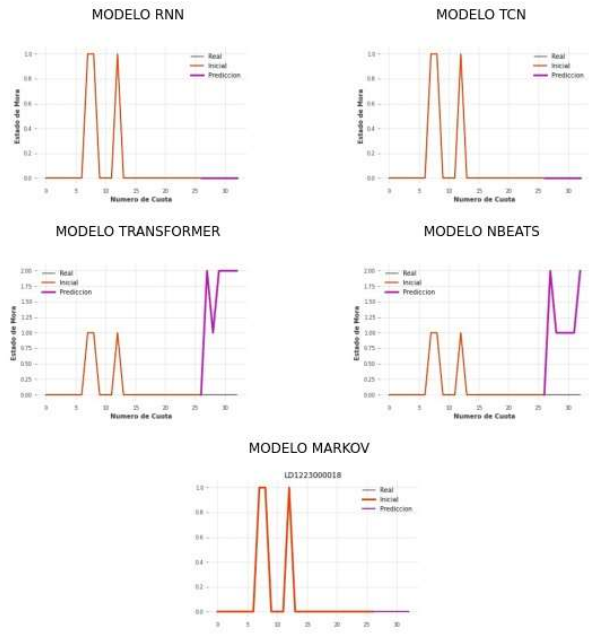
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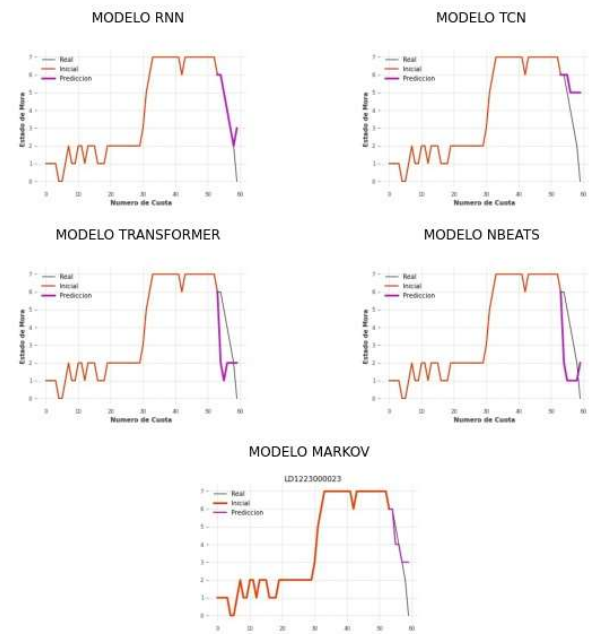
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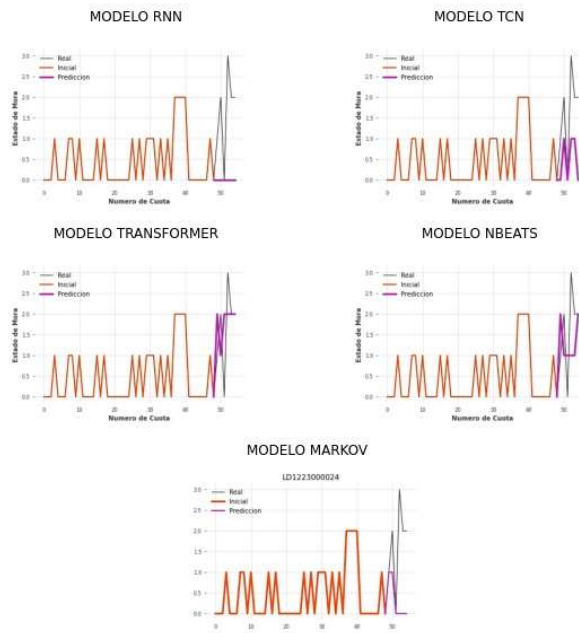
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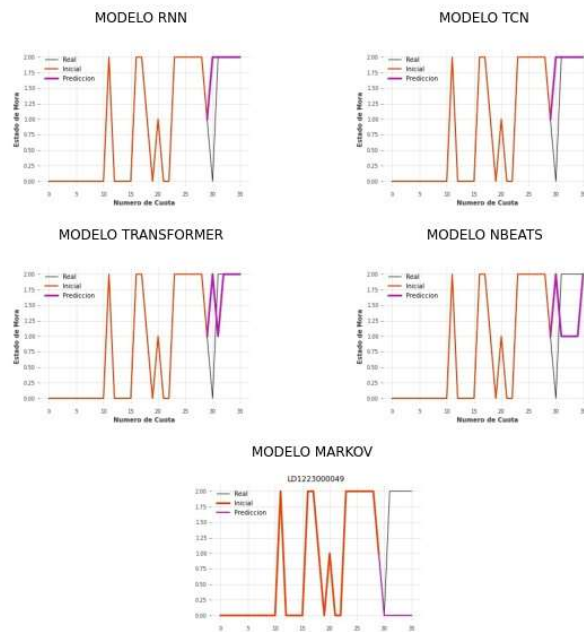
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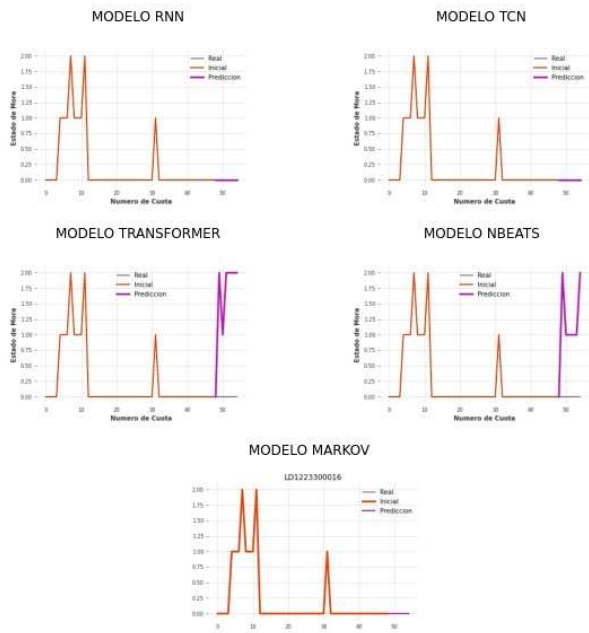
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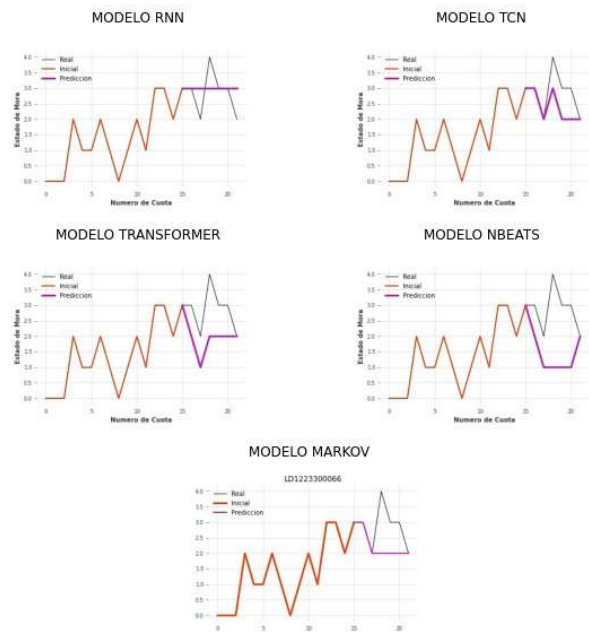
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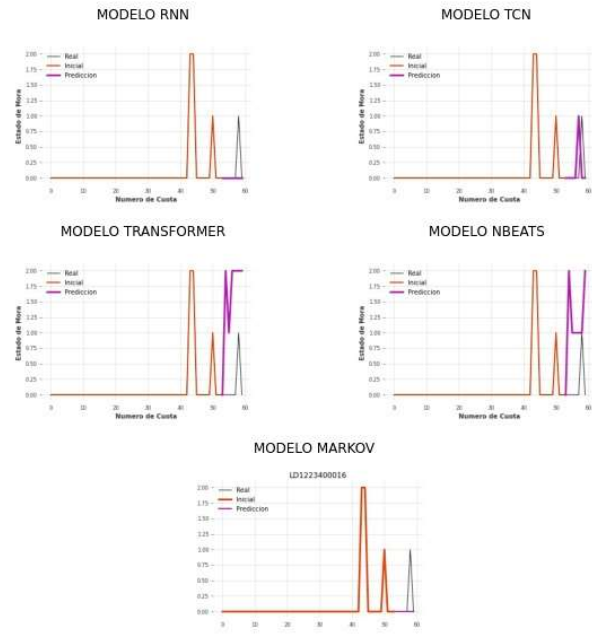
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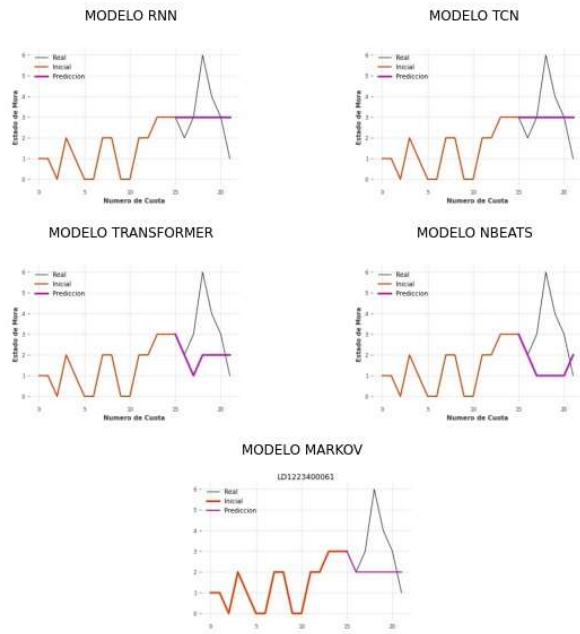
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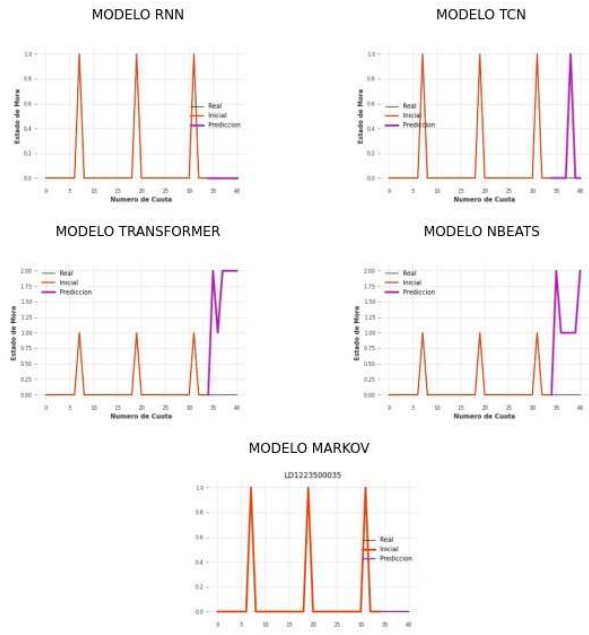
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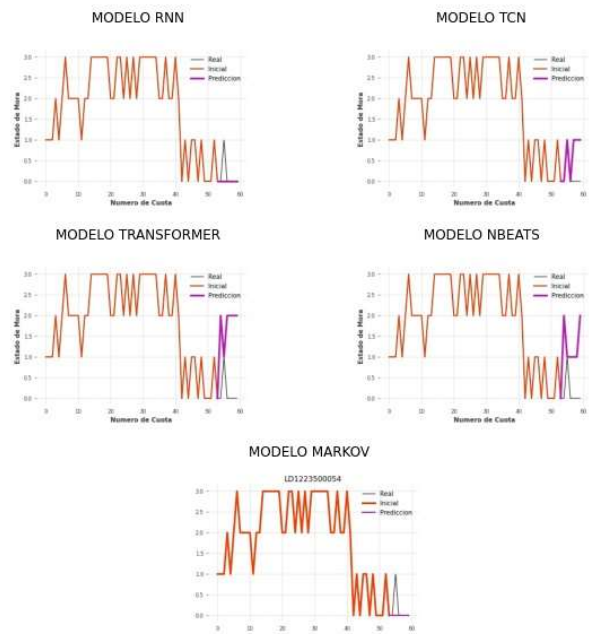
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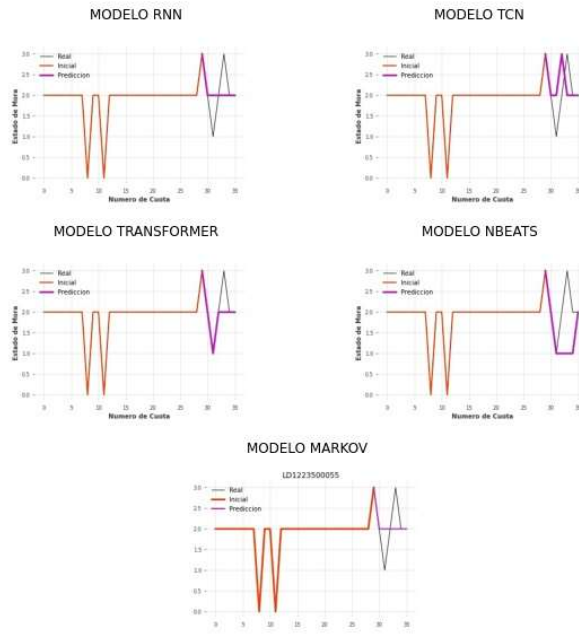


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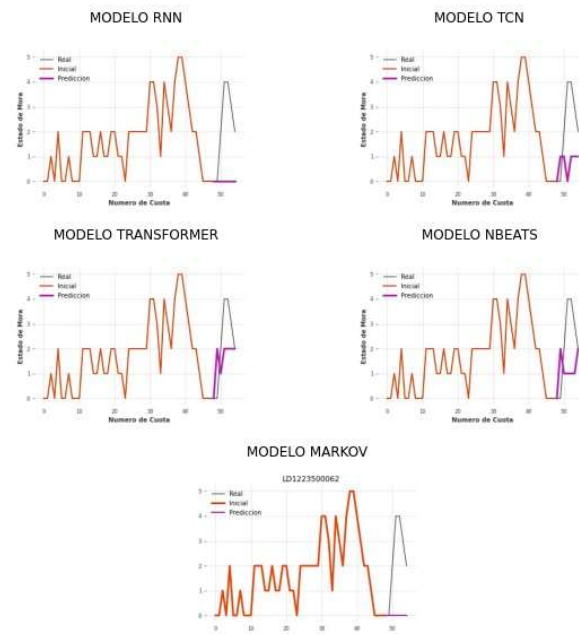




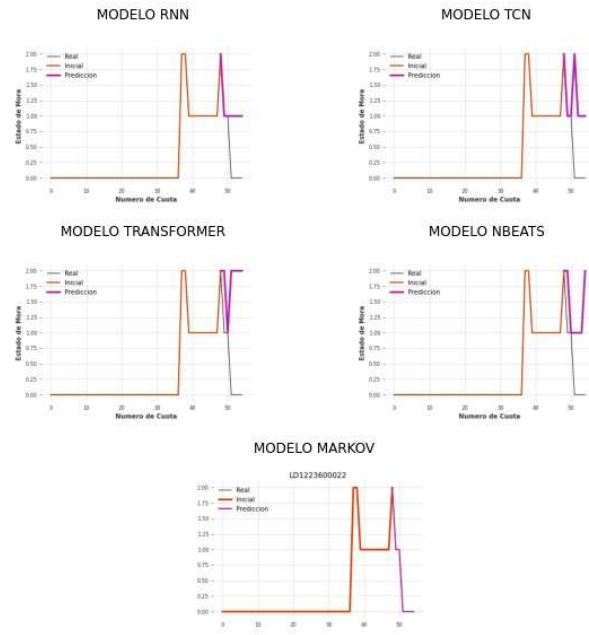
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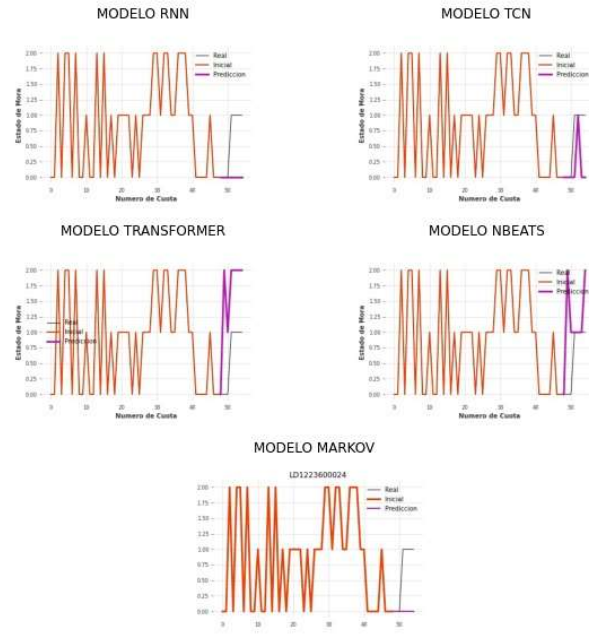
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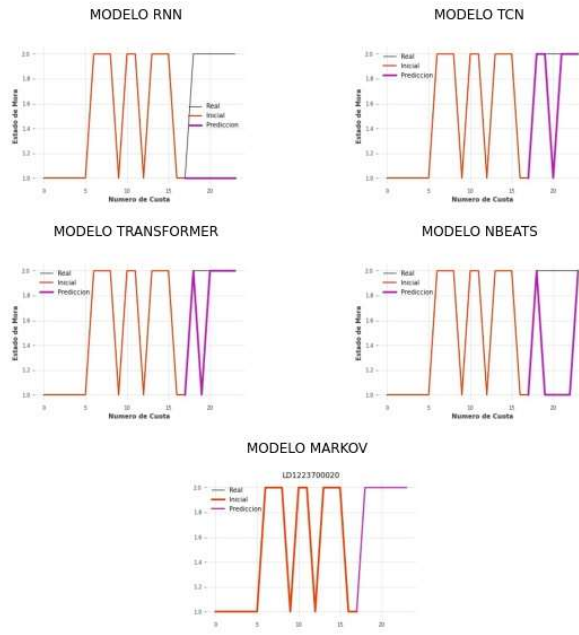
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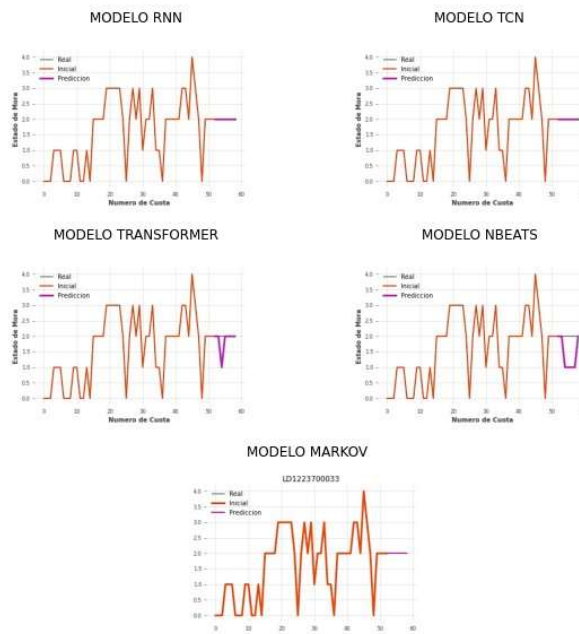
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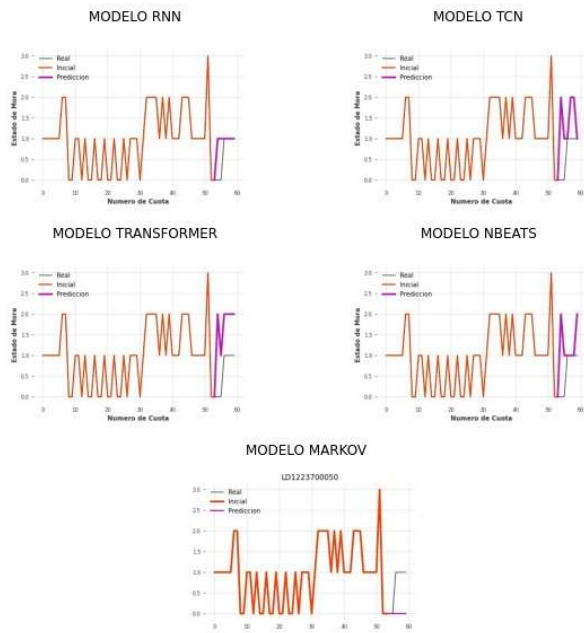
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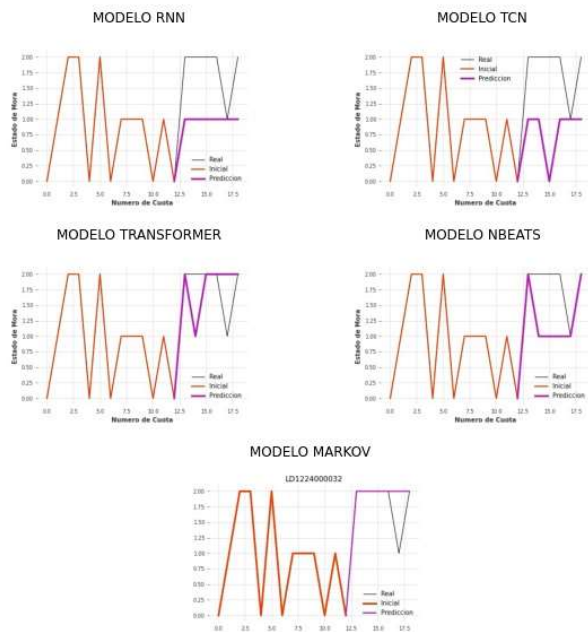
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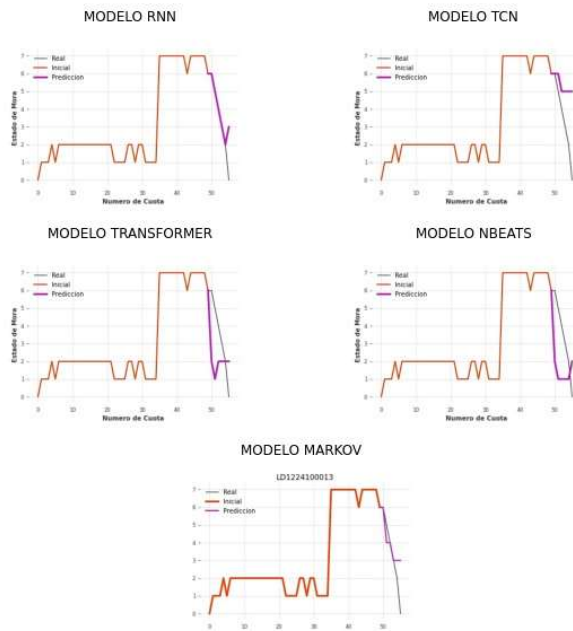
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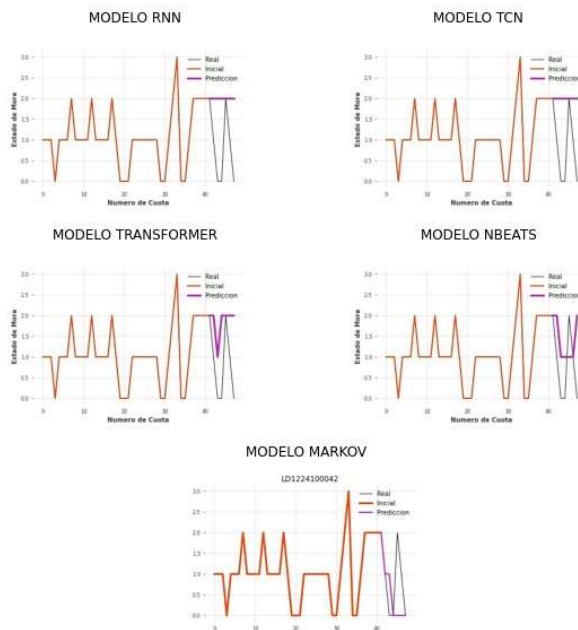
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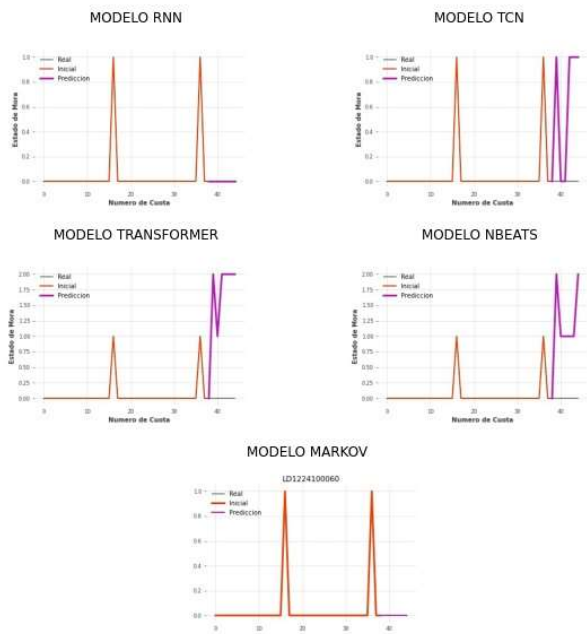
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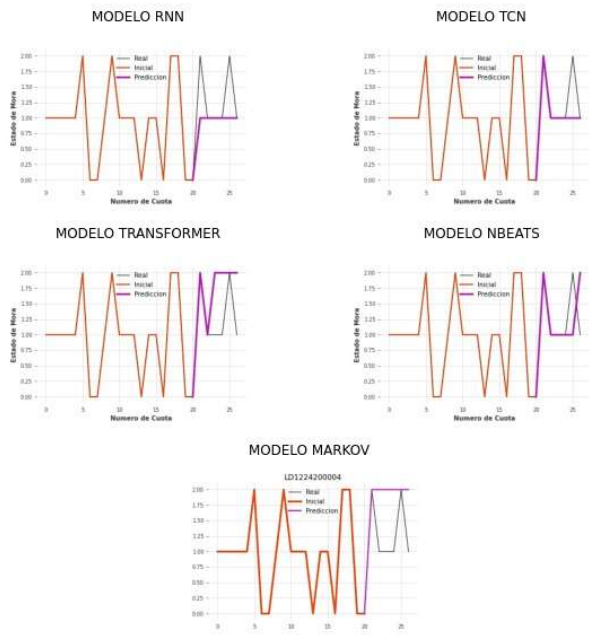
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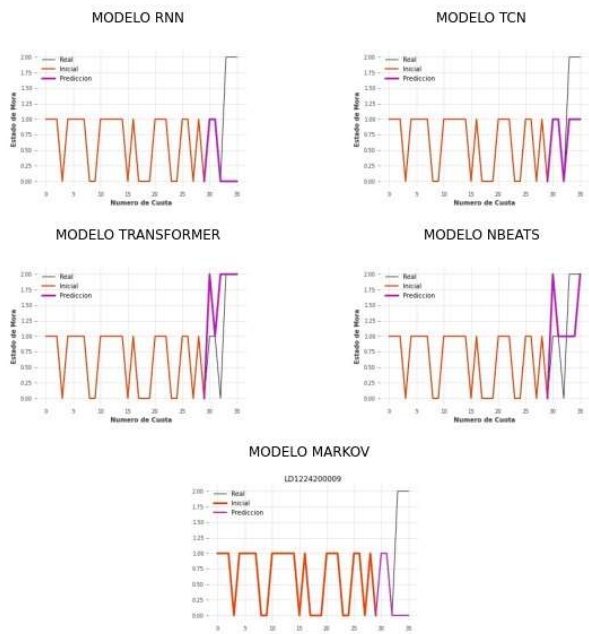
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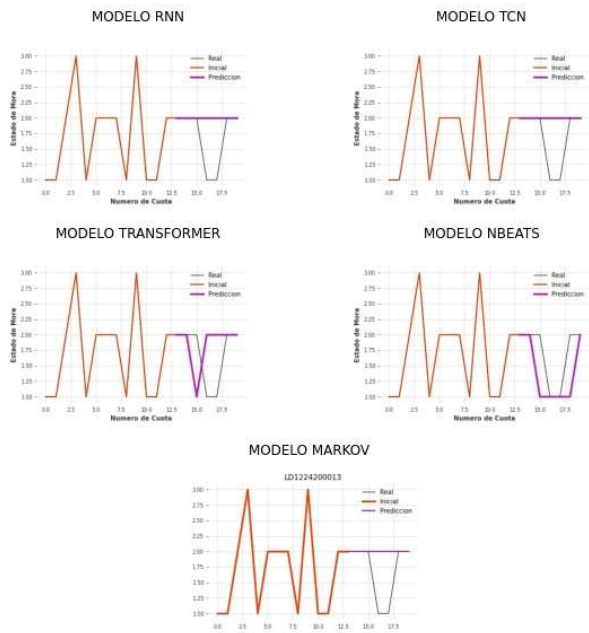
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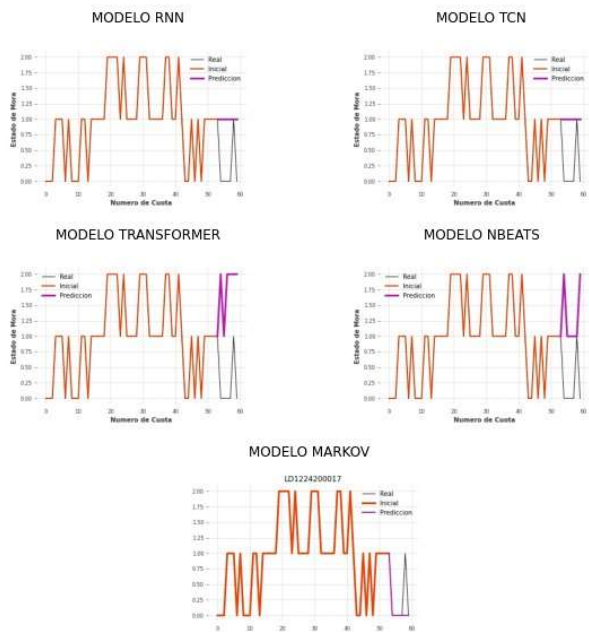
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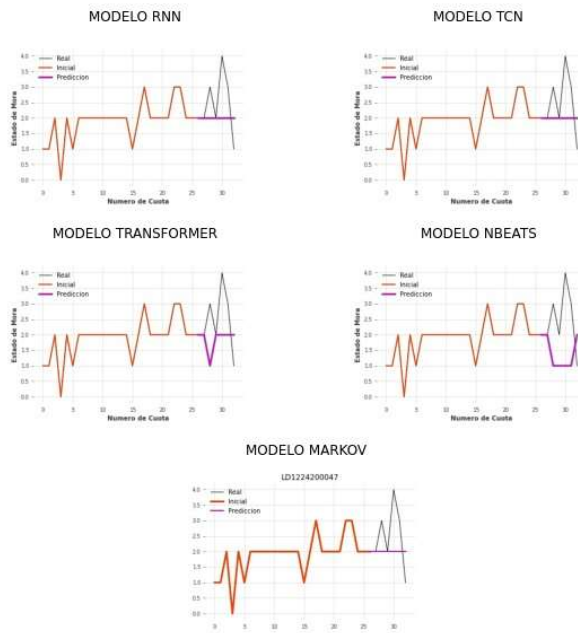


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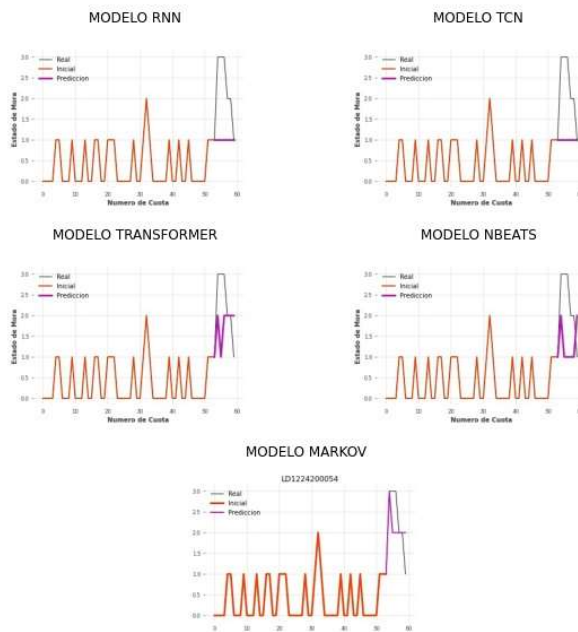




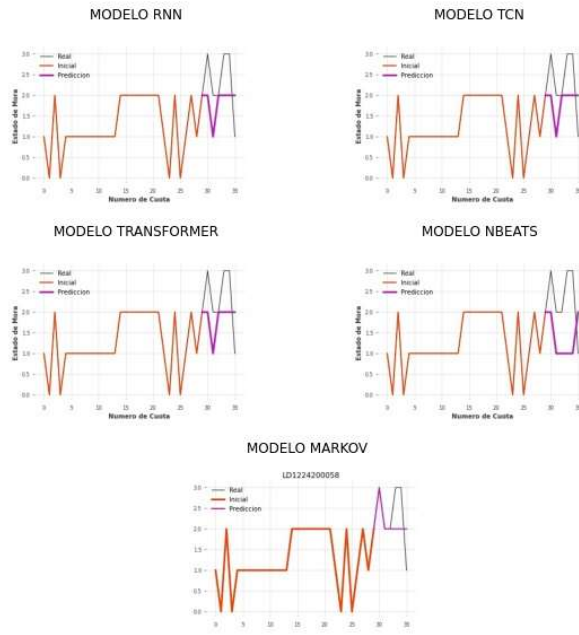
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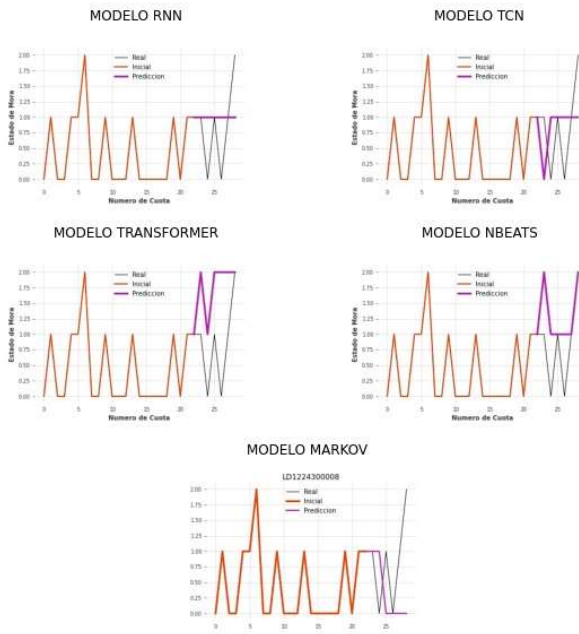
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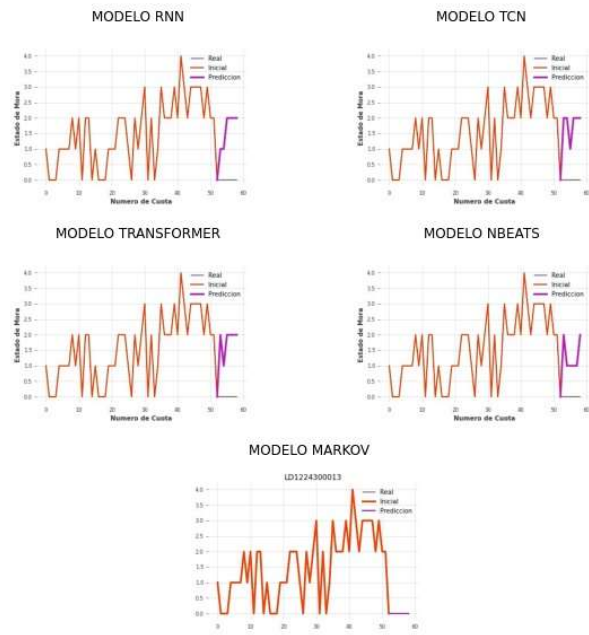
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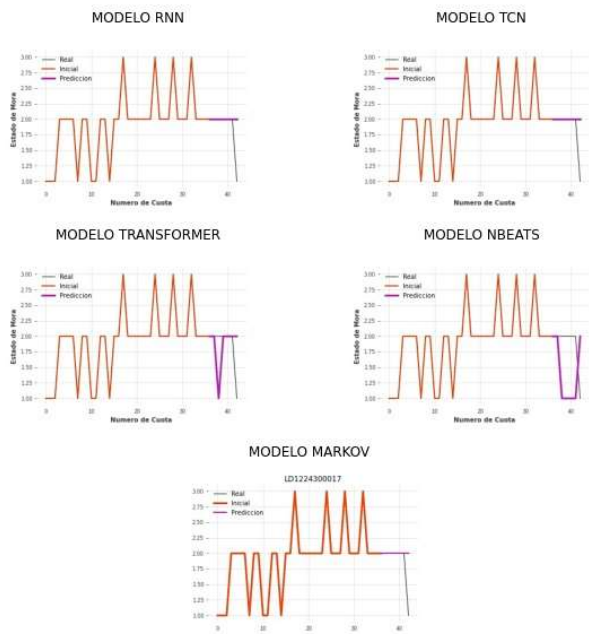
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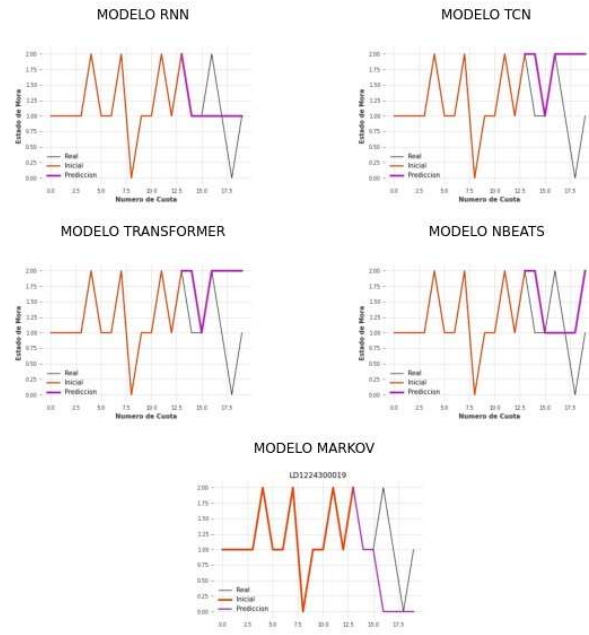
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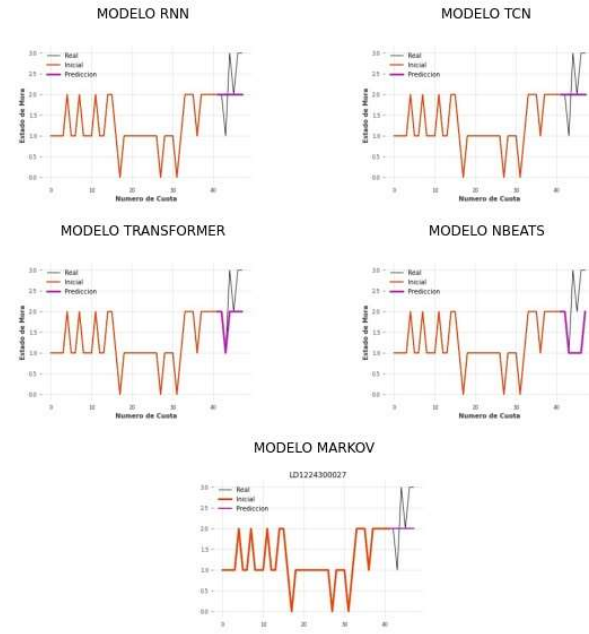
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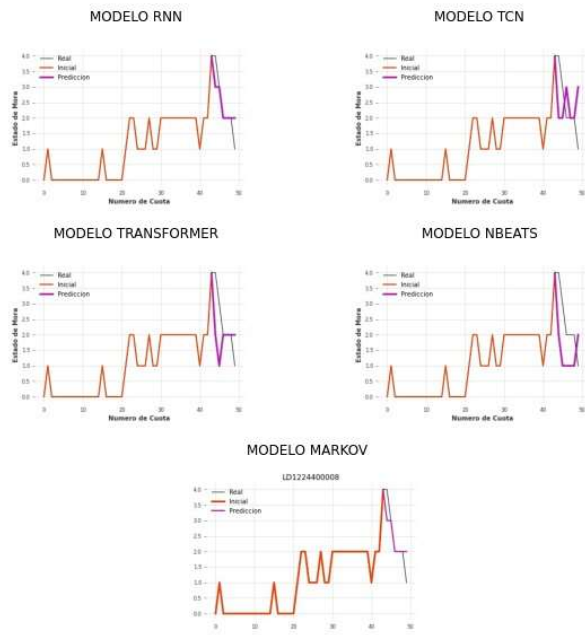
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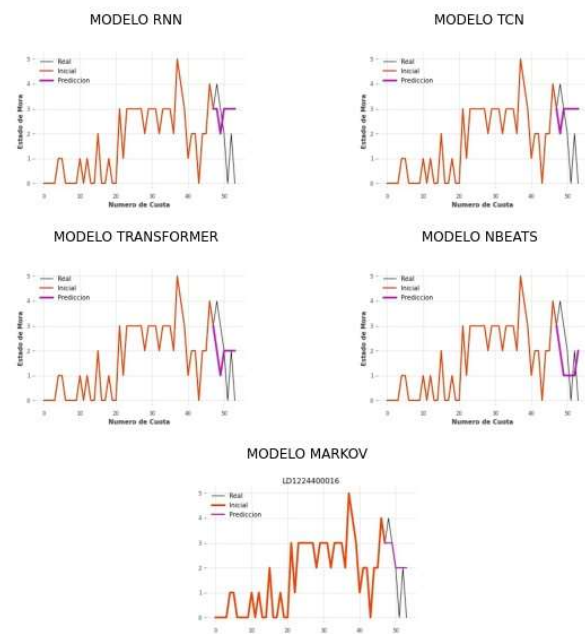
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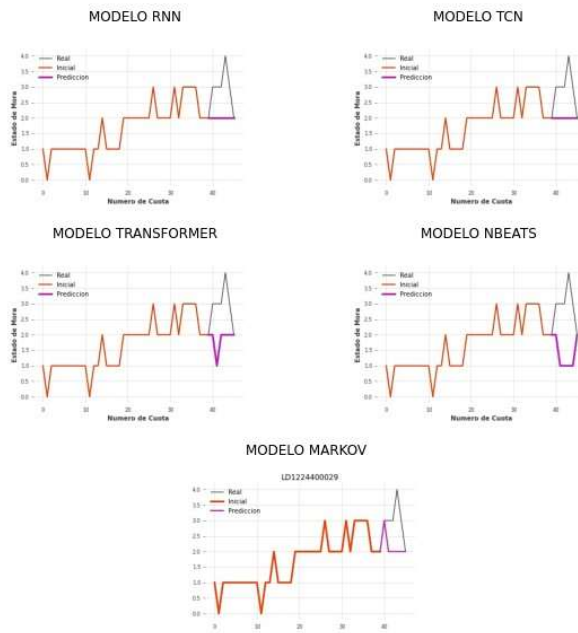
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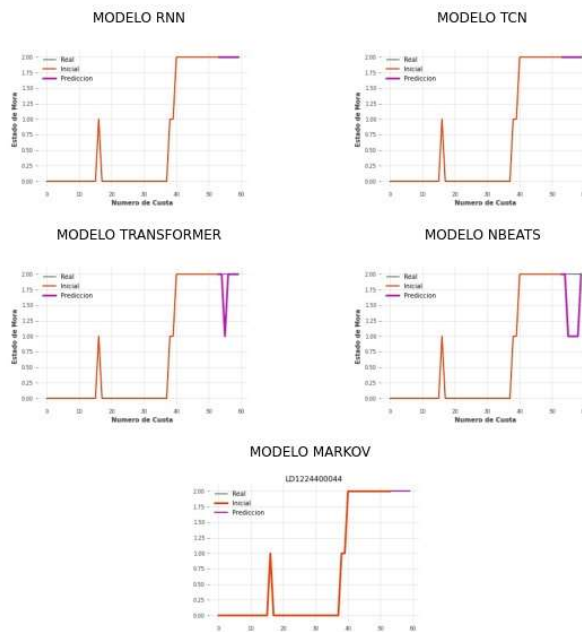
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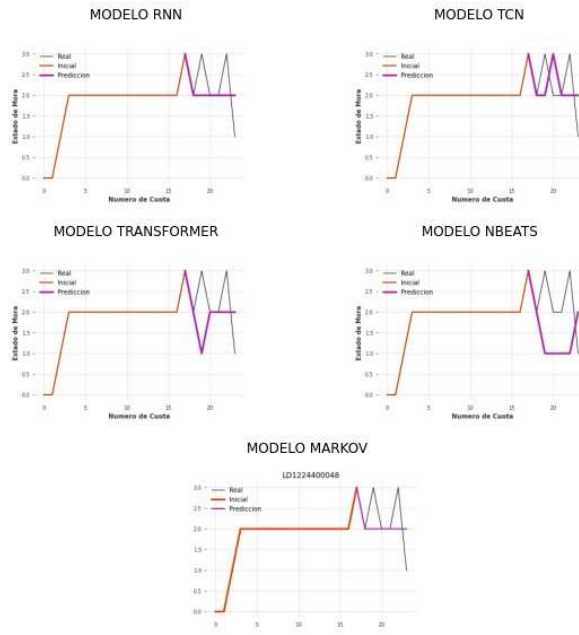
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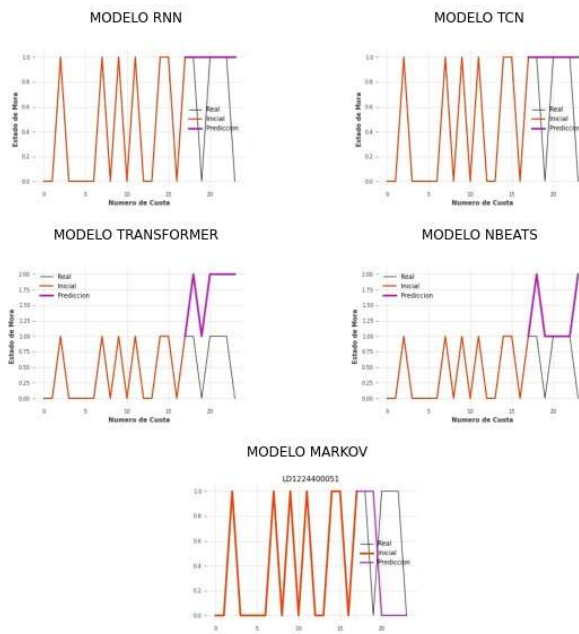
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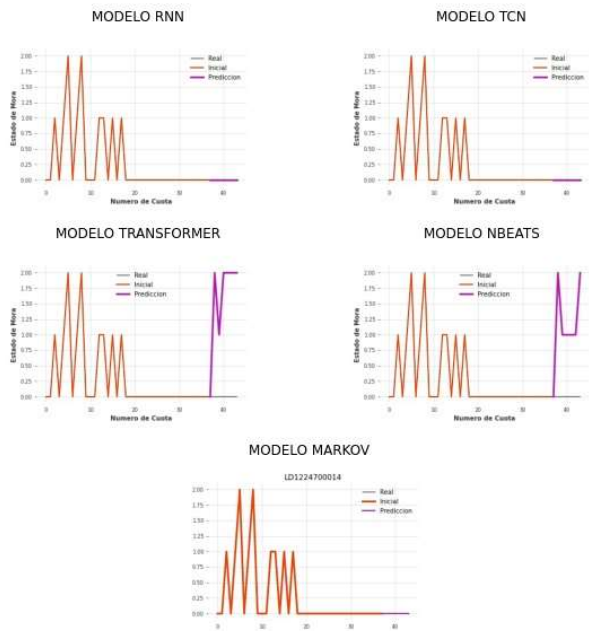
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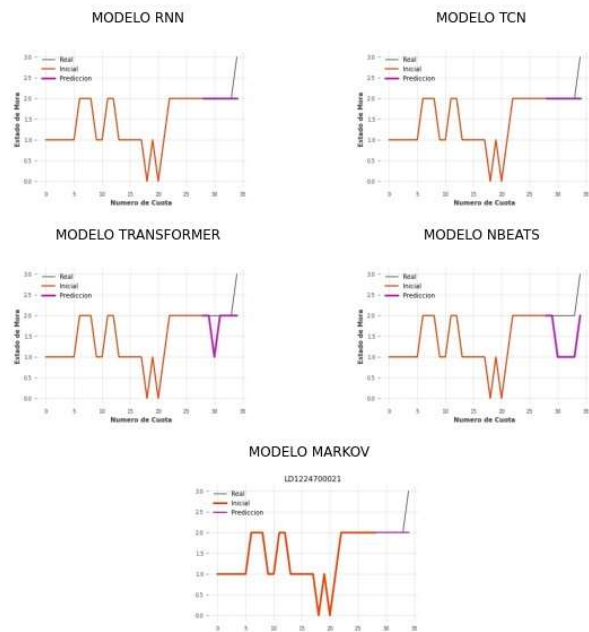
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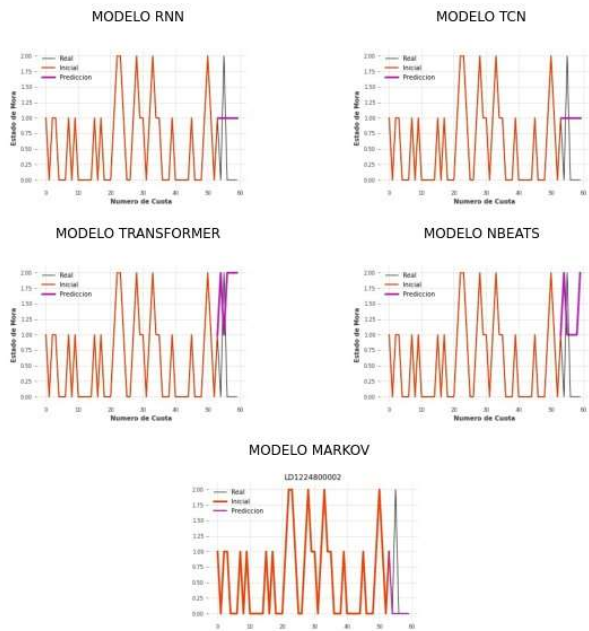


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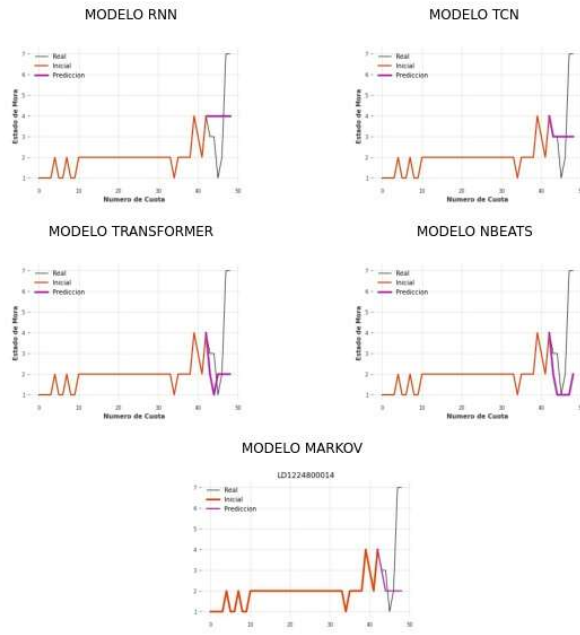
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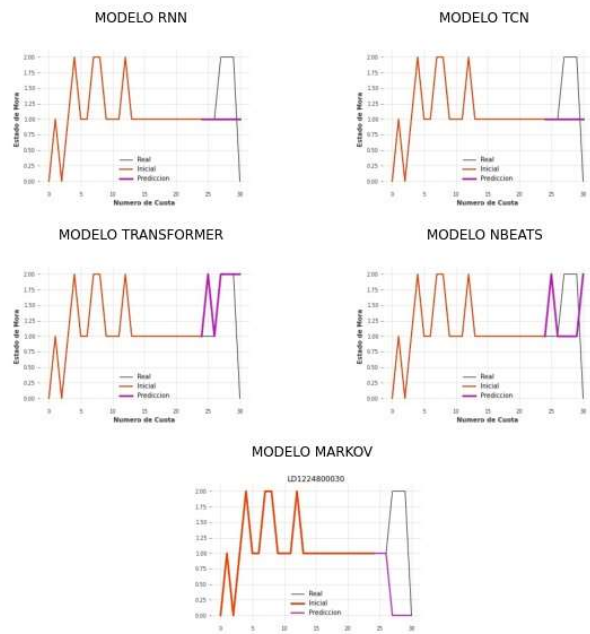
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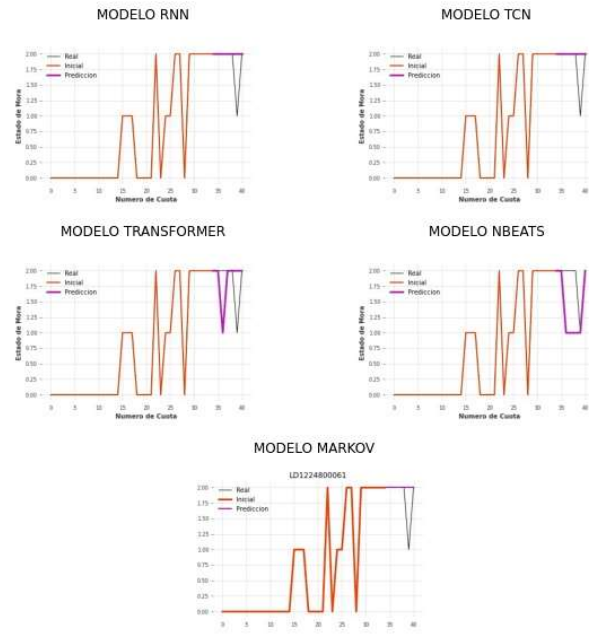
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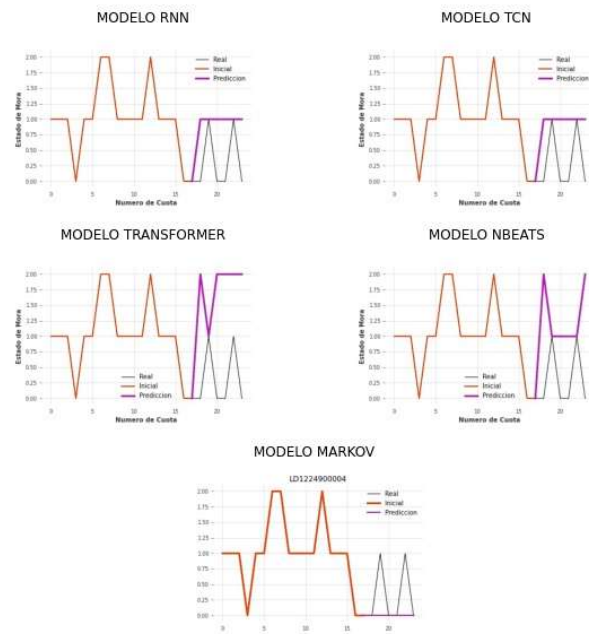
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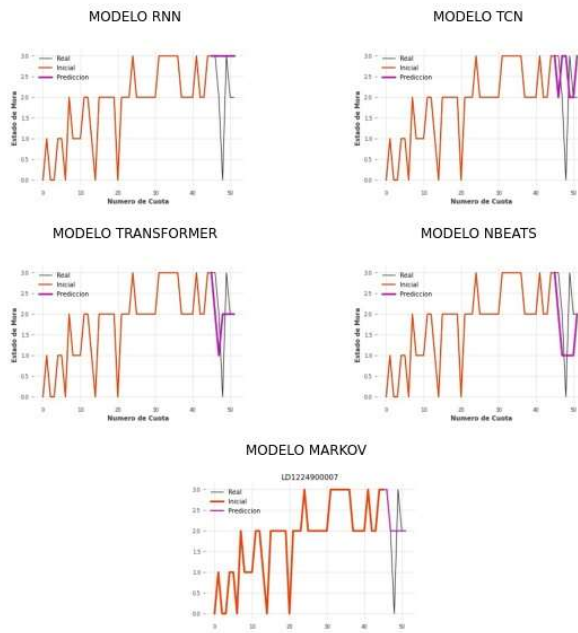
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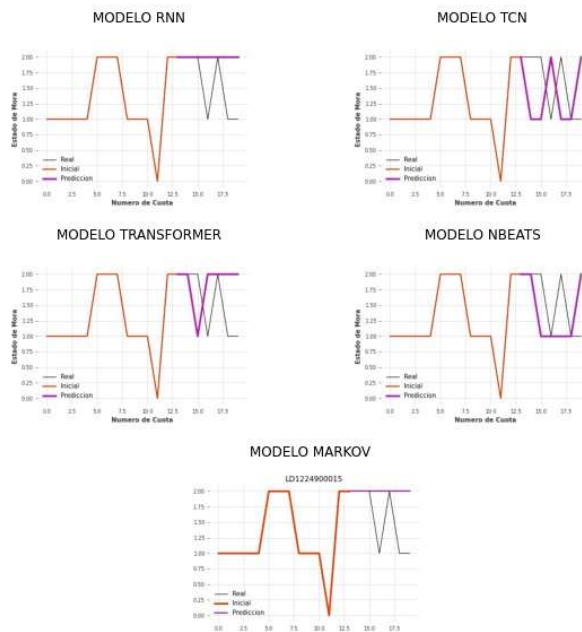
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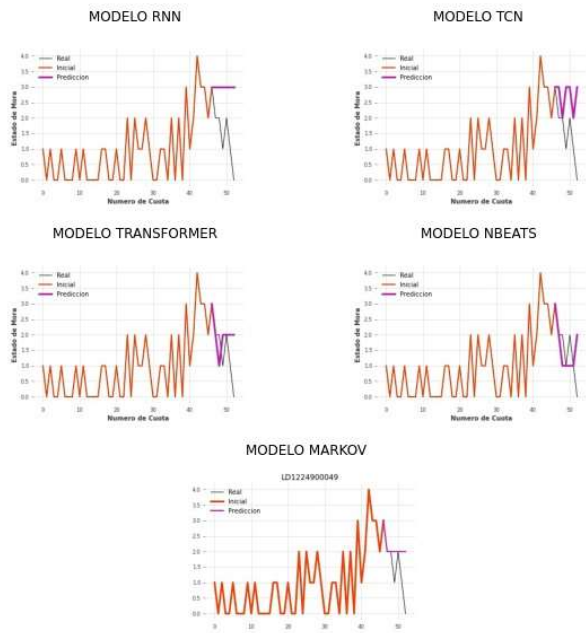
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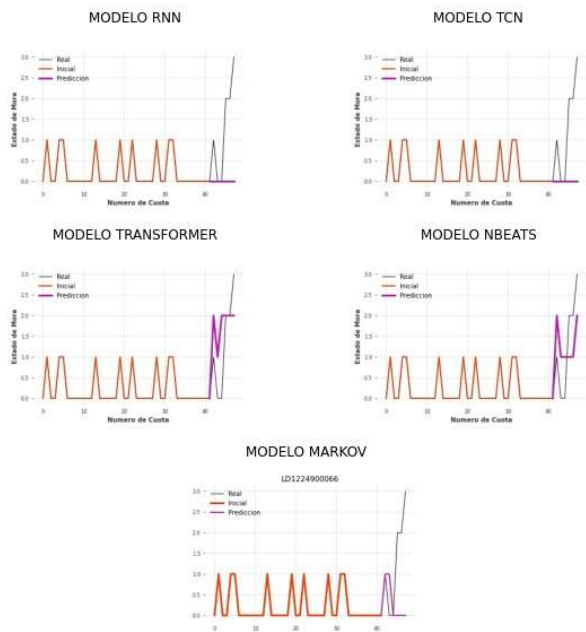
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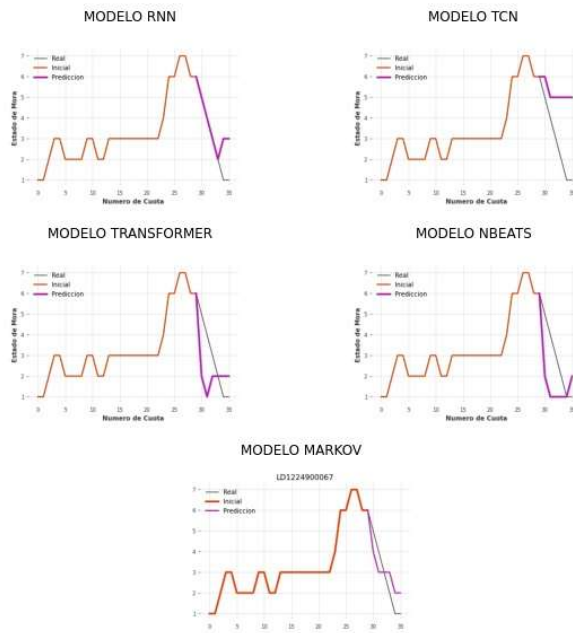
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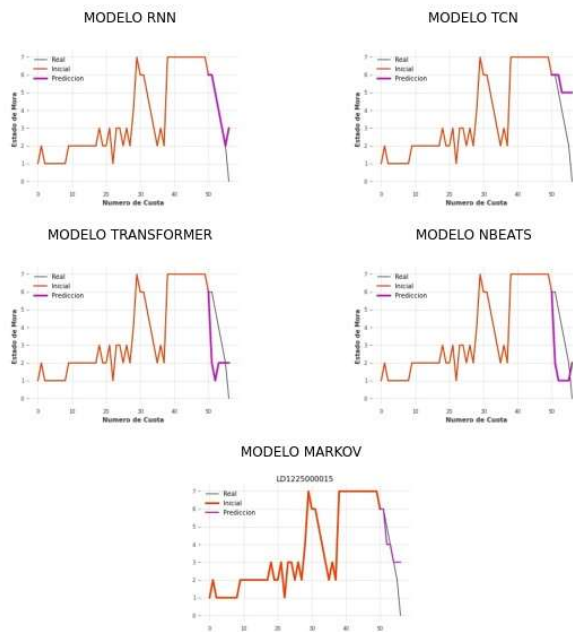
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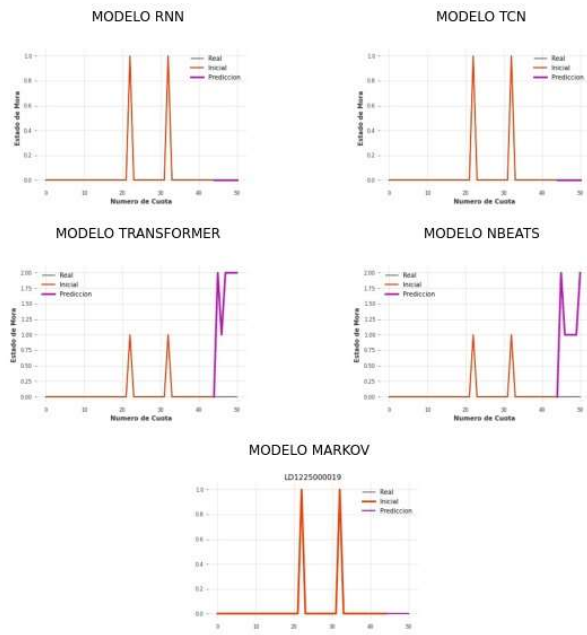
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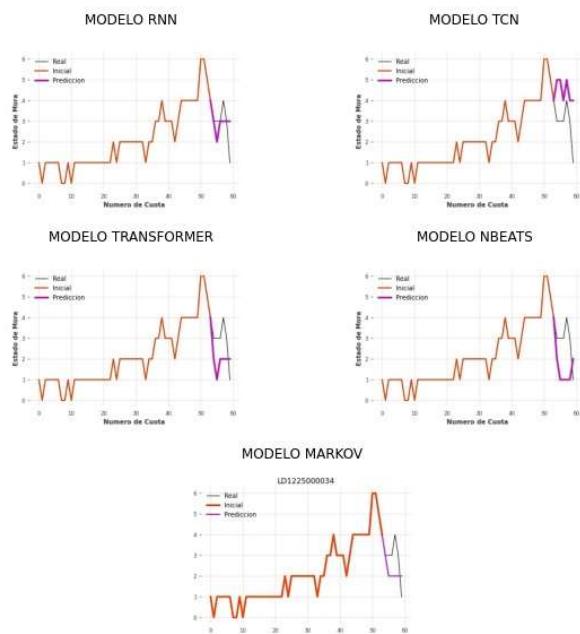
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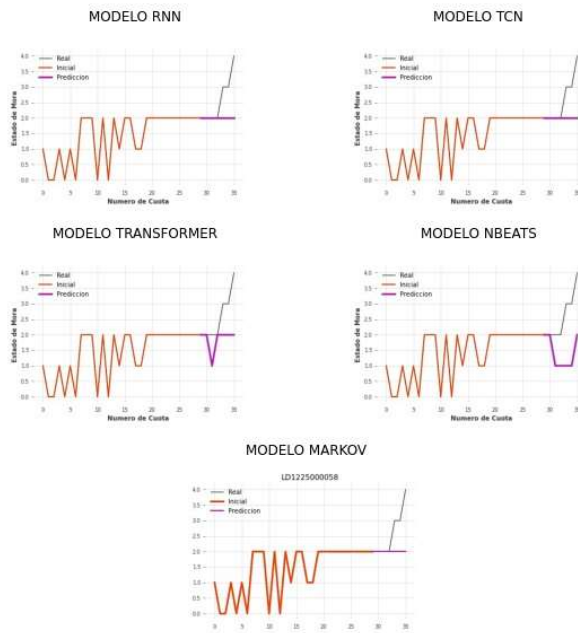
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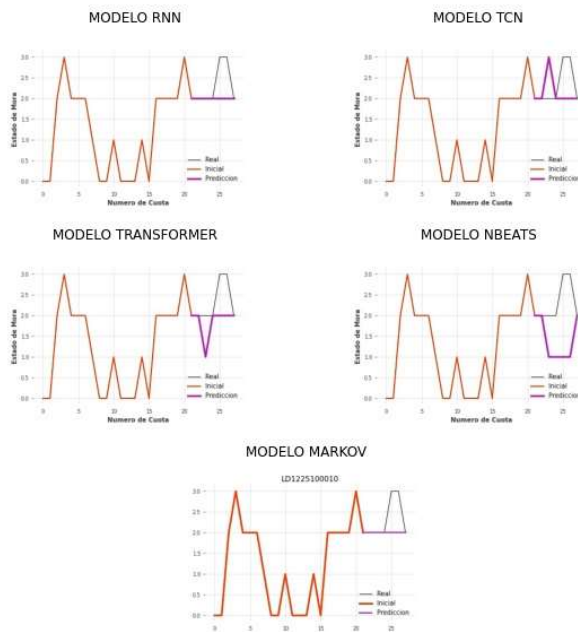
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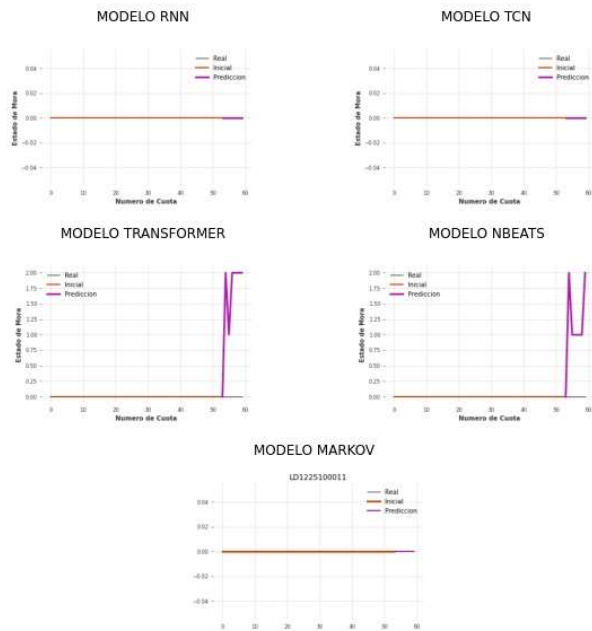


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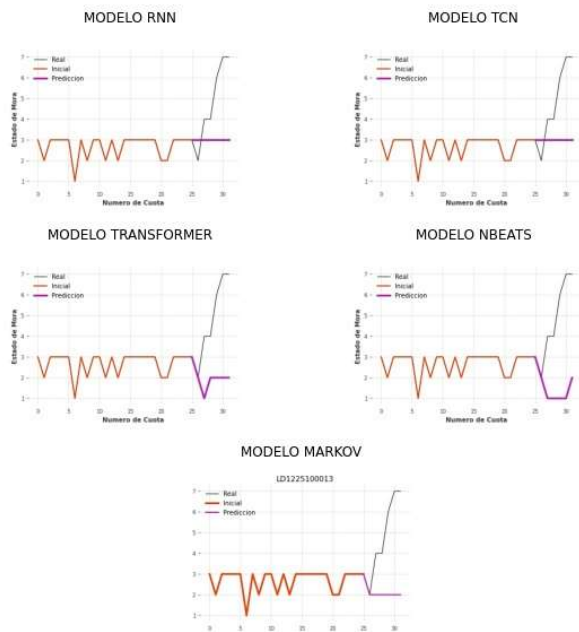




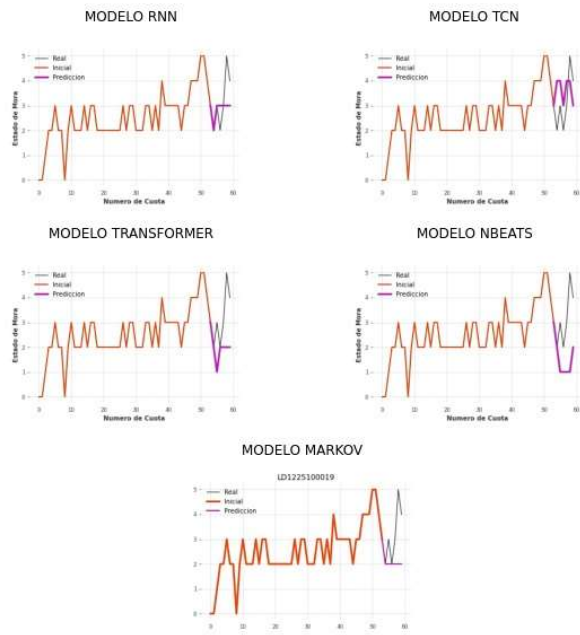
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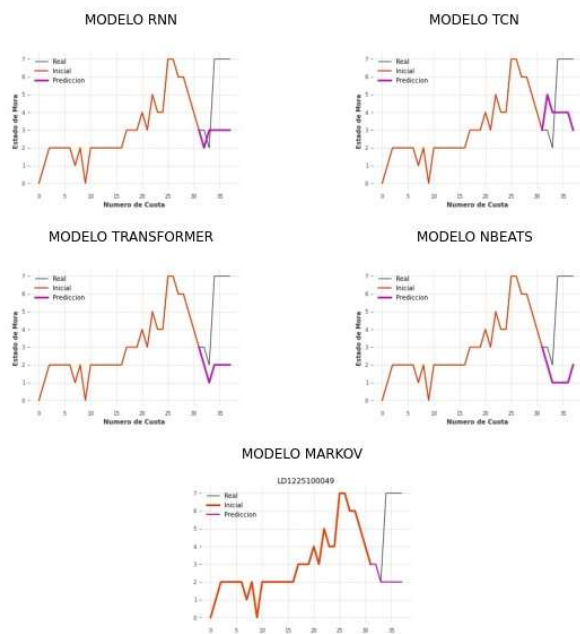
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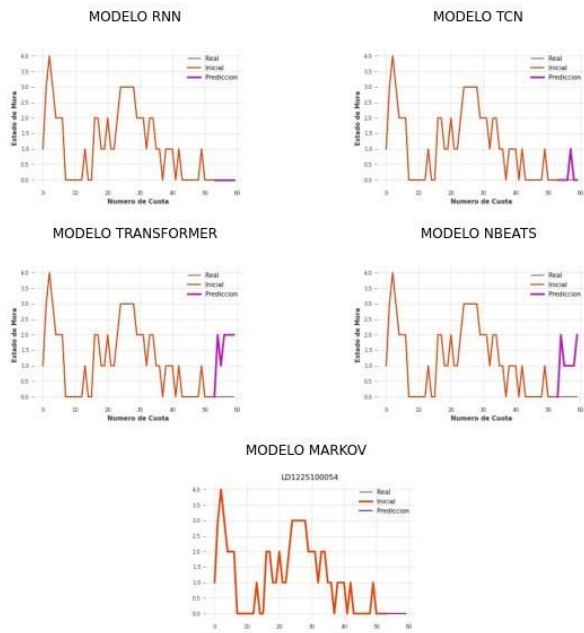
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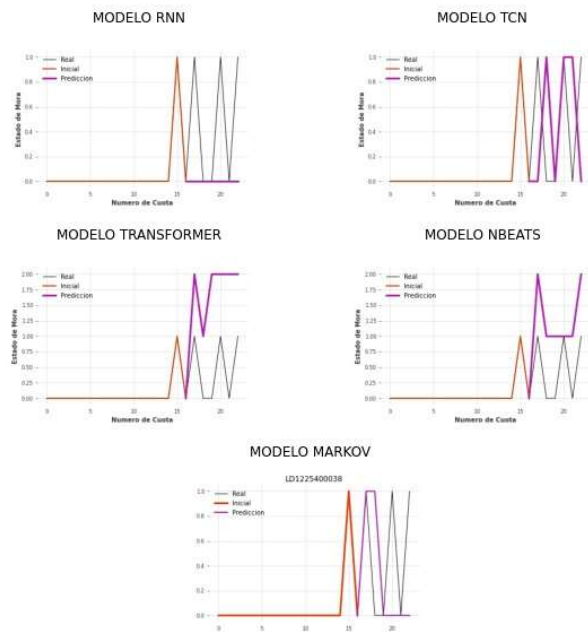
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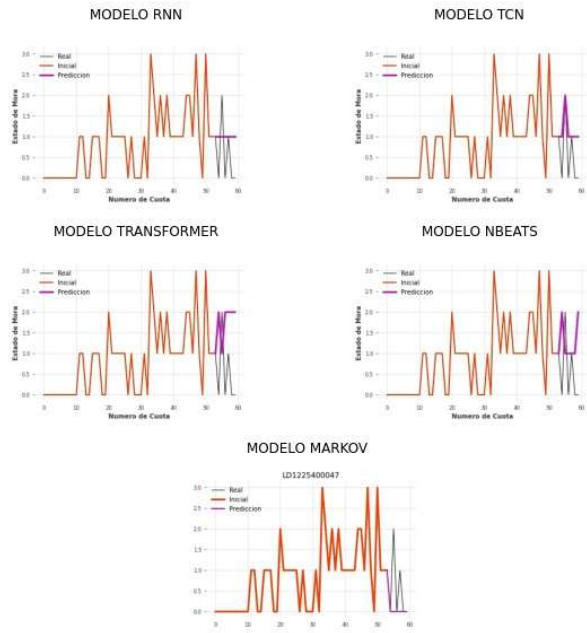
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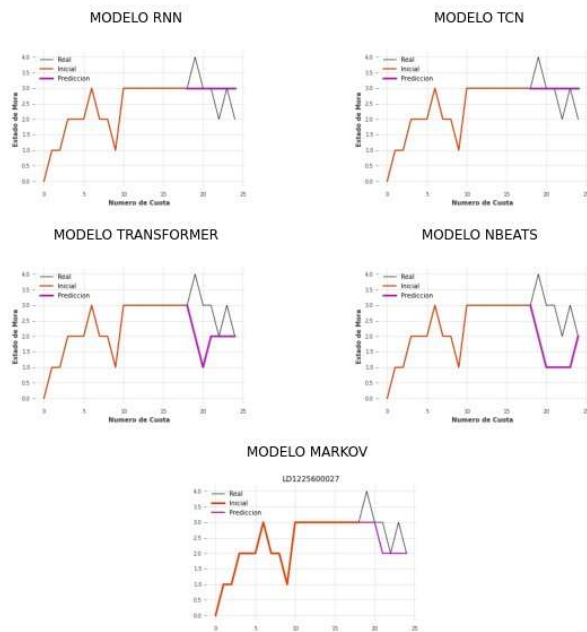
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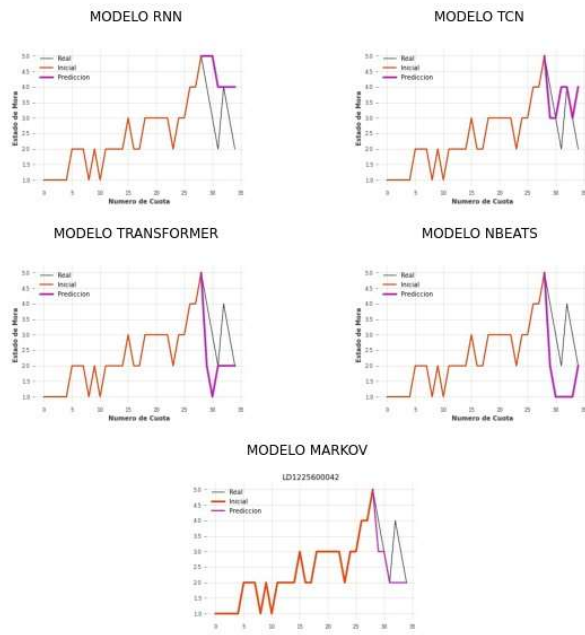
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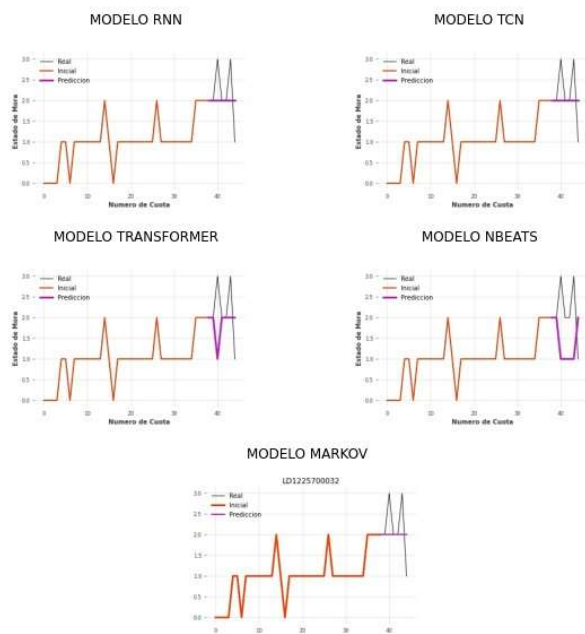
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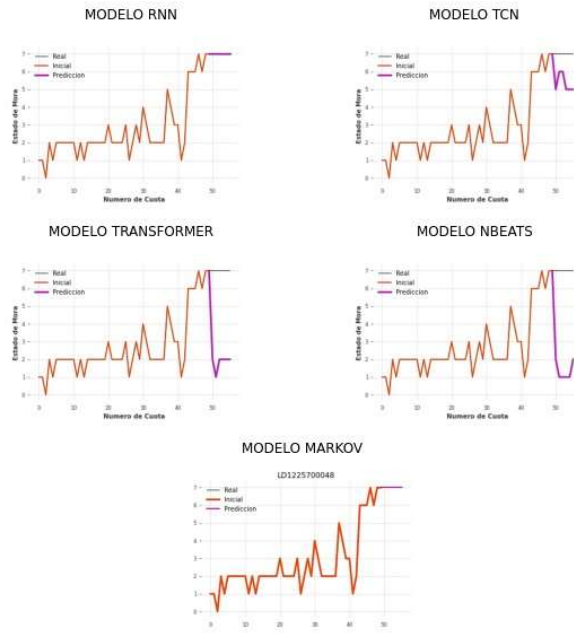
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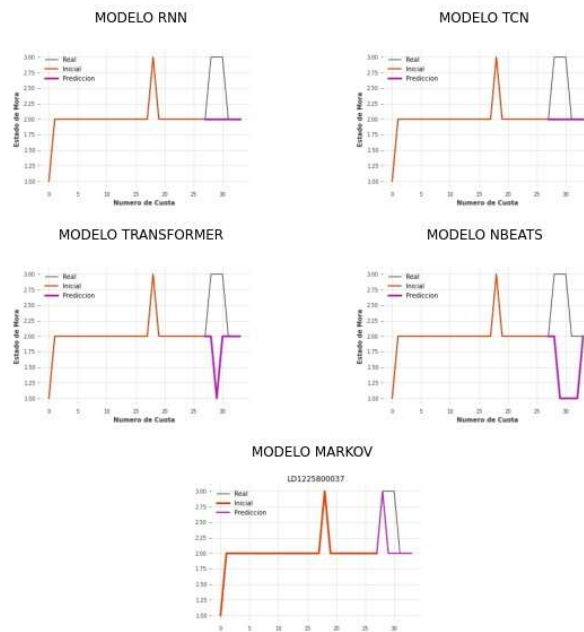
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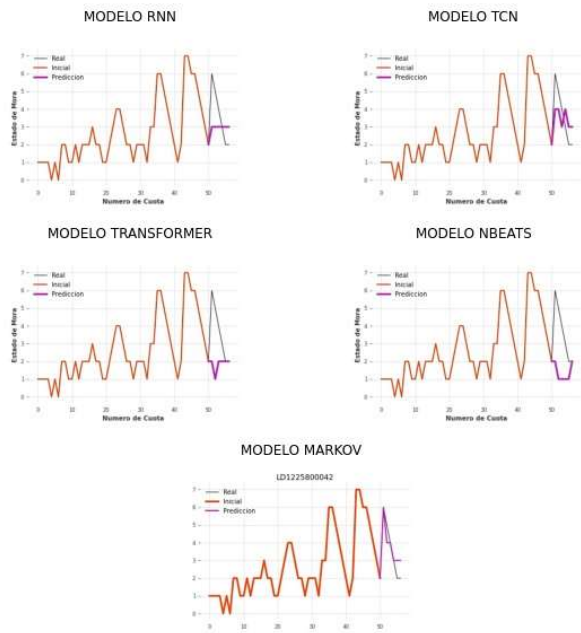
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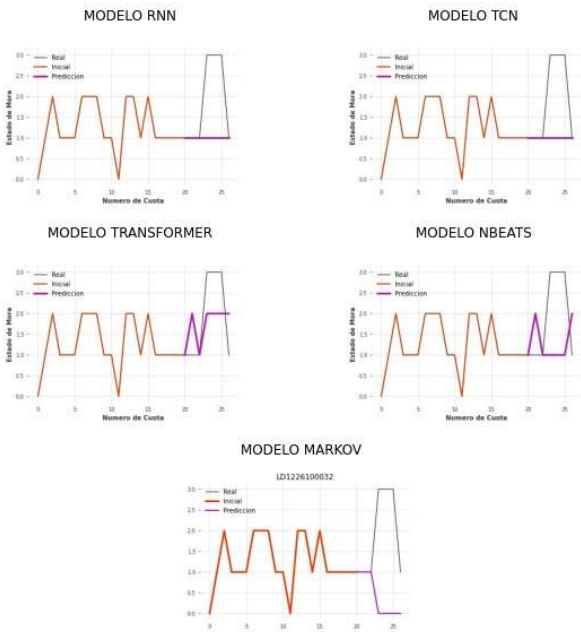
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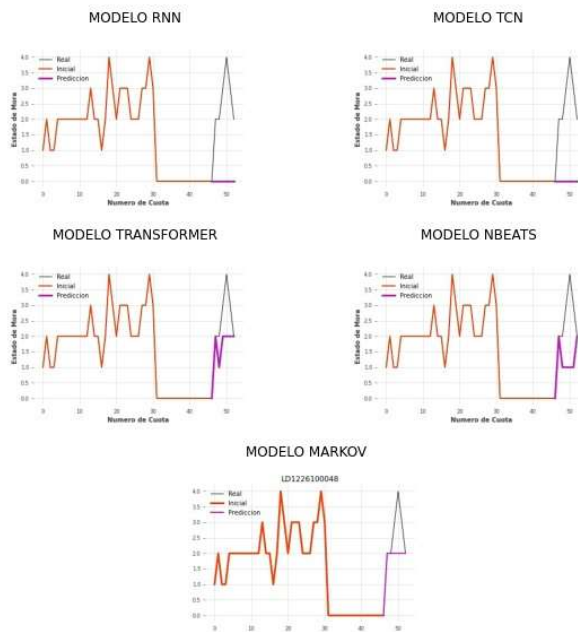
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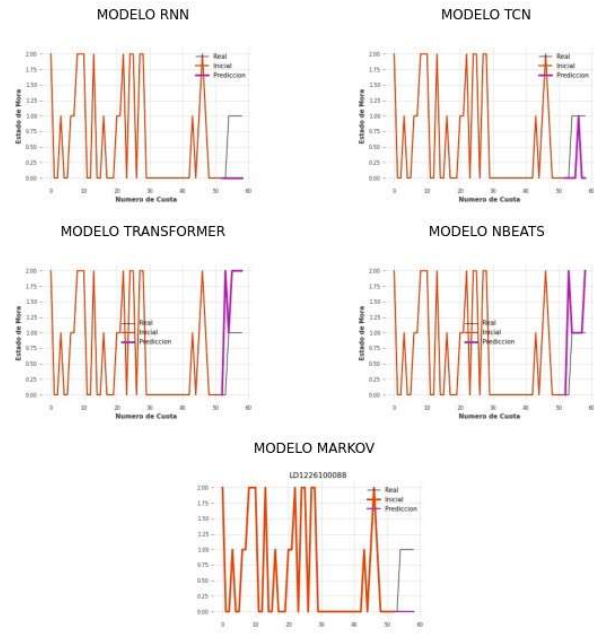


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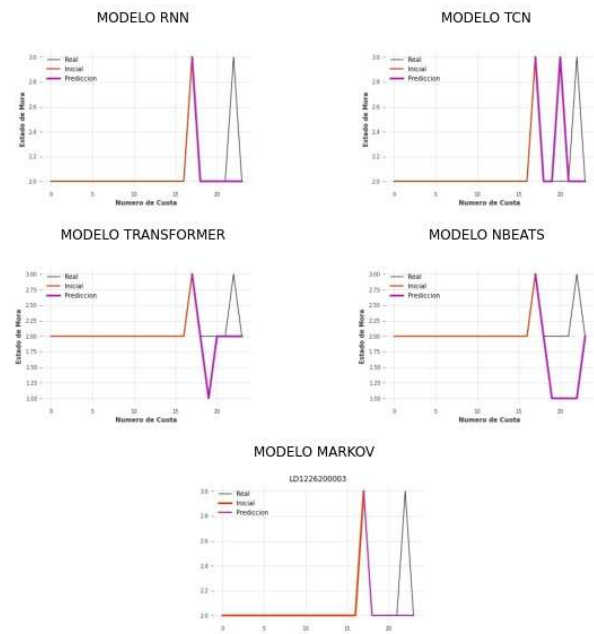




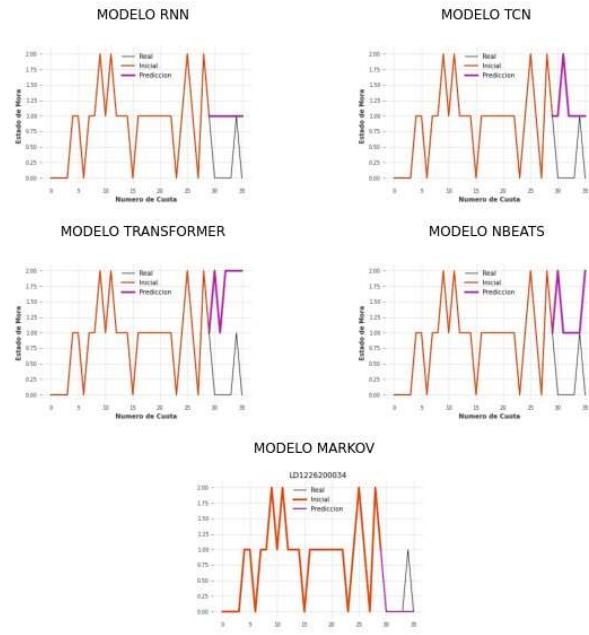
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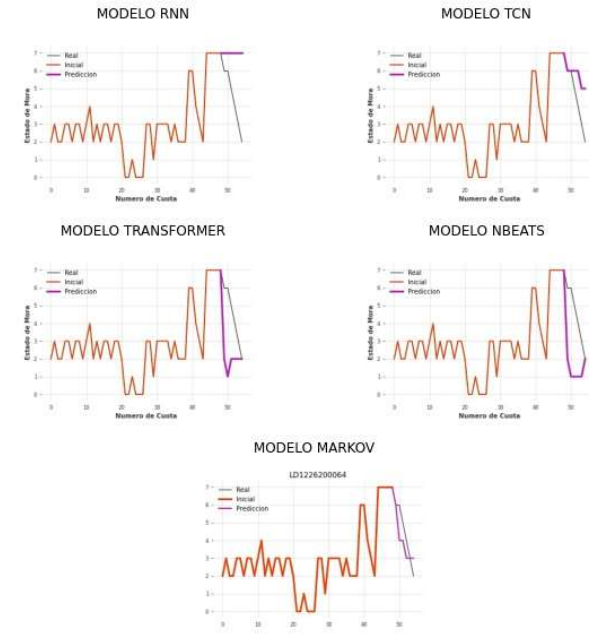
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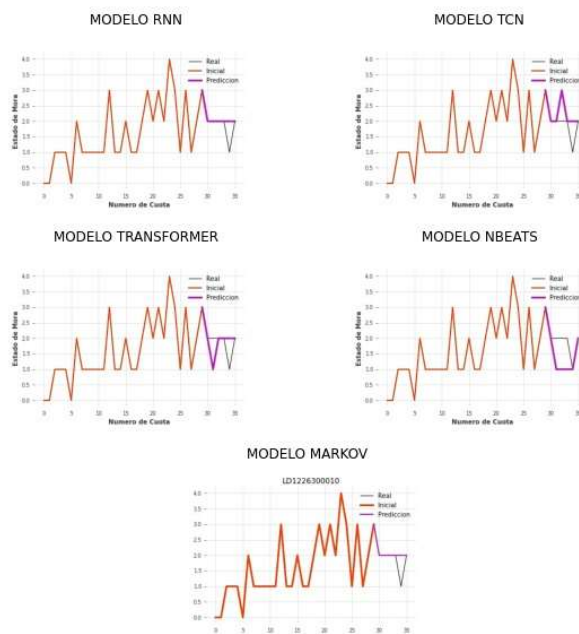
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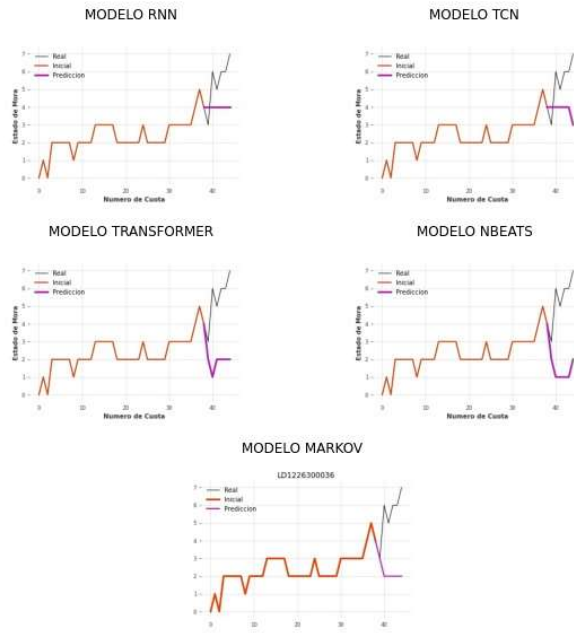
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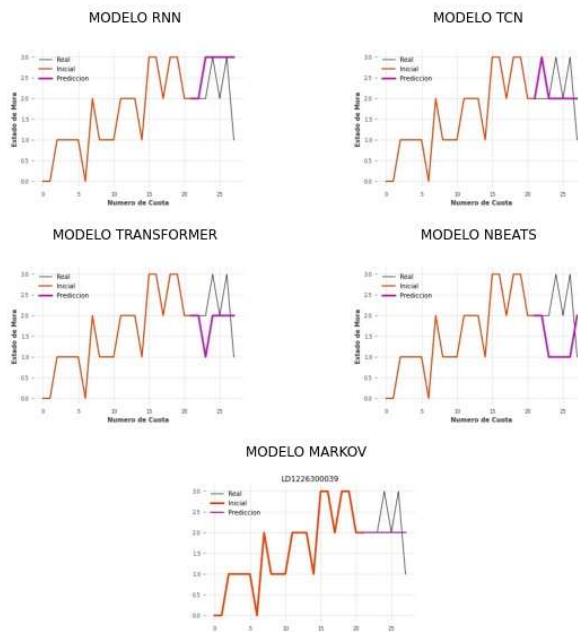
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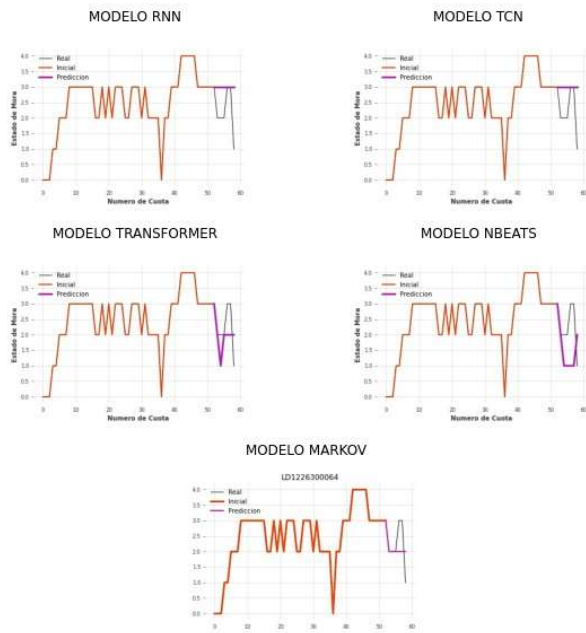
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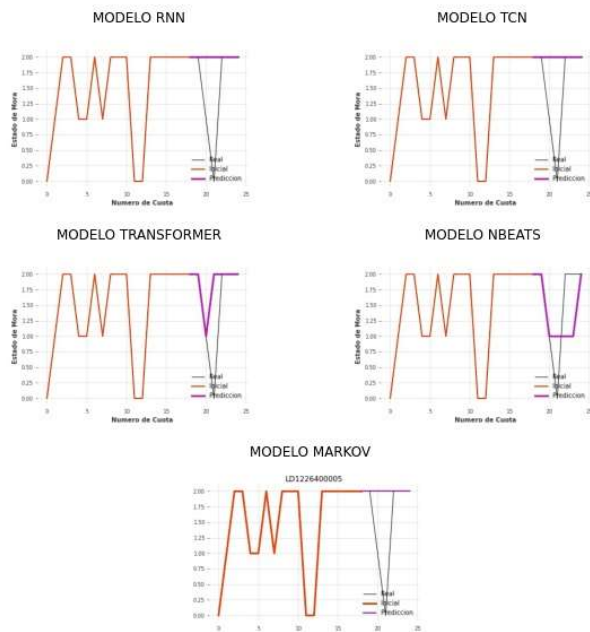
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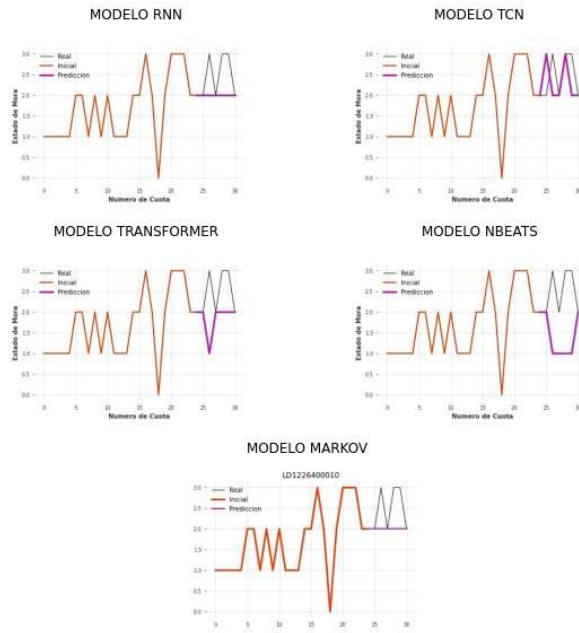
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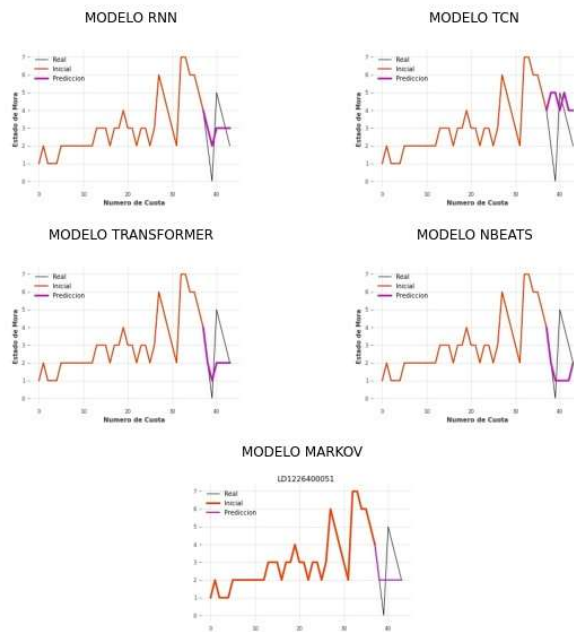
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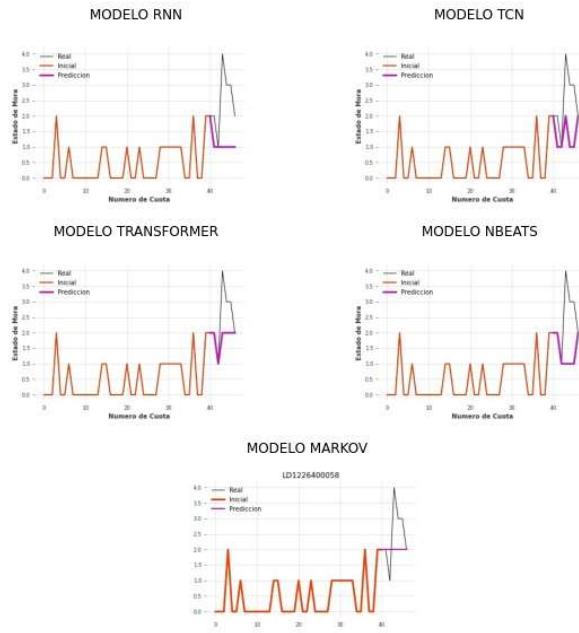
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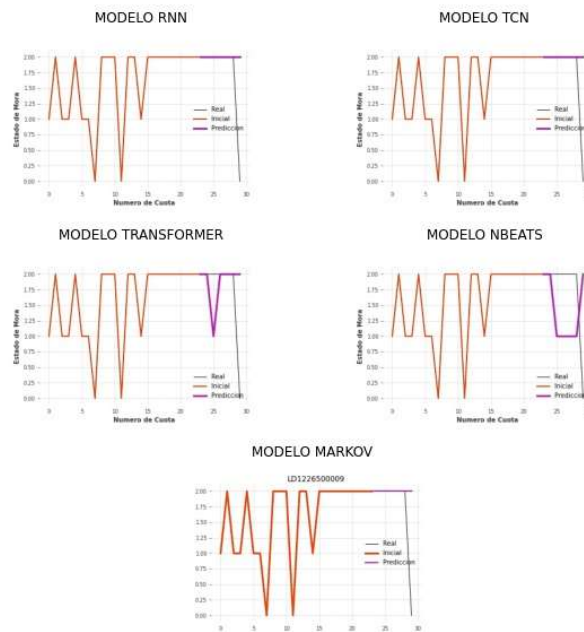
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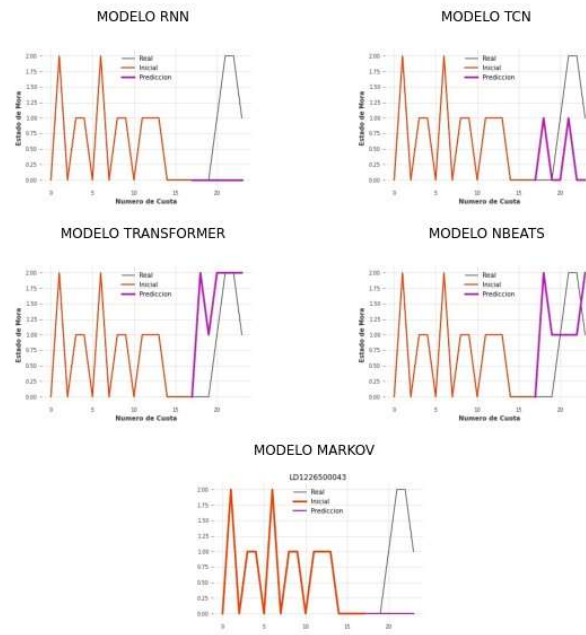
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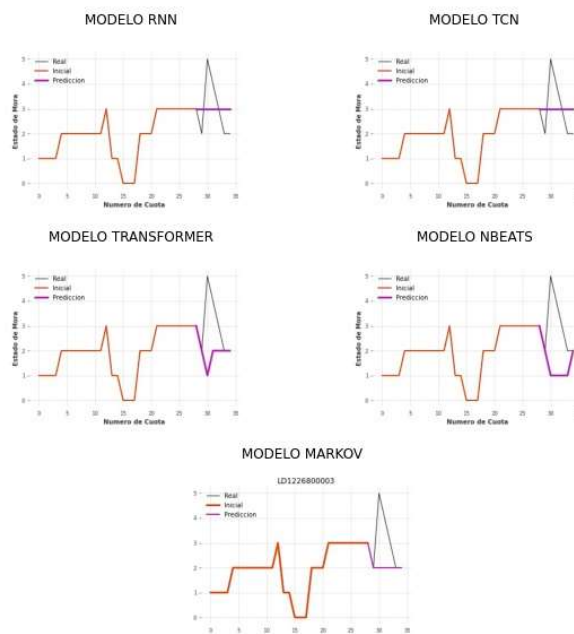
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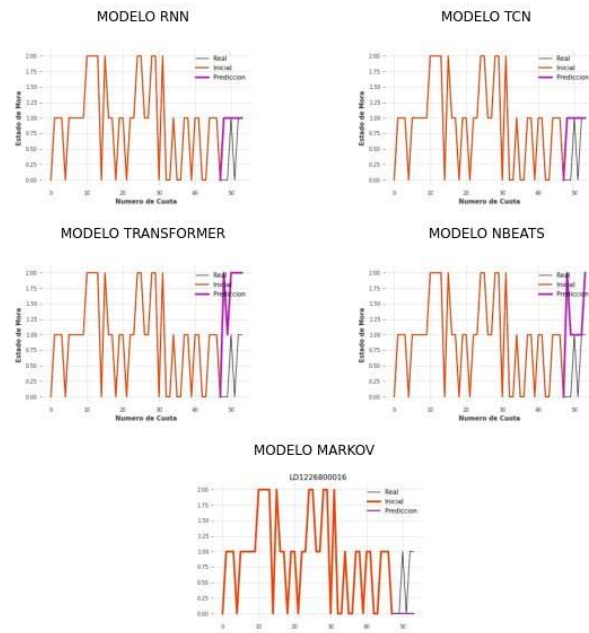


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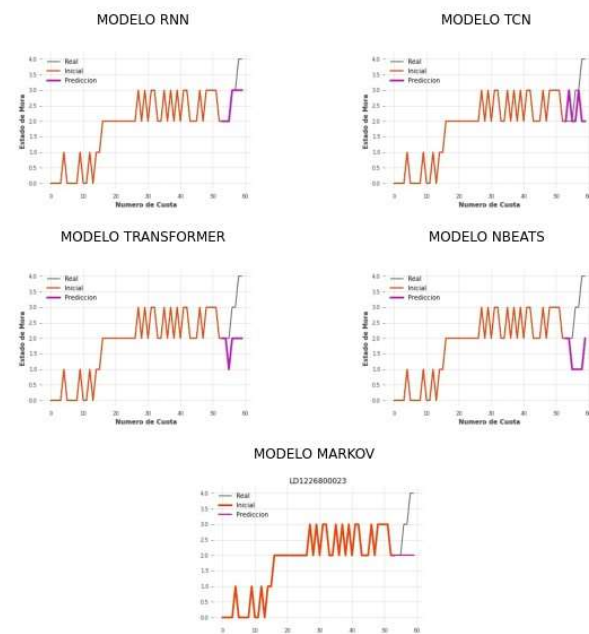




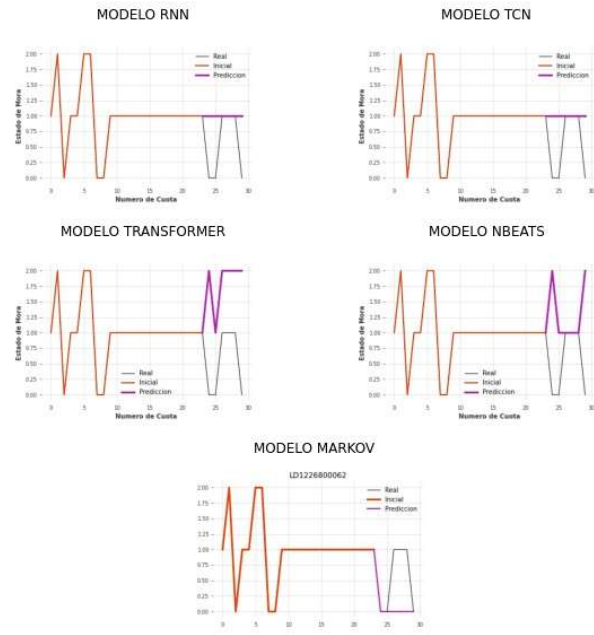
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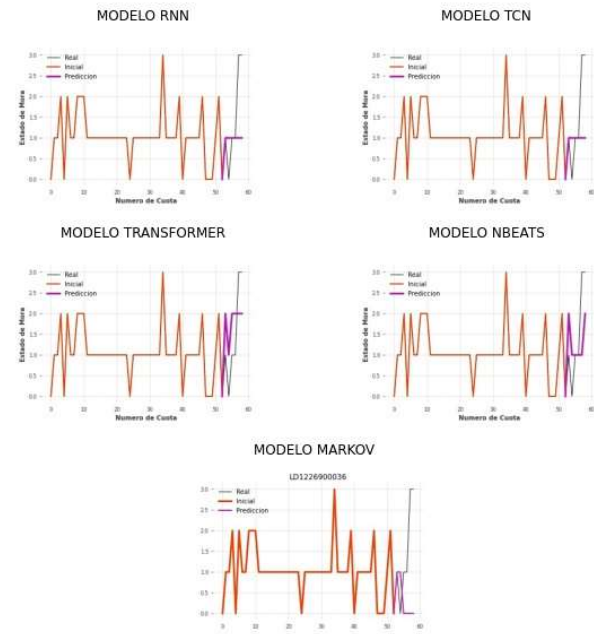
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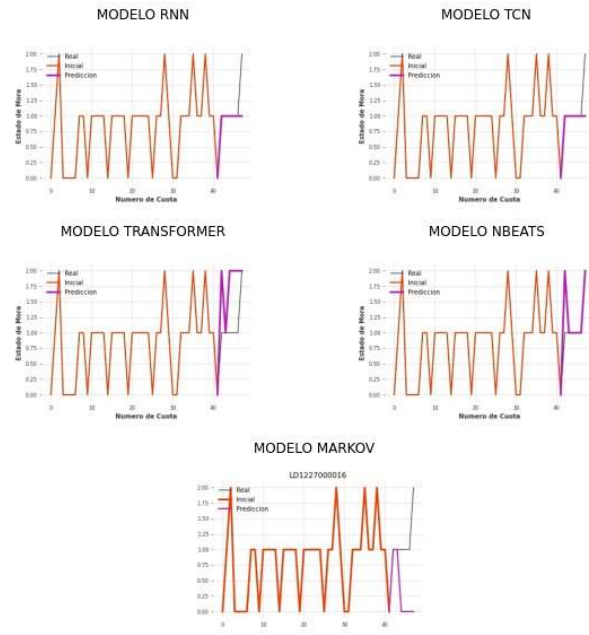
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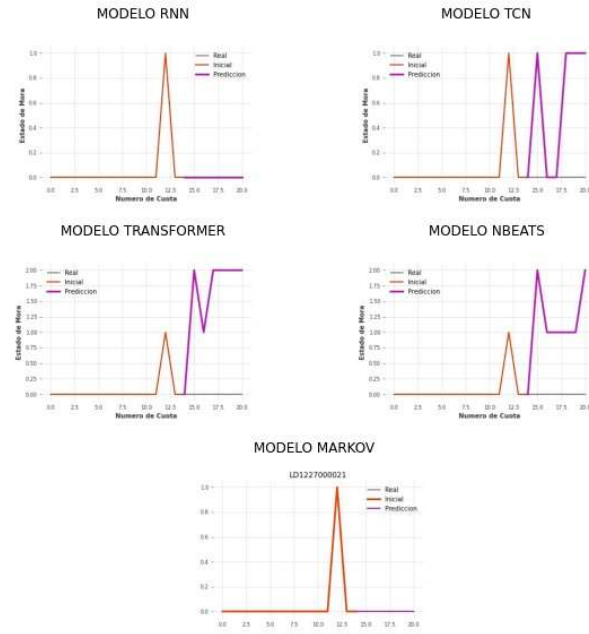
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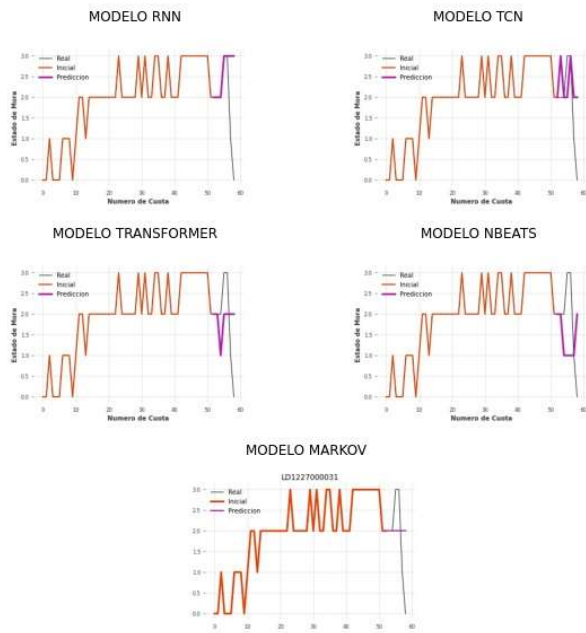
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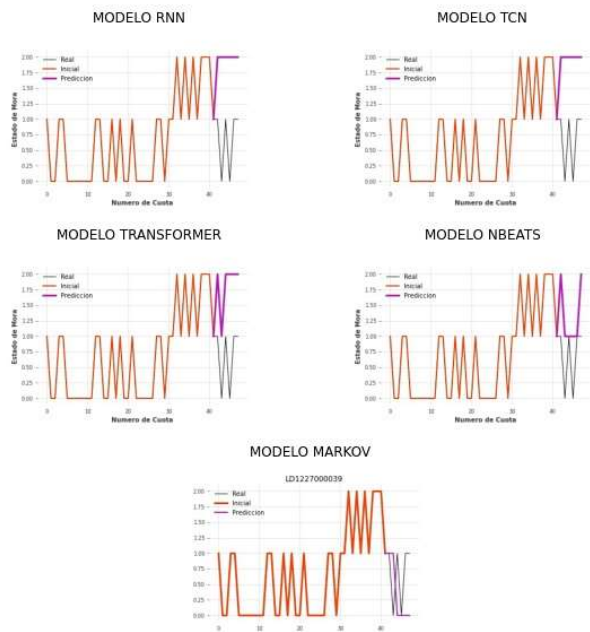
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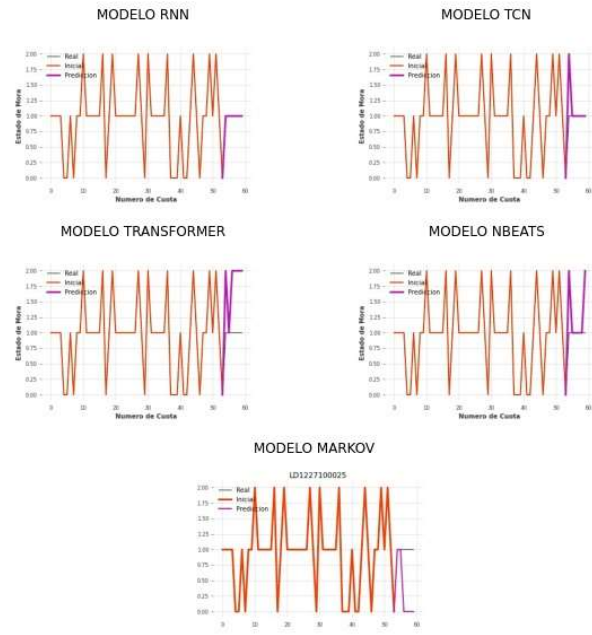
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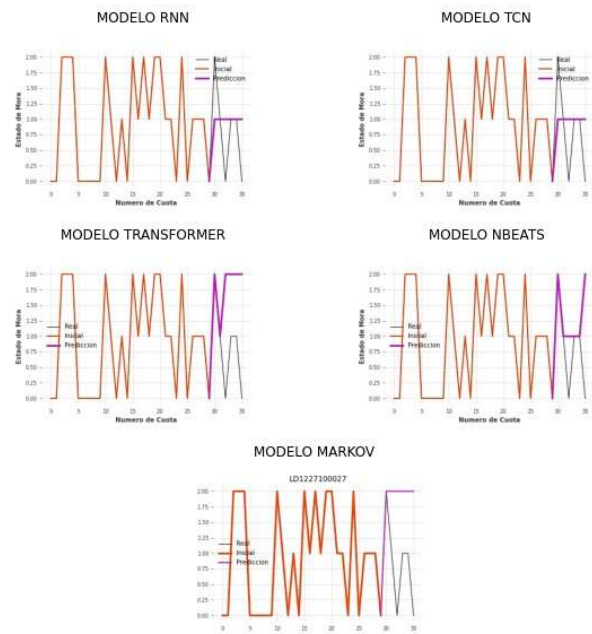
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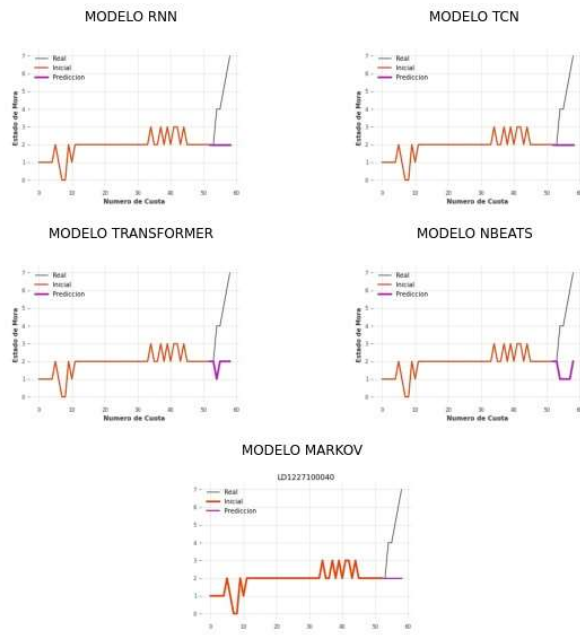
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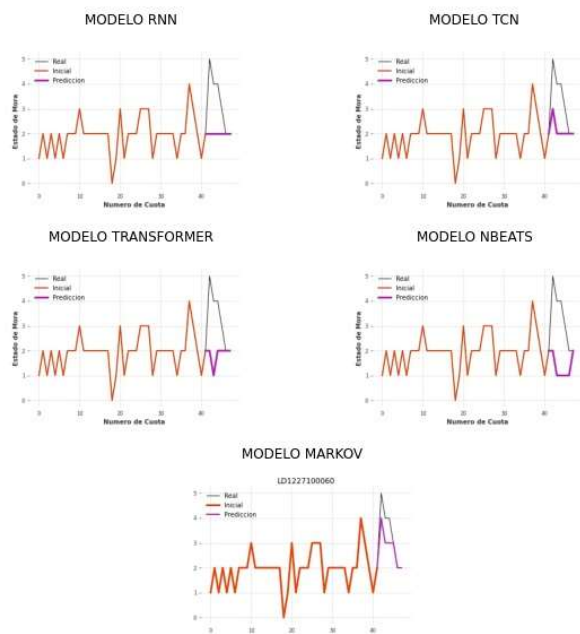
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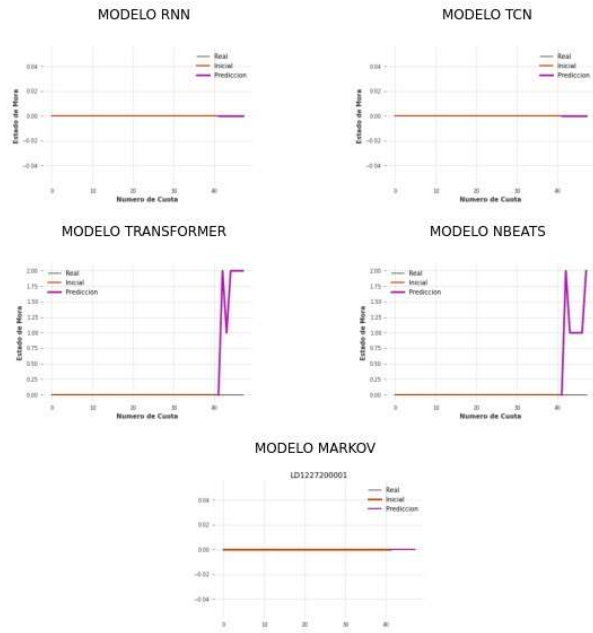
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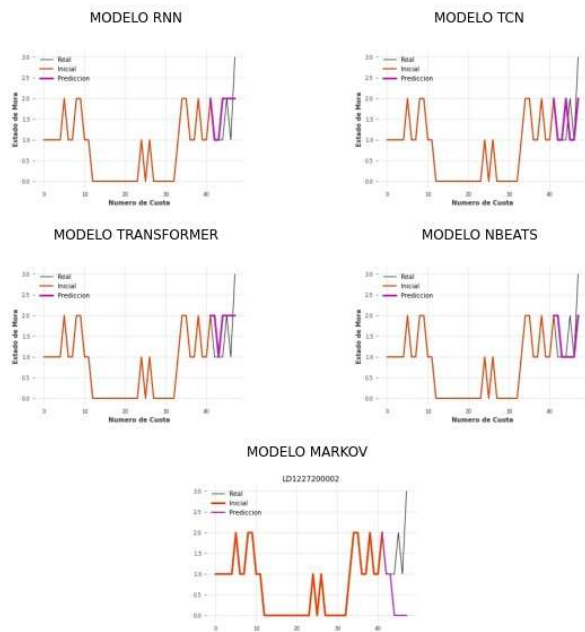
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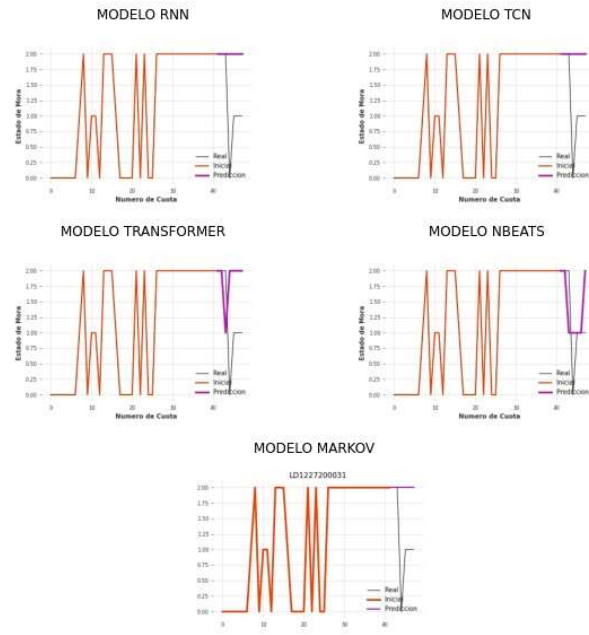
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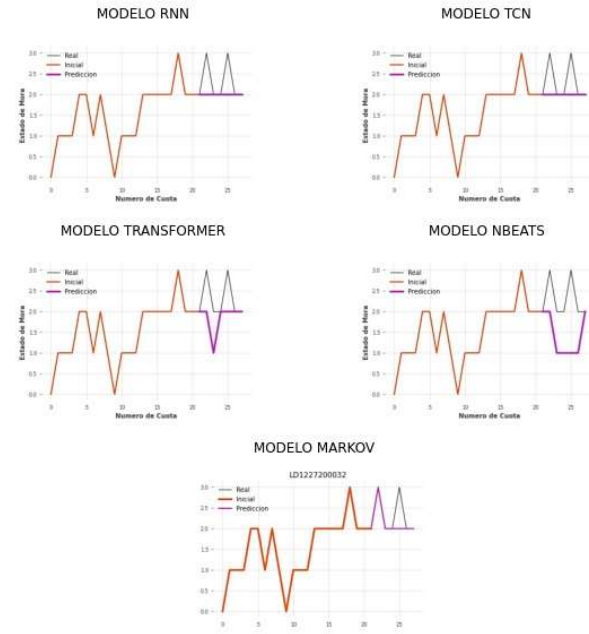
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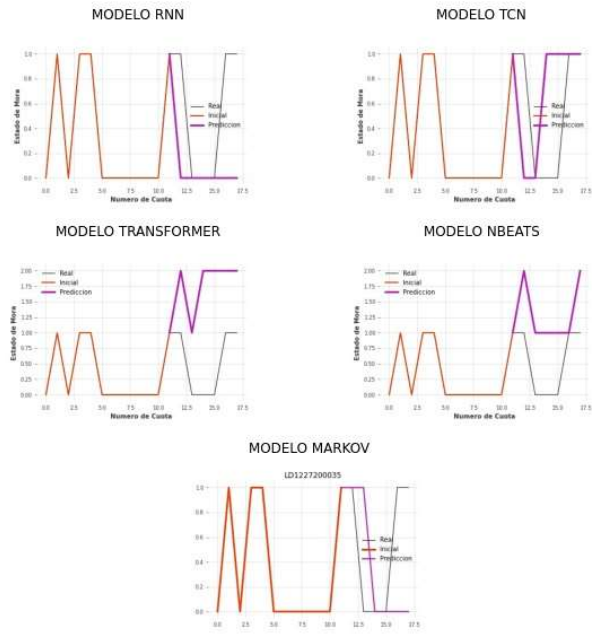


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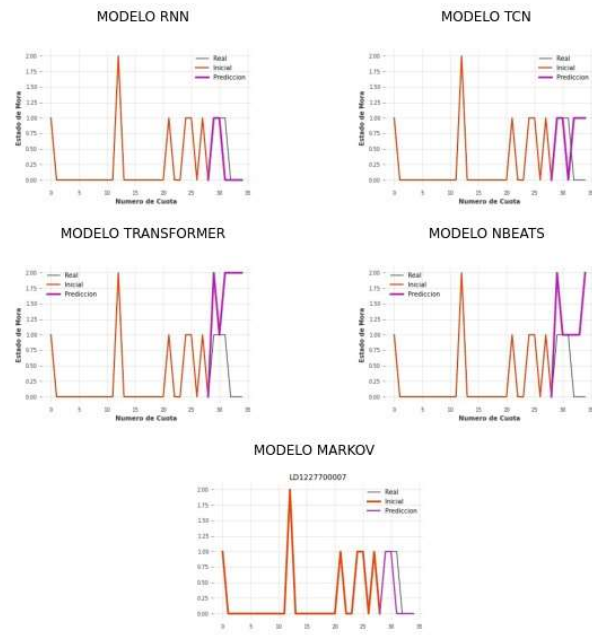
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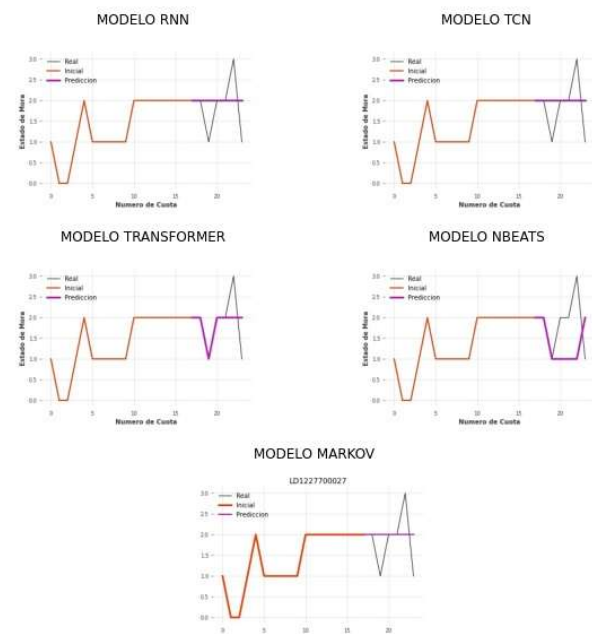
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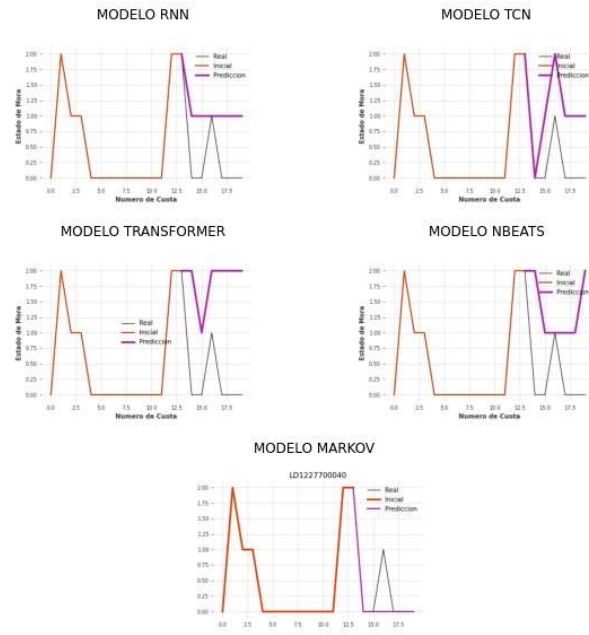
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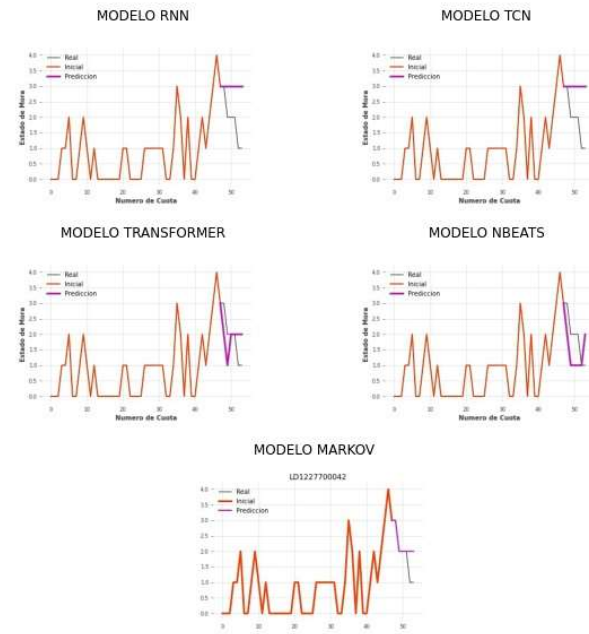
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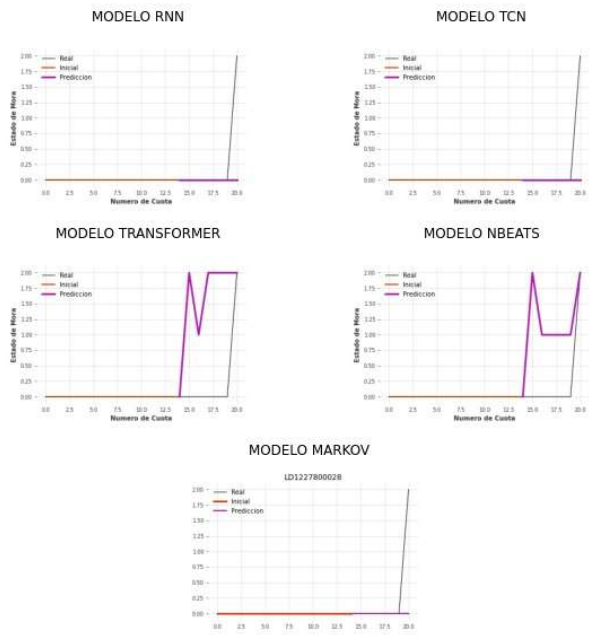
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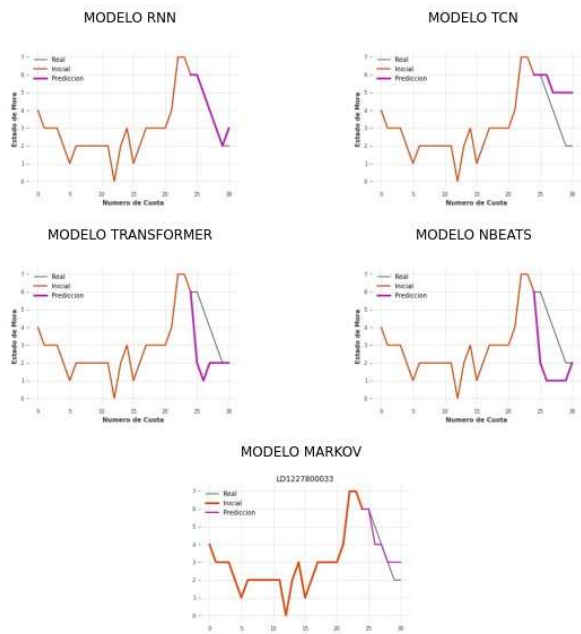
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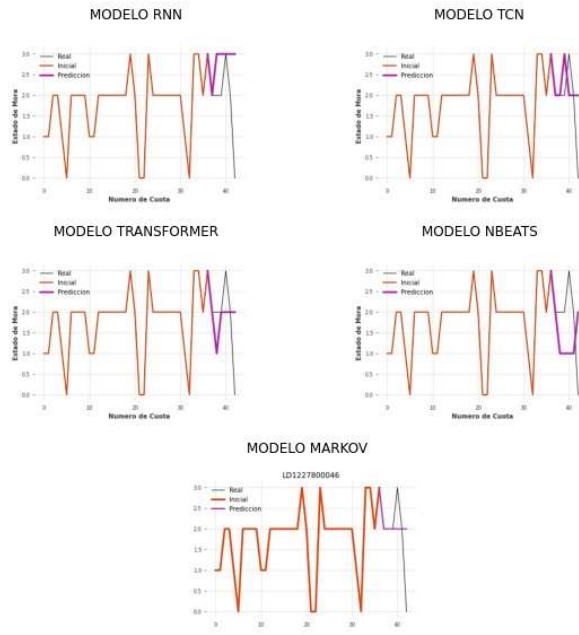
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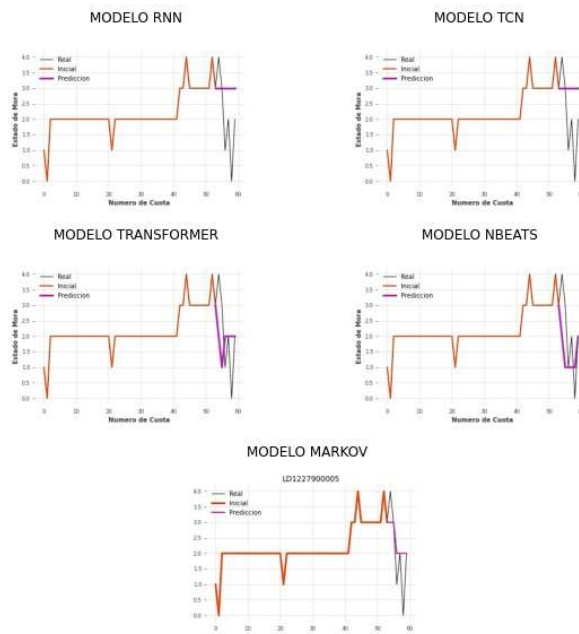
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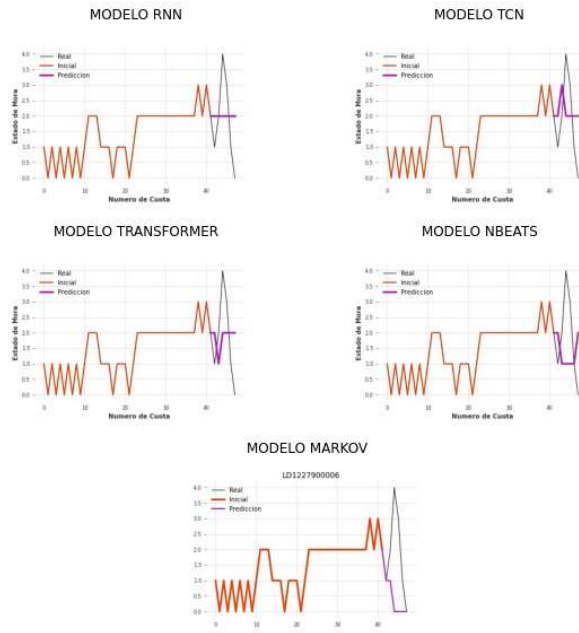
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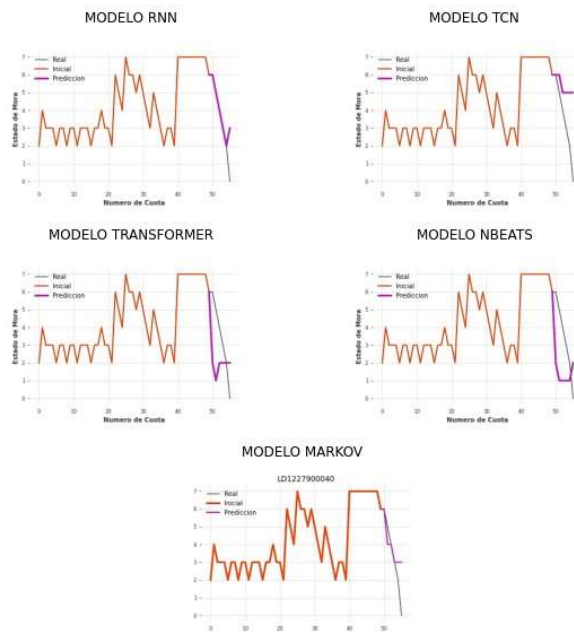
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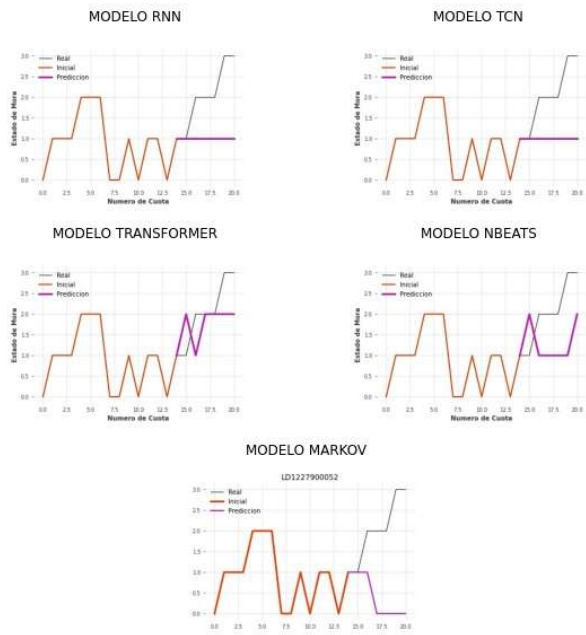
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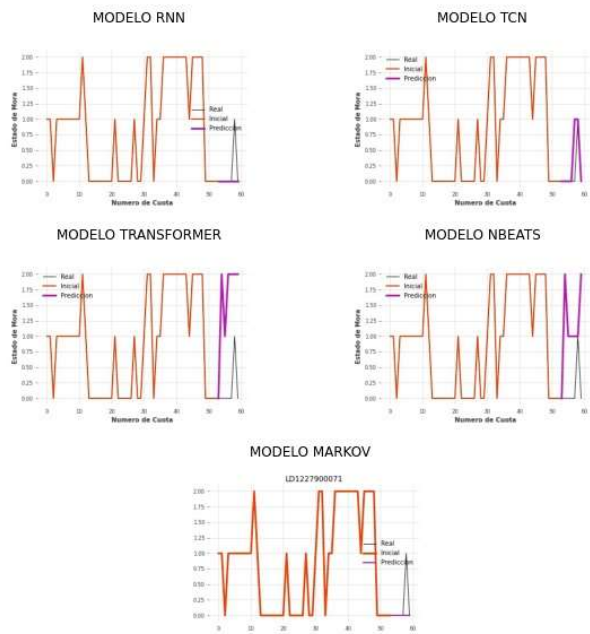
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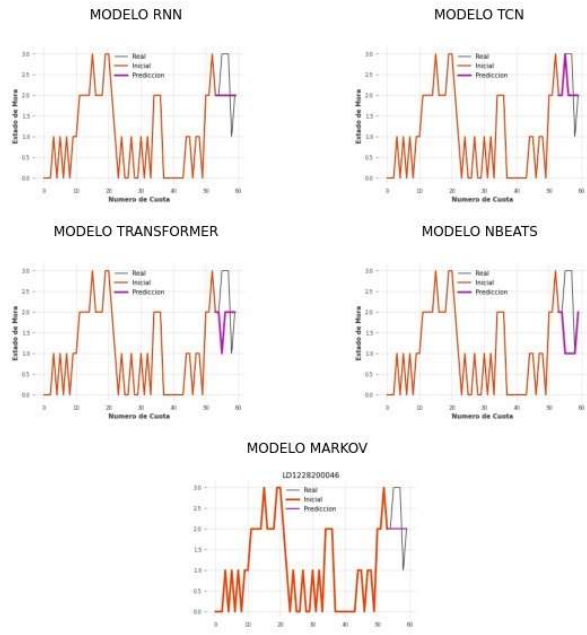
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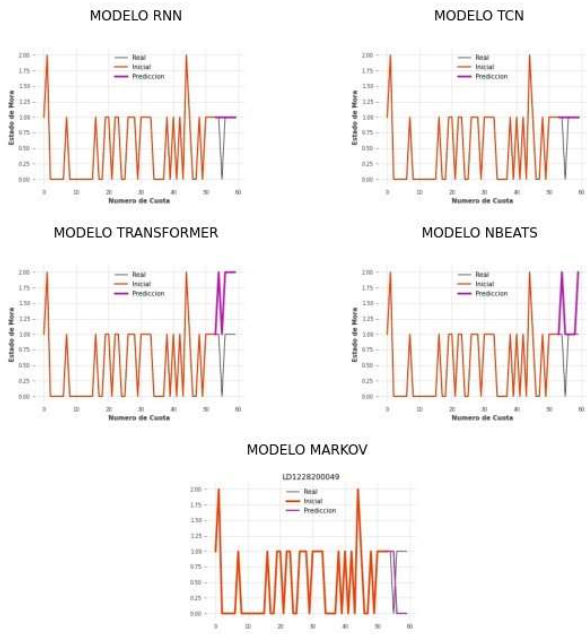
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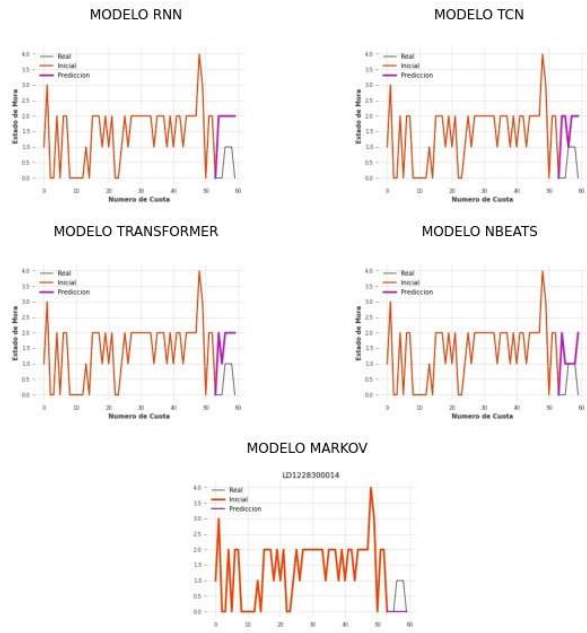


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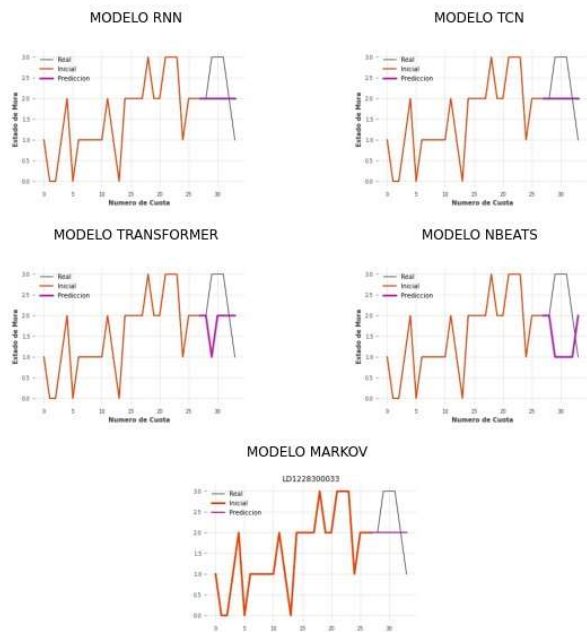




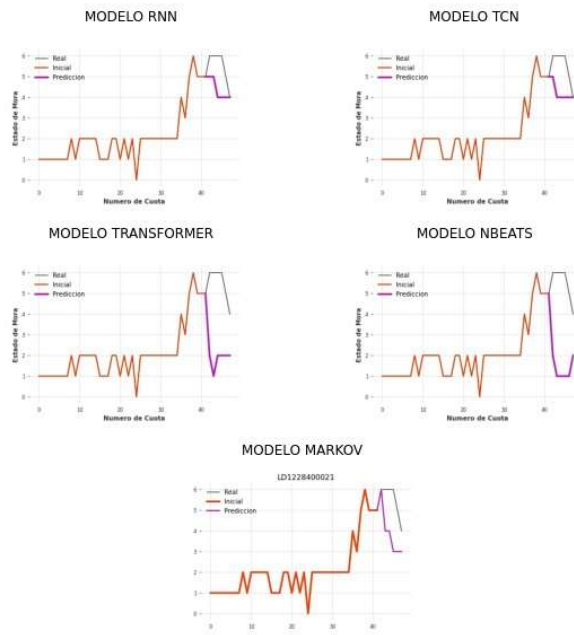
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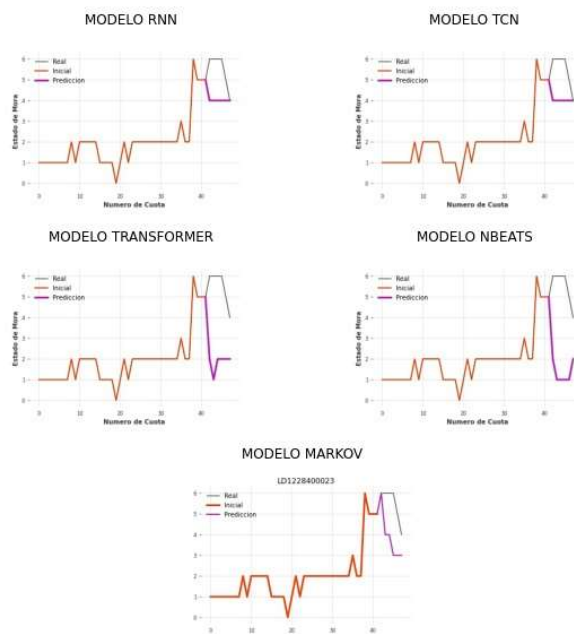
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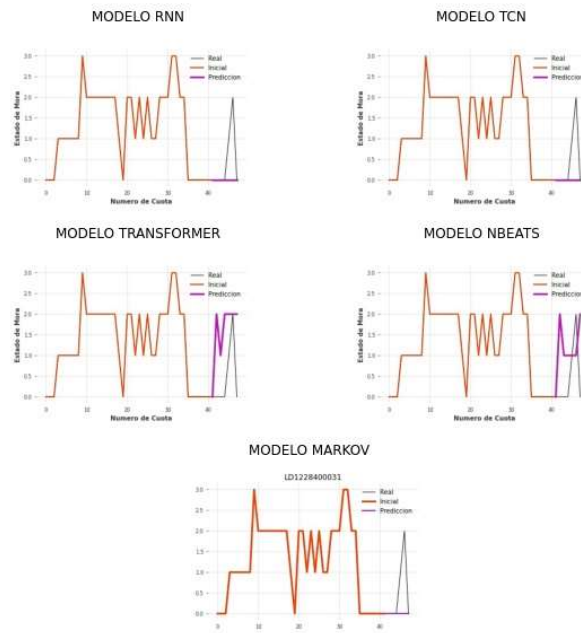
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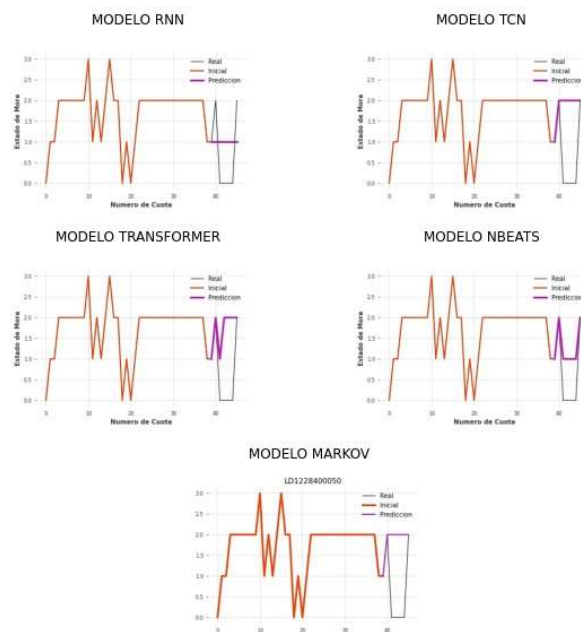
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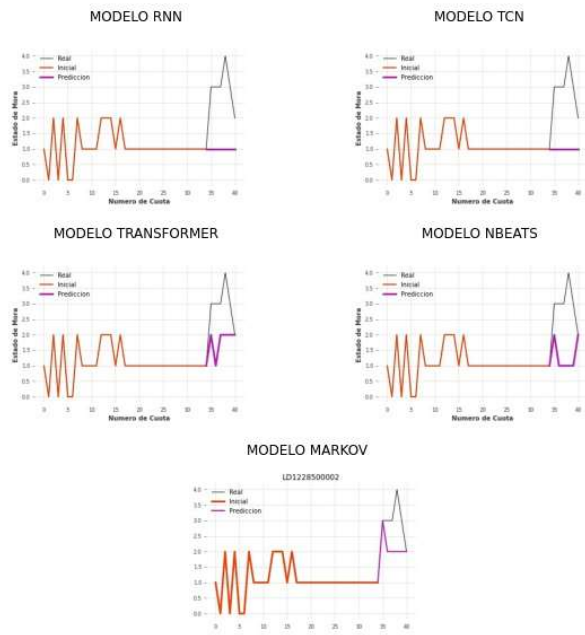
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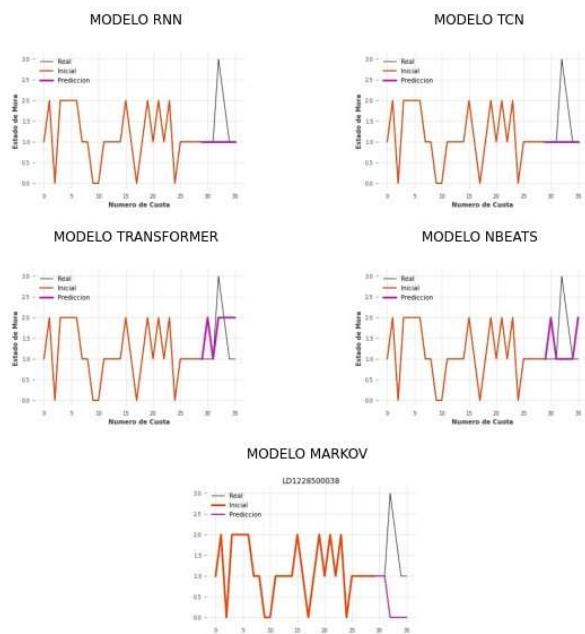
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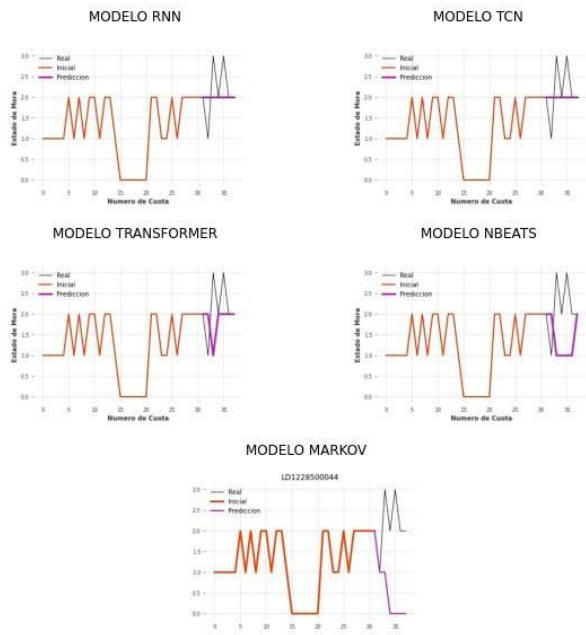
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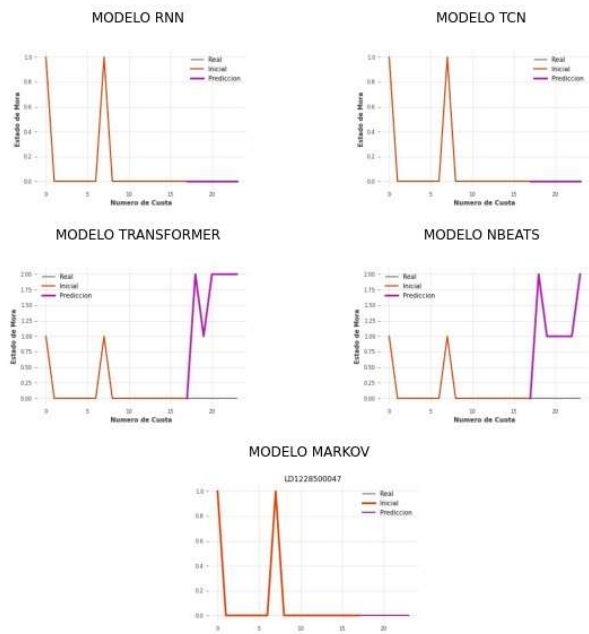
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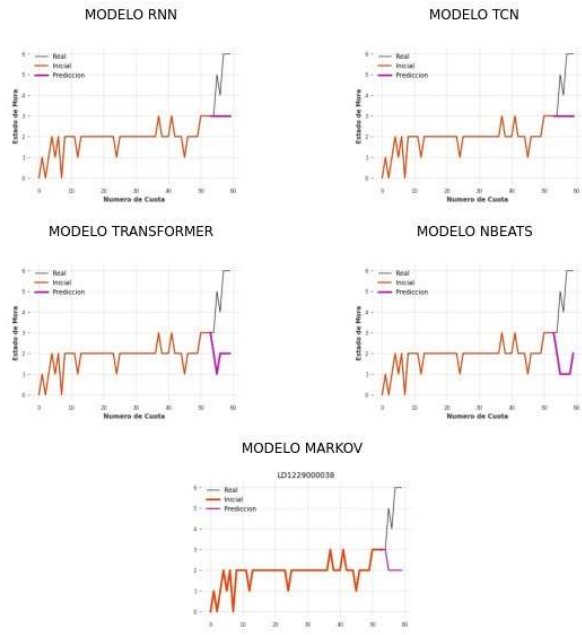
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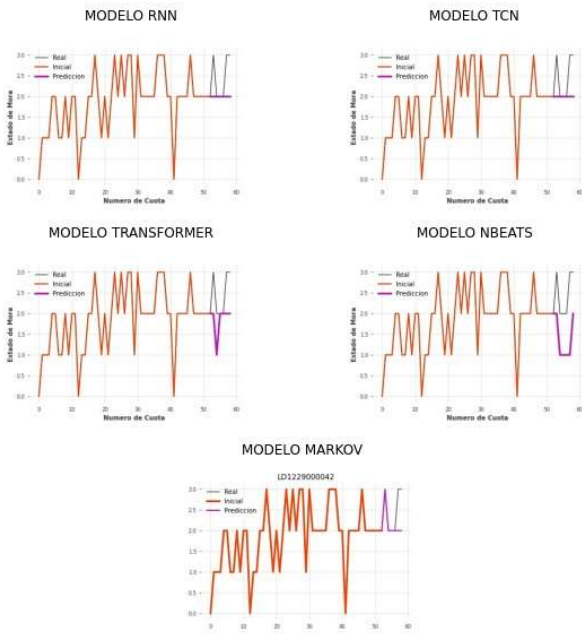
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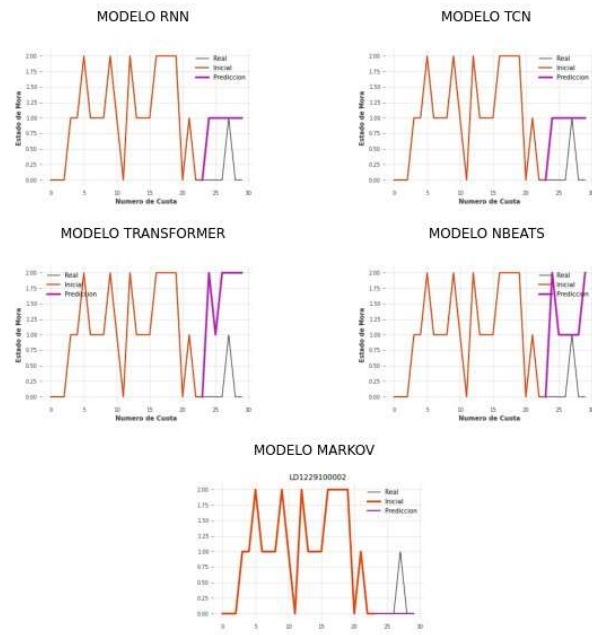
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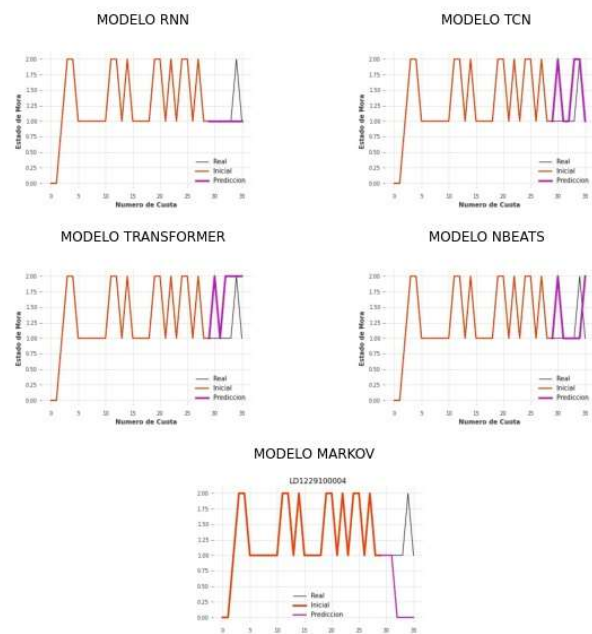
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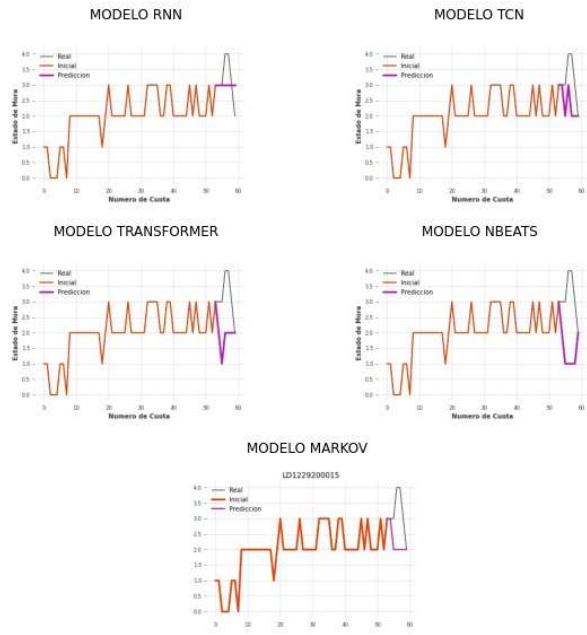
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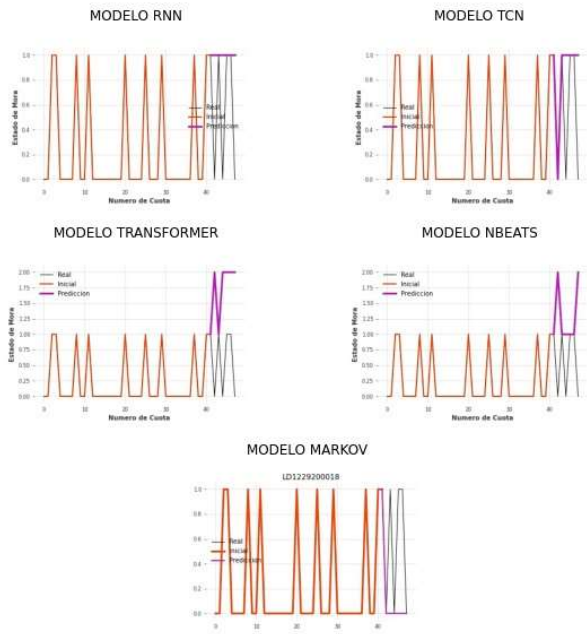
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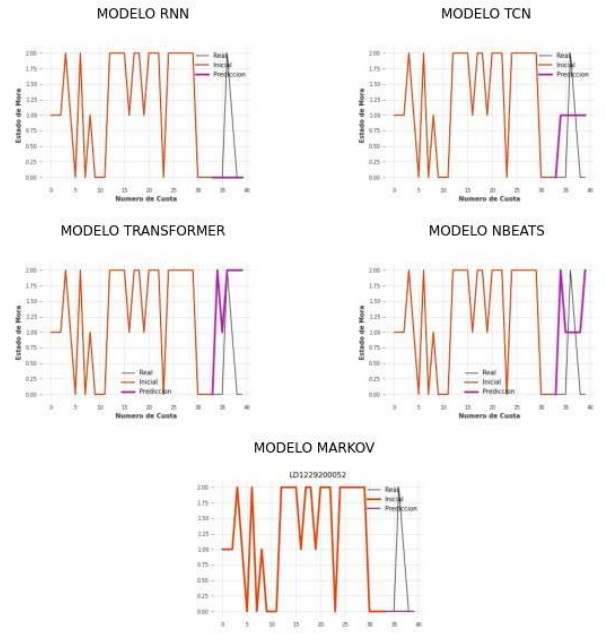




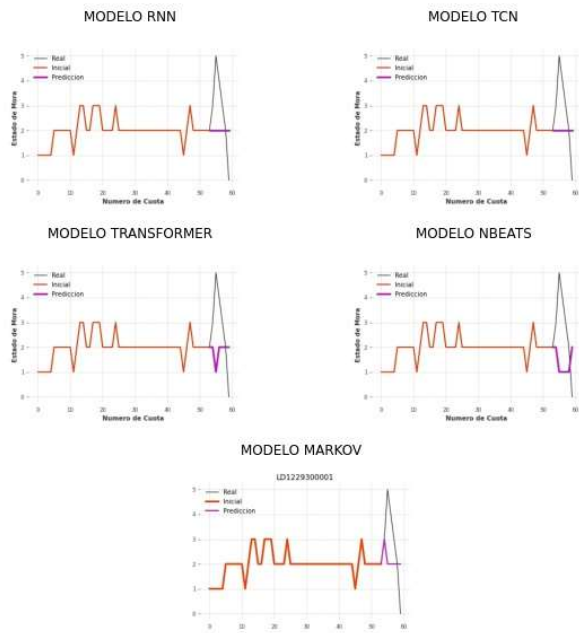
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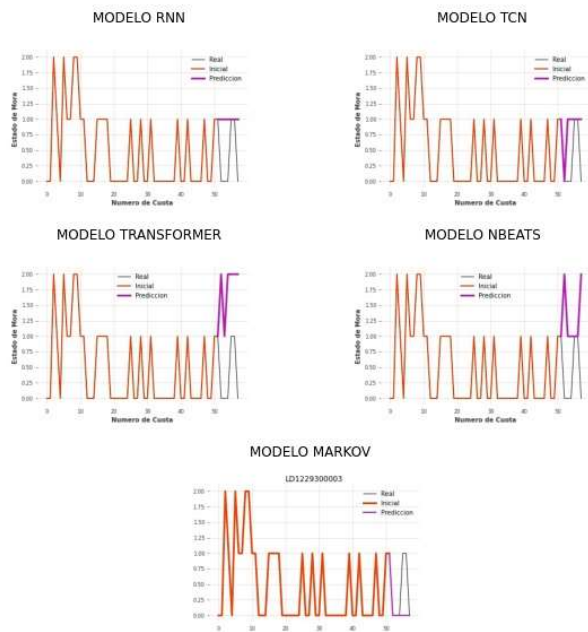
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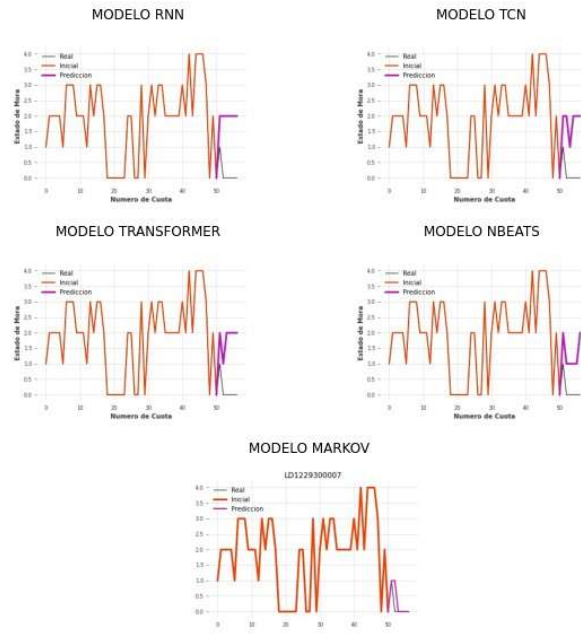
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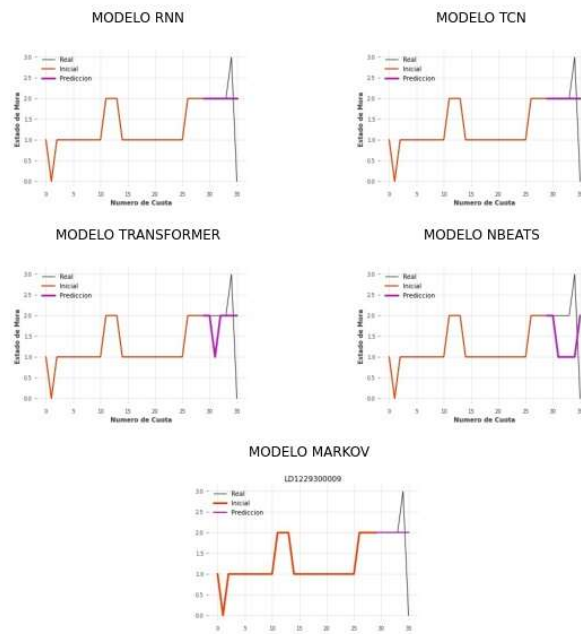
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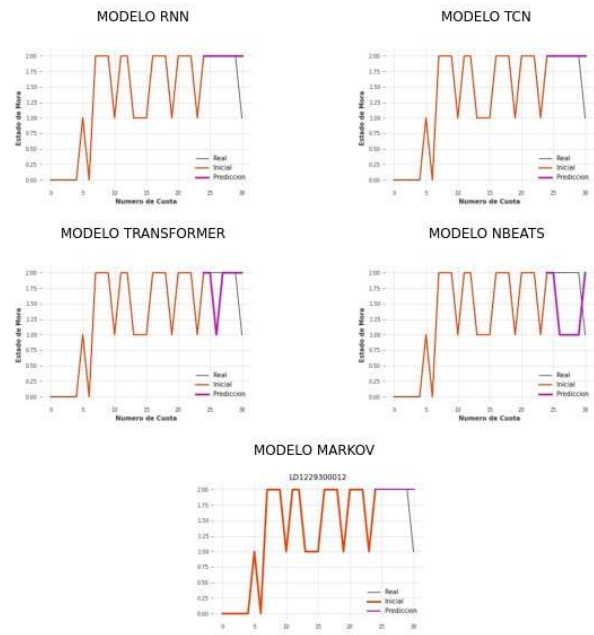
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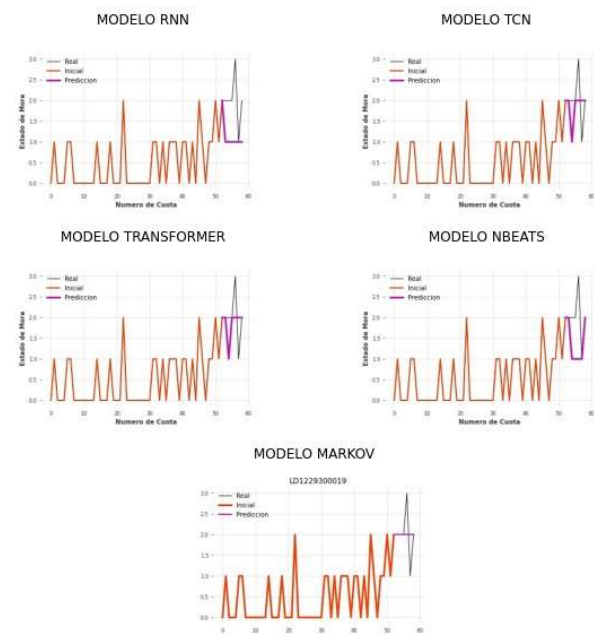
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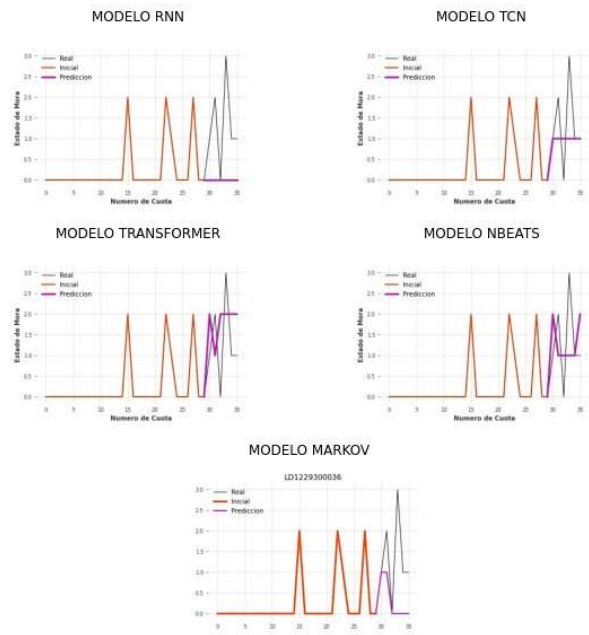
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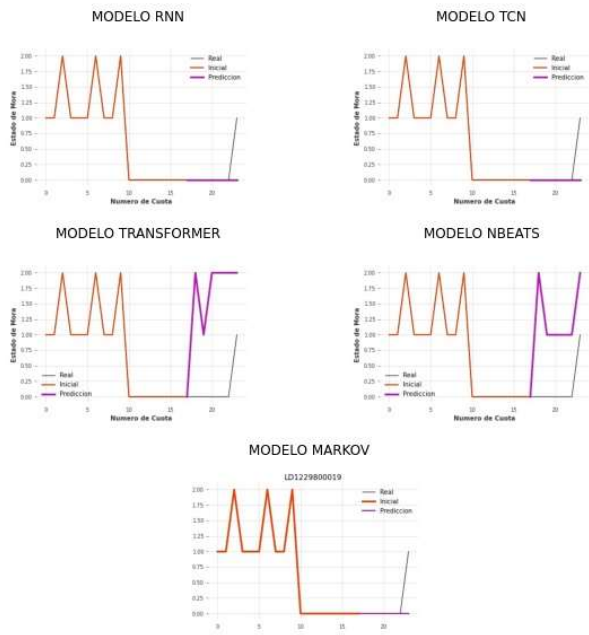
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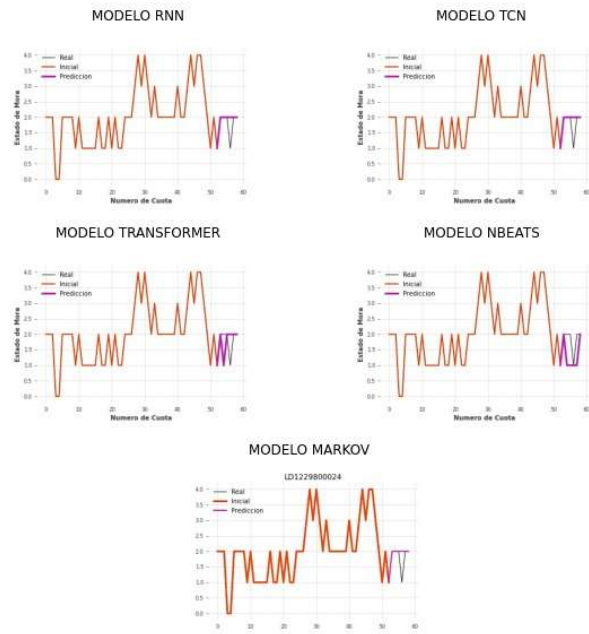
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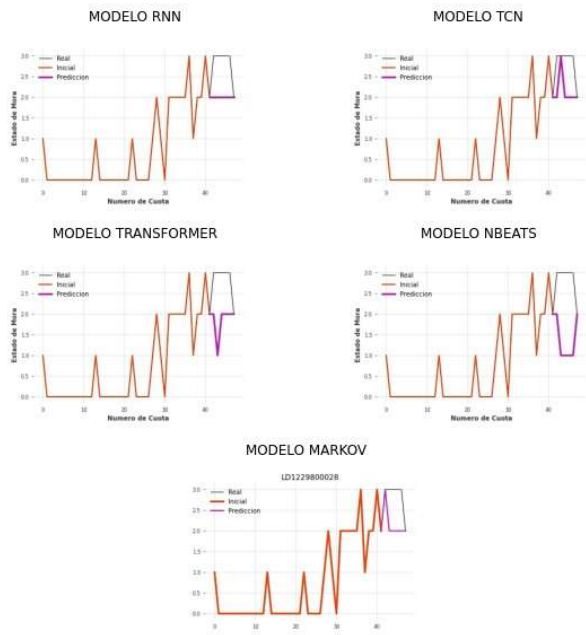
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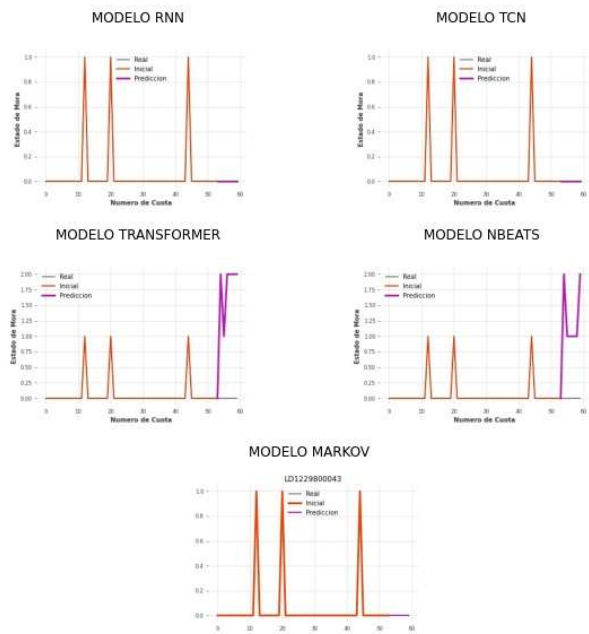
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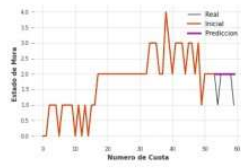


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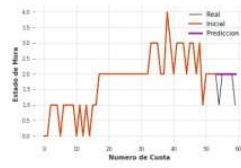


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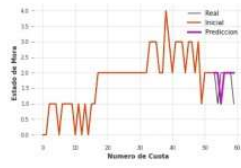
MODELO RNN



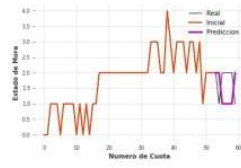
MODELO TCN



MODELO TRANSFORMER



MODELO NBEATS

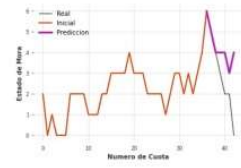


MODELO MARKOV

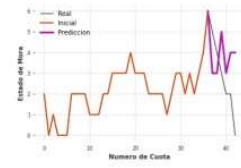


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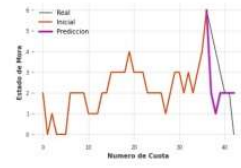
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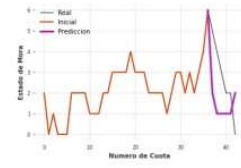
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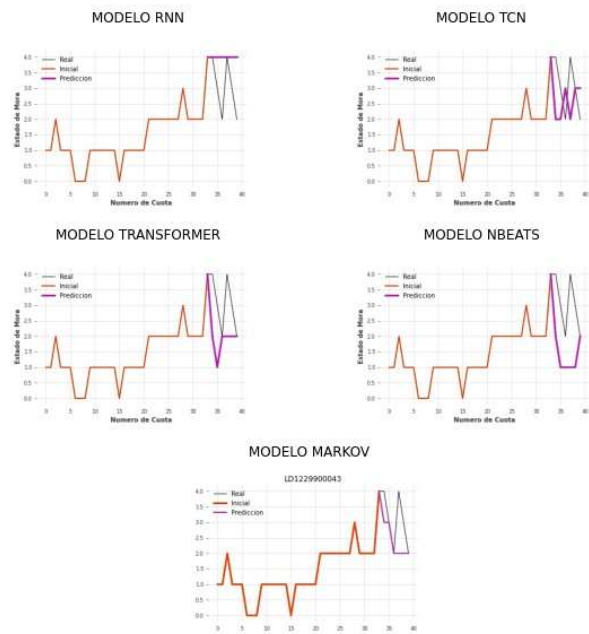




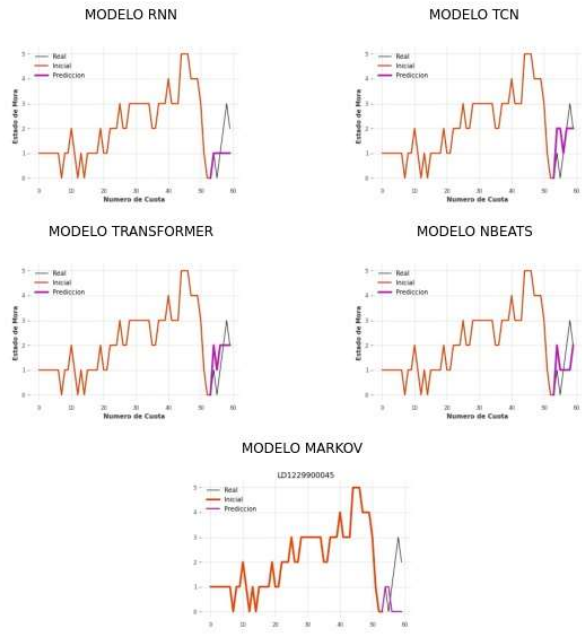
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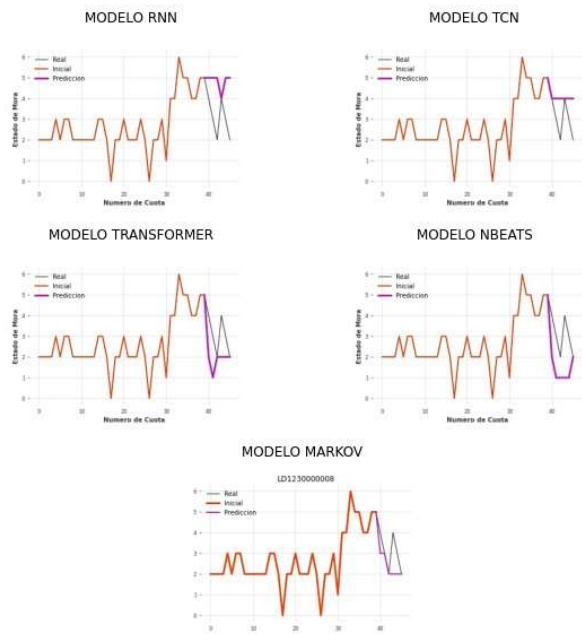
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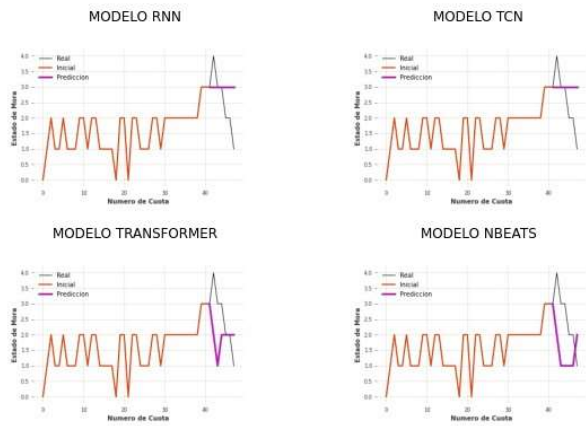
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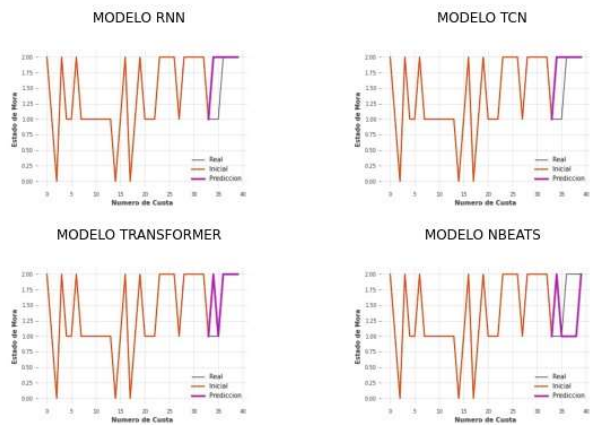
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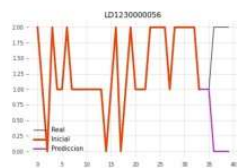
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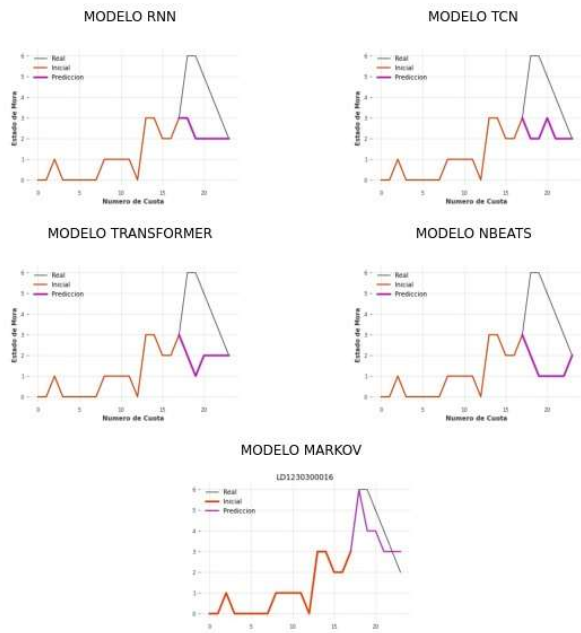
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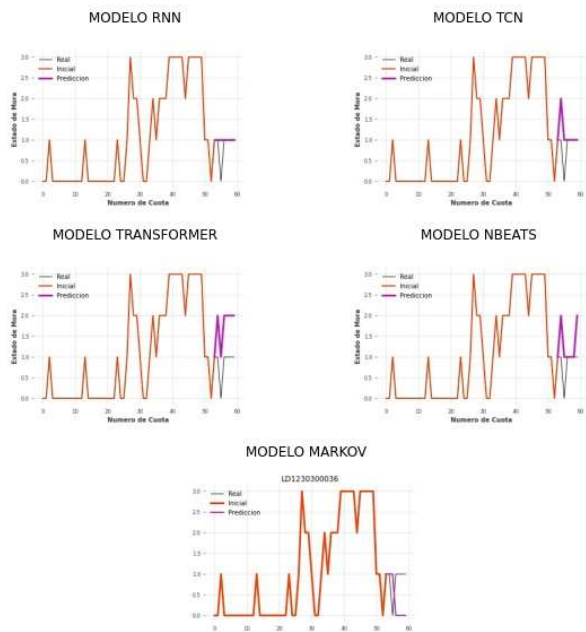
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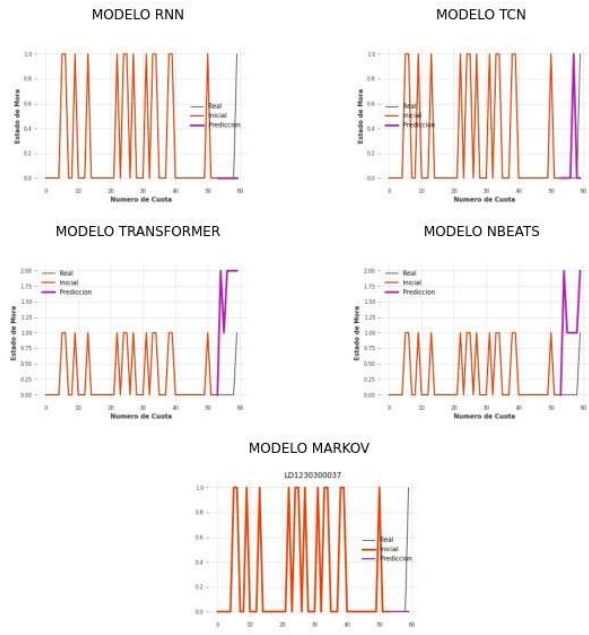
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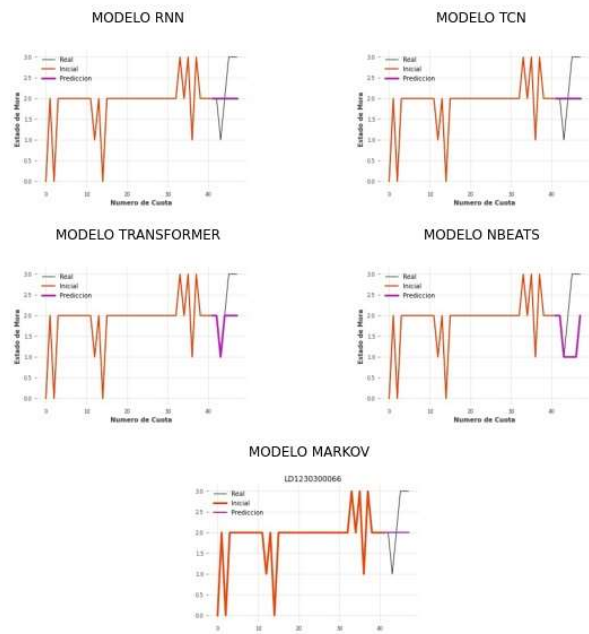
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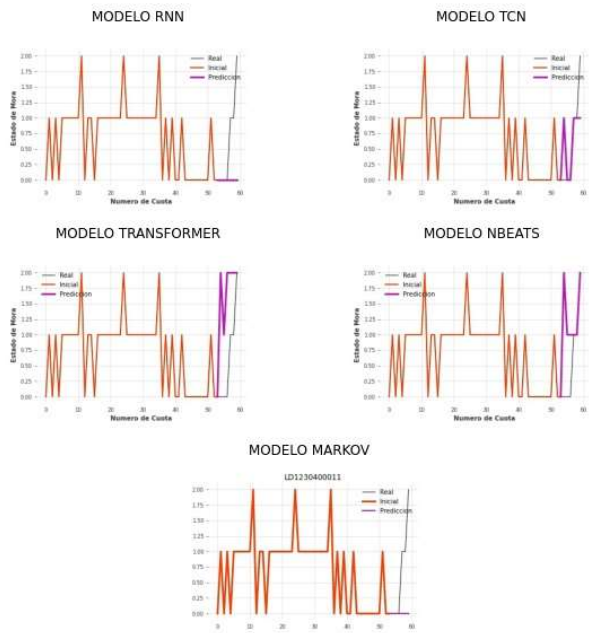
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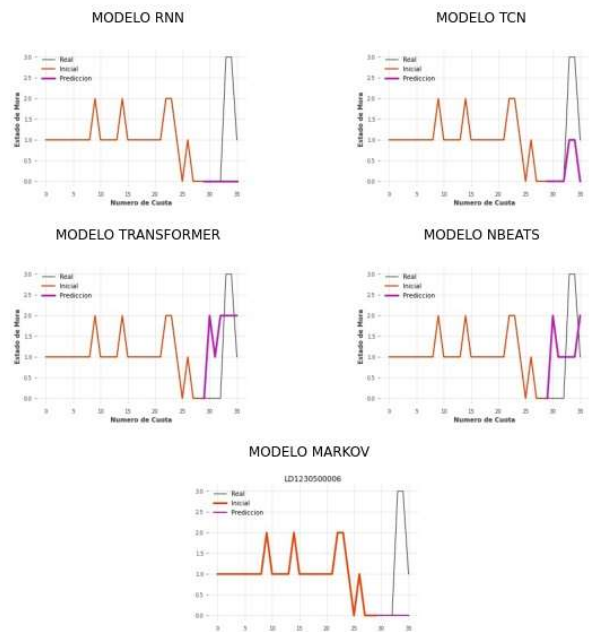
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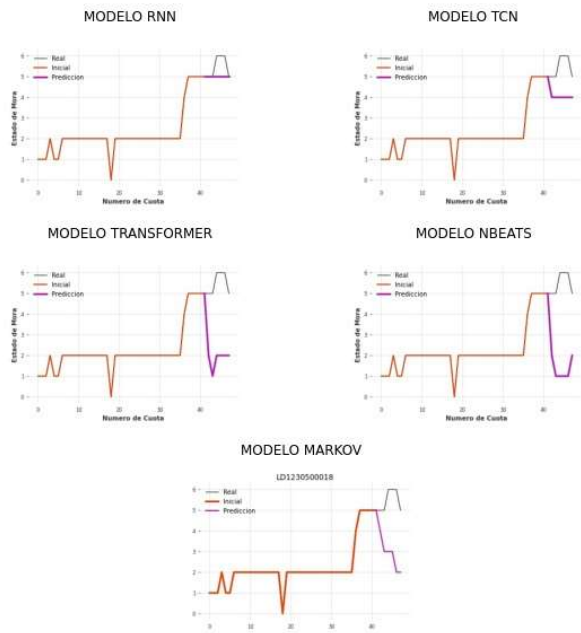
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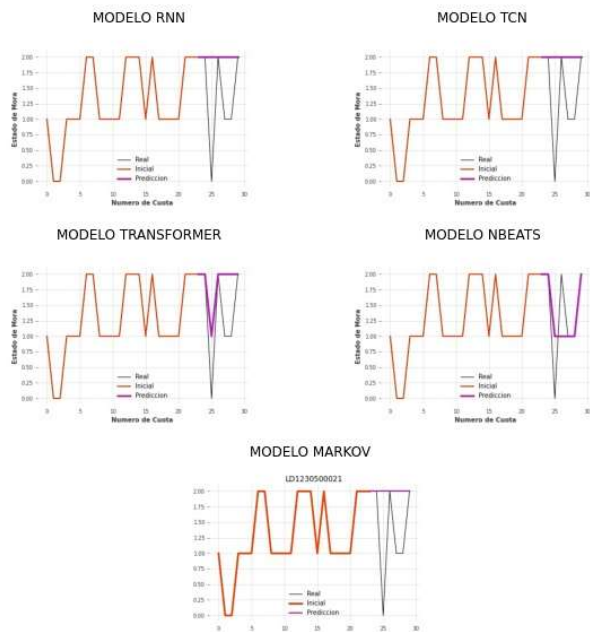
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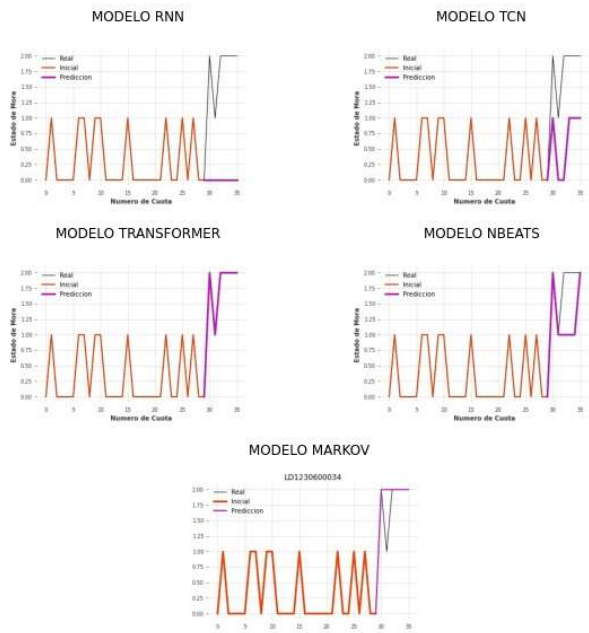
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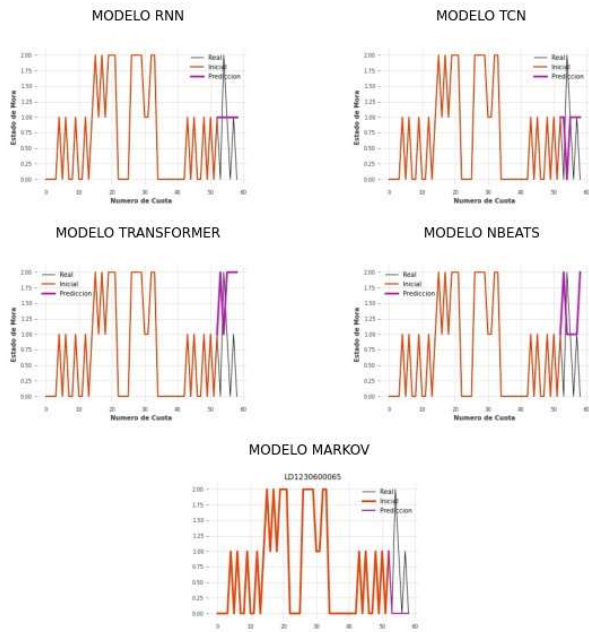
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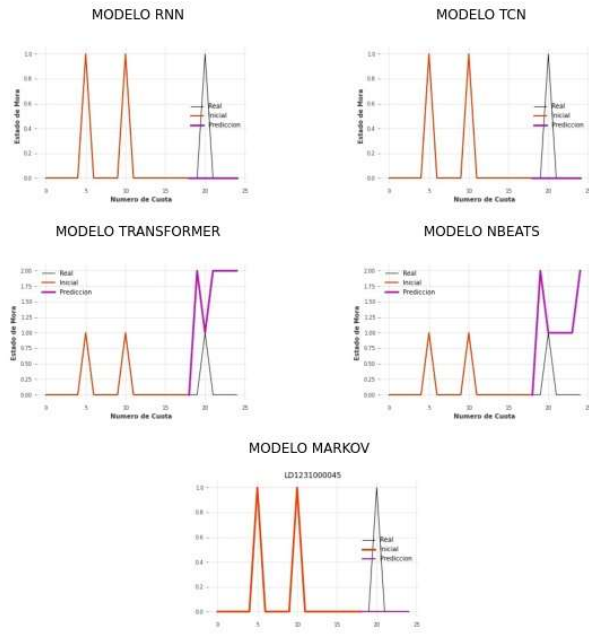


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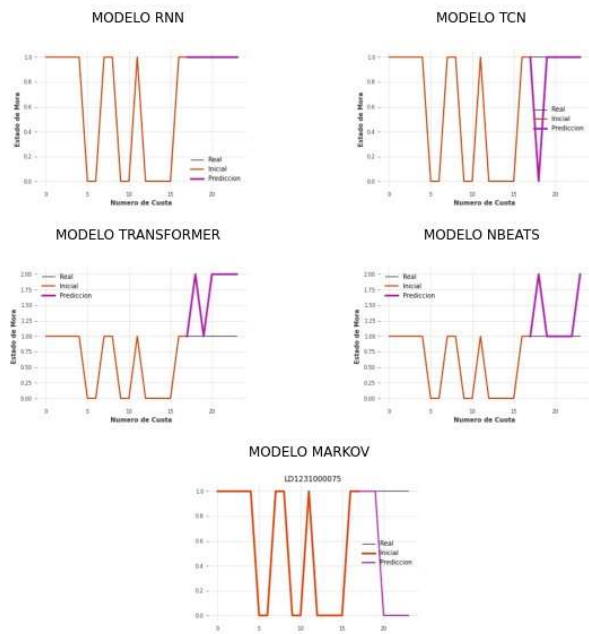




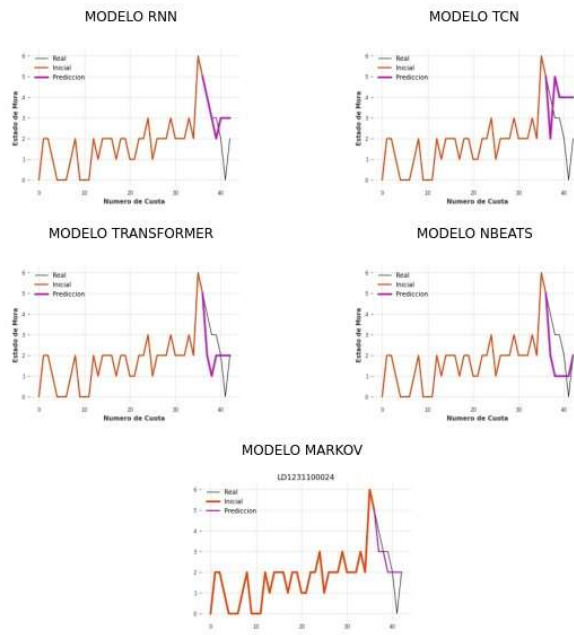
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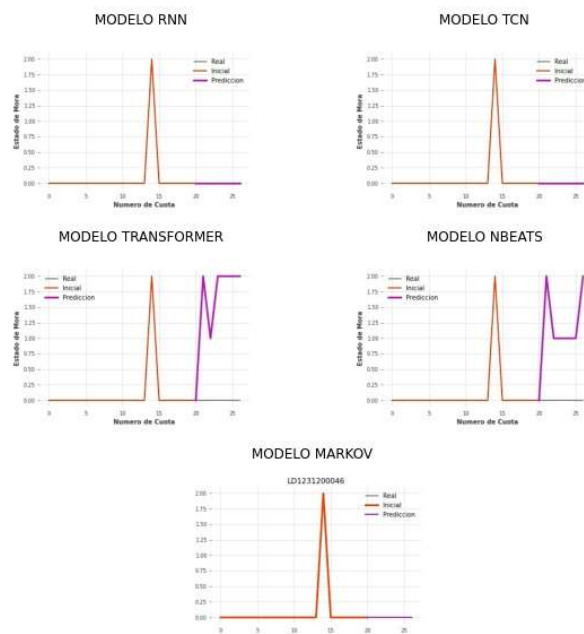
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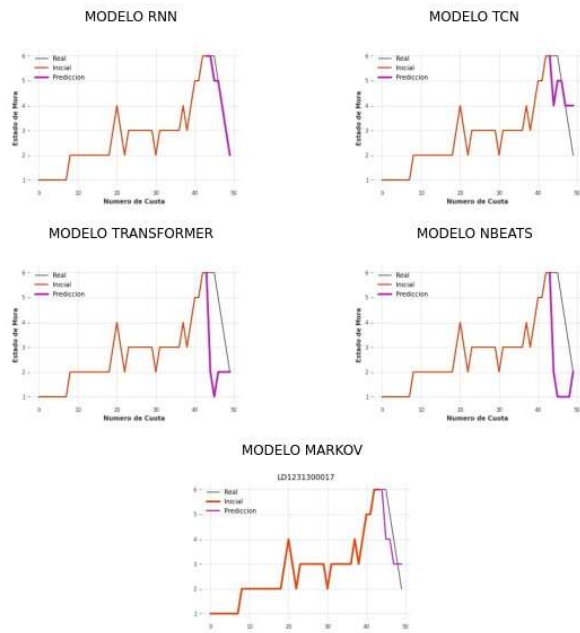
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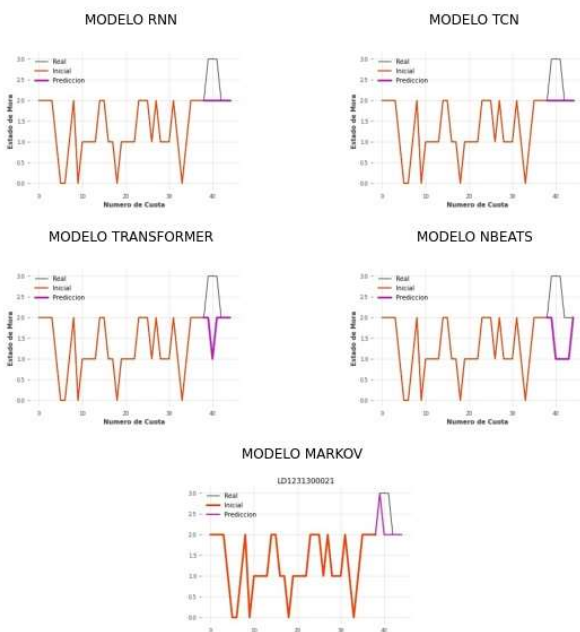
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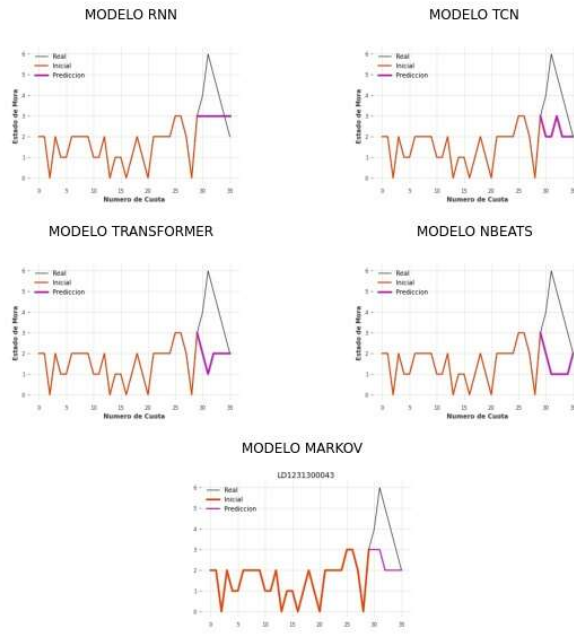
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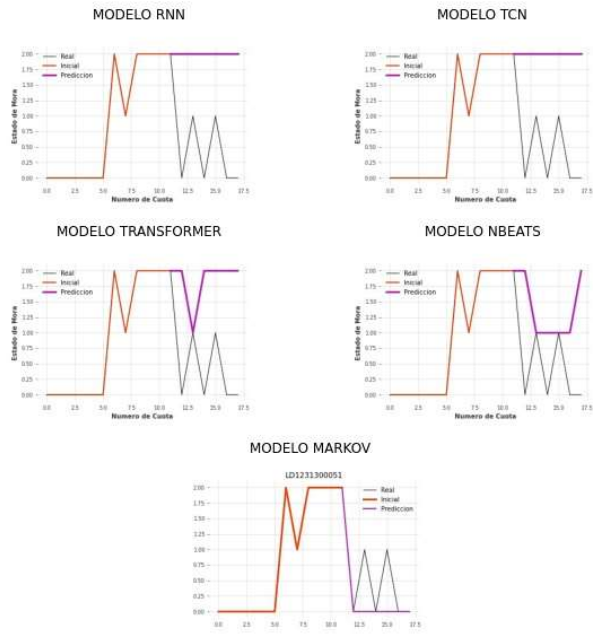
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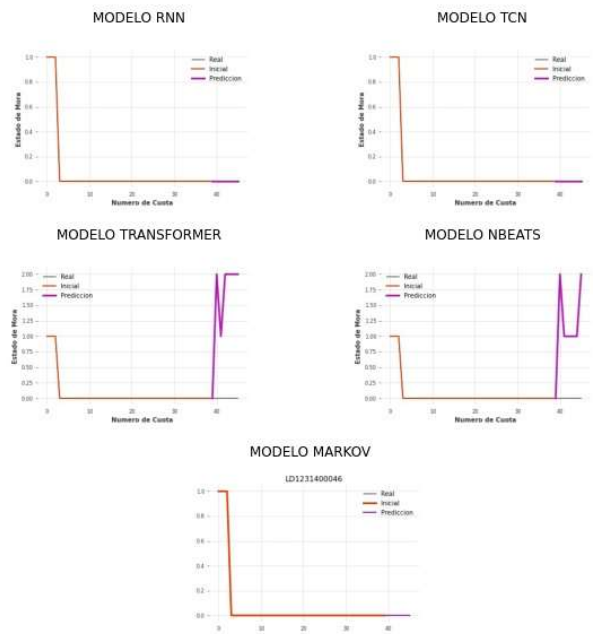
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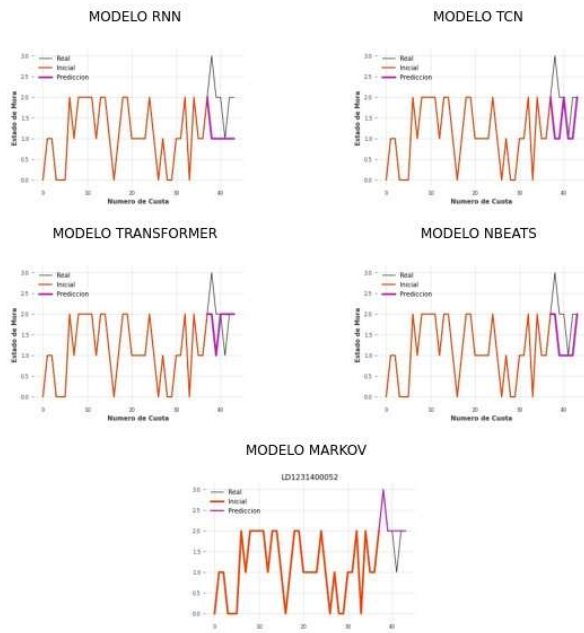
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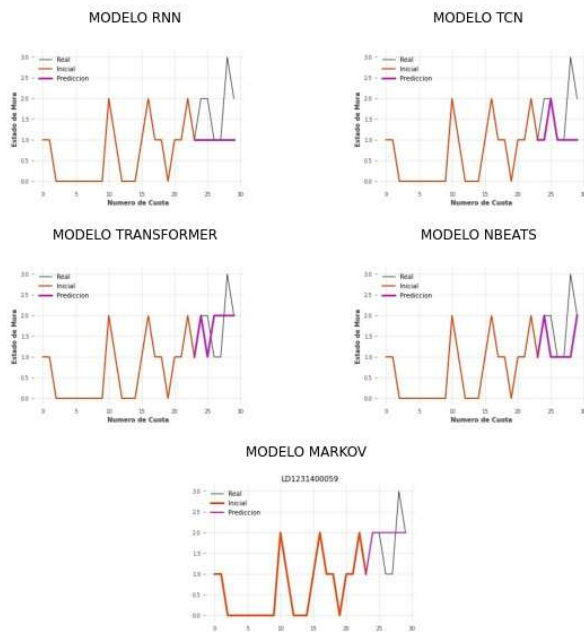
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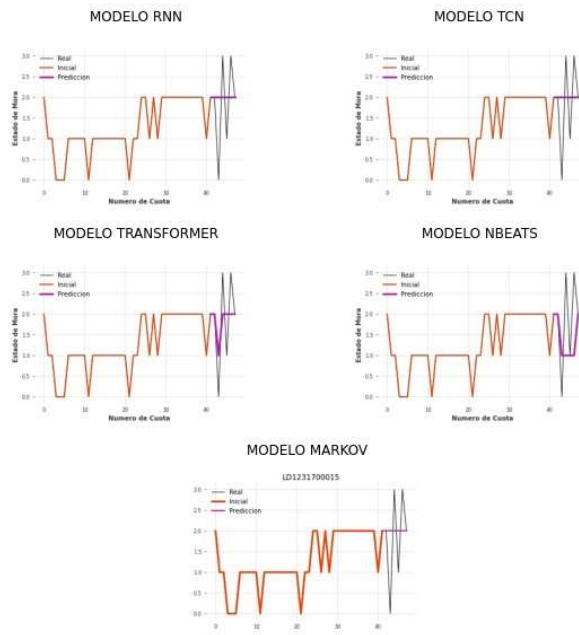
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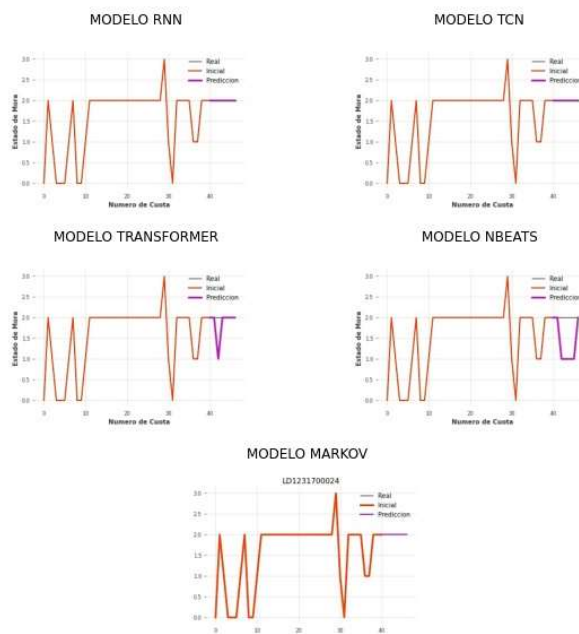
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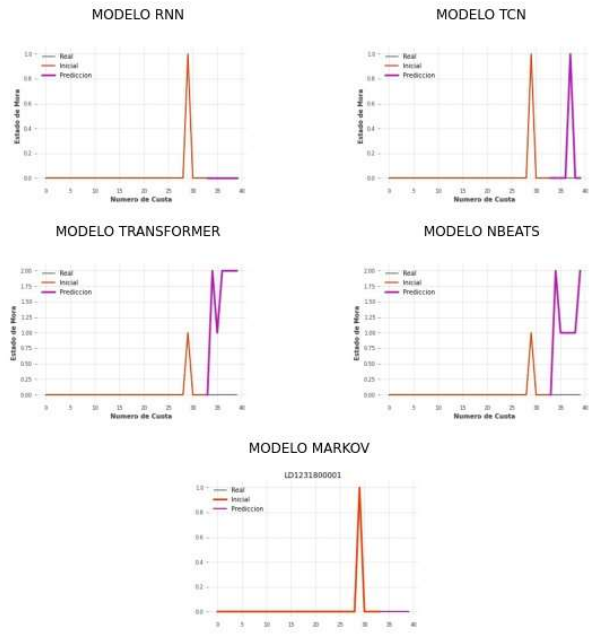
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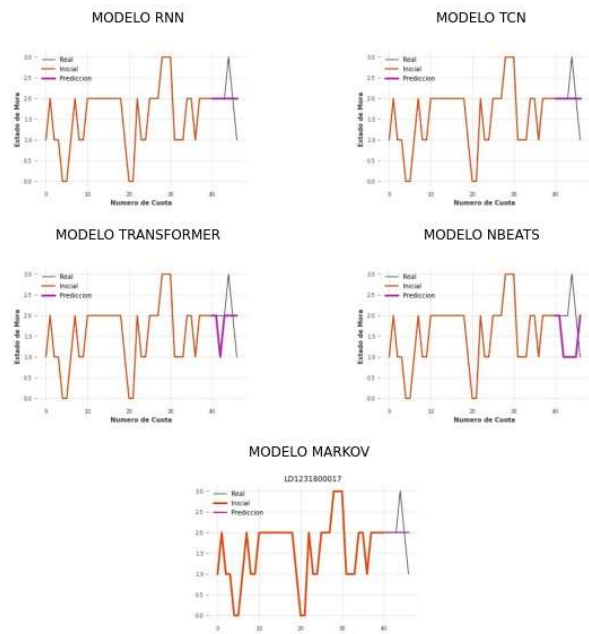
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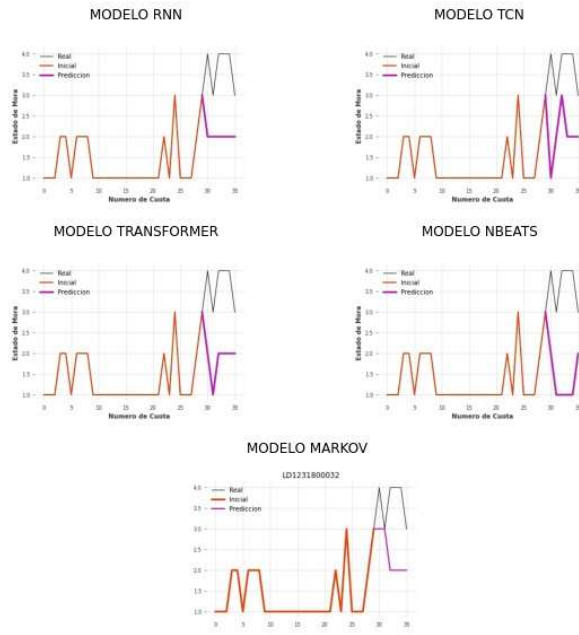


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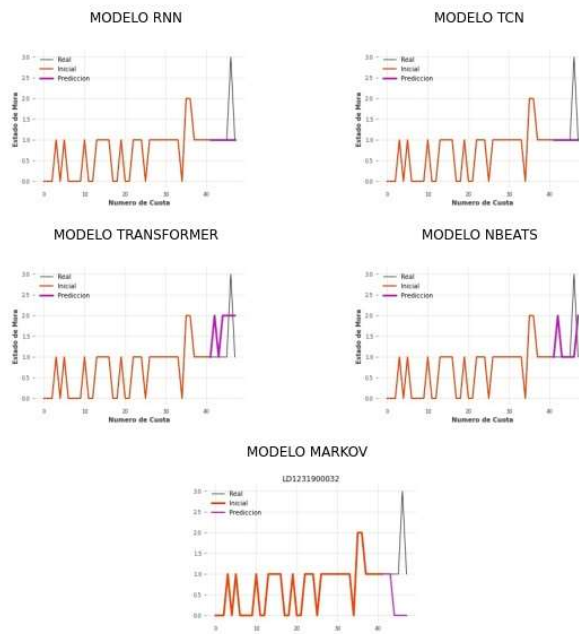




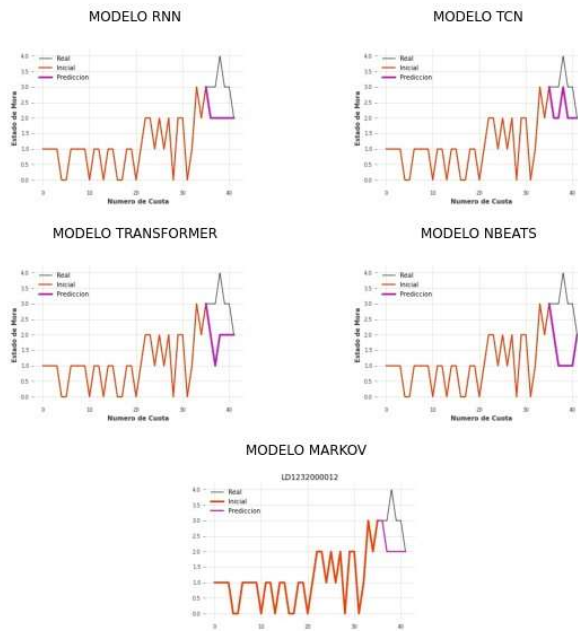
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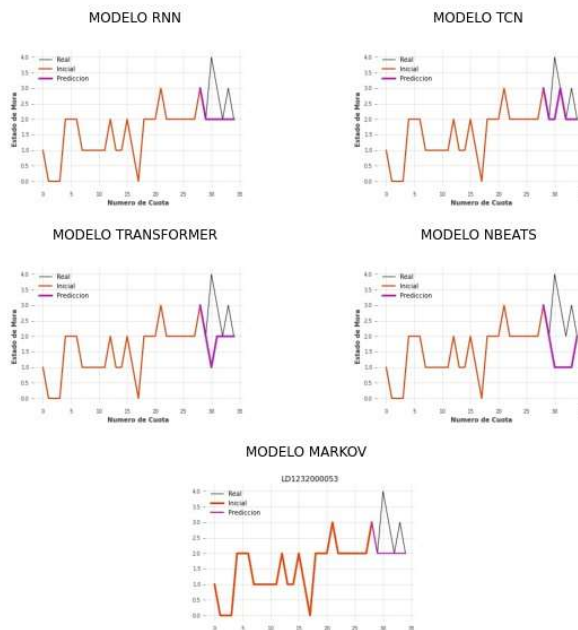
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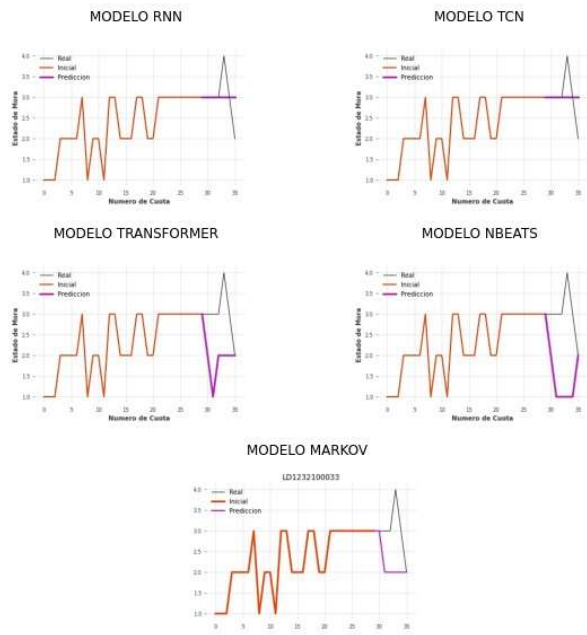
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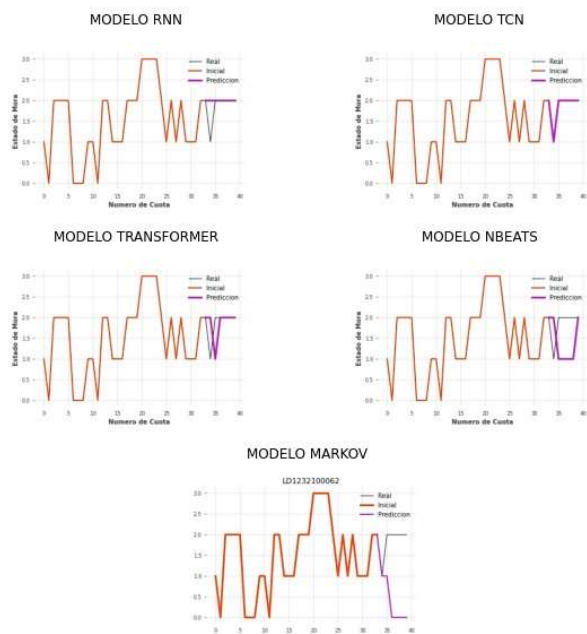
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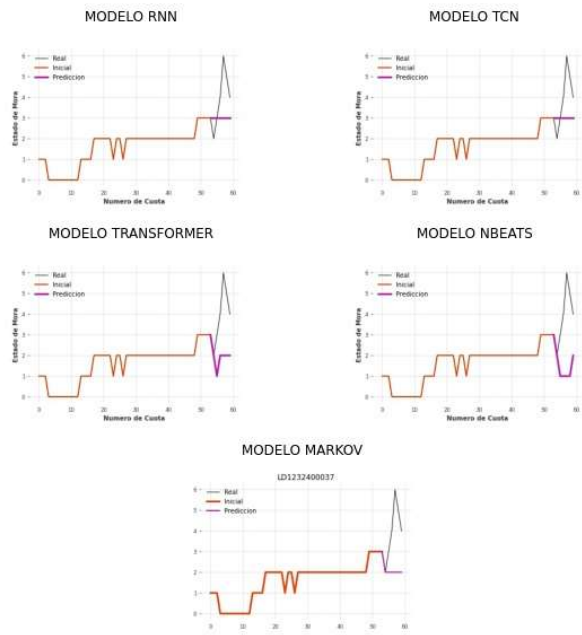
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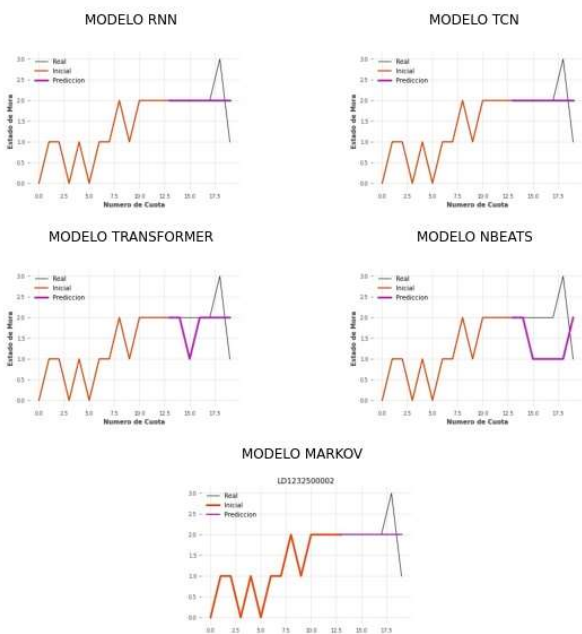
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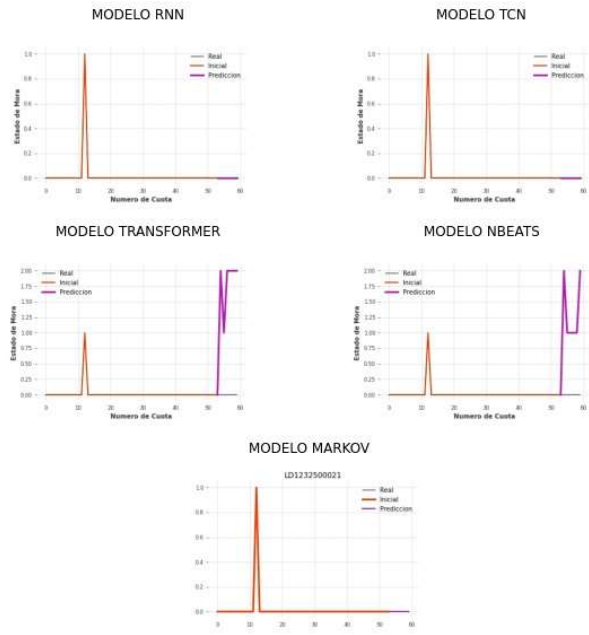
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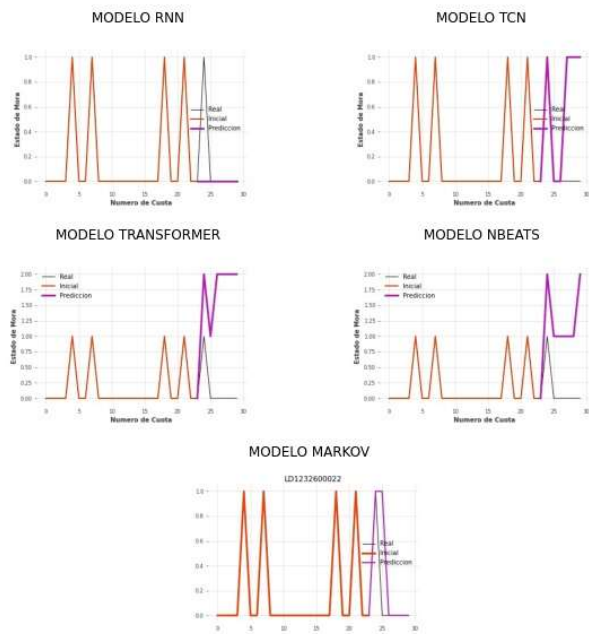
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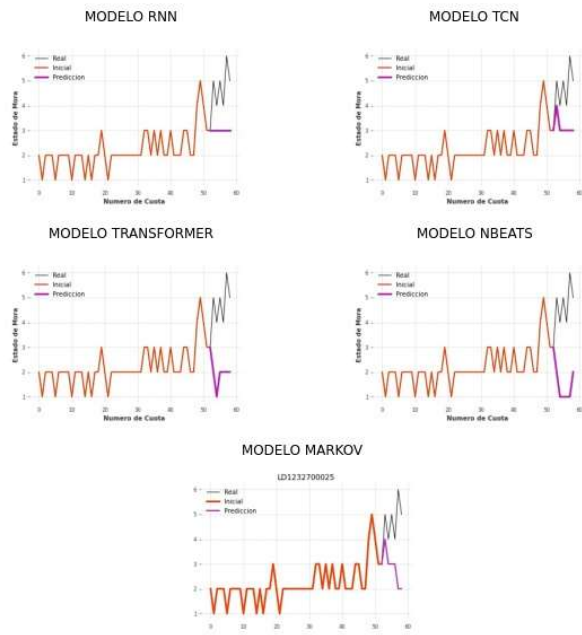
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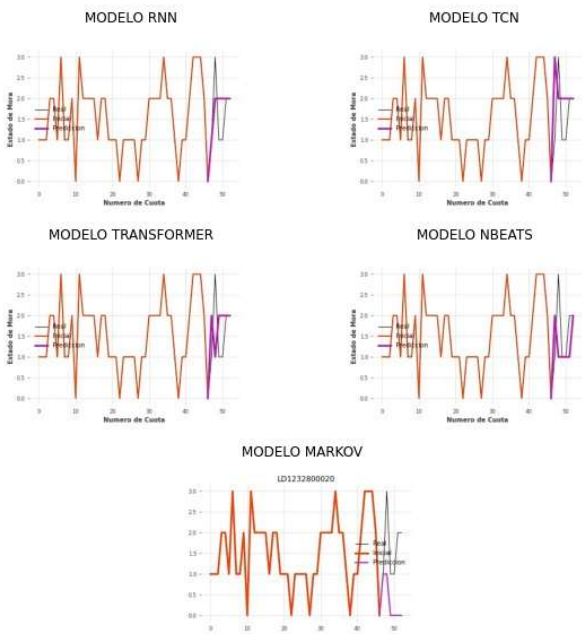
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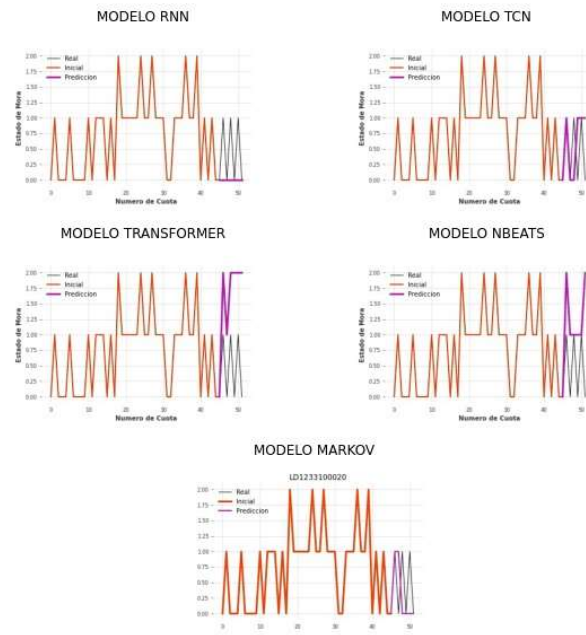
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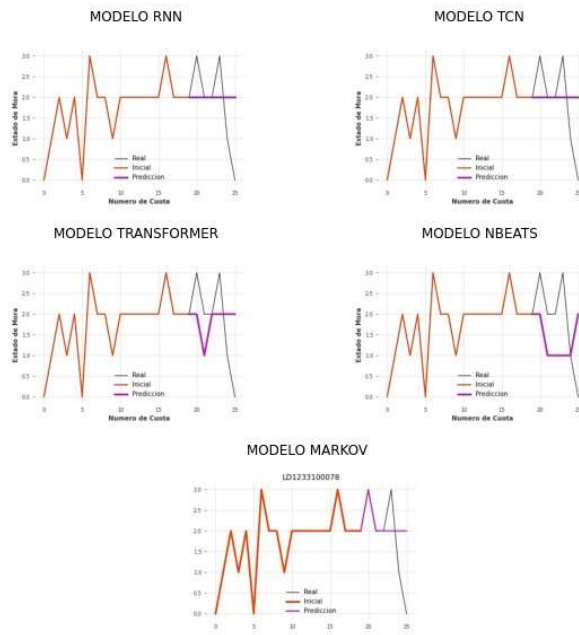
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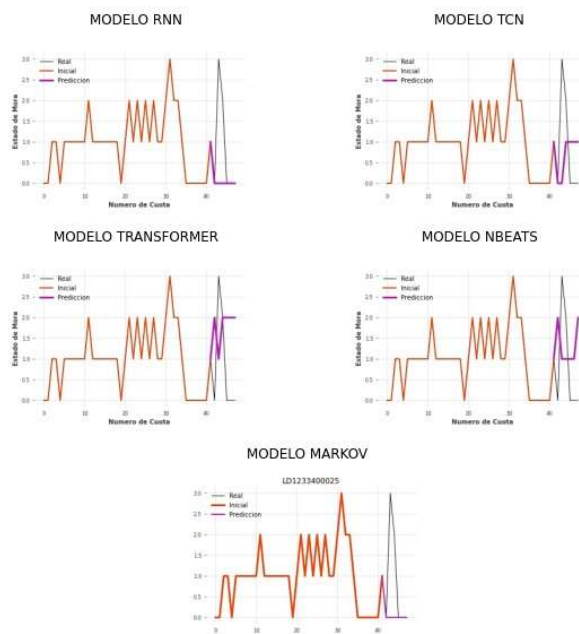
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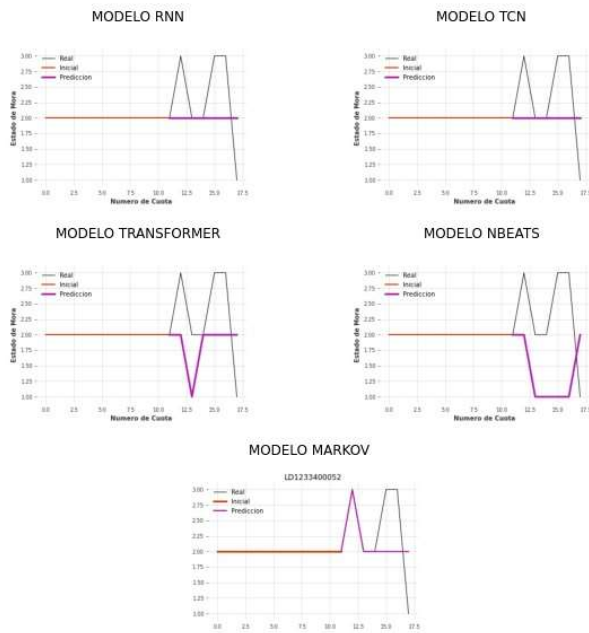


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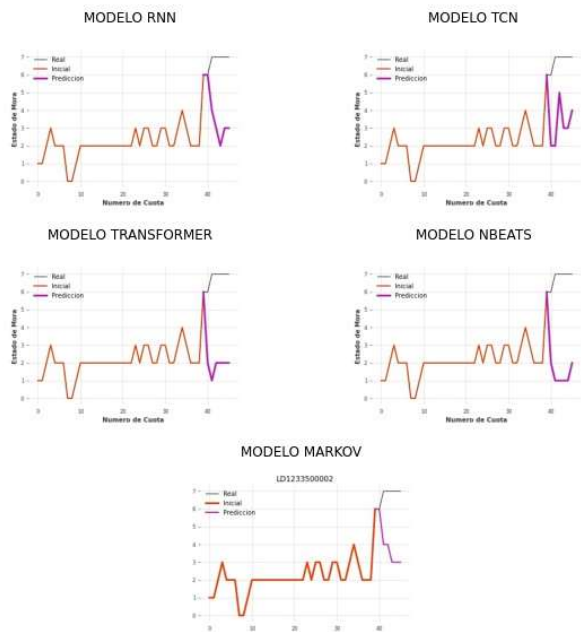




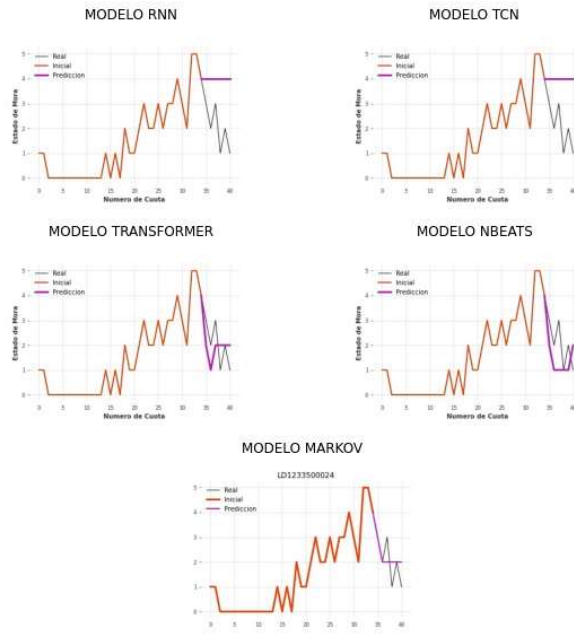
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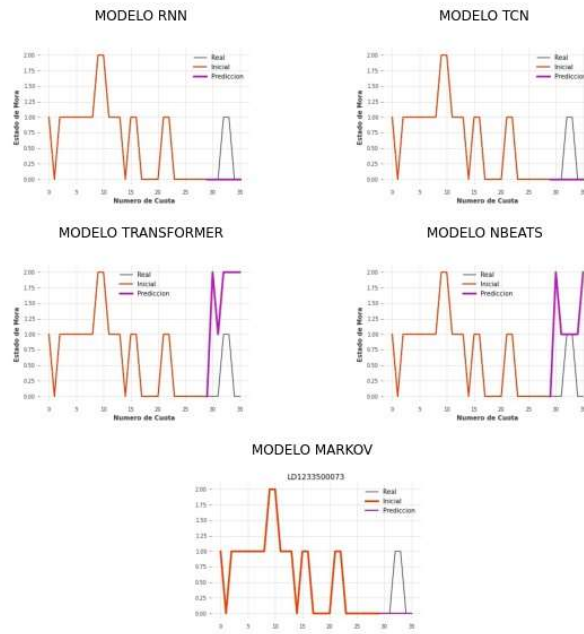
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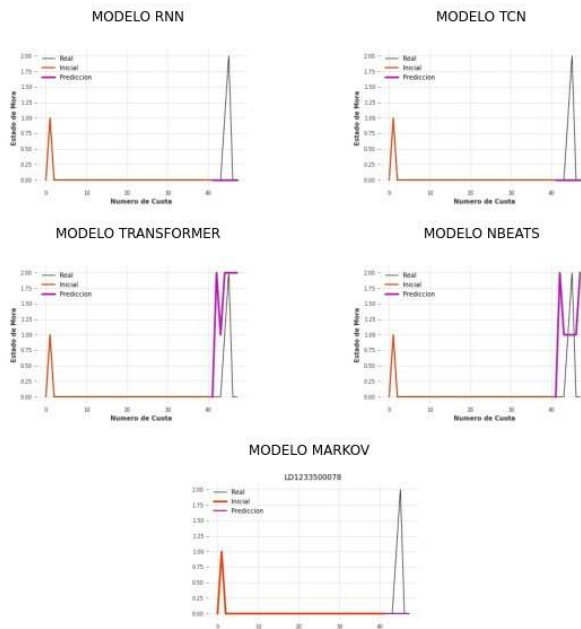
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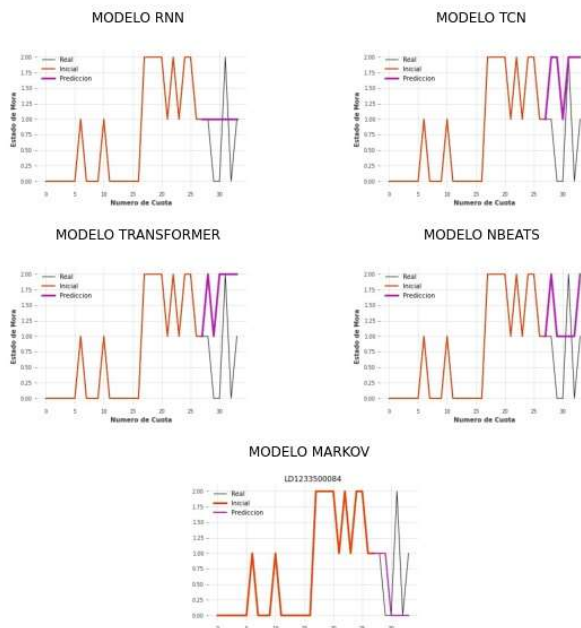
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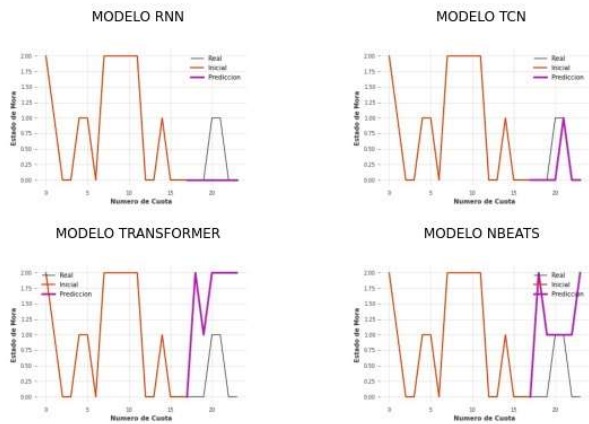
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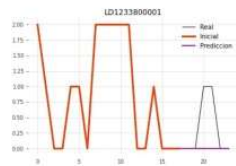
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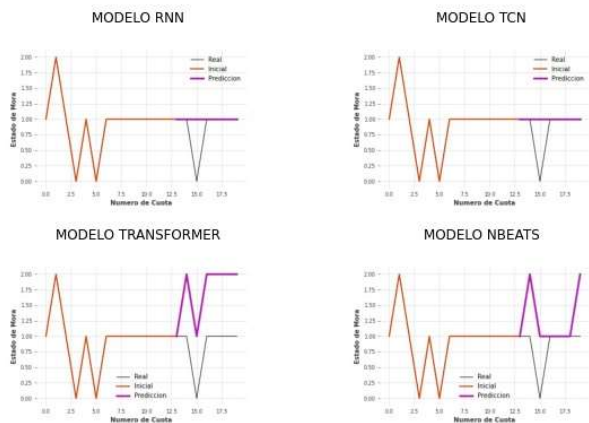
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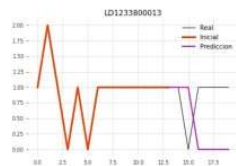
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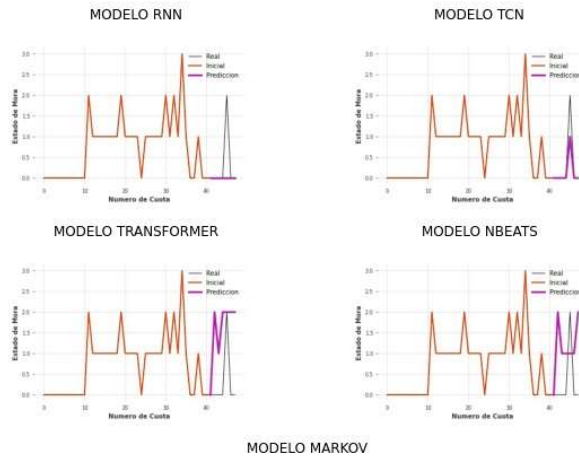
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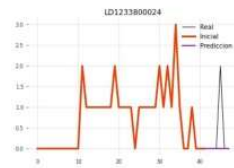
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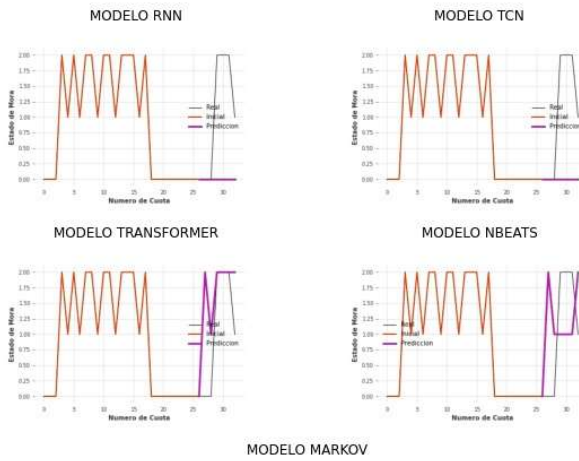
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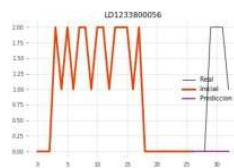
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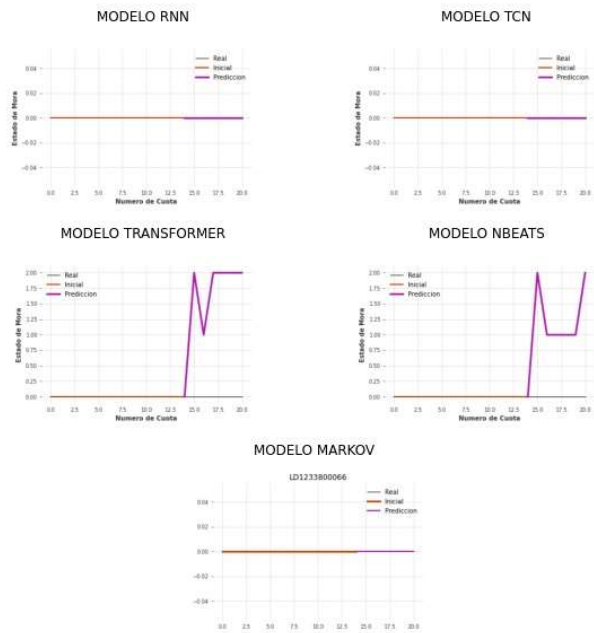
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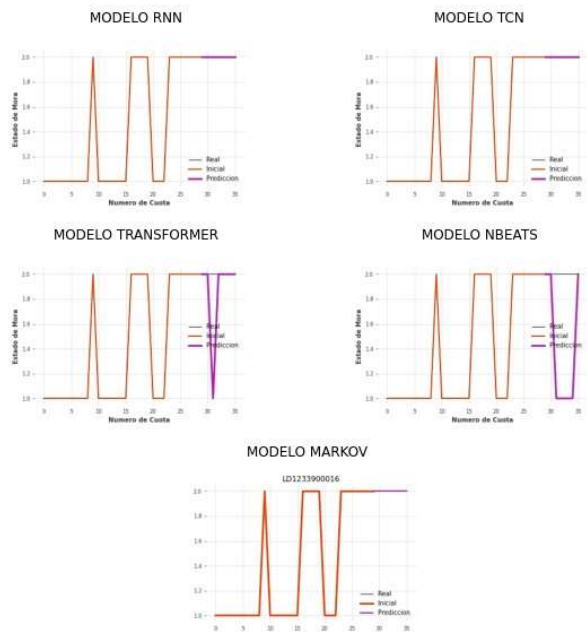
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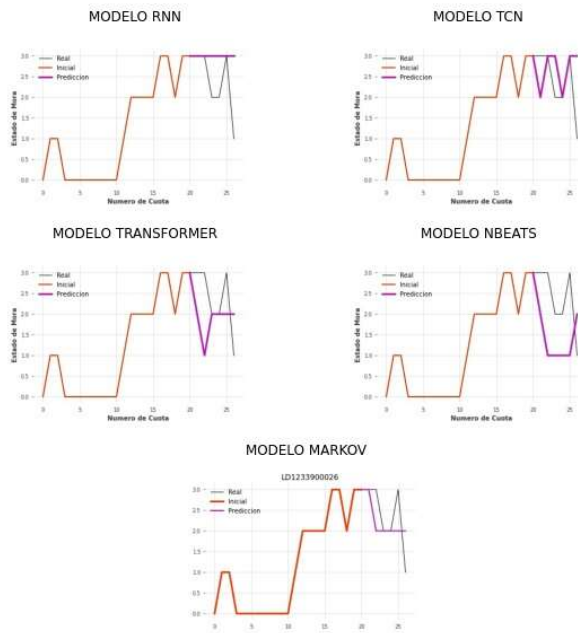
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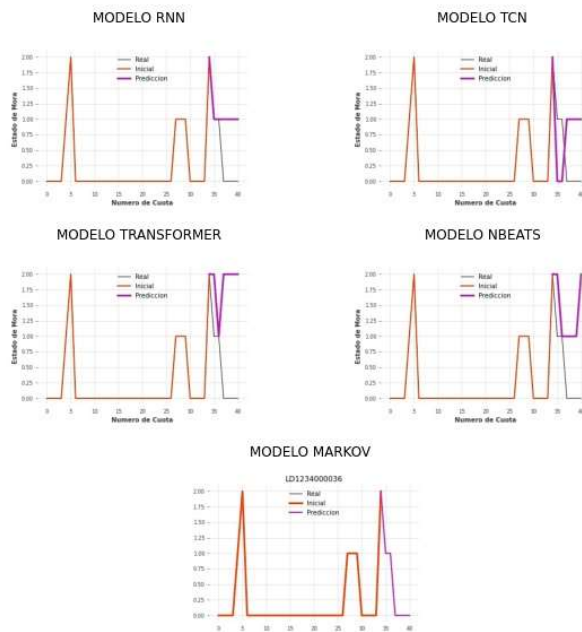
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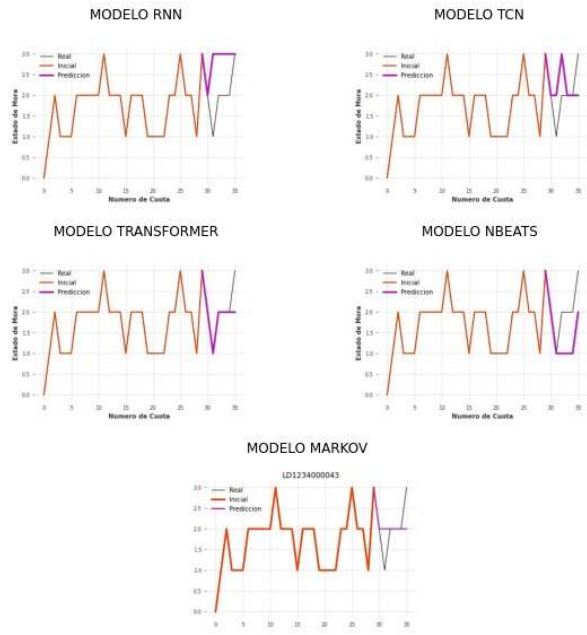
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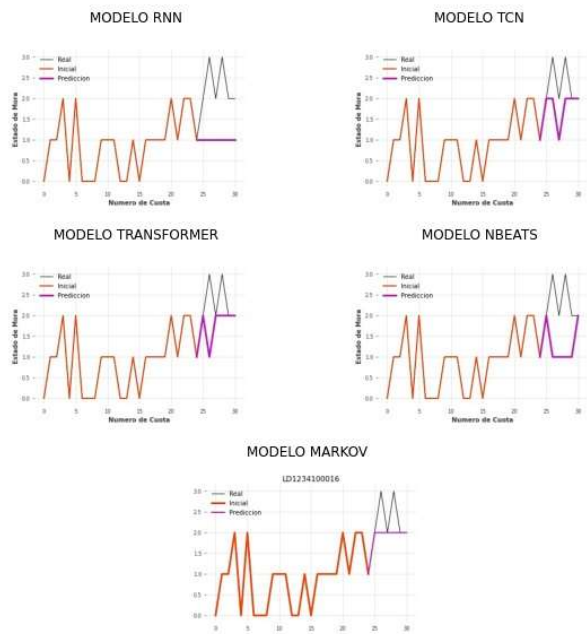
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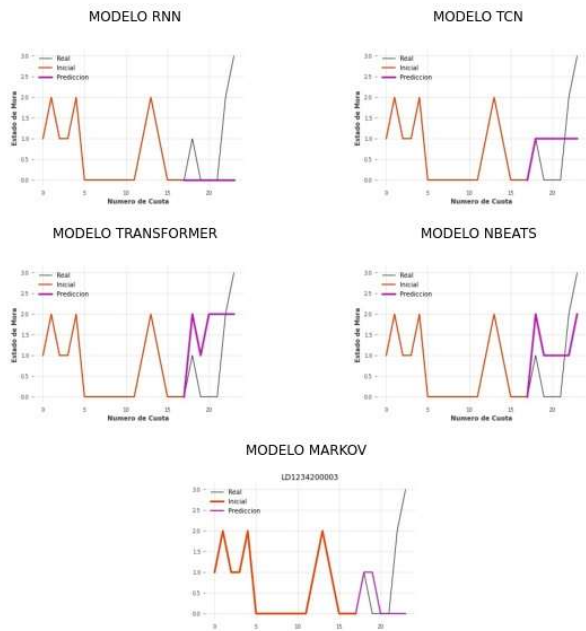


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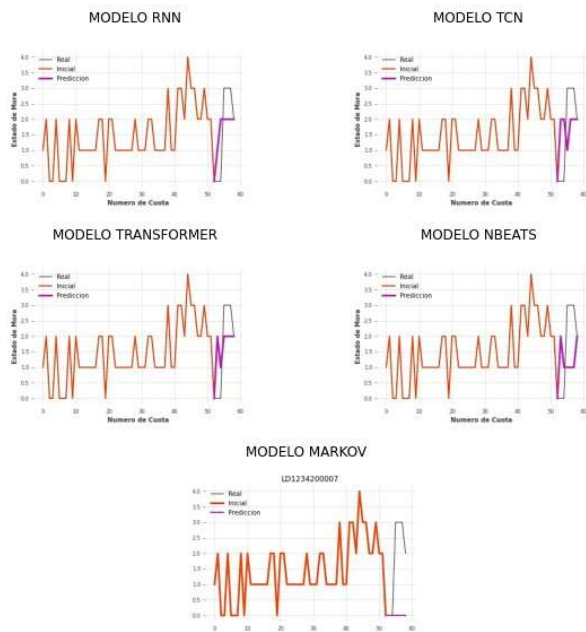




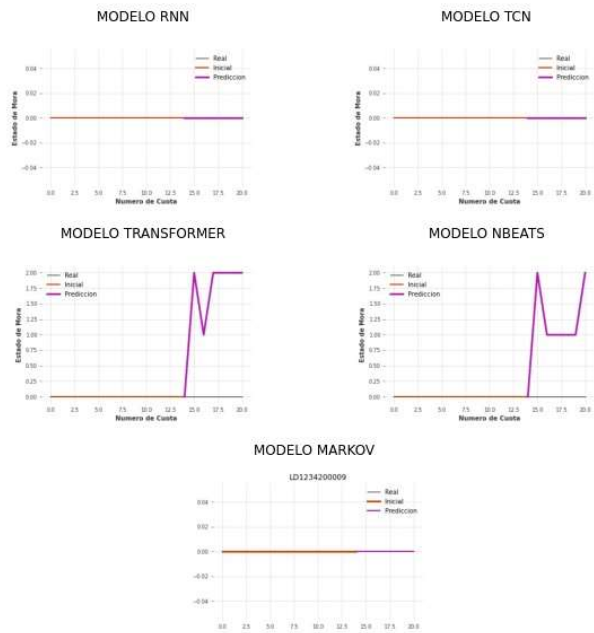
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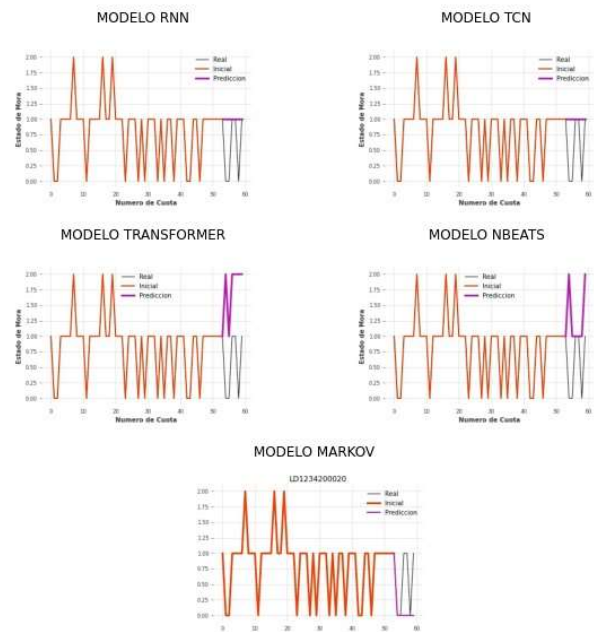
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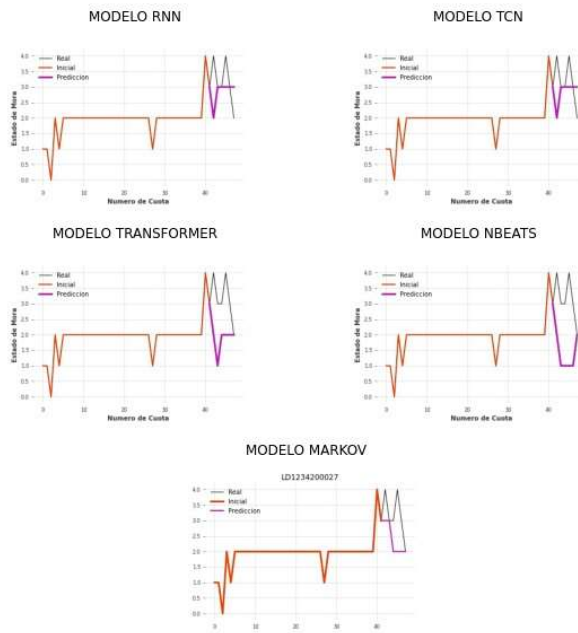
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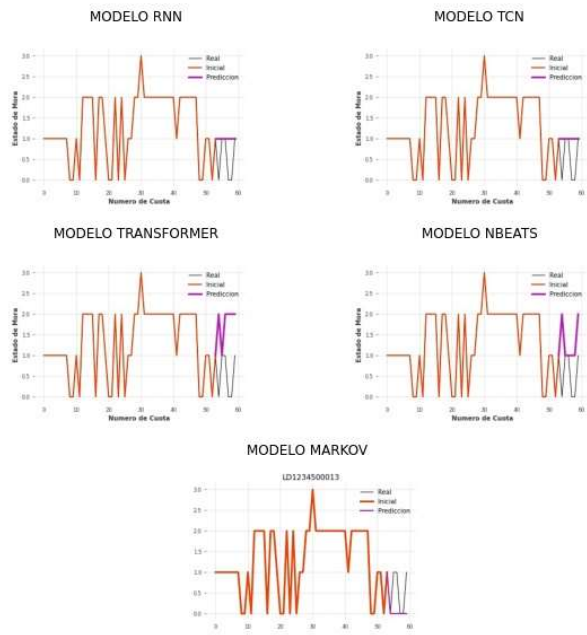
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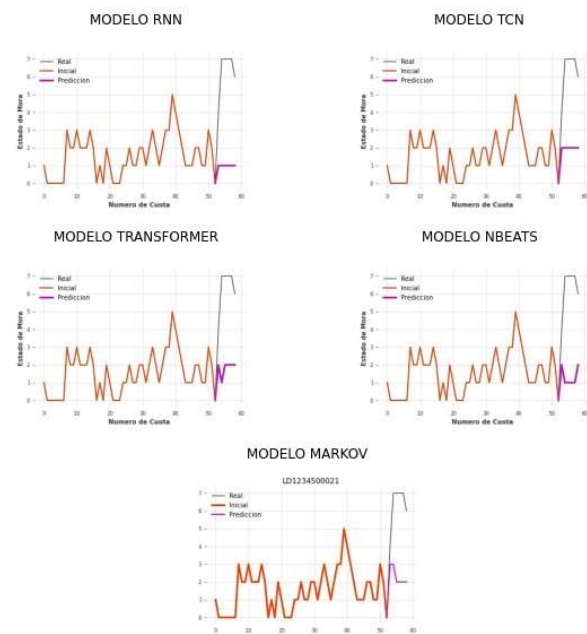
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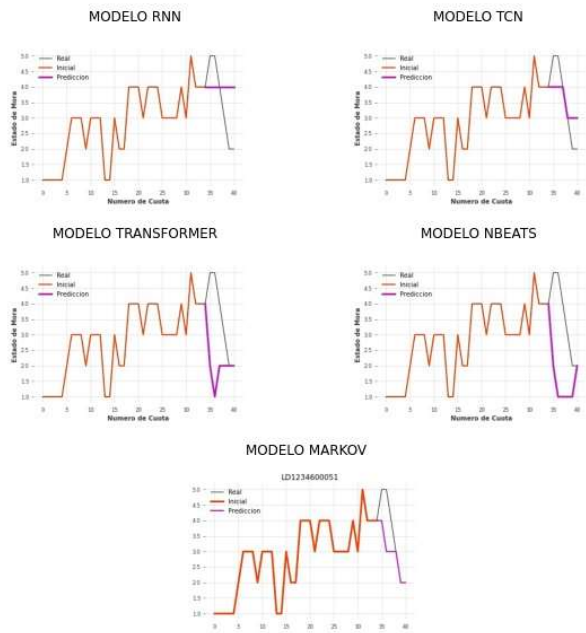
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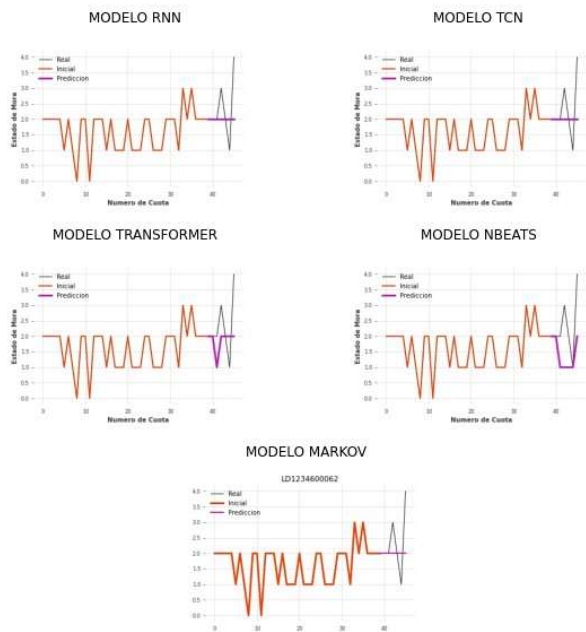
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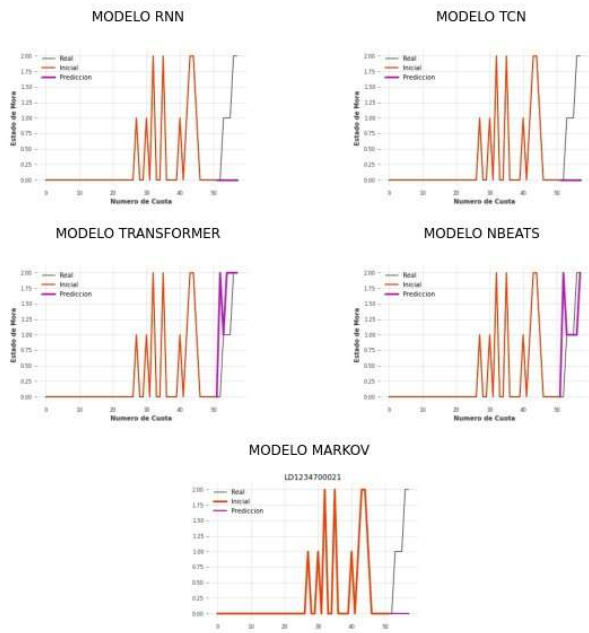
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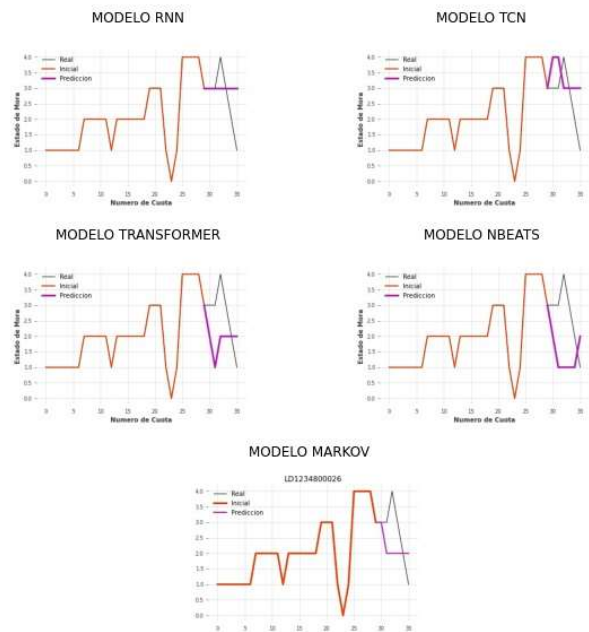
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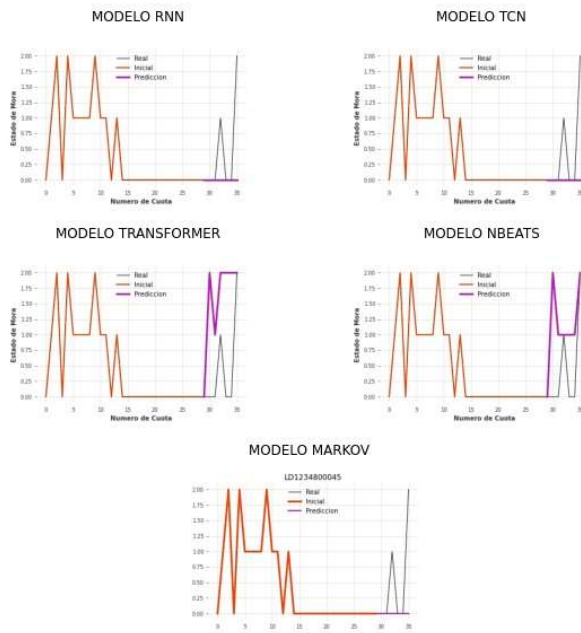
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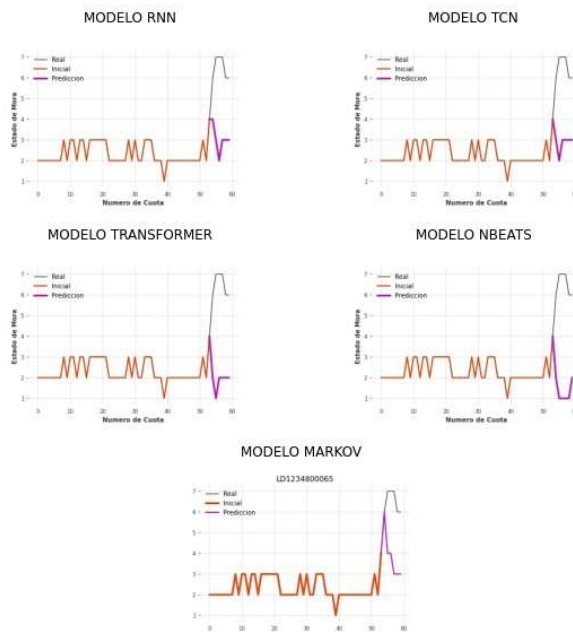
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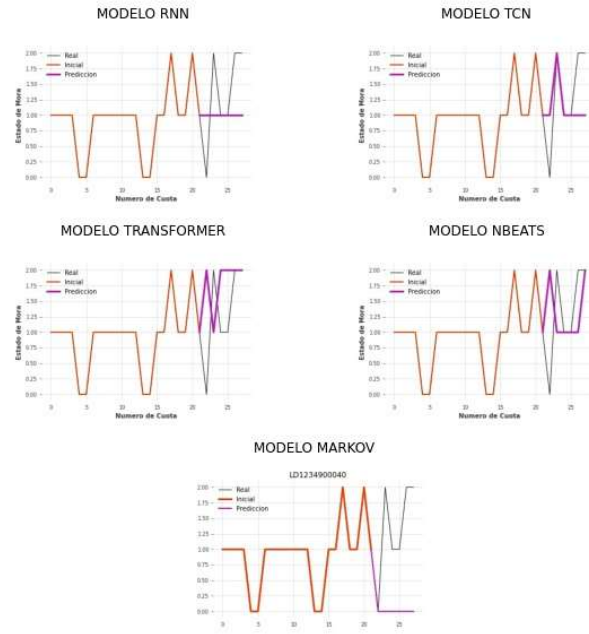
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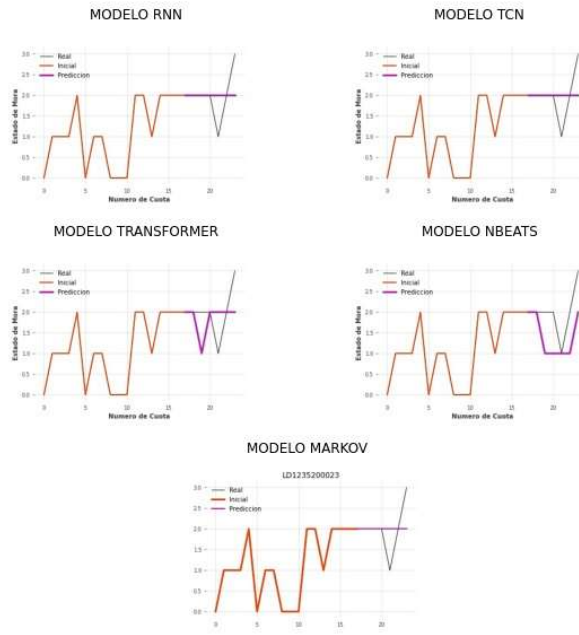


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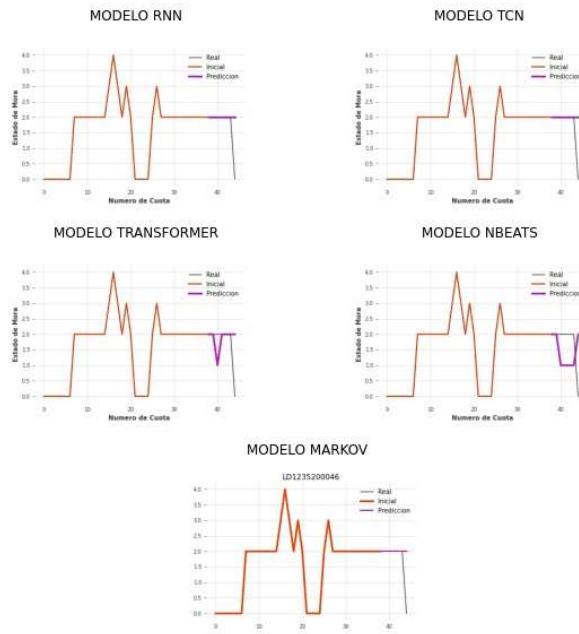




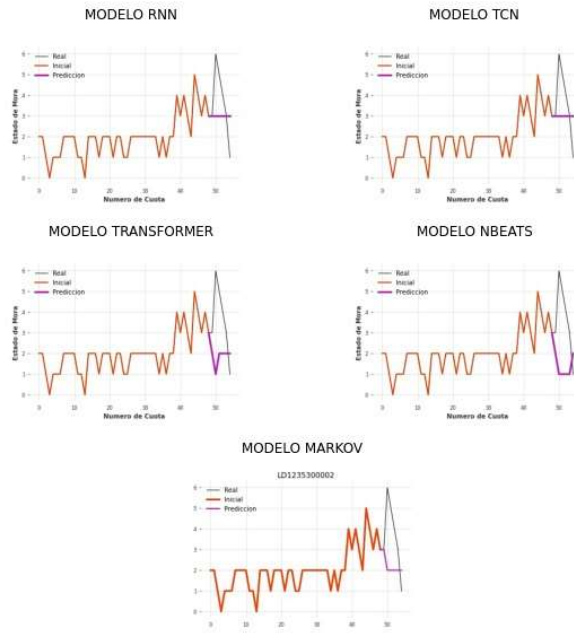
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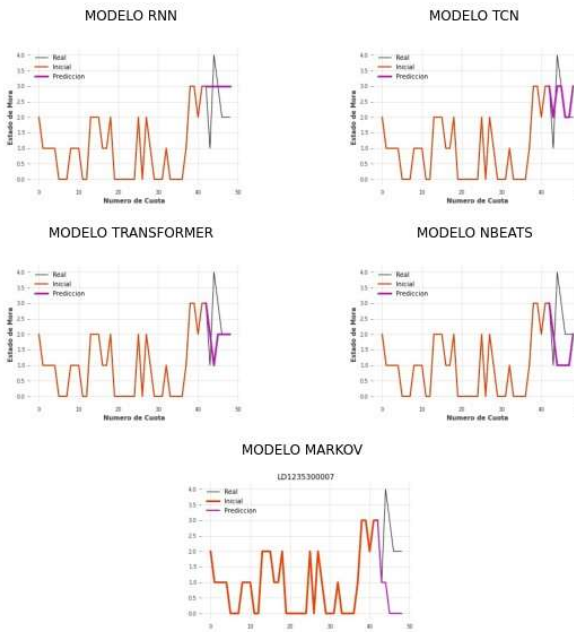
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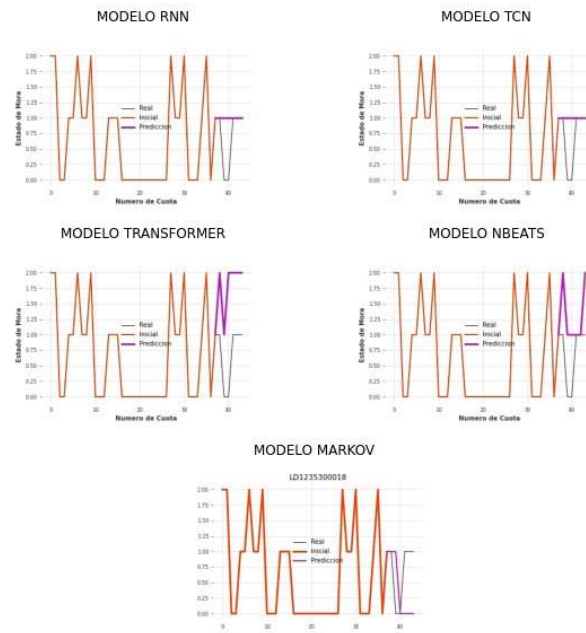
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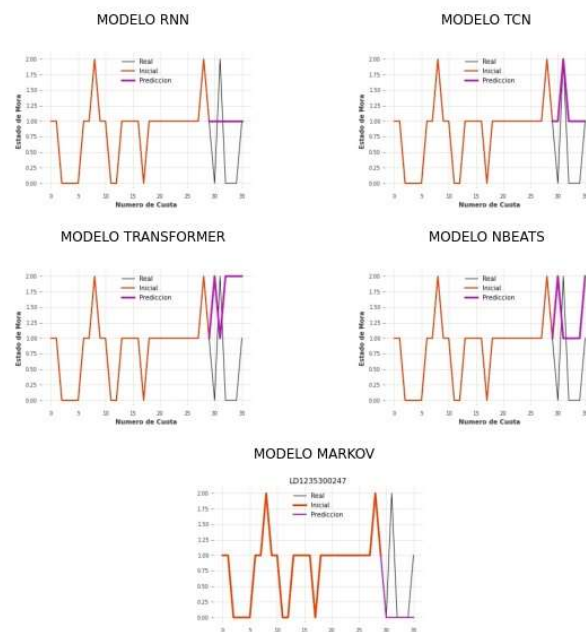
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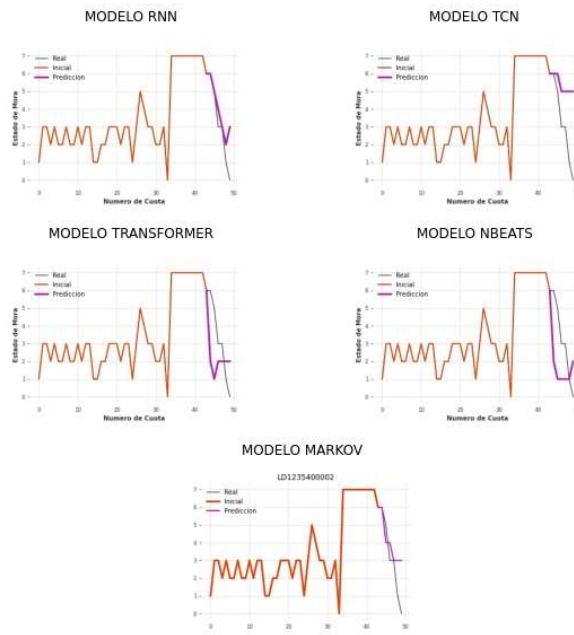
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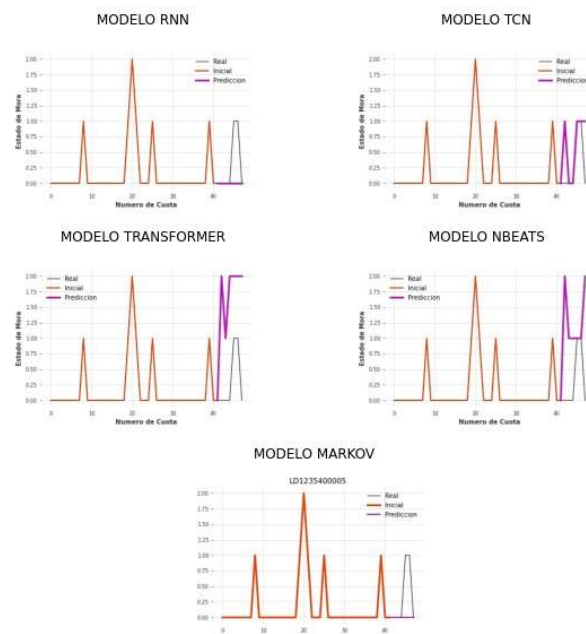
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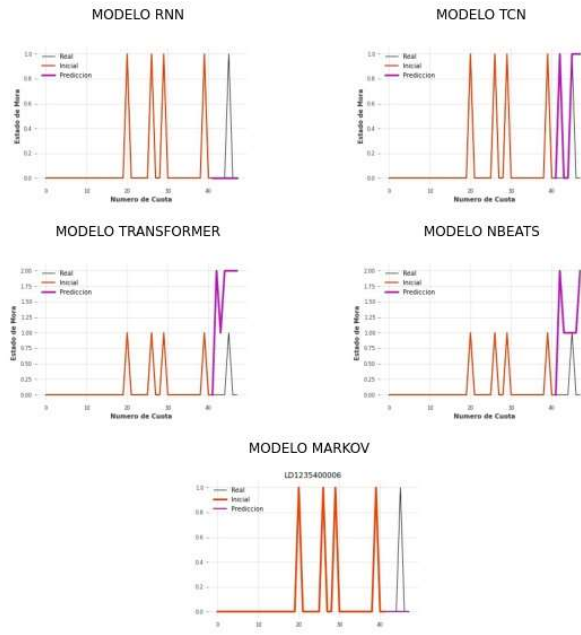
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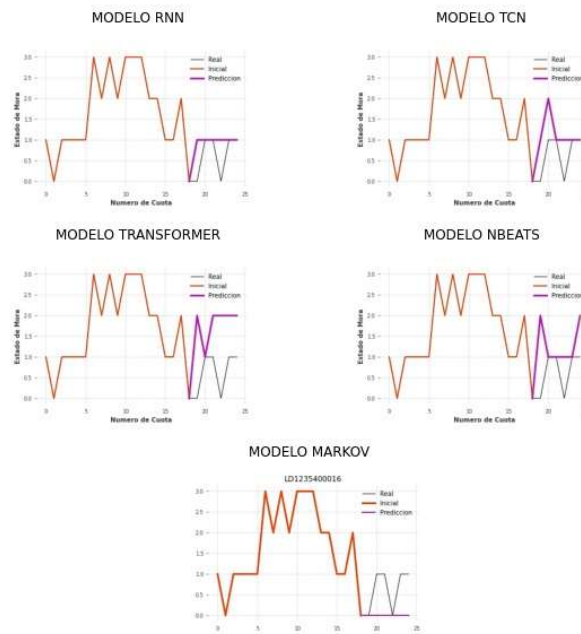
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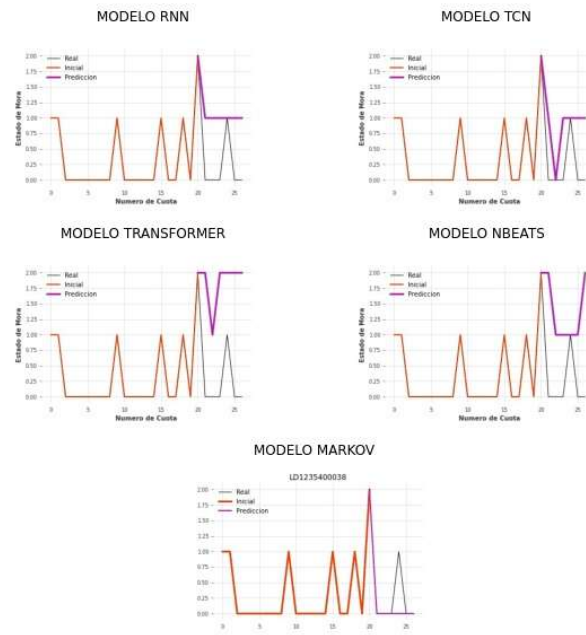
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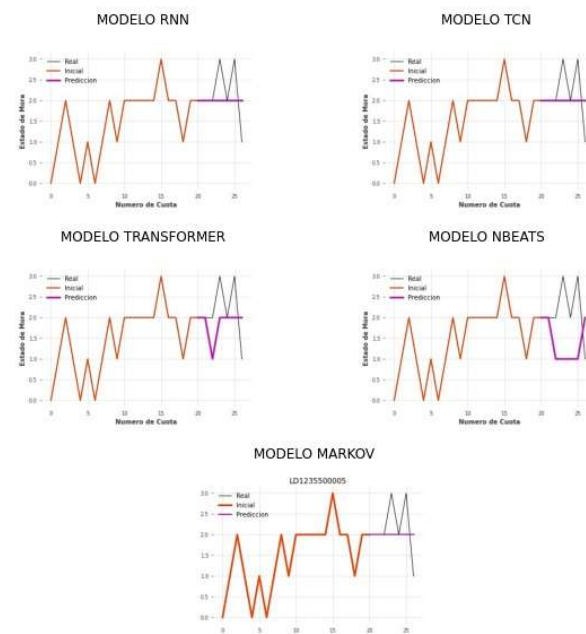
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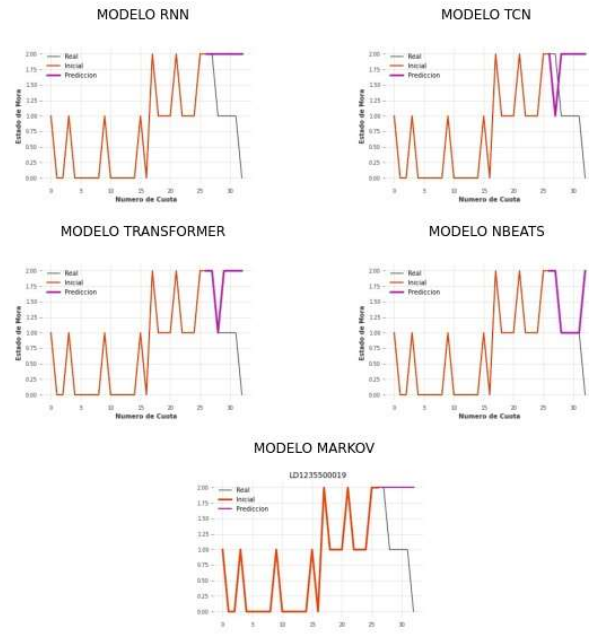
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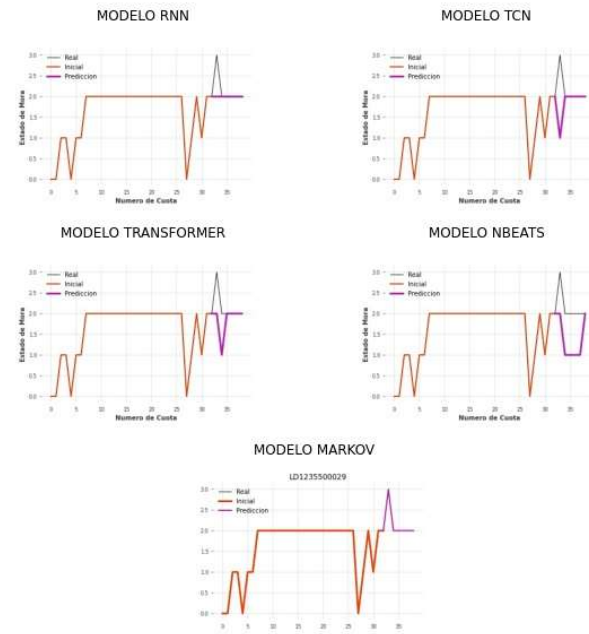
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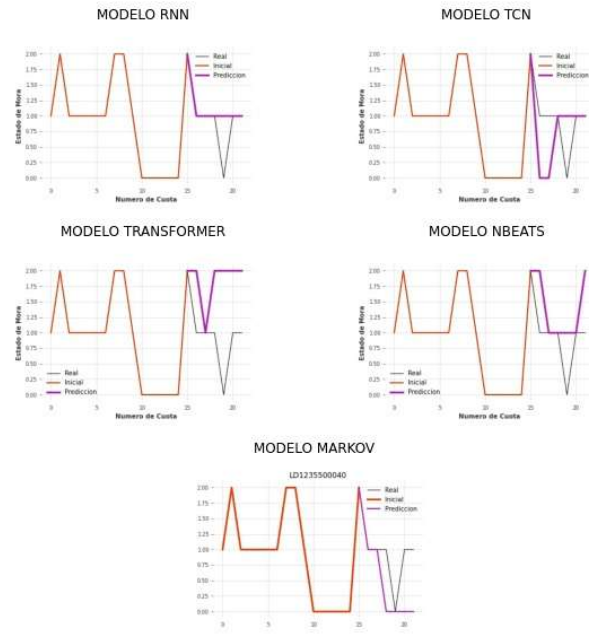
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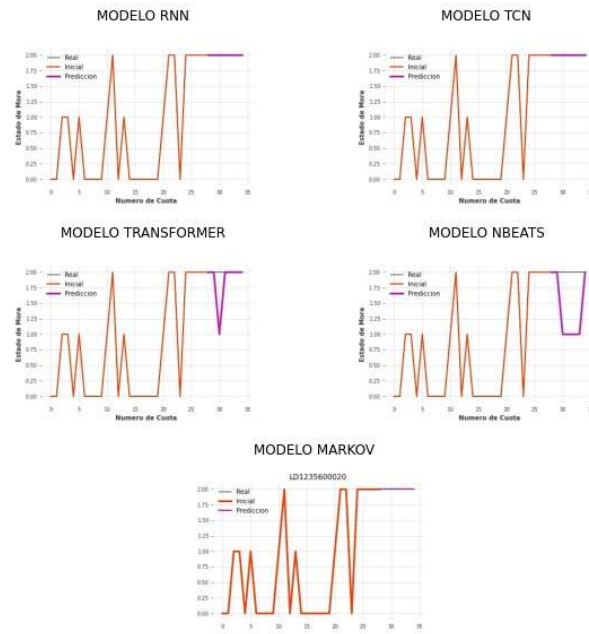
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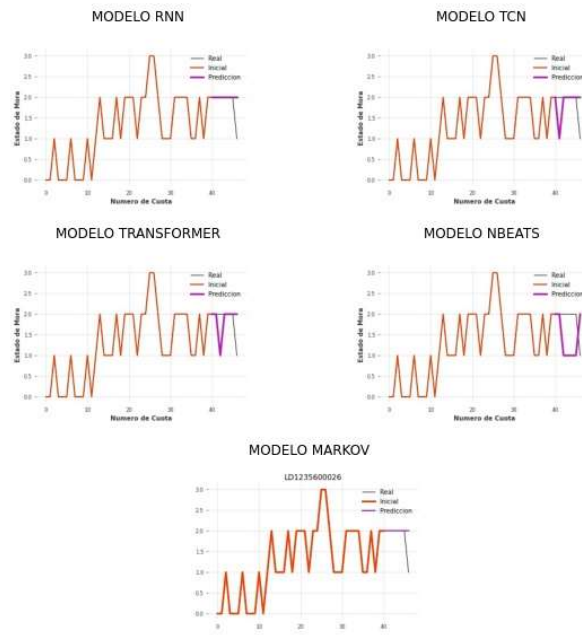


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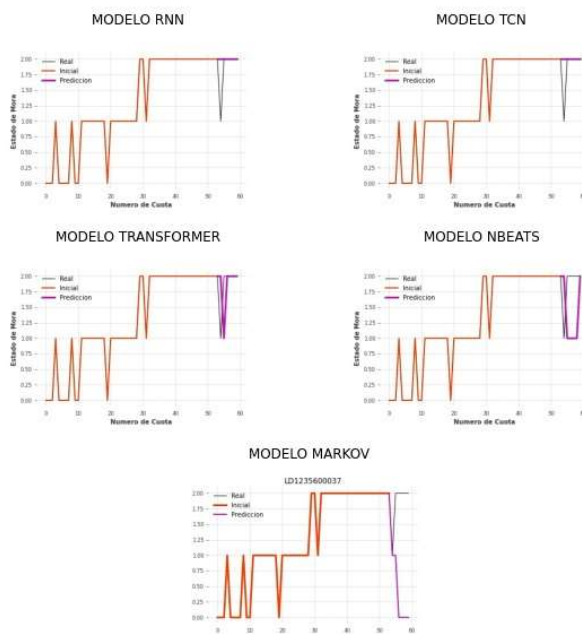




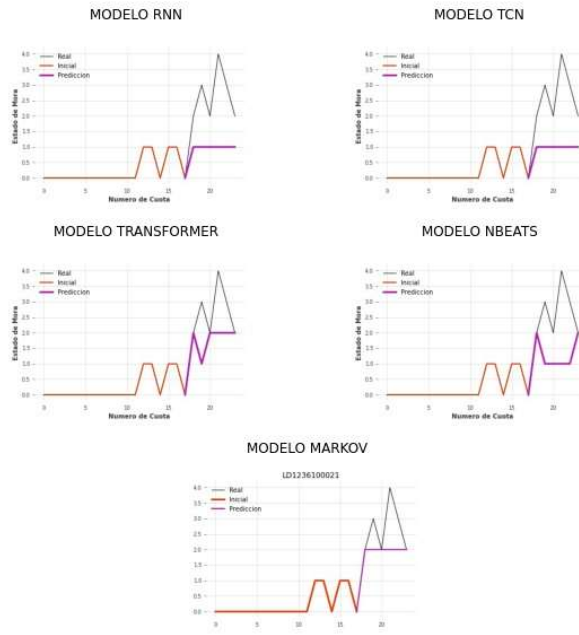
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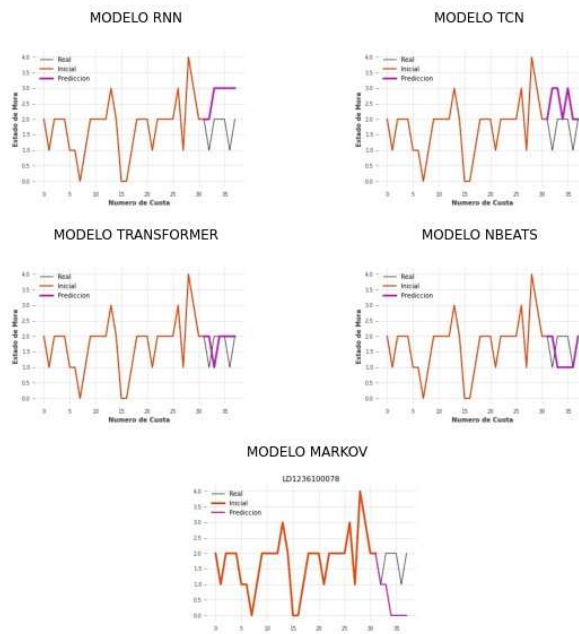
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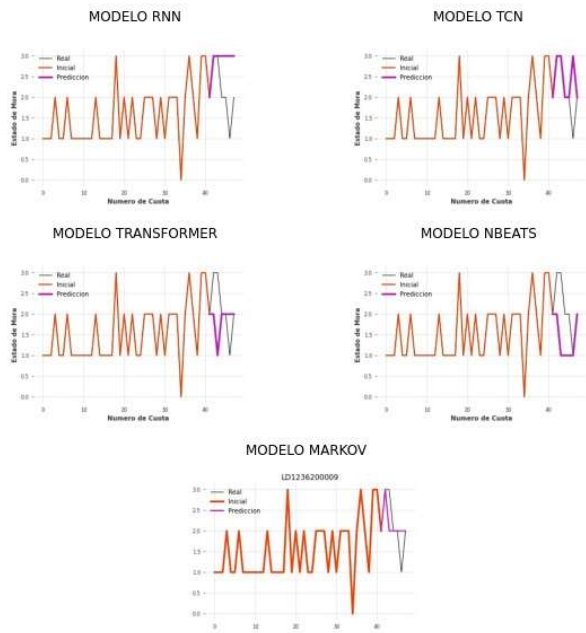
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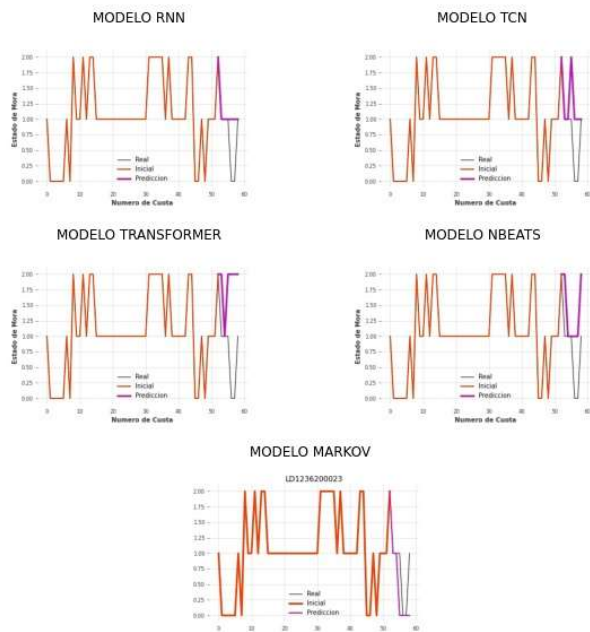
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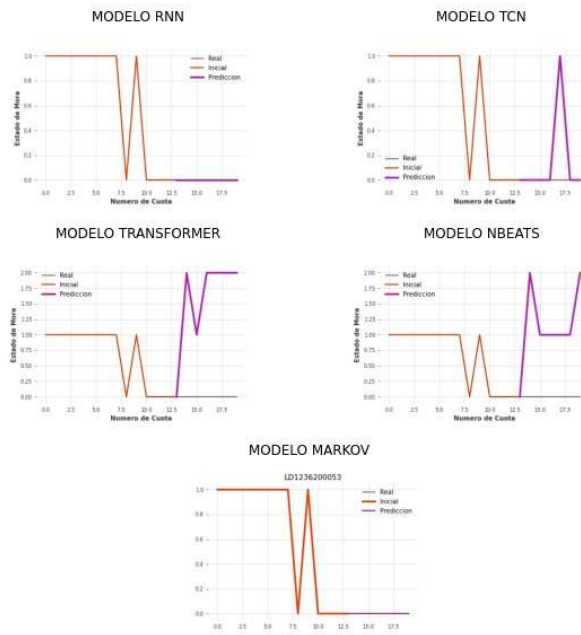
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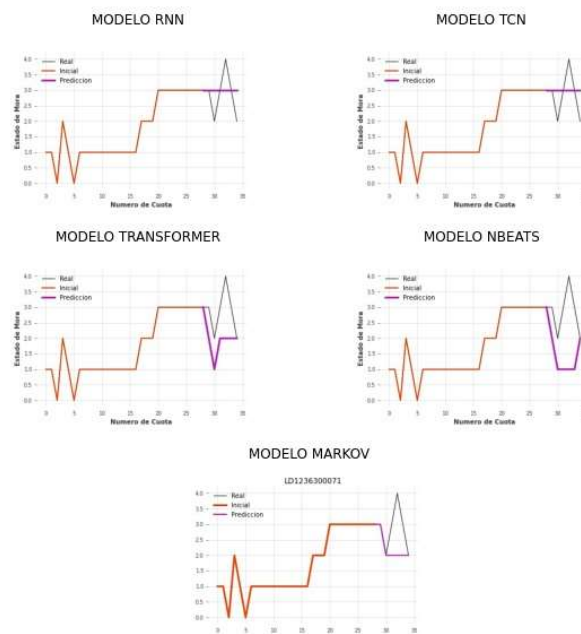
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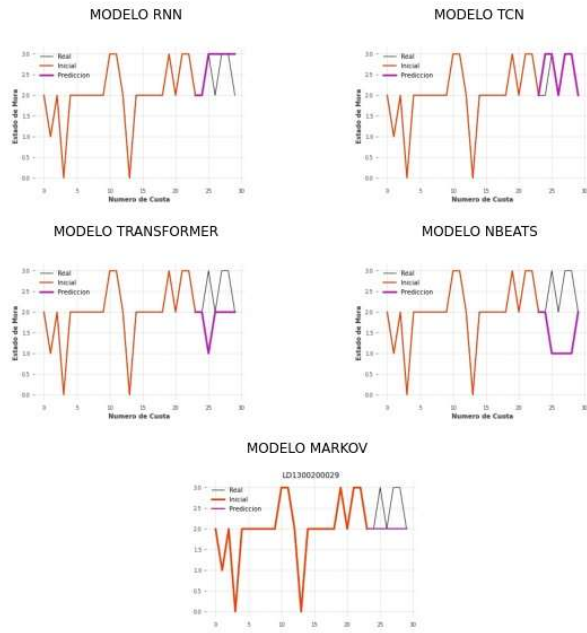
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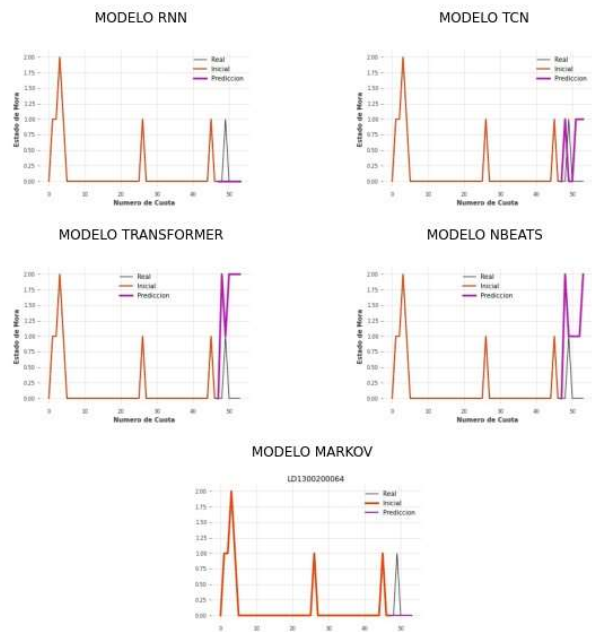
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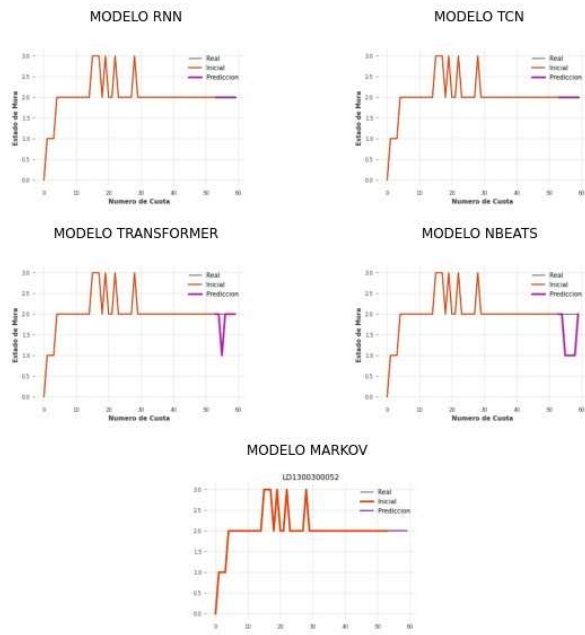
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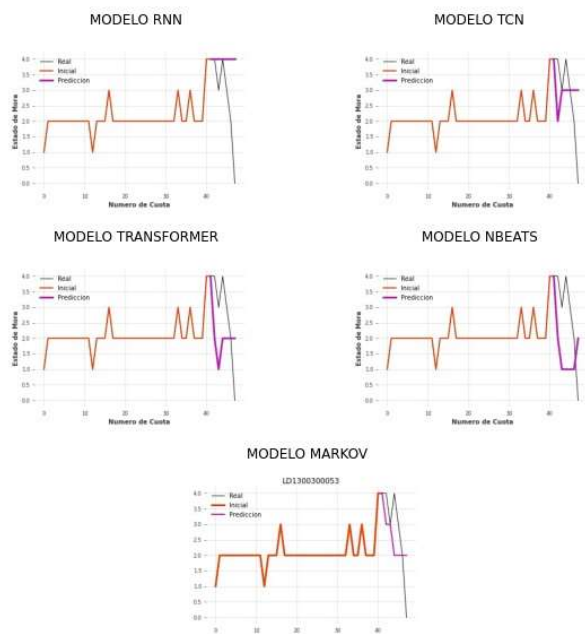
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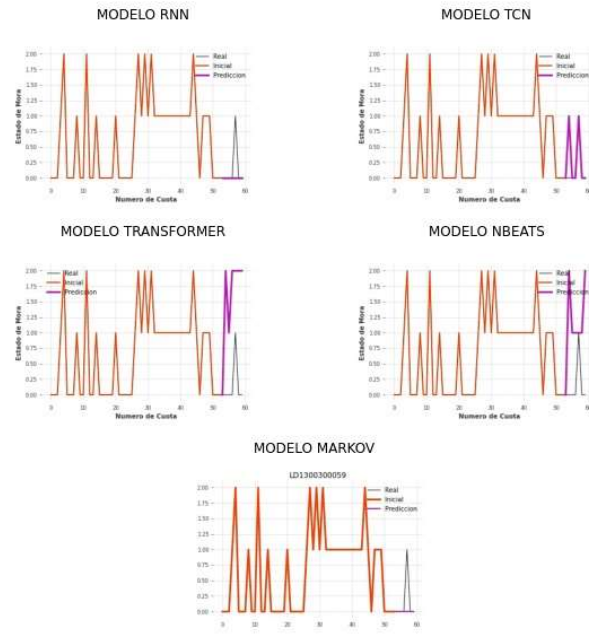
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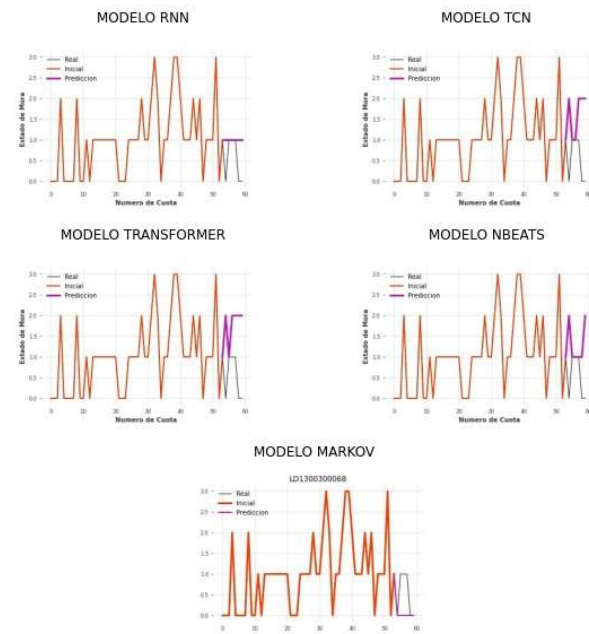
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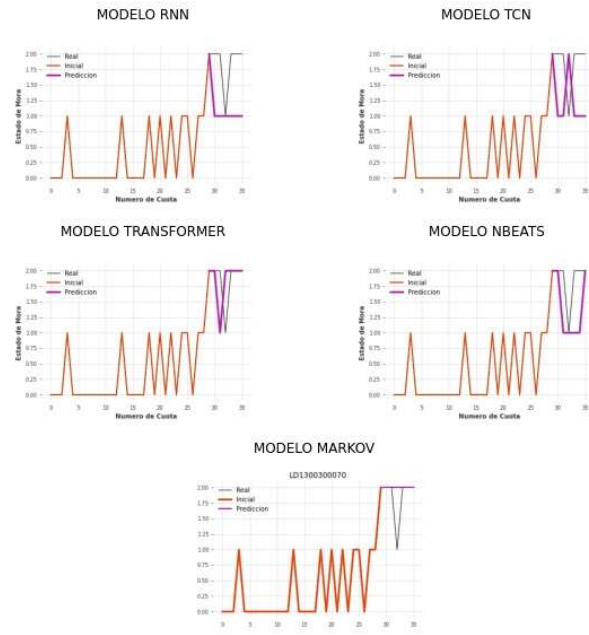
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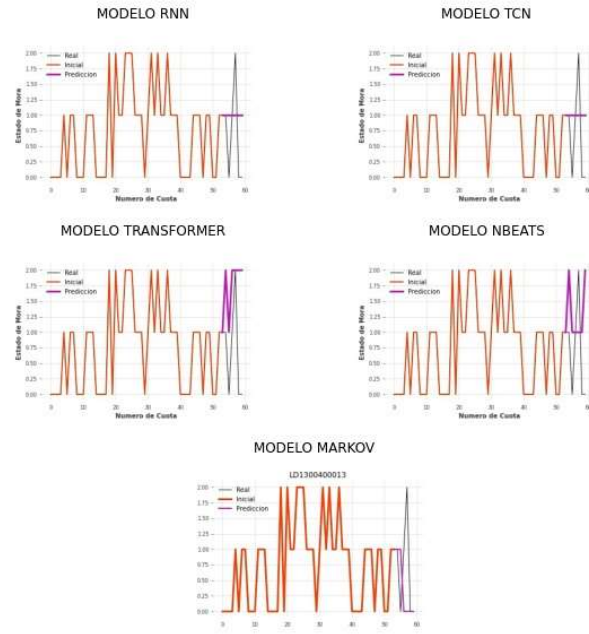
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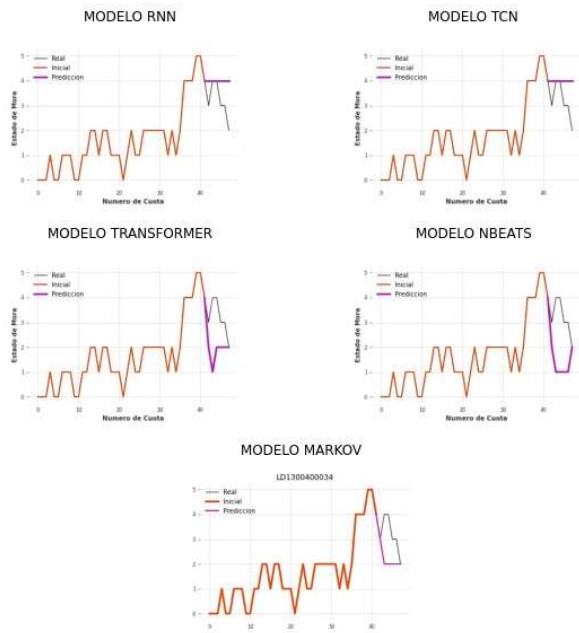


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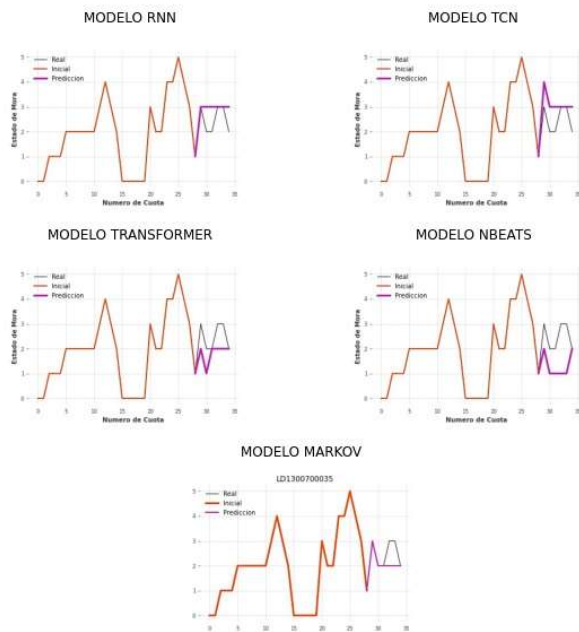




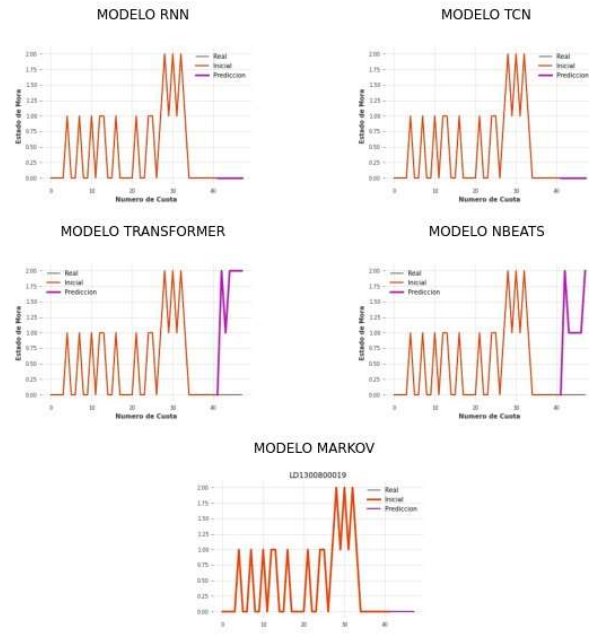
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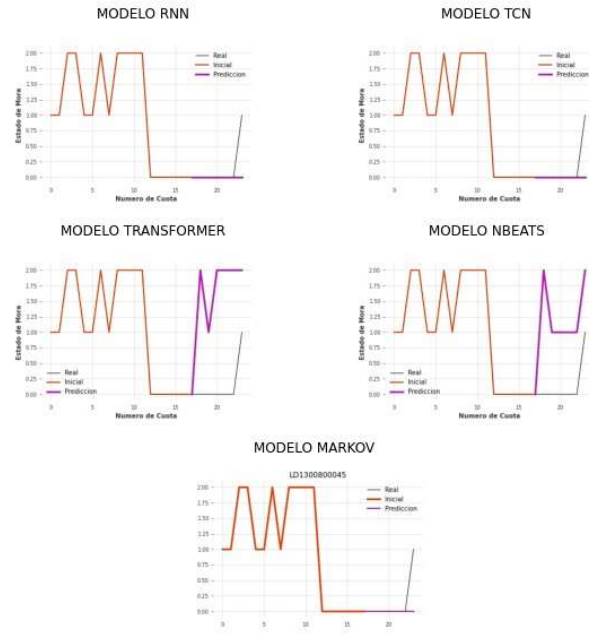
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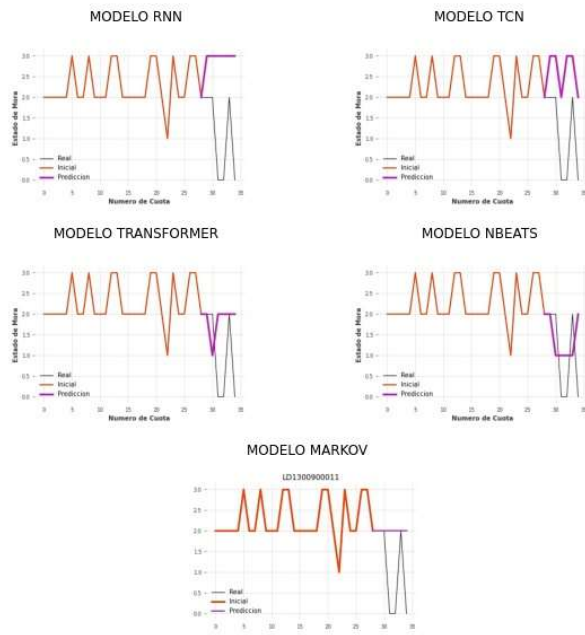
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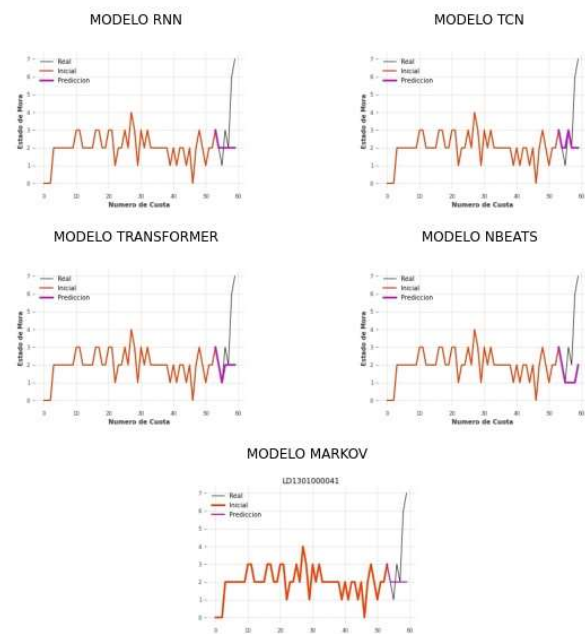
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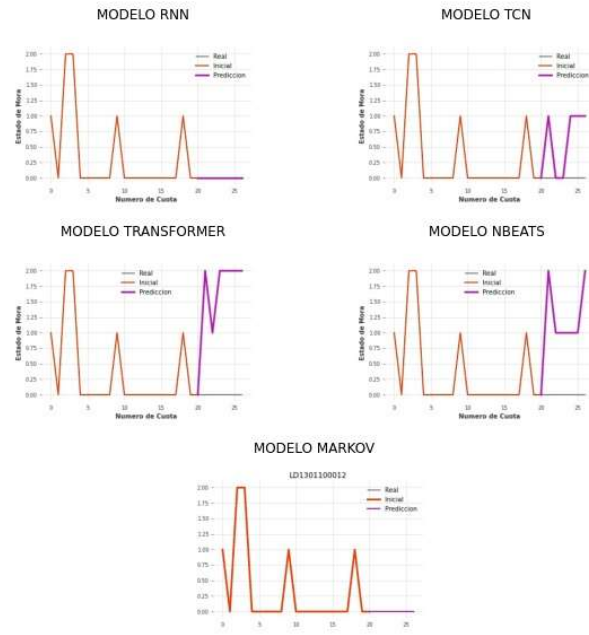
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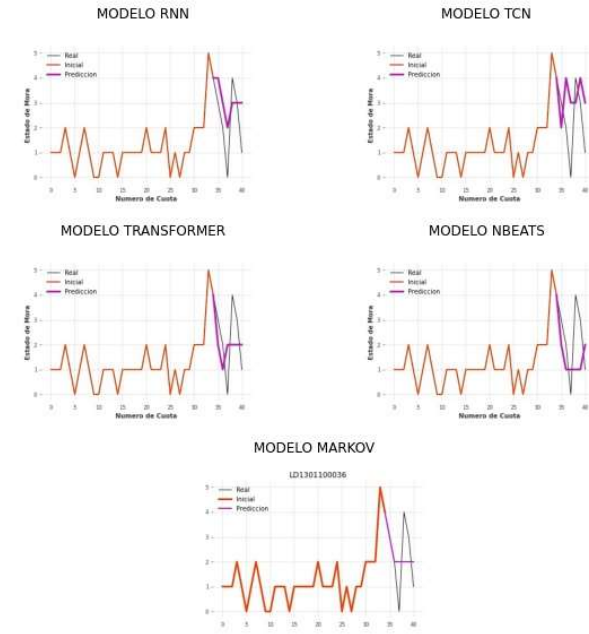
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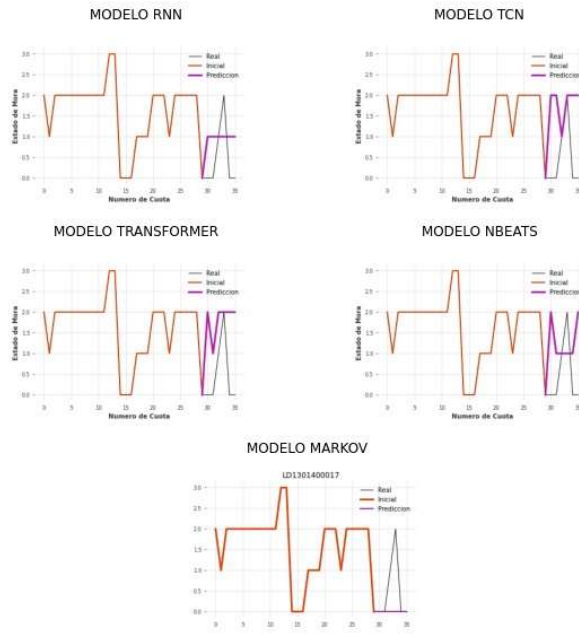
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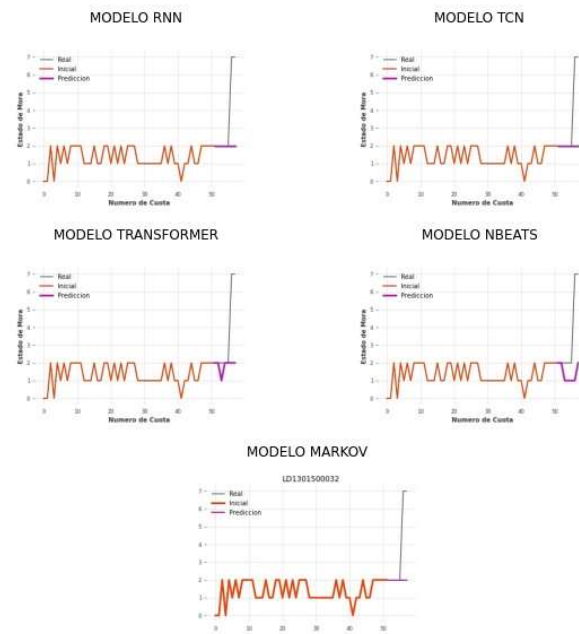
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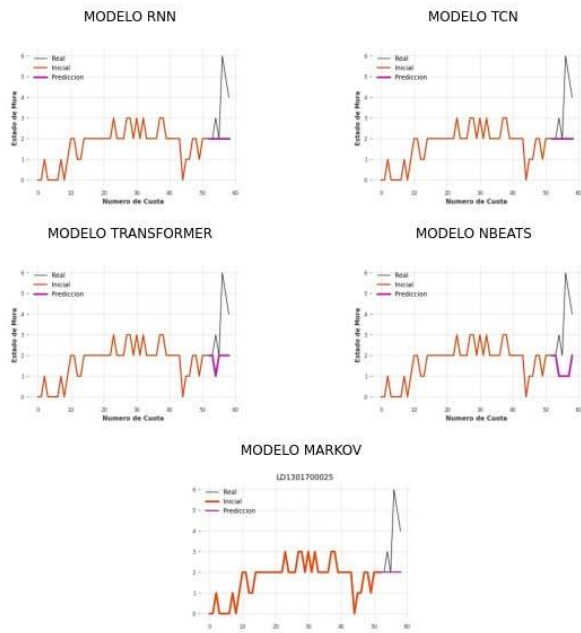
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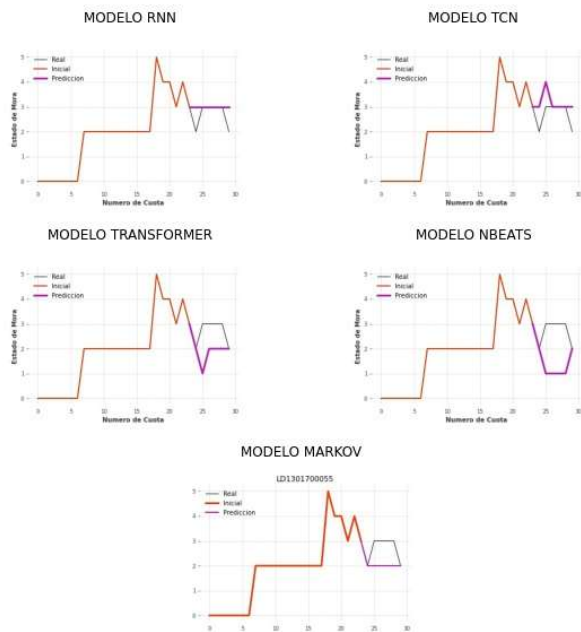
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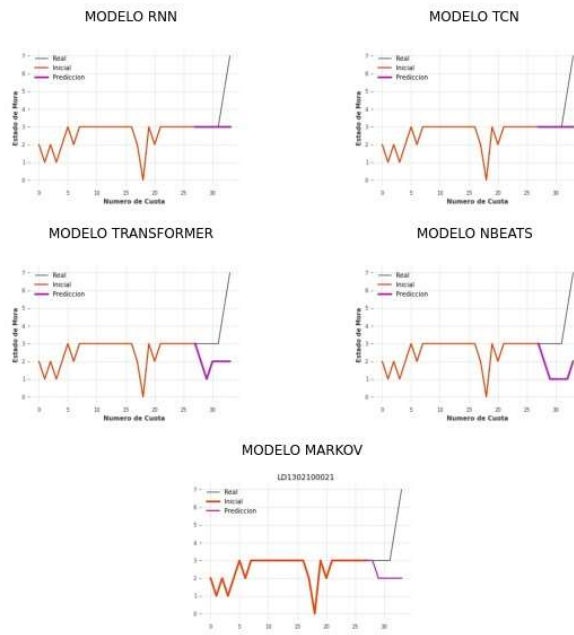
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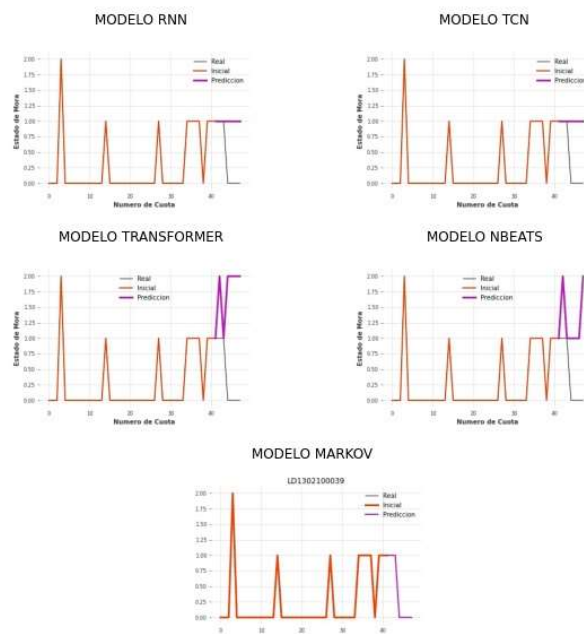
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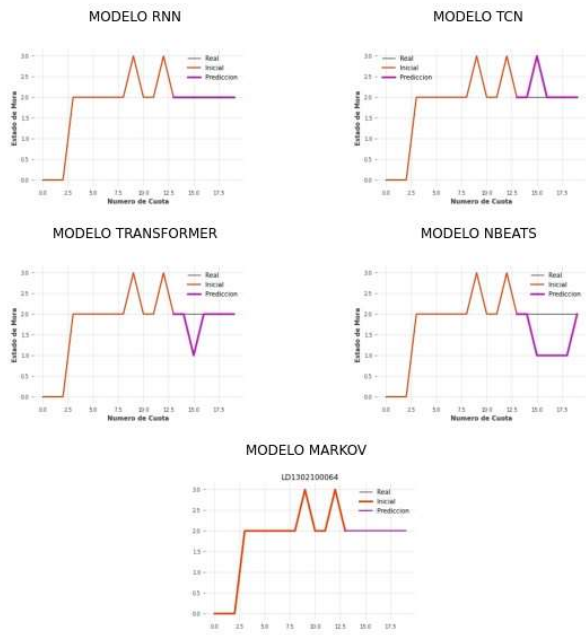
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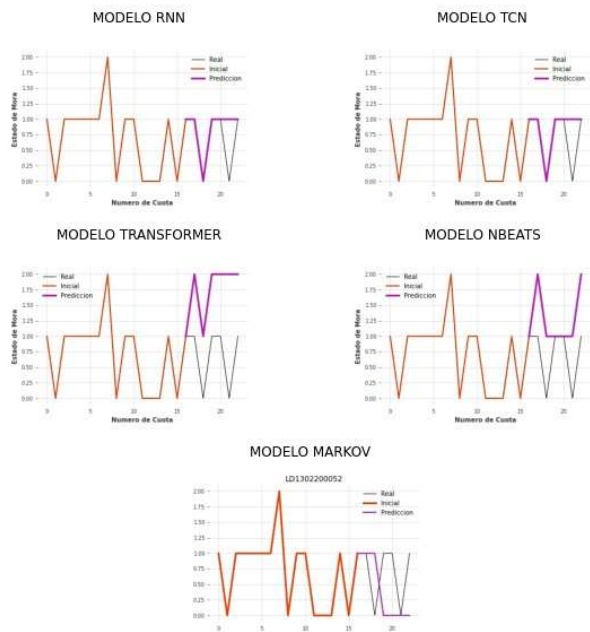
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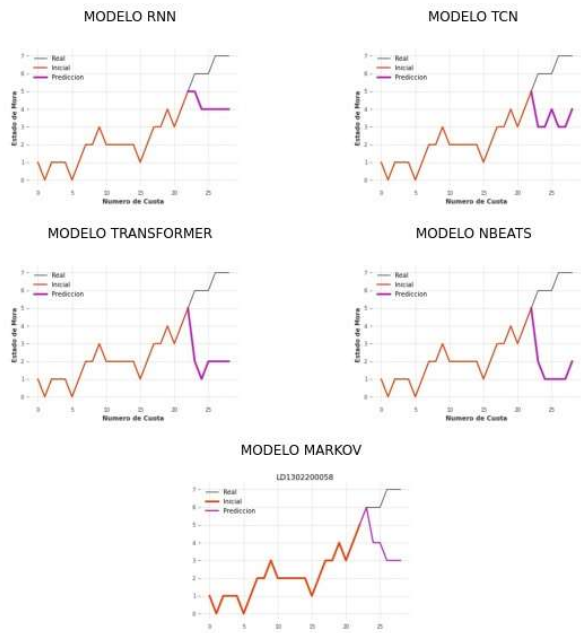


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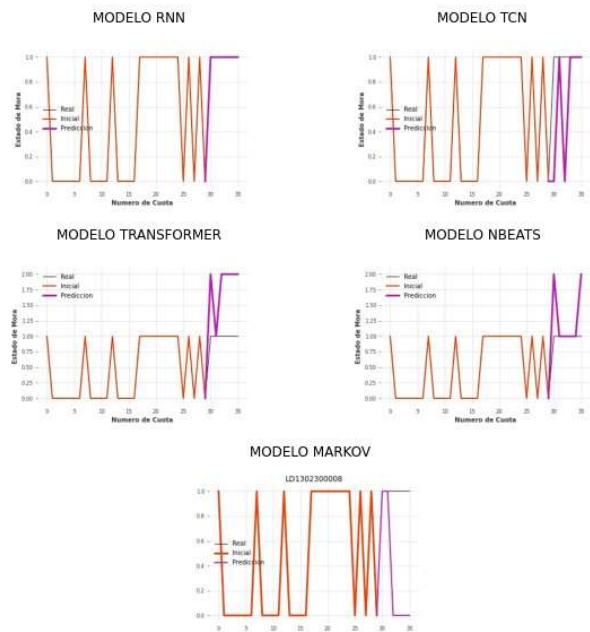




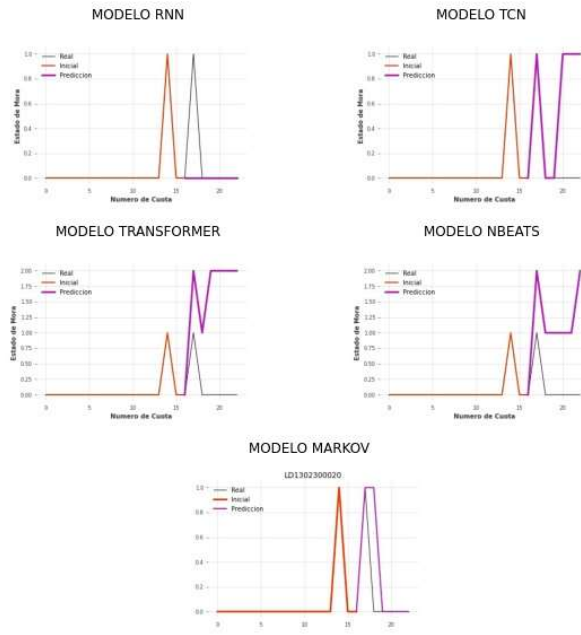
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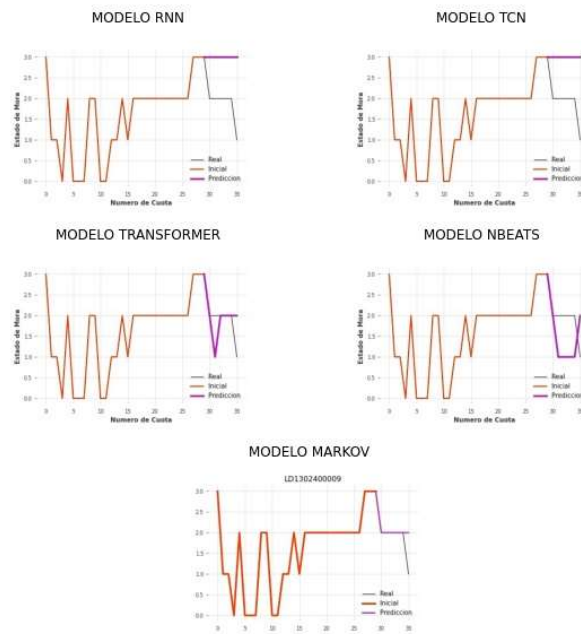
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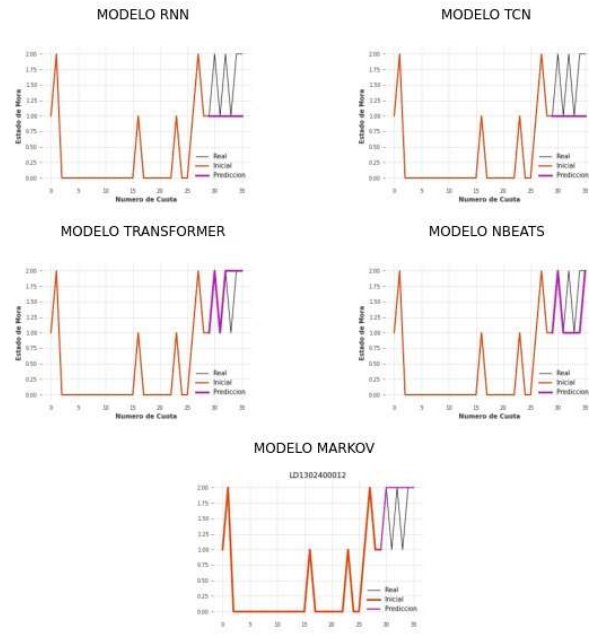
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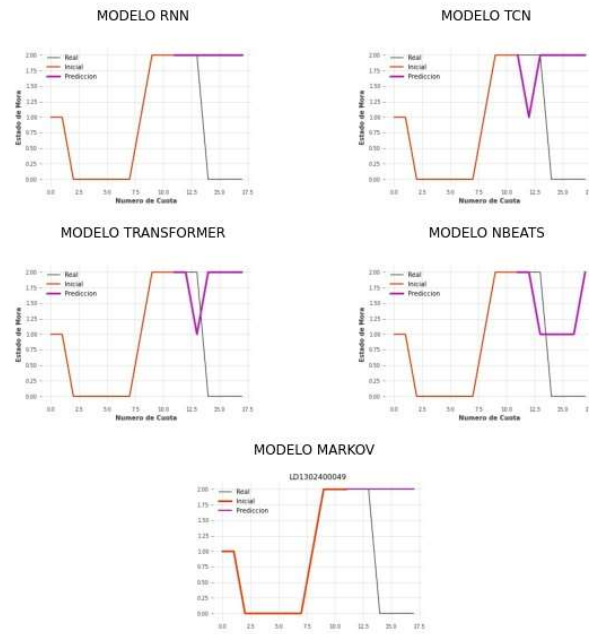
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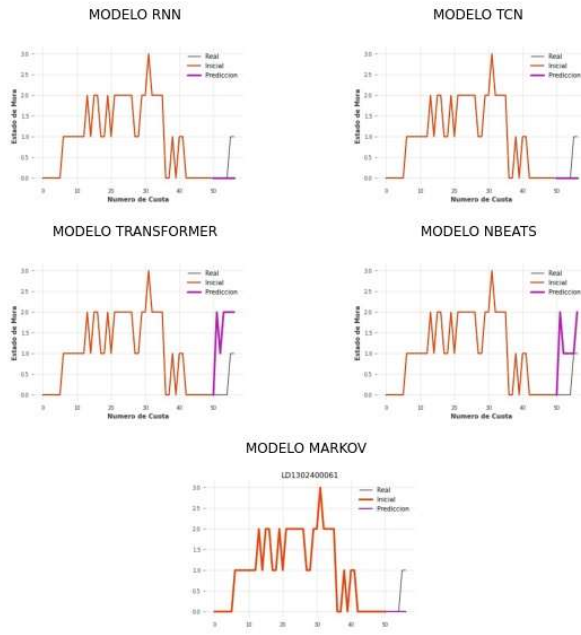
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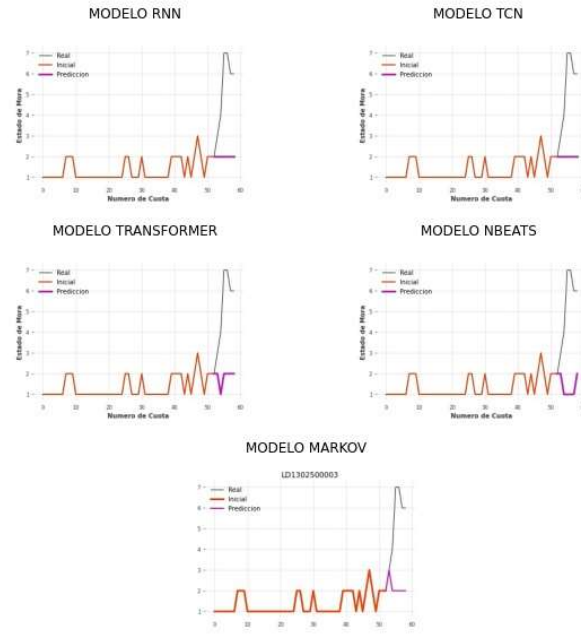
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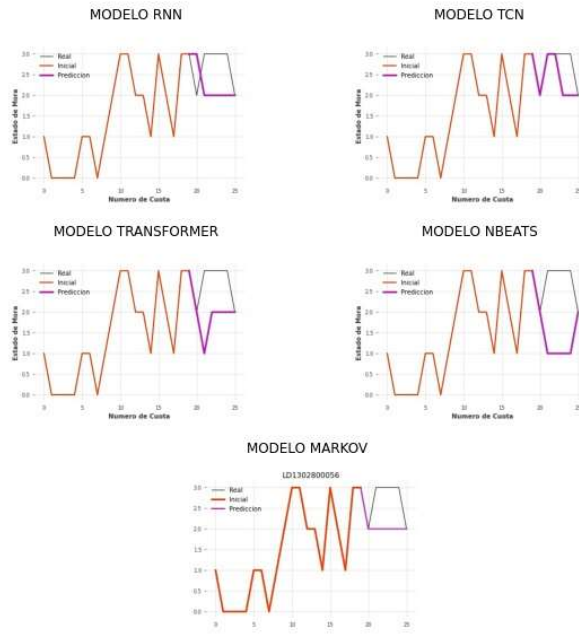
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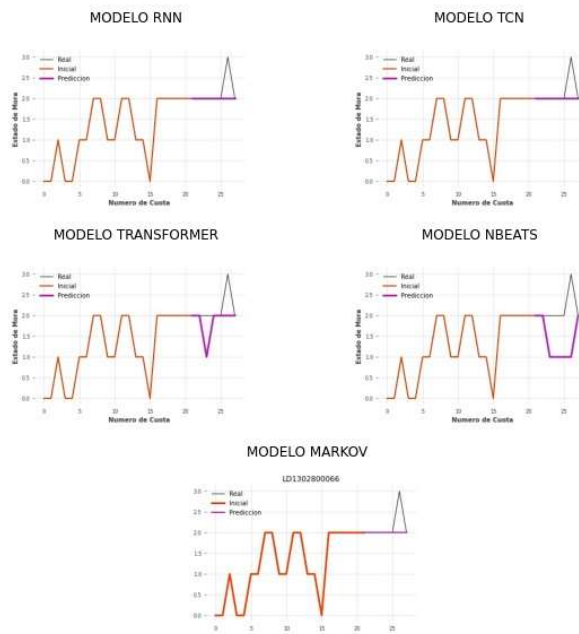
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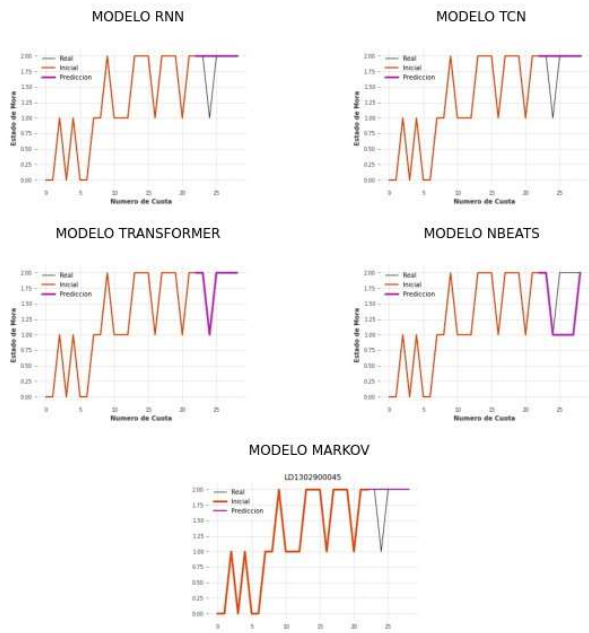
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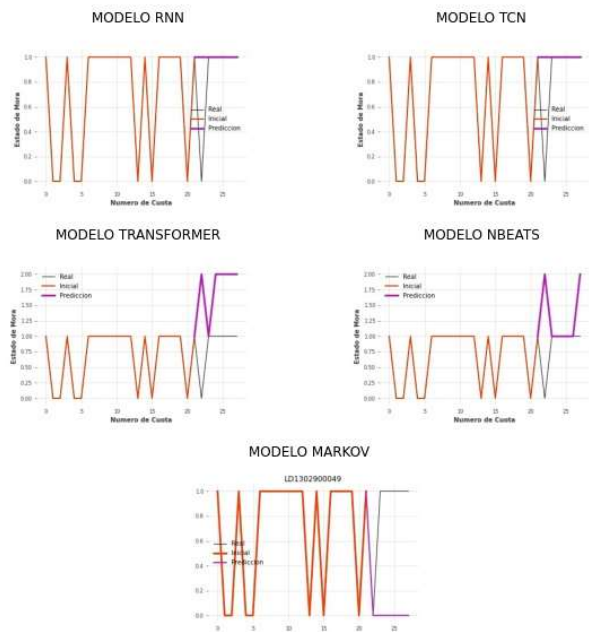
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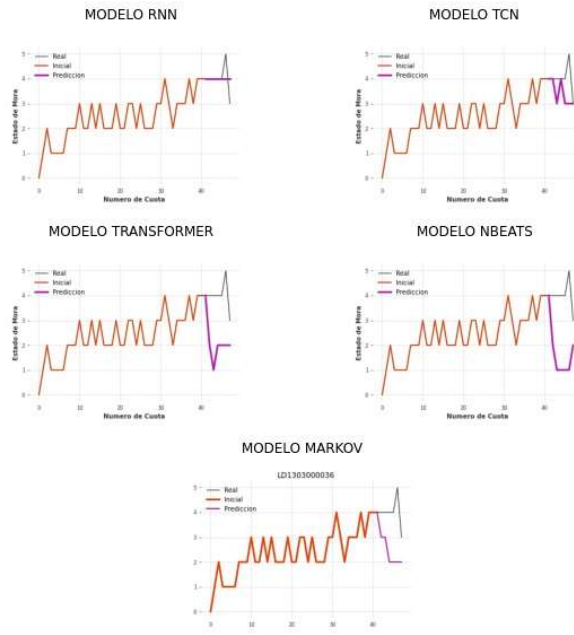
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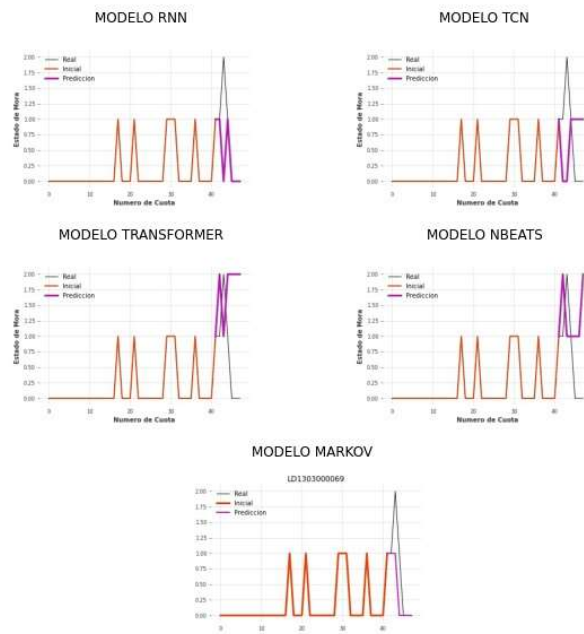
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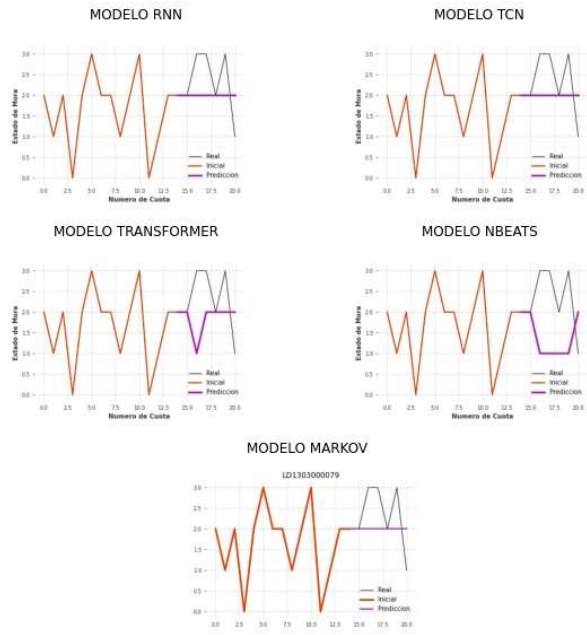
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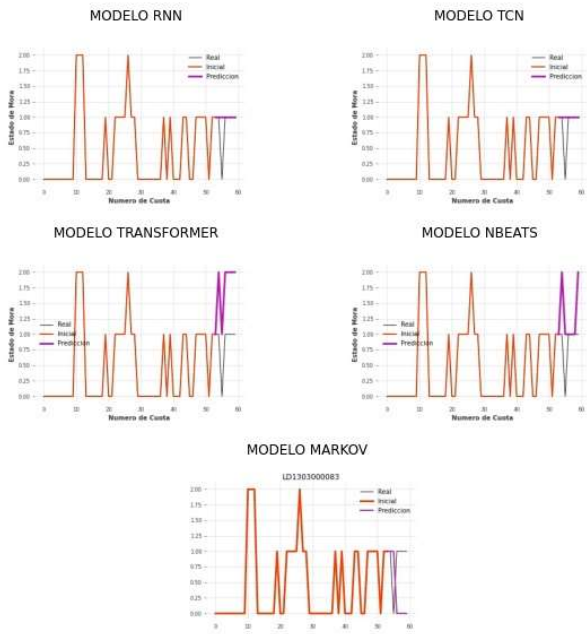
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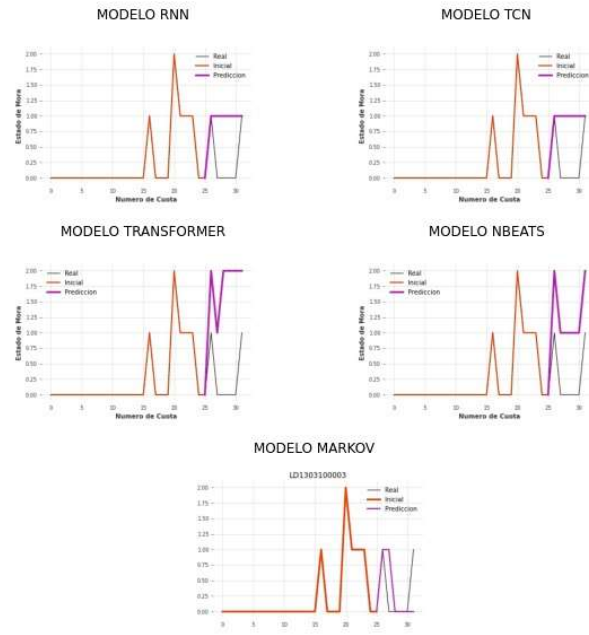


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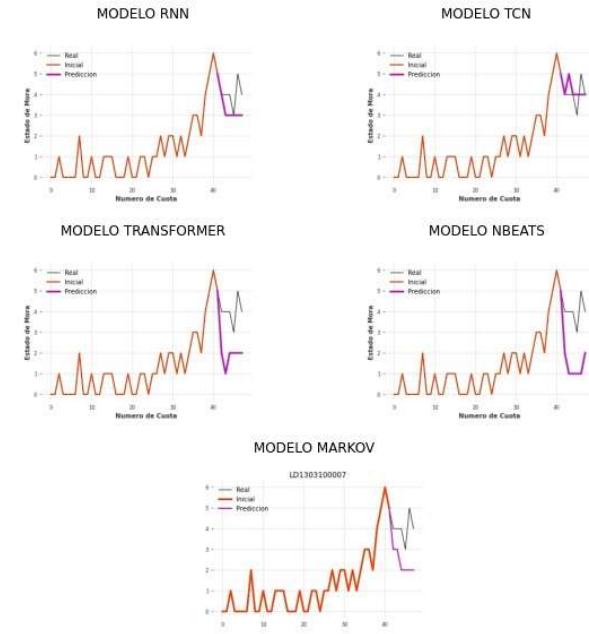




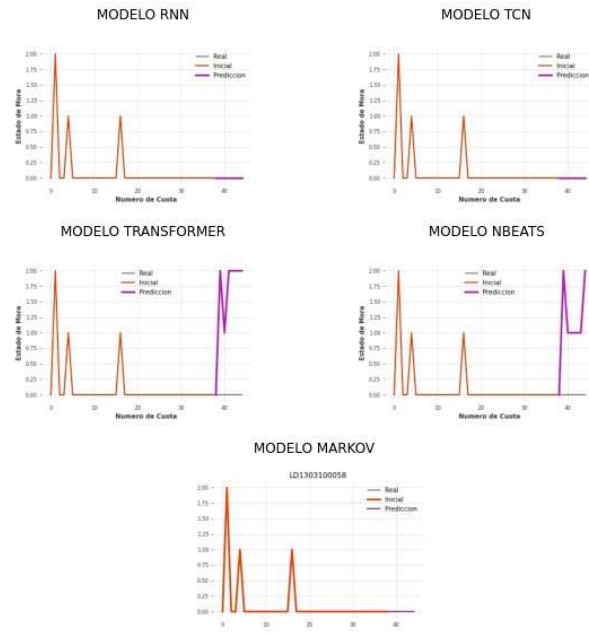
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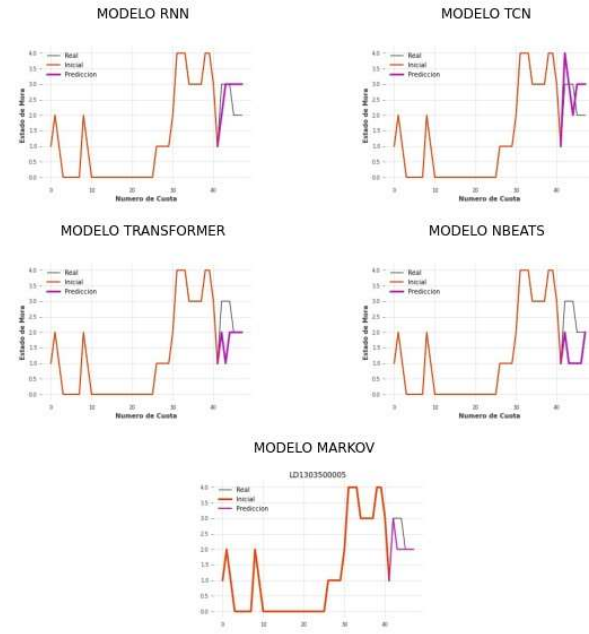
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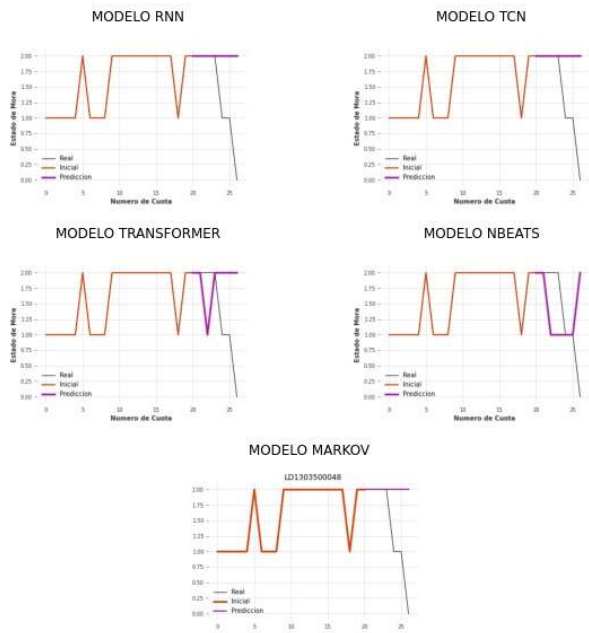
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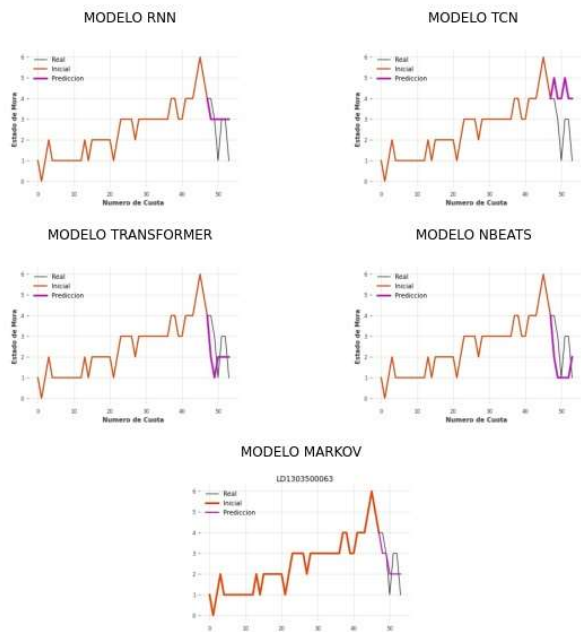
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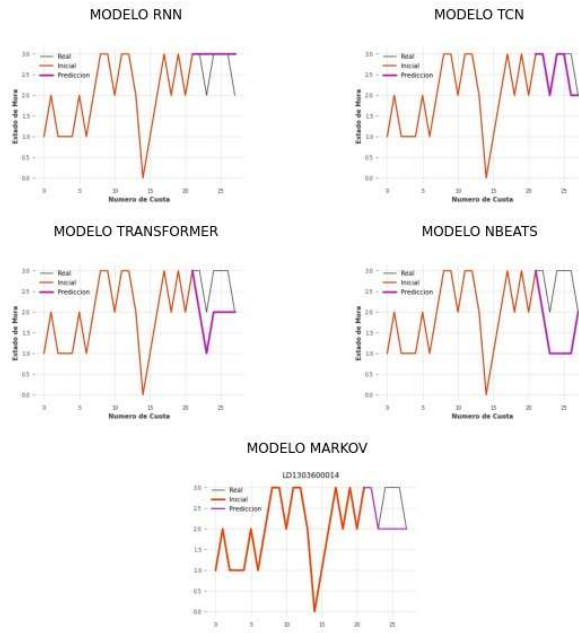
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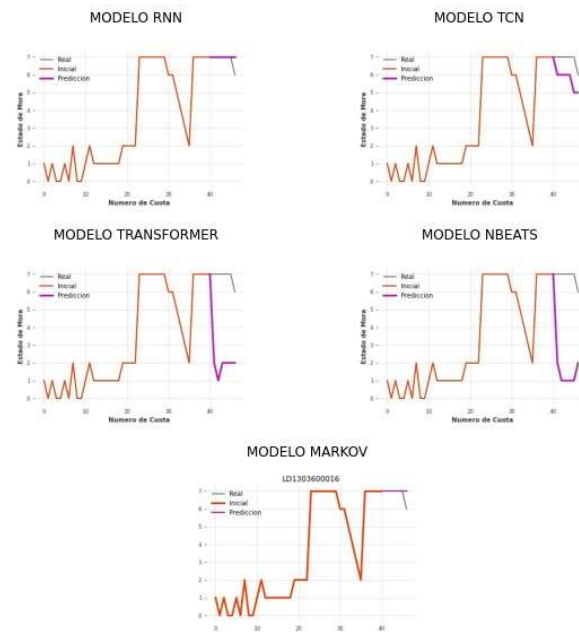
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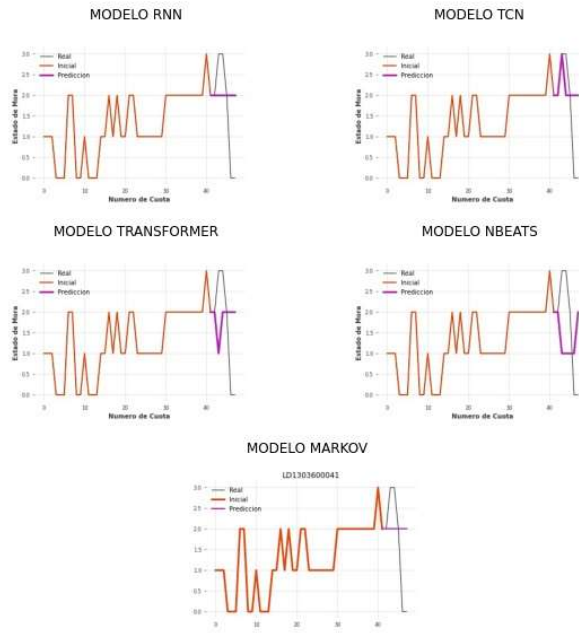
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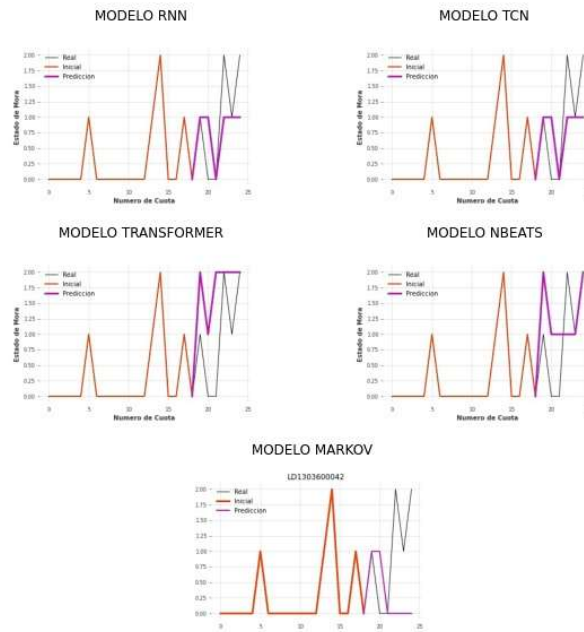
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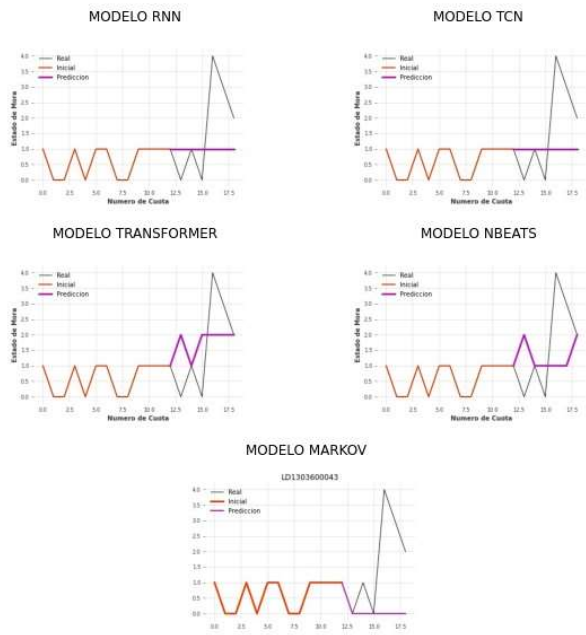
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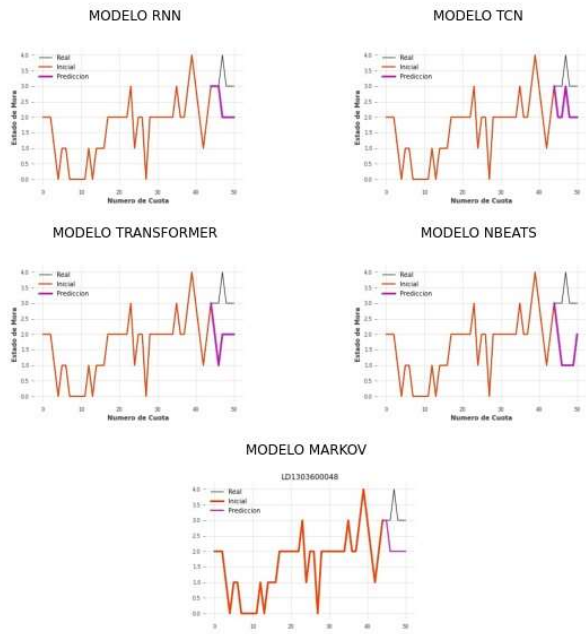
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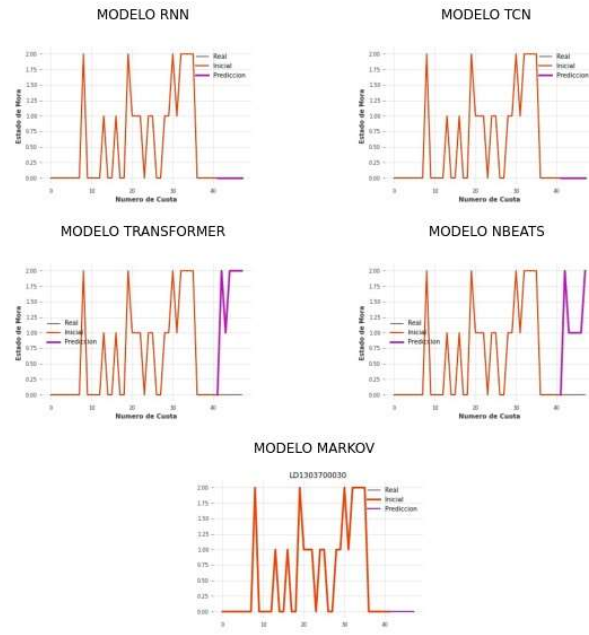
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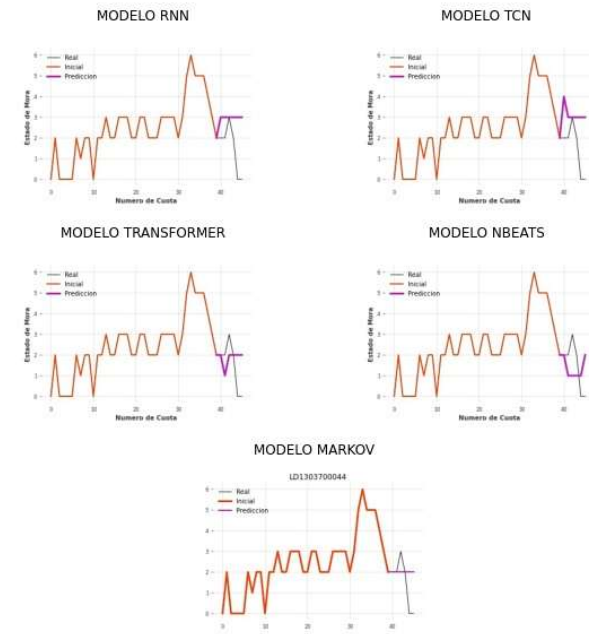
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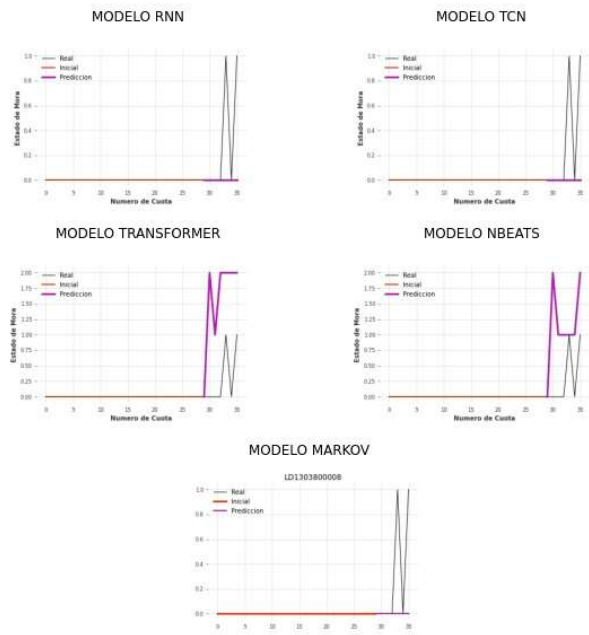
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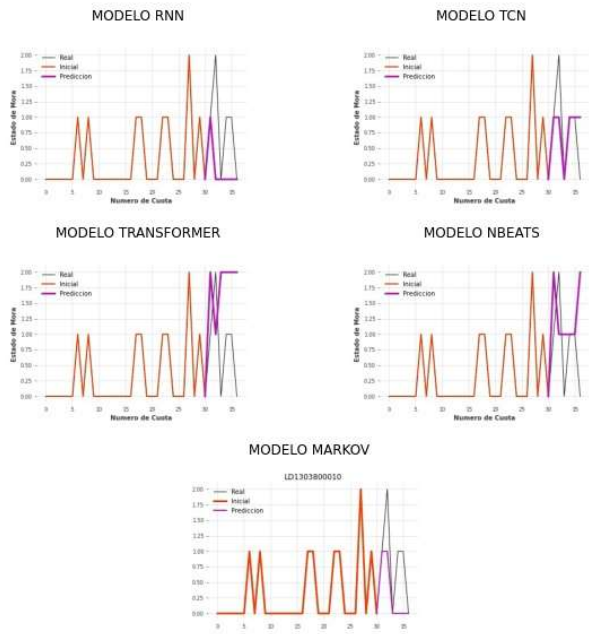
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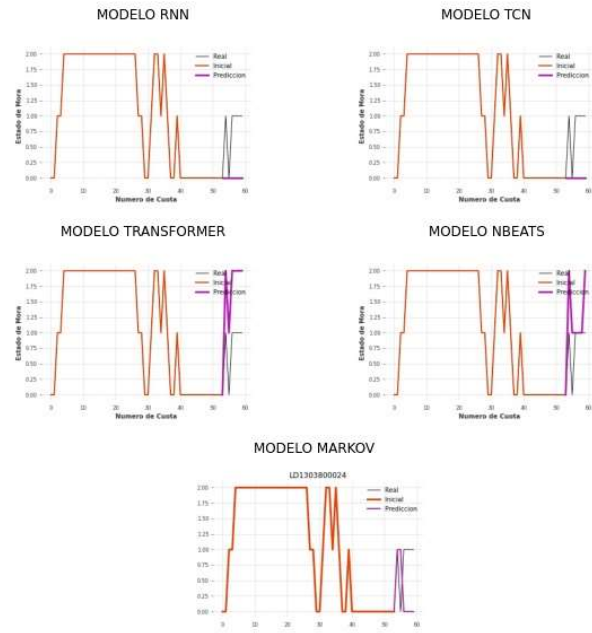


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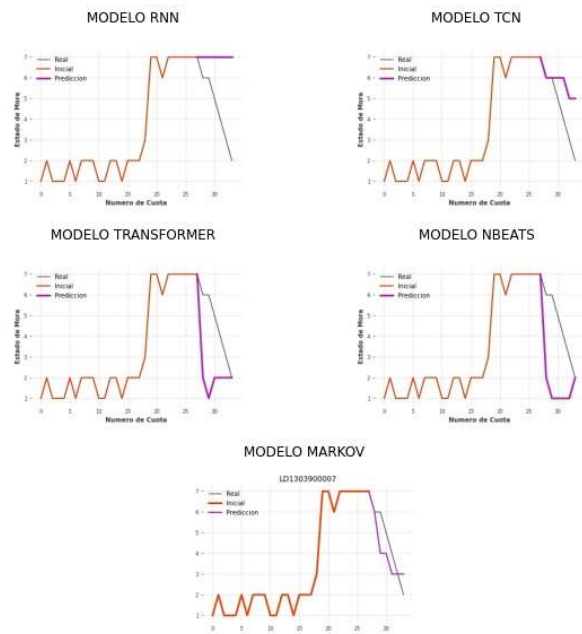




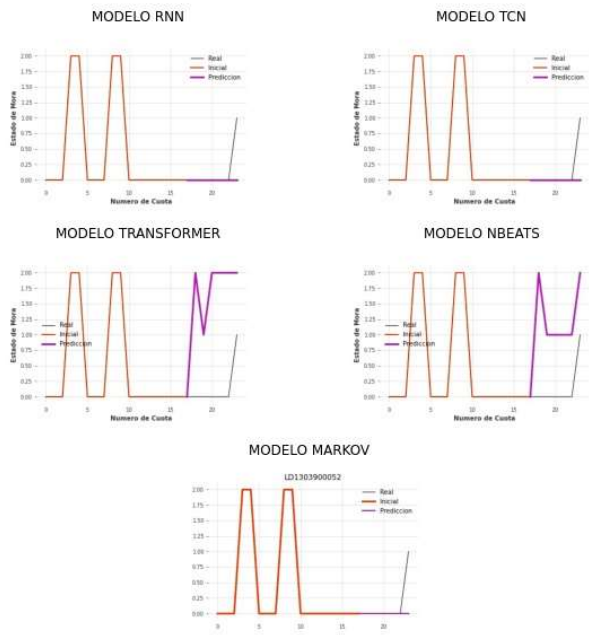
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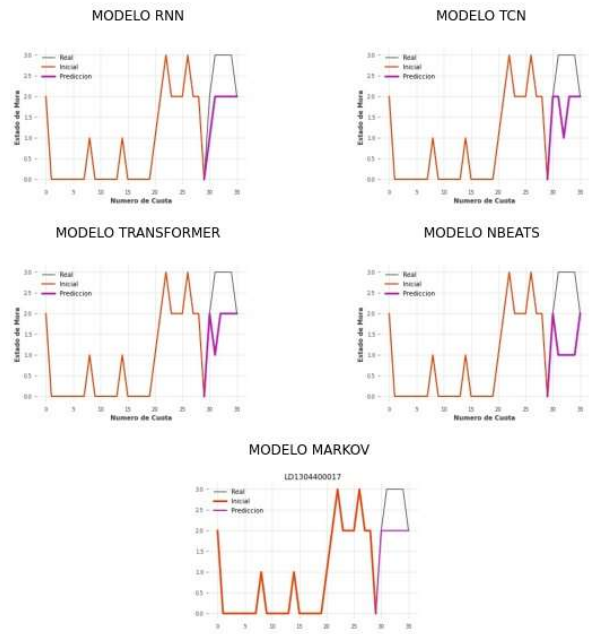
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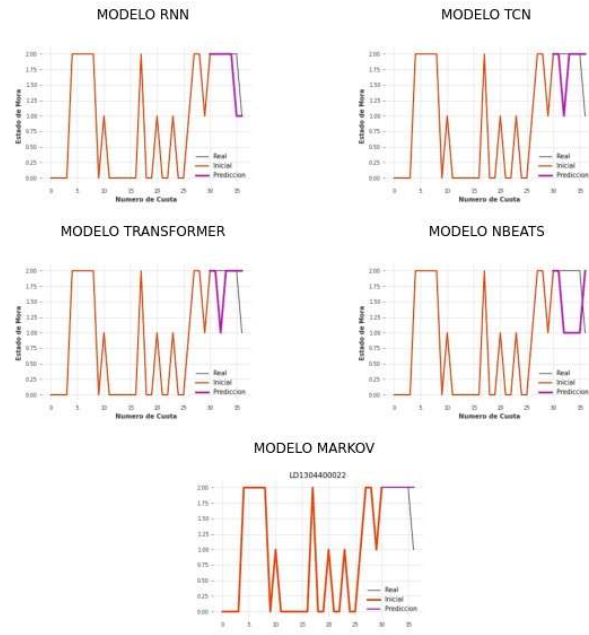
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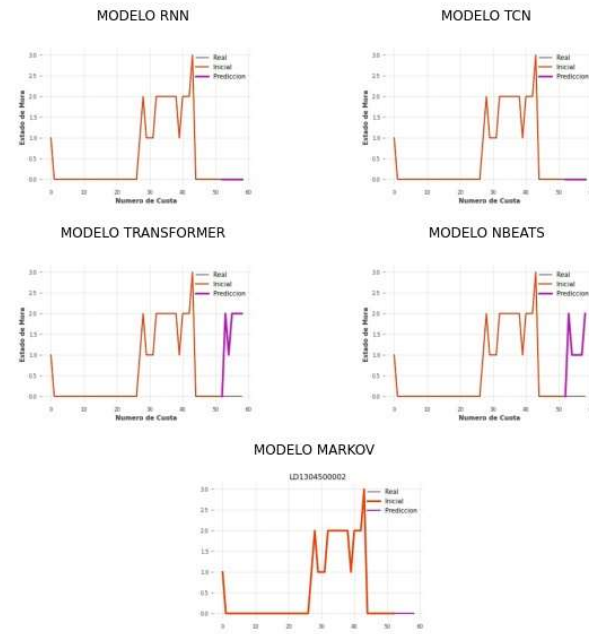
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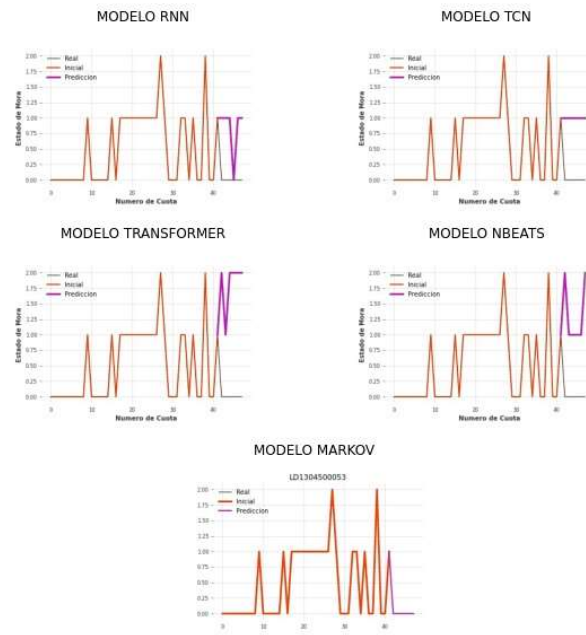
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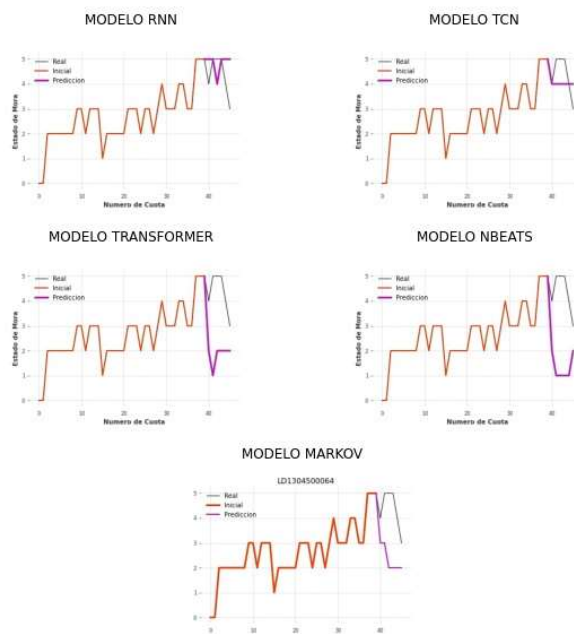
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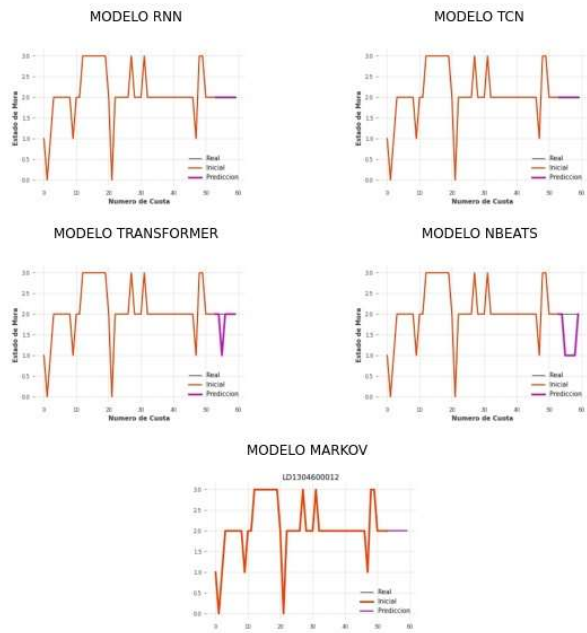
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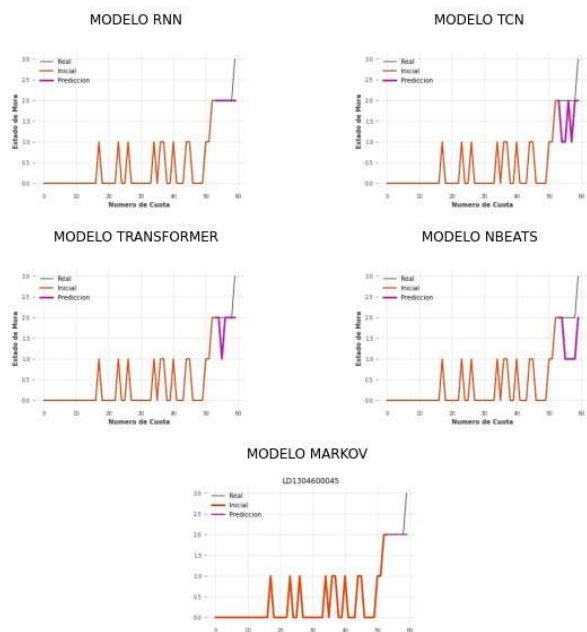
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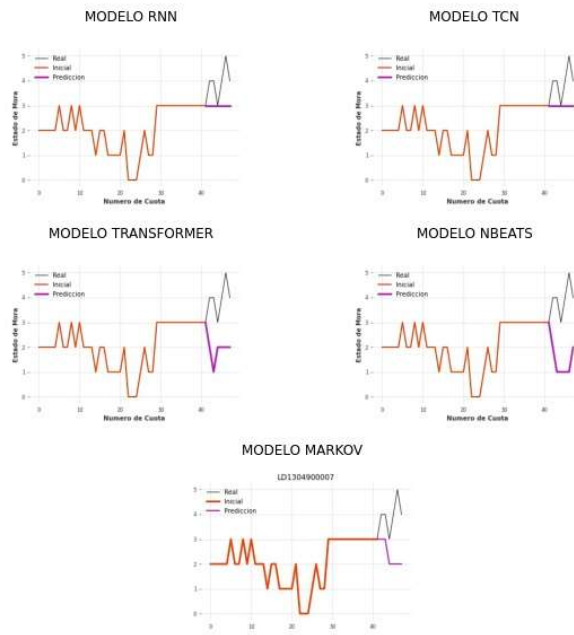
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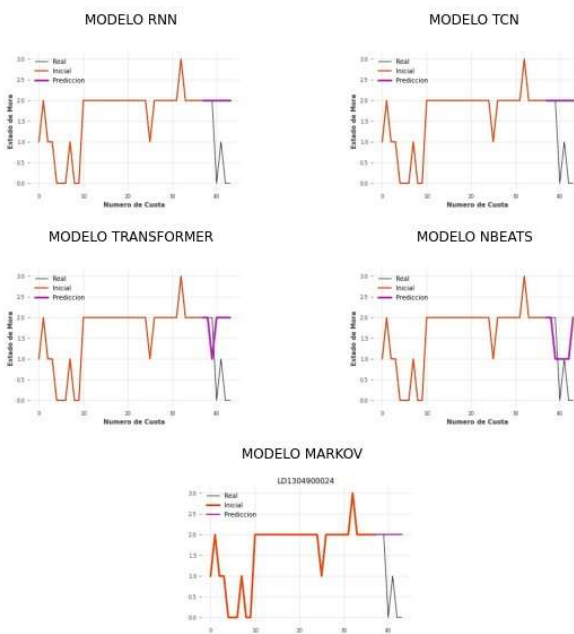
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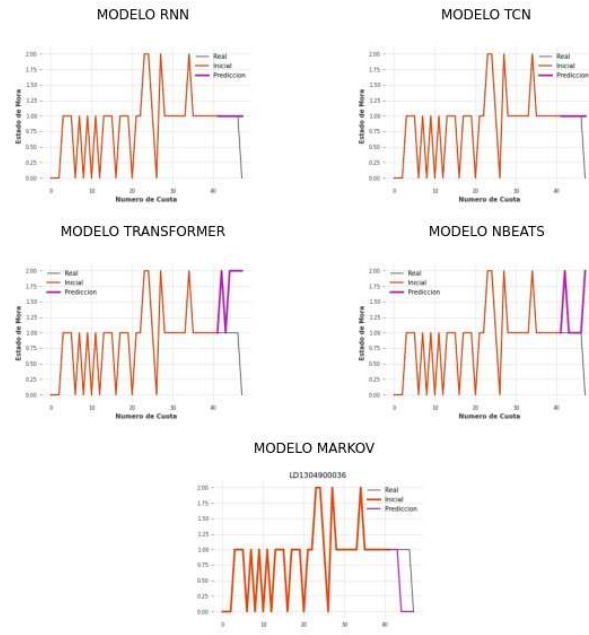
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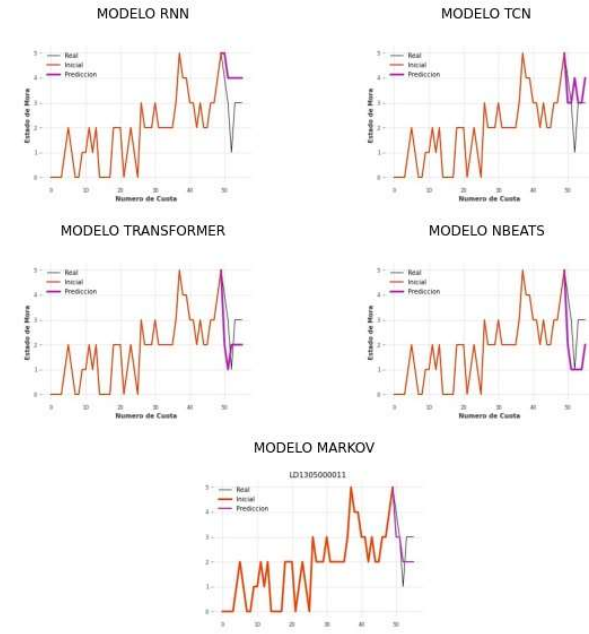
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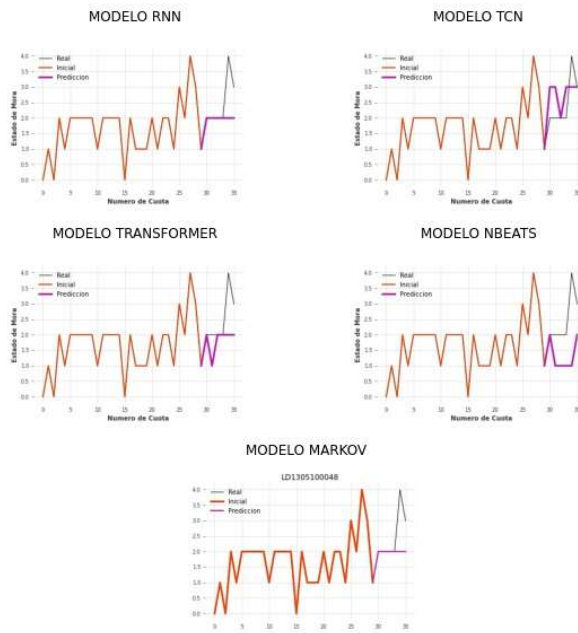
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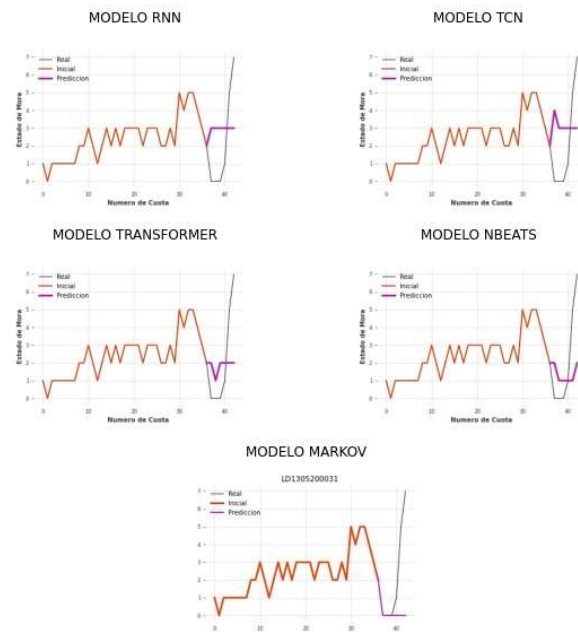
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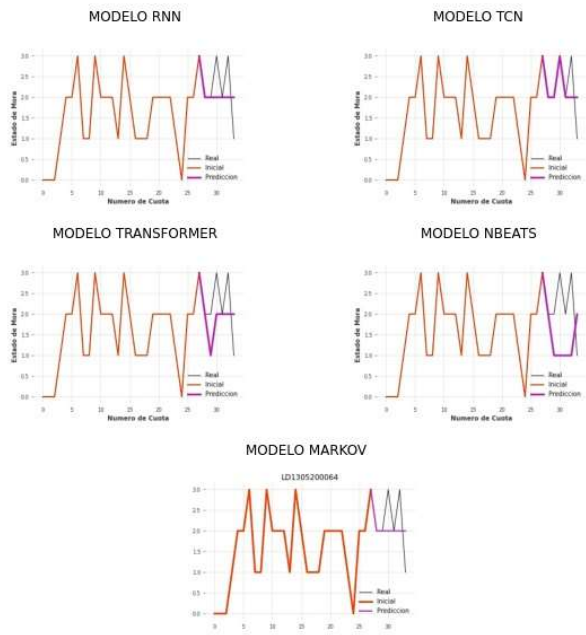


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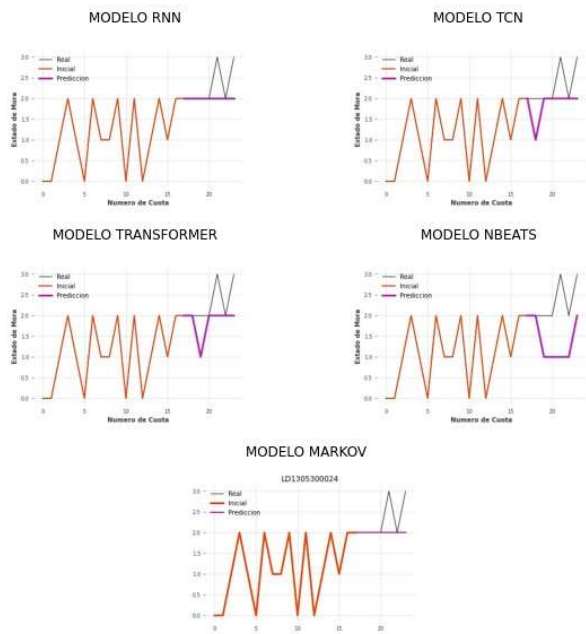




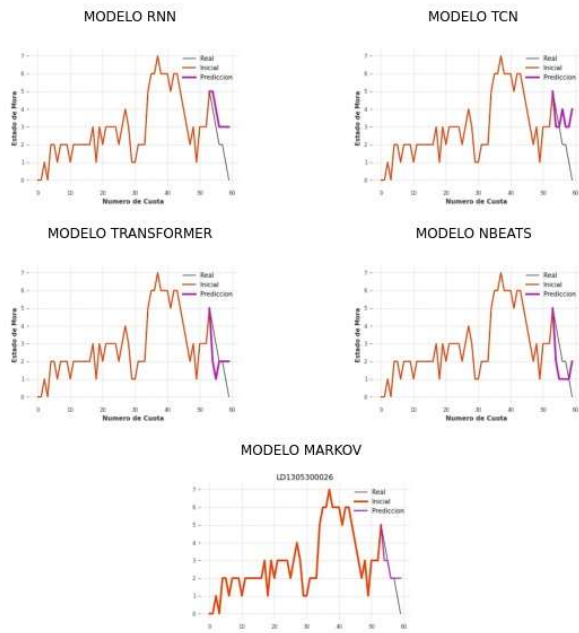
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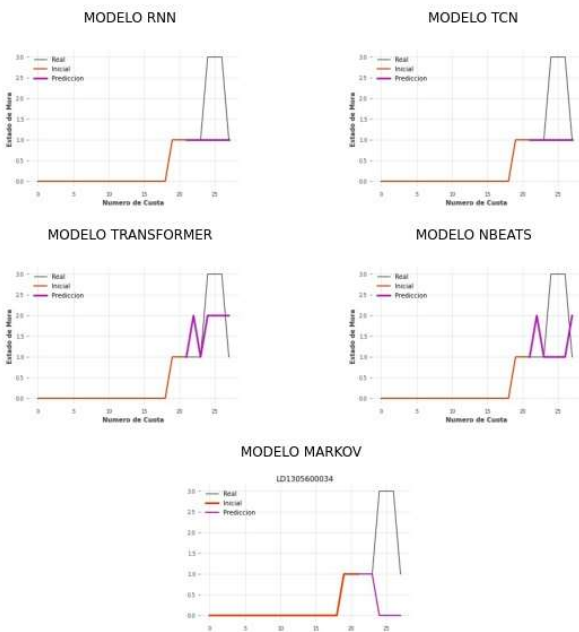
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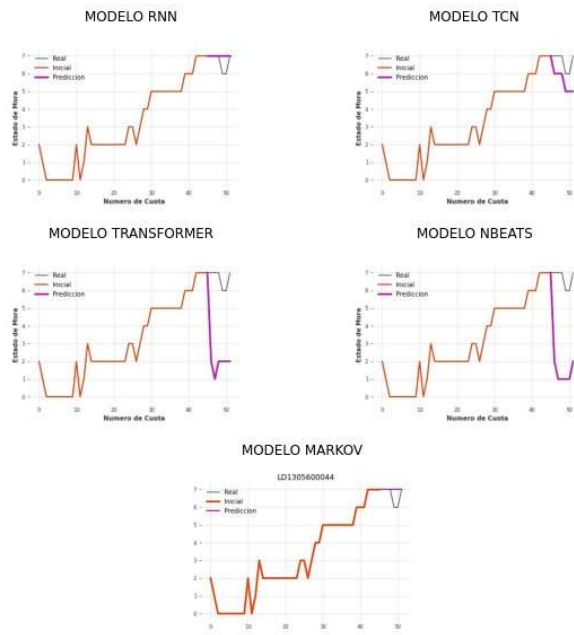
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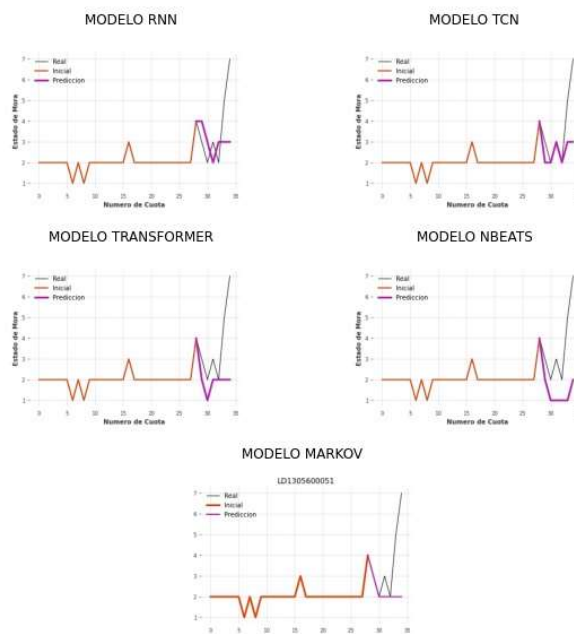
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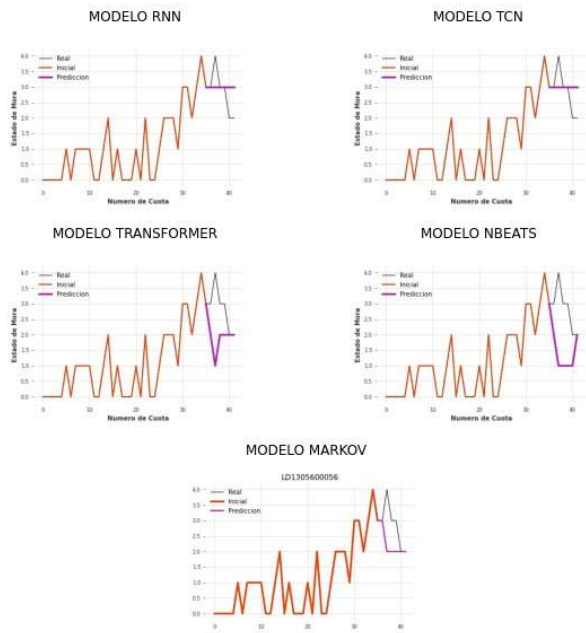
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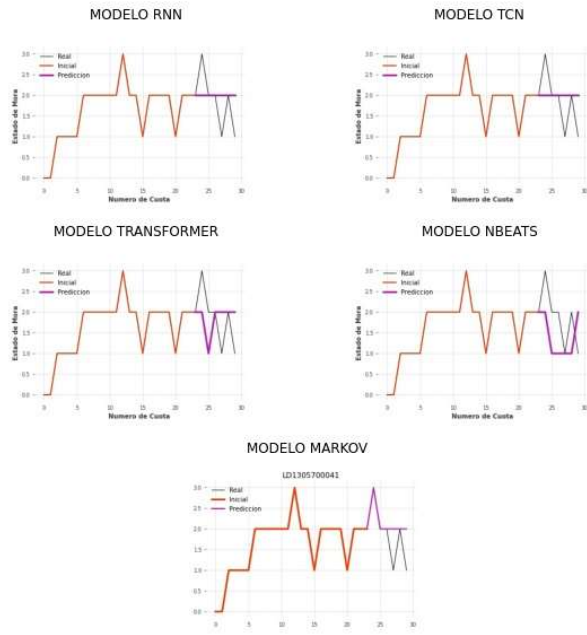
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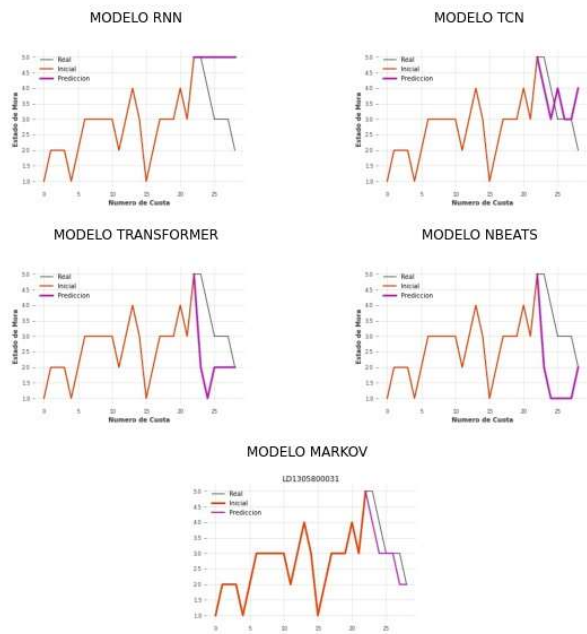
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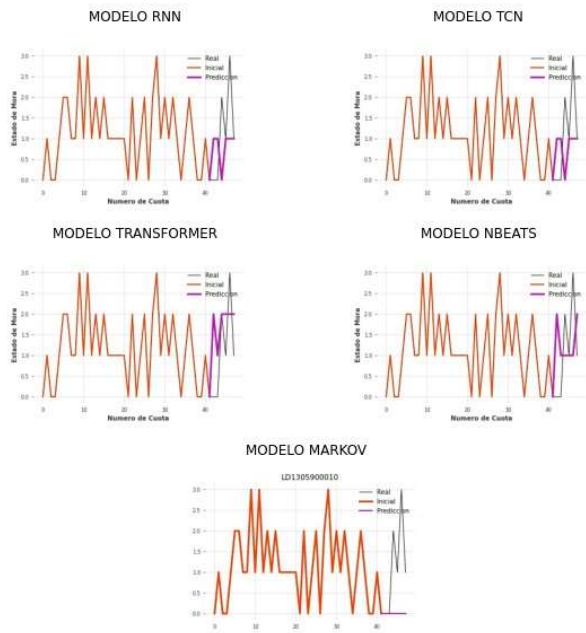
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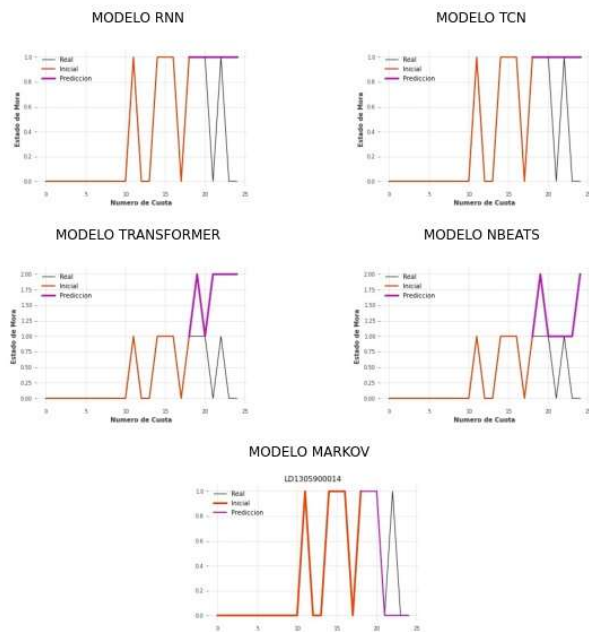
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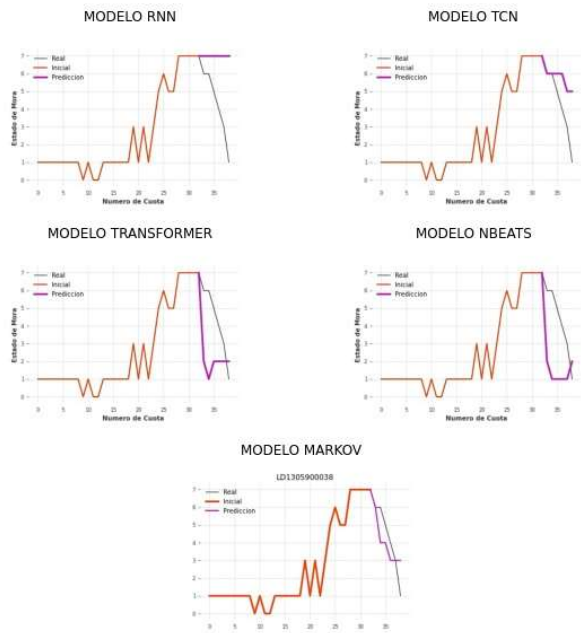
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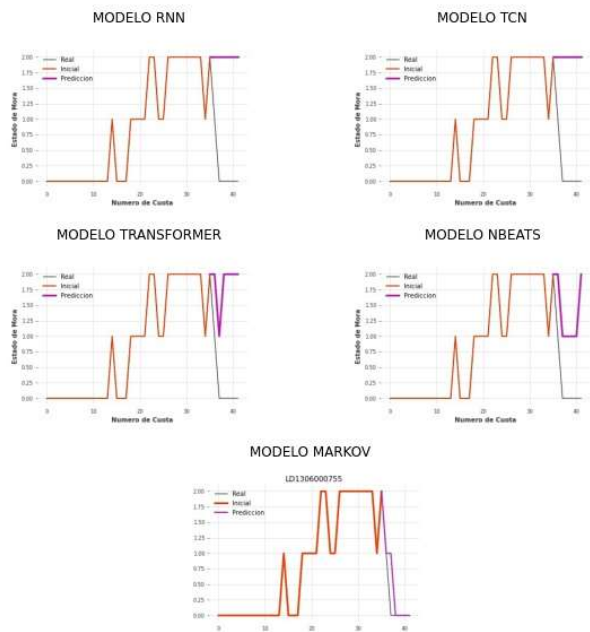
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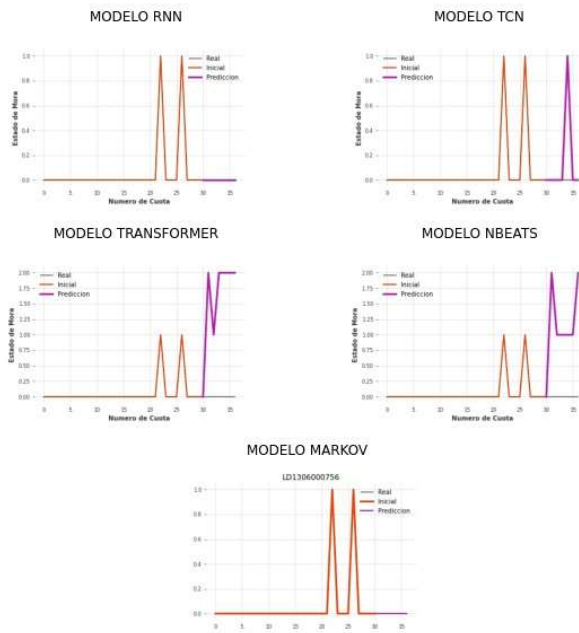
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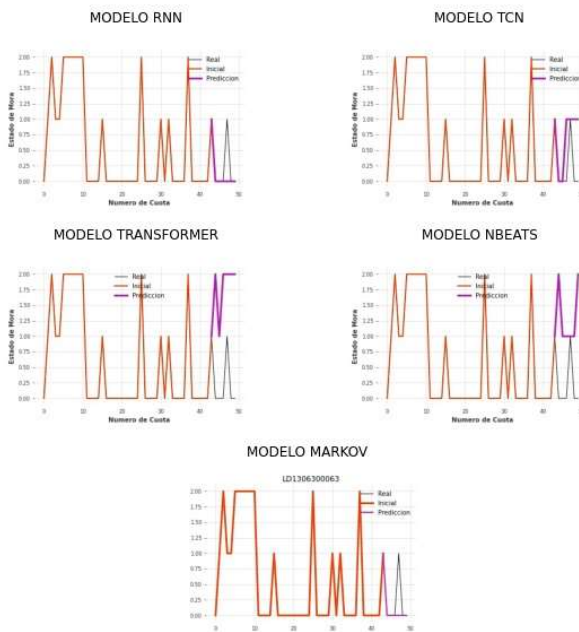
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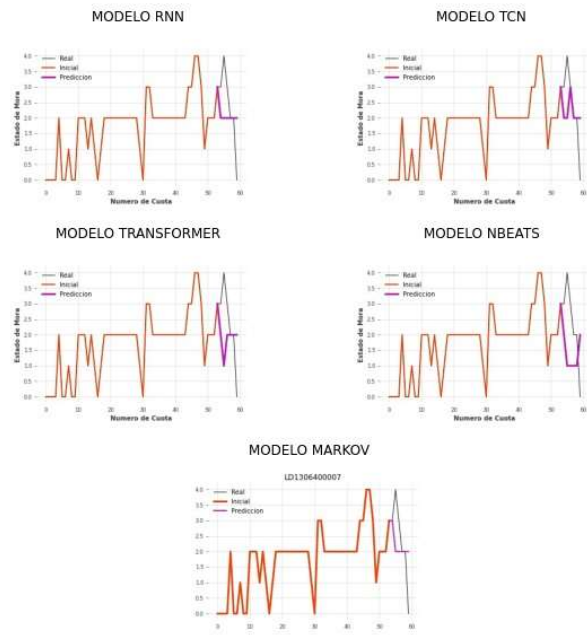


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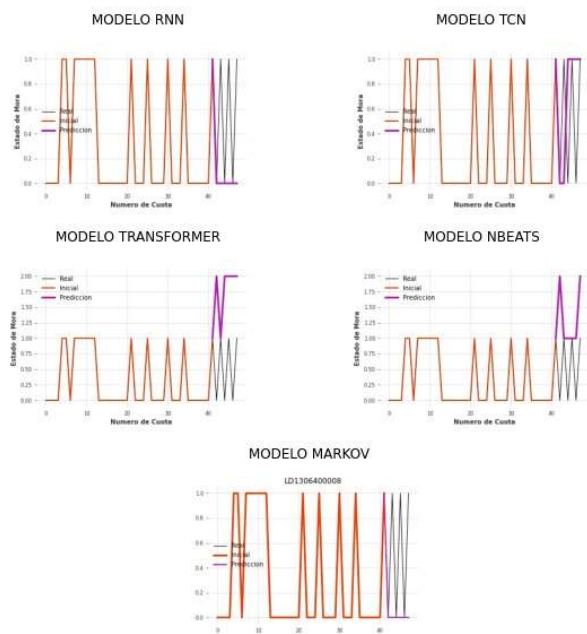




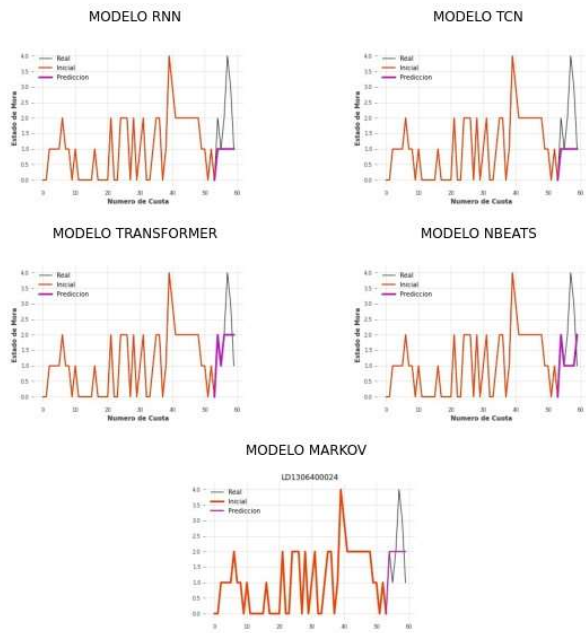
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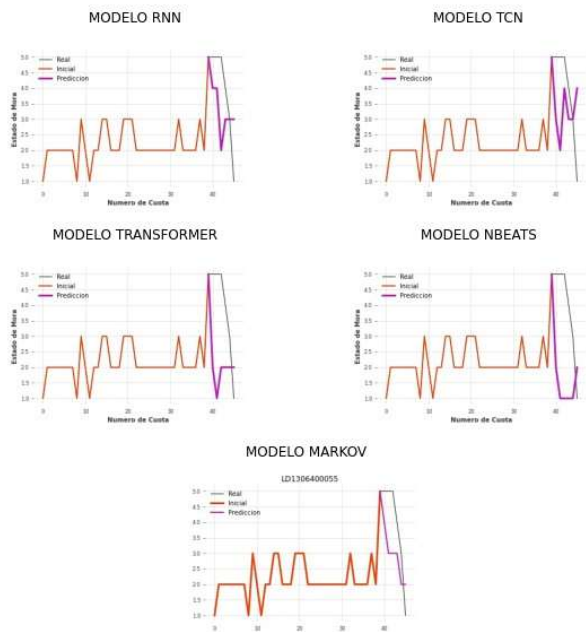
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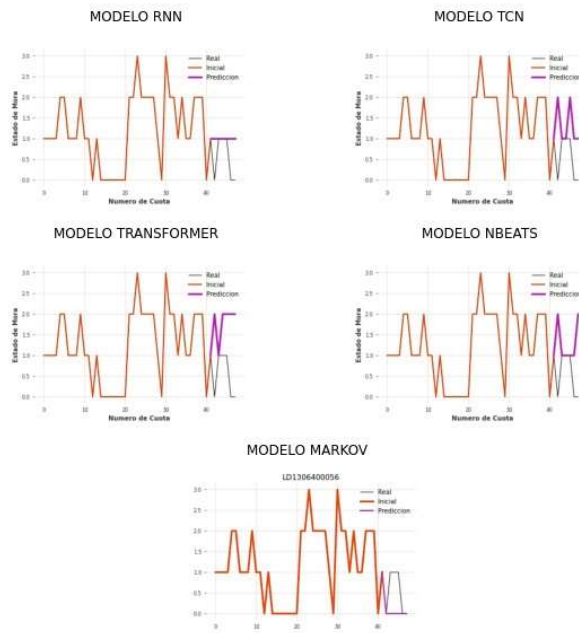
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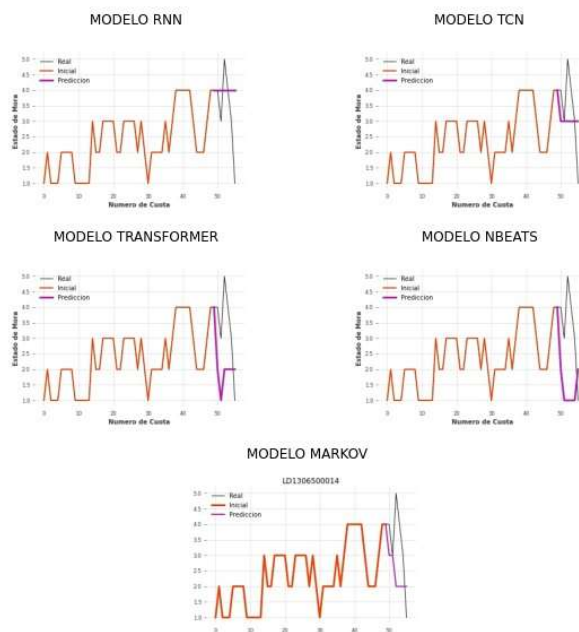
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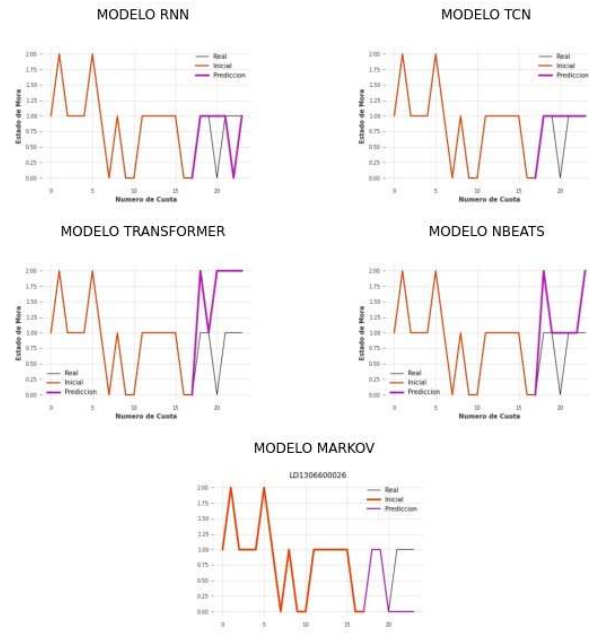
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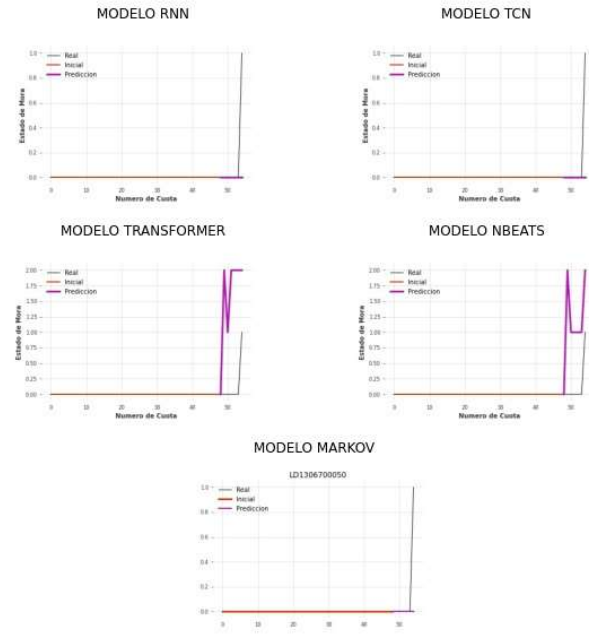
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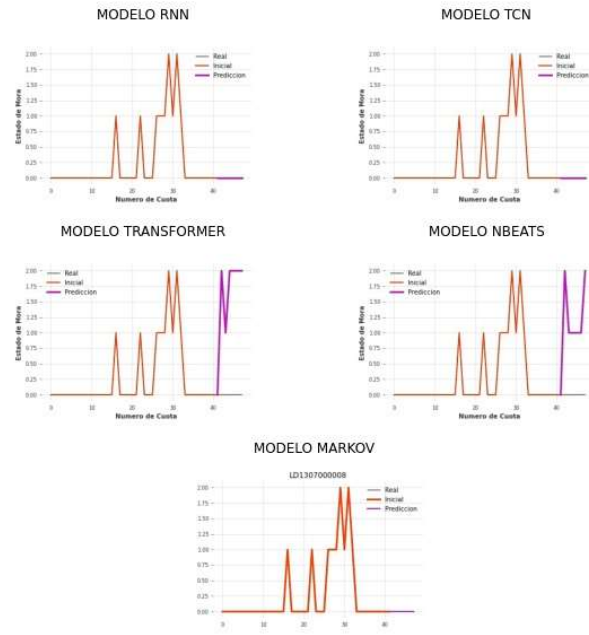
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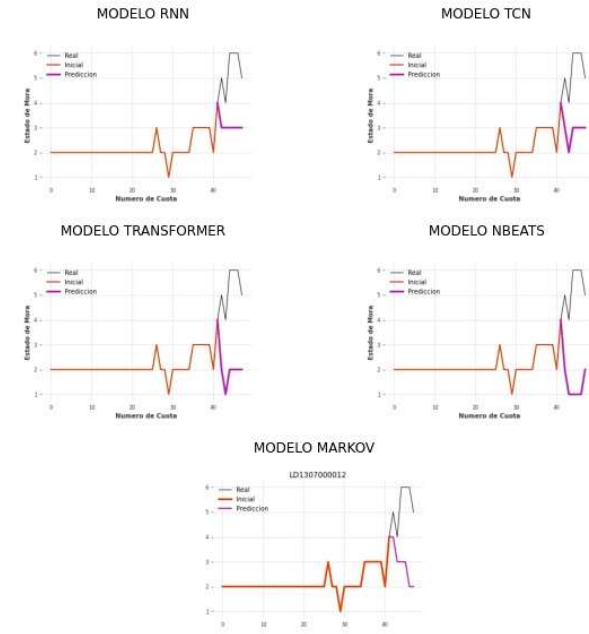
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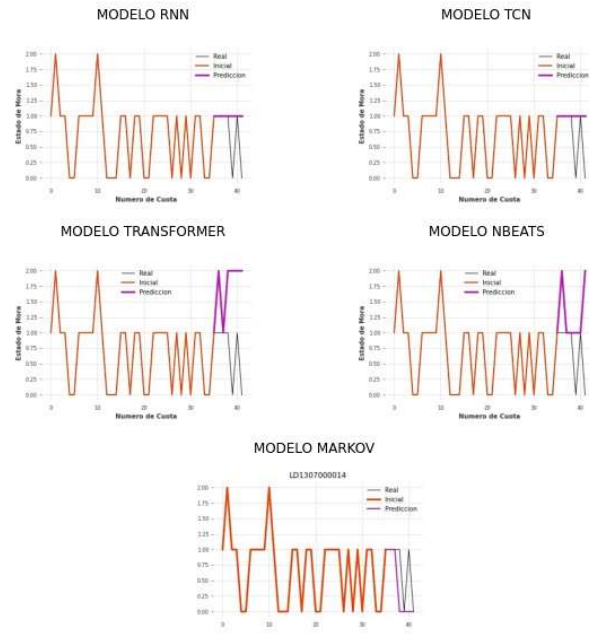
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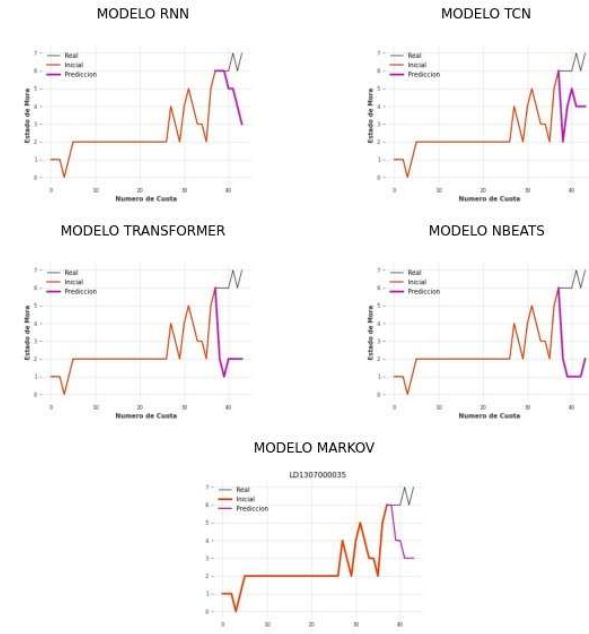
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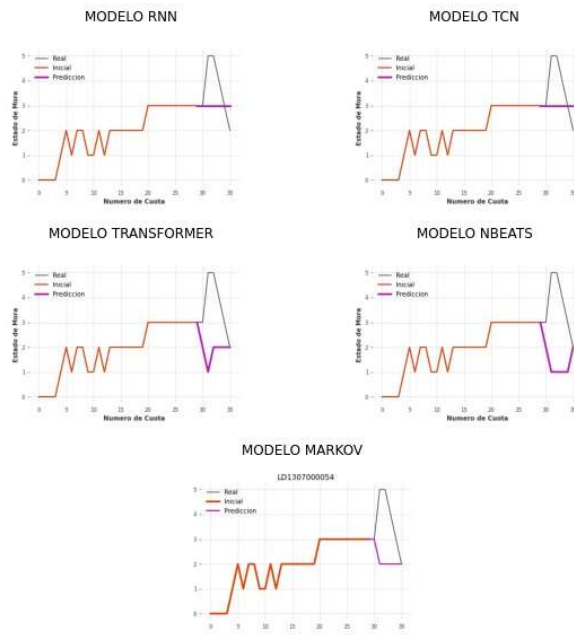
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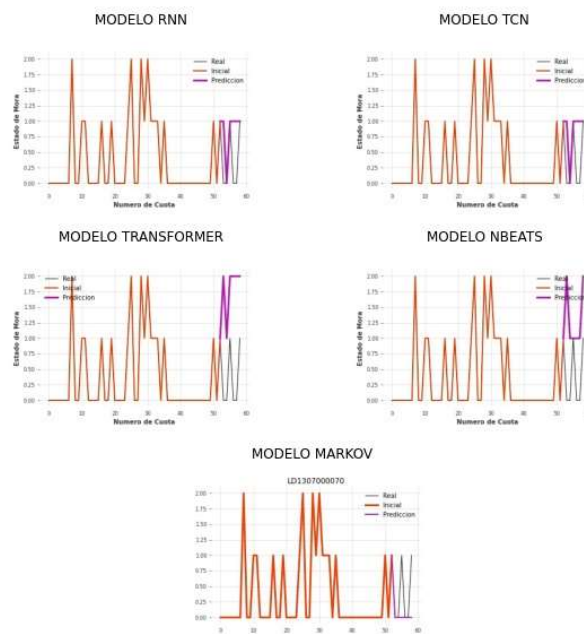
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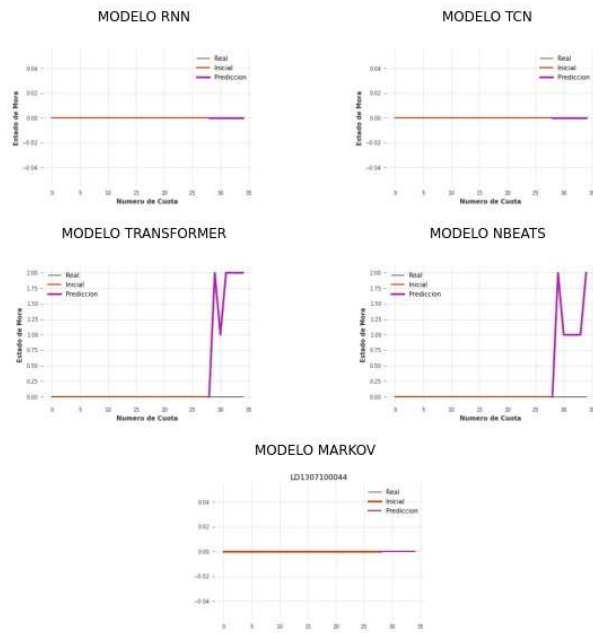
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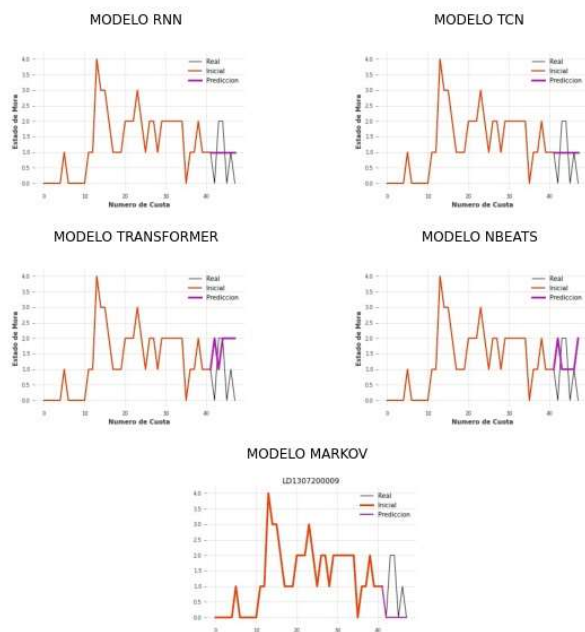
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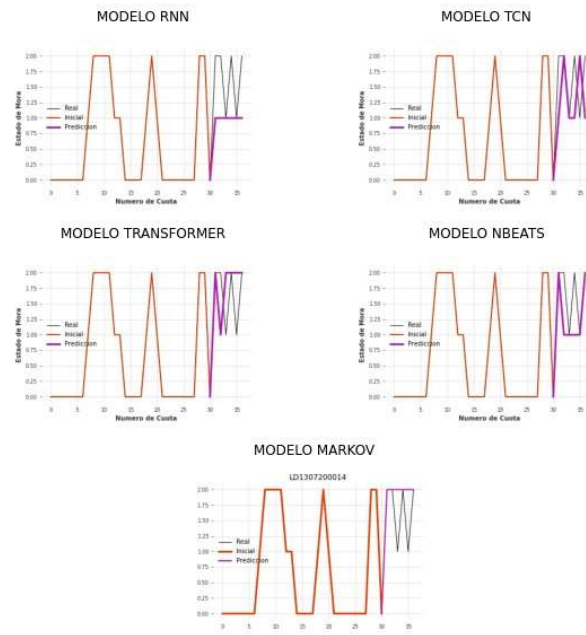


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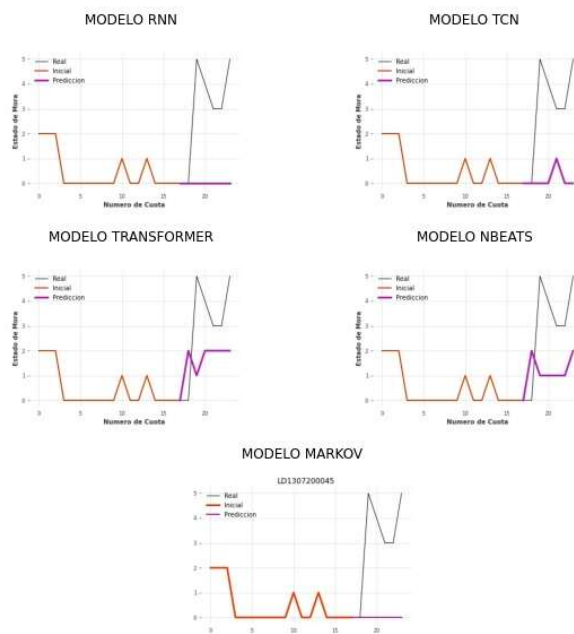




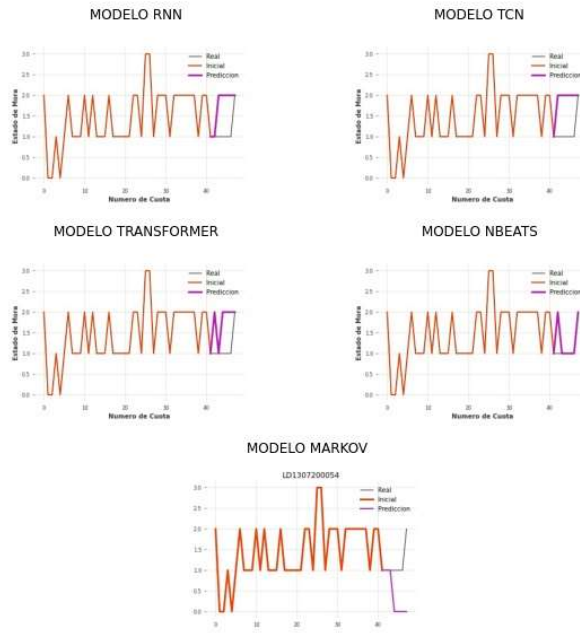
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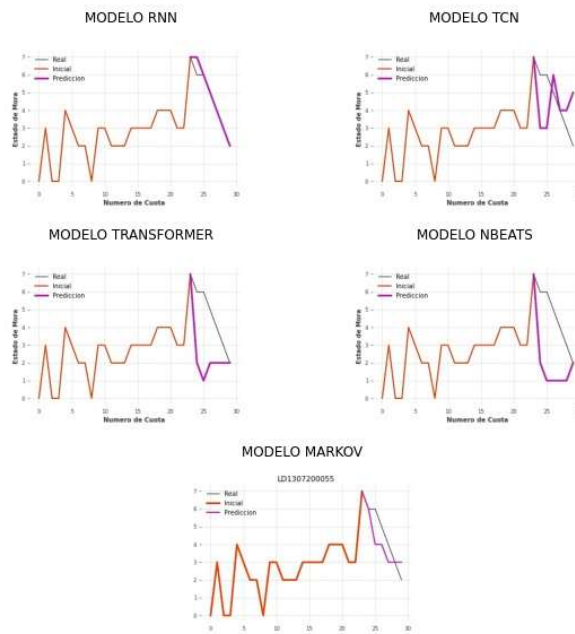
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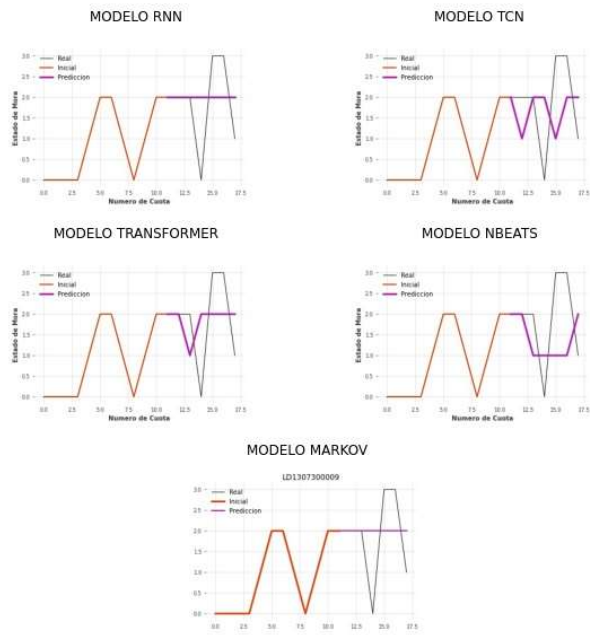
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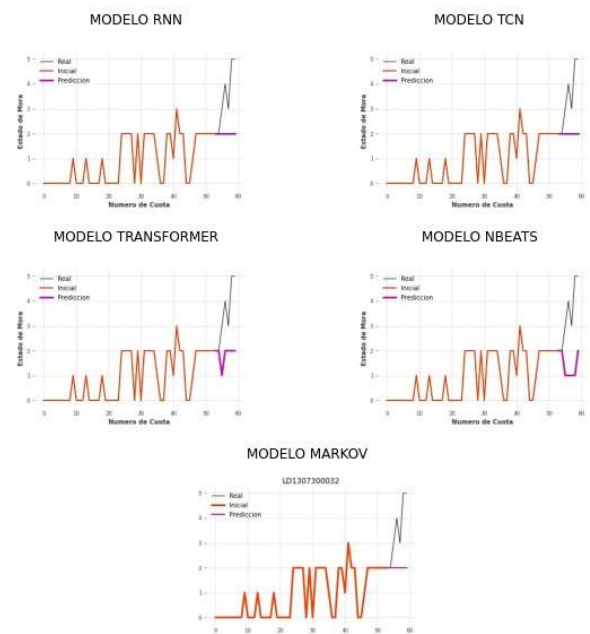
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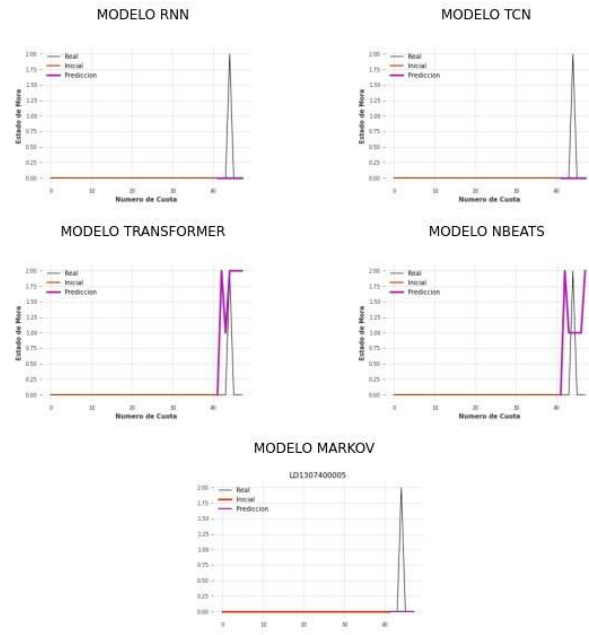
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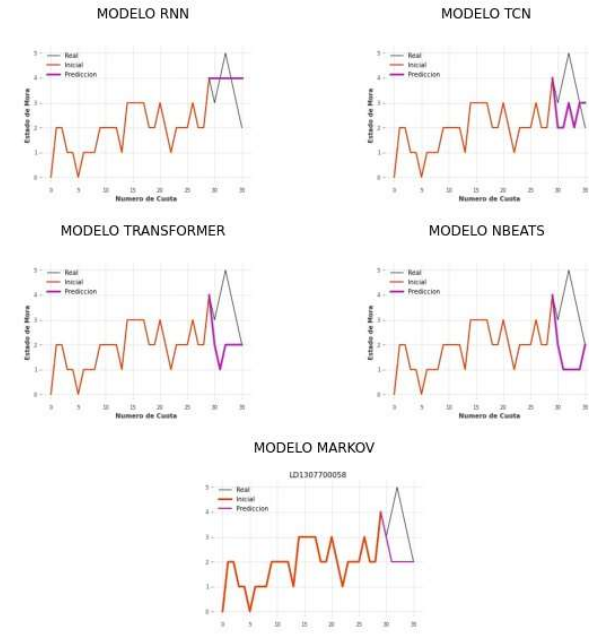
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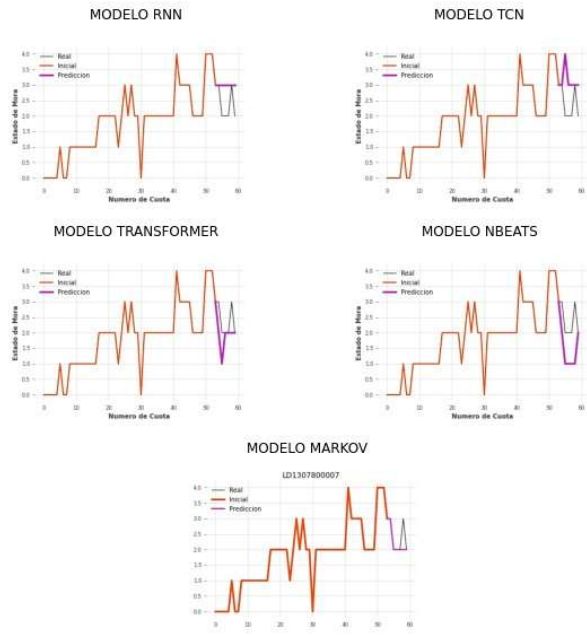
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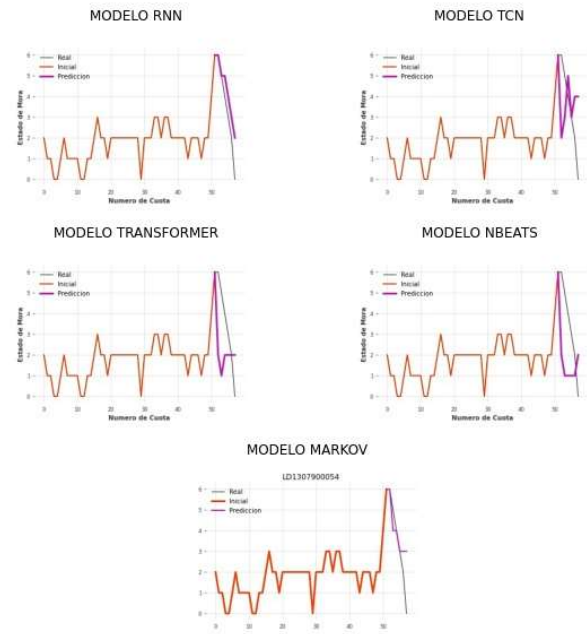
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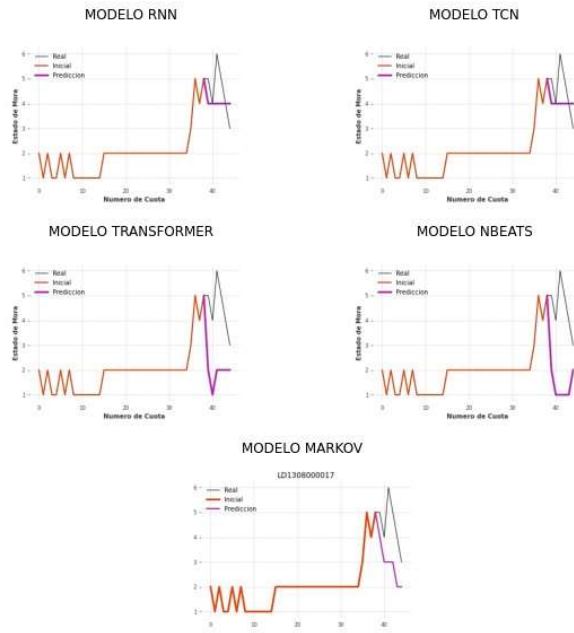
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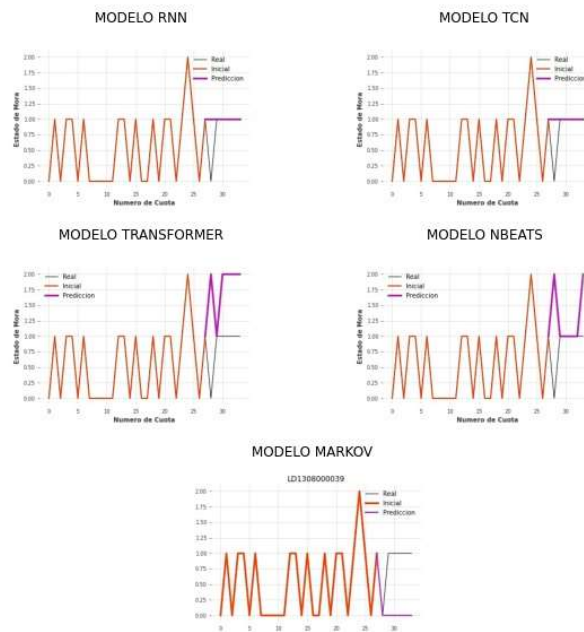
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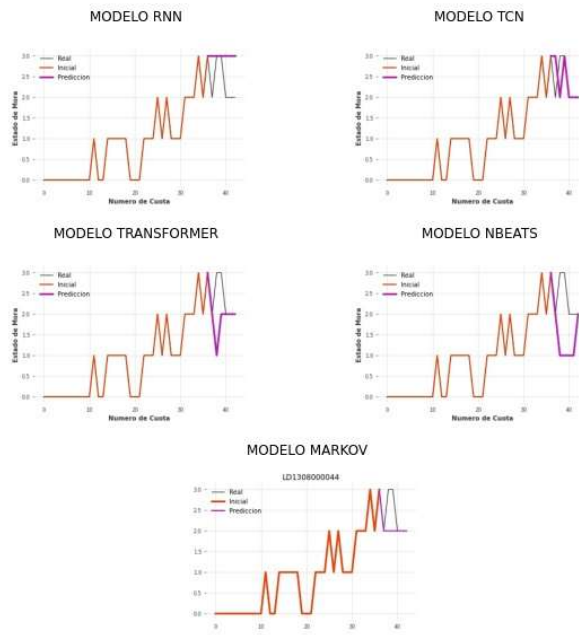
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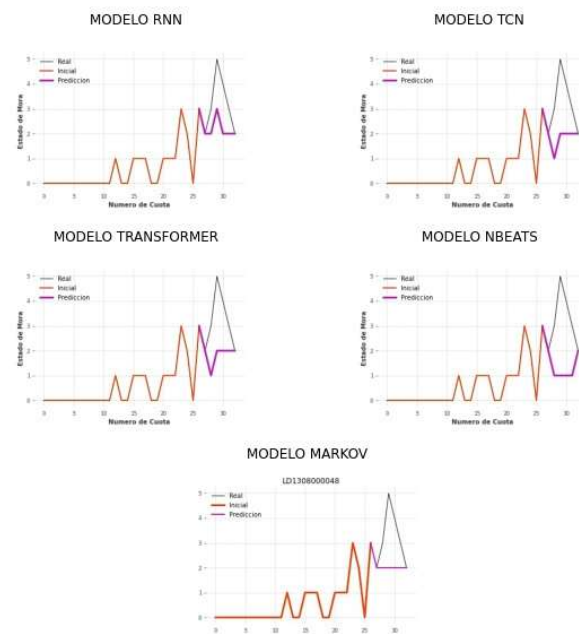
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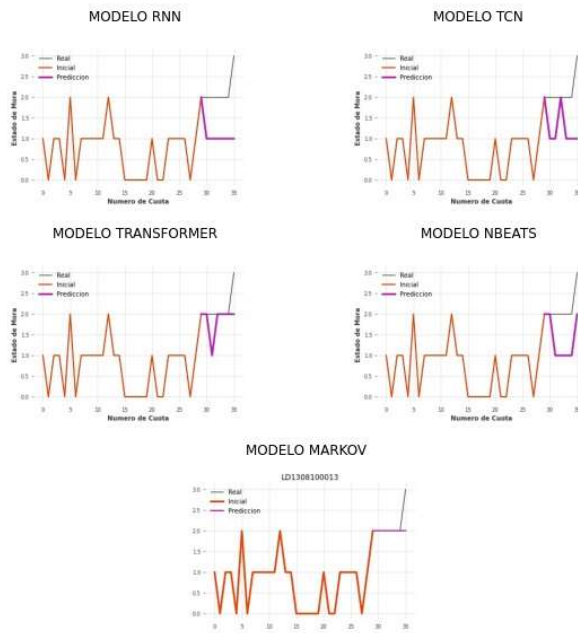
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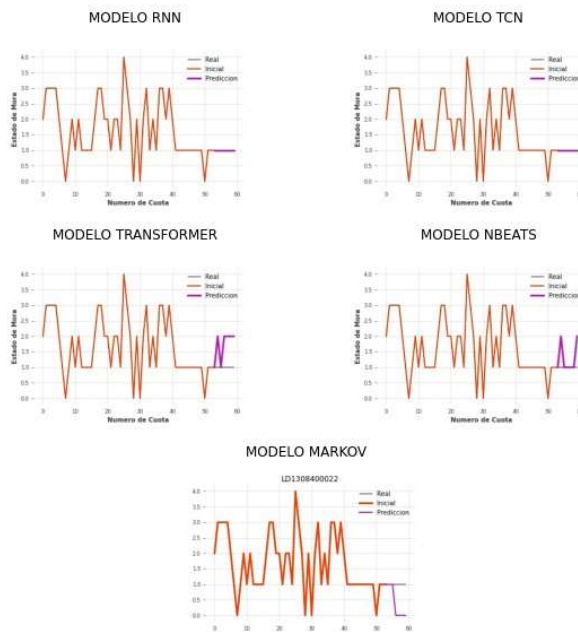
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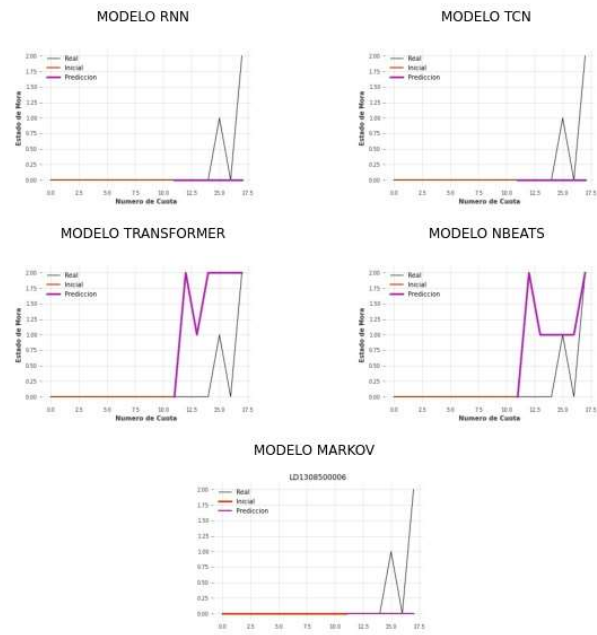


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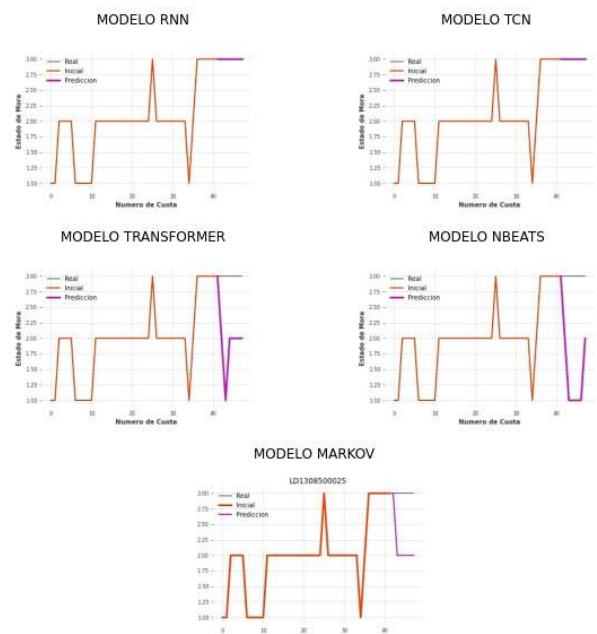




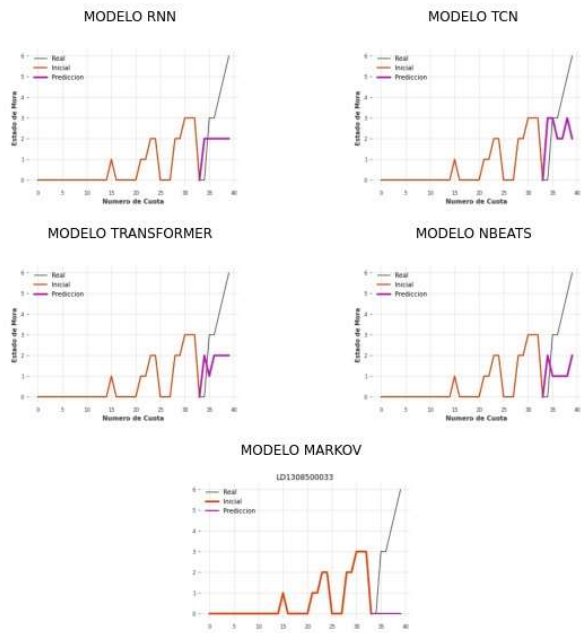
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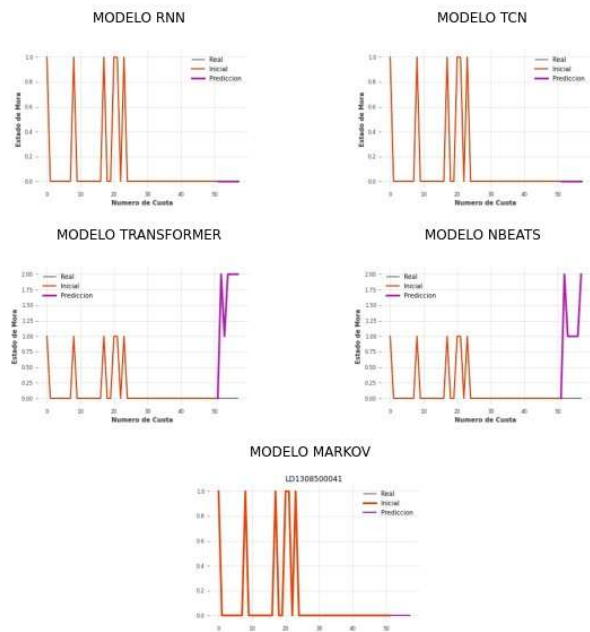
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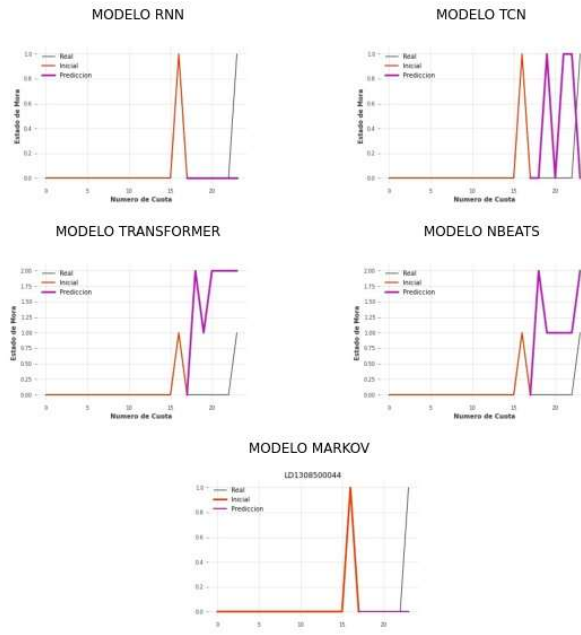
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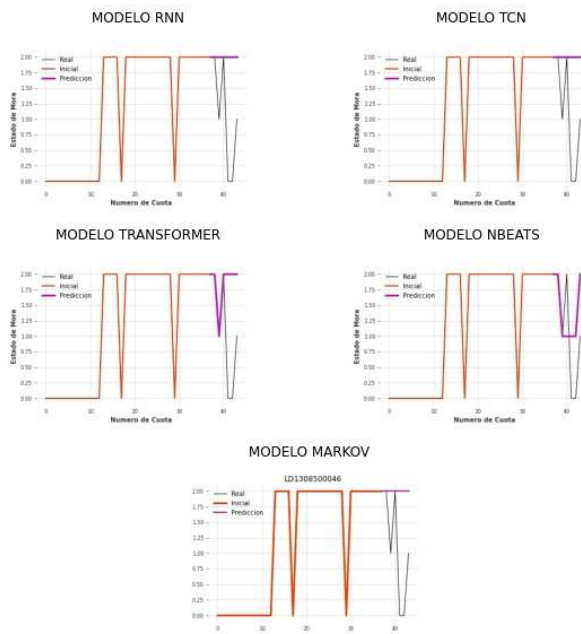
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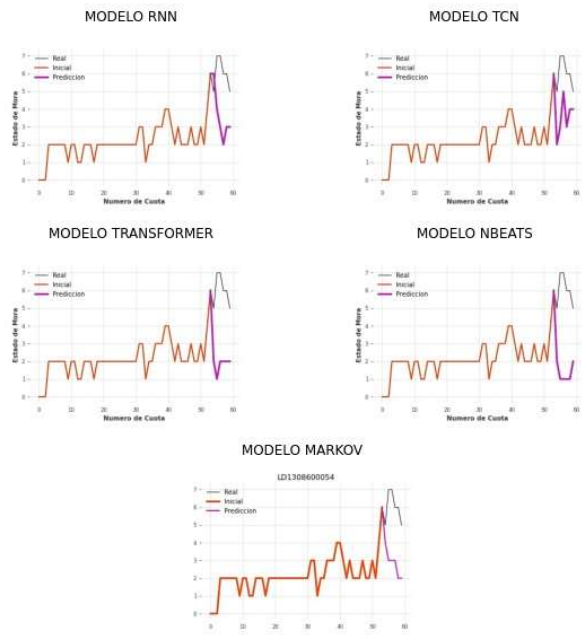
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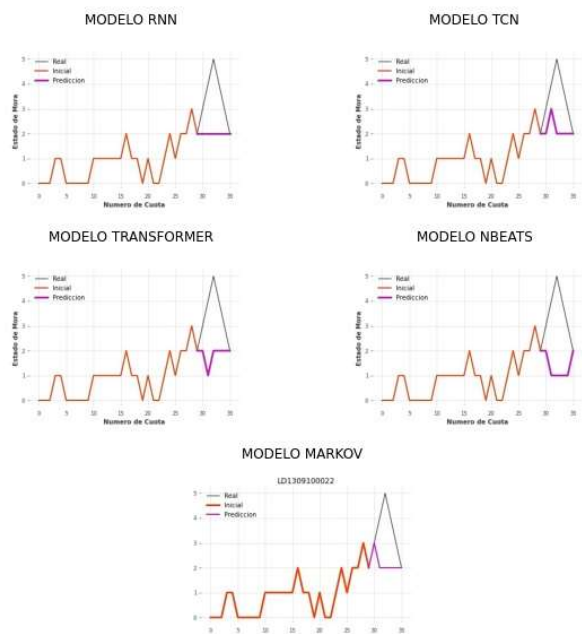
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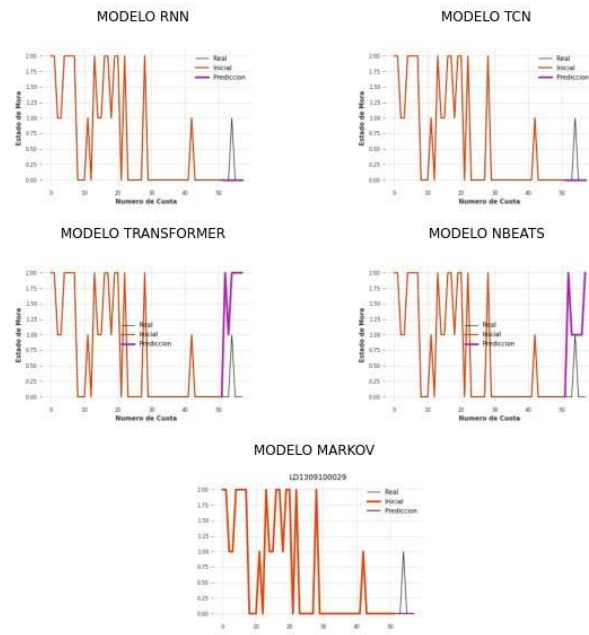
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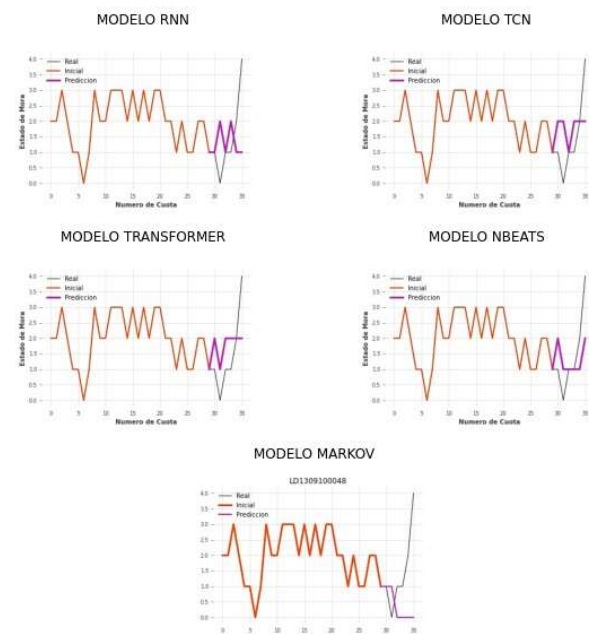
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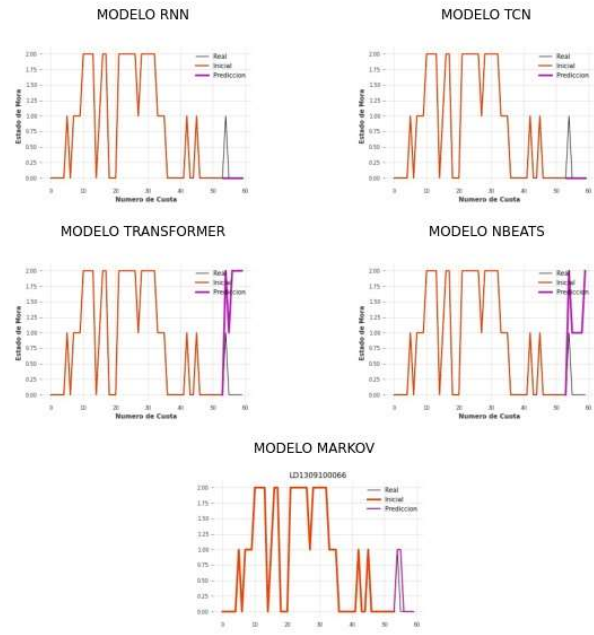
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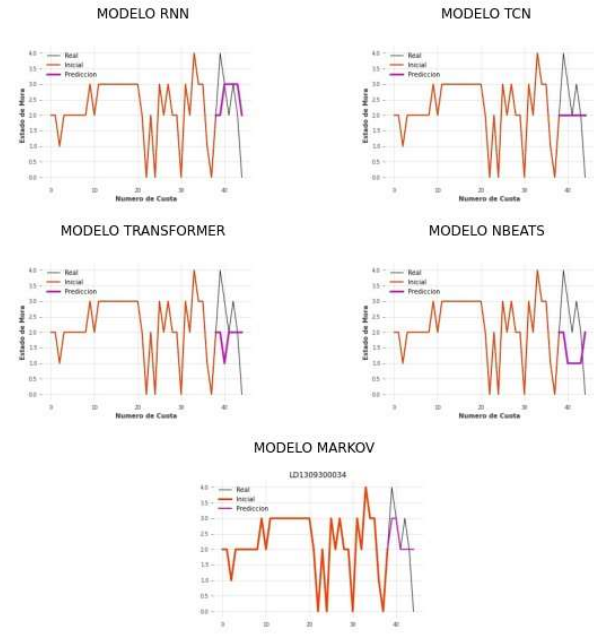
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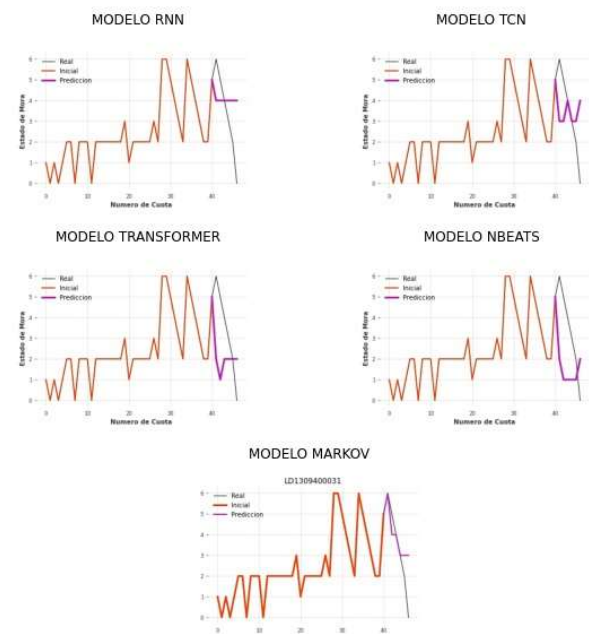
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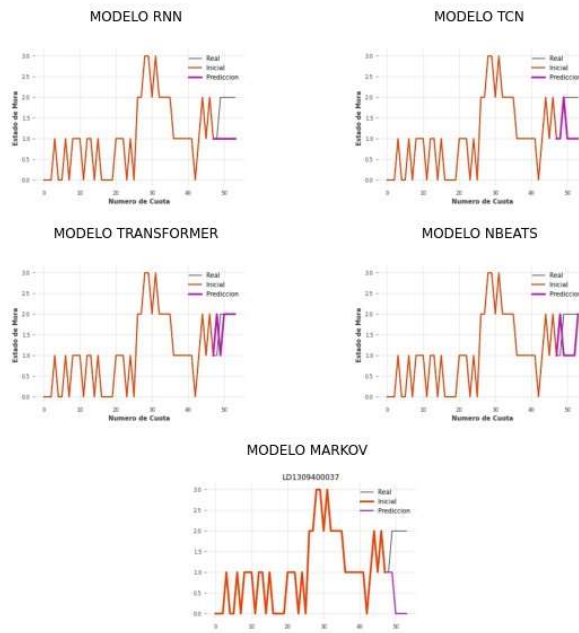
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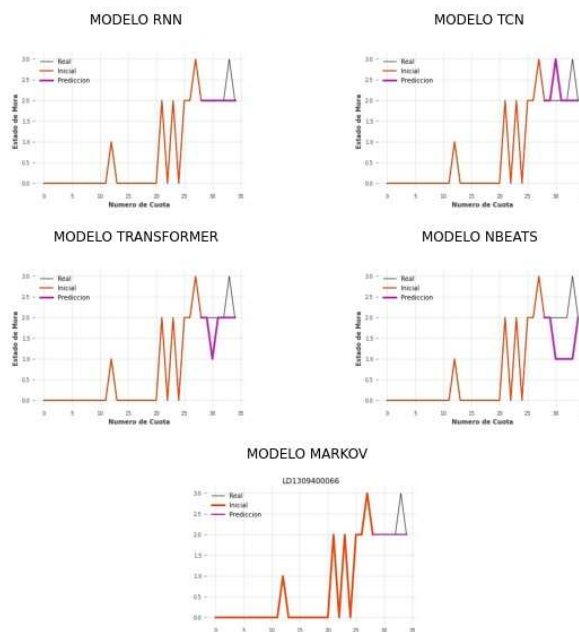
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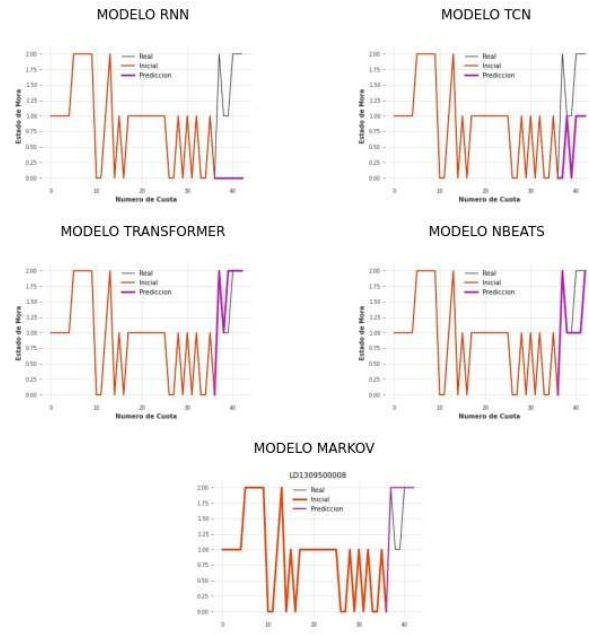


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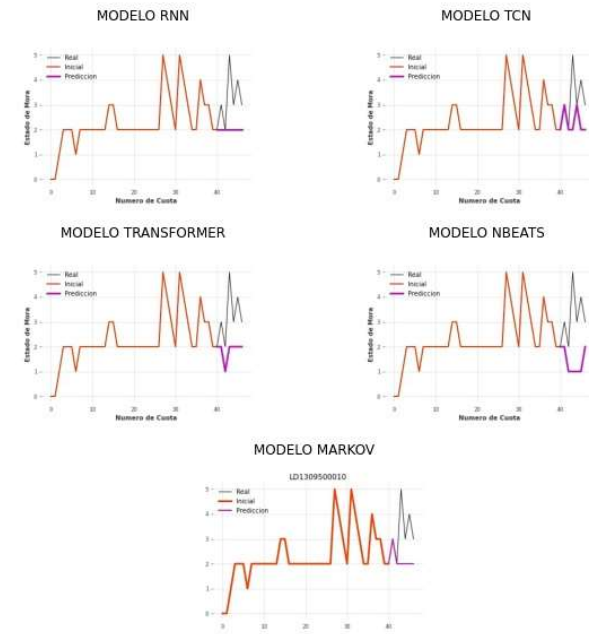




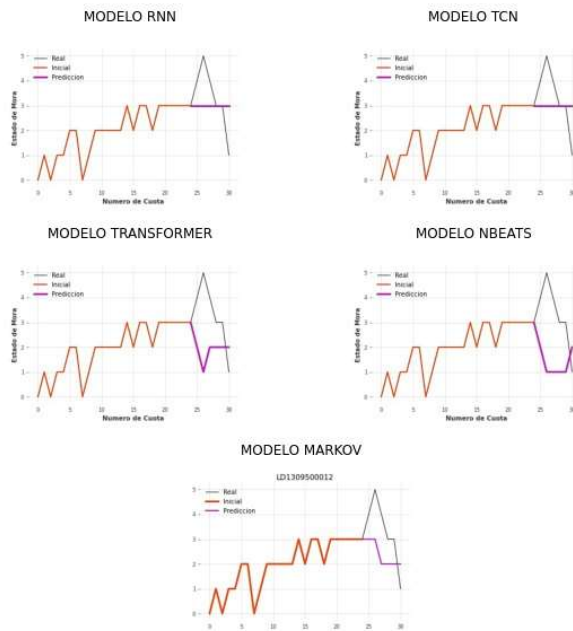
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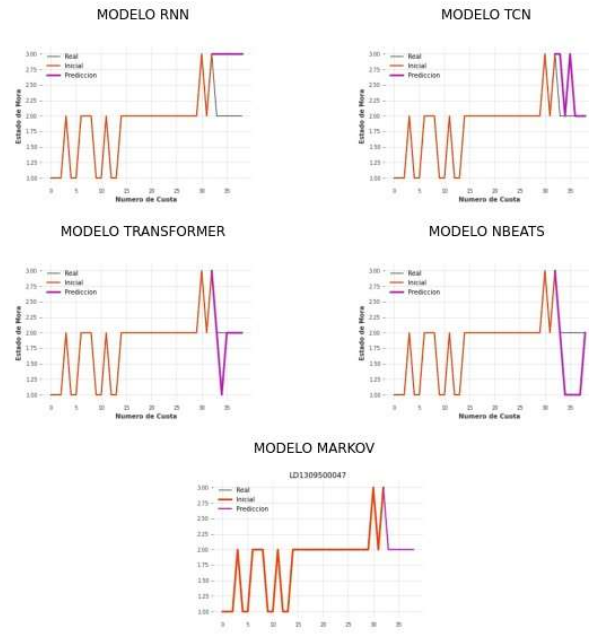
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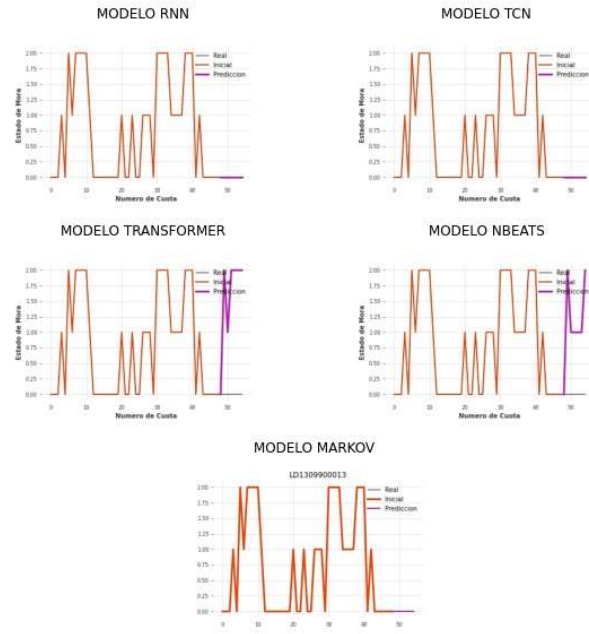
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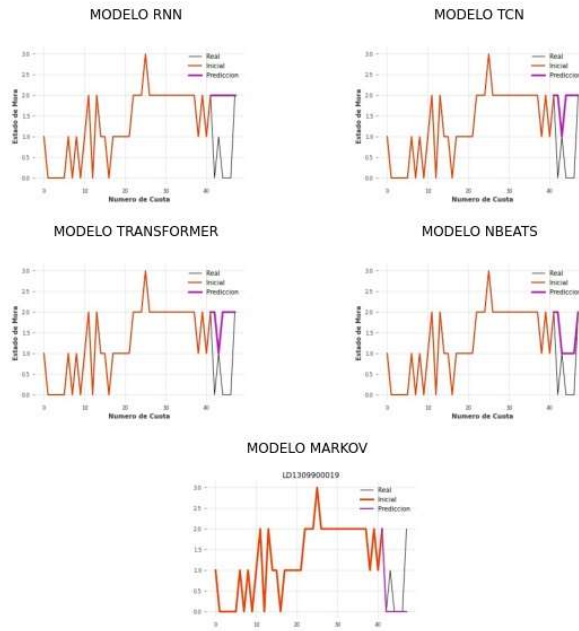
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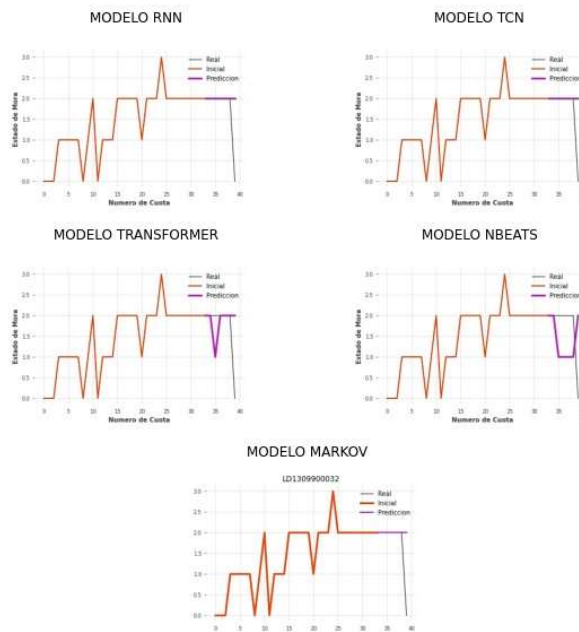
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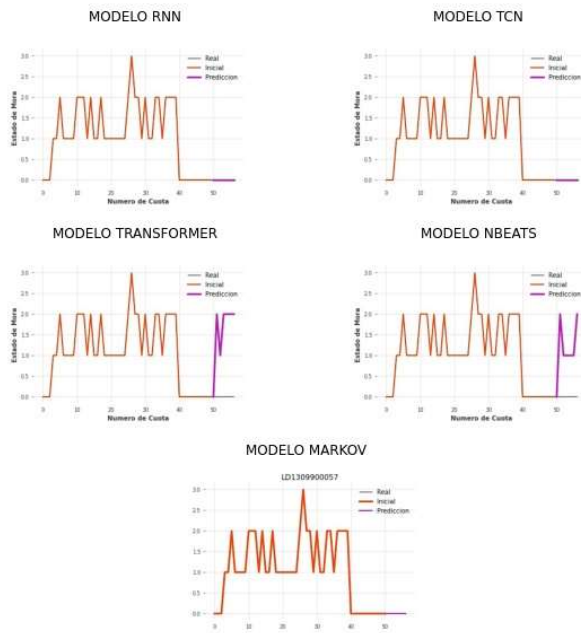
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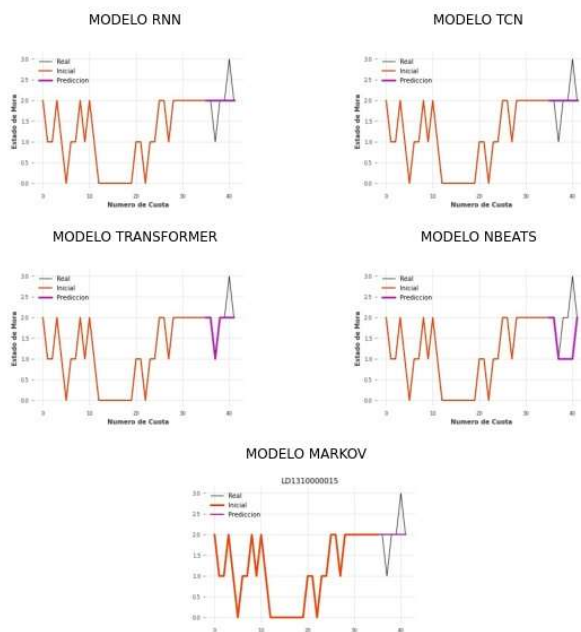
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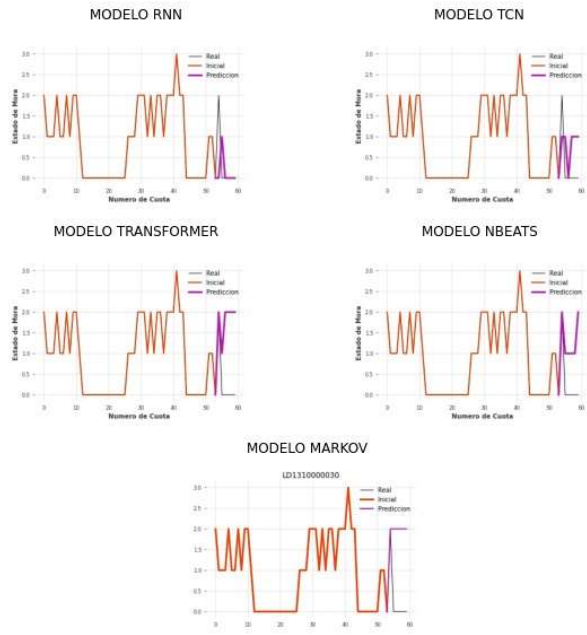
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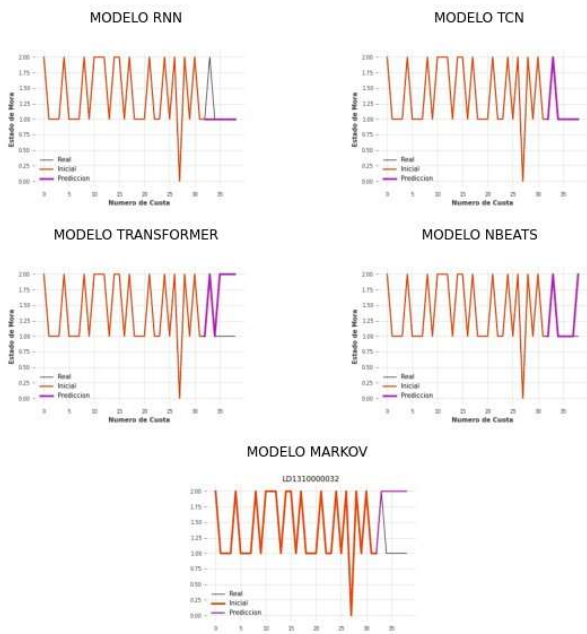
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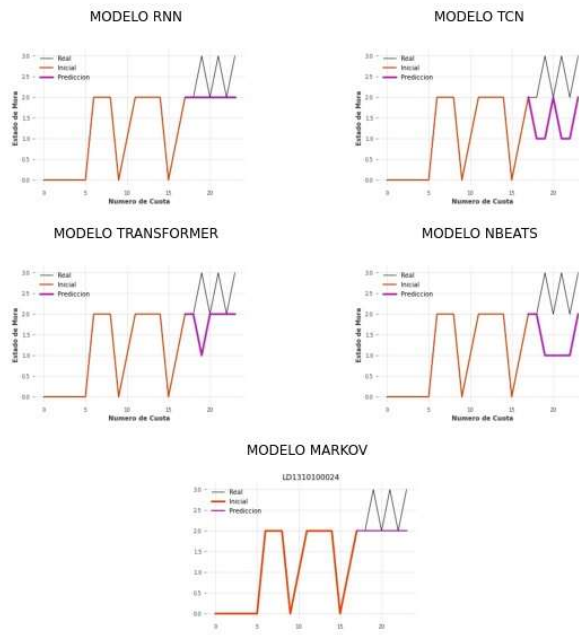
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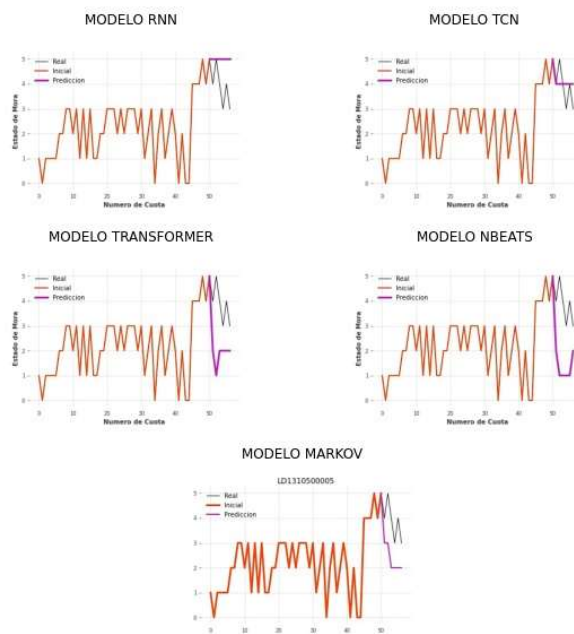
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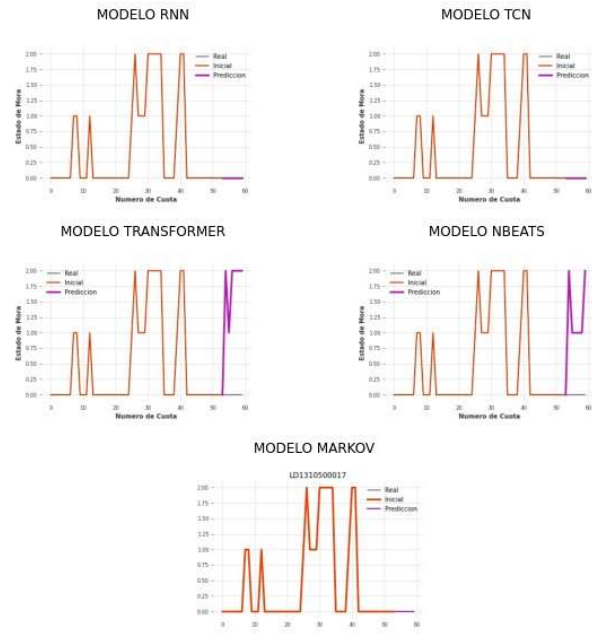
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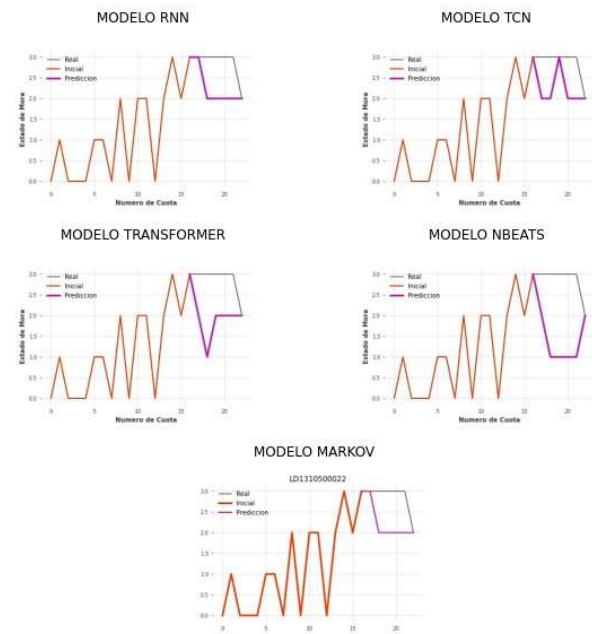
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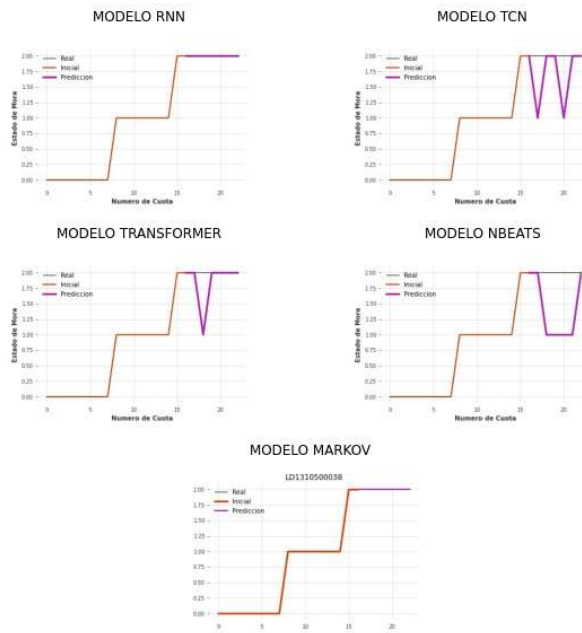


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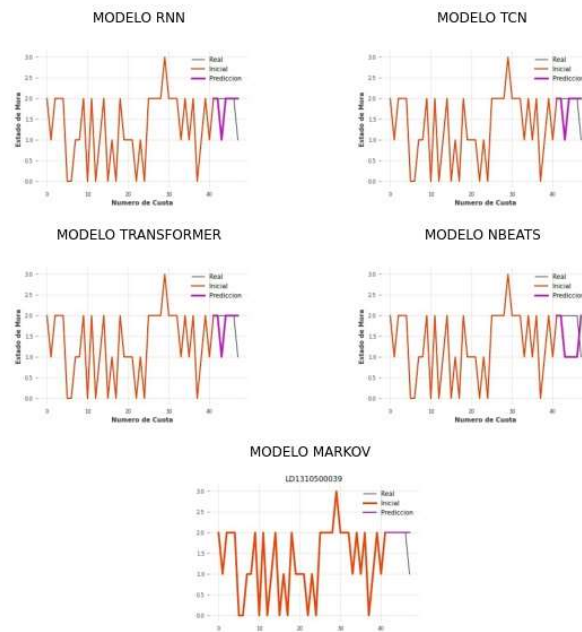




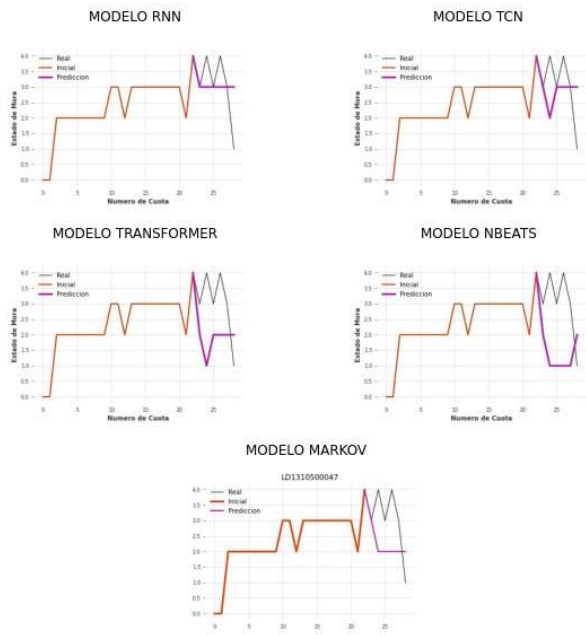
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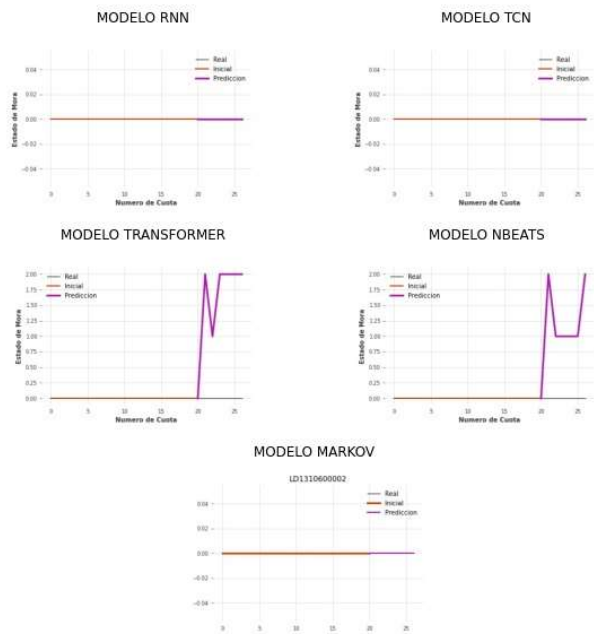
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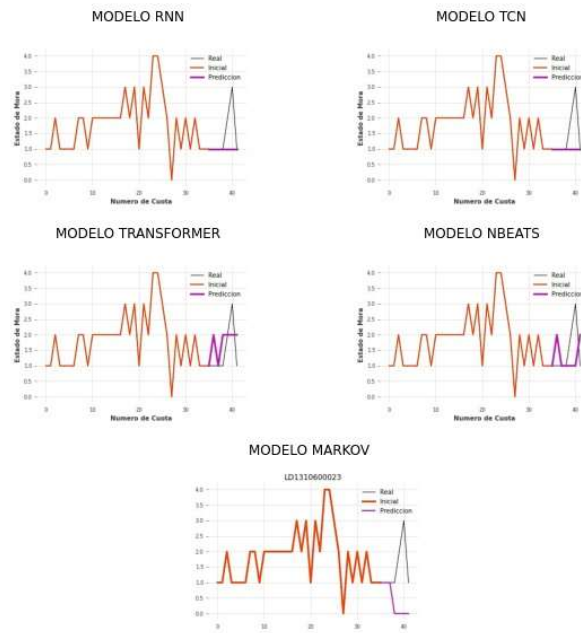
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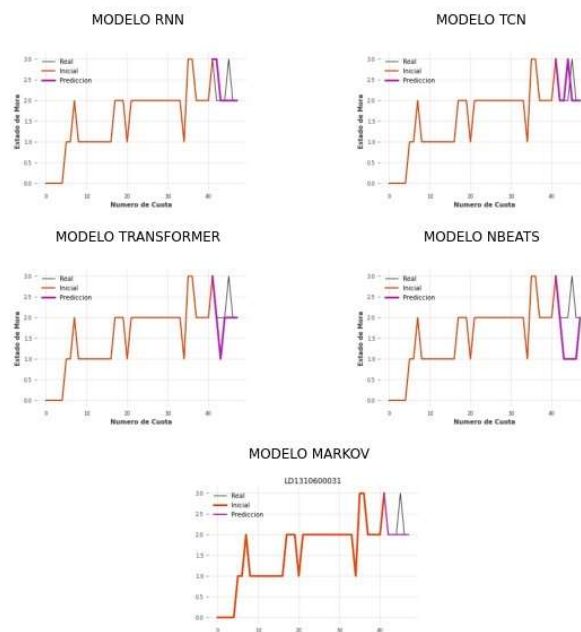
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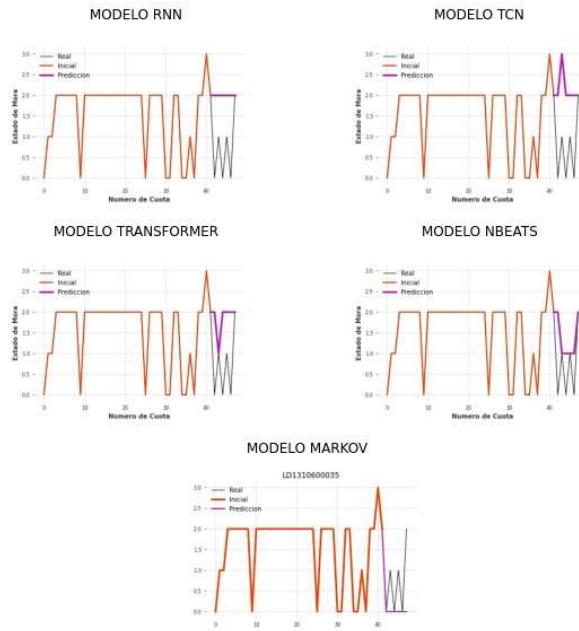
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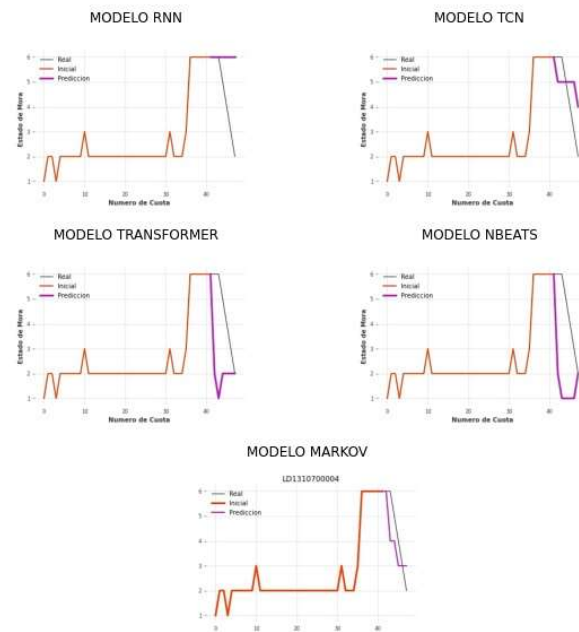
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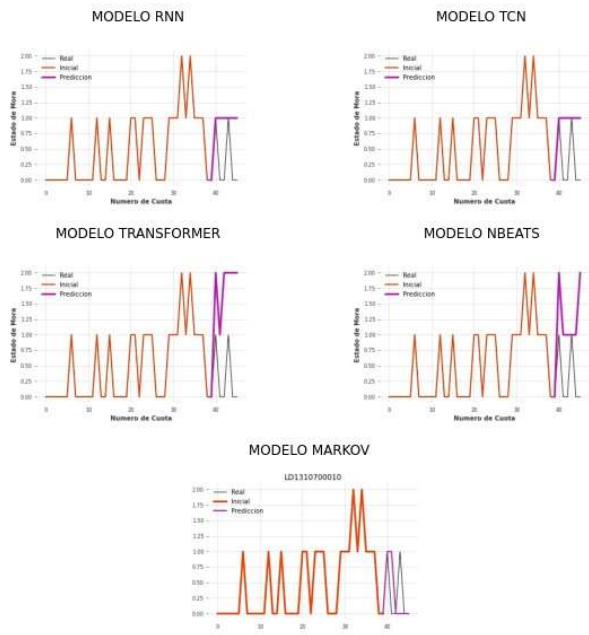
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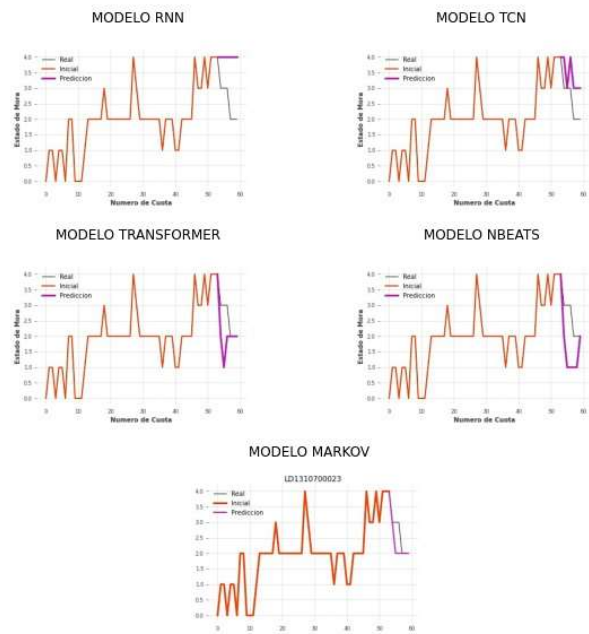
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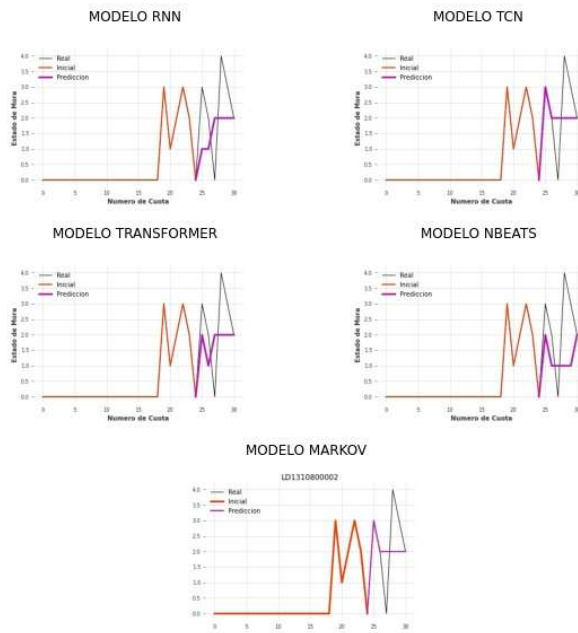
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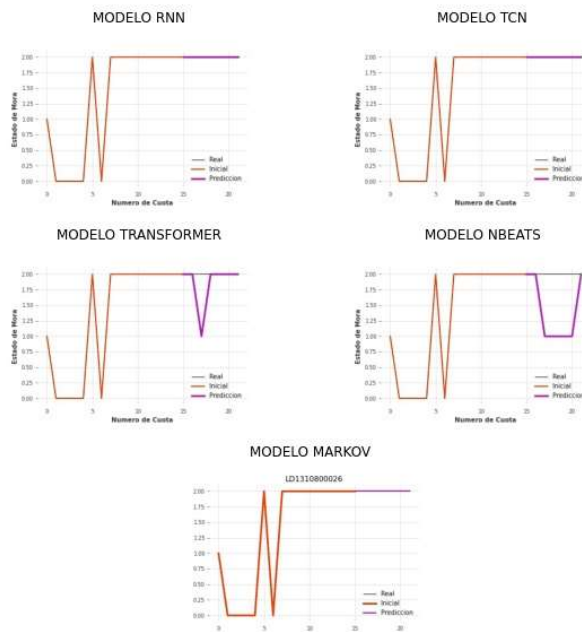
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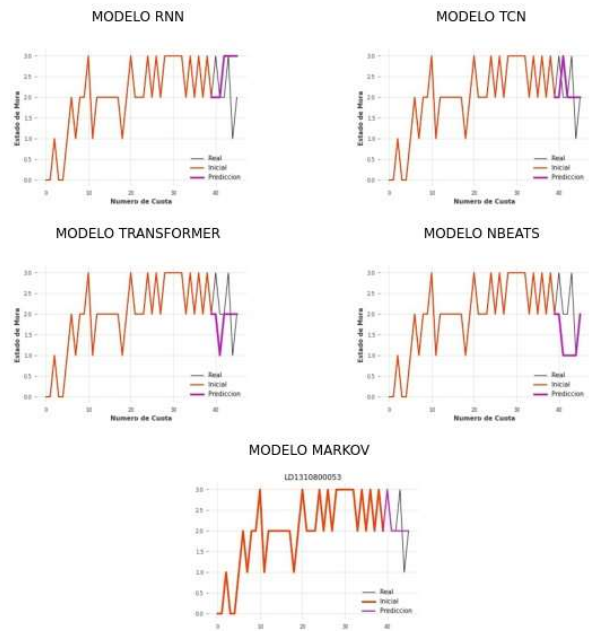
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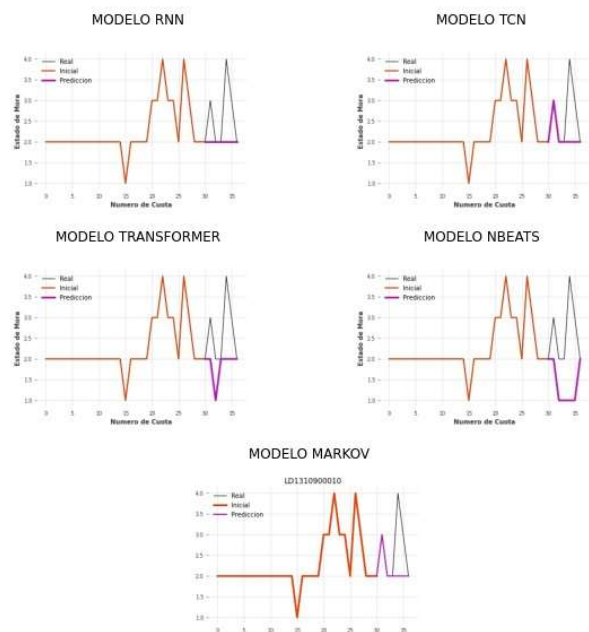
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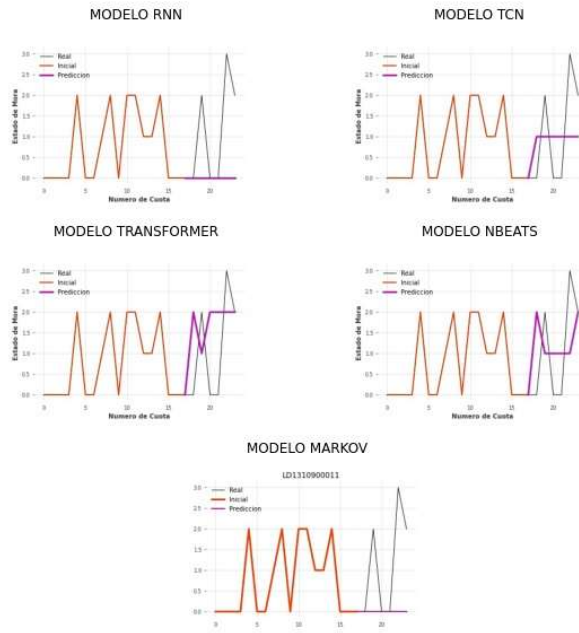
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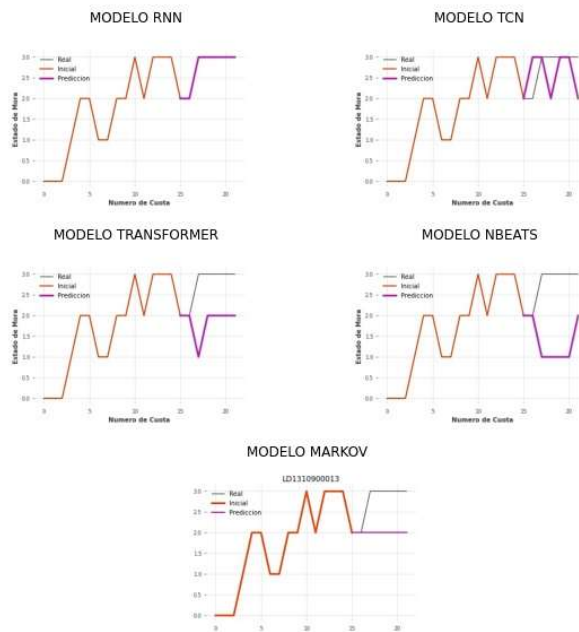
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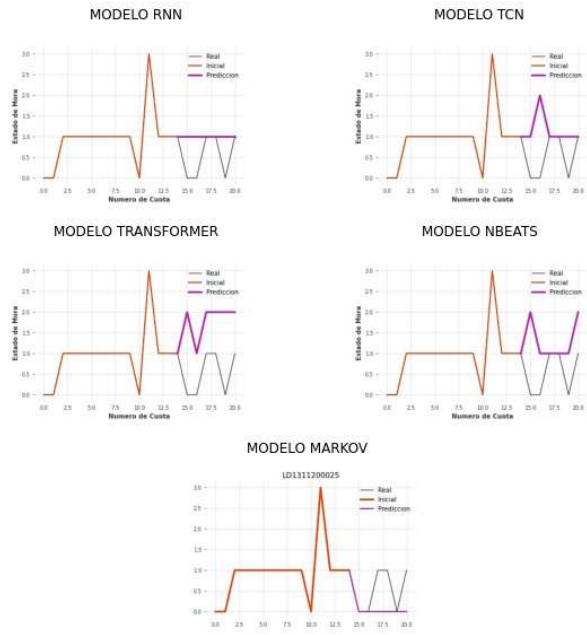


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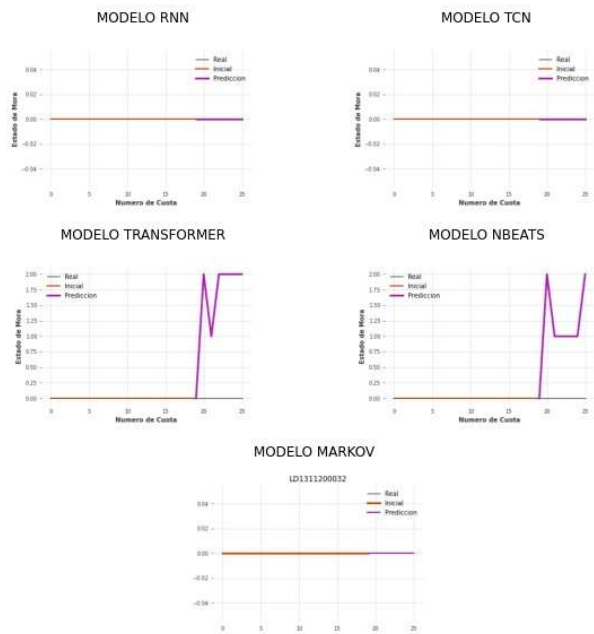




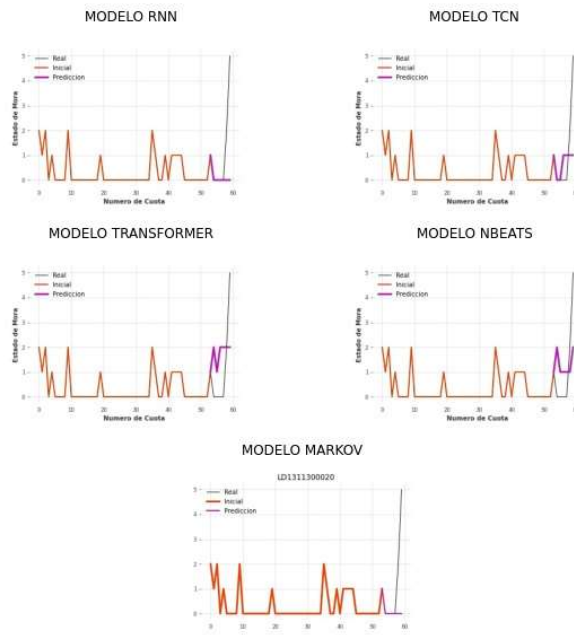
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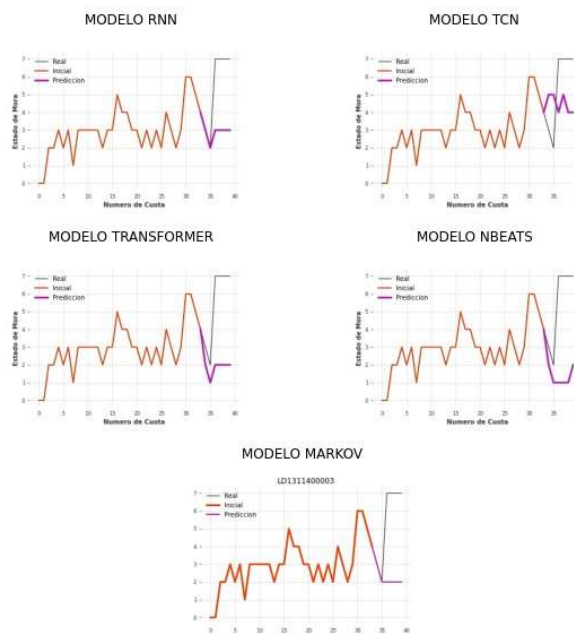
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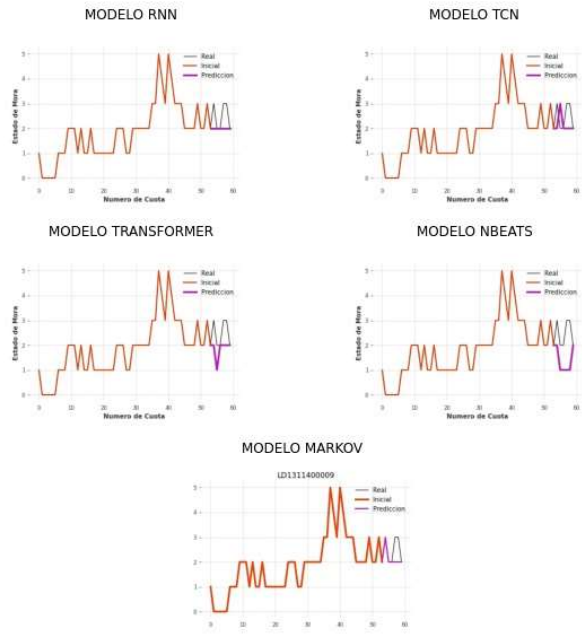
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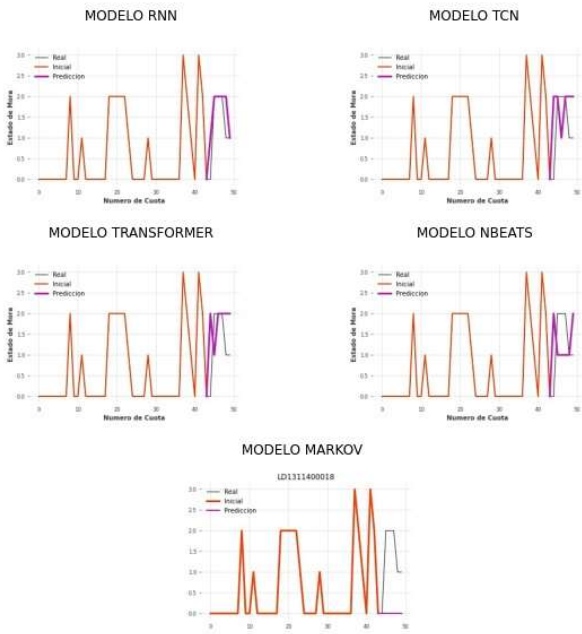
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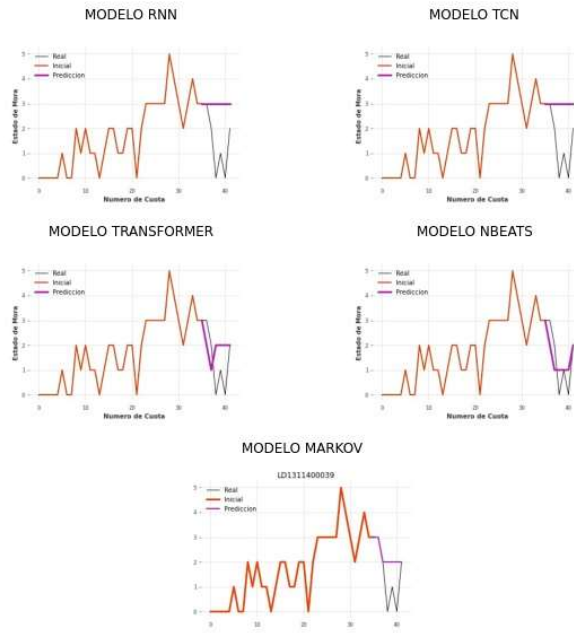
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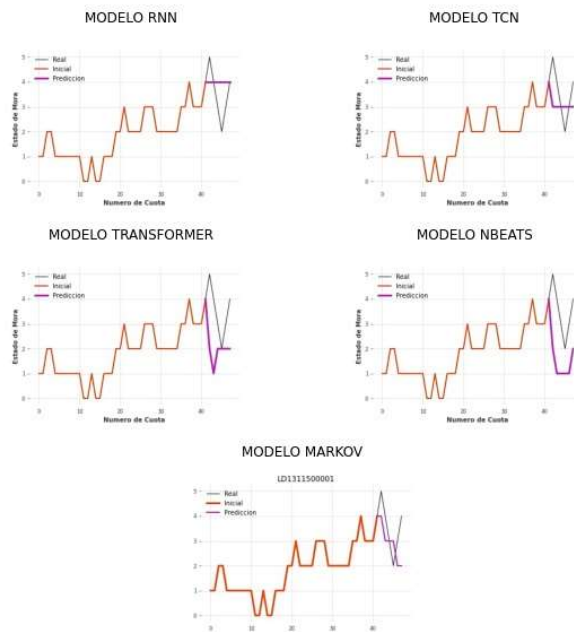
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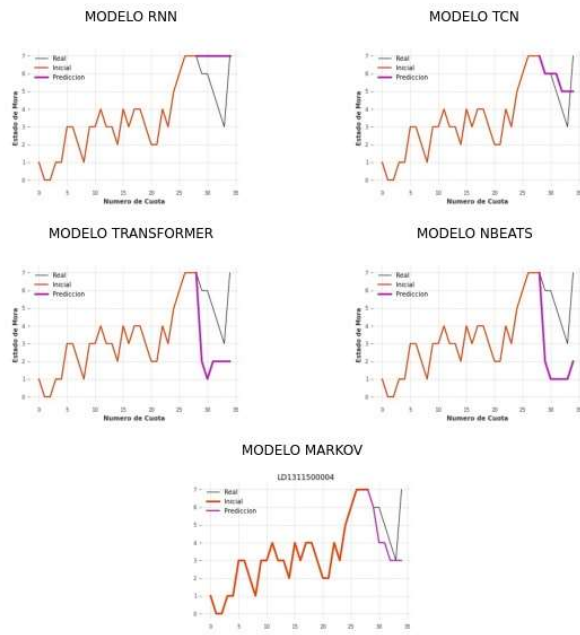
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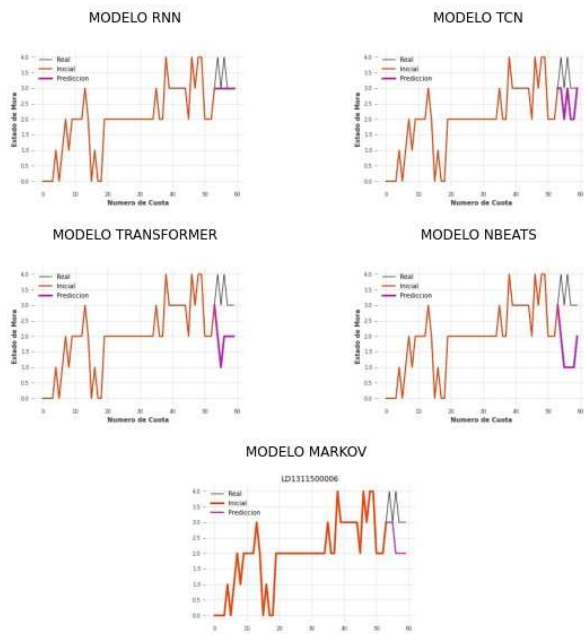
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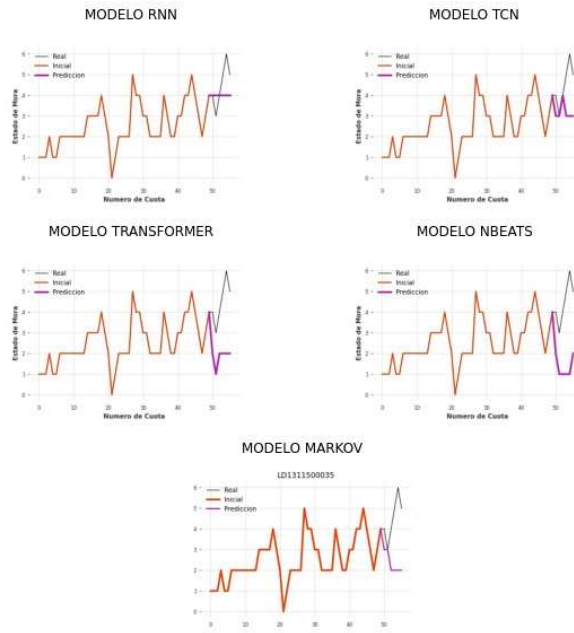
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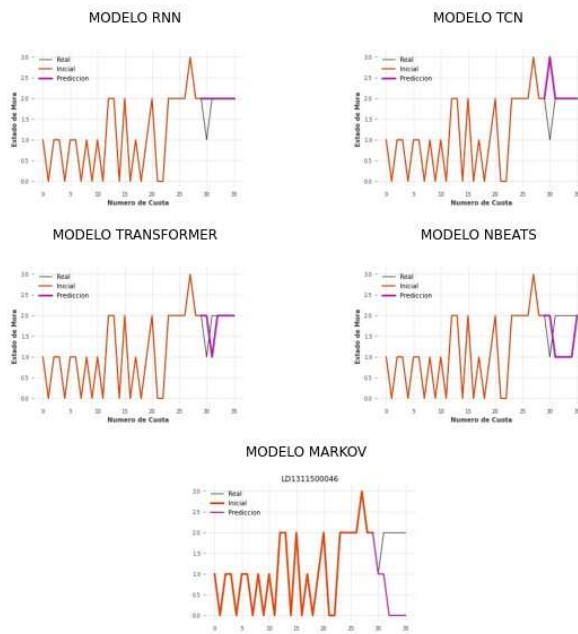
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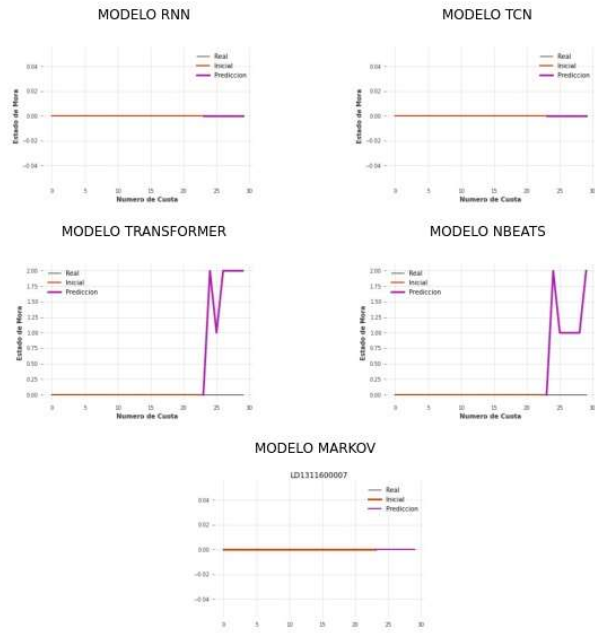
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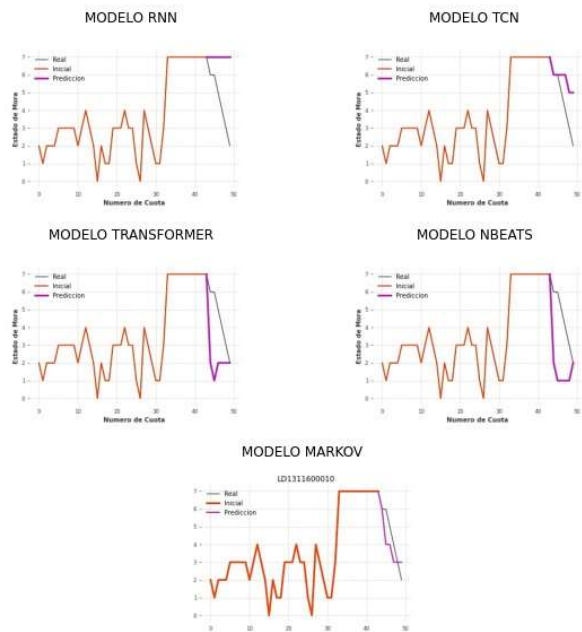
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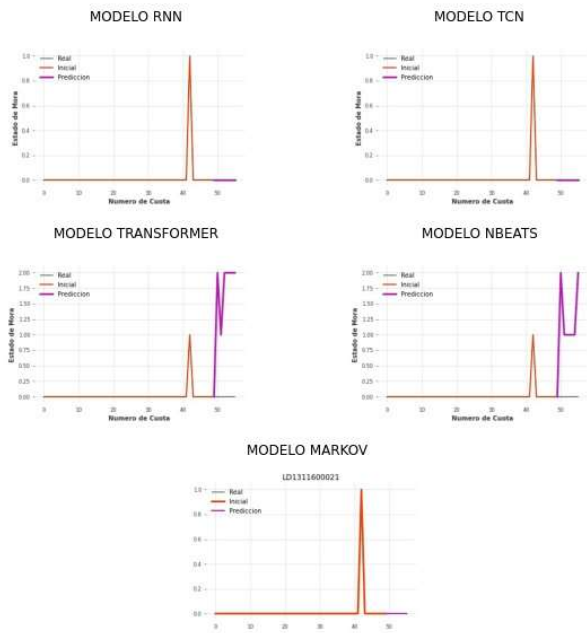
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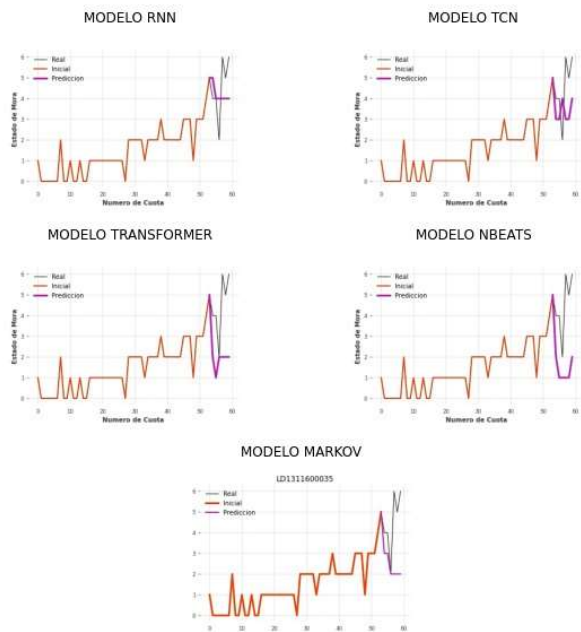
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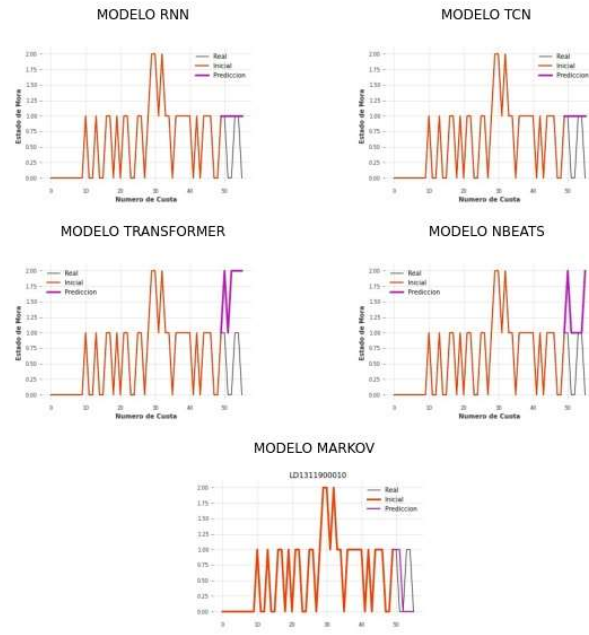


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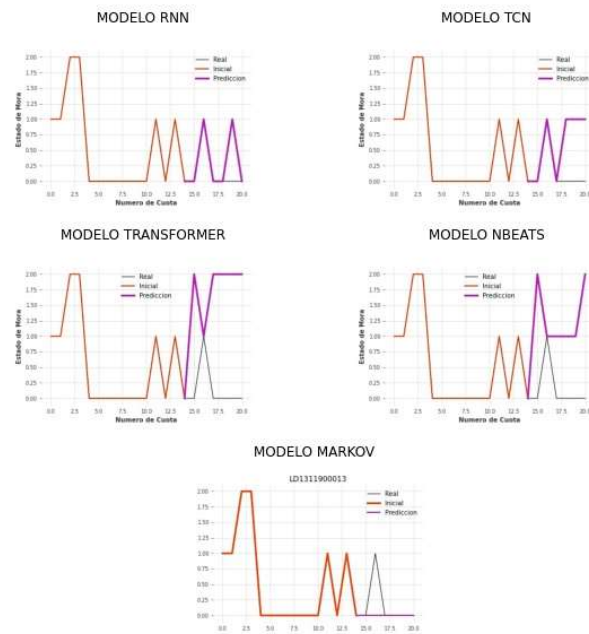




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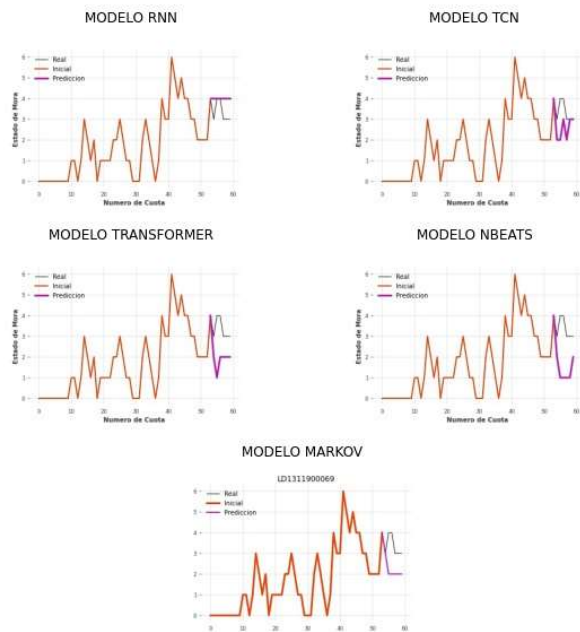
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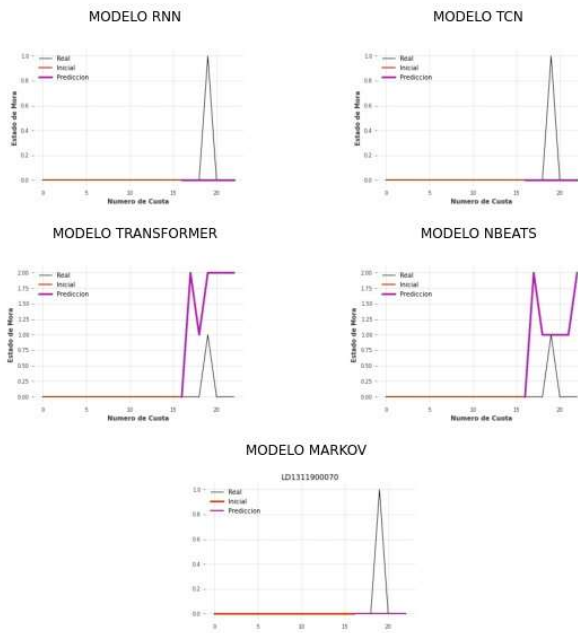
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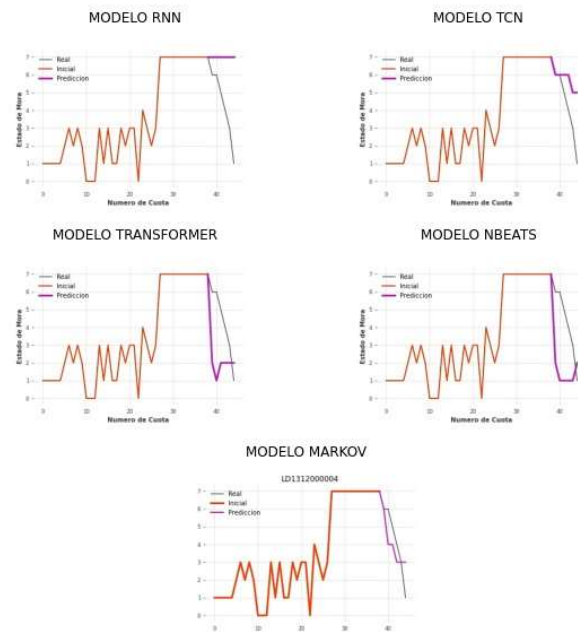
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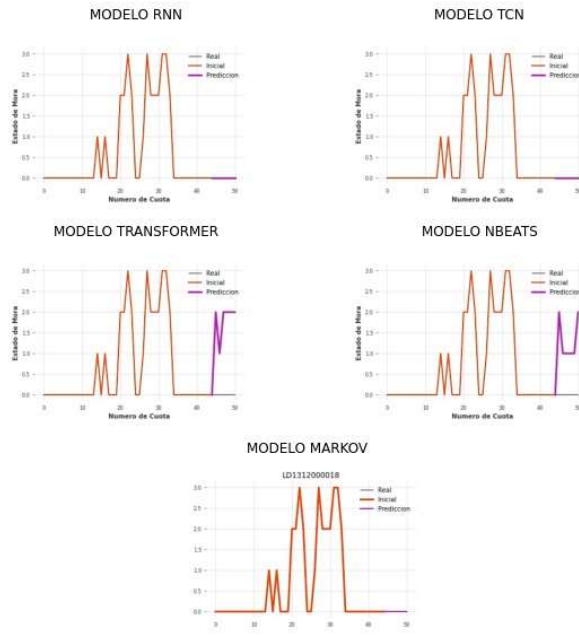
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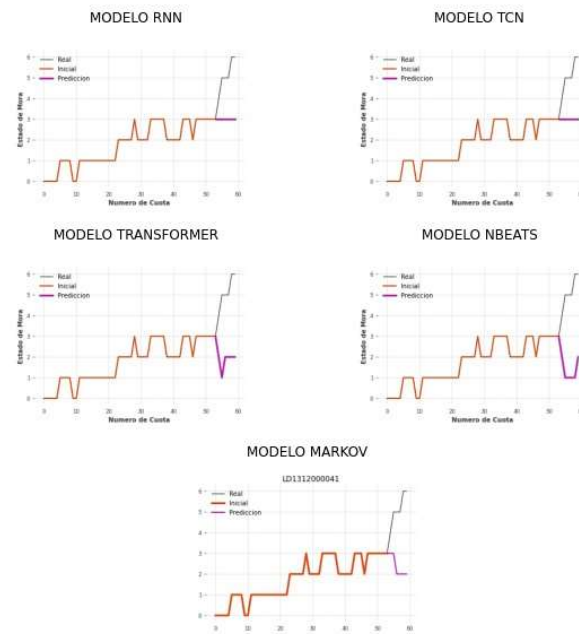
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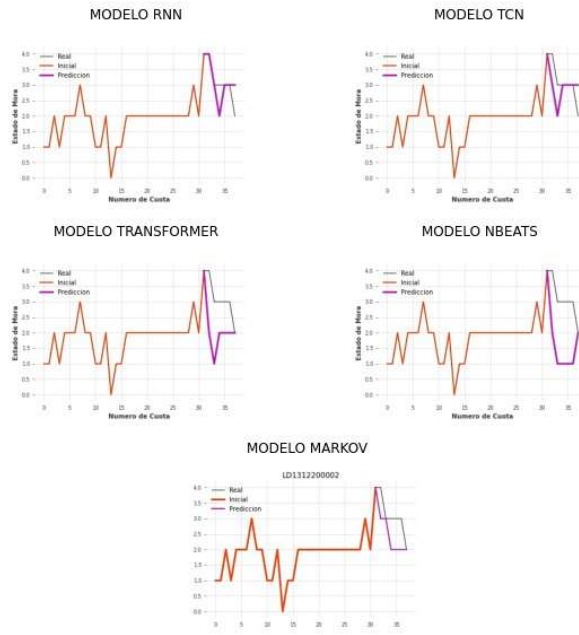
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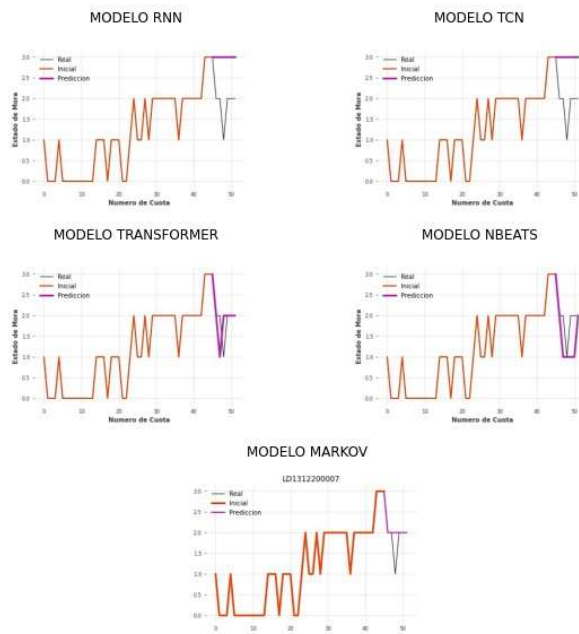
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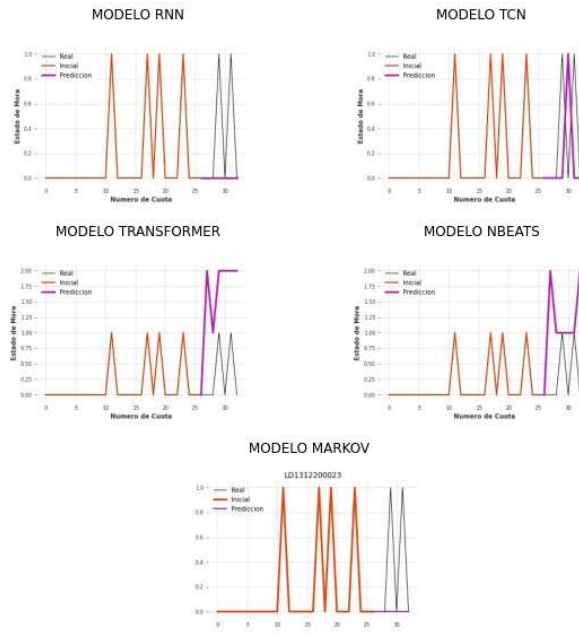
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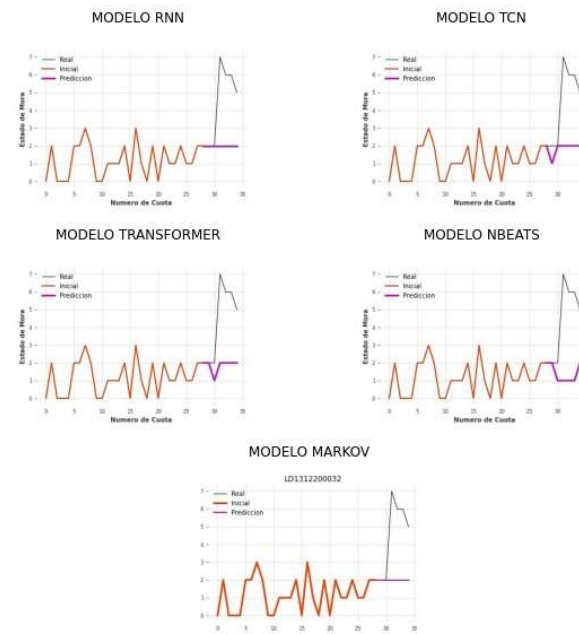
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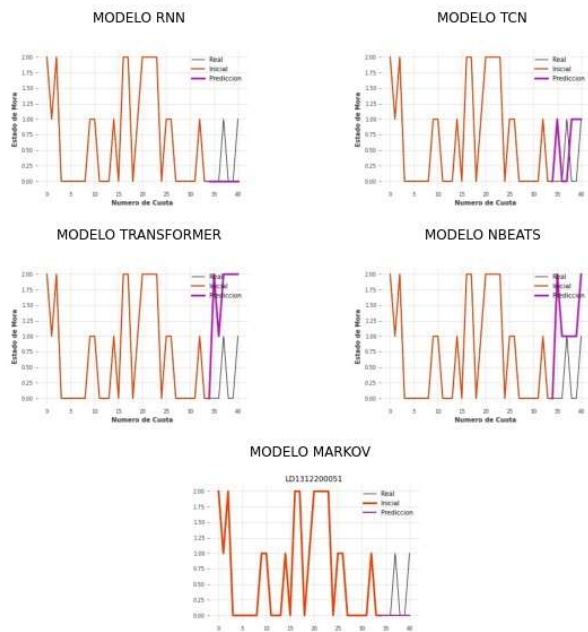
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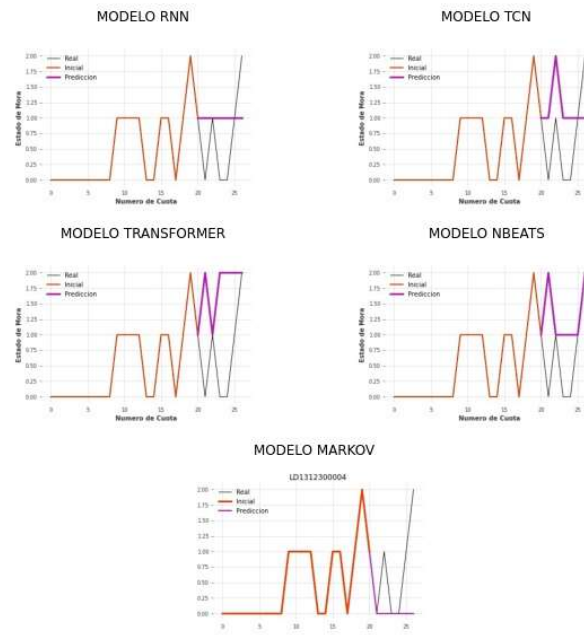
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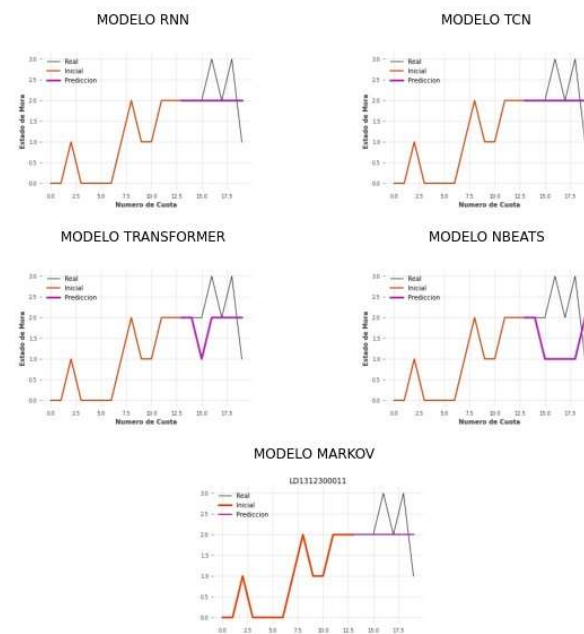
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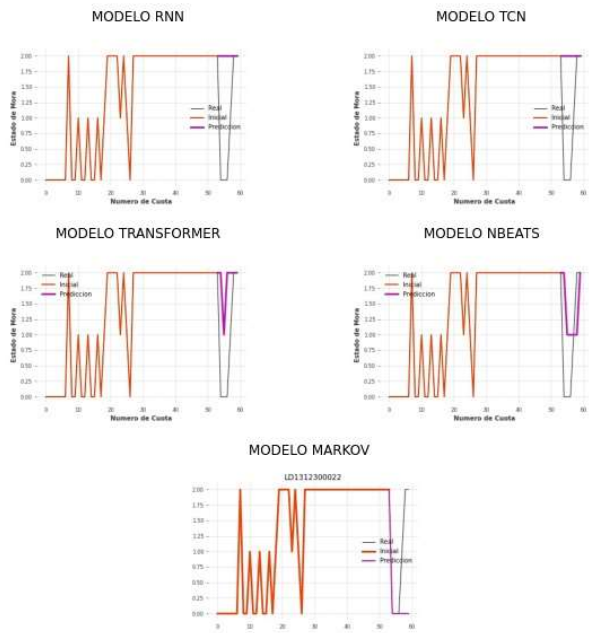


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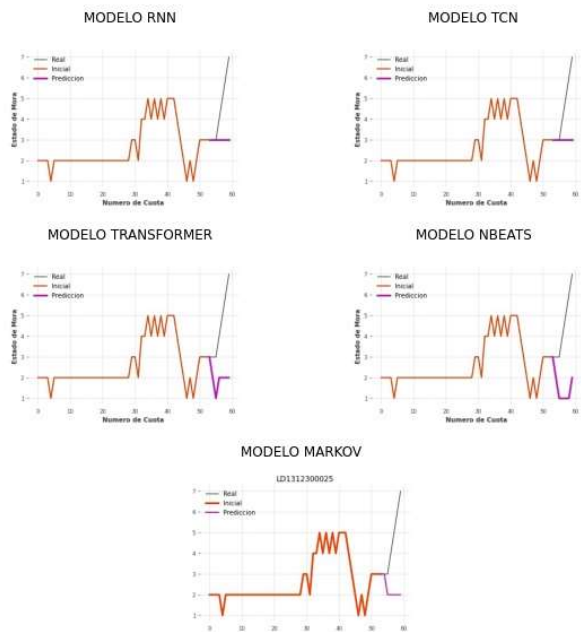




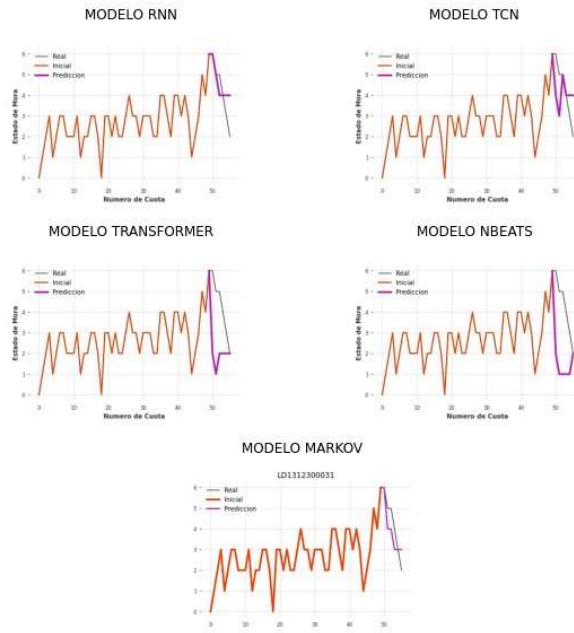
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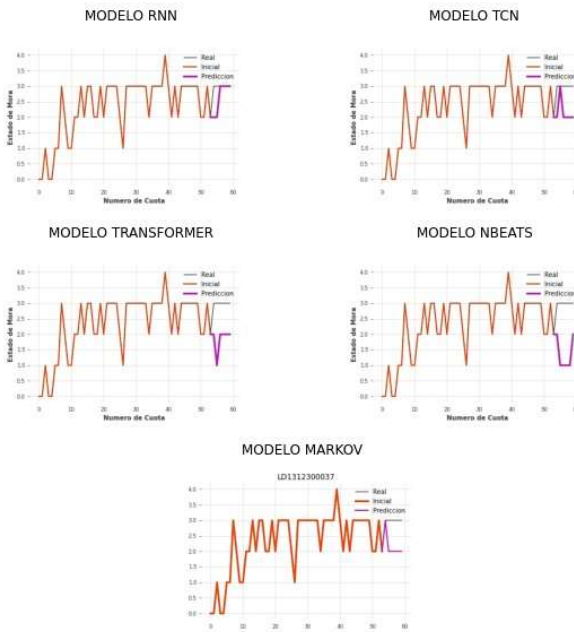
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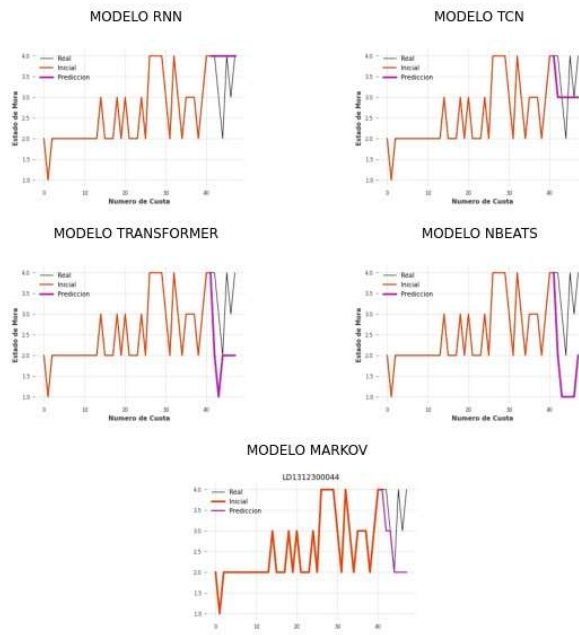
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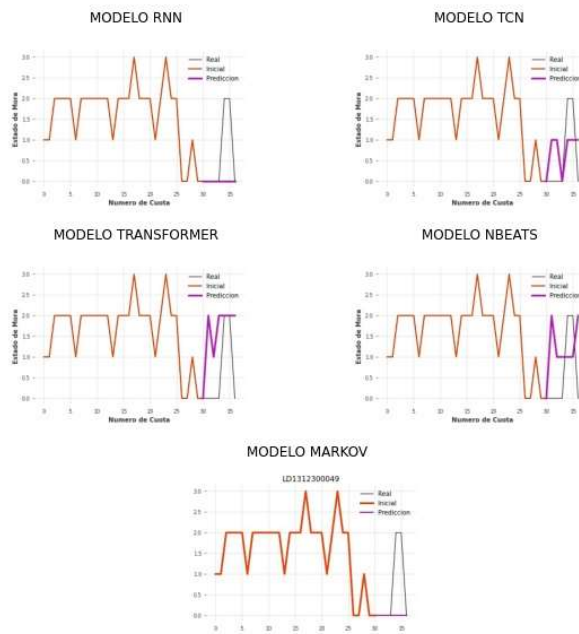
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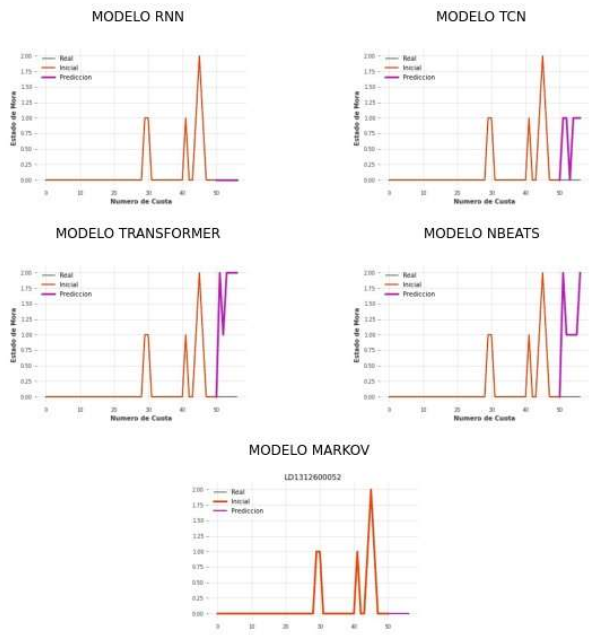
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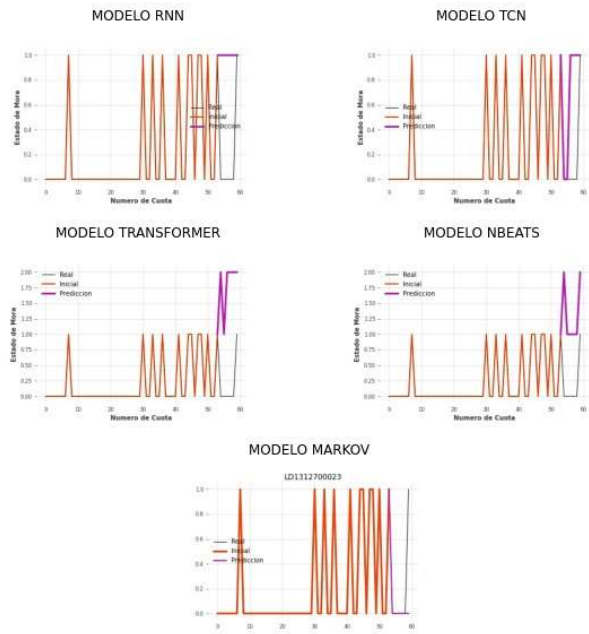
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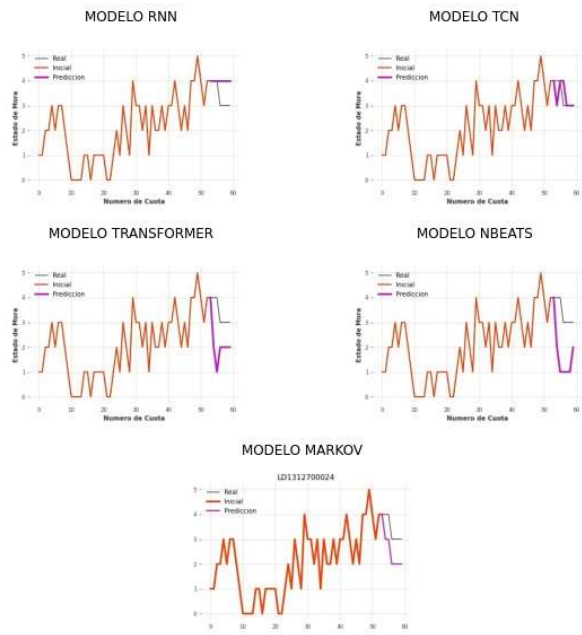
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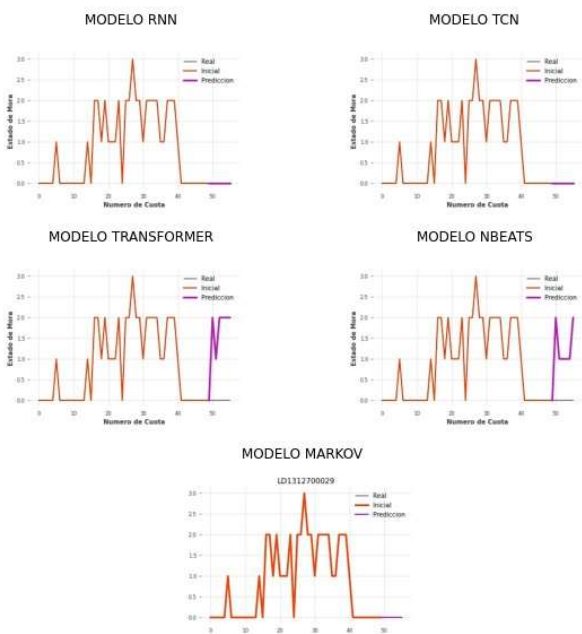
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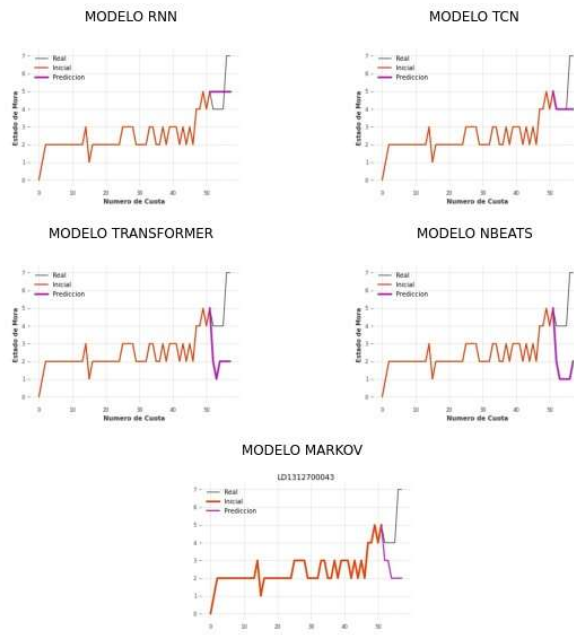
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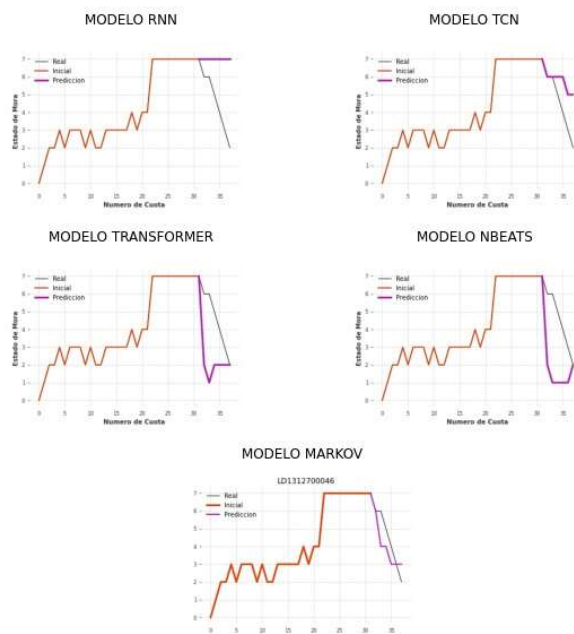
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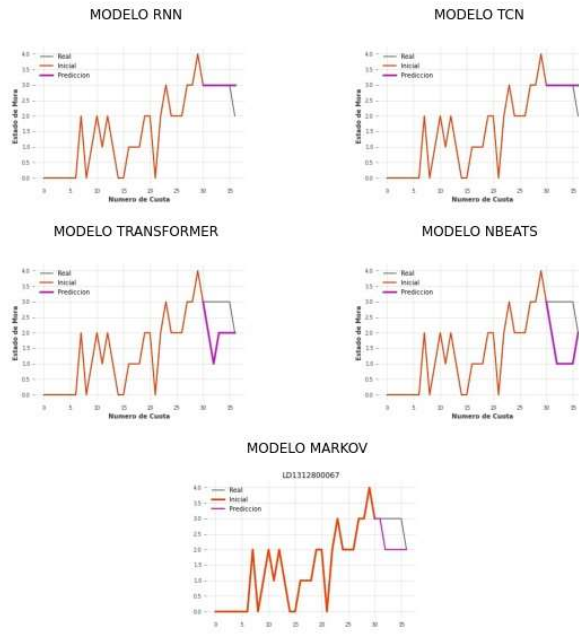
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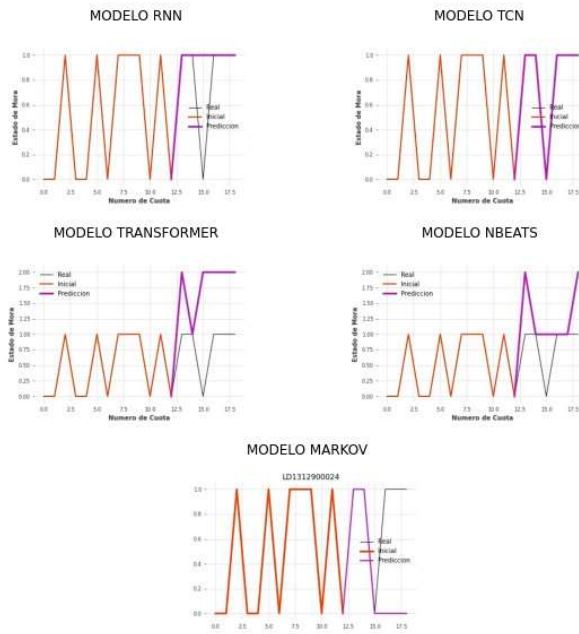
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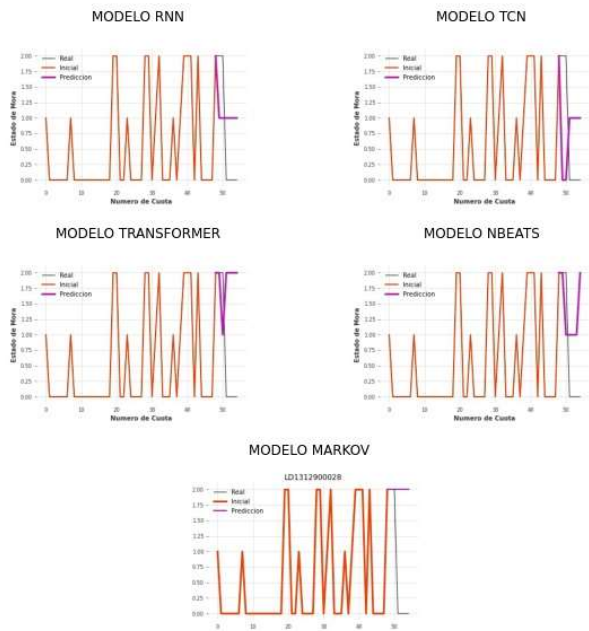
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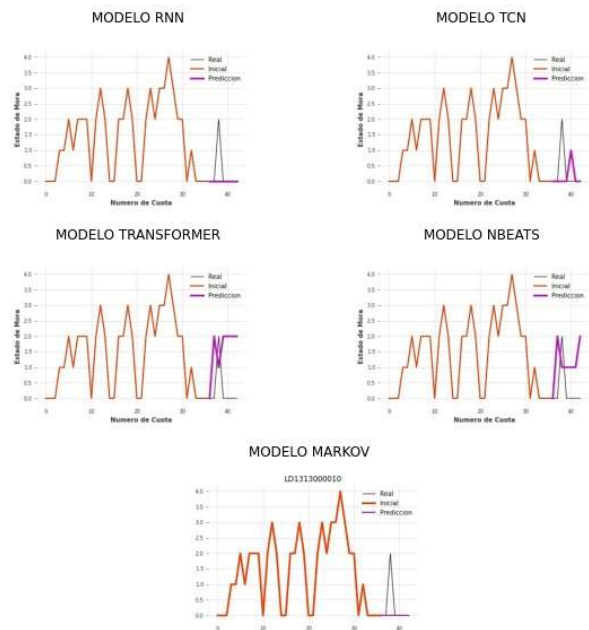
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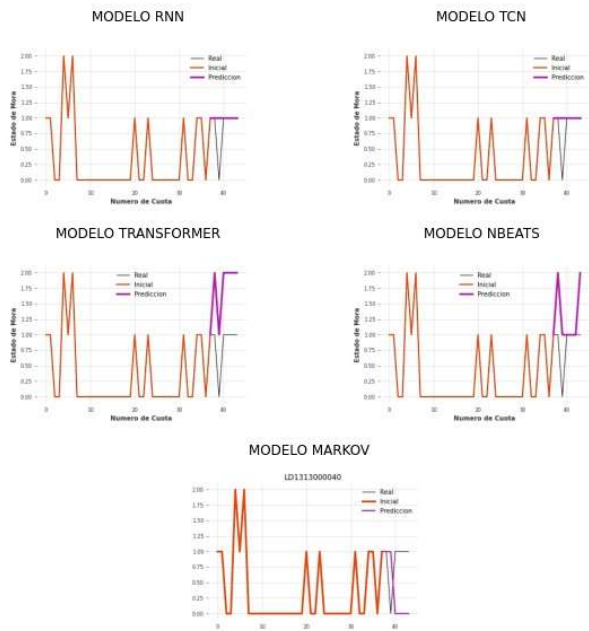


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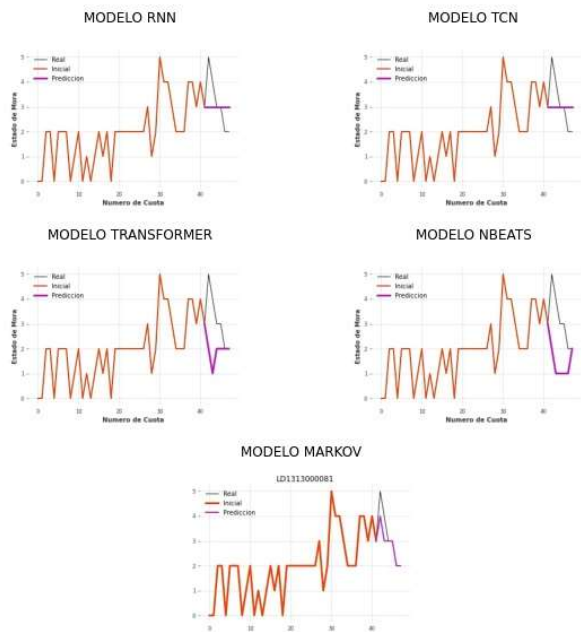




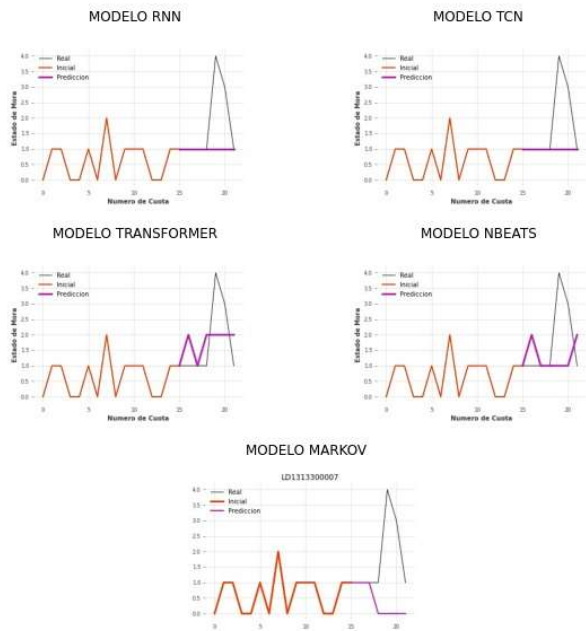
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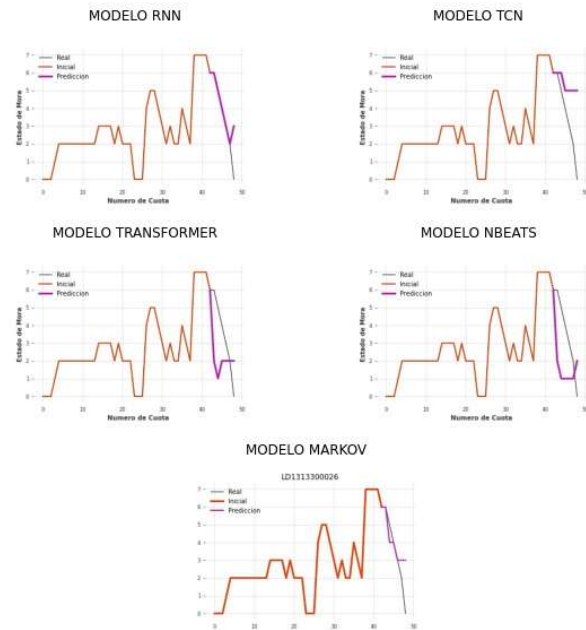
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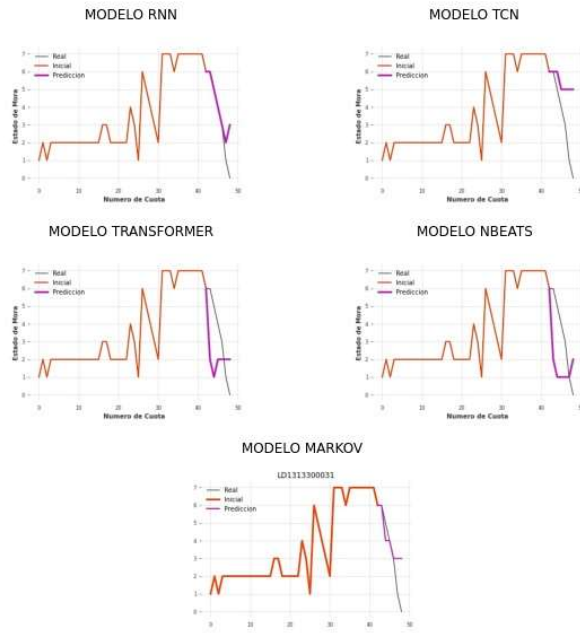
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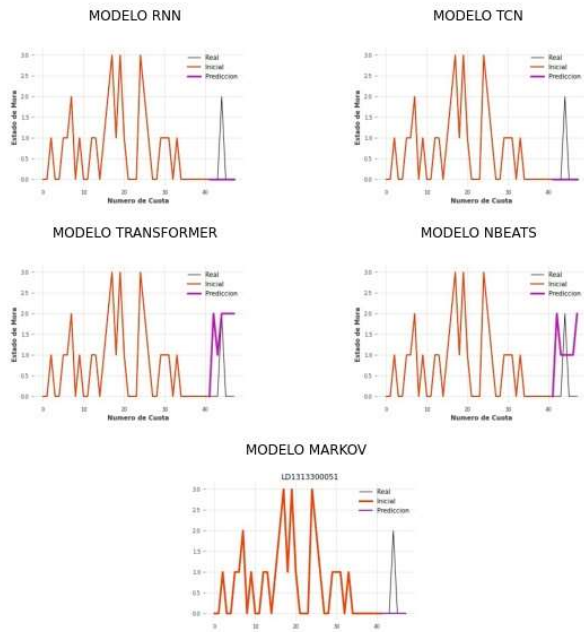
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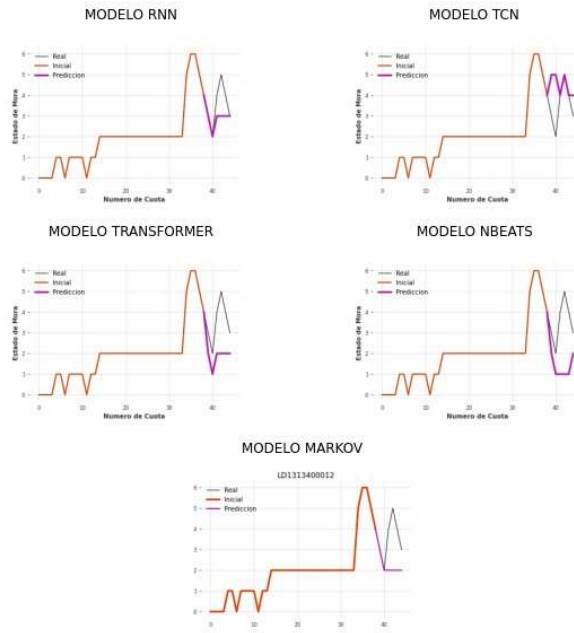
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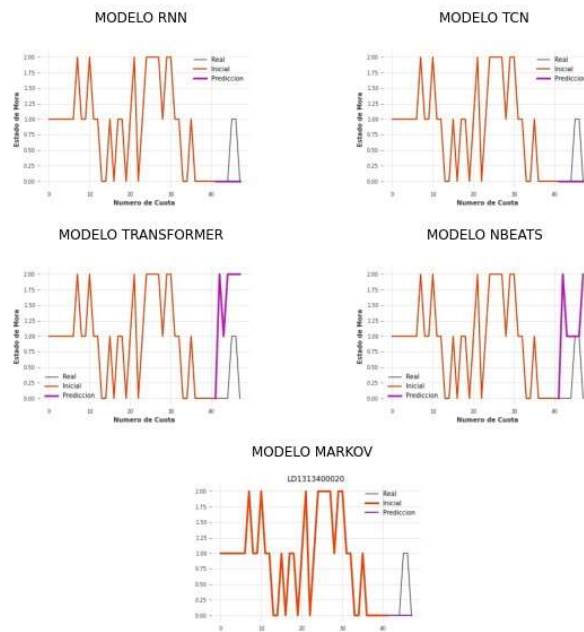
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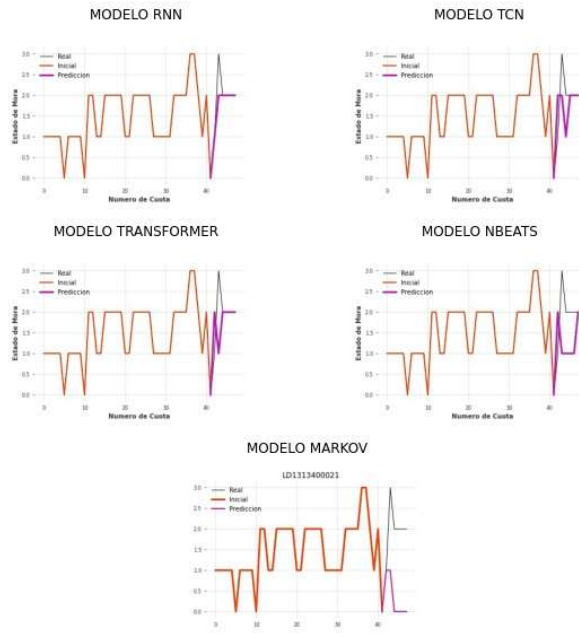
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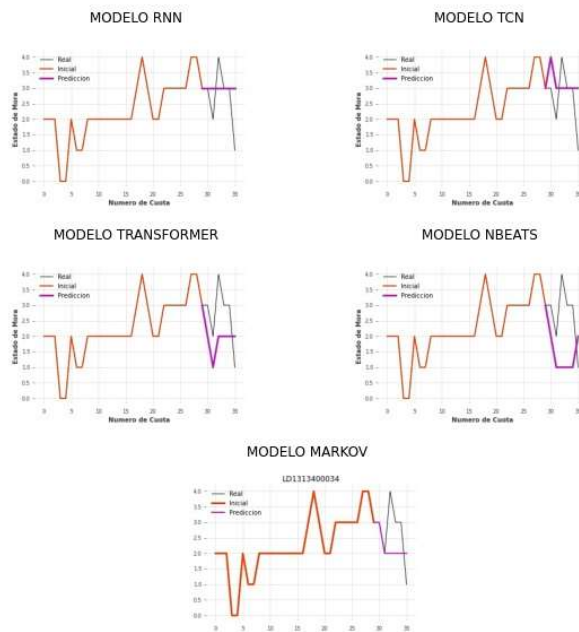
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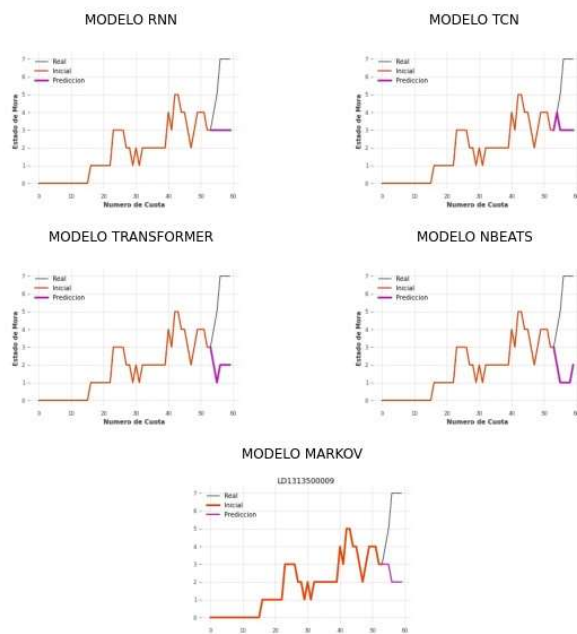
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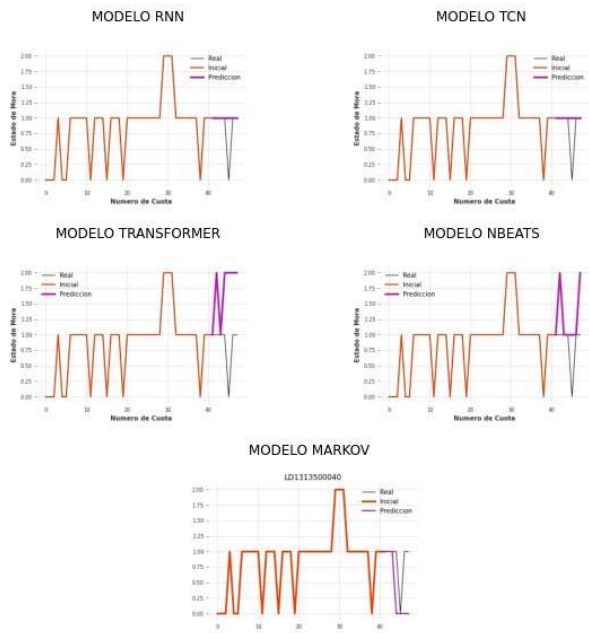
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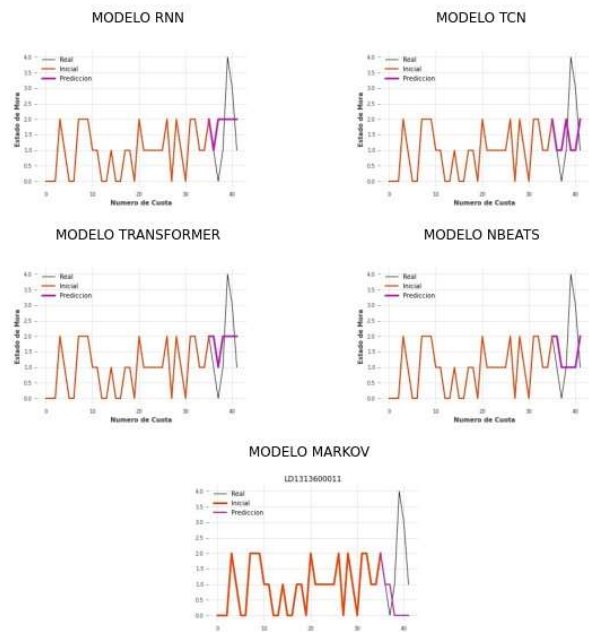
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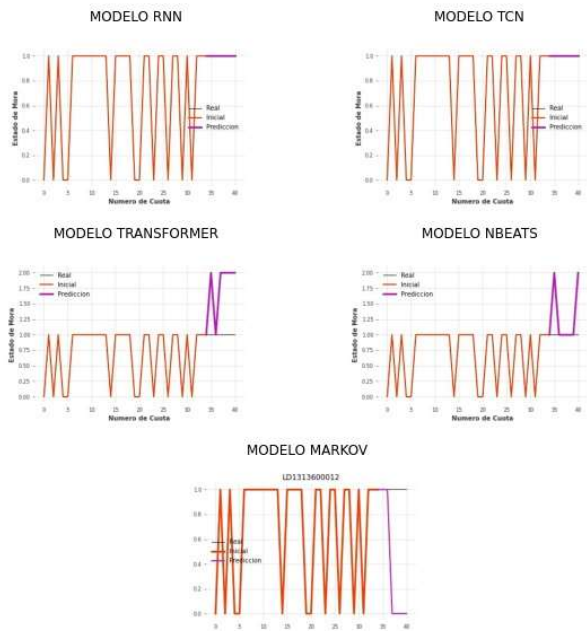
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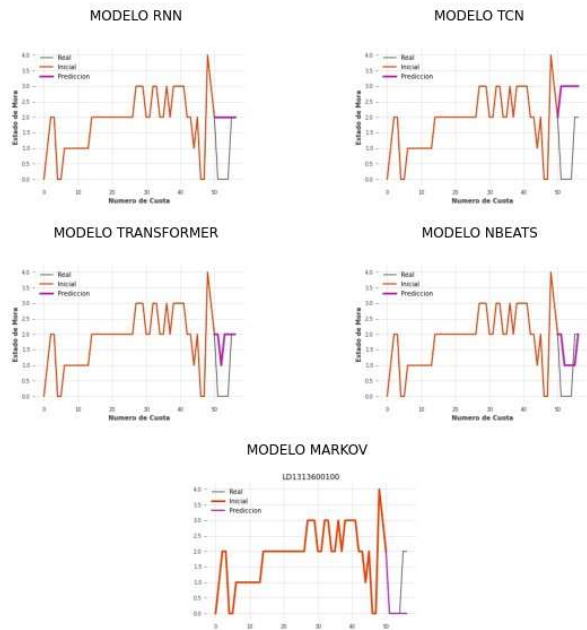
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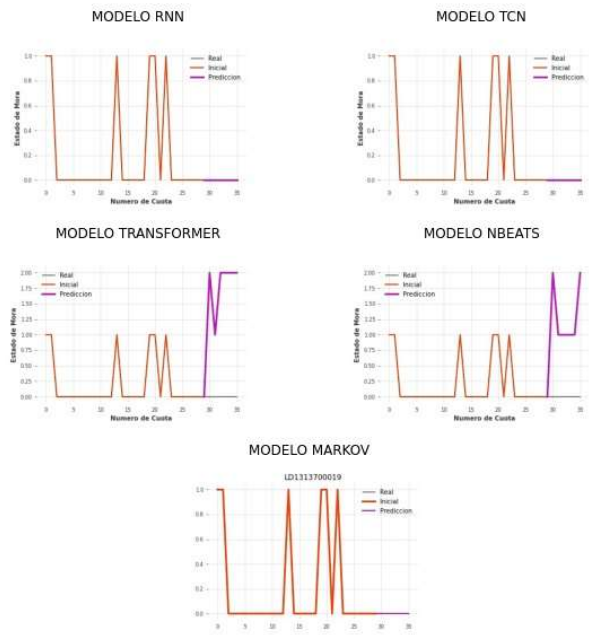


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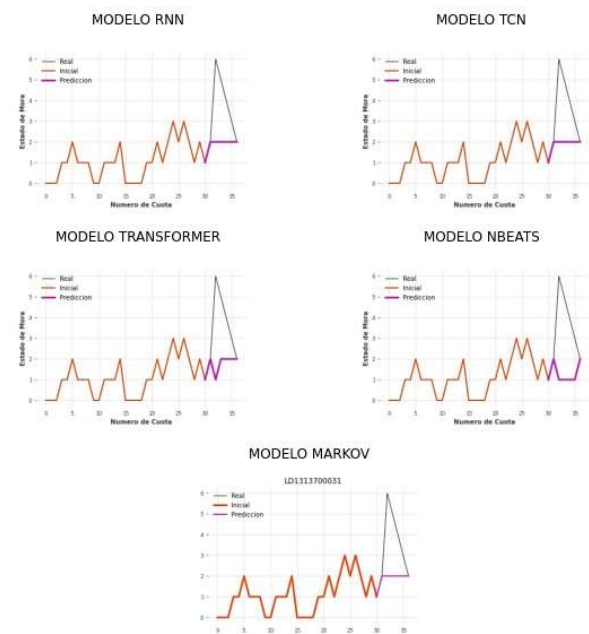




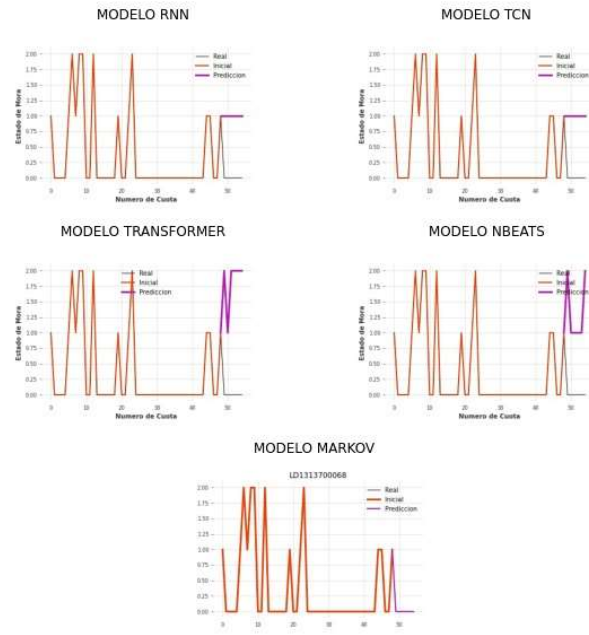
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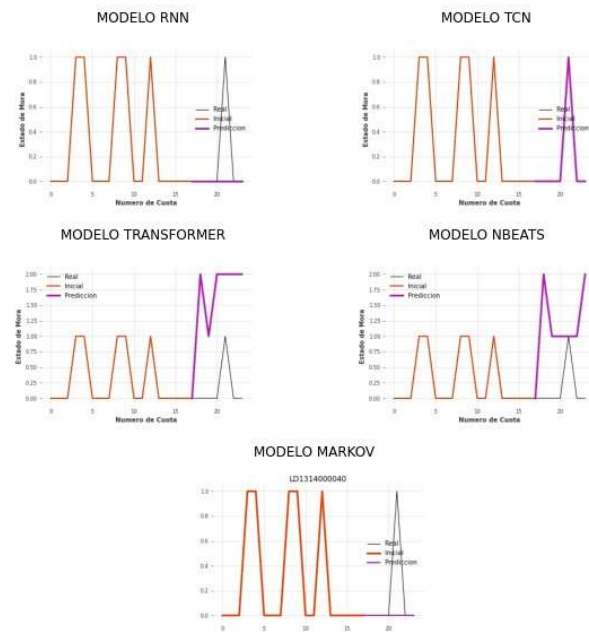
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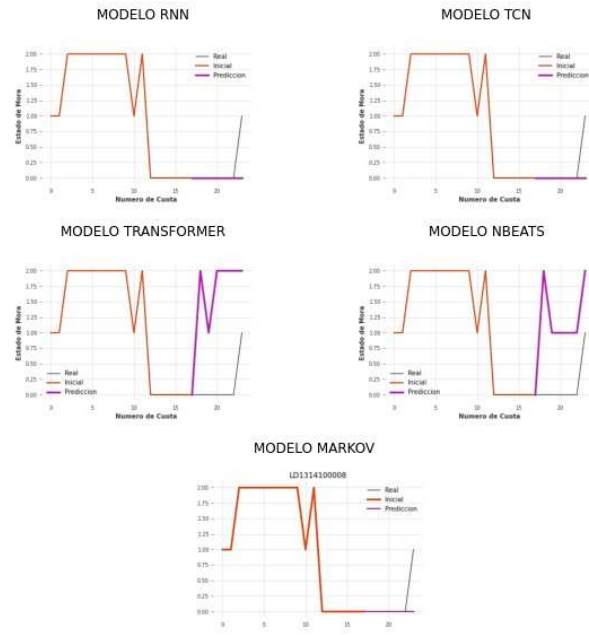
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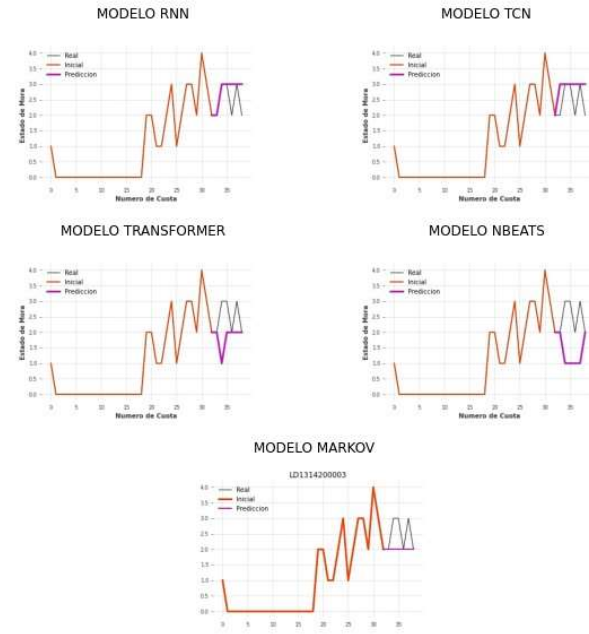
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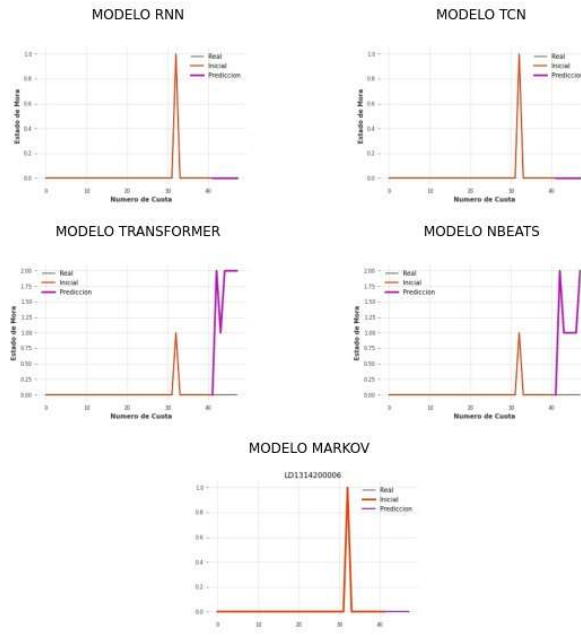
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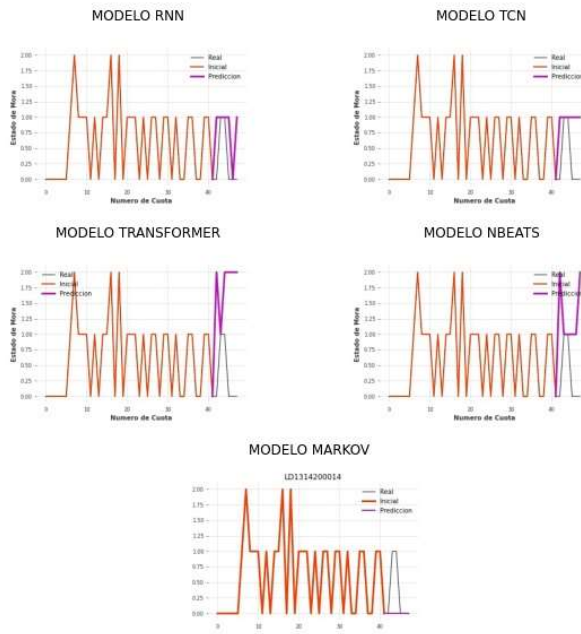
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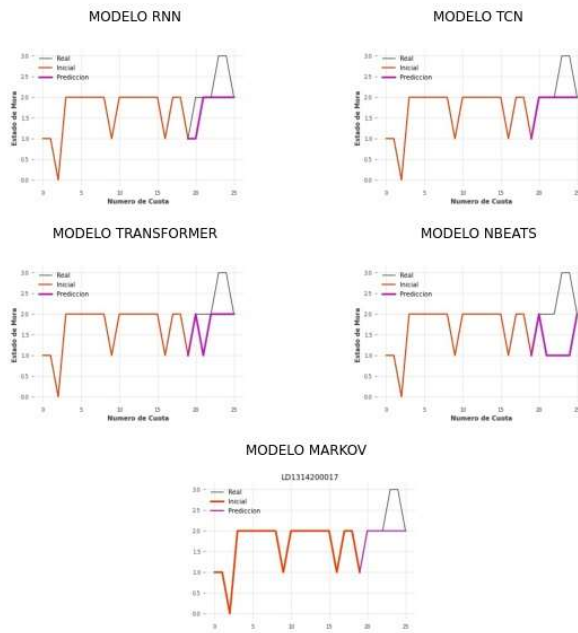
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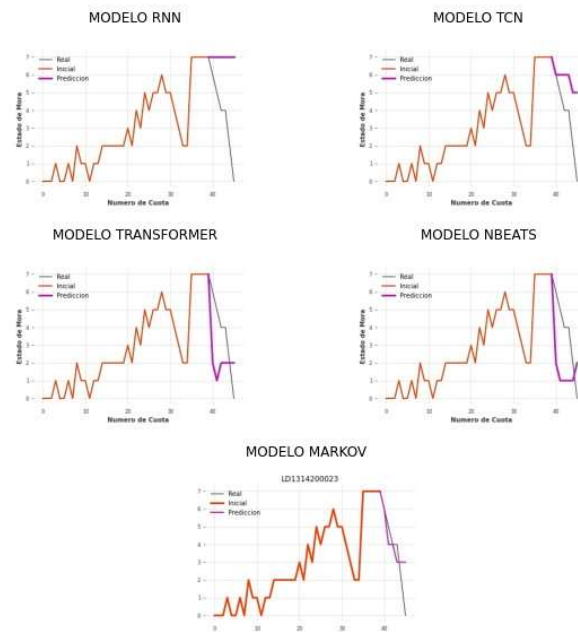
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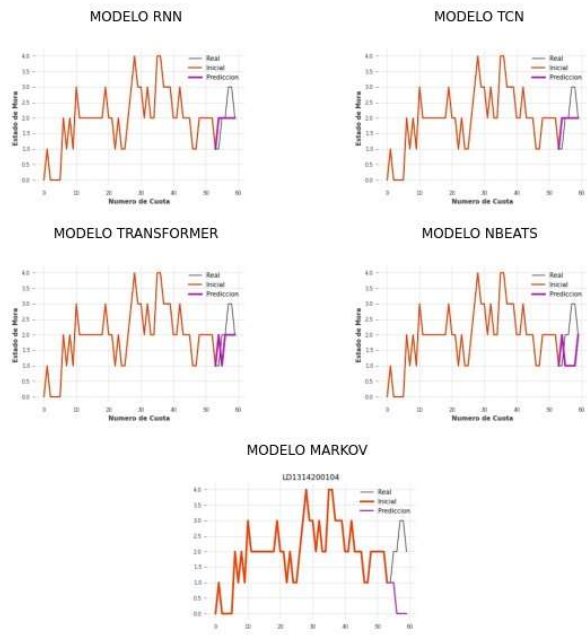
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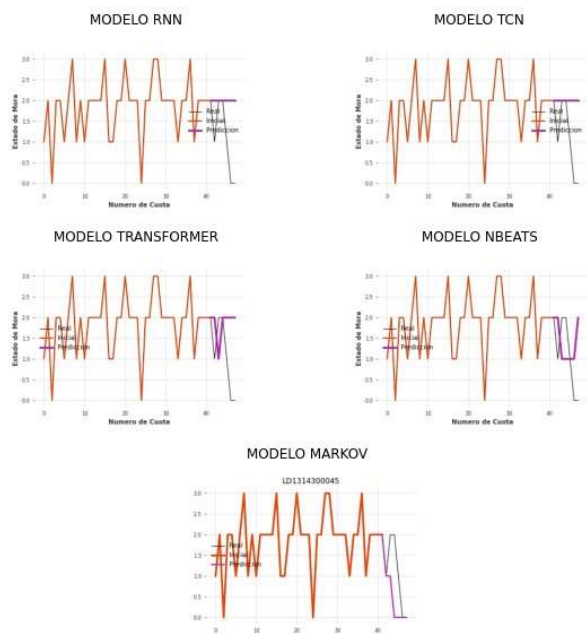
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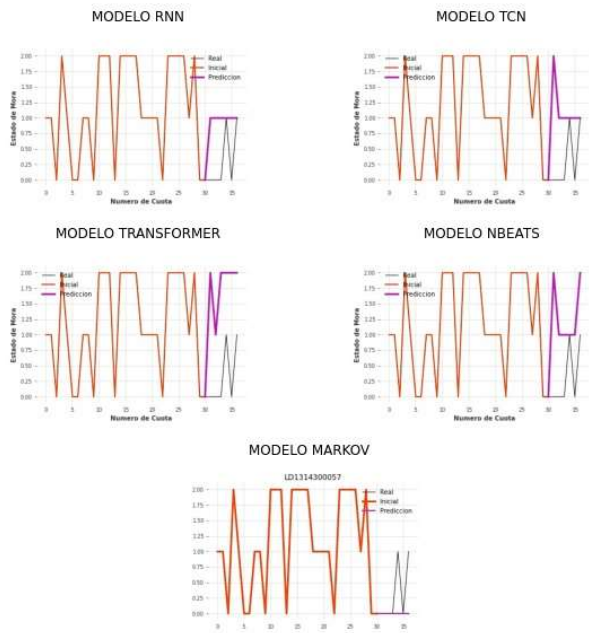
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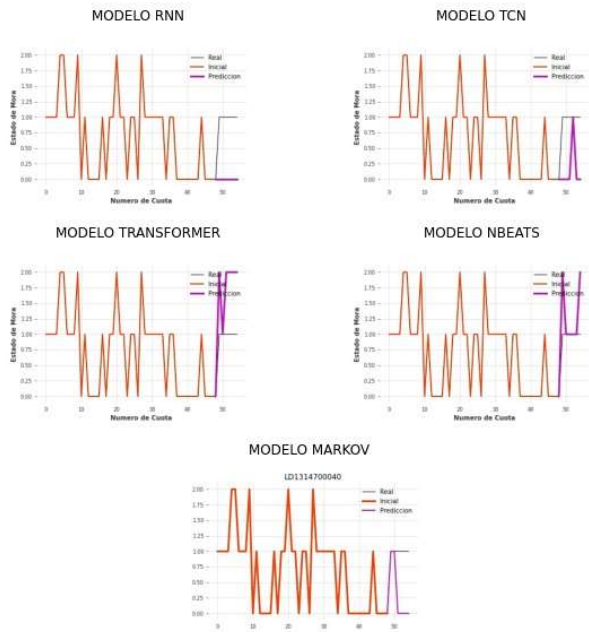
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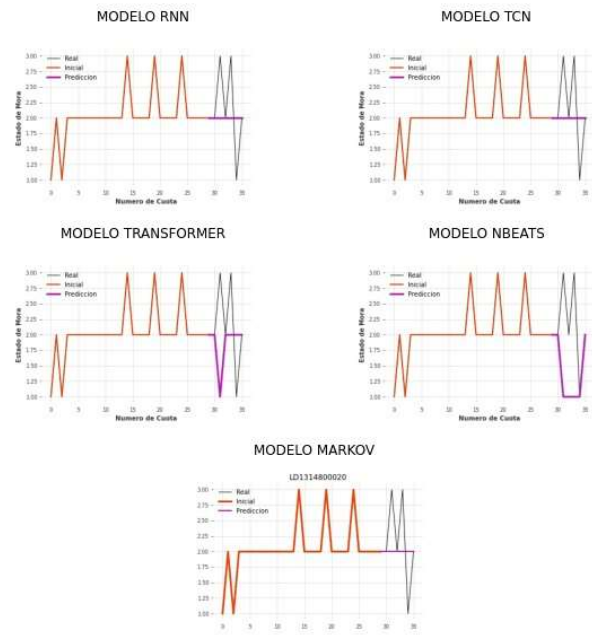
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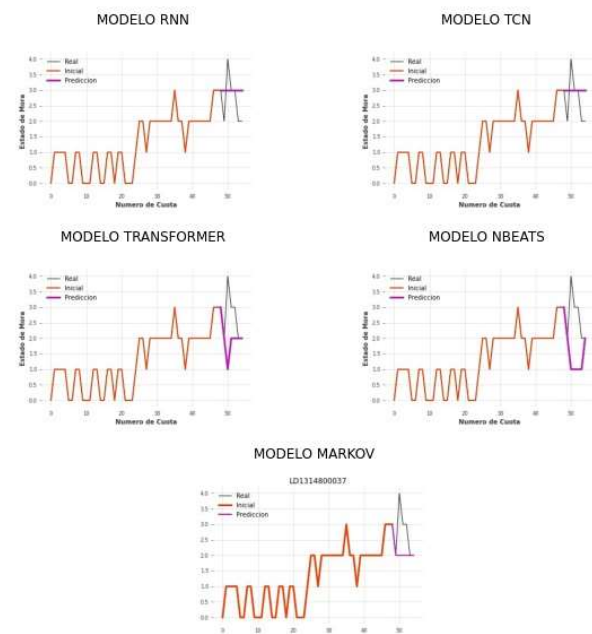
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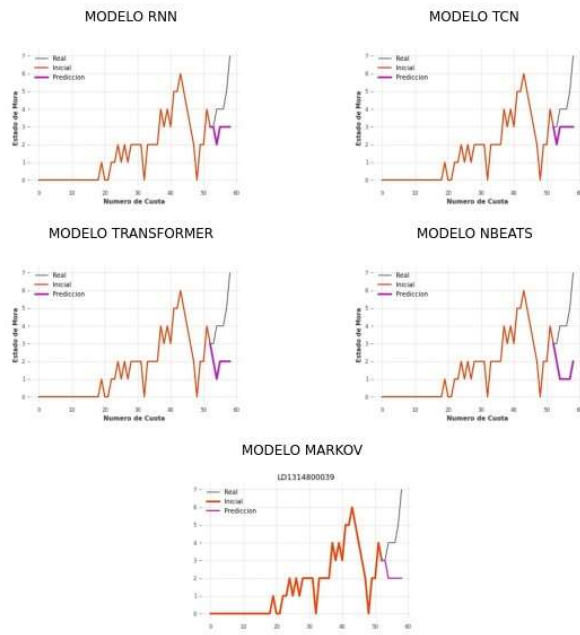


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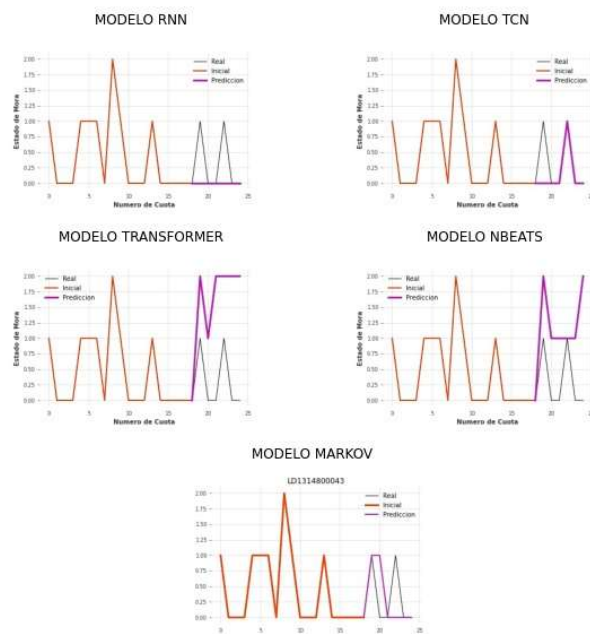




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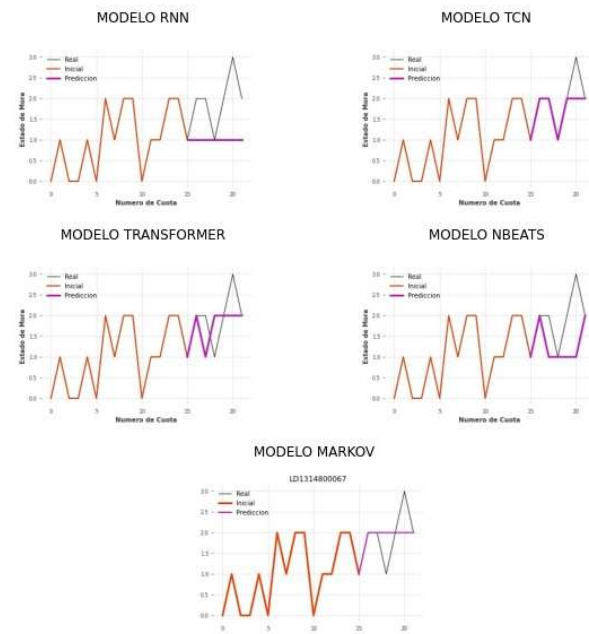
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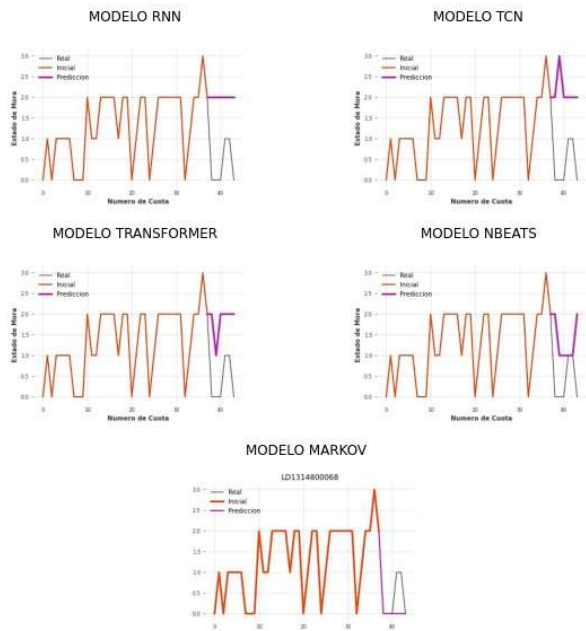
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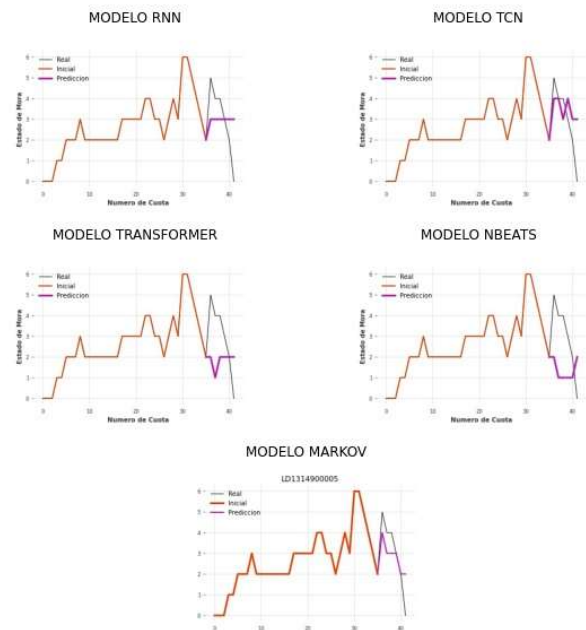
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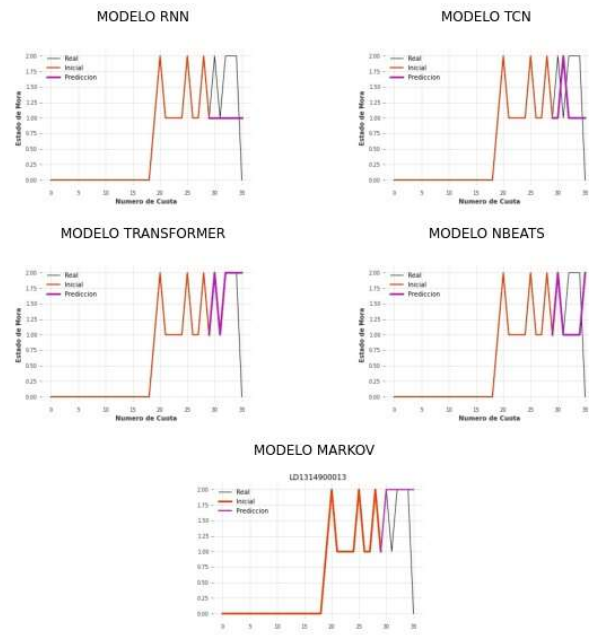
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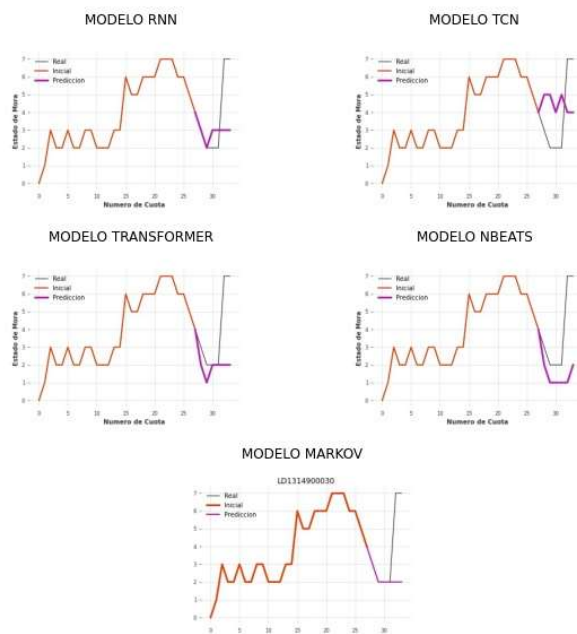
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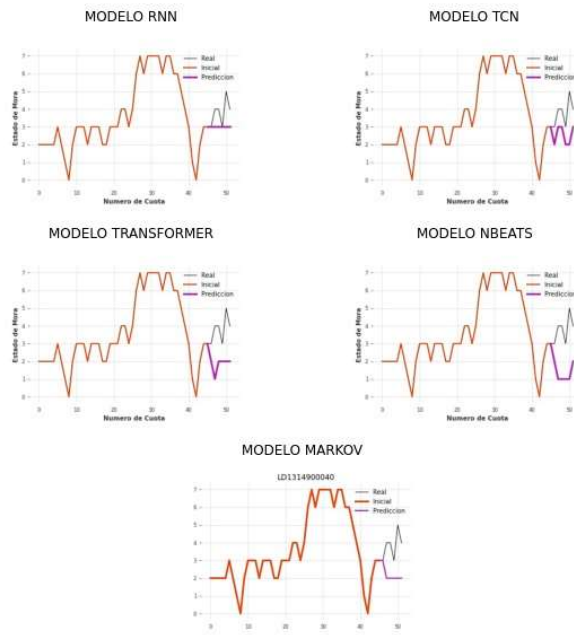
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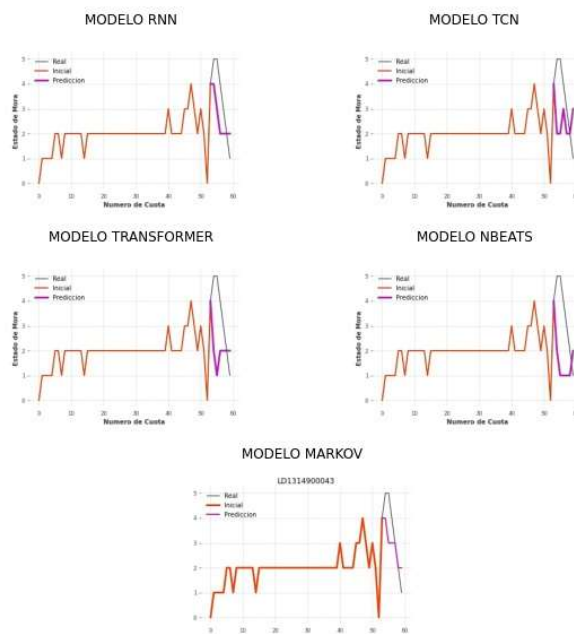
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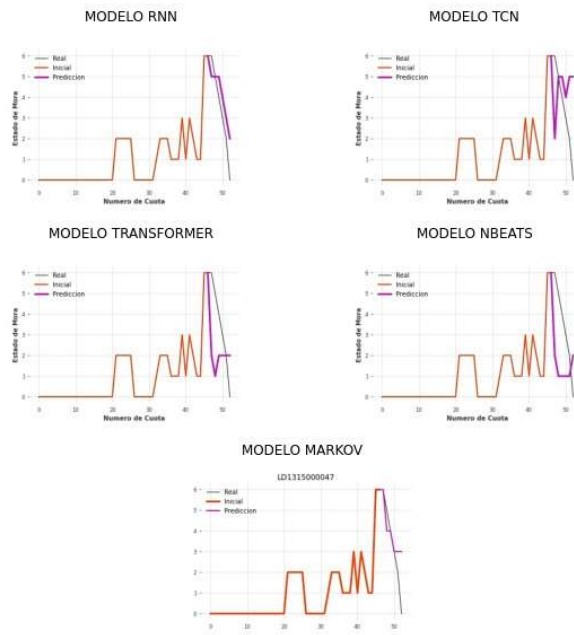
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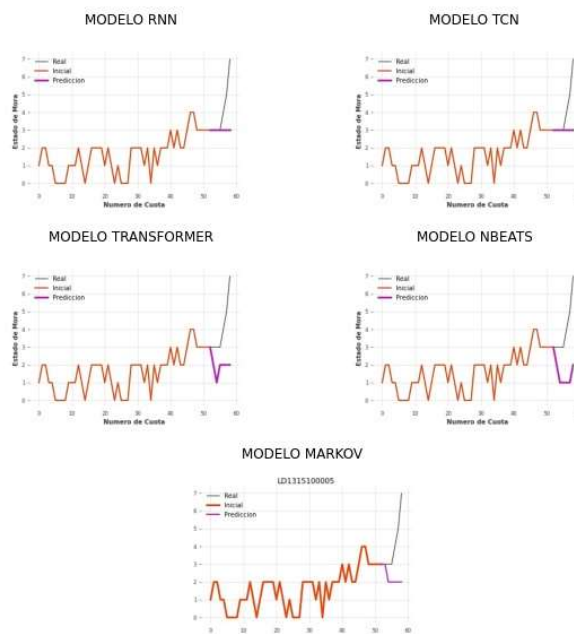
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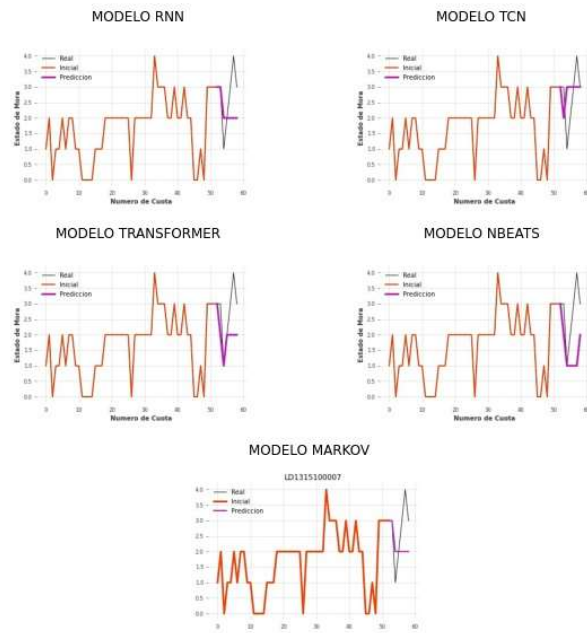
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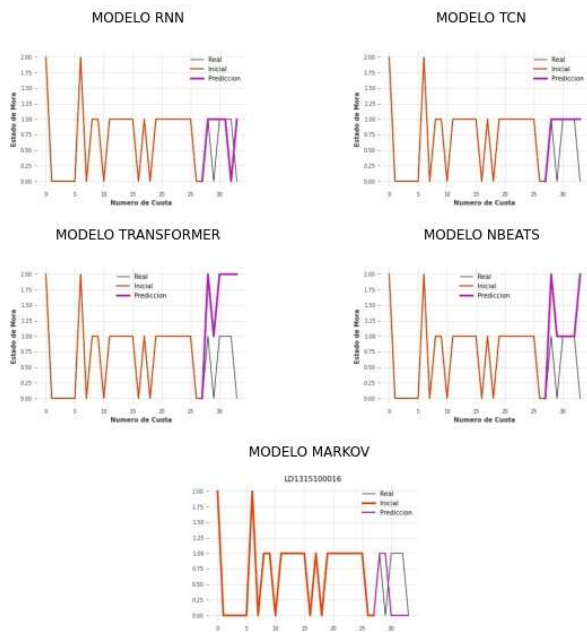
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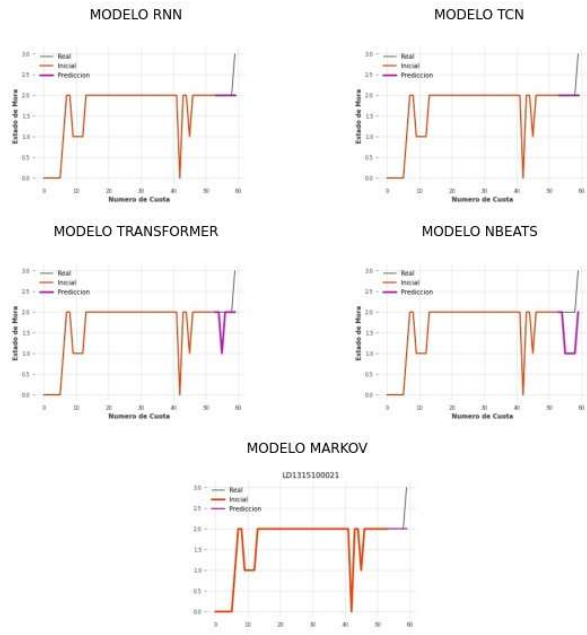
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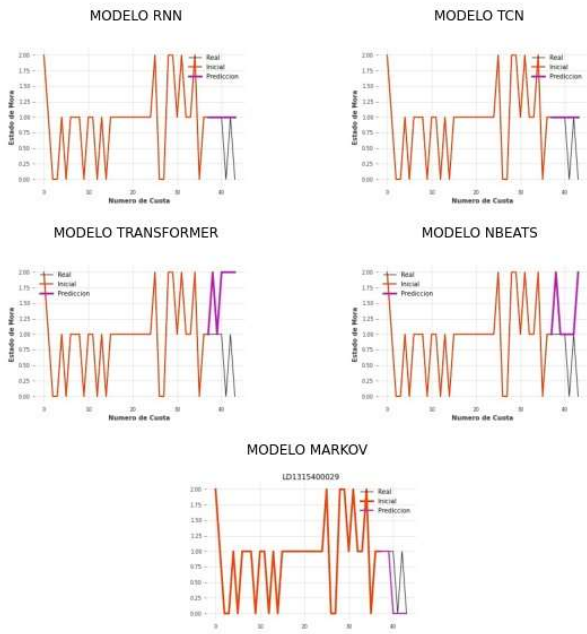
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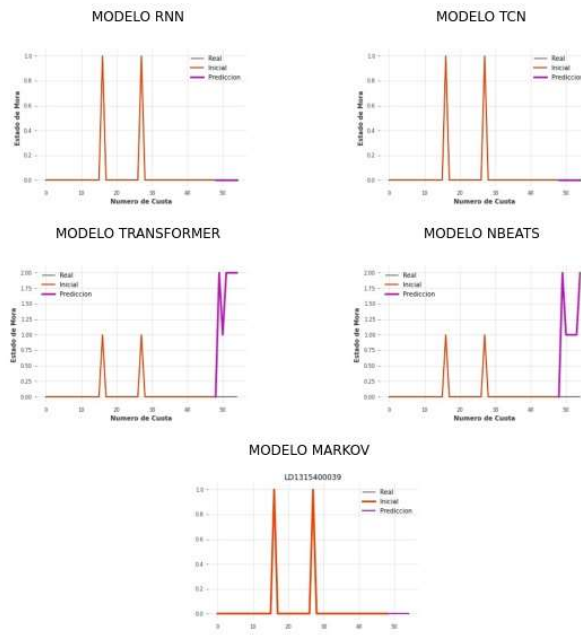


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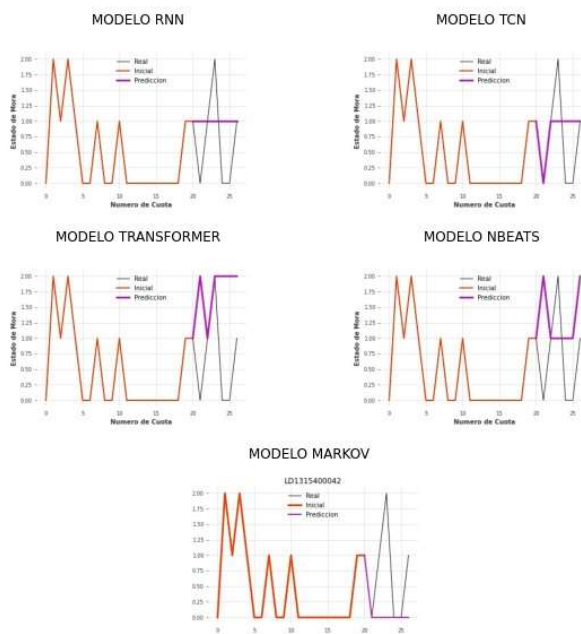




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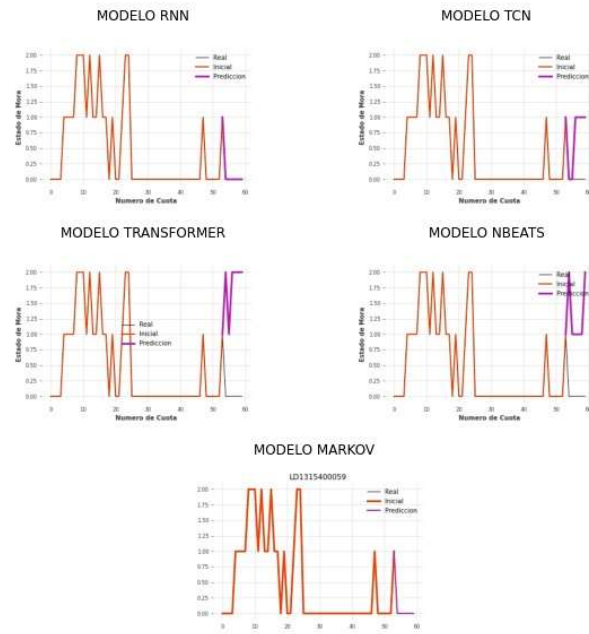
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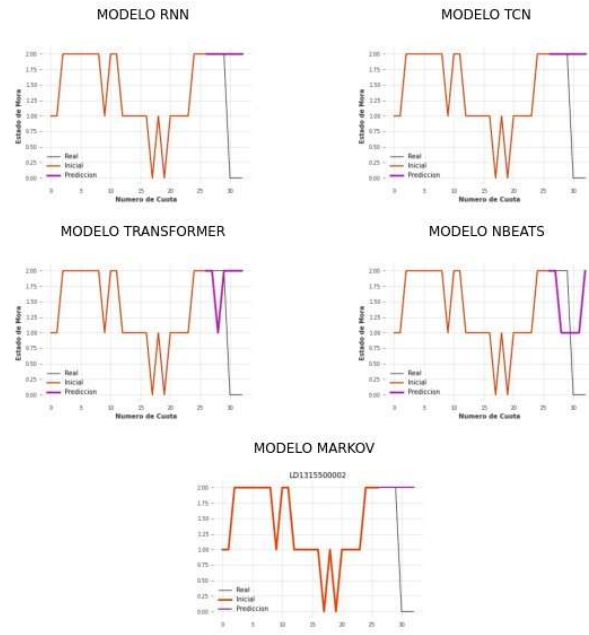
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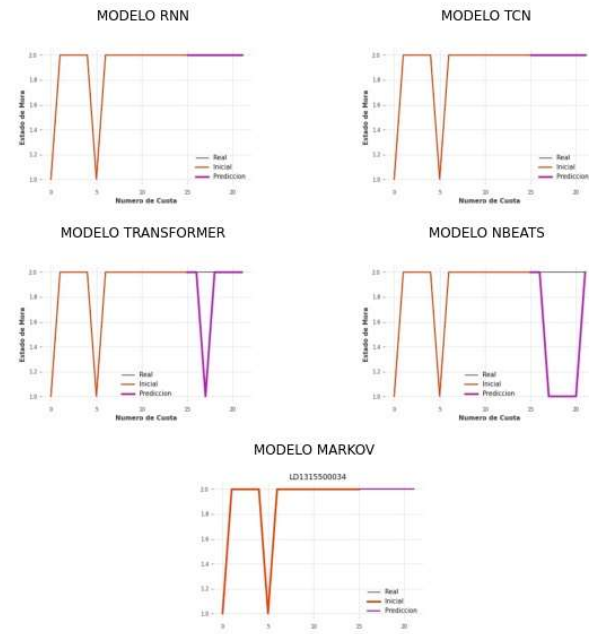
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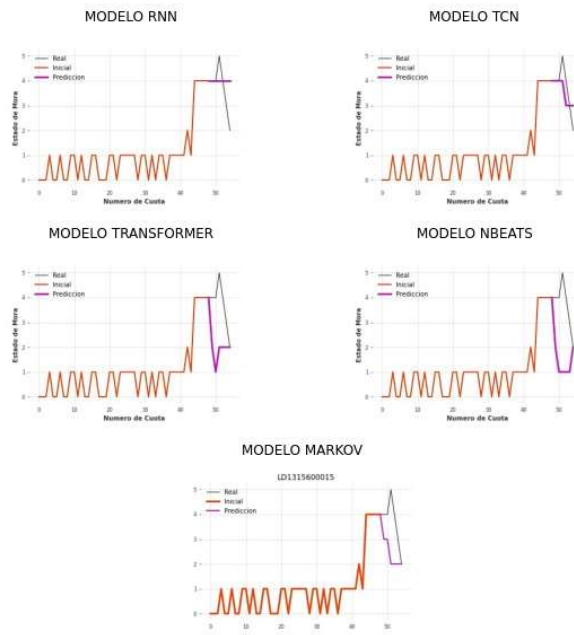
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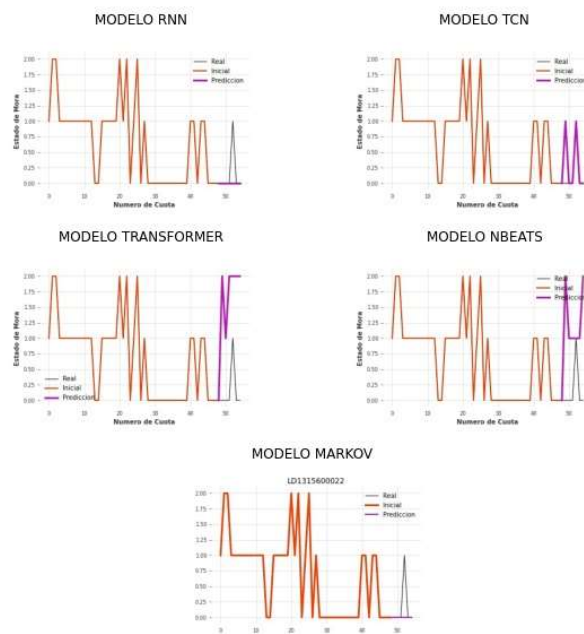
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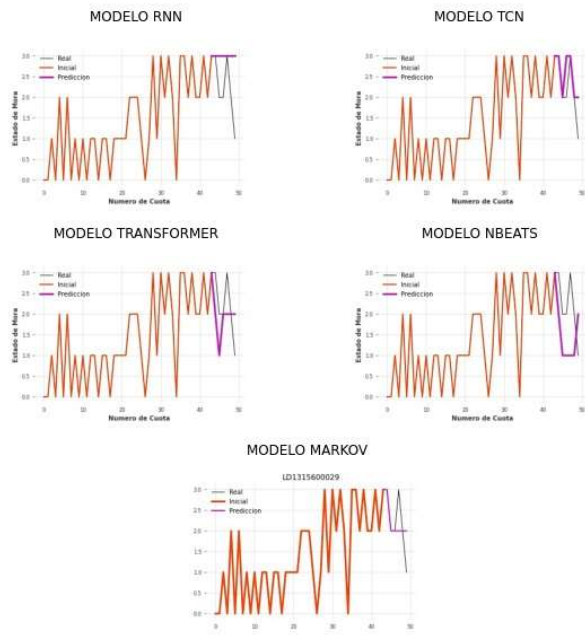
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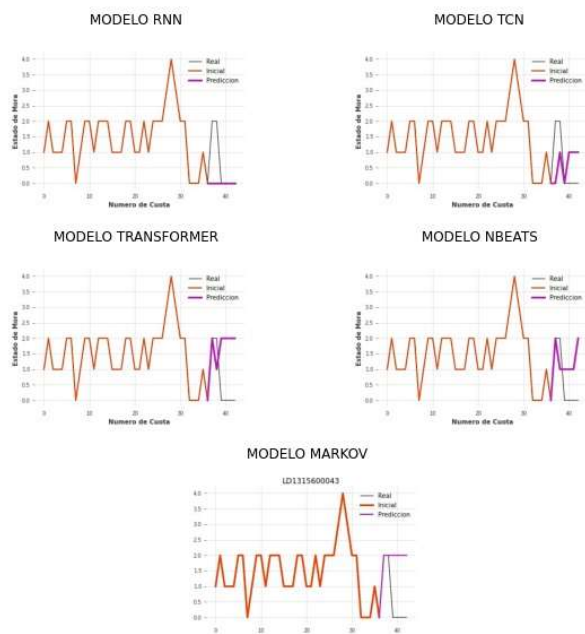
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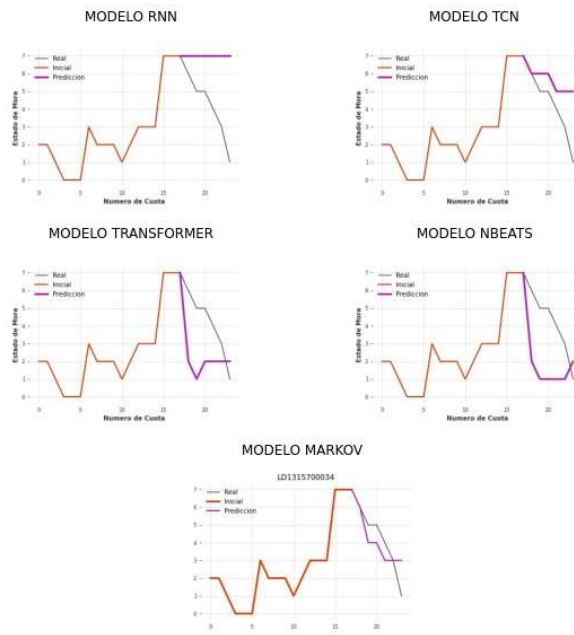
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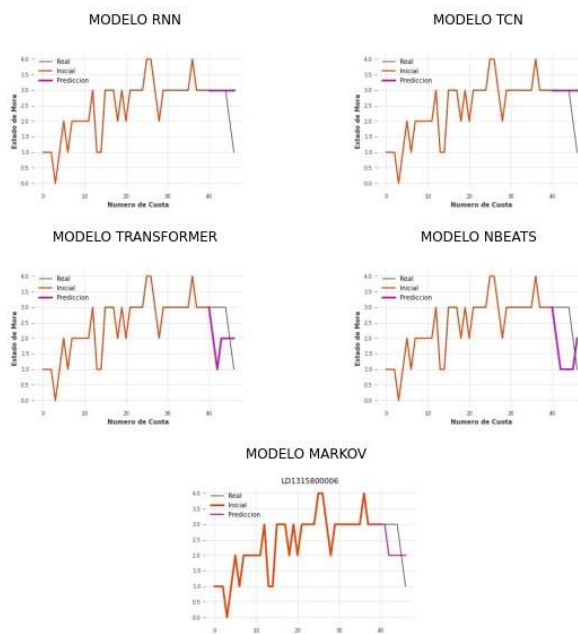
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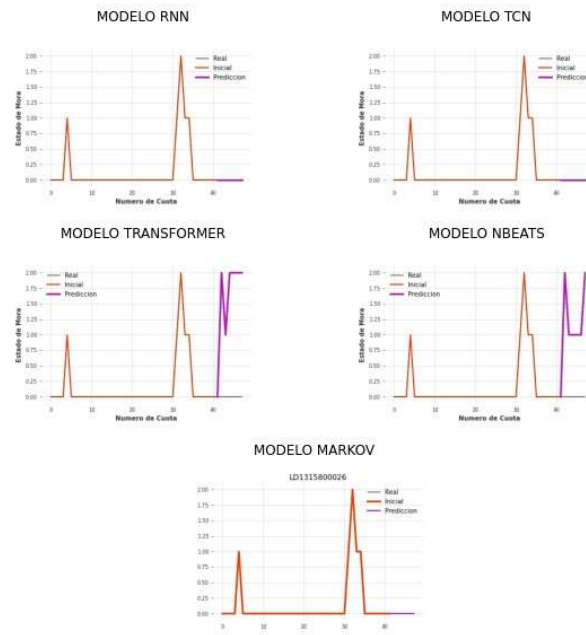
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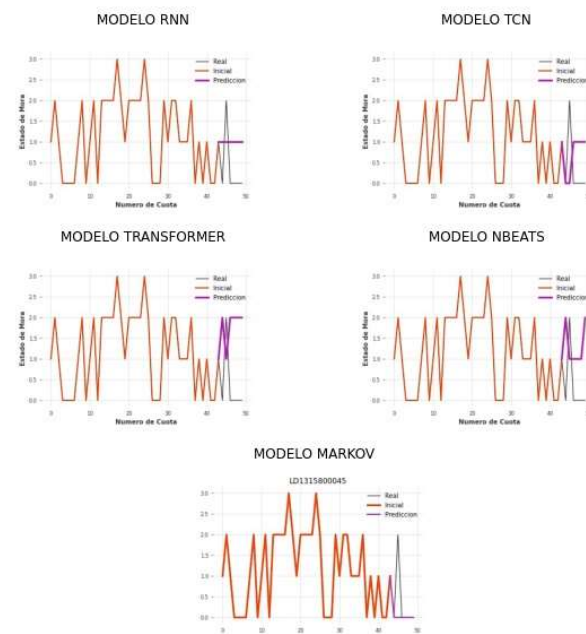
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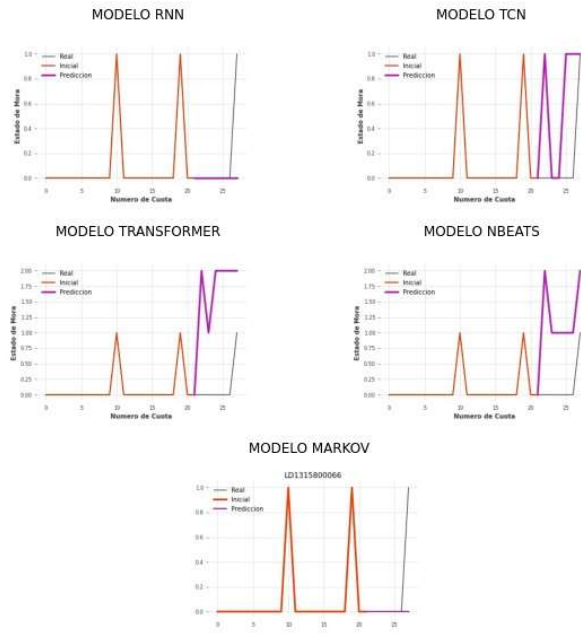
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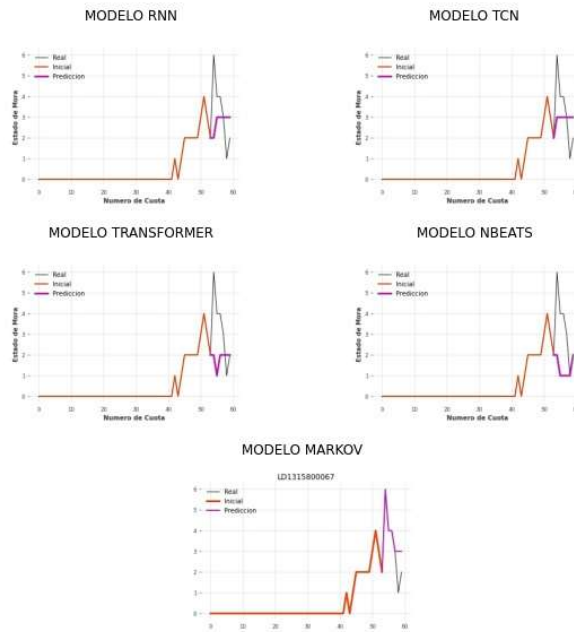
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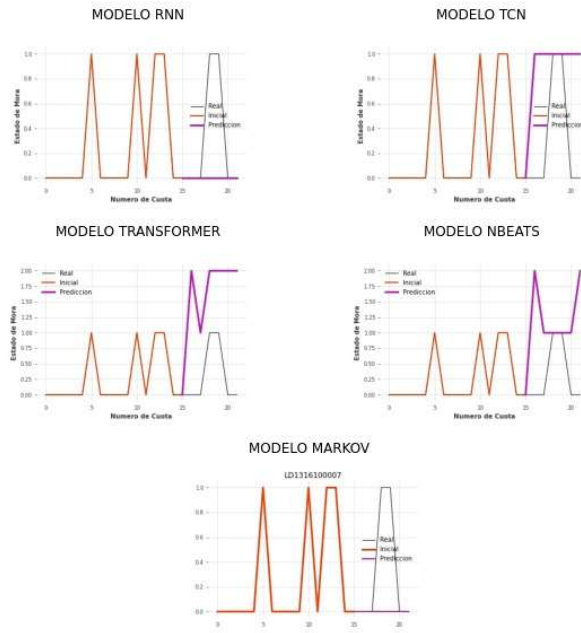


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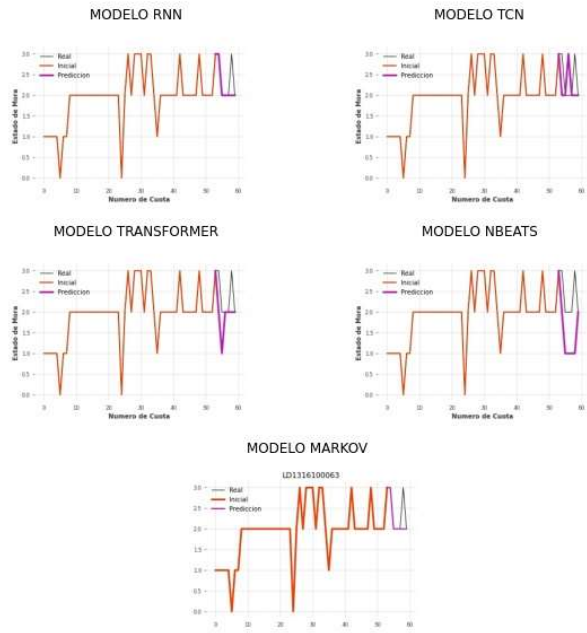
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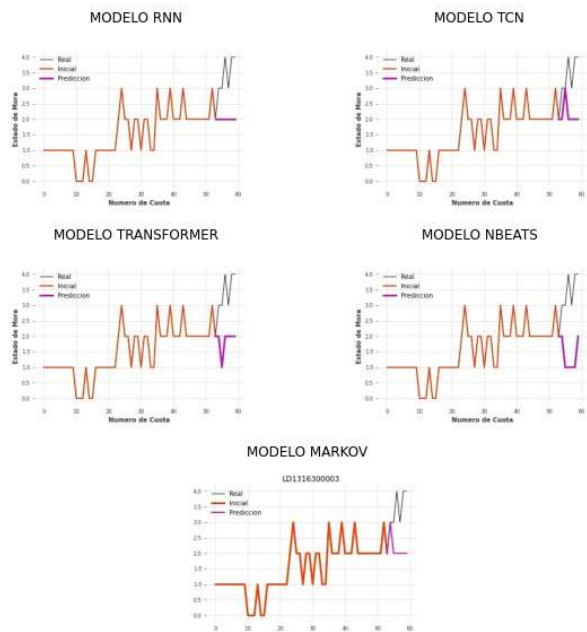
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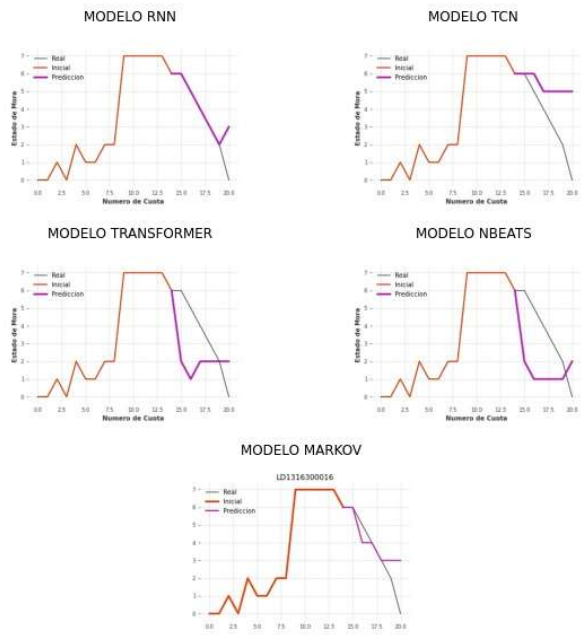
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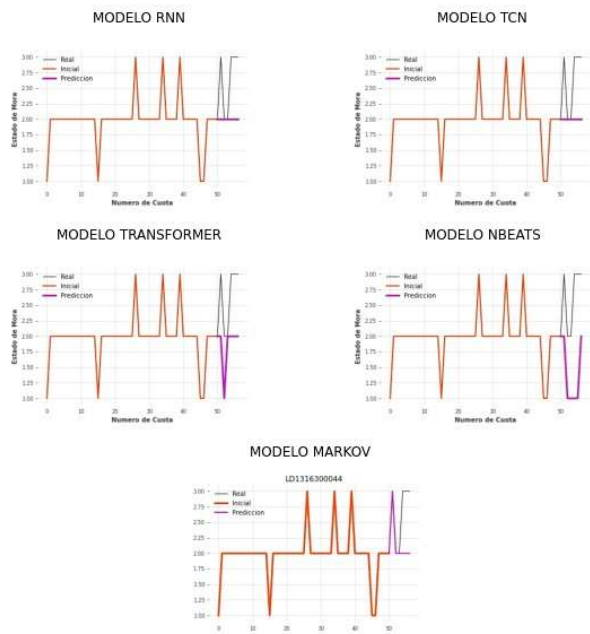
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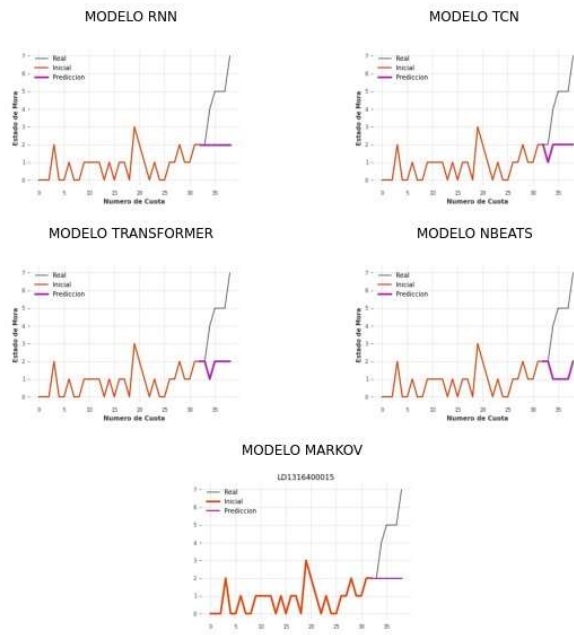
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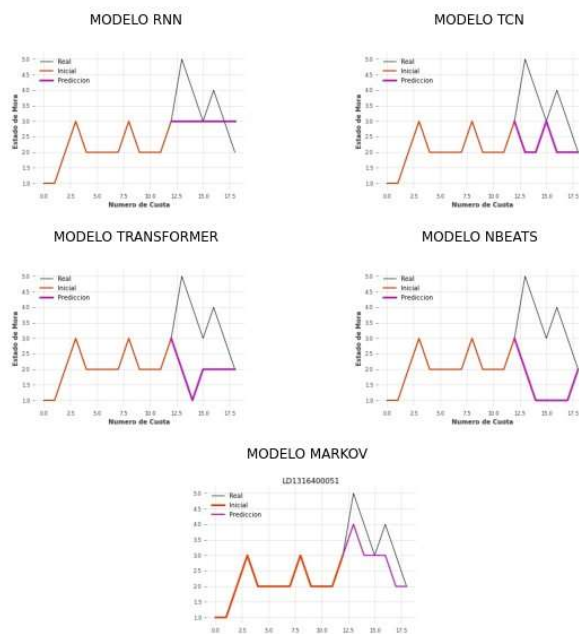
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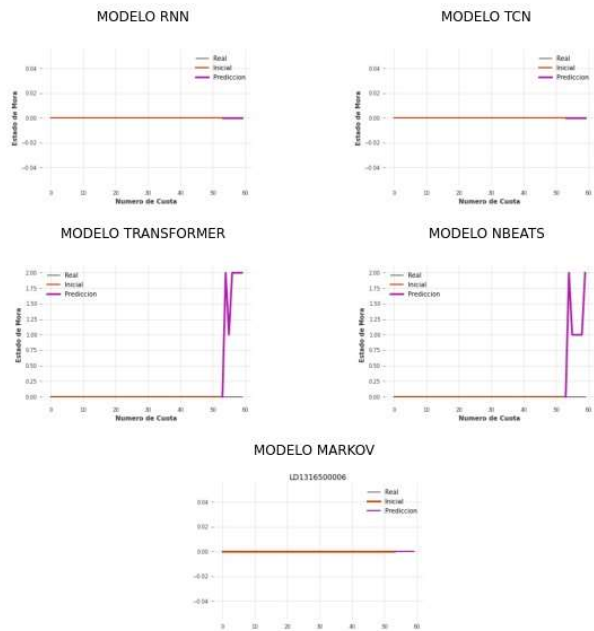
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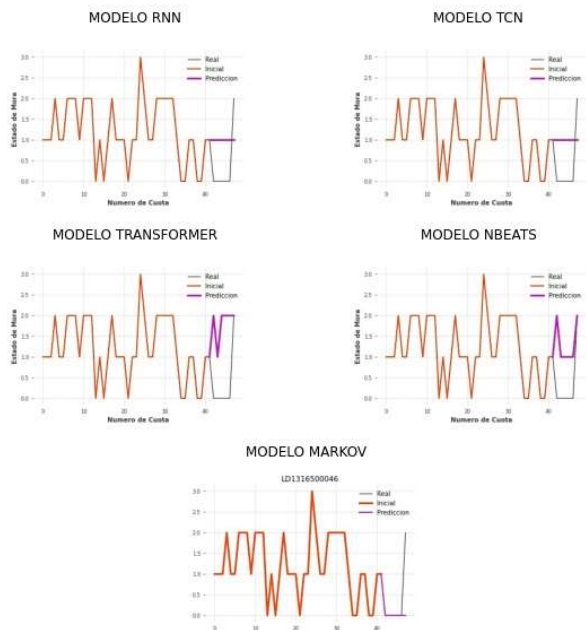
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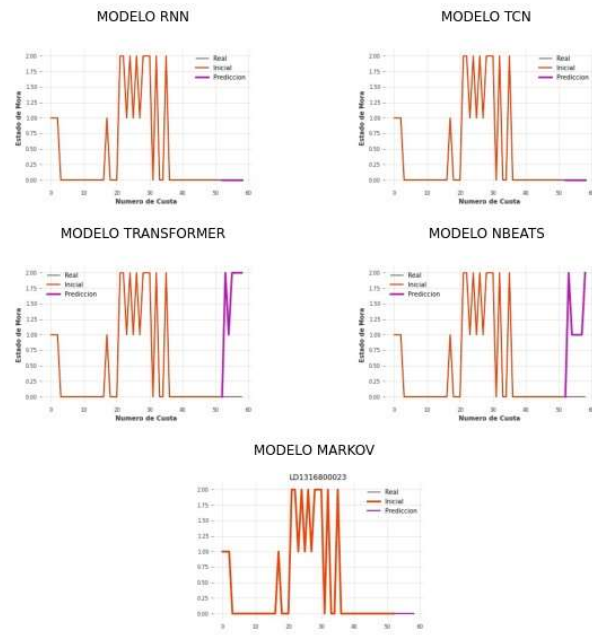
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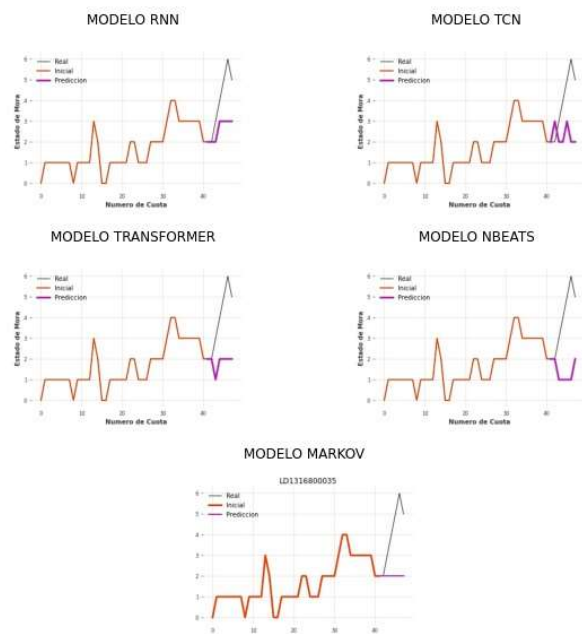
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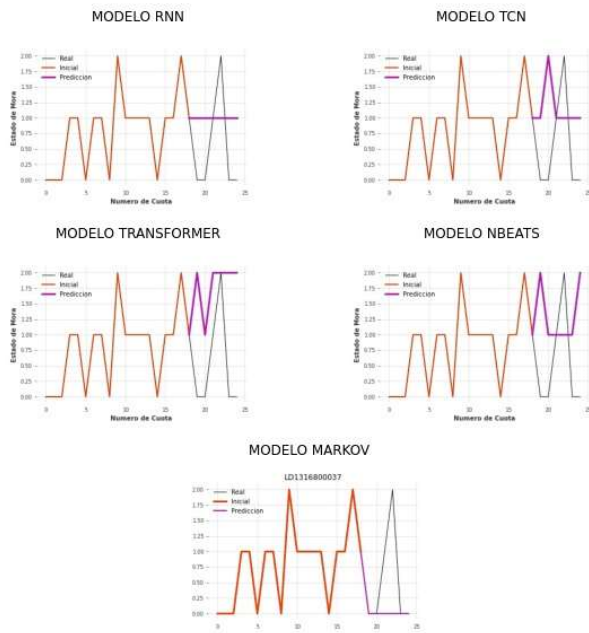
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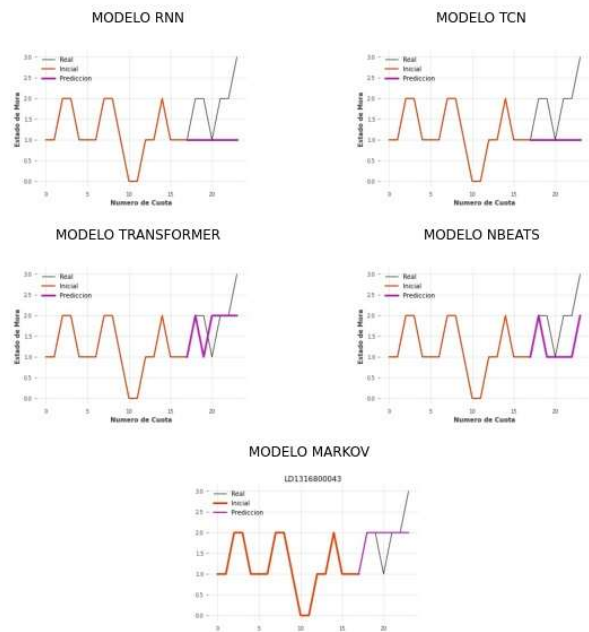
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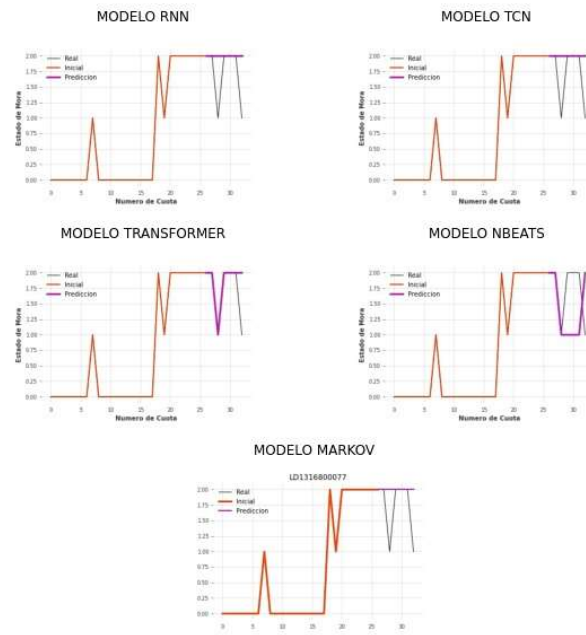
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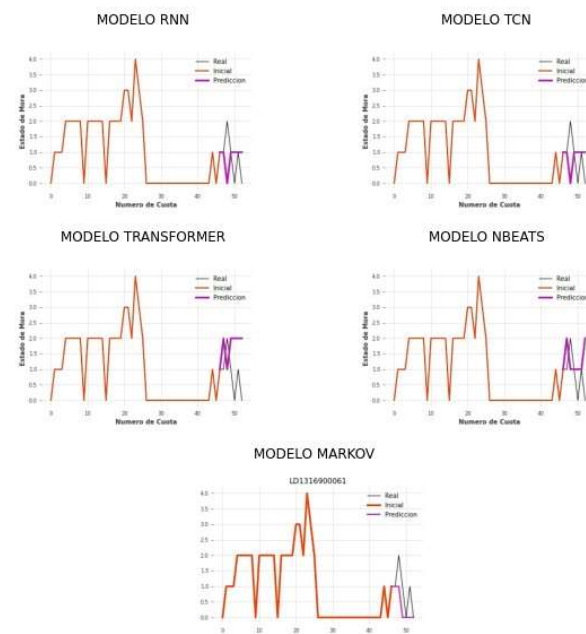
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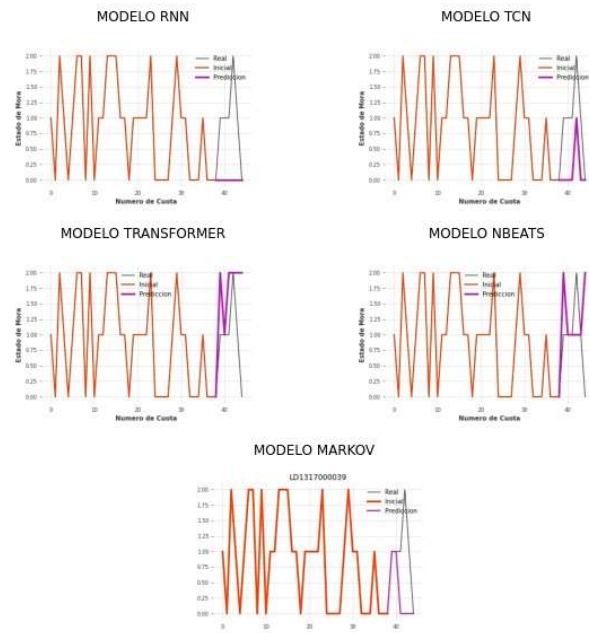


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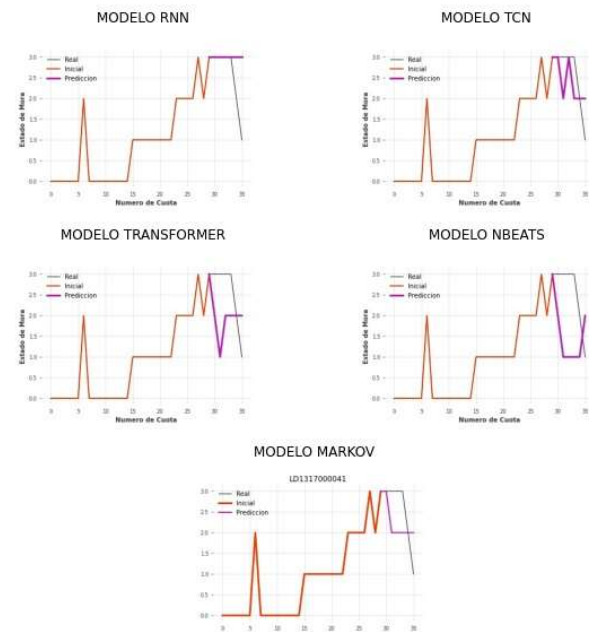




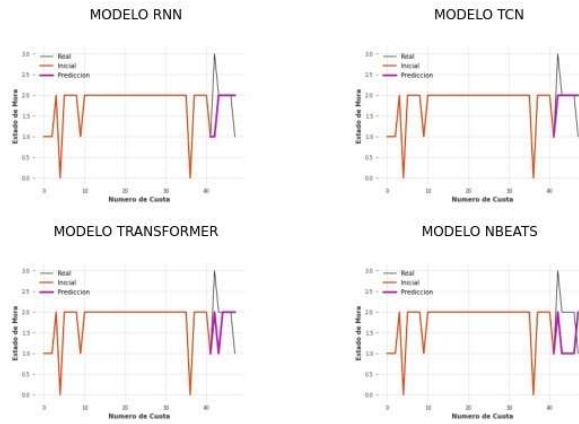
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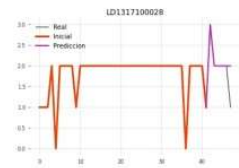
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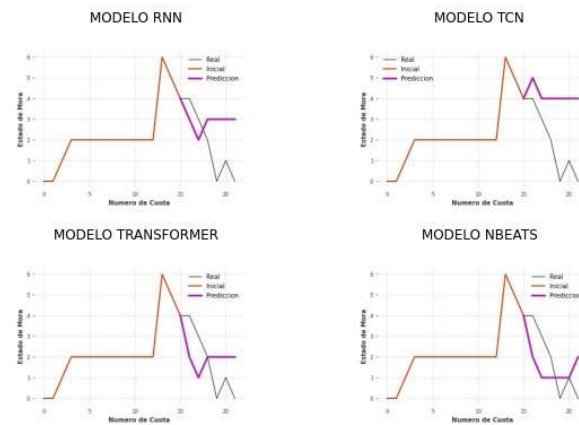
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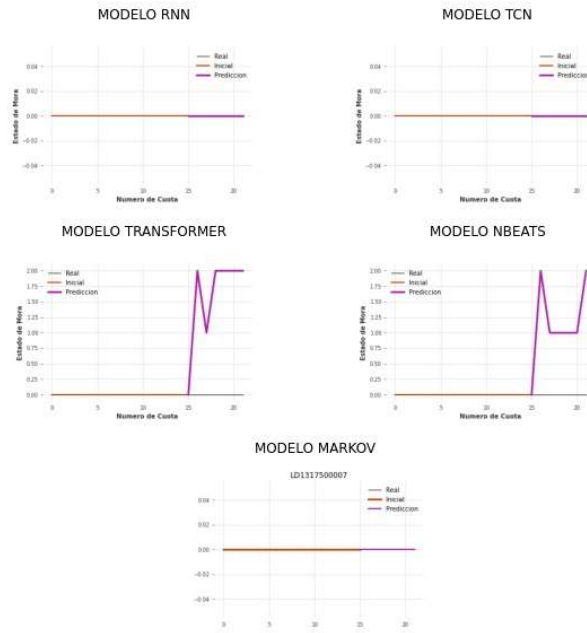
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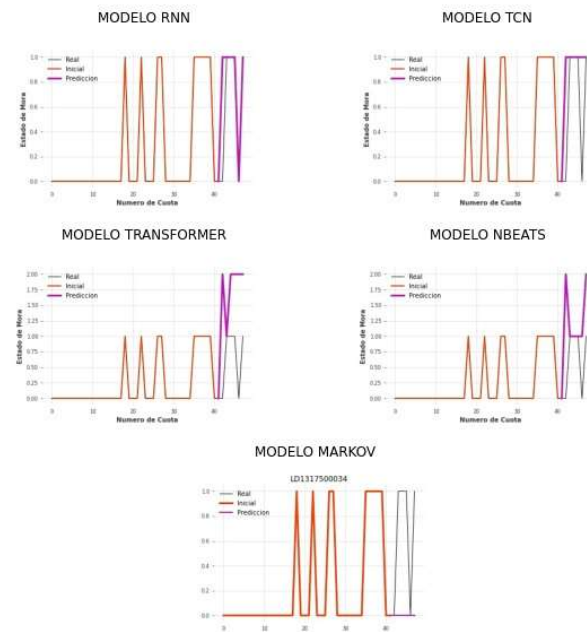
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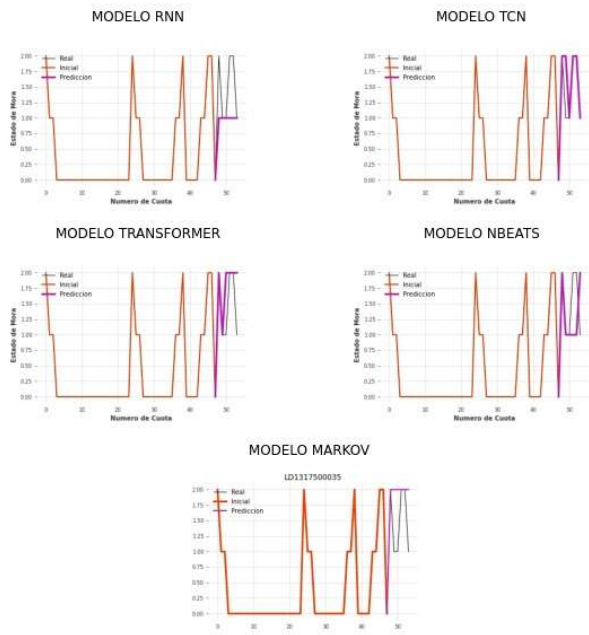
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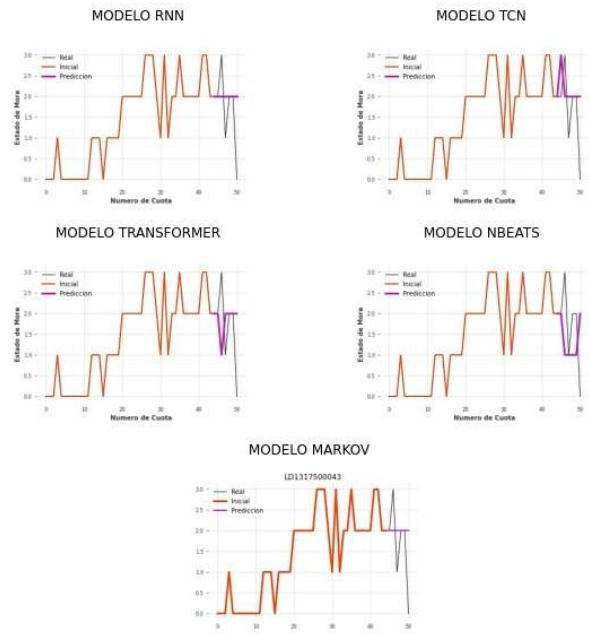
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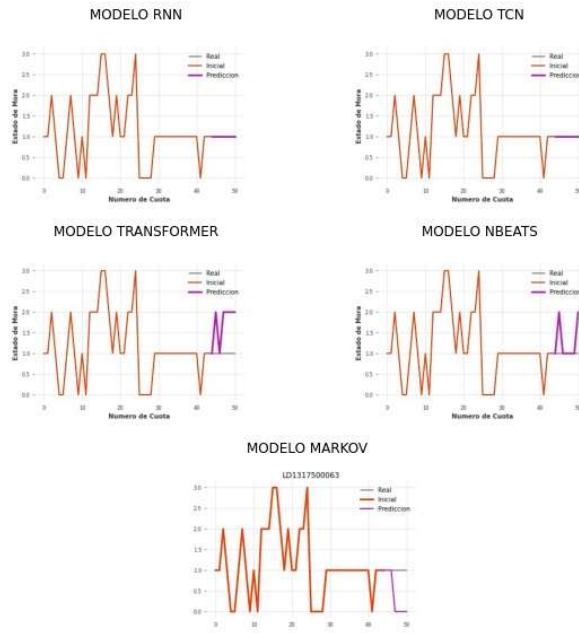
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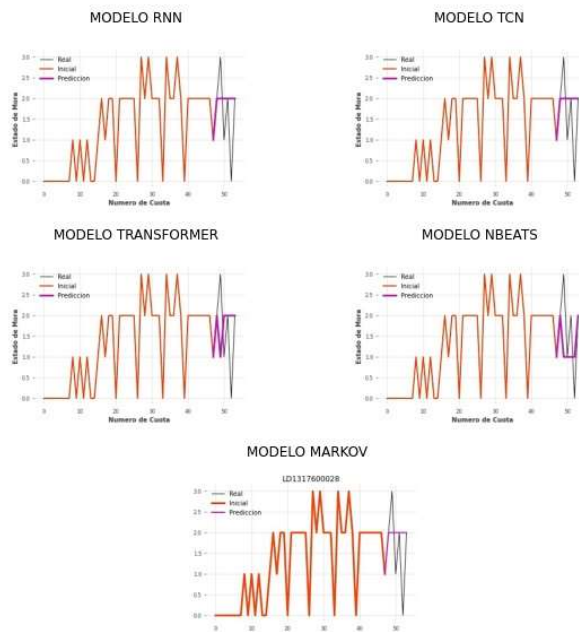
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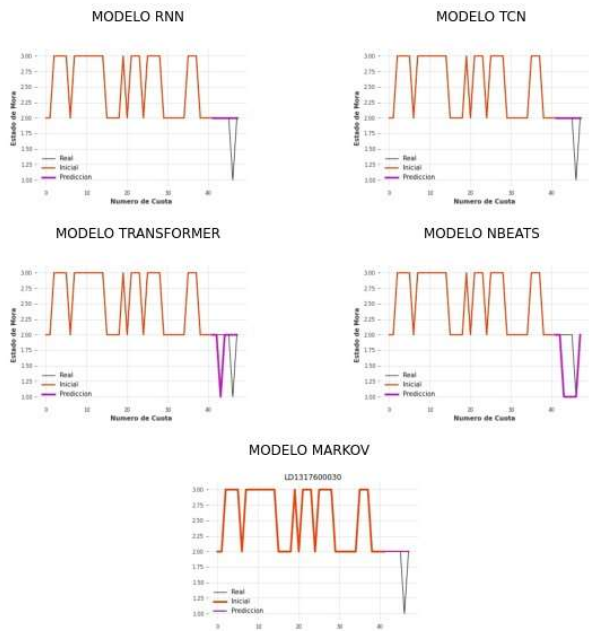
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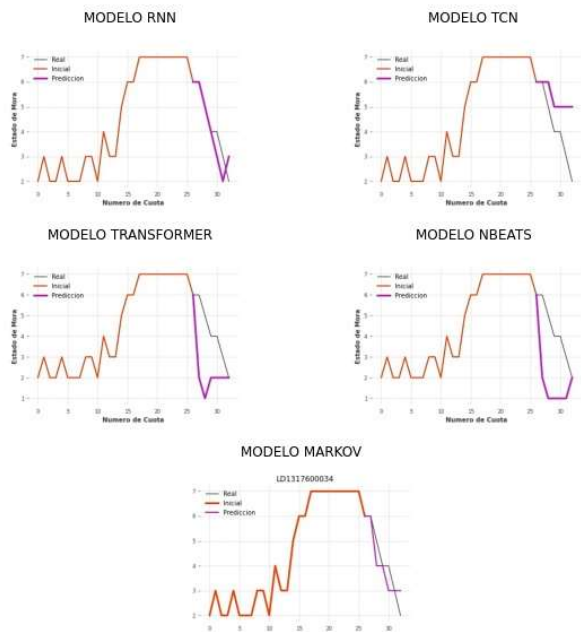
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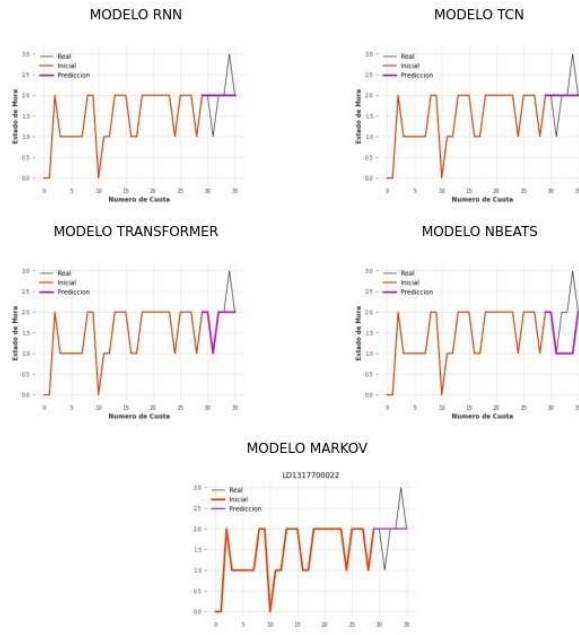
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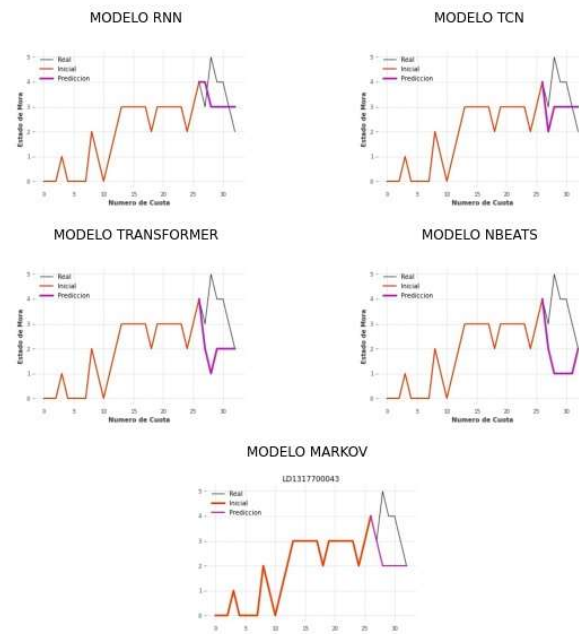
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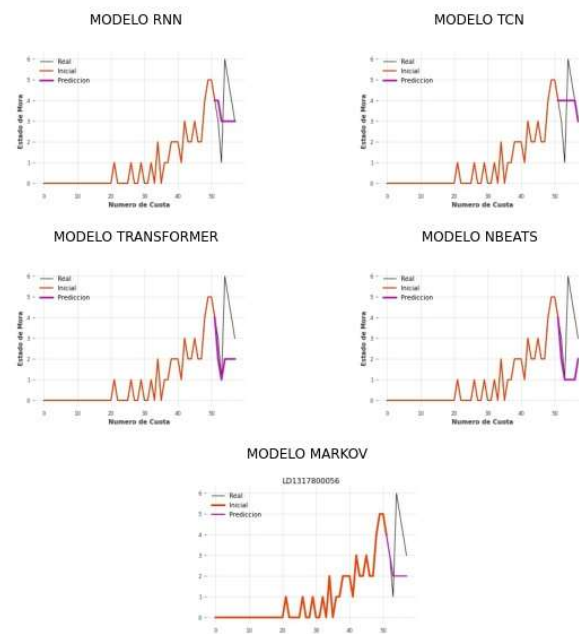
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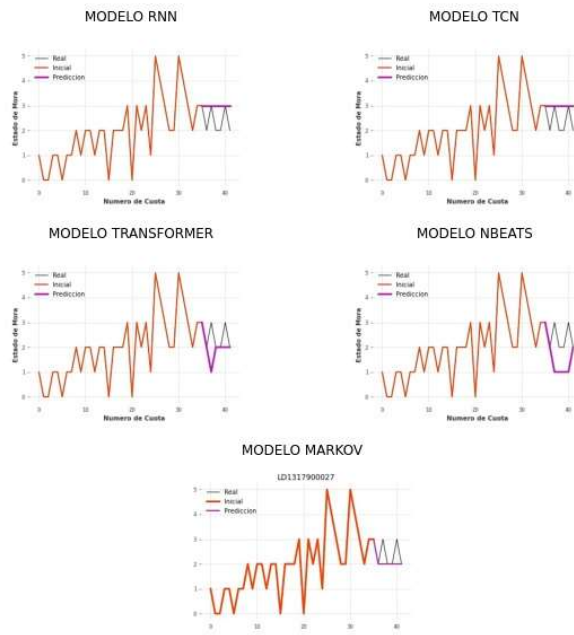


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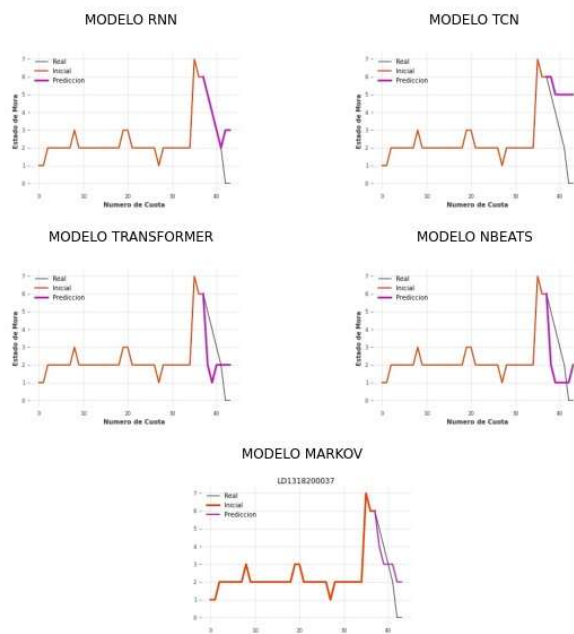




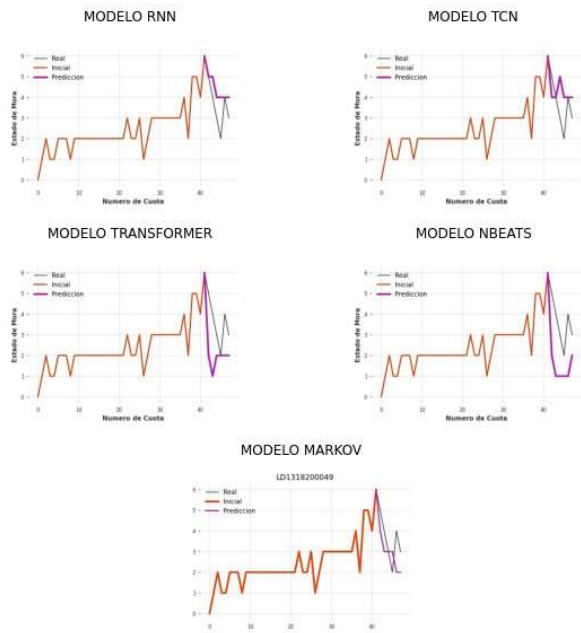
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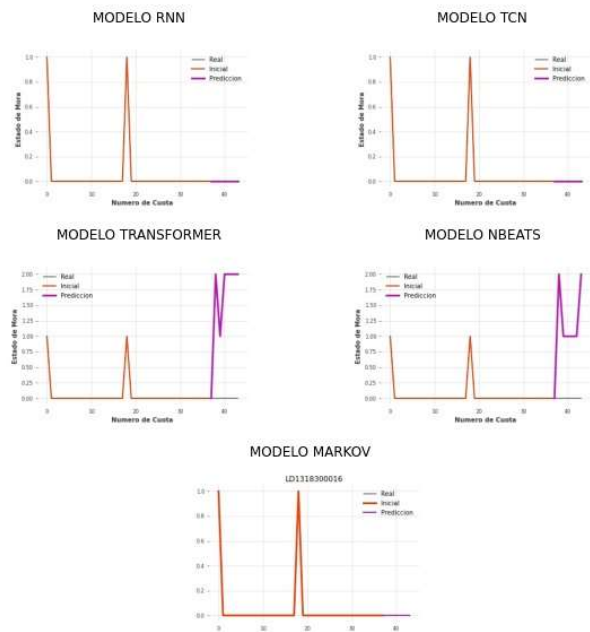
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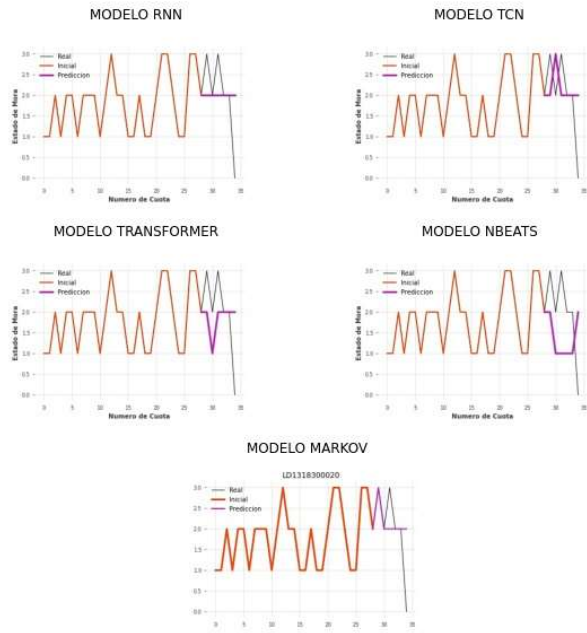
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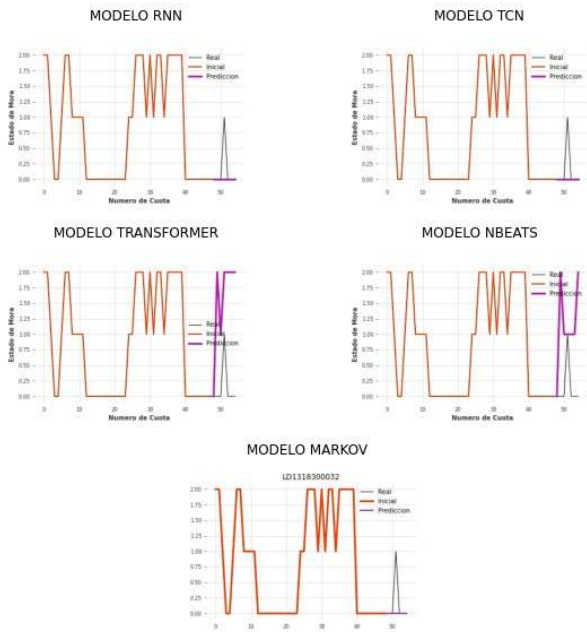
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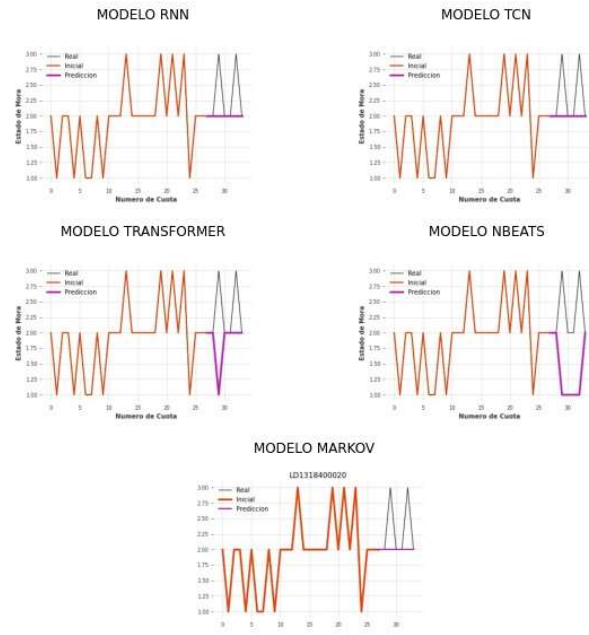
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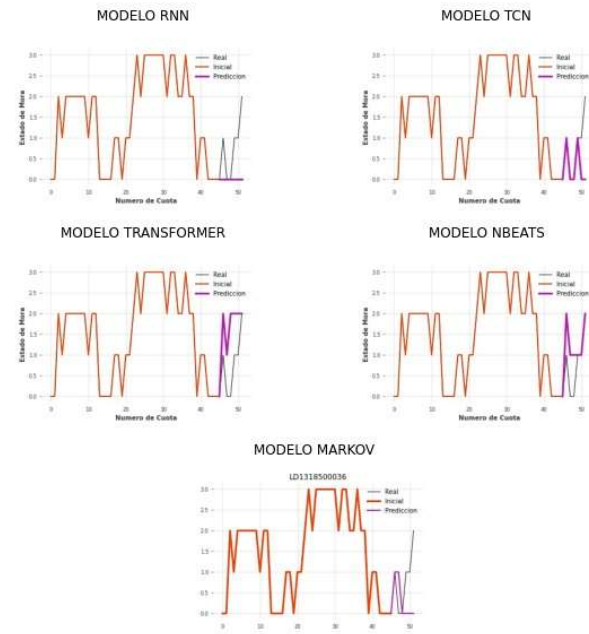
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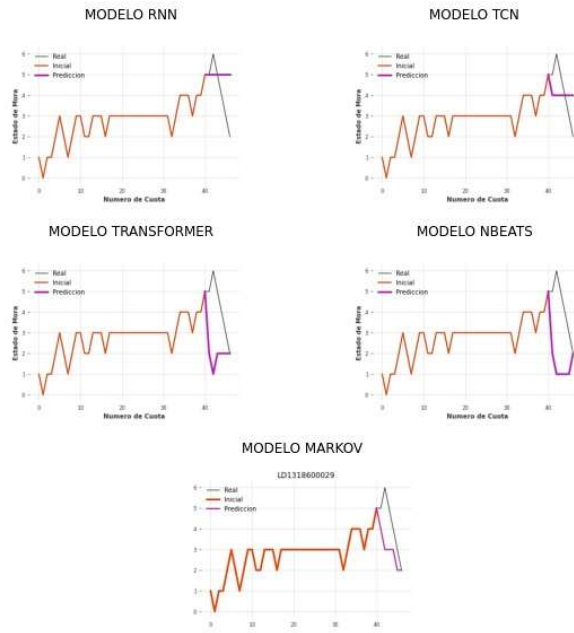
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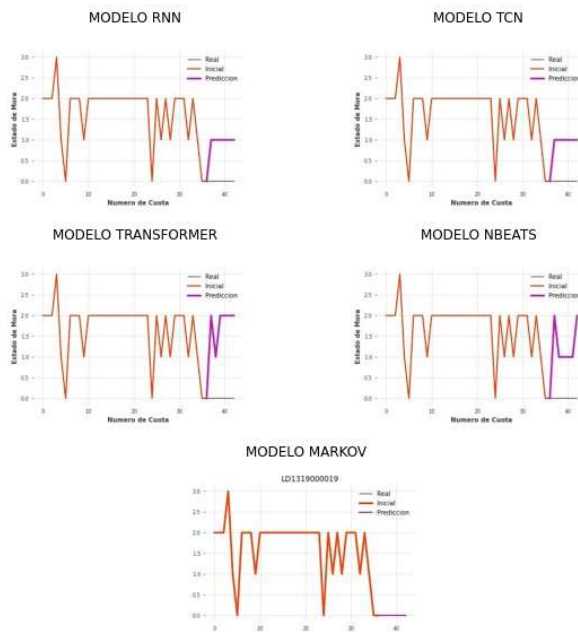
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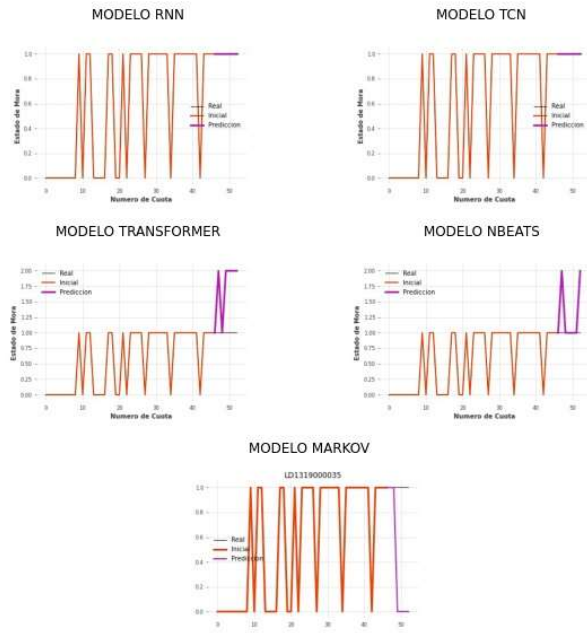
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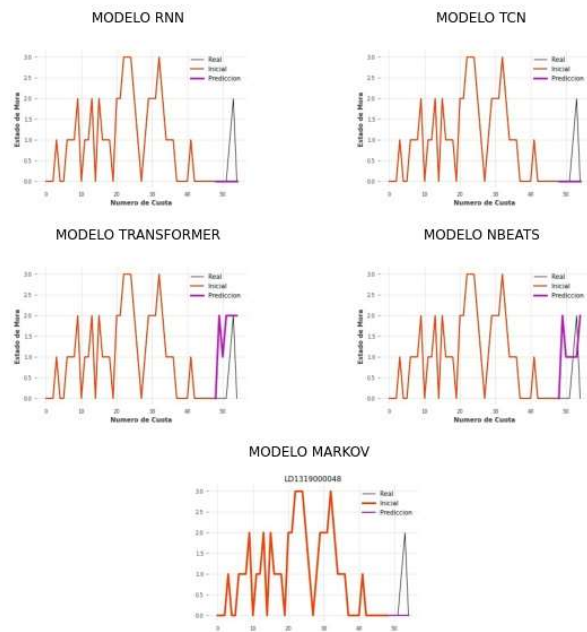
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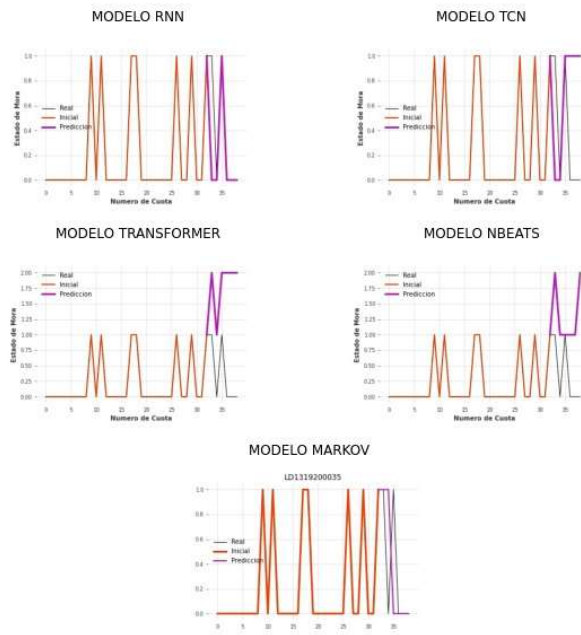
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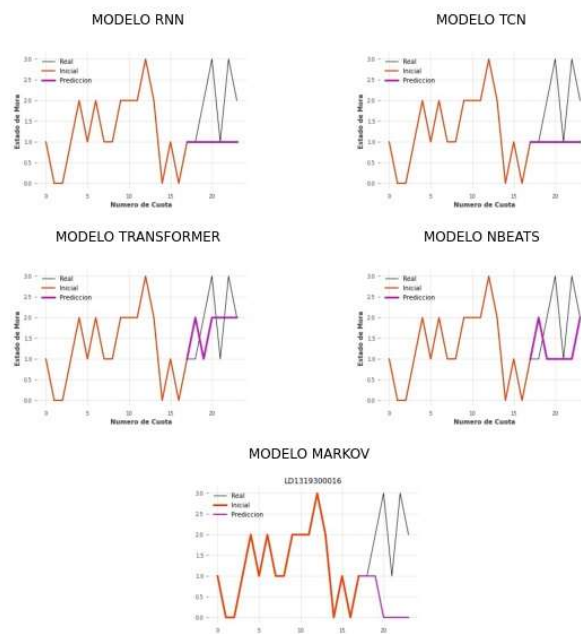
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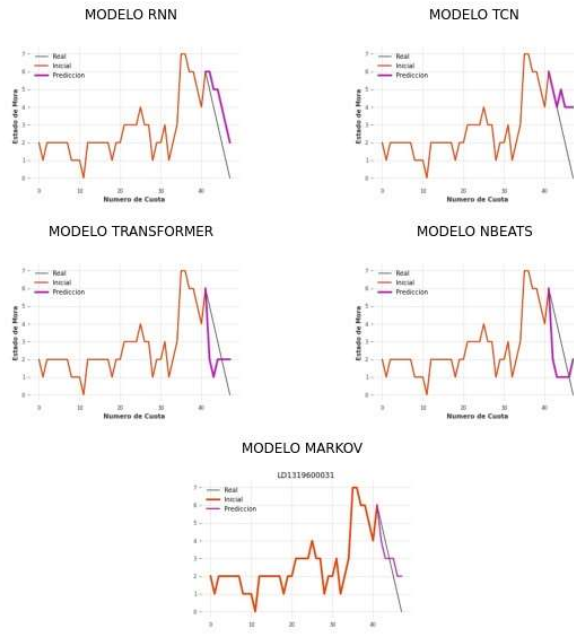
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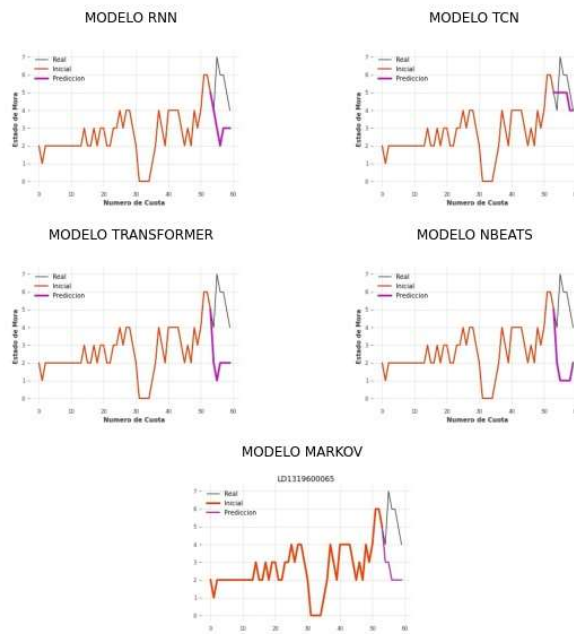
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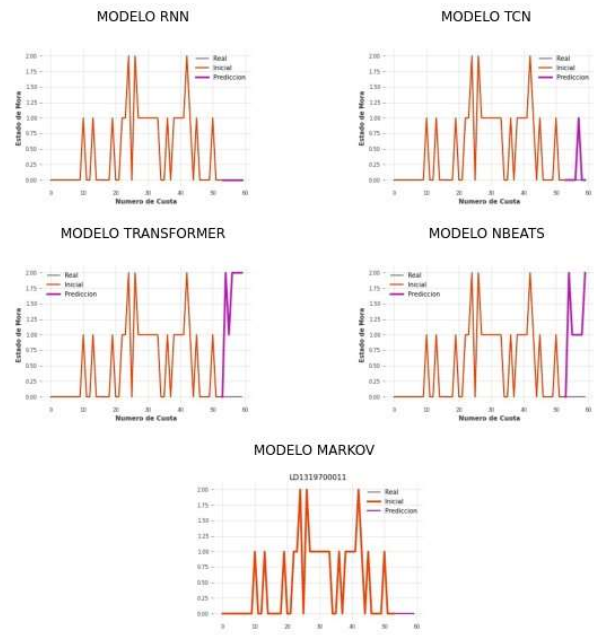


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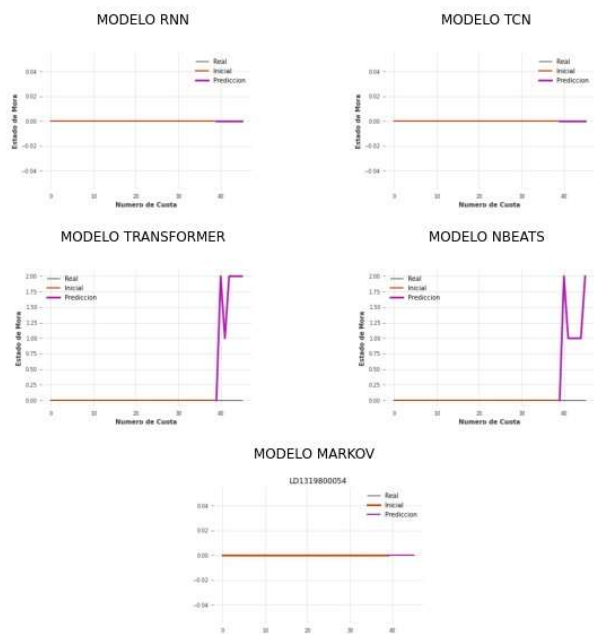




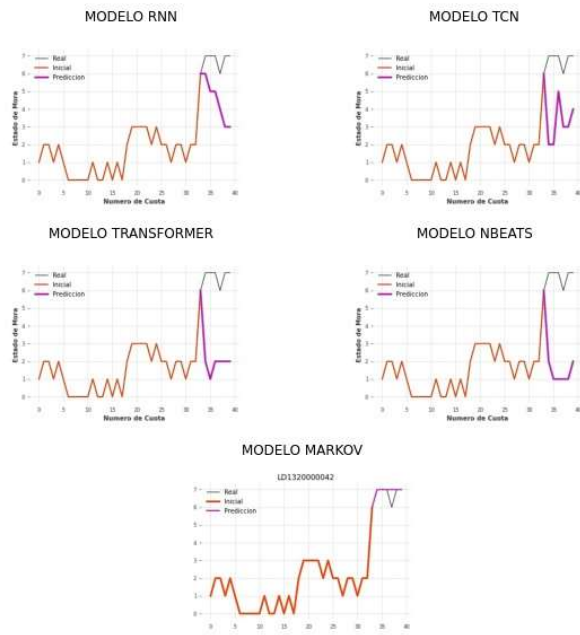
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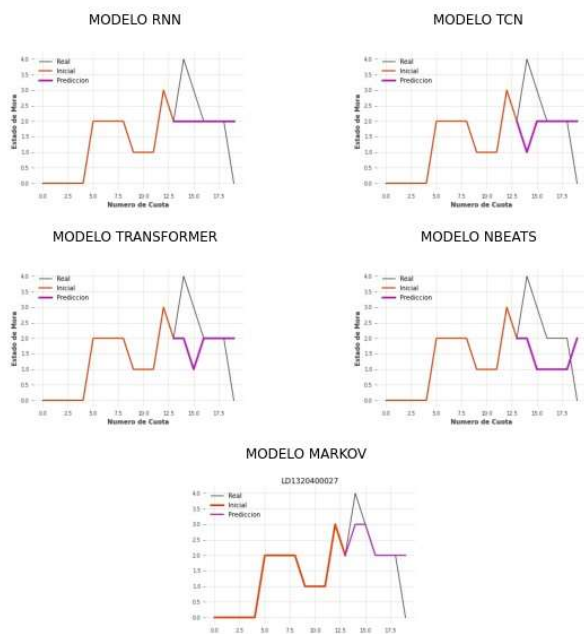
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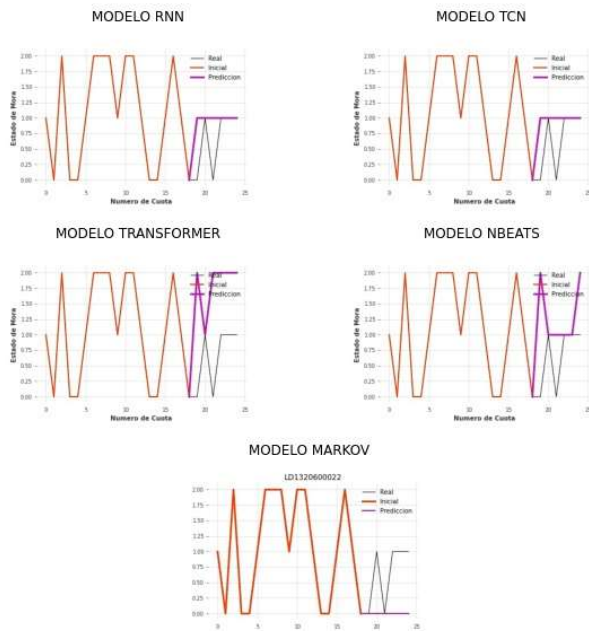
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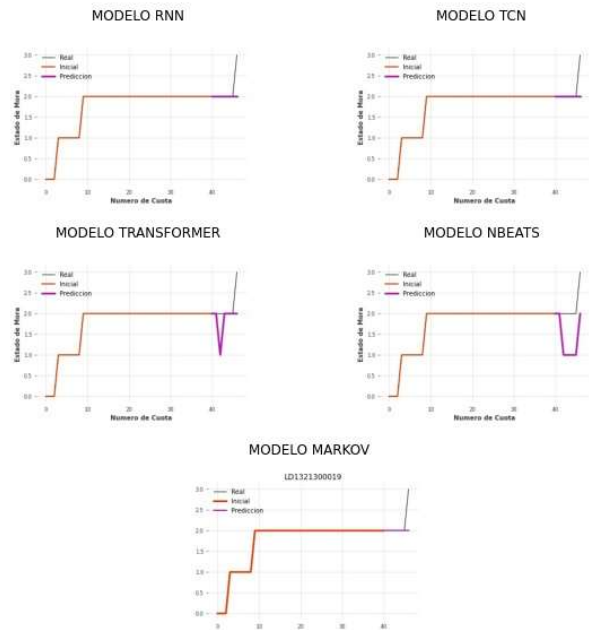
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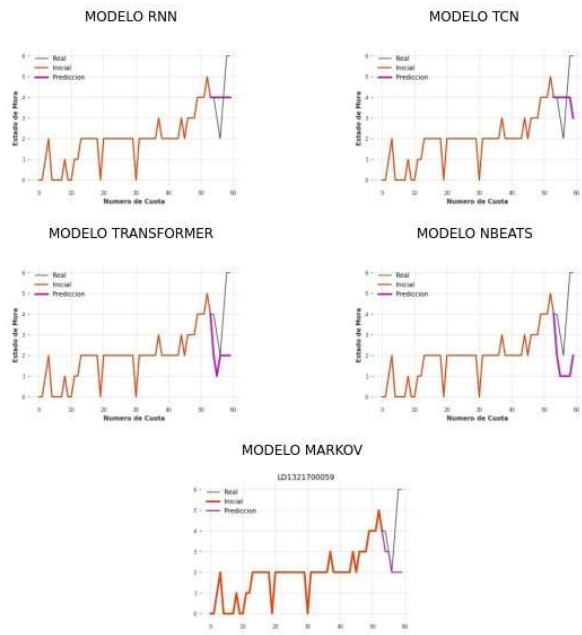
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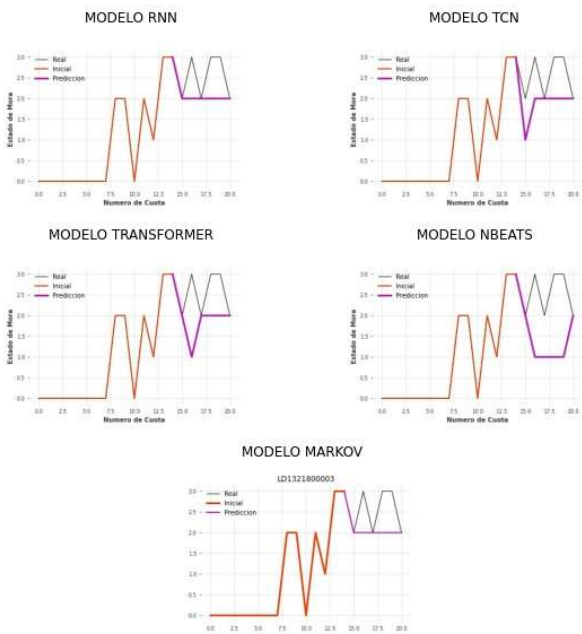
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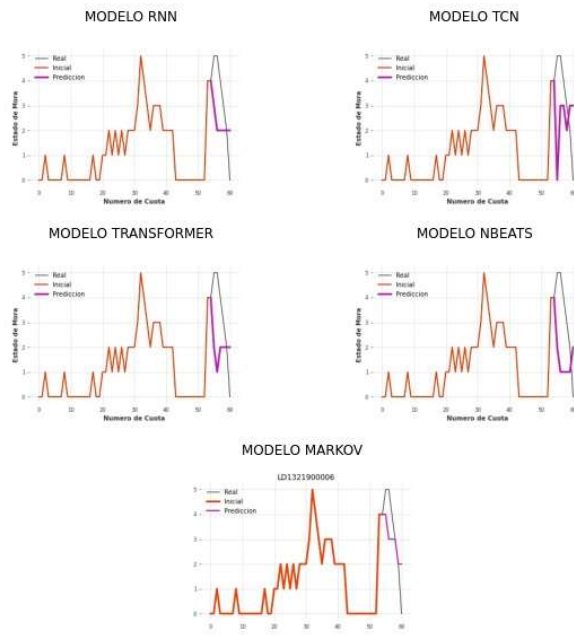
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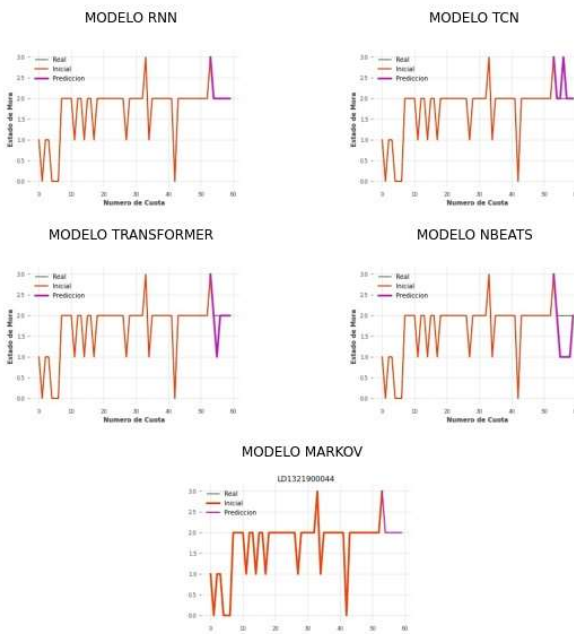
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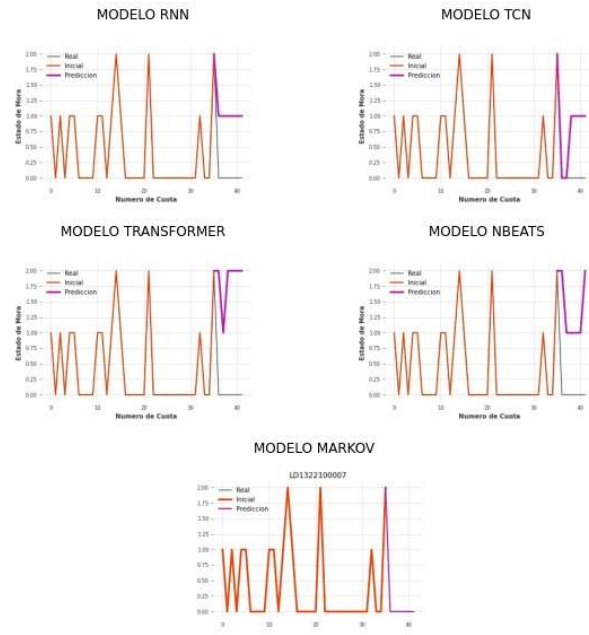
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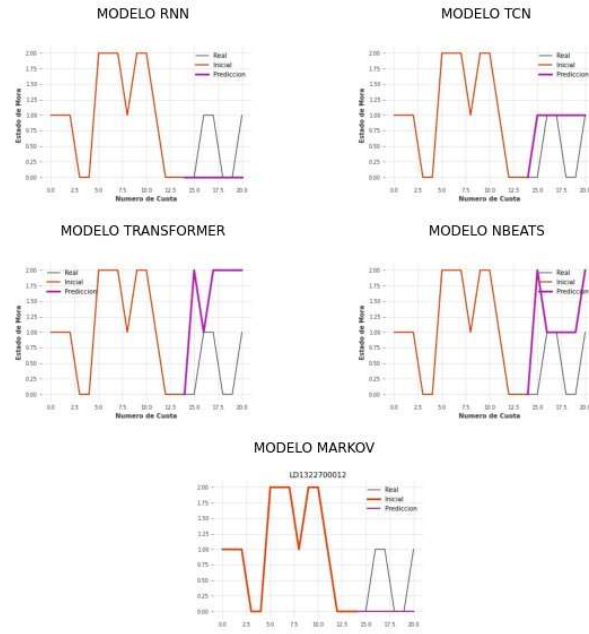
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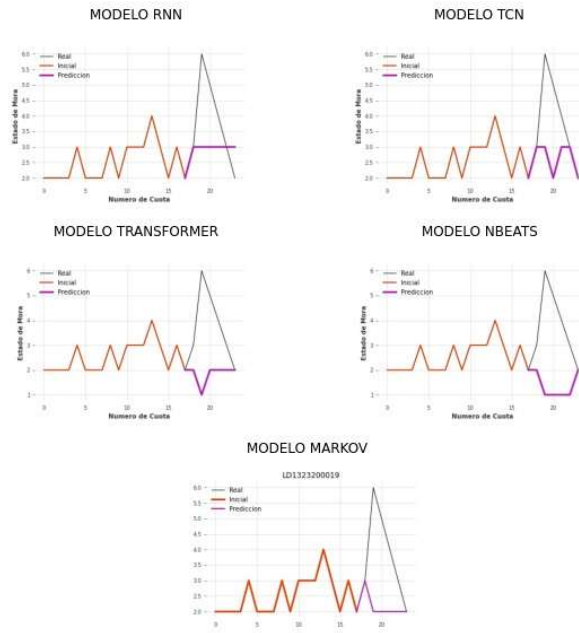
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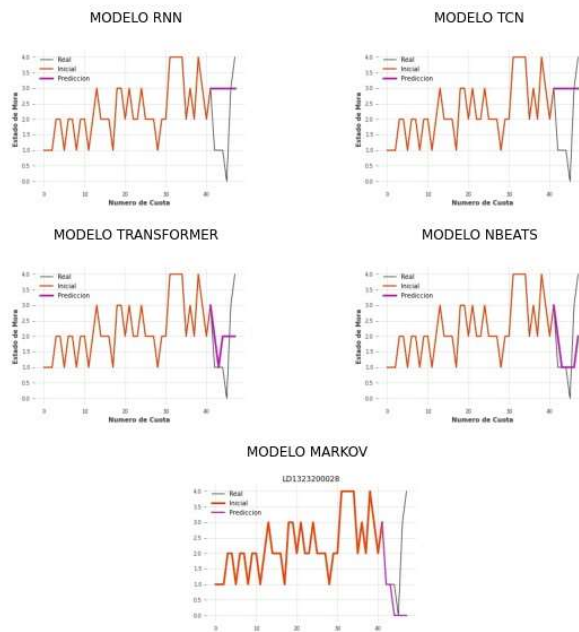
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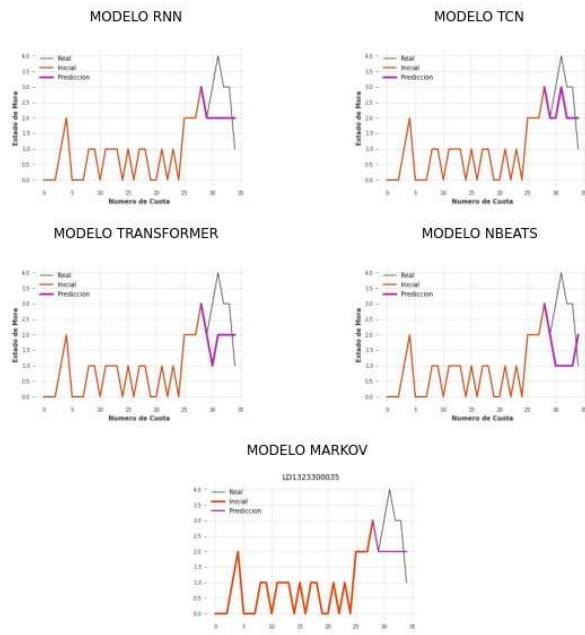
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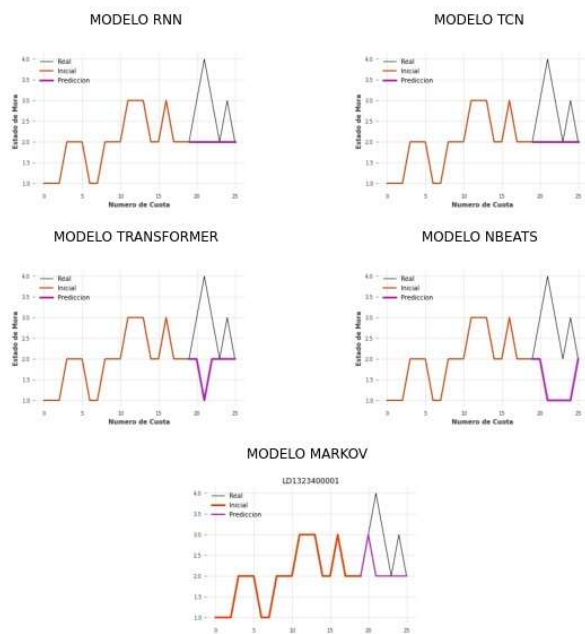
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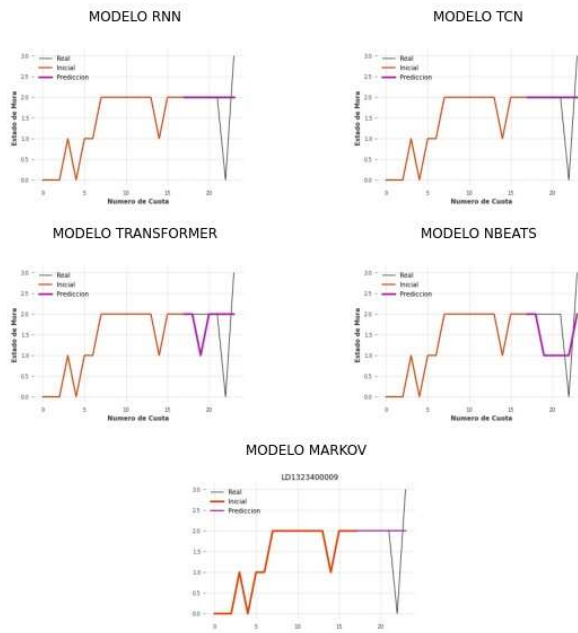


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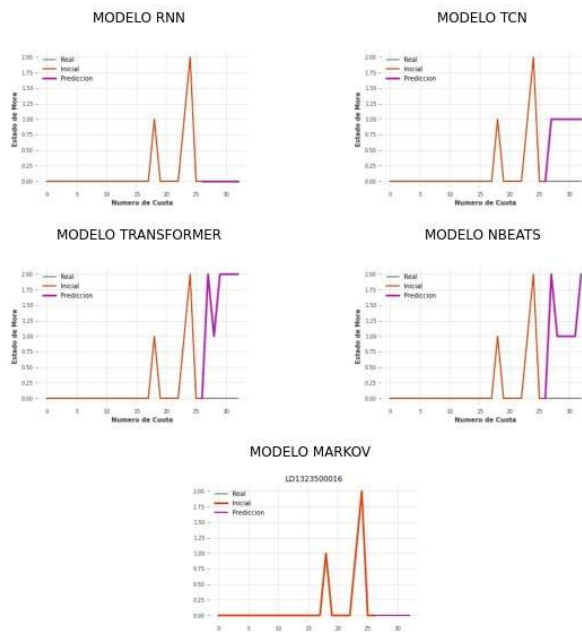




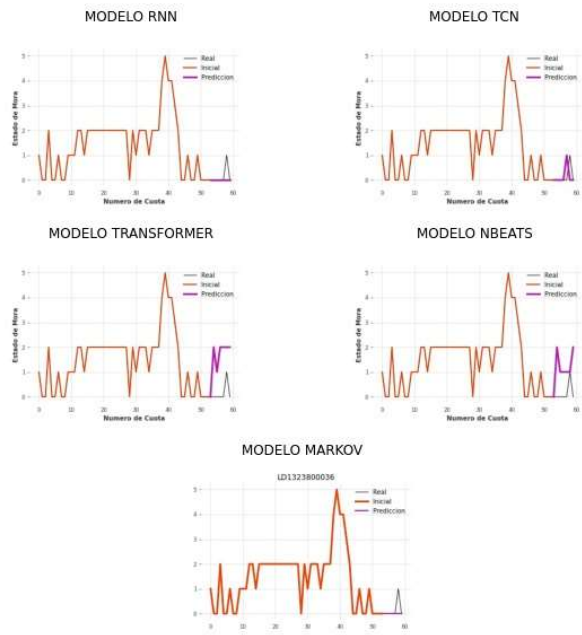
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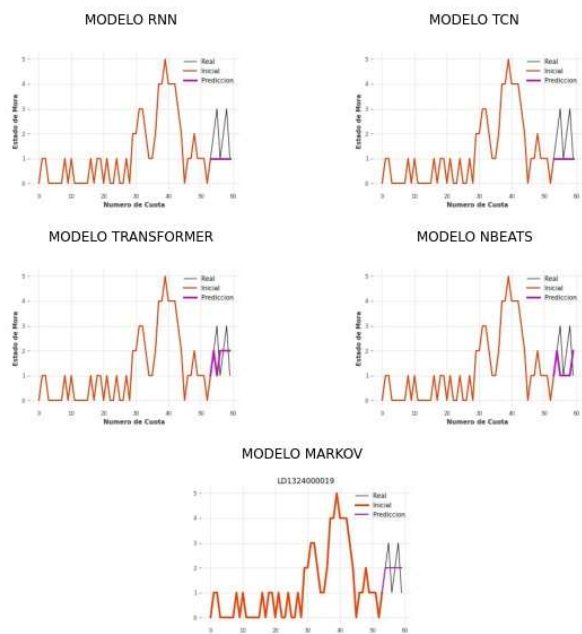
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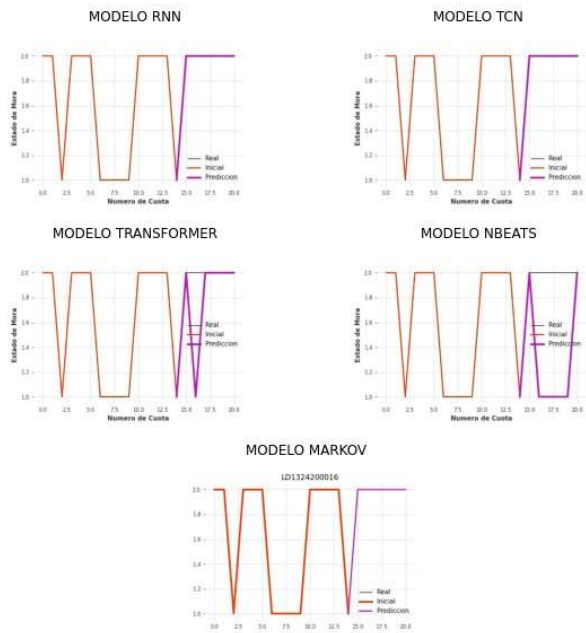
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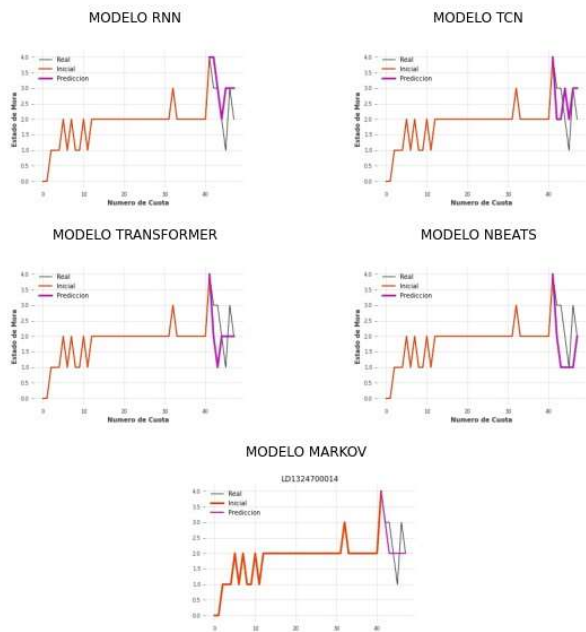
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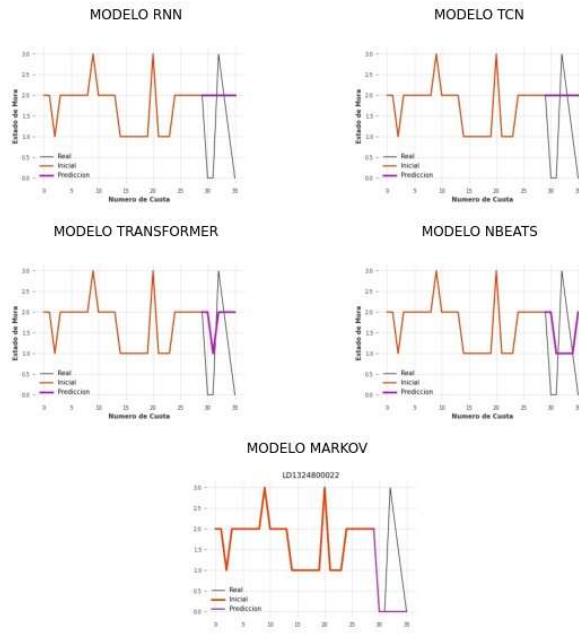
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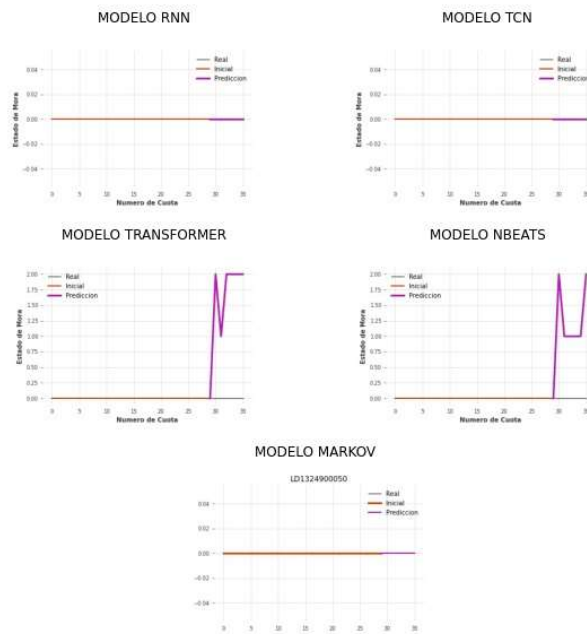
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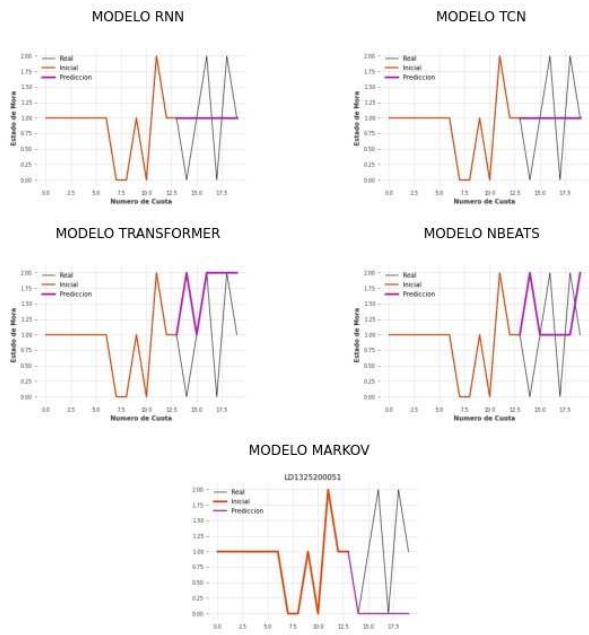
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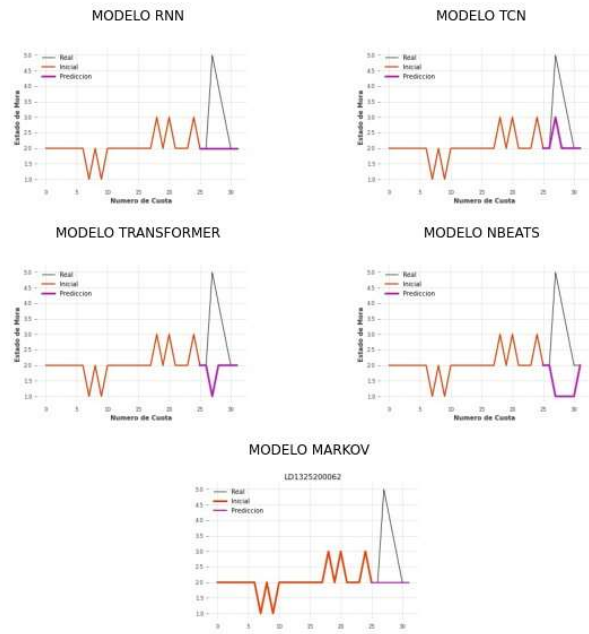
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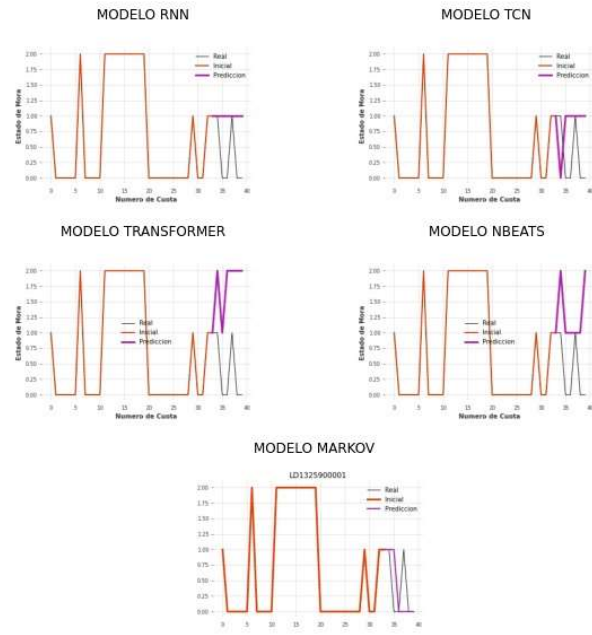
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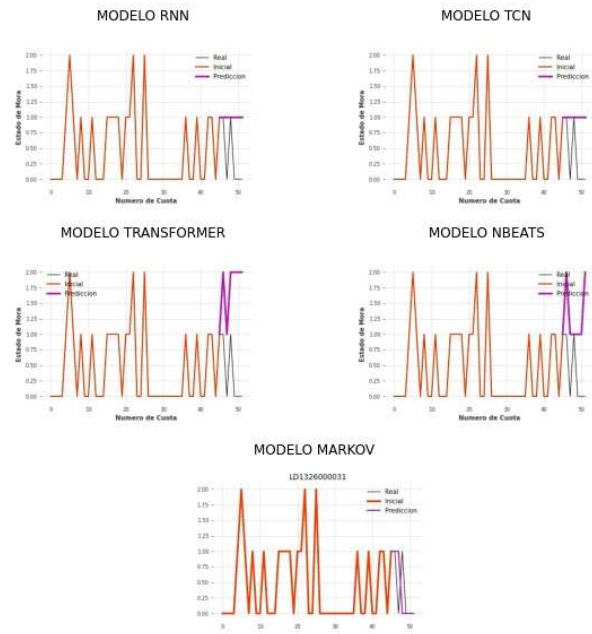
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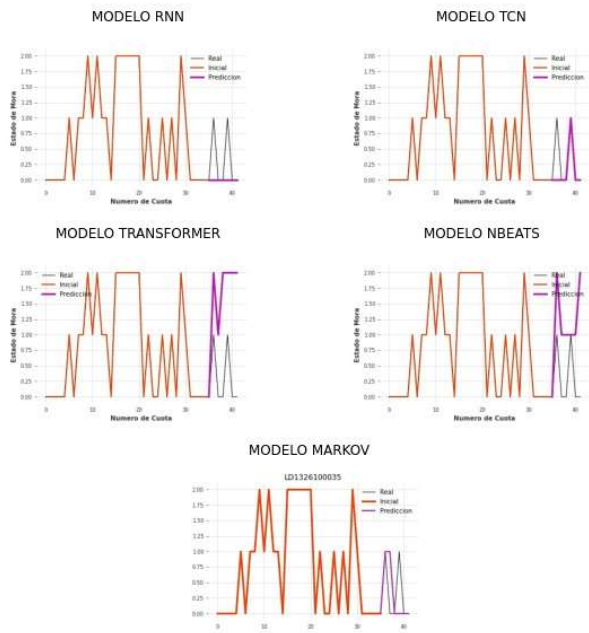
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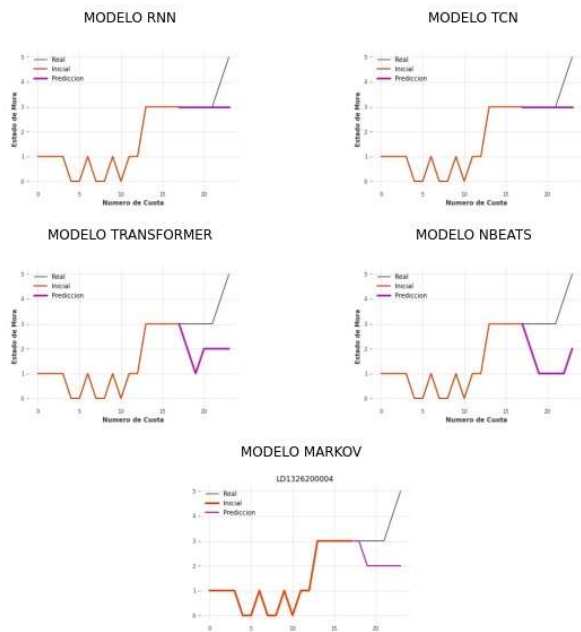
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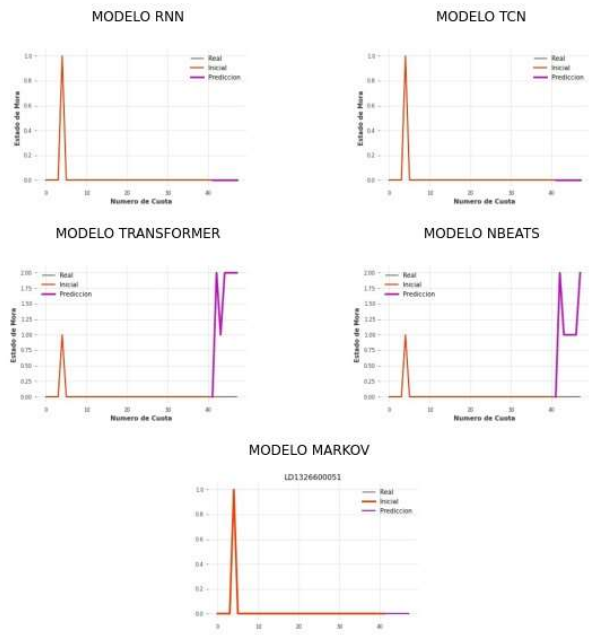
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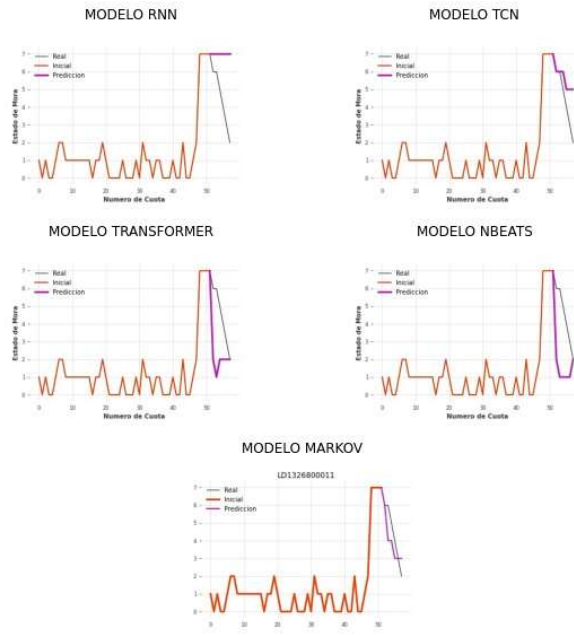


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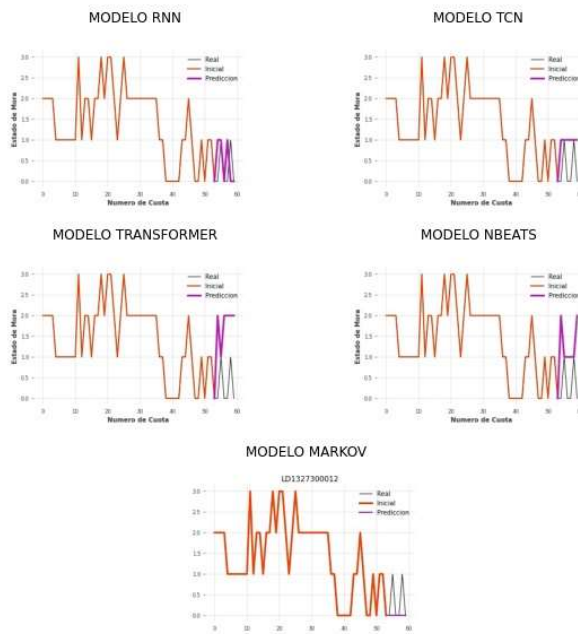




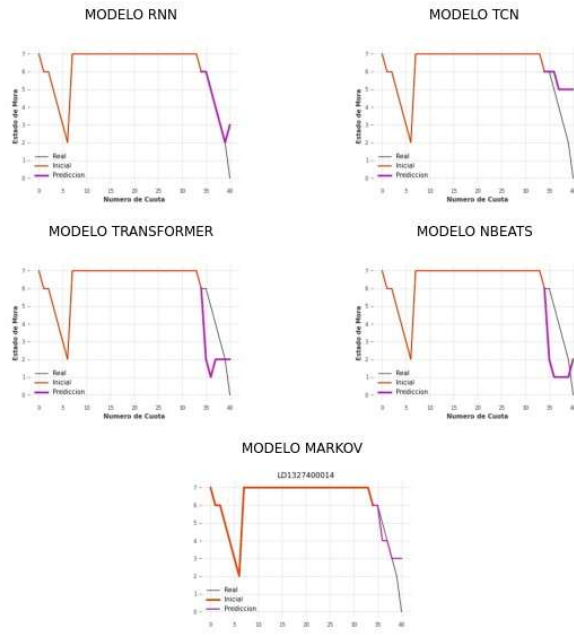
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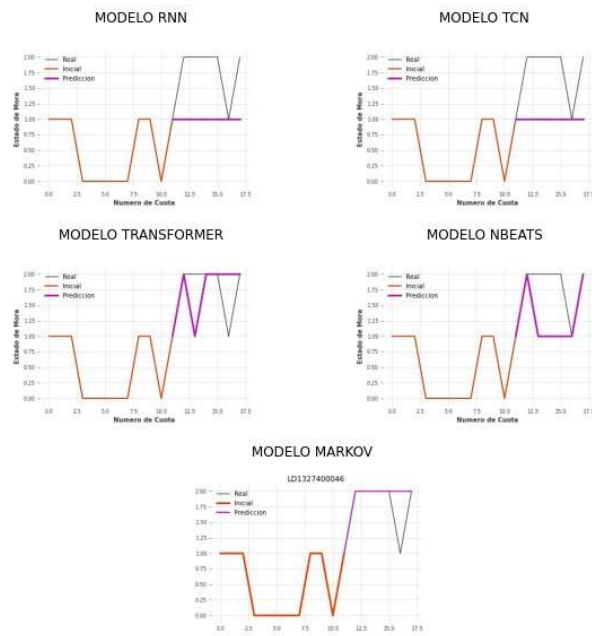
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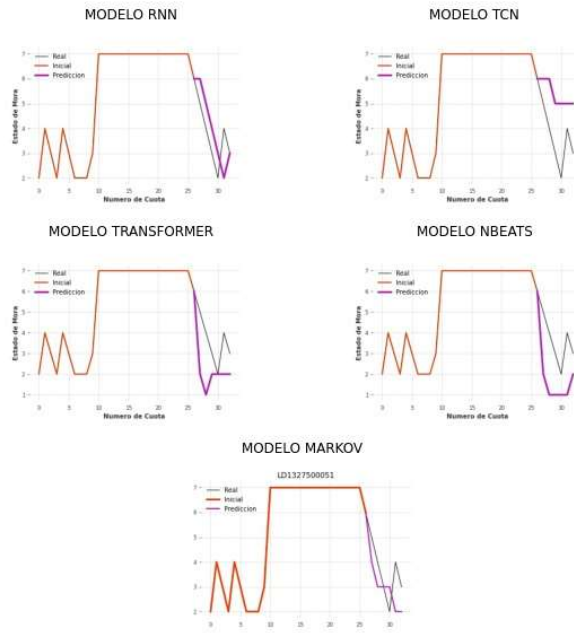
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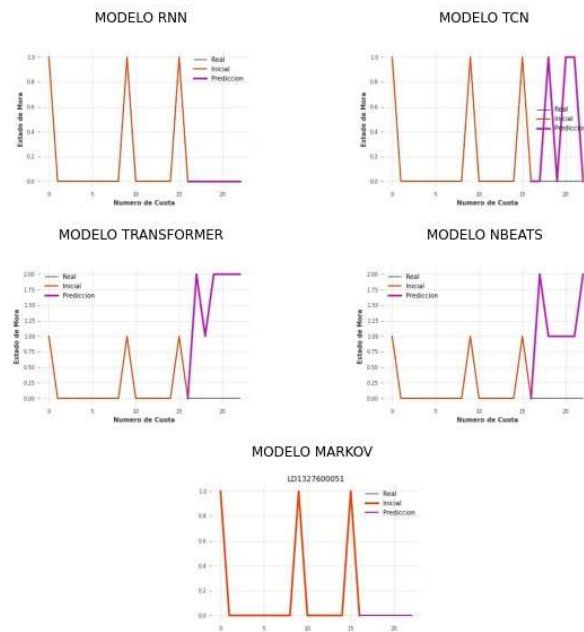
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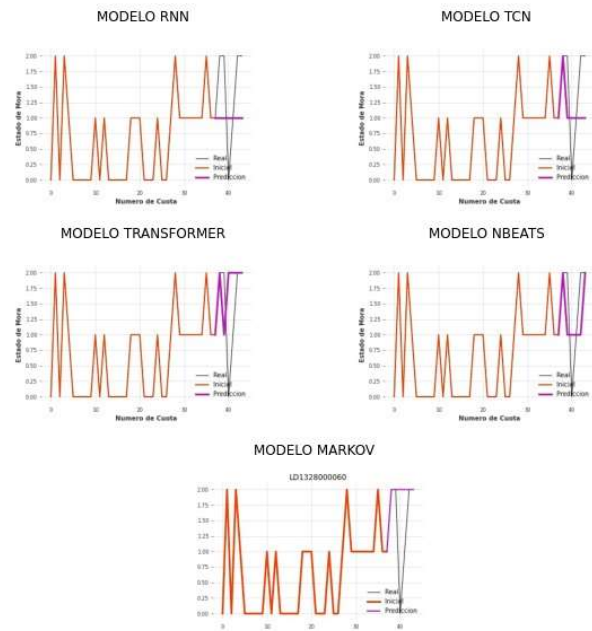
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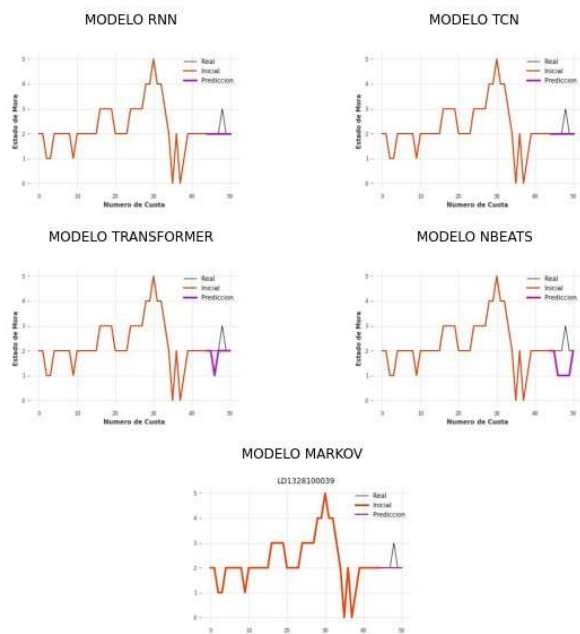
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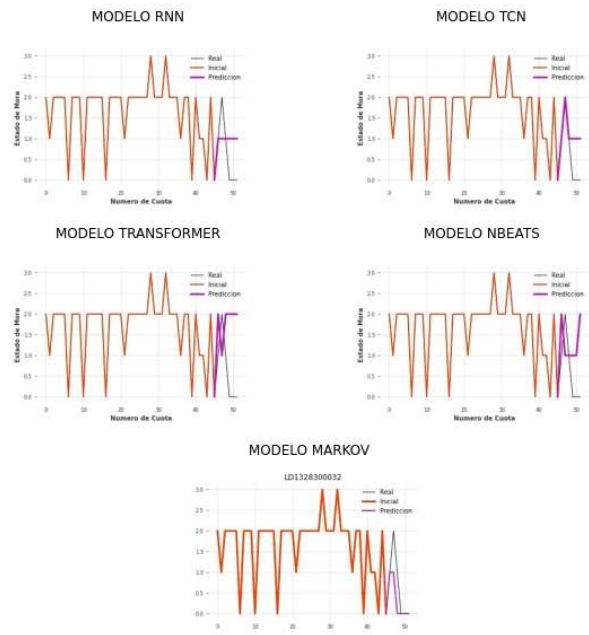
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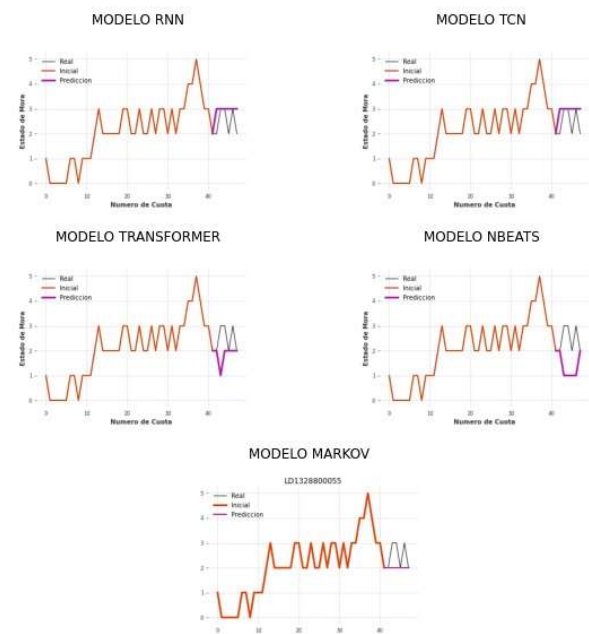
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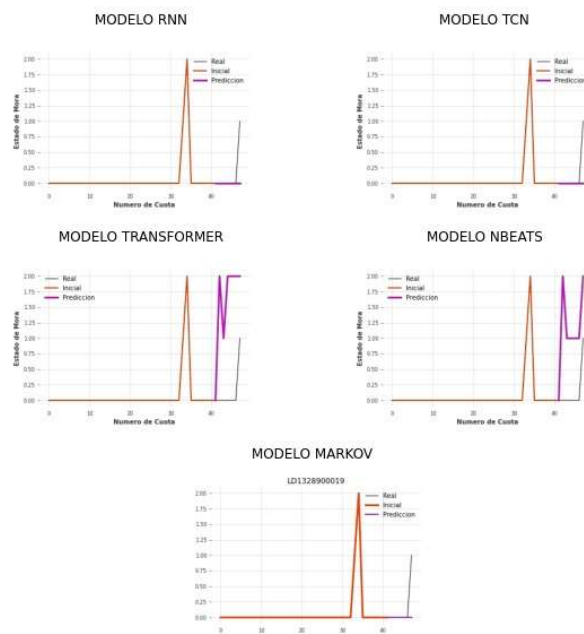
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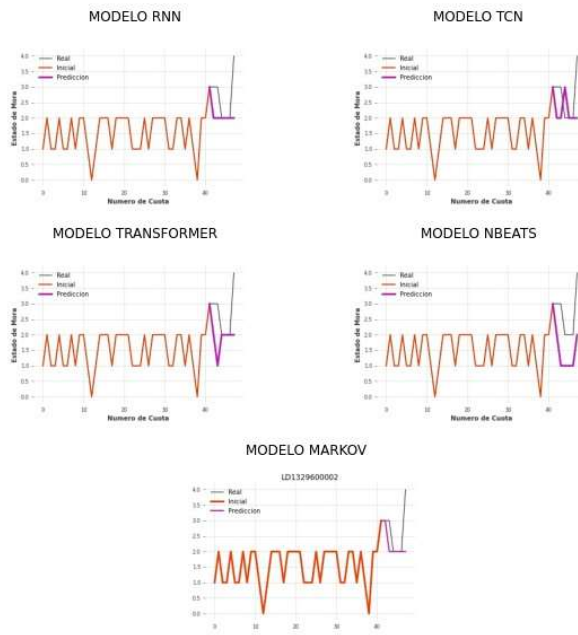
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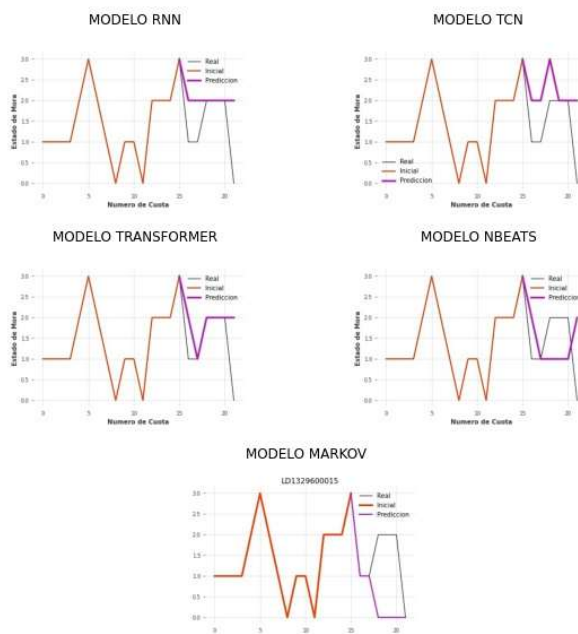
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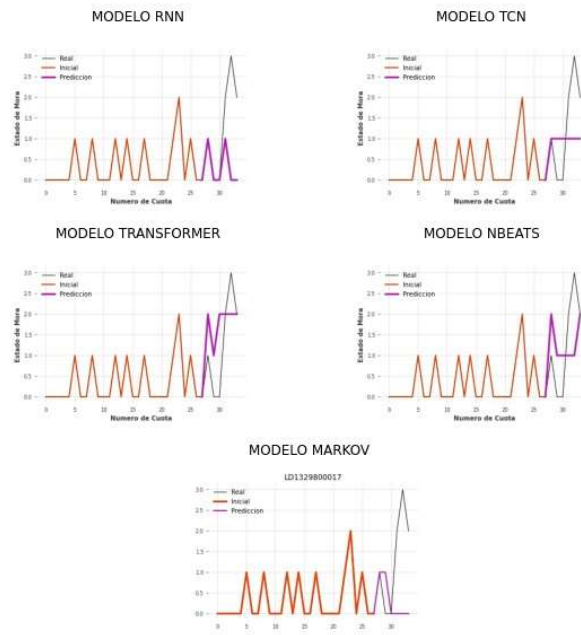
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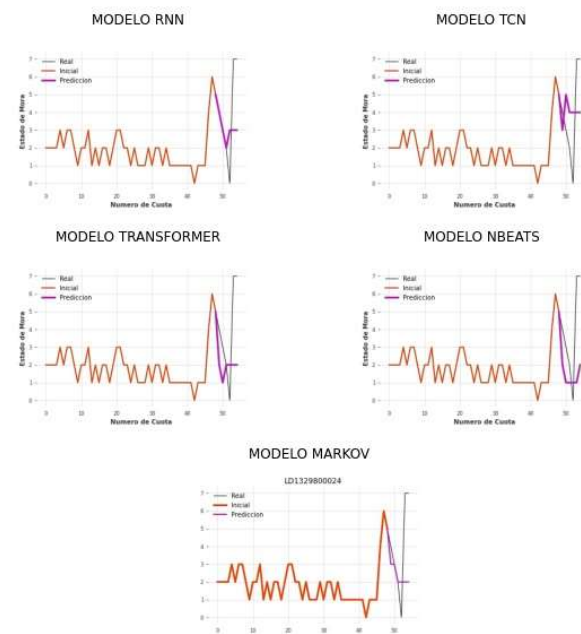
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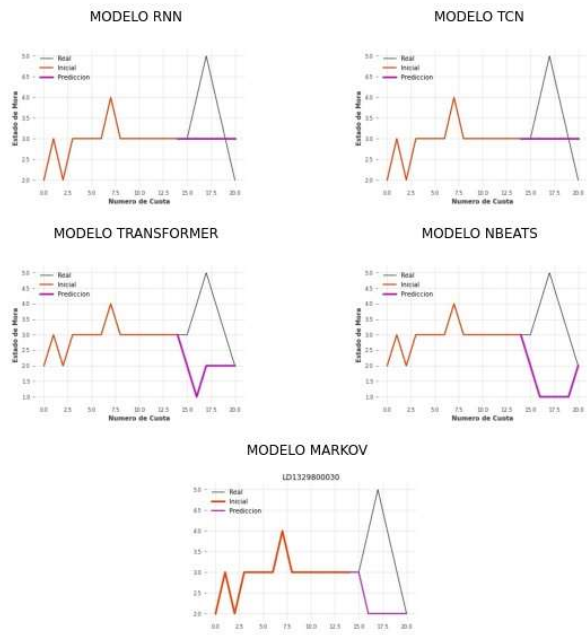


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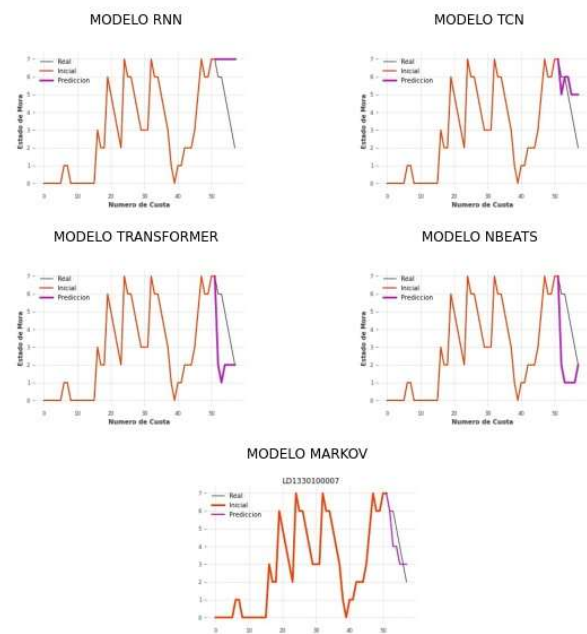




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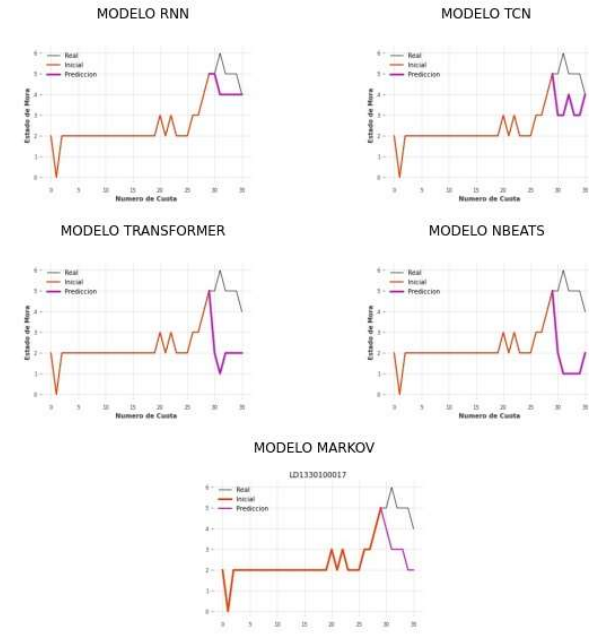
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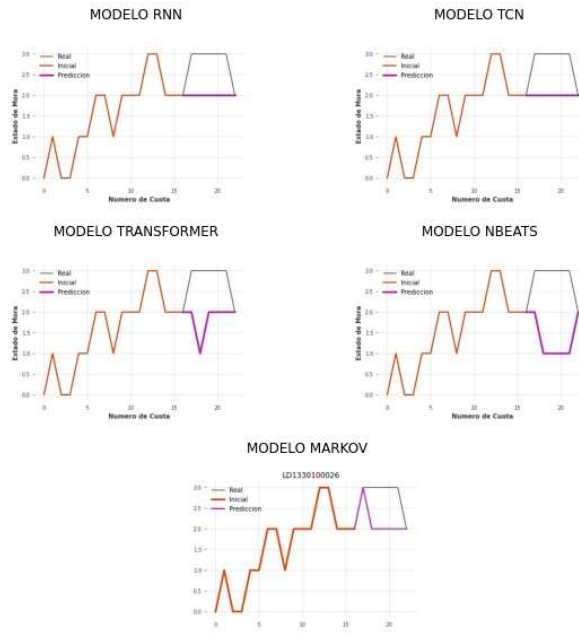
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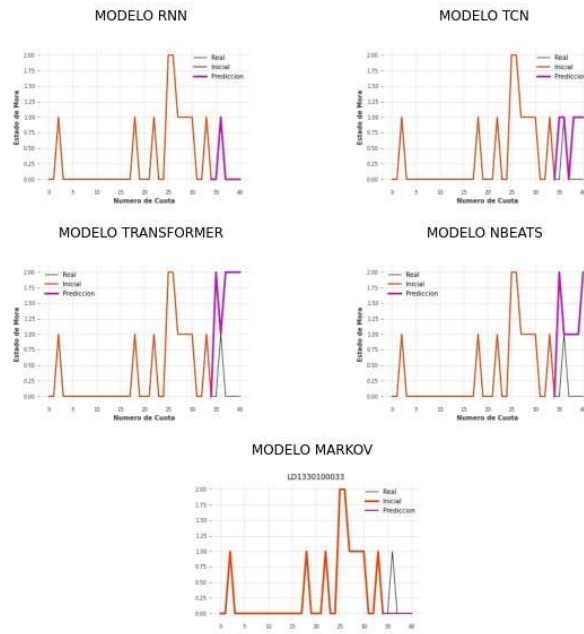
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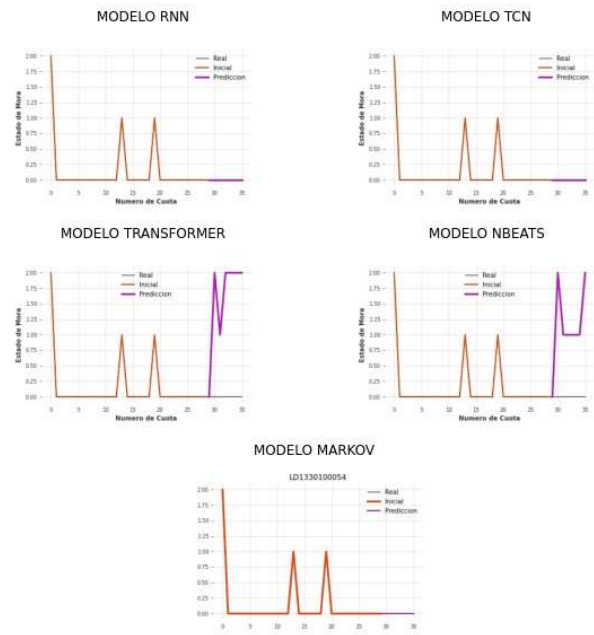
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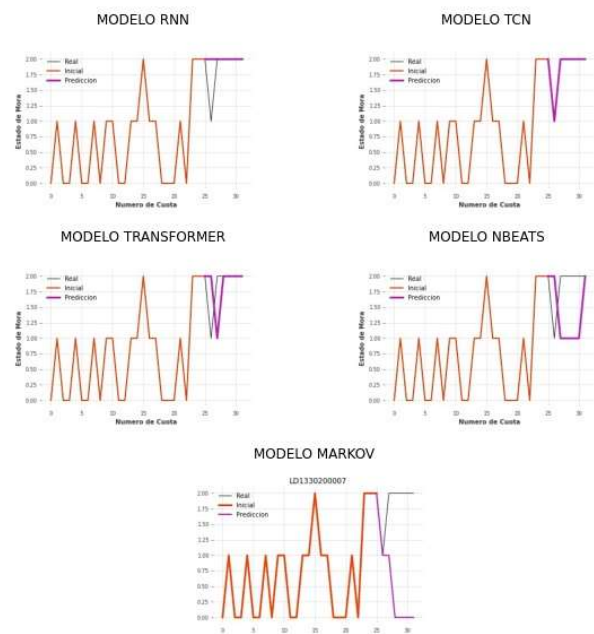
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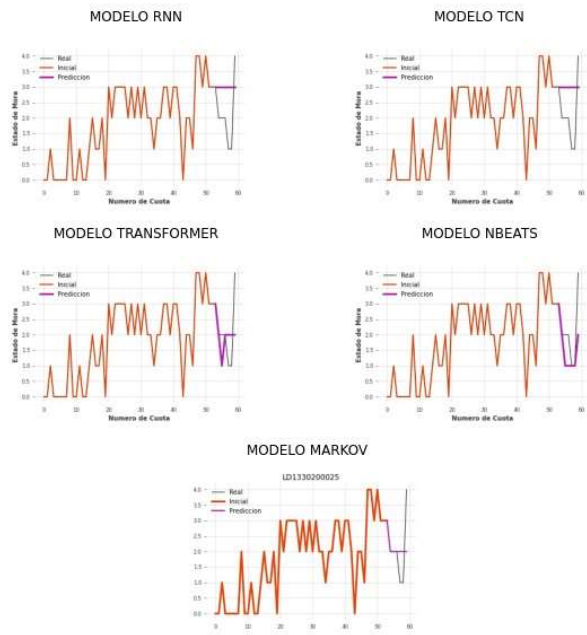
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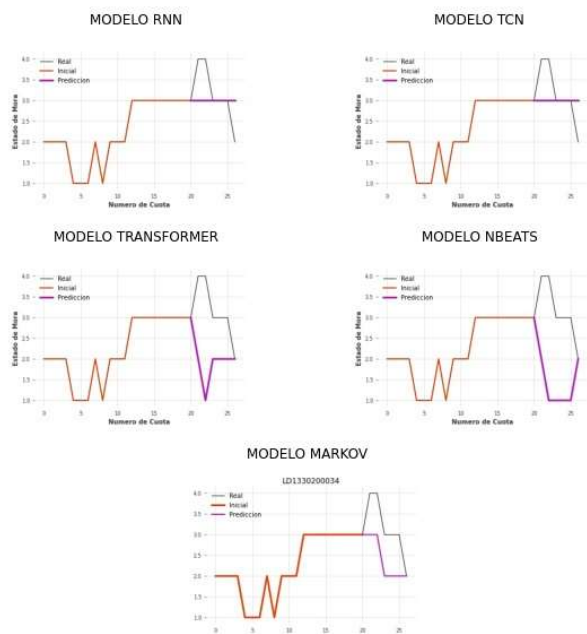
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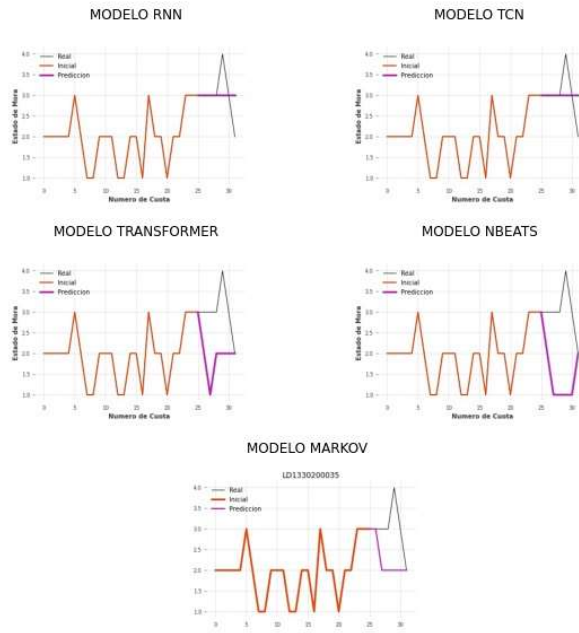
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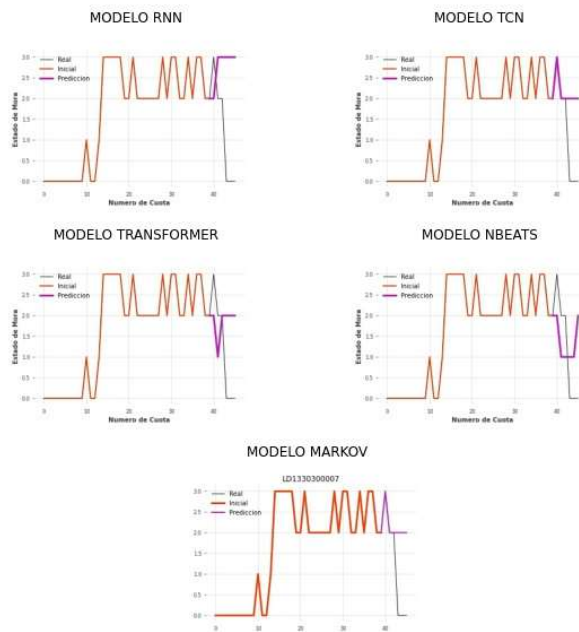
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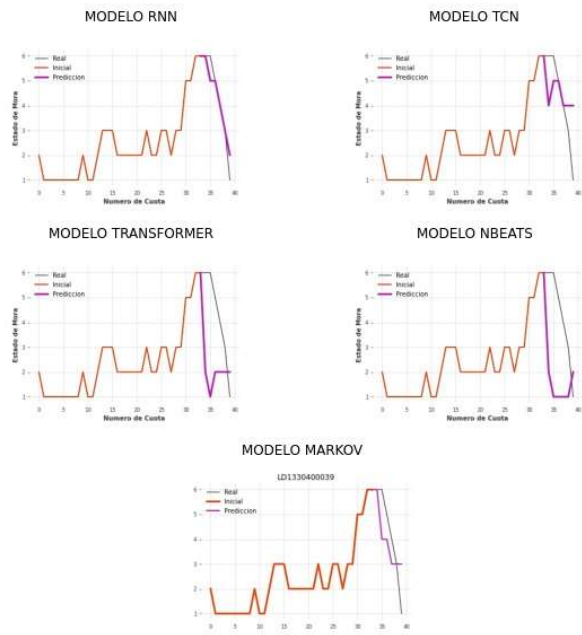
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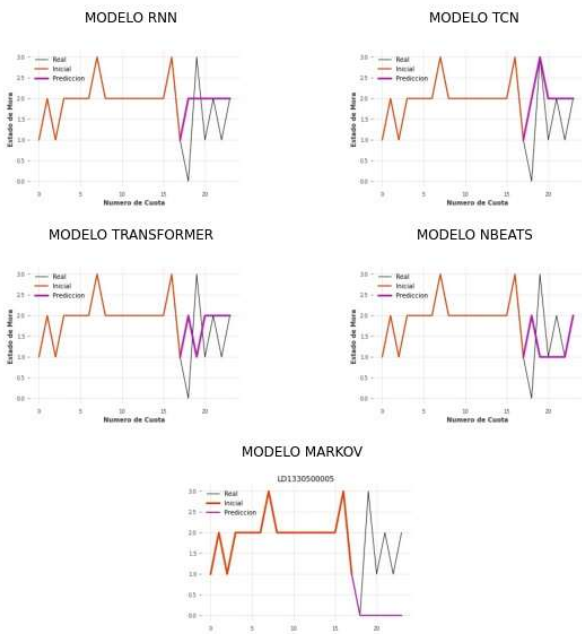
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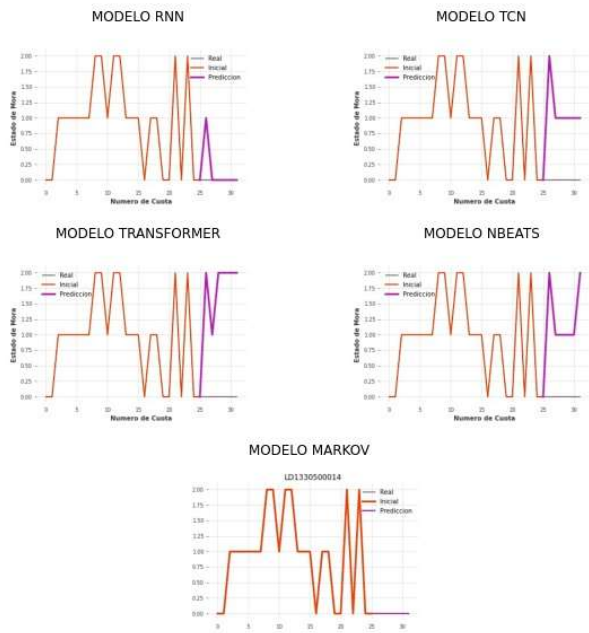
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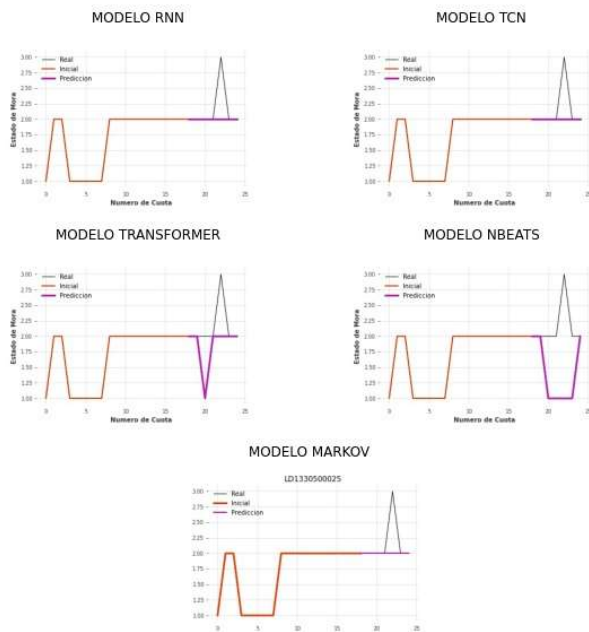
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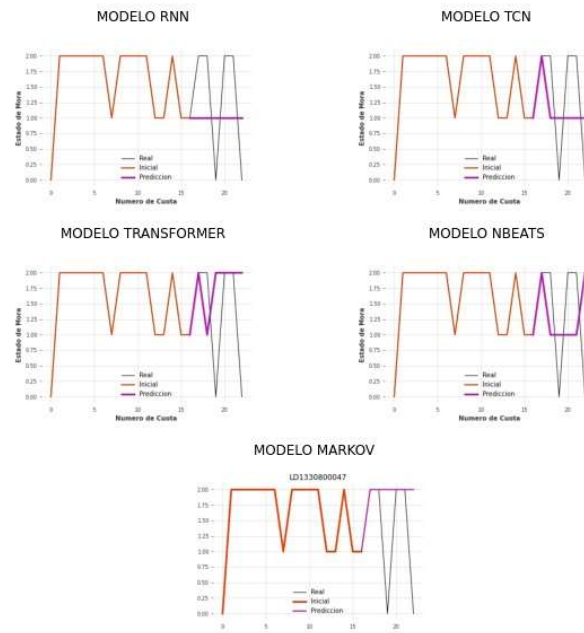


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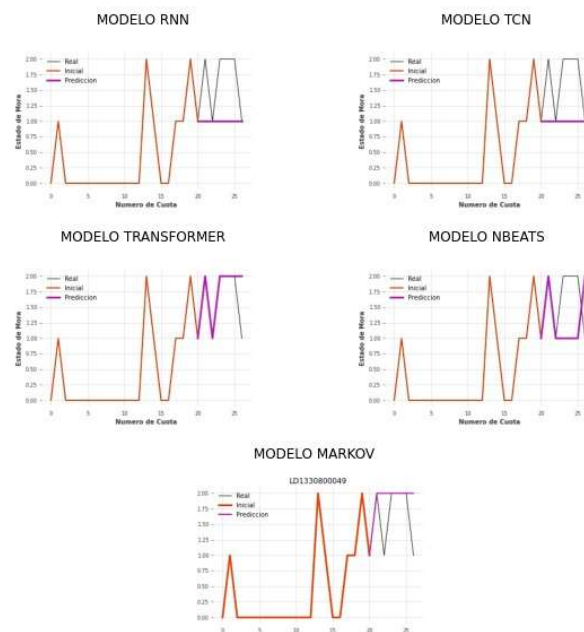




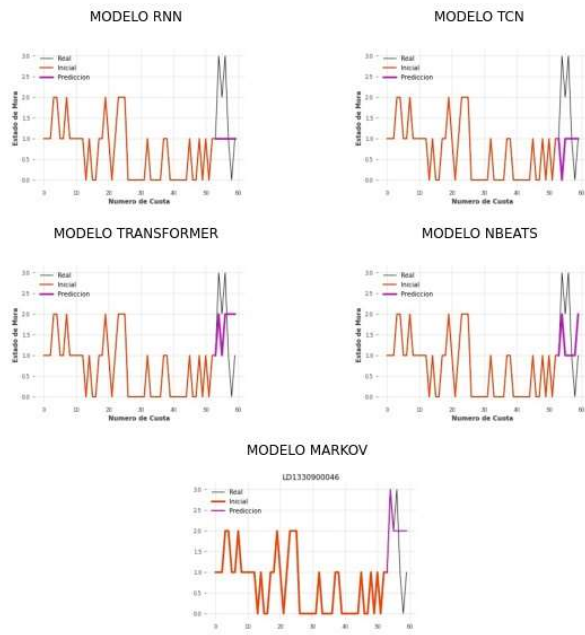
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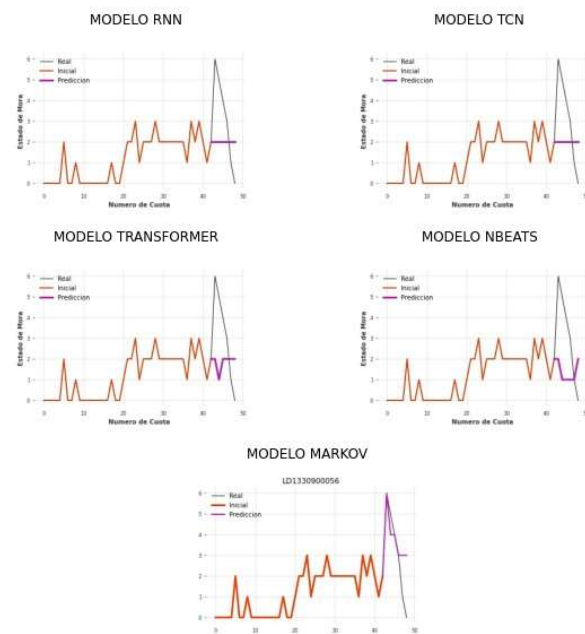
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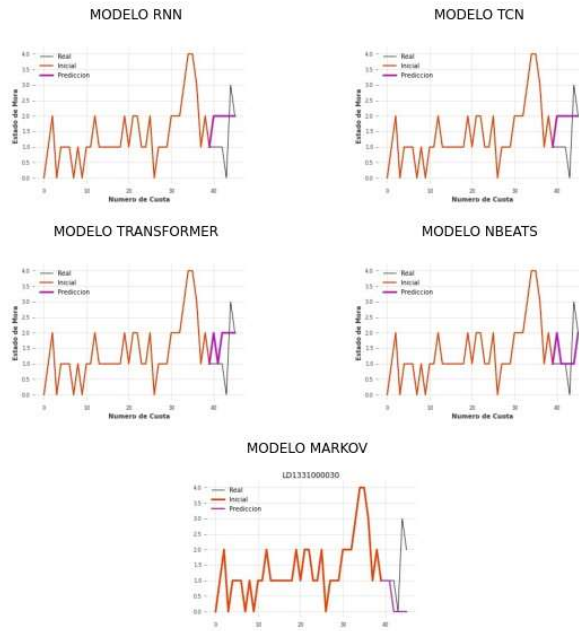
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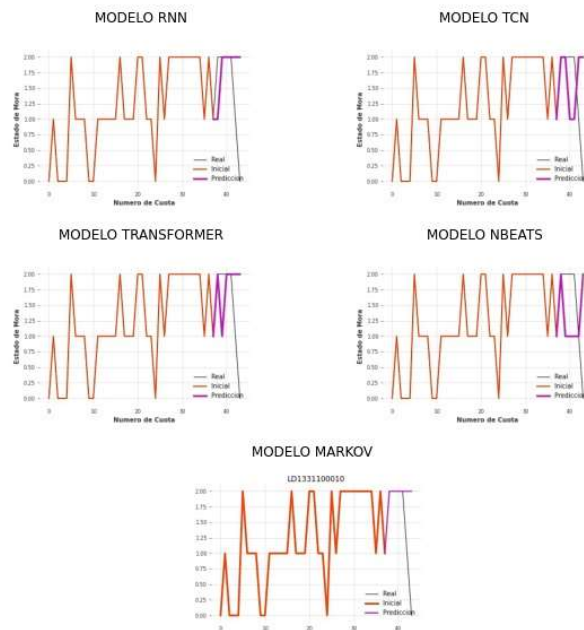
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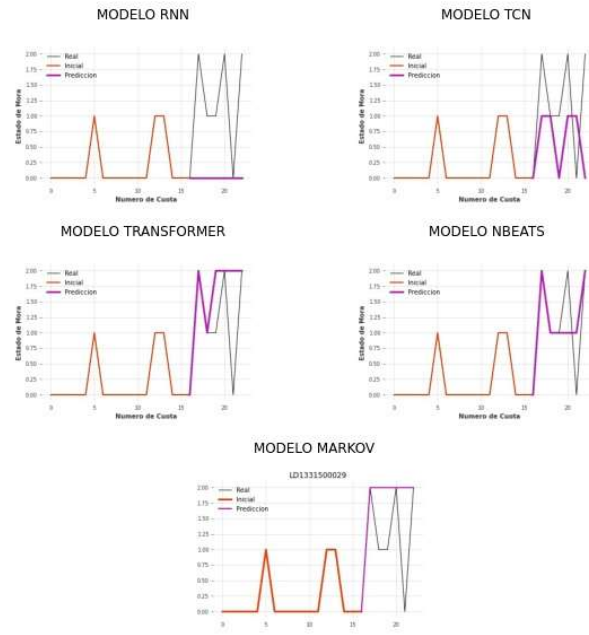
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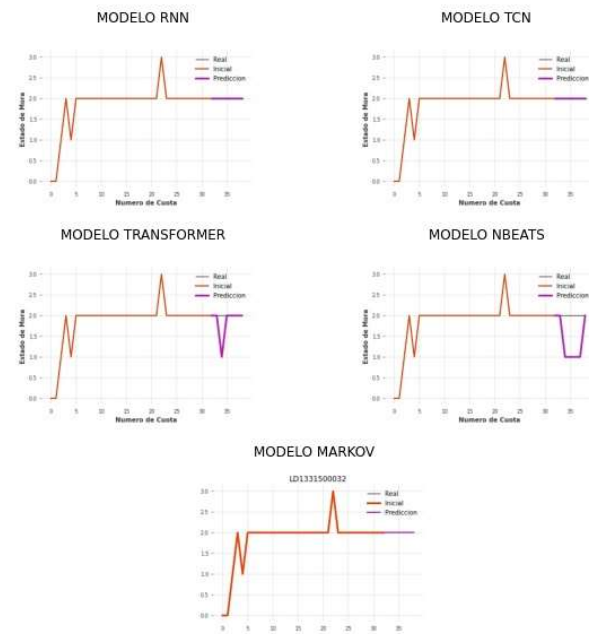
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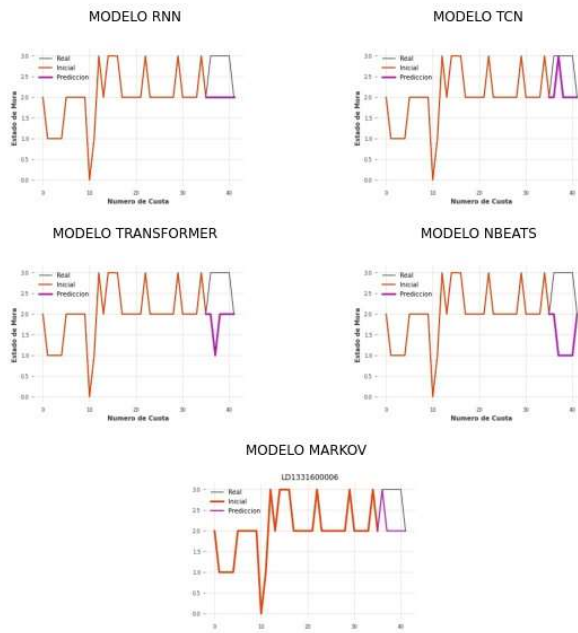
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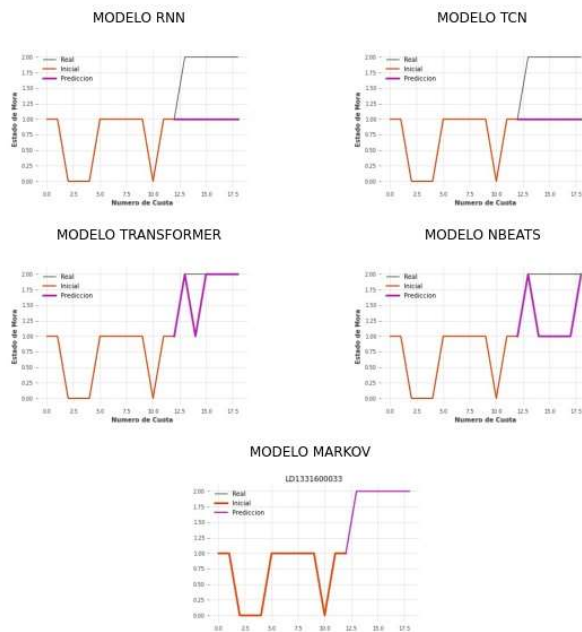
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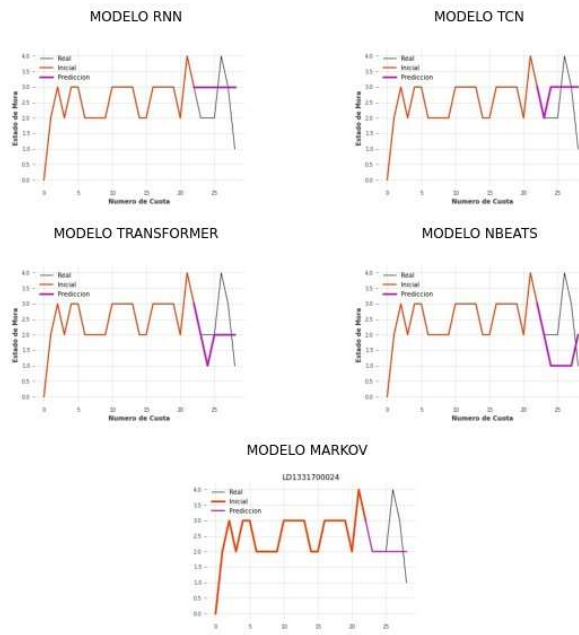
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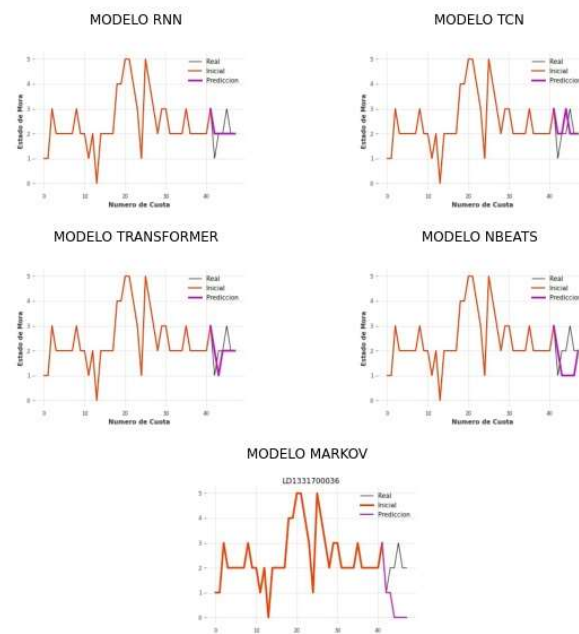
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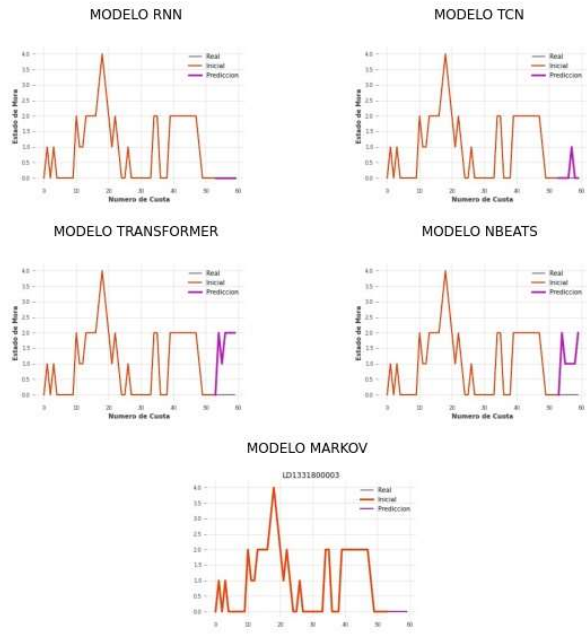
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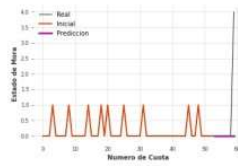


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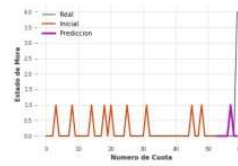


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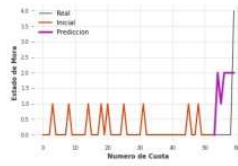
MODELO RNN



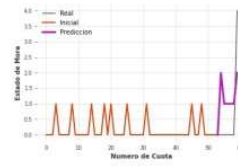
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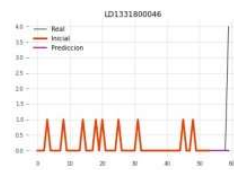
MODELO TRANSFORMER



MODELO NBEATS

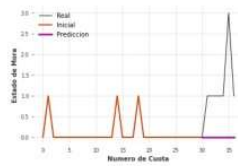


MODELO MARKOV

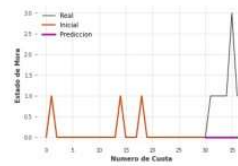


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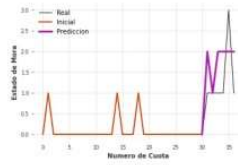
MODELO RNN



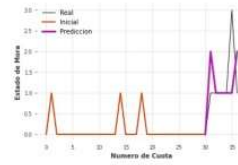
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MODELO TRANSFORMER



MODELO NBEATS

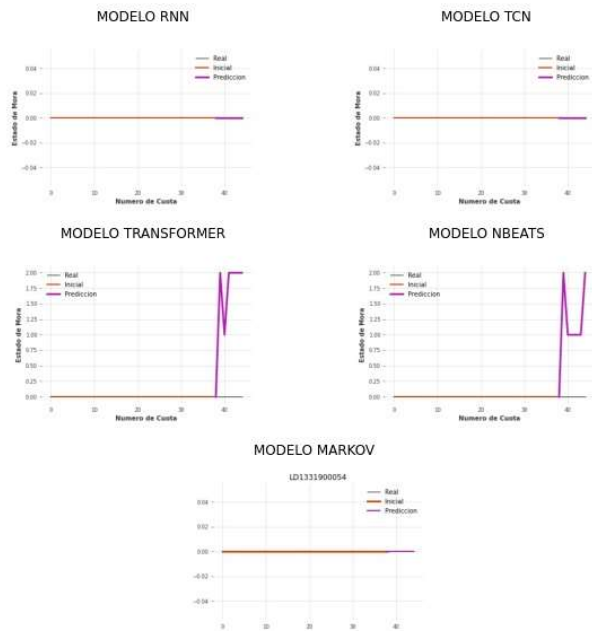


MODELO MARKOV

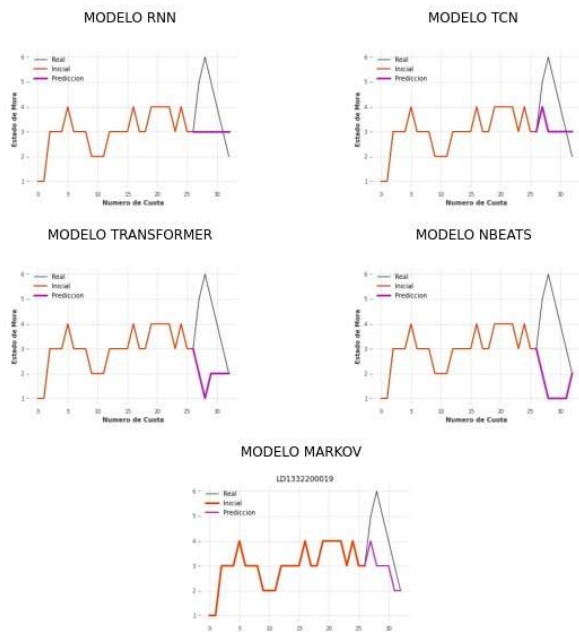




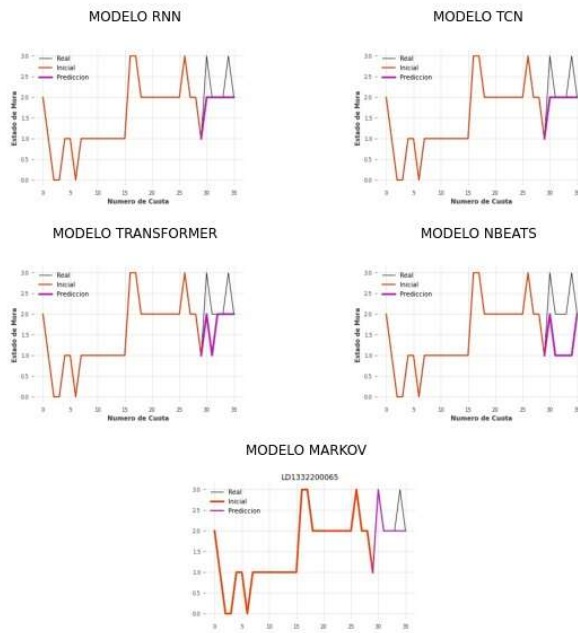
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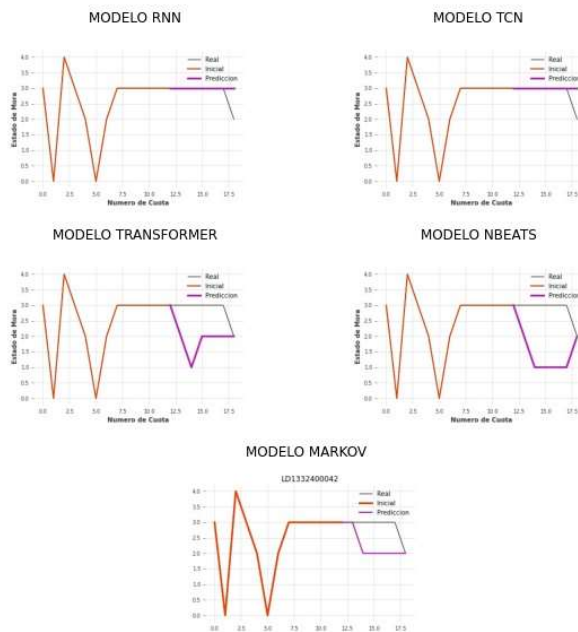
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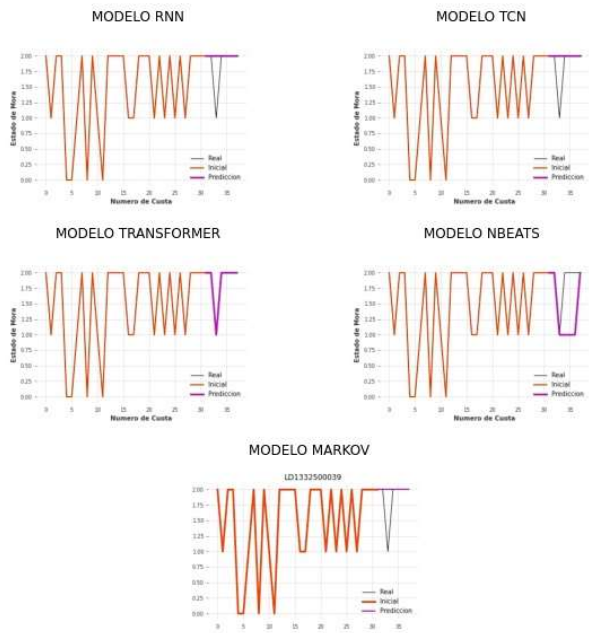
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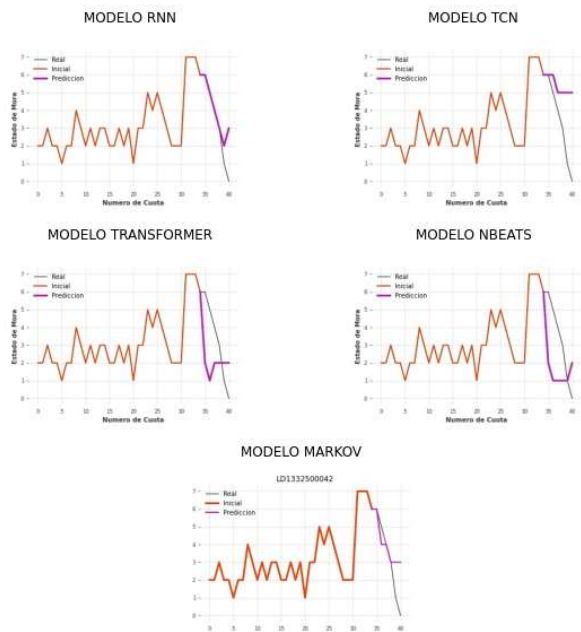
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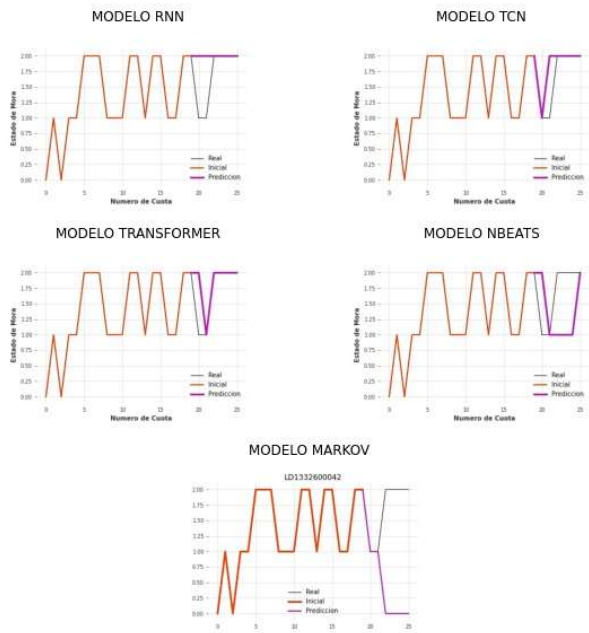
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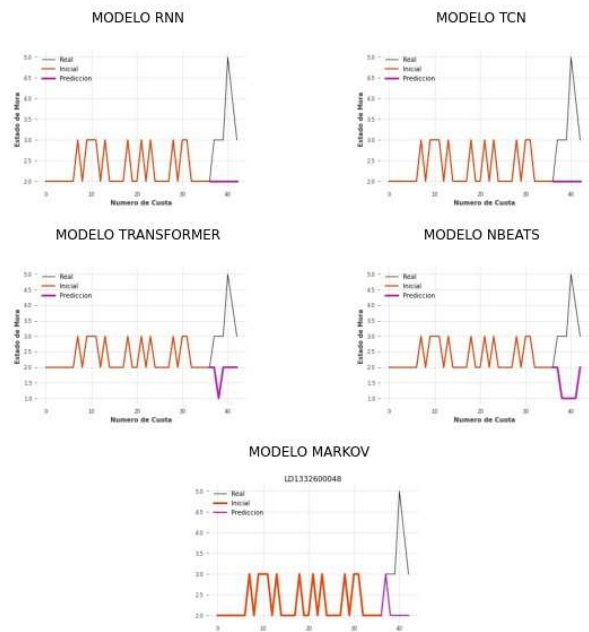
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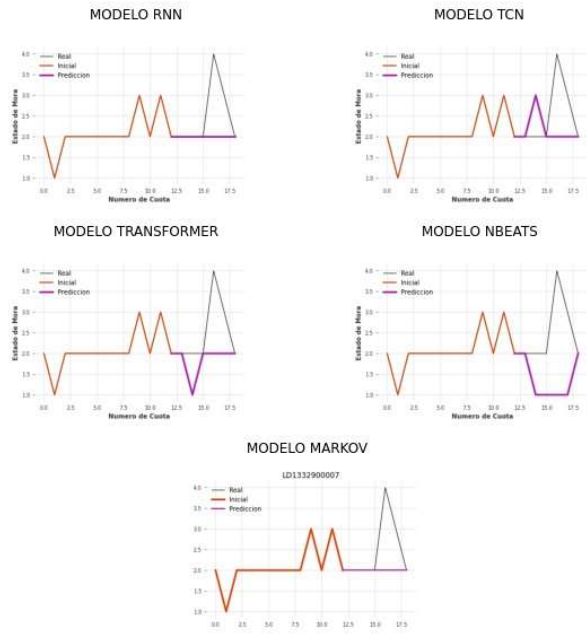
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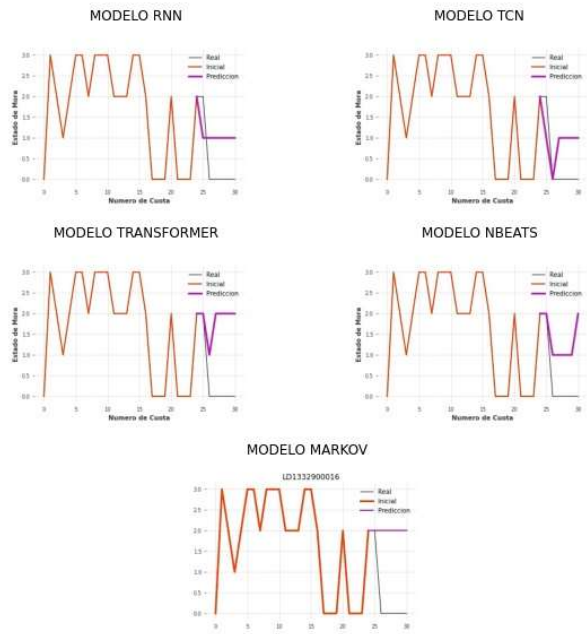
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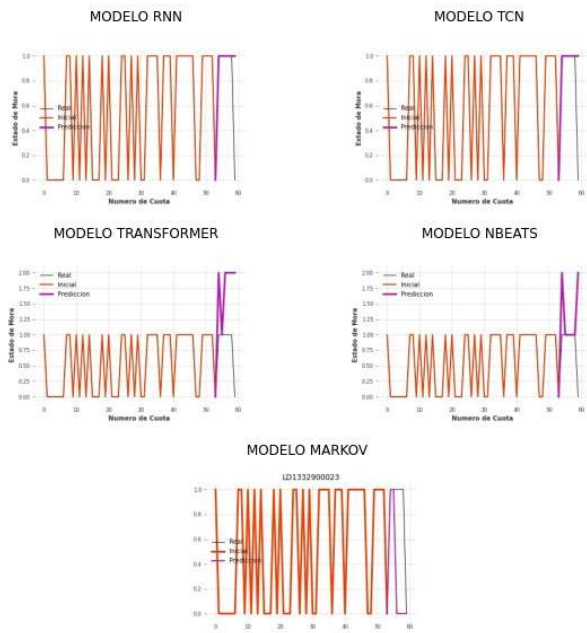
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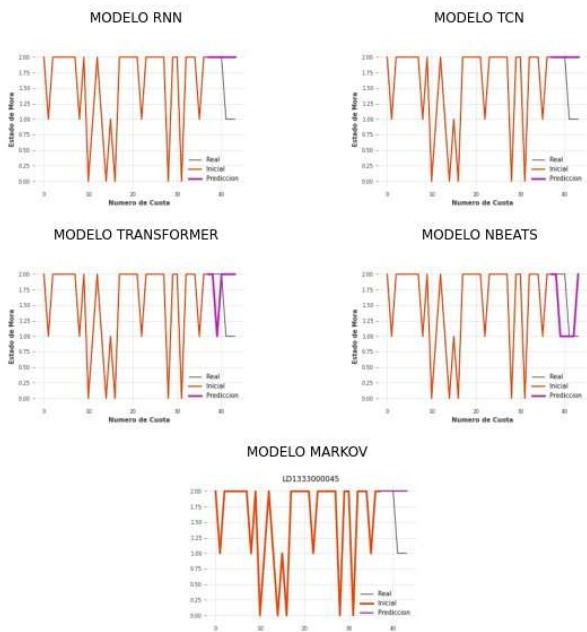
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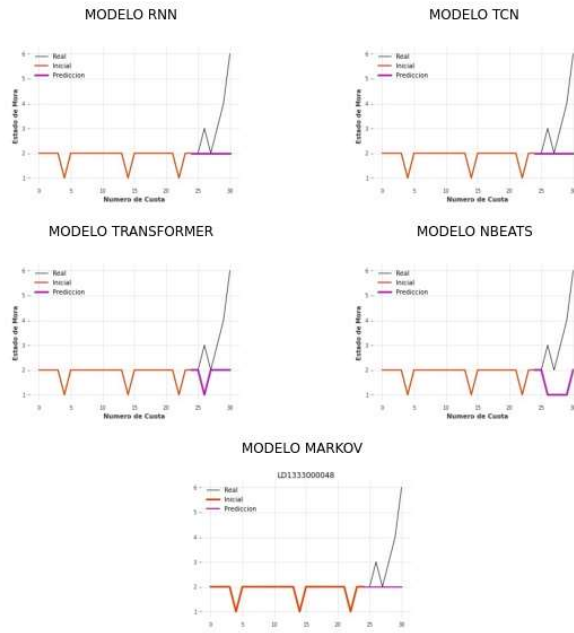
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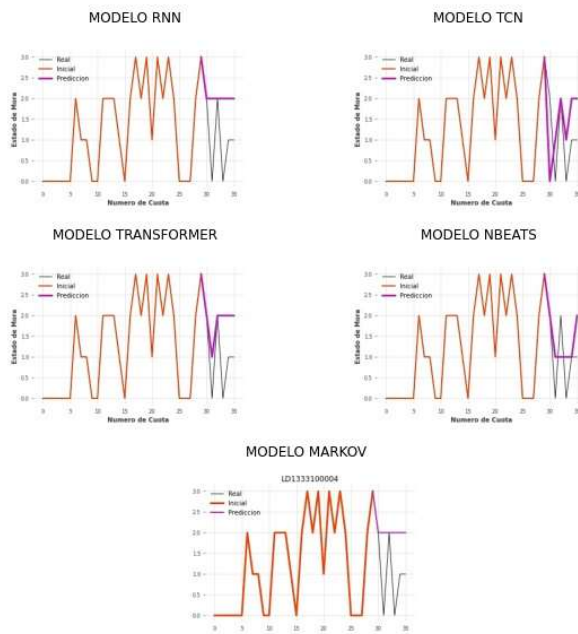
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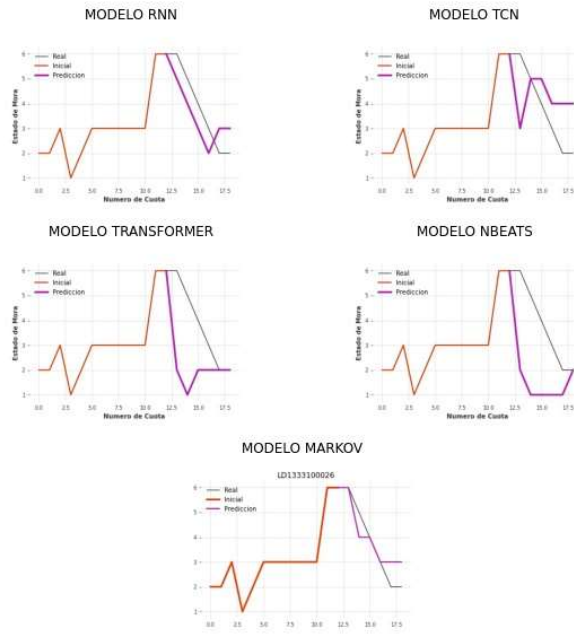
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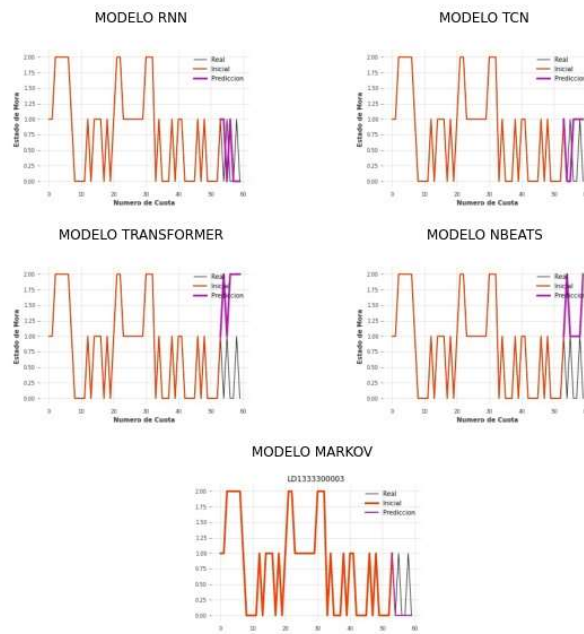
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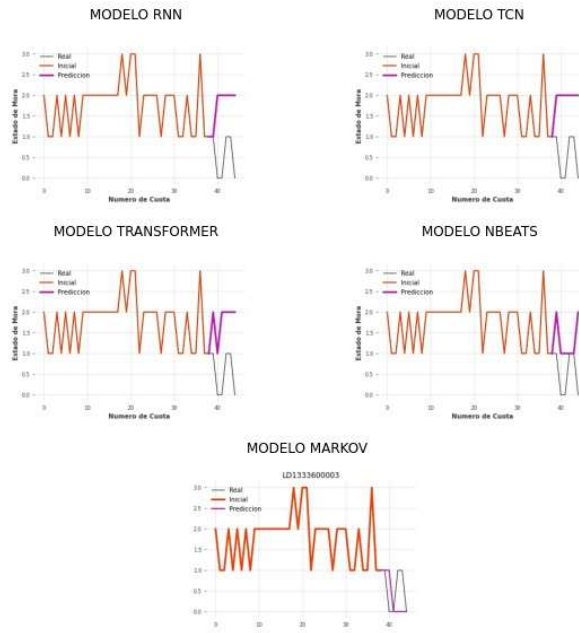


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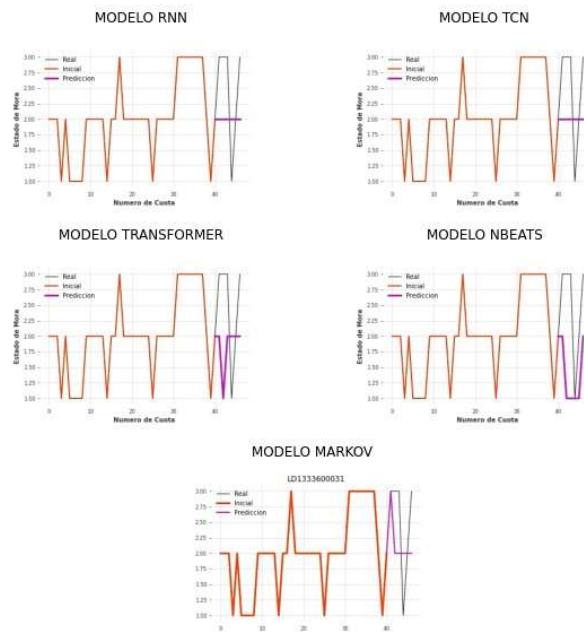




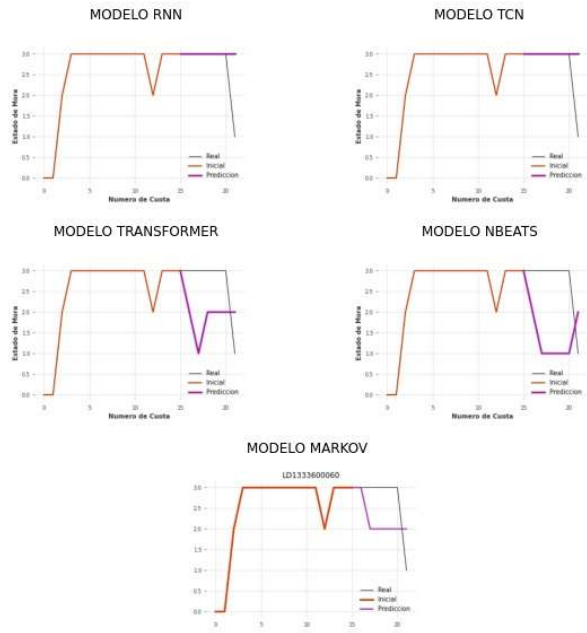
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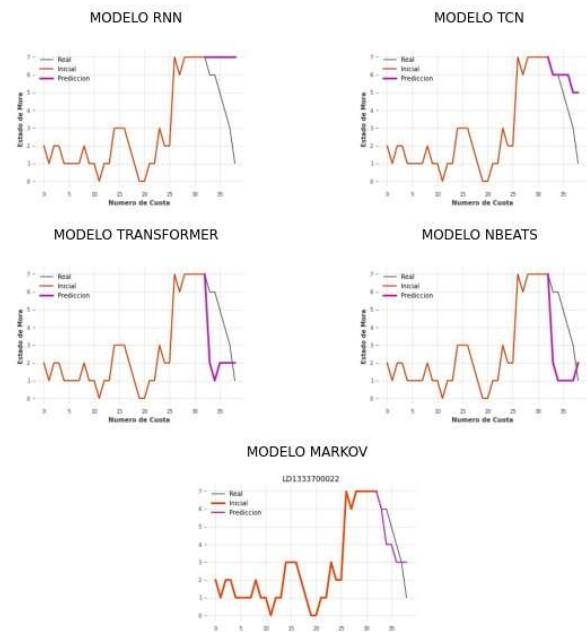
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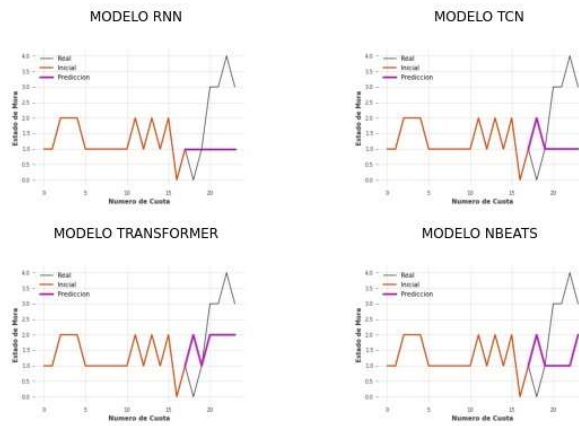
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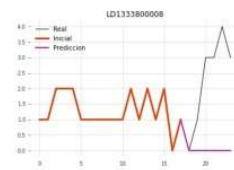
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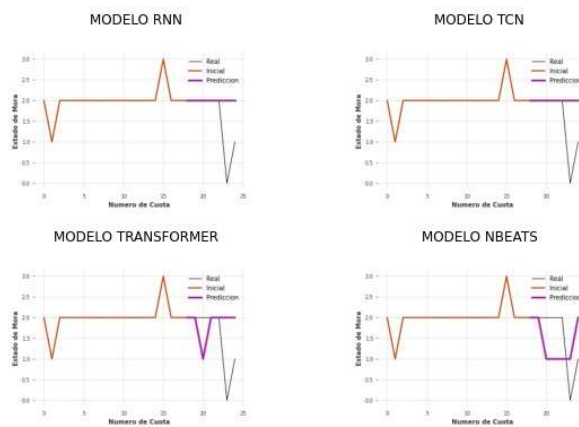
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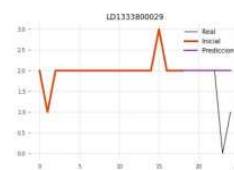
MODELO MARKOV



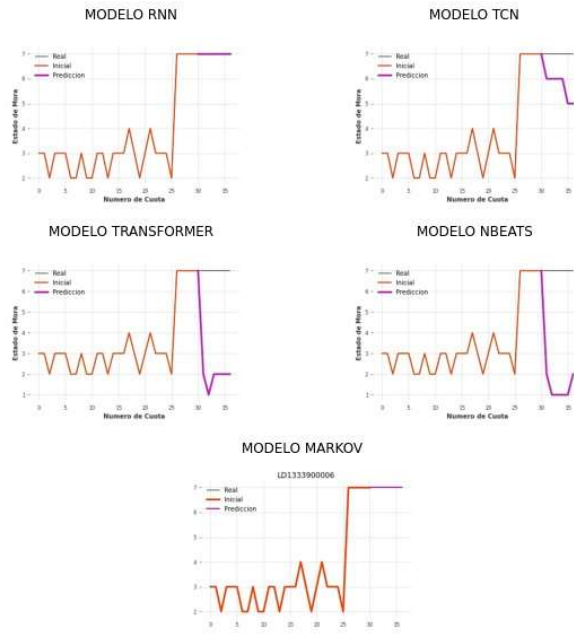
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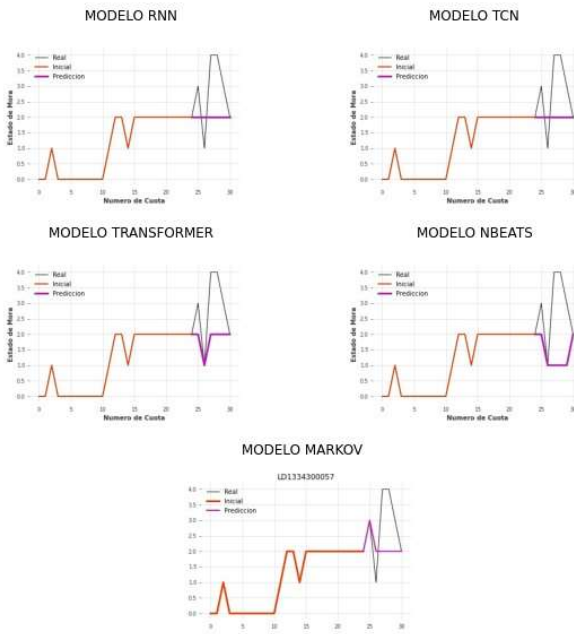
MODELO MARKOV



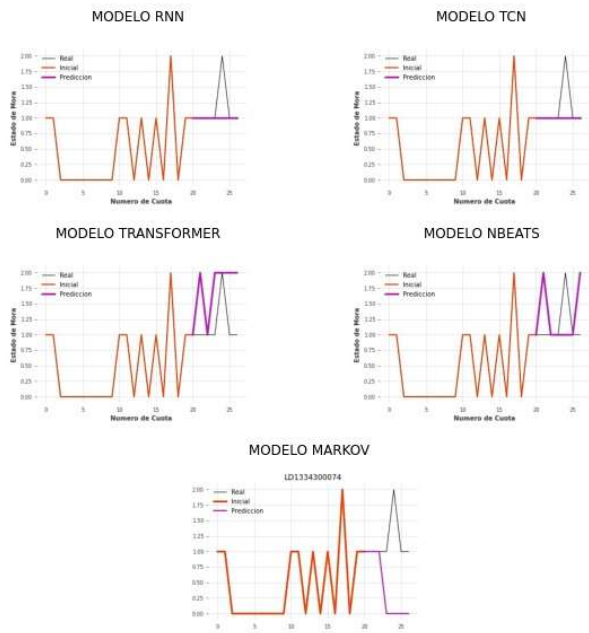
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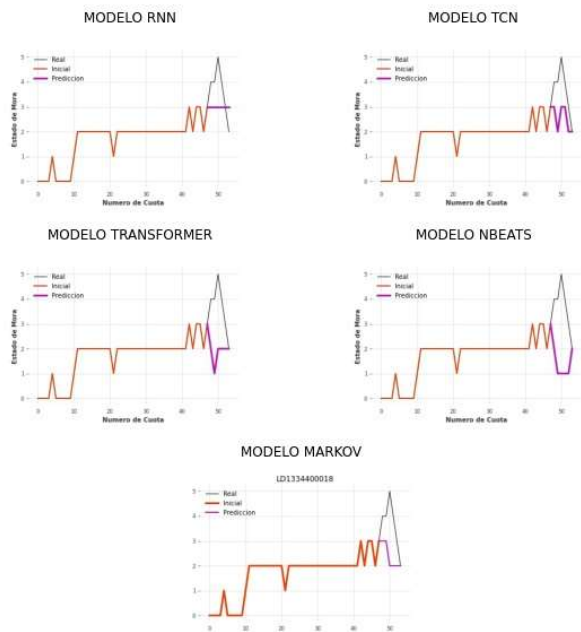
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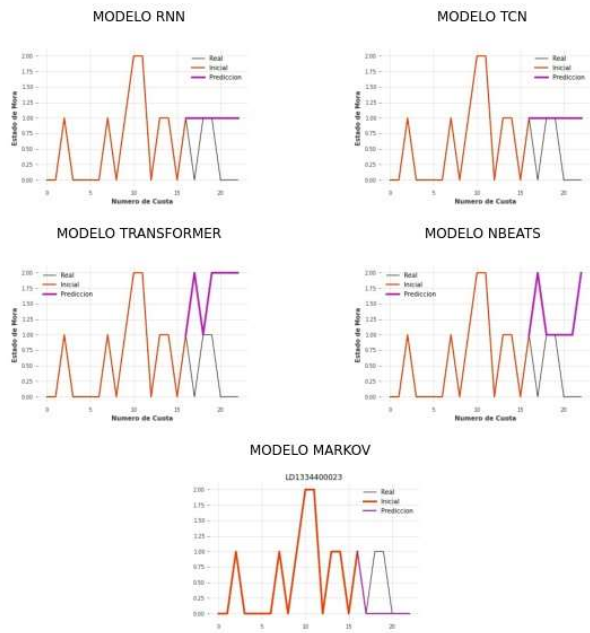
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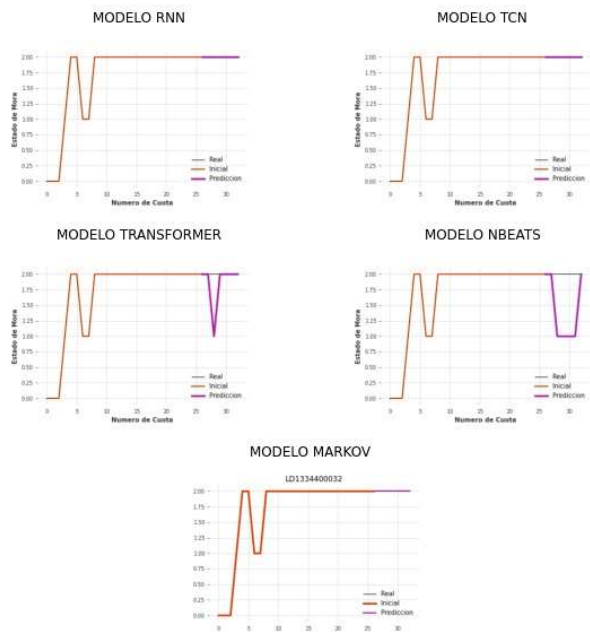
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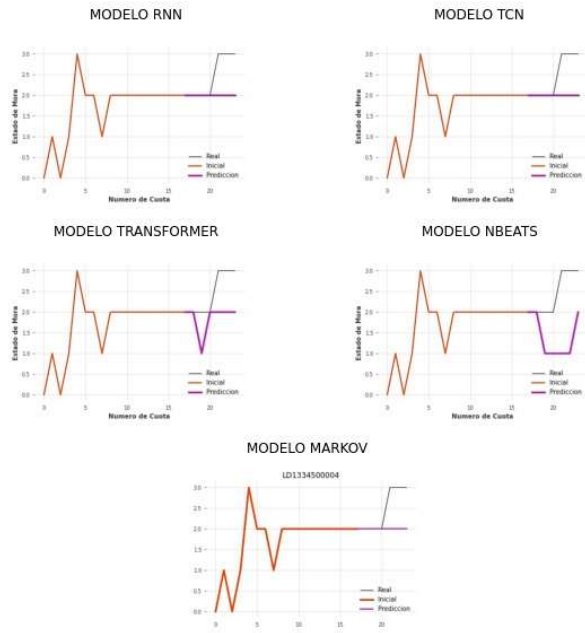
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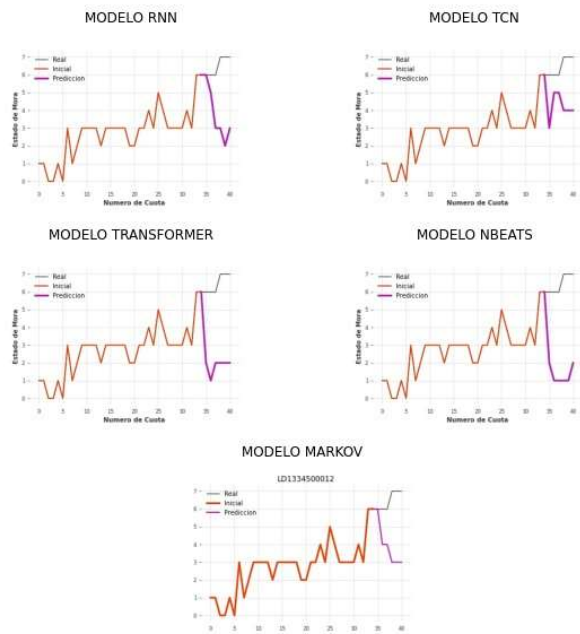
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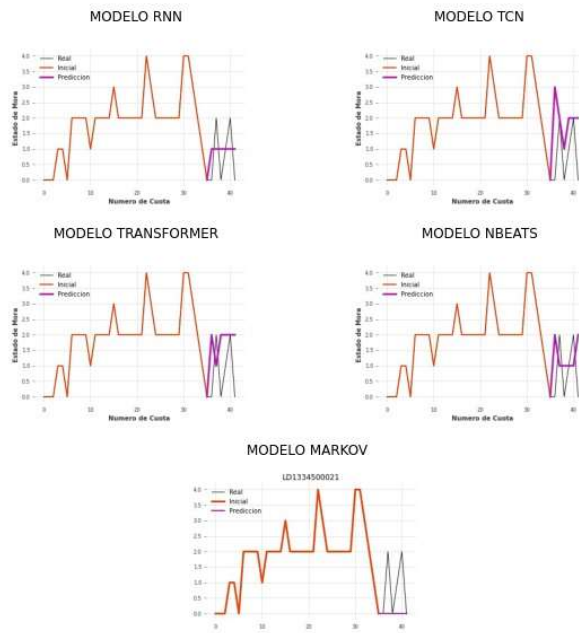
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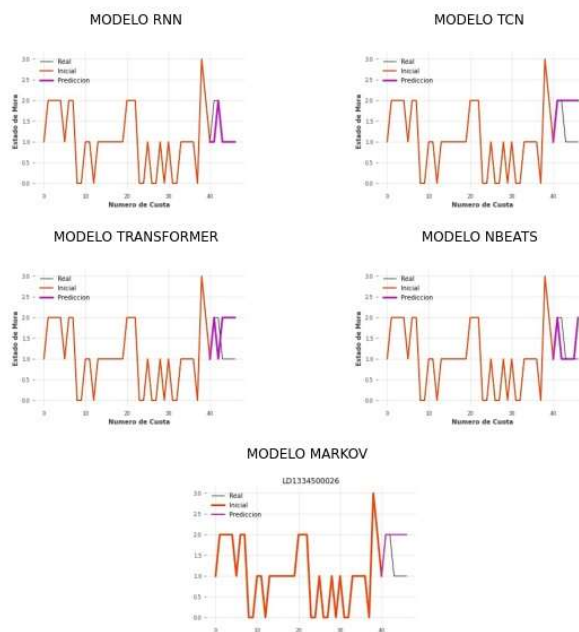
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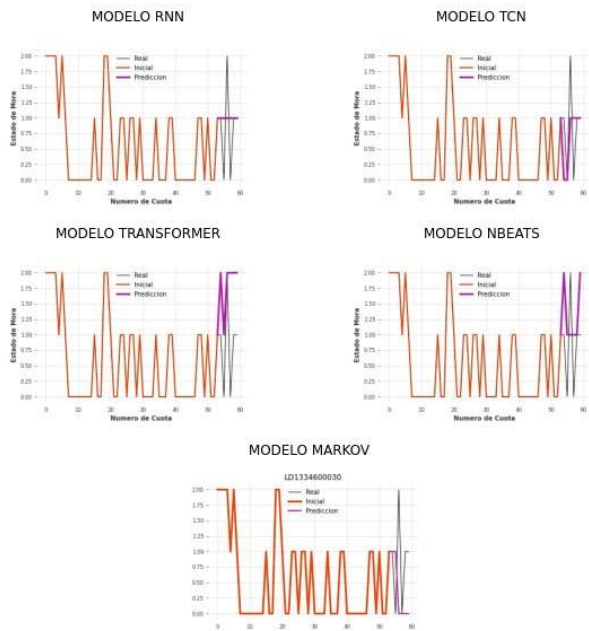


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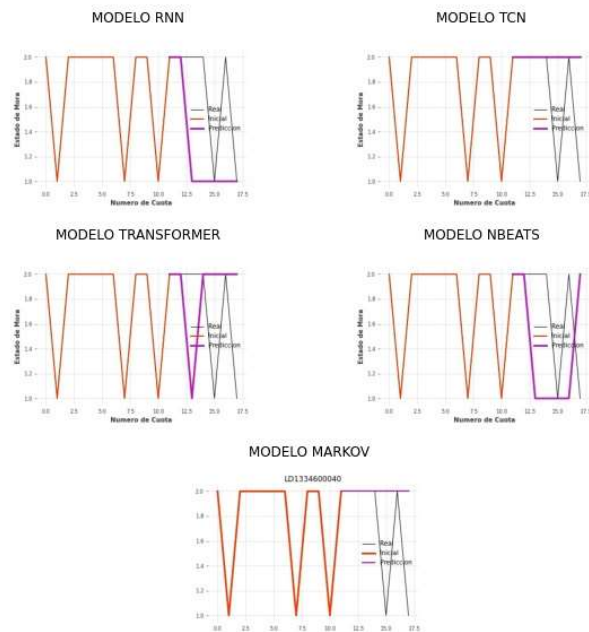




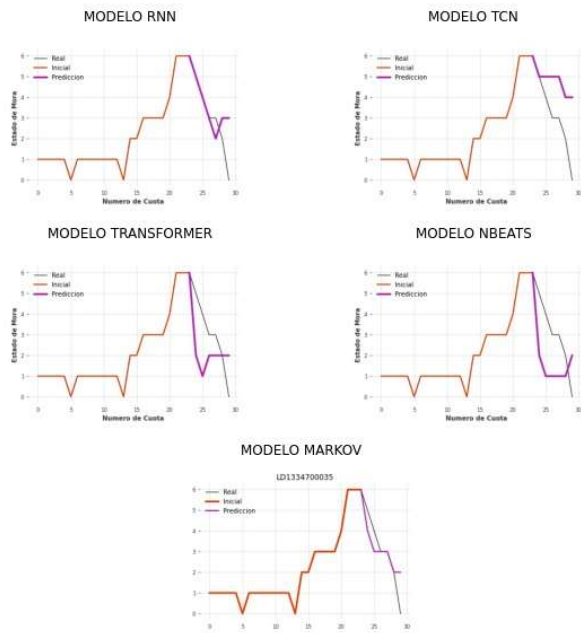
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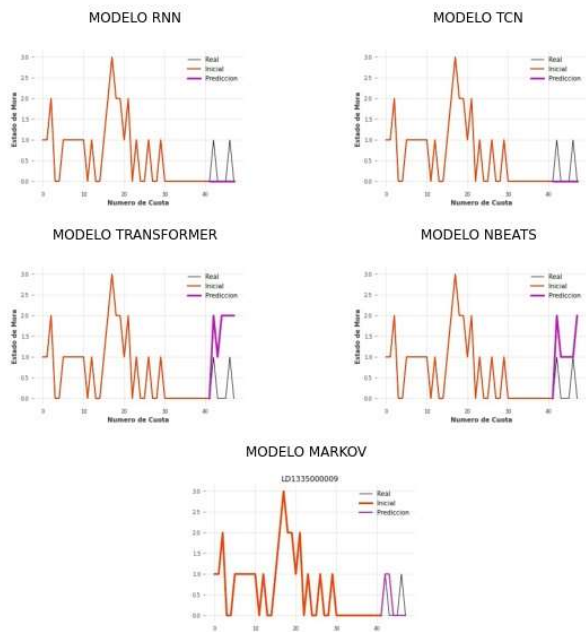
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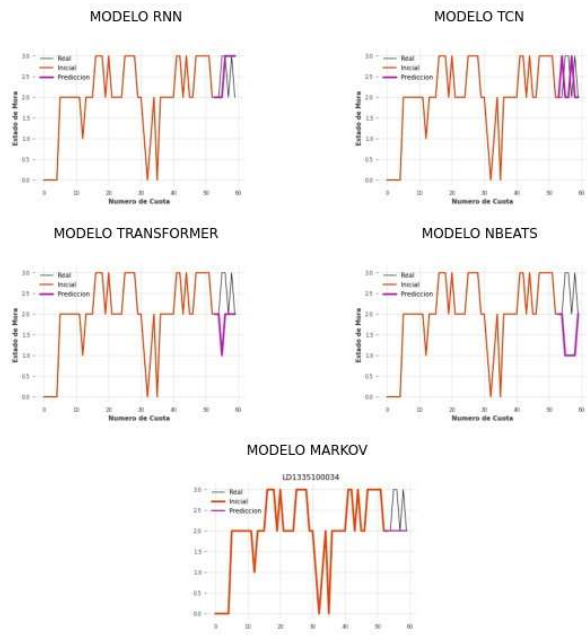
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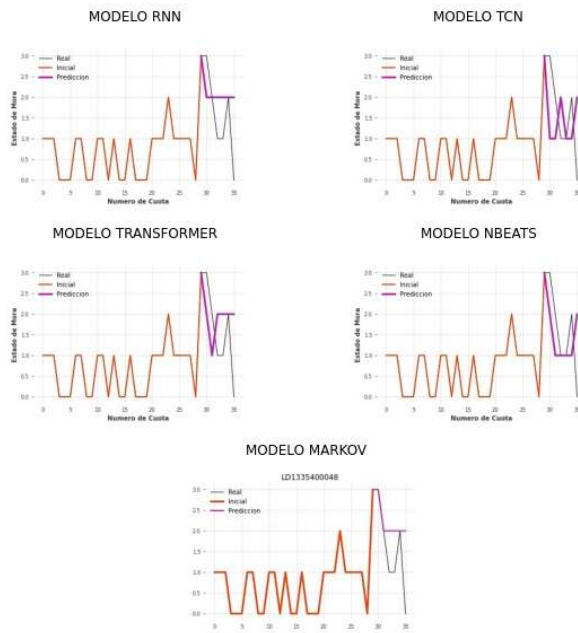
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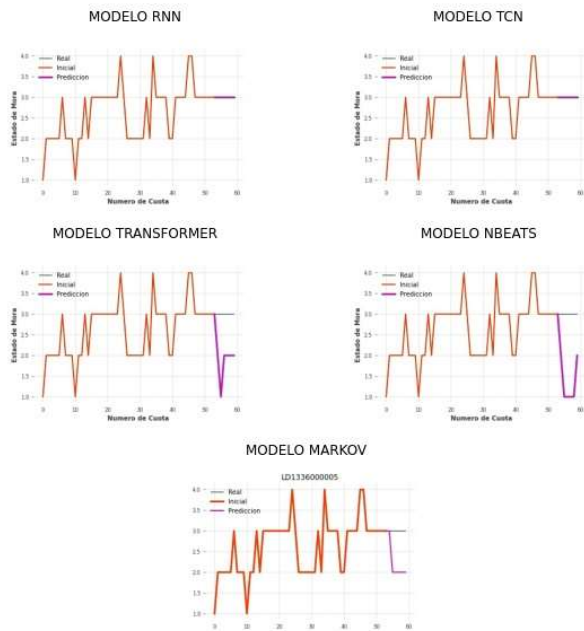
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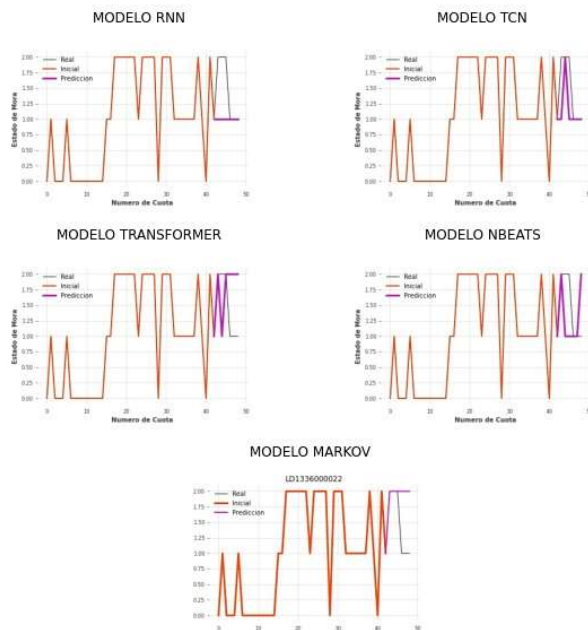
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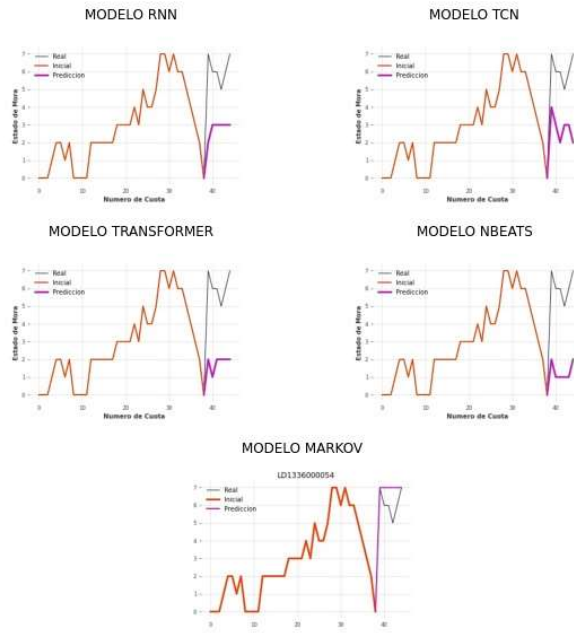
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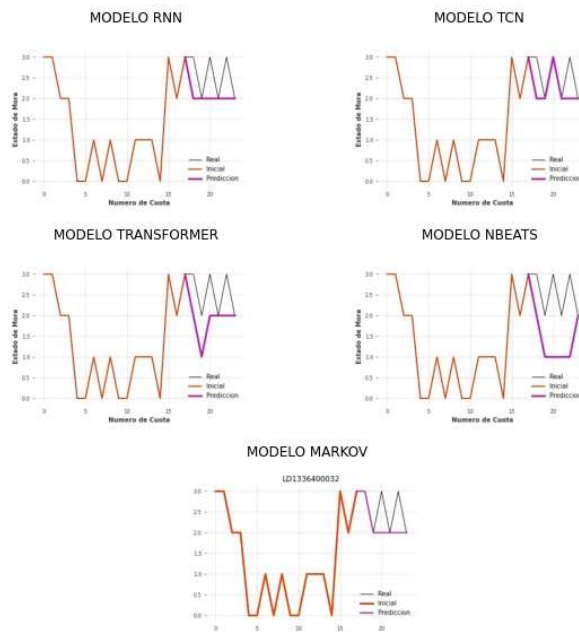
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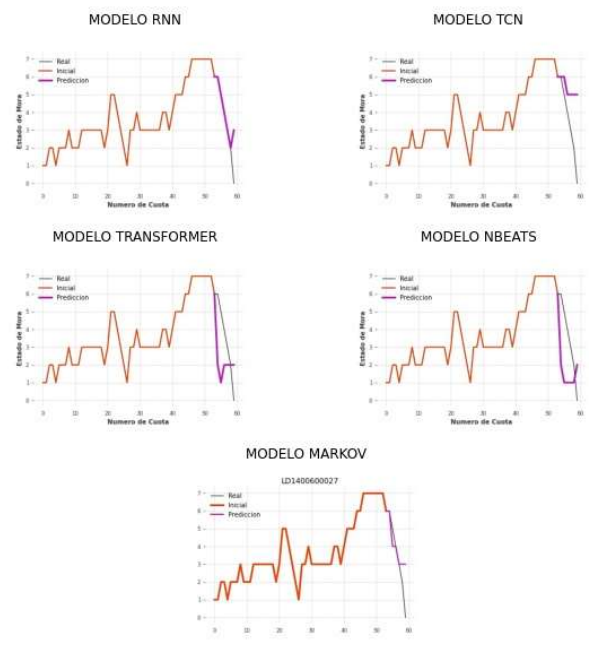
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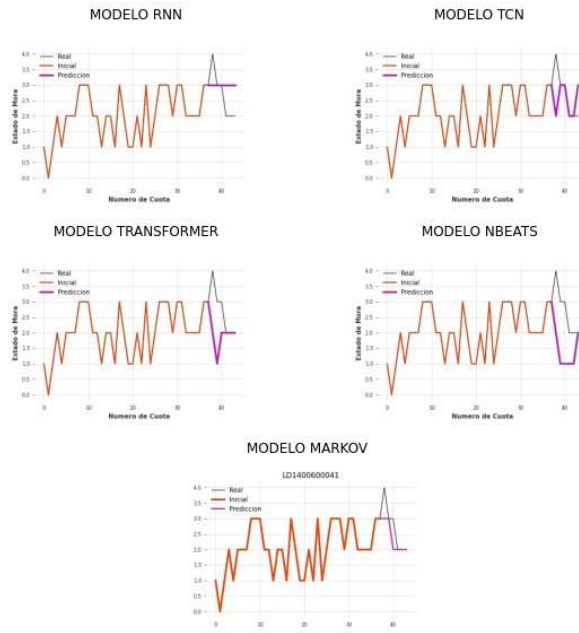
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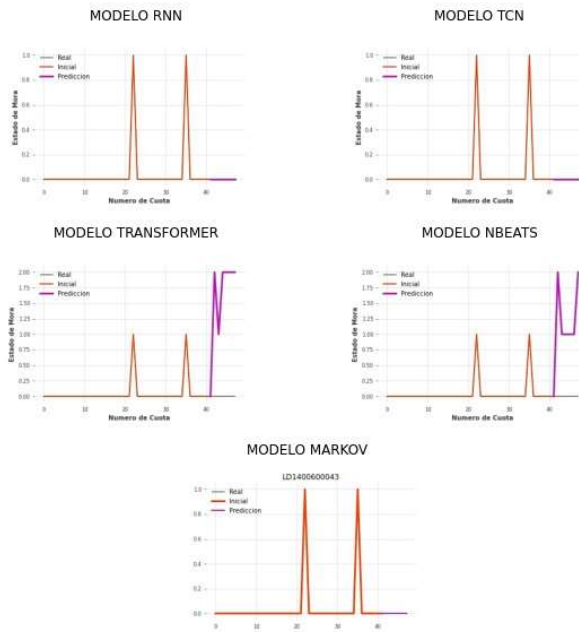
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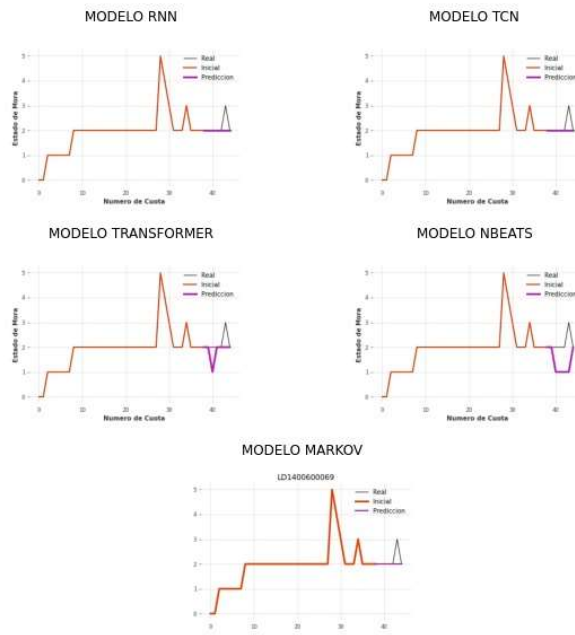


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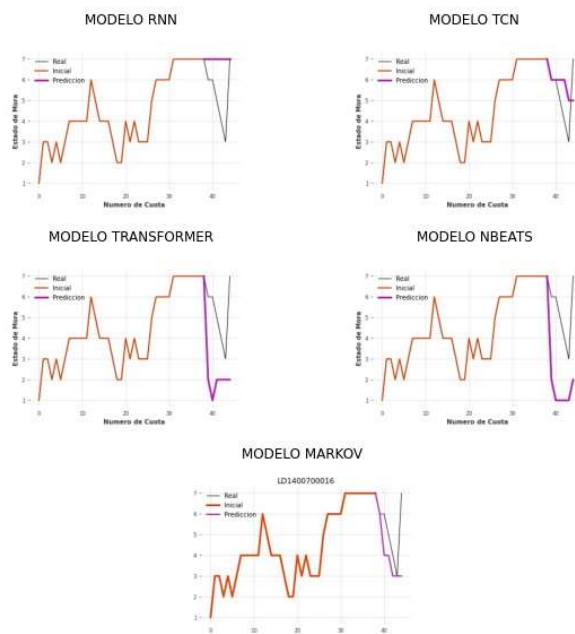




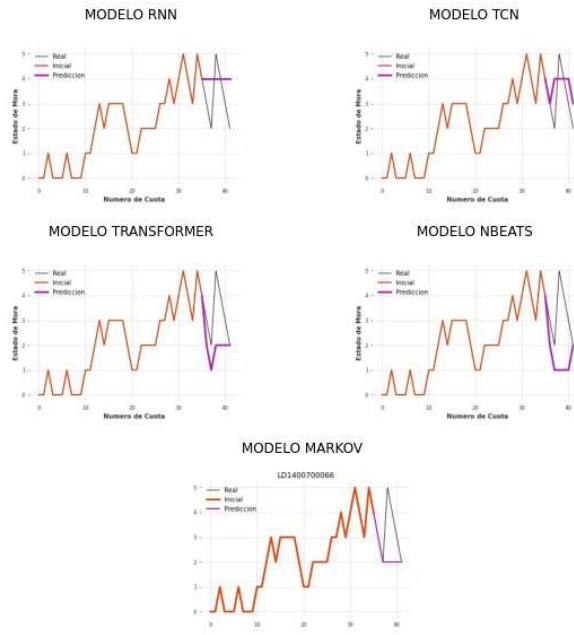
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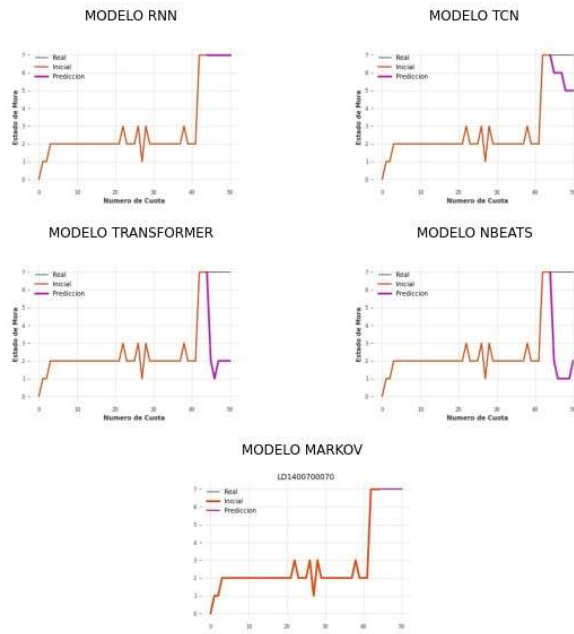
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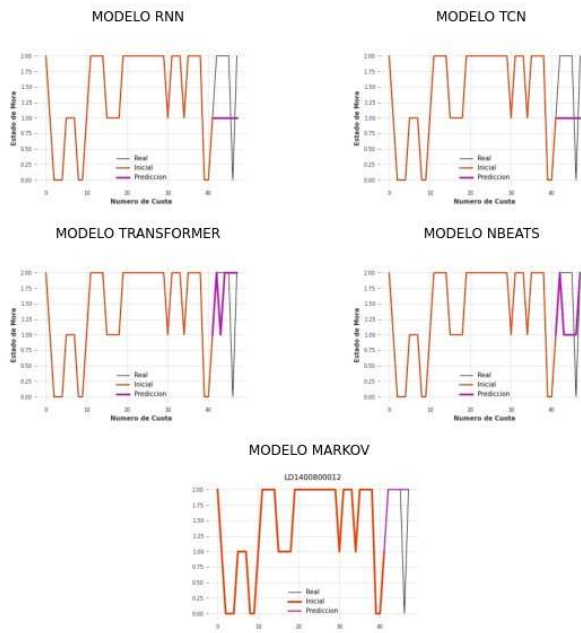
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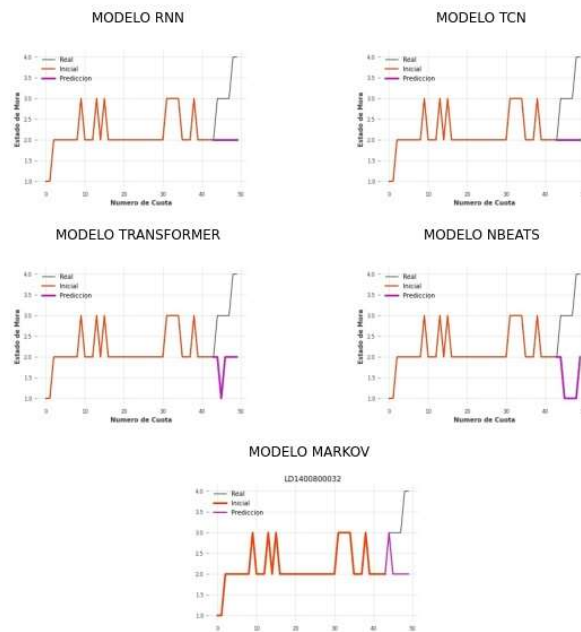
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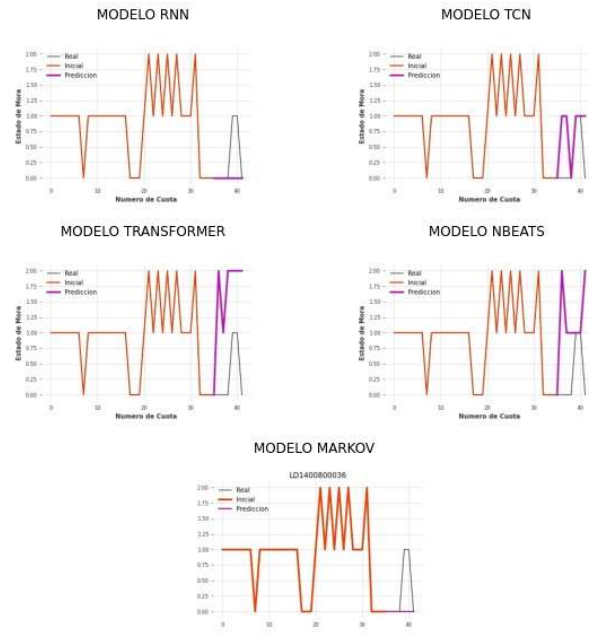
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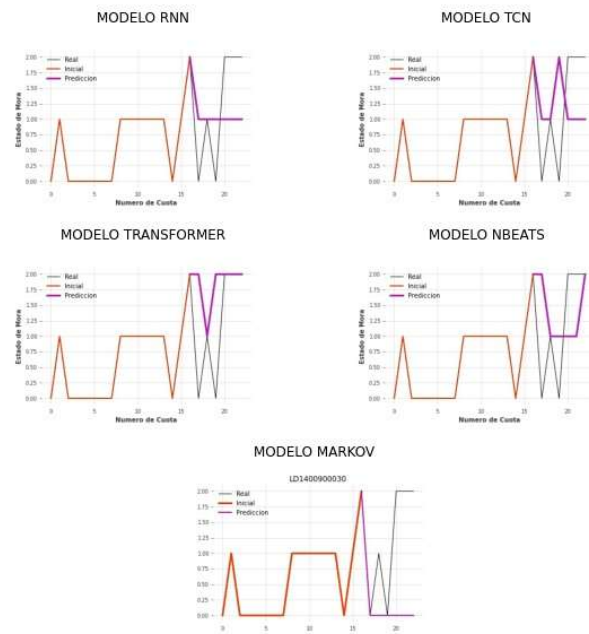
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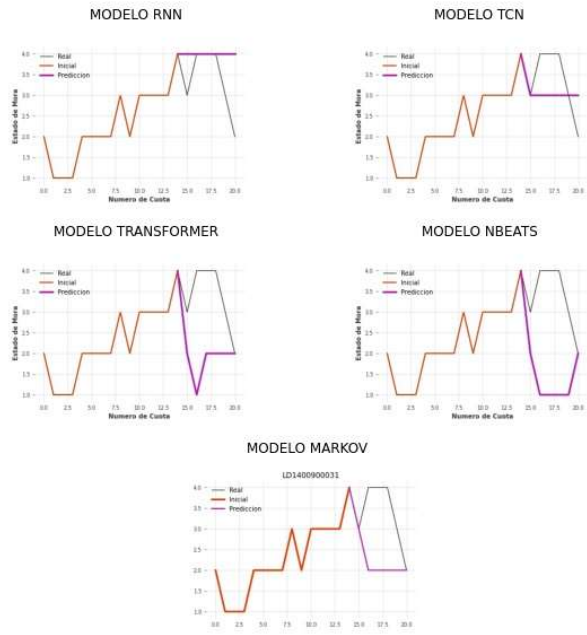
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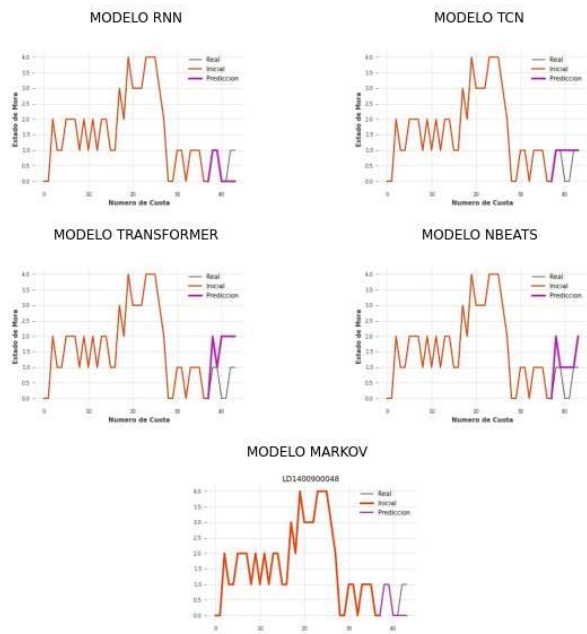
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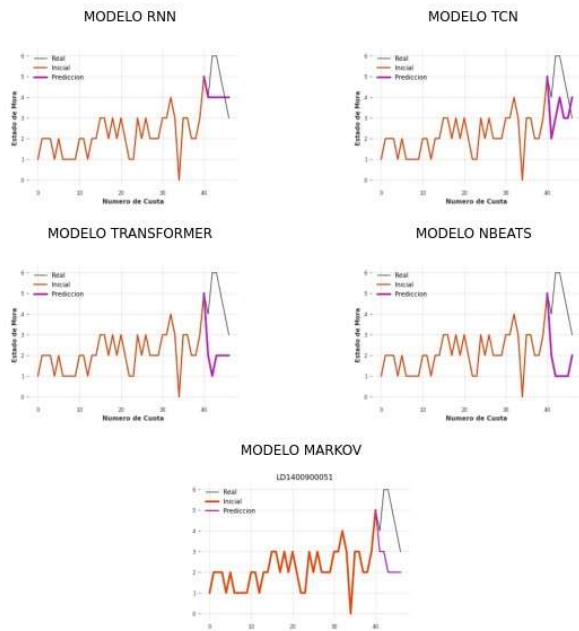
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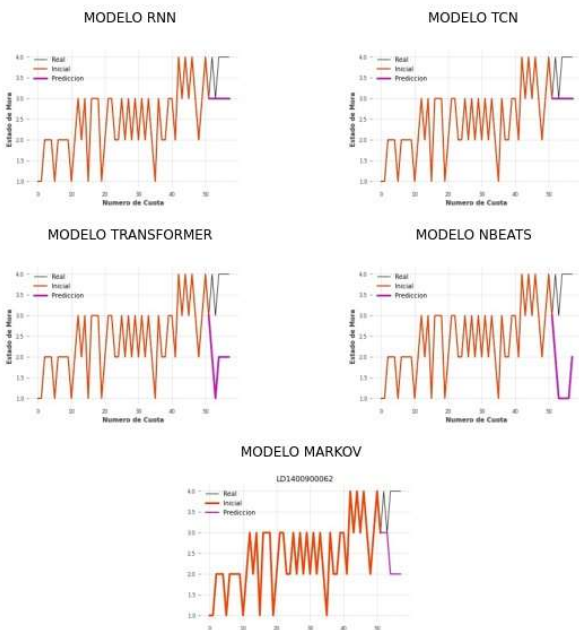
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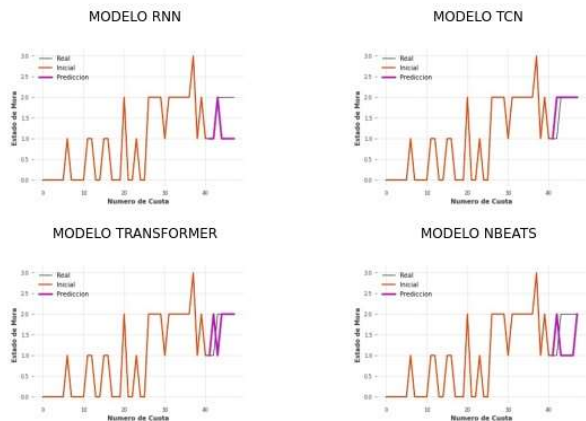
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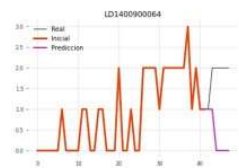
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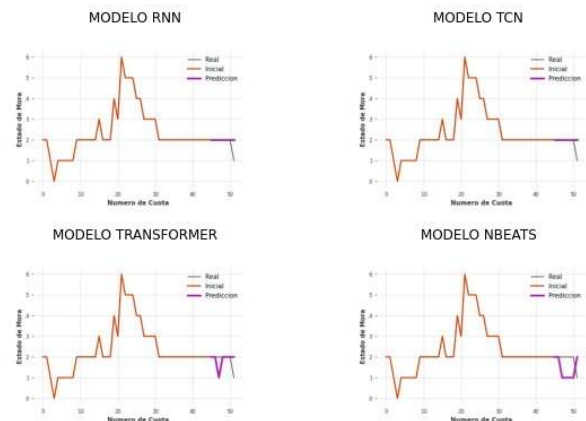
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MODELO MARKOV



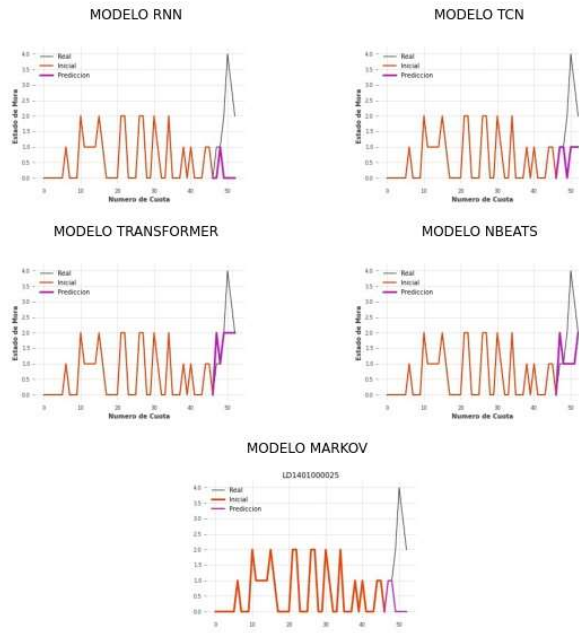
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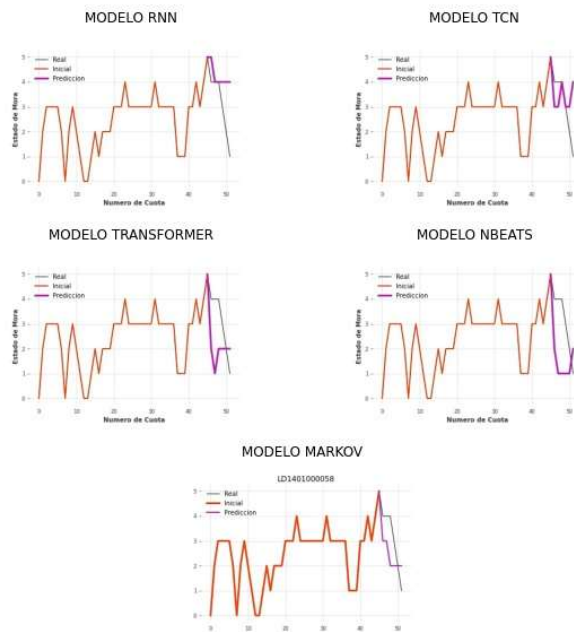
MODELO MARKOV



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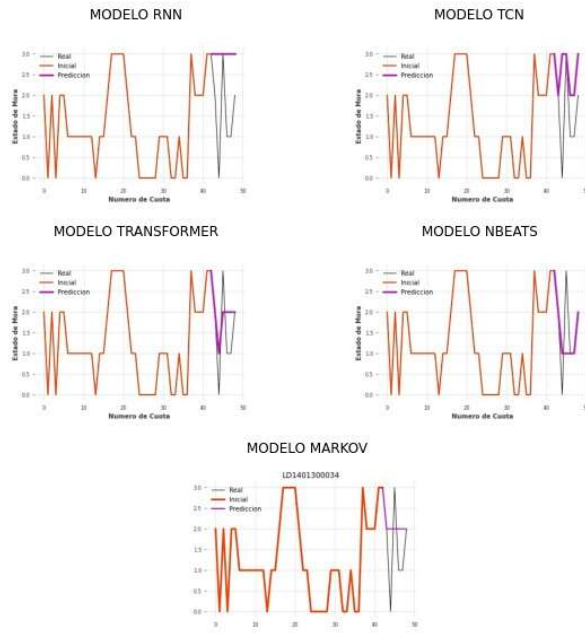


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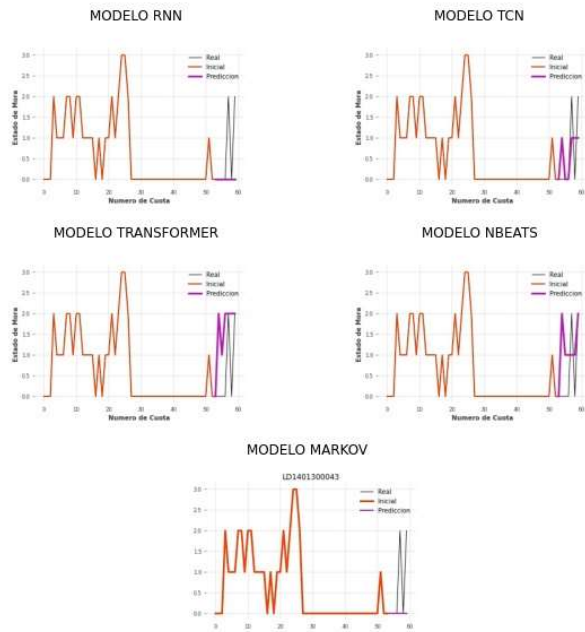




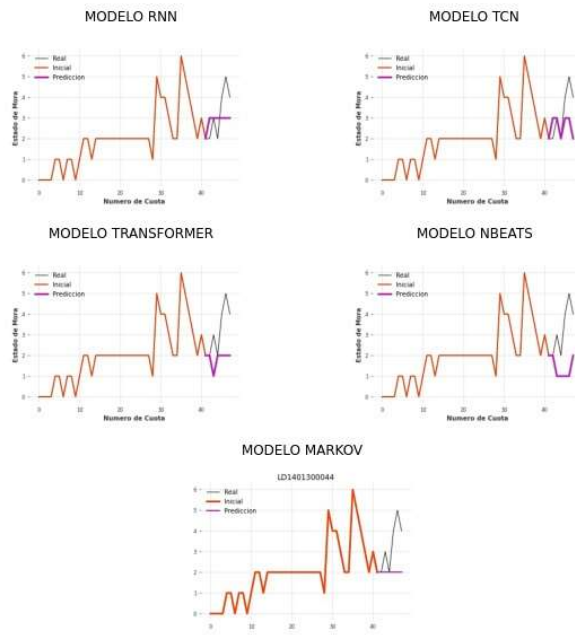
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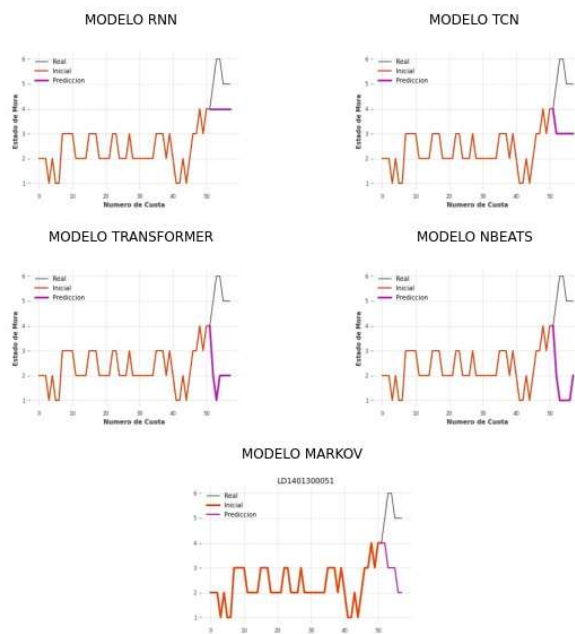
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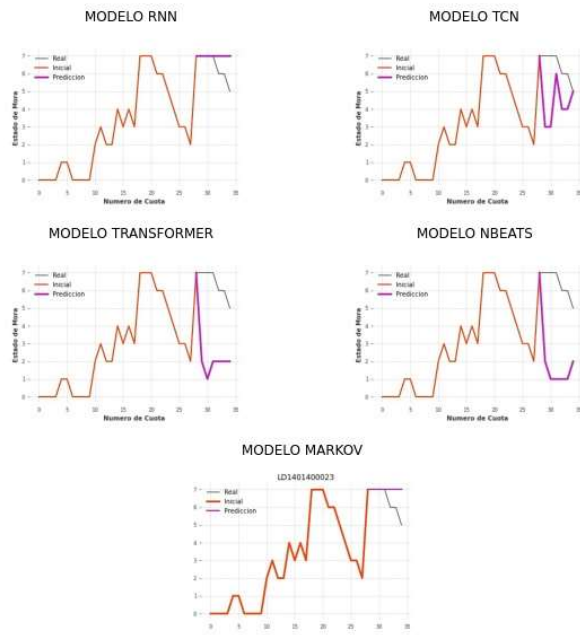
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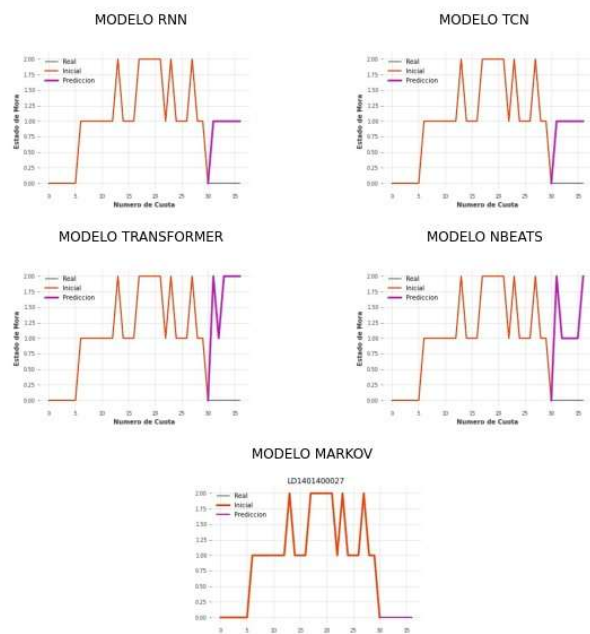
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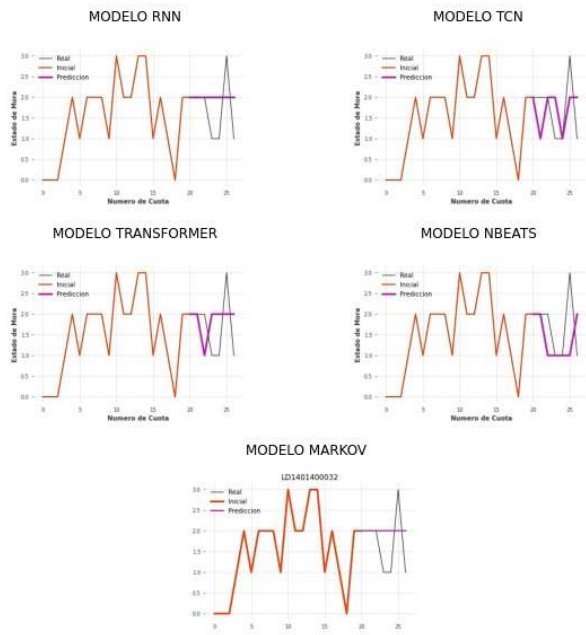
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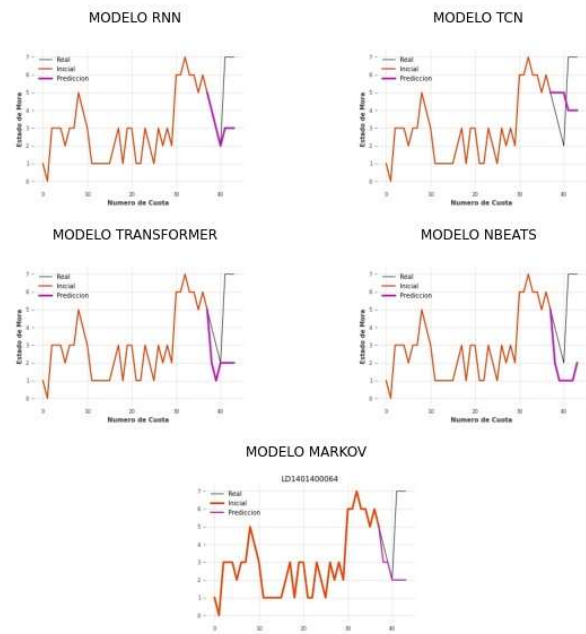
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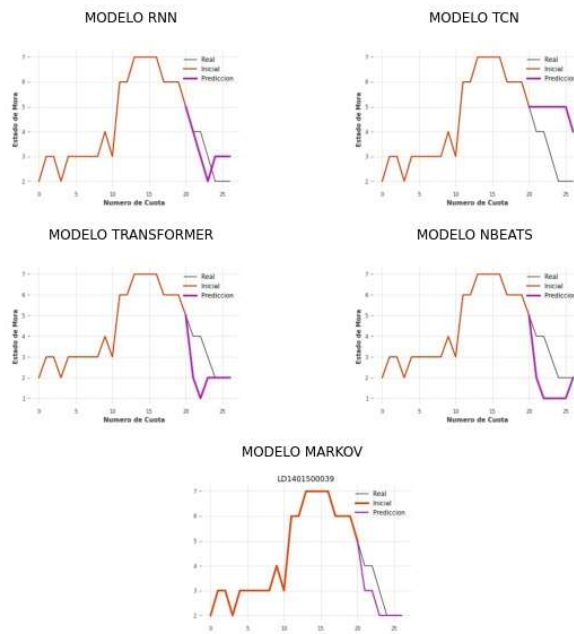
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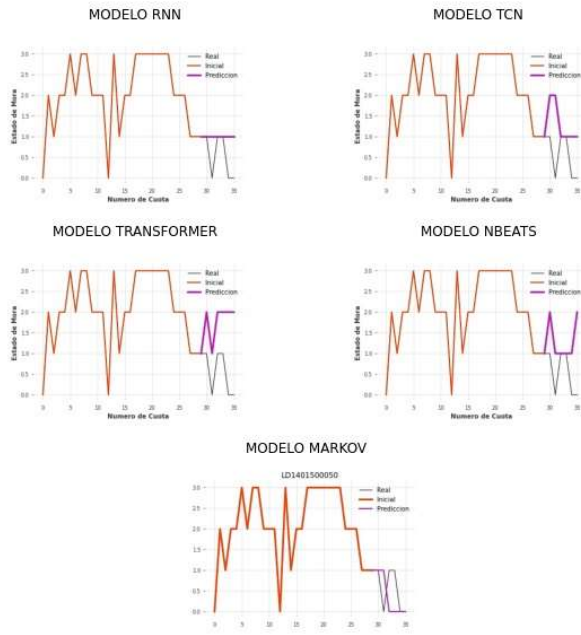
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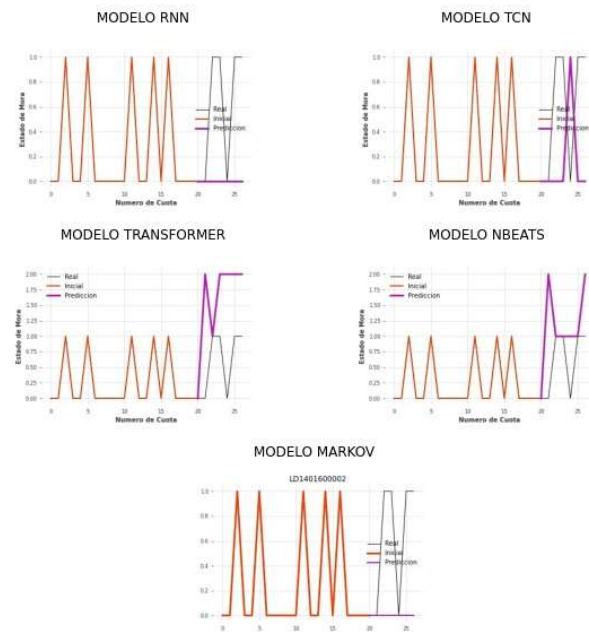
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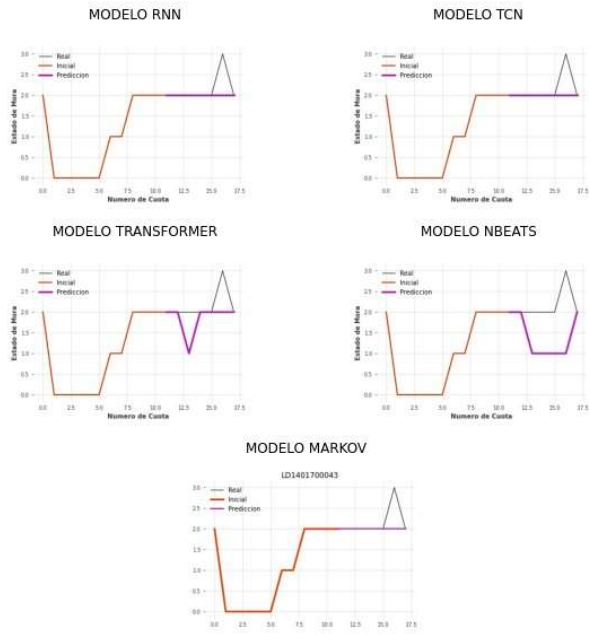
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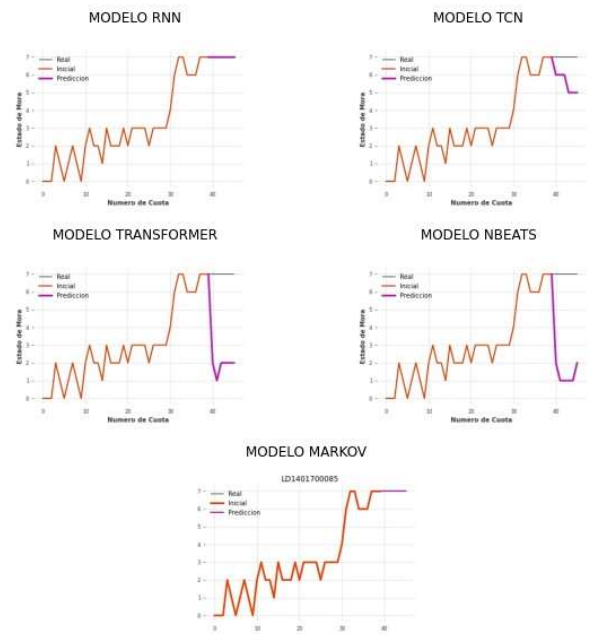
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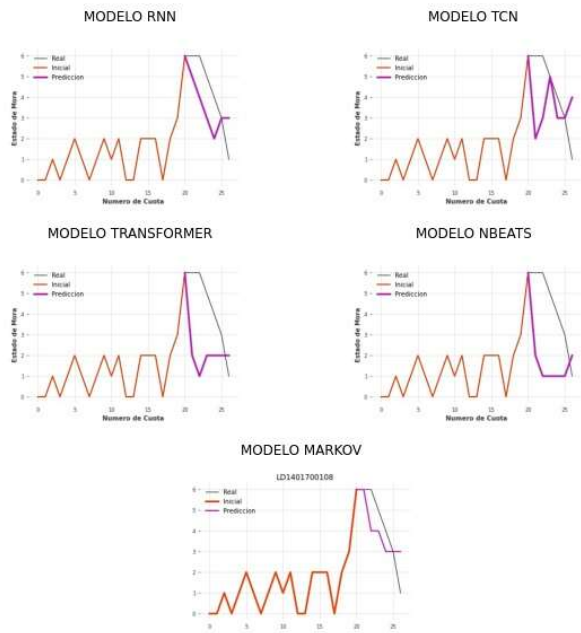
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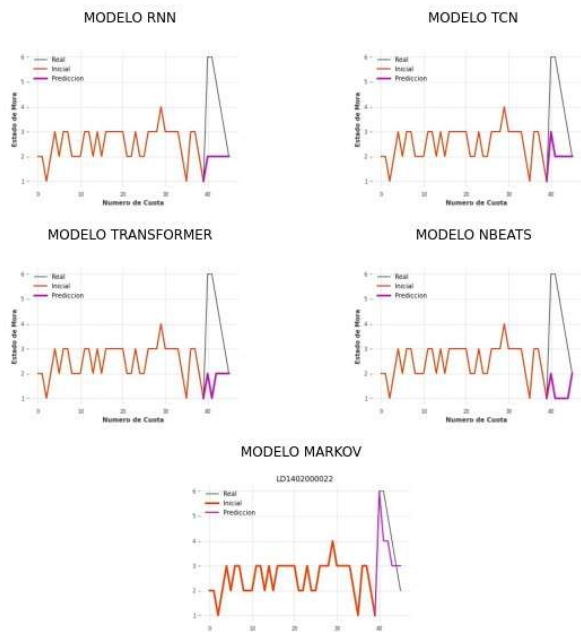
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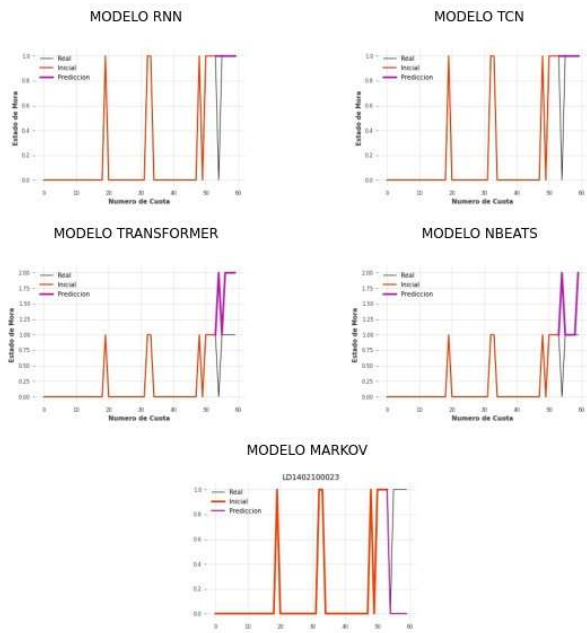


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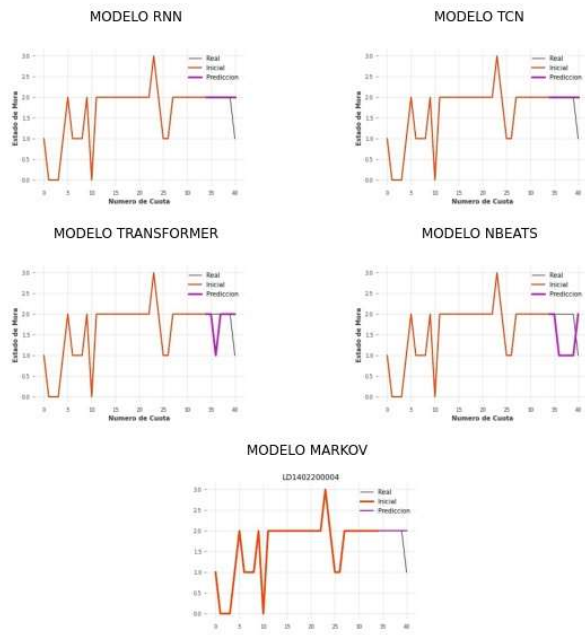
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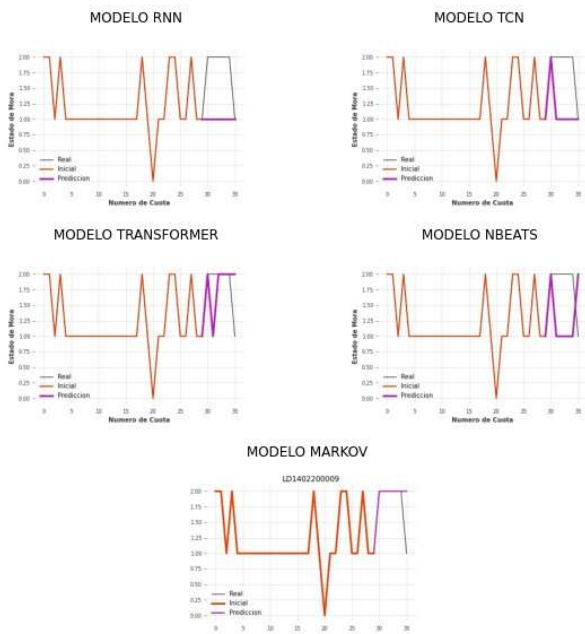
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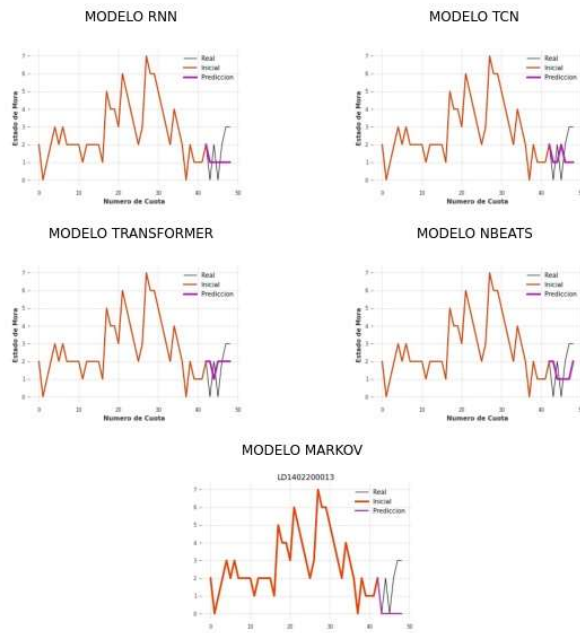
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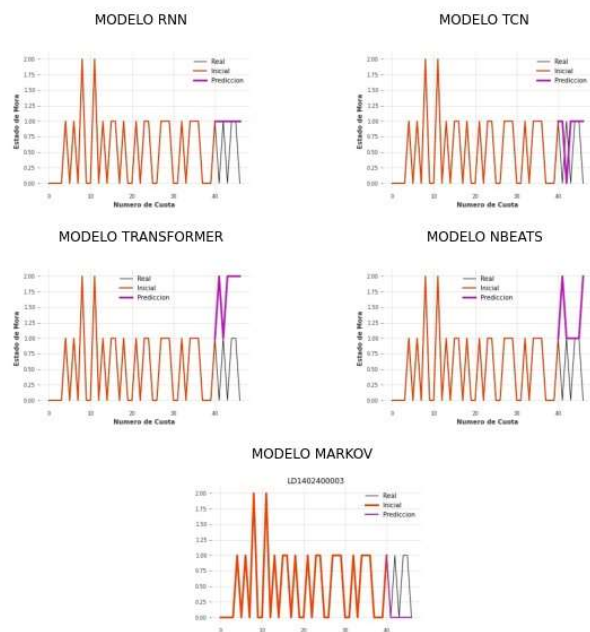
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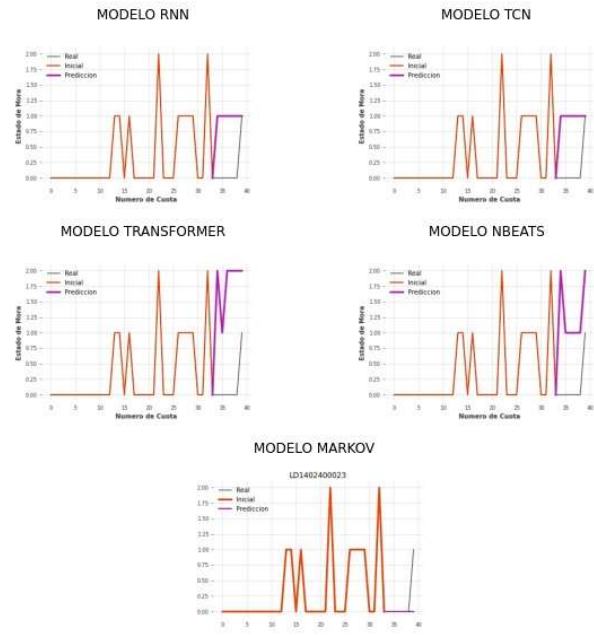
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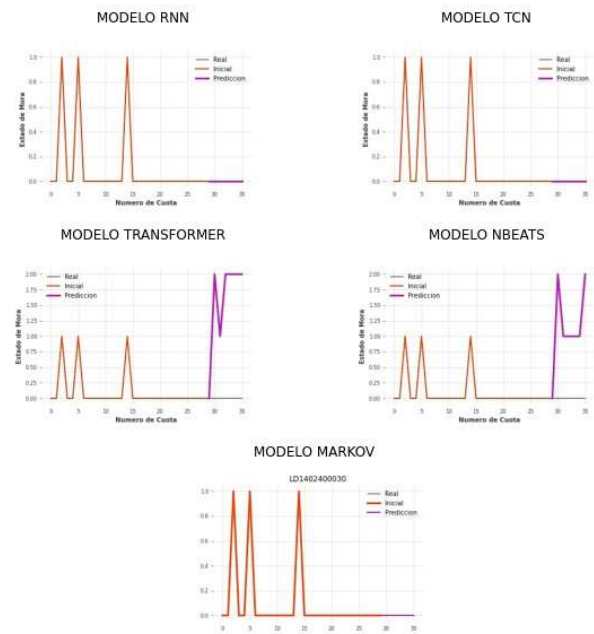
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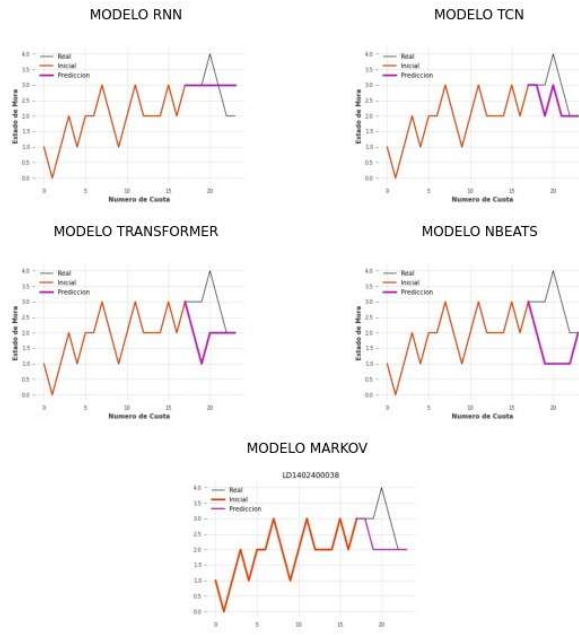
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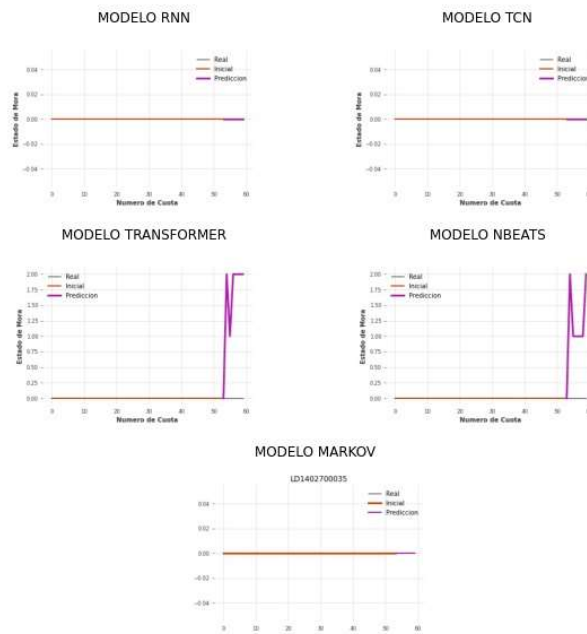
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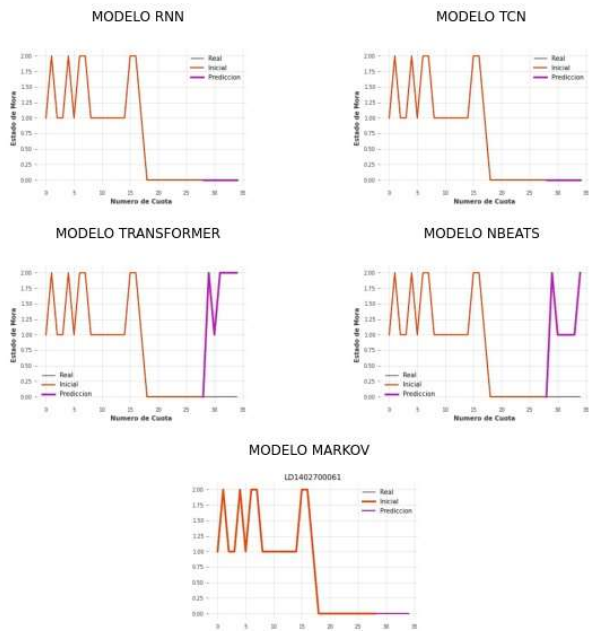
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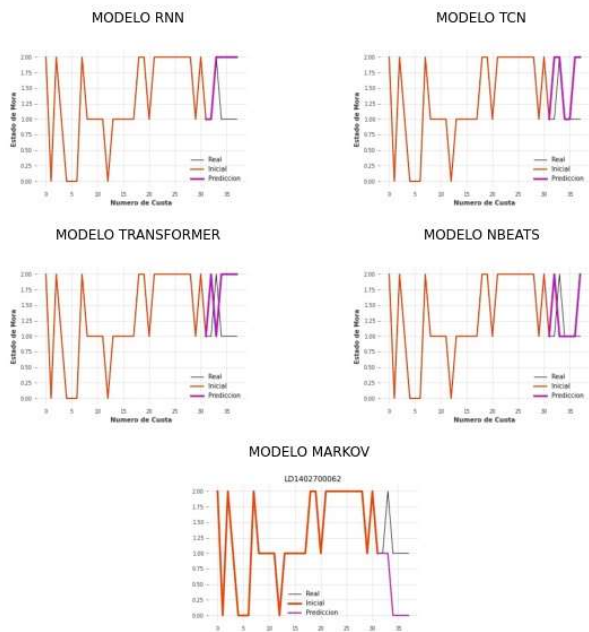
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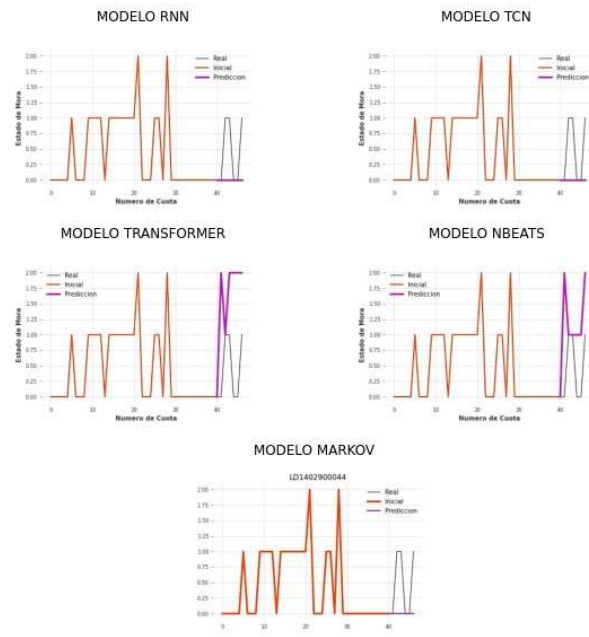
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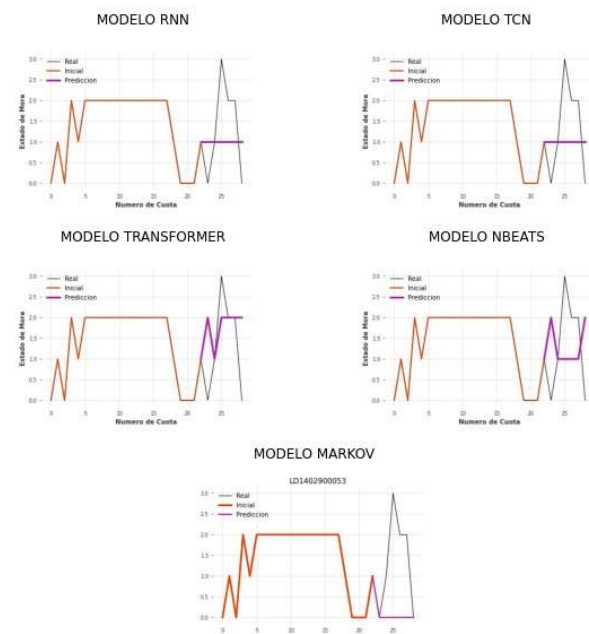
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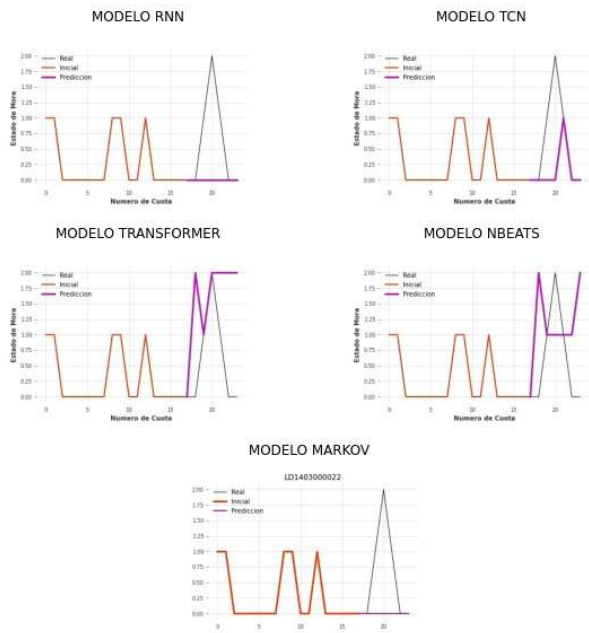
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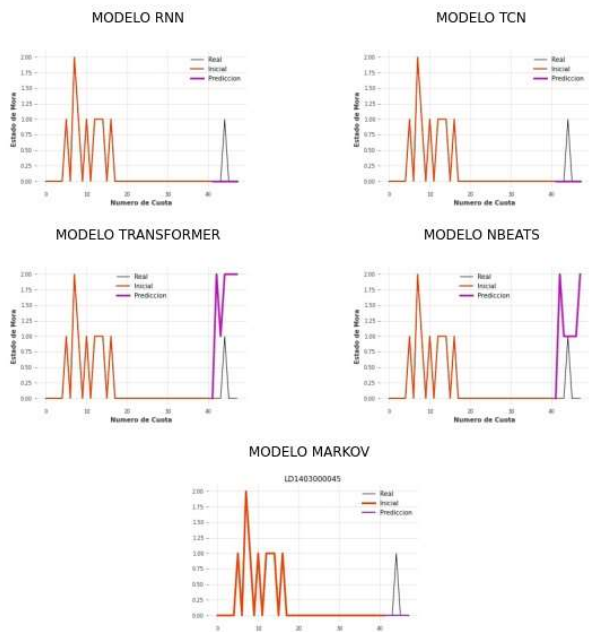
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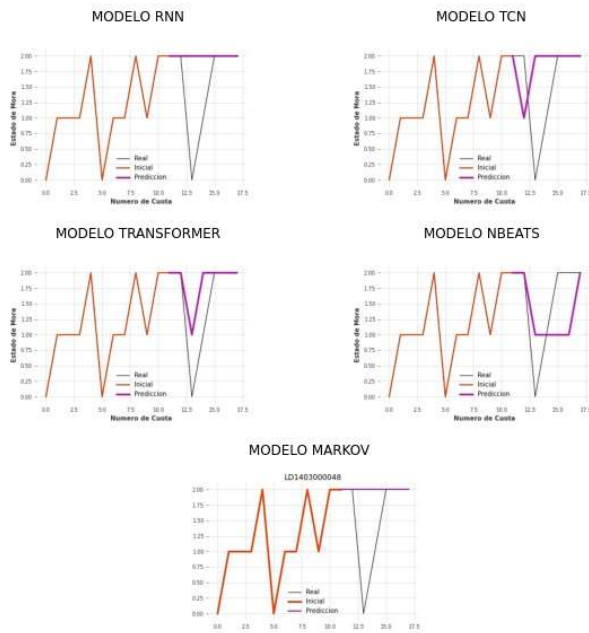


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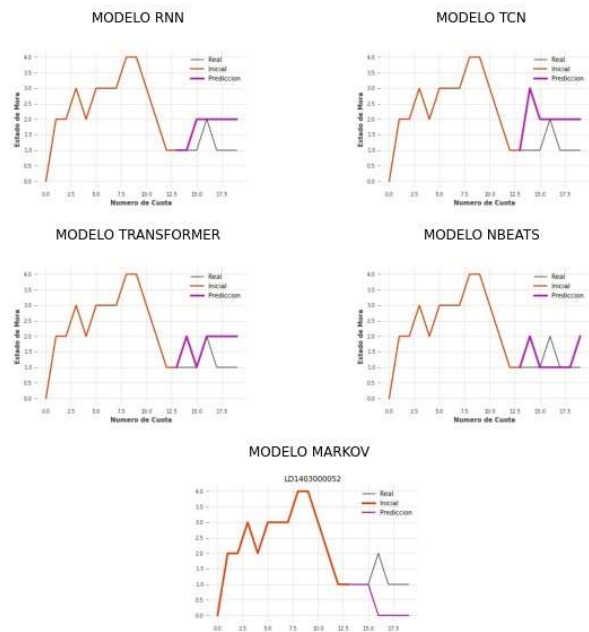




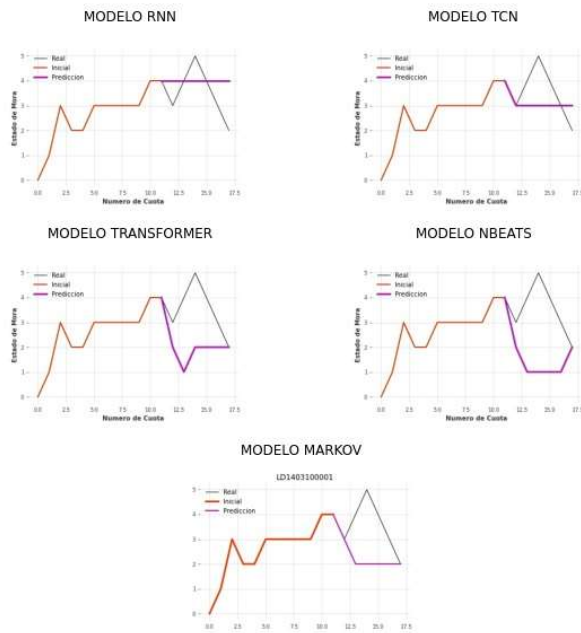
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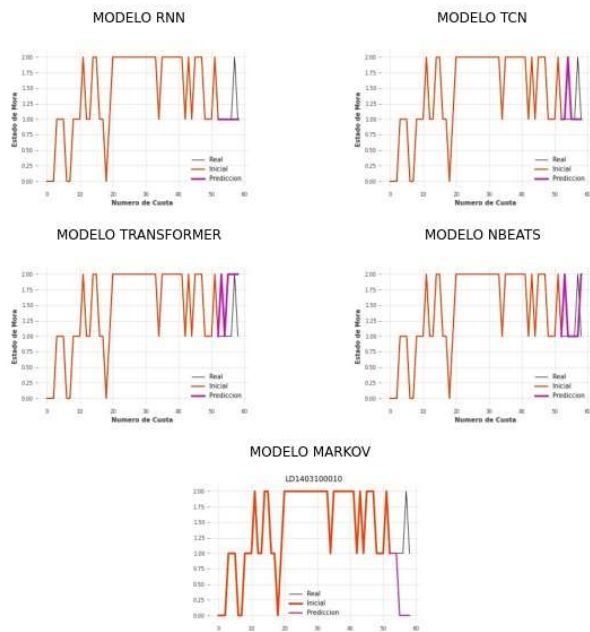
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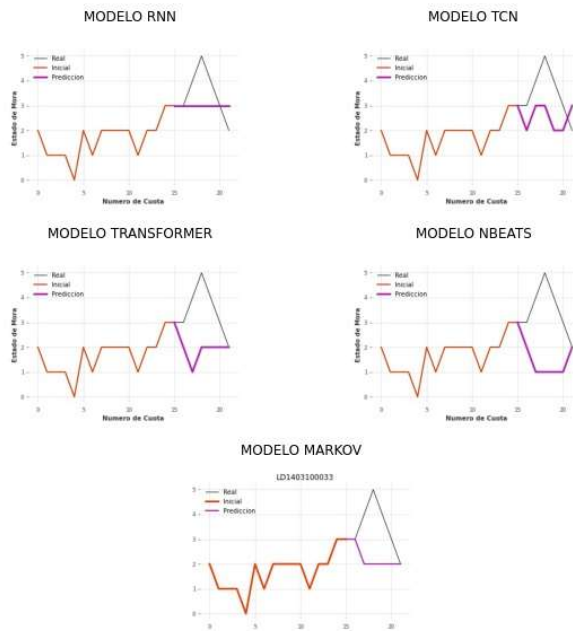
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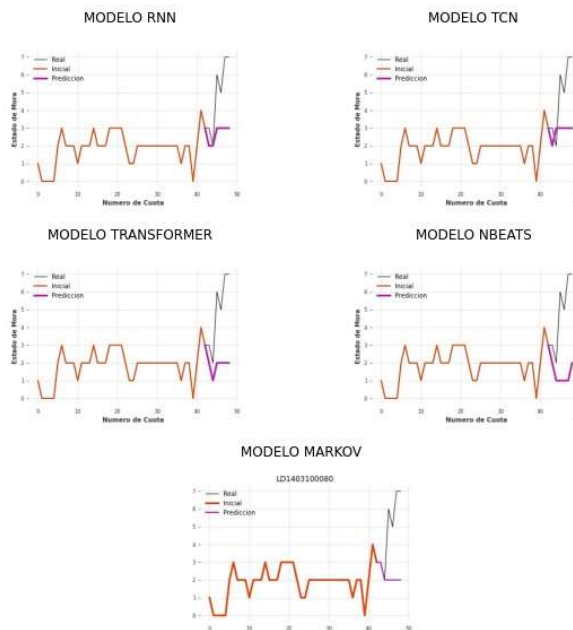
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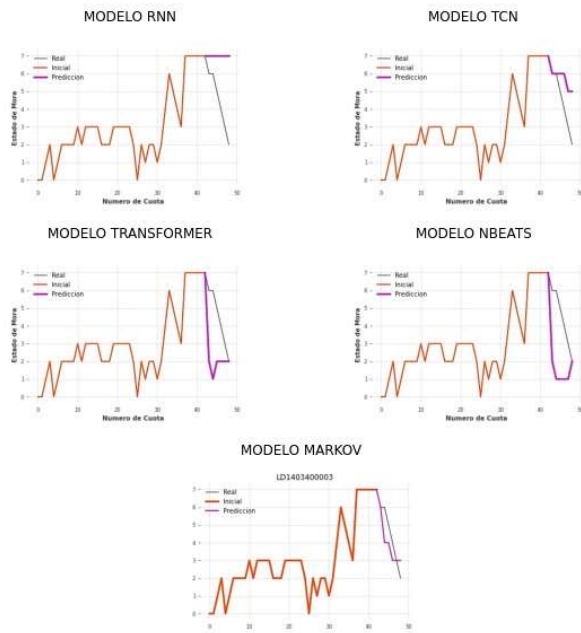
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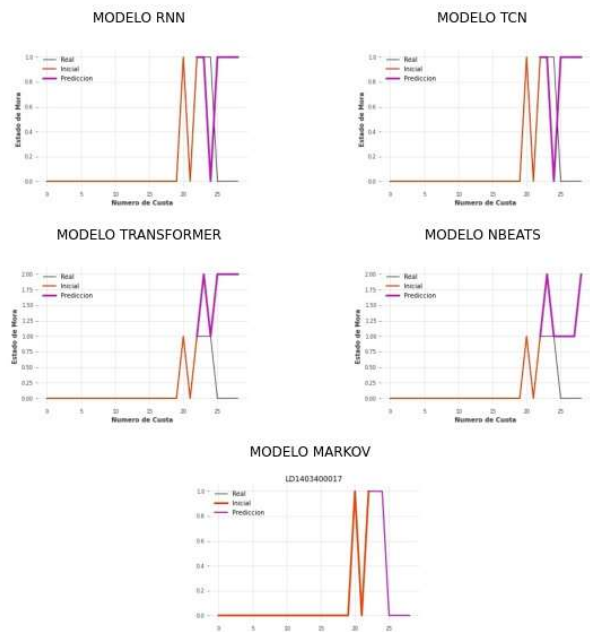
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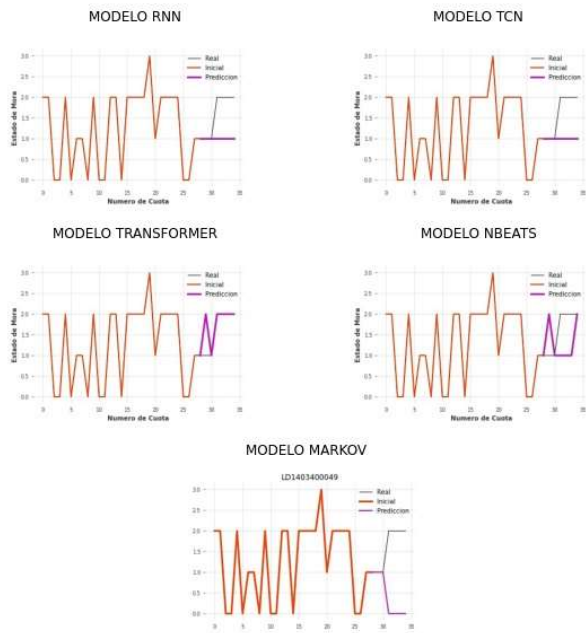
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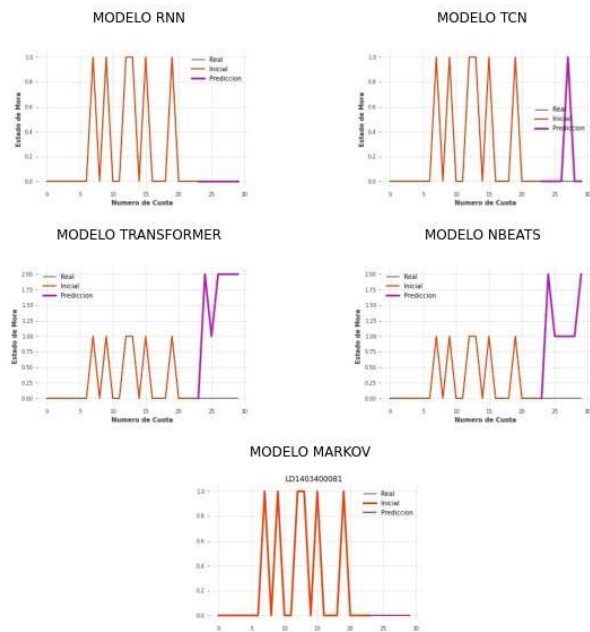
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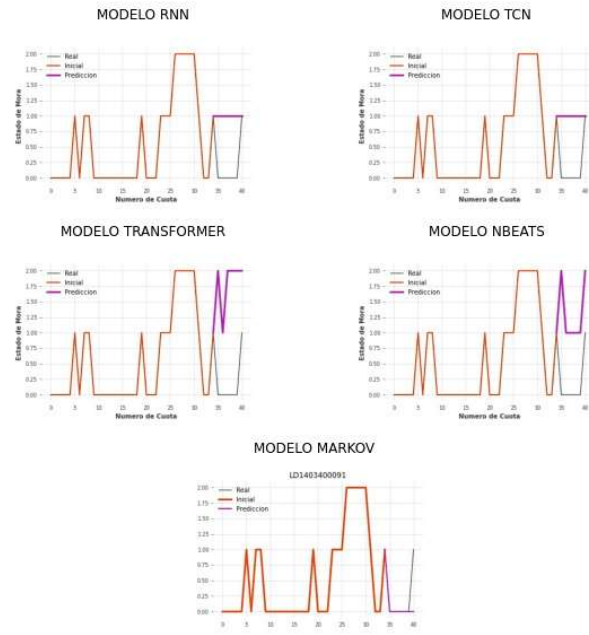
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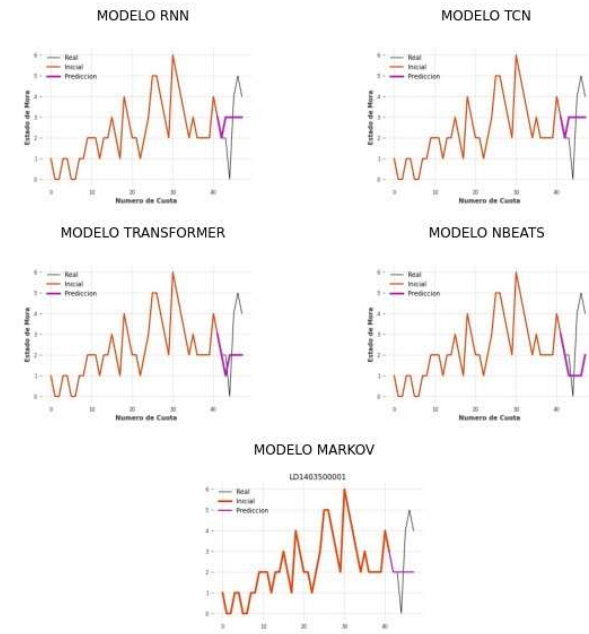
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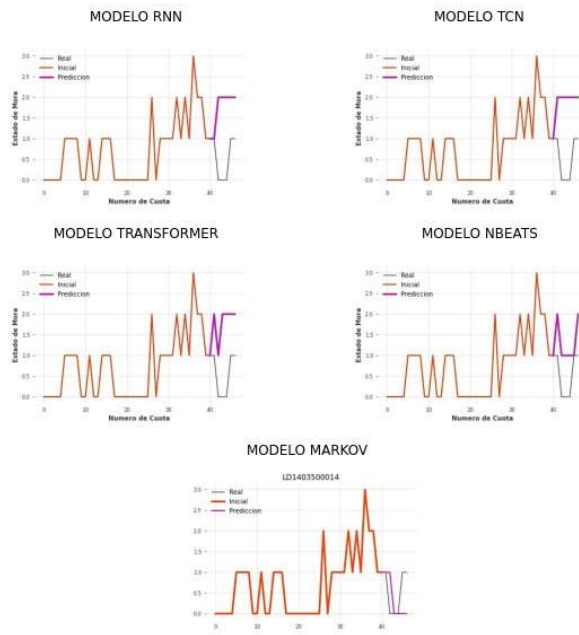
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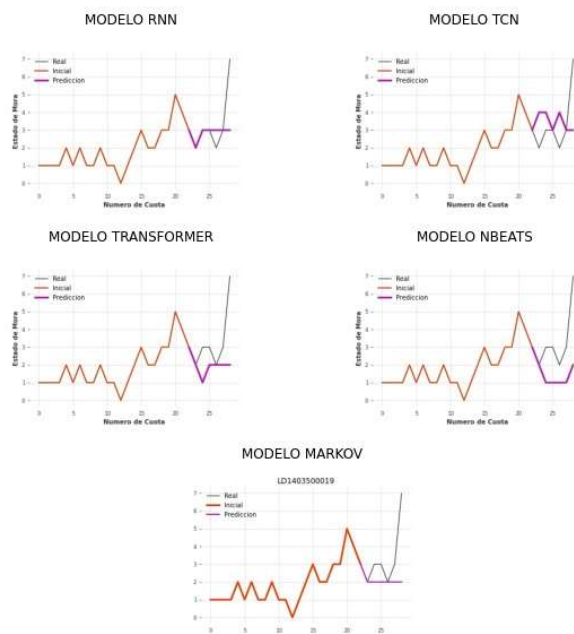
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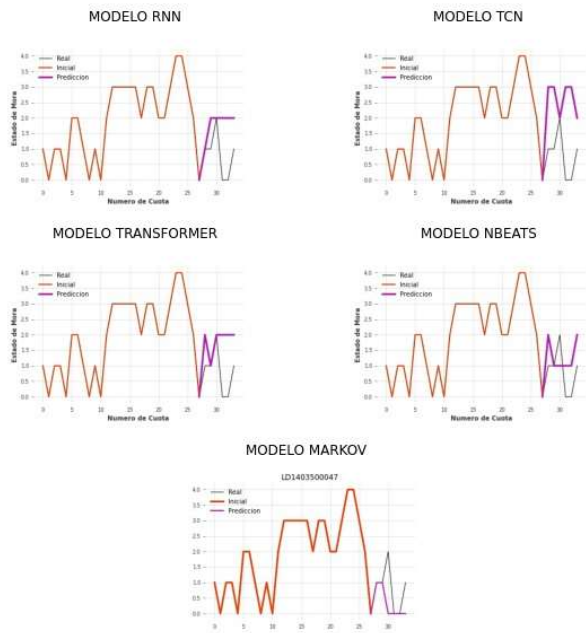
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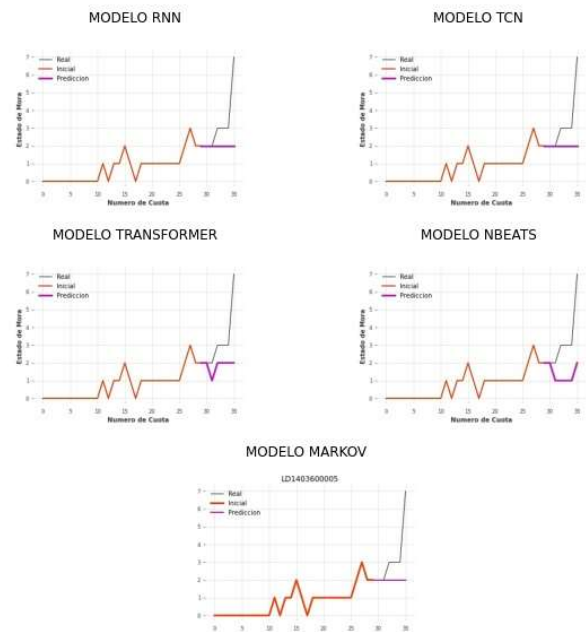
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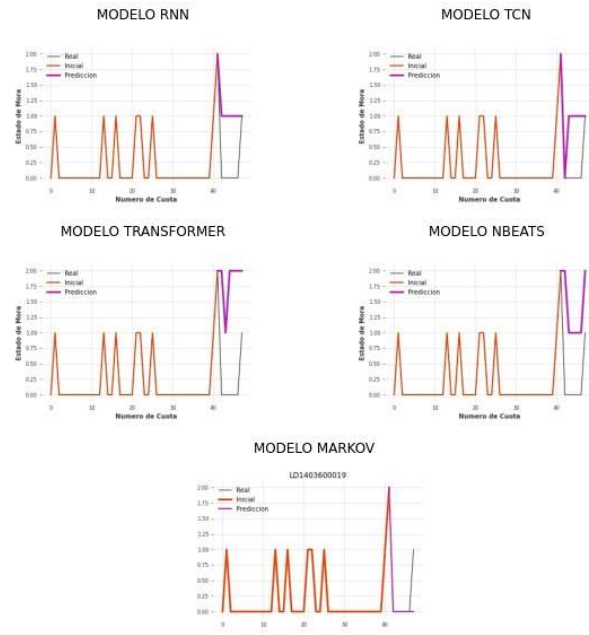


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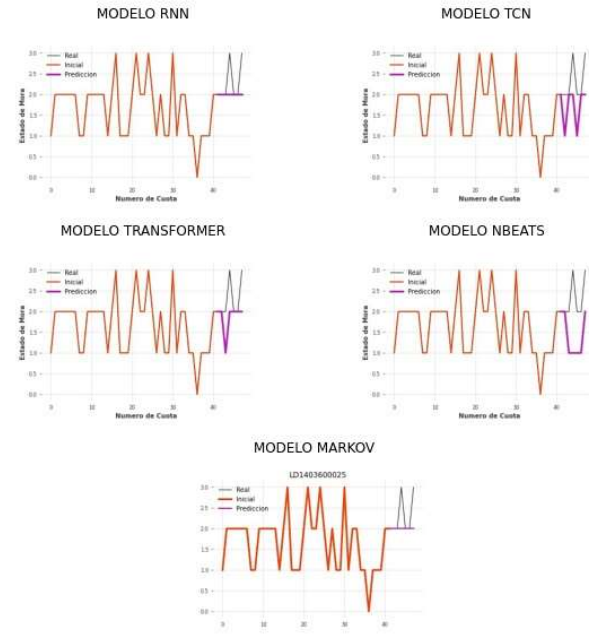




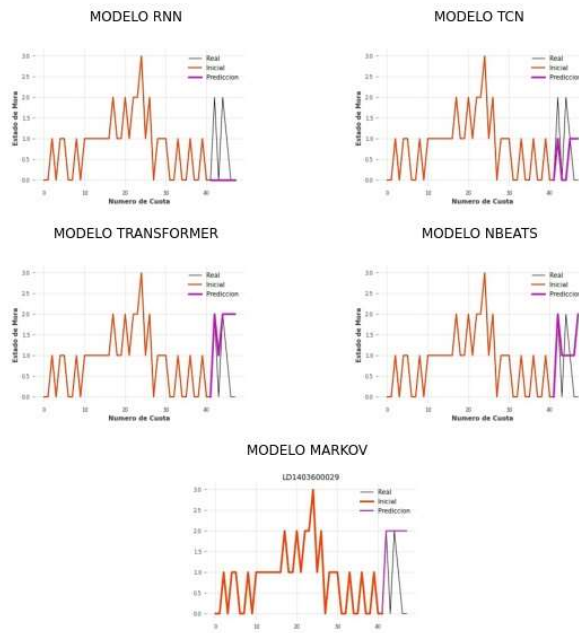
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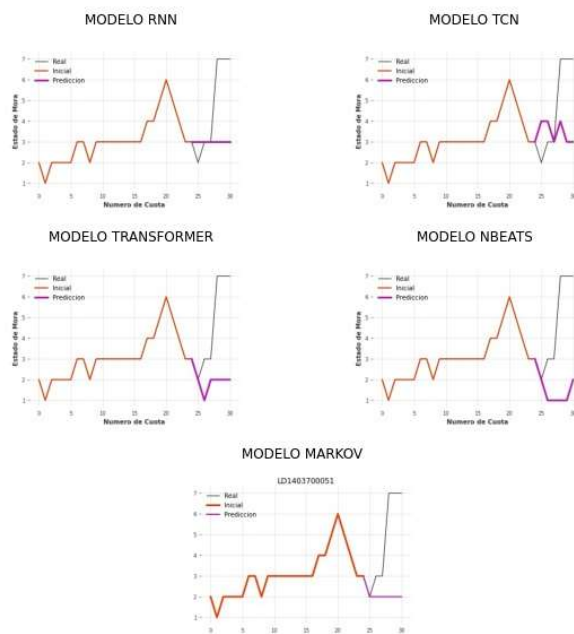
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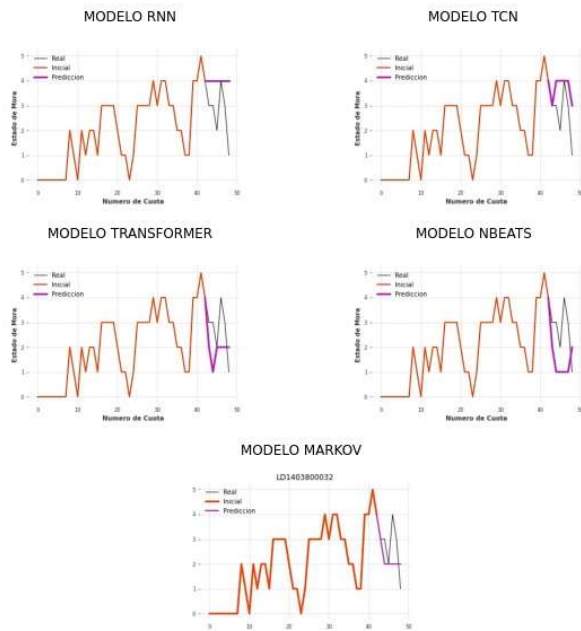
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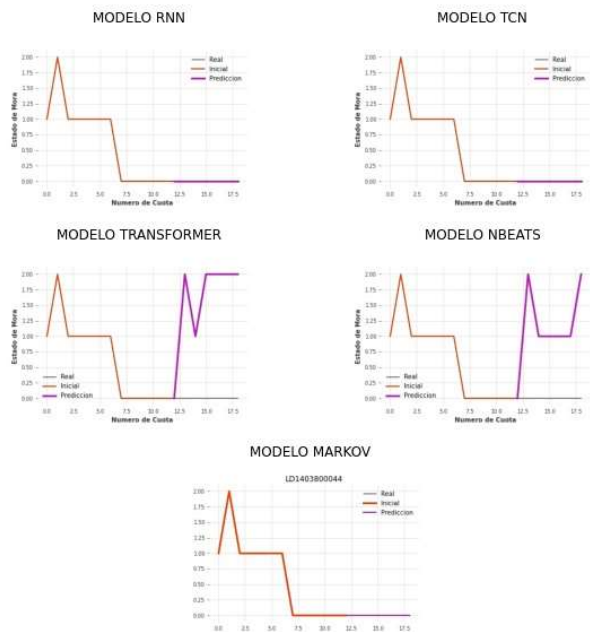
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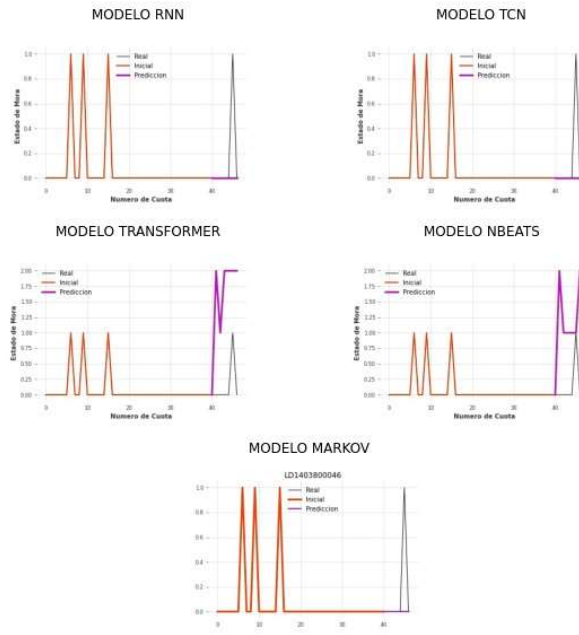
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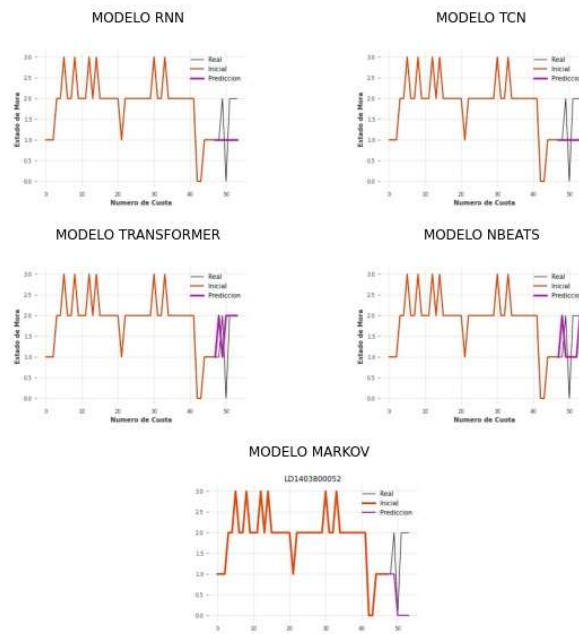
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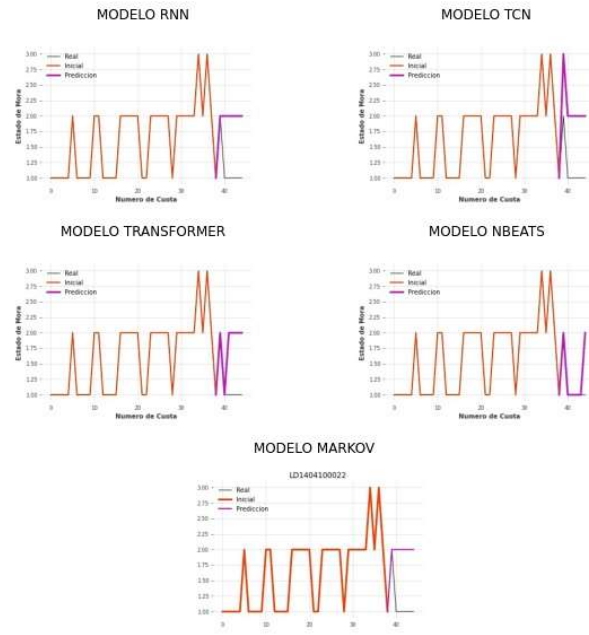
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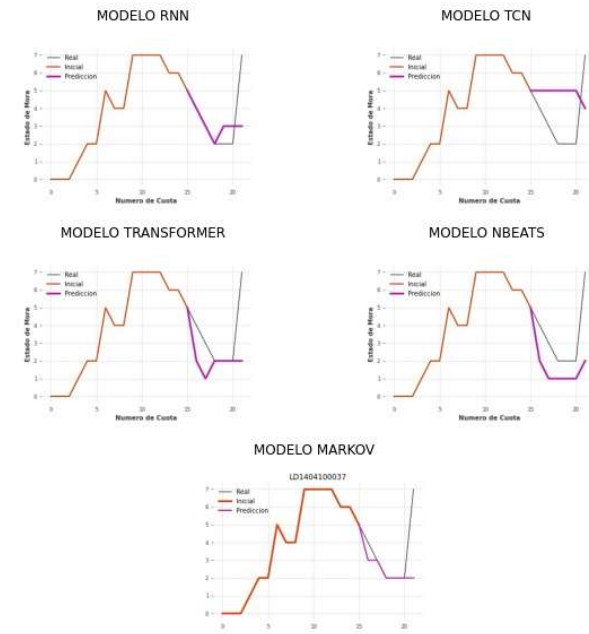
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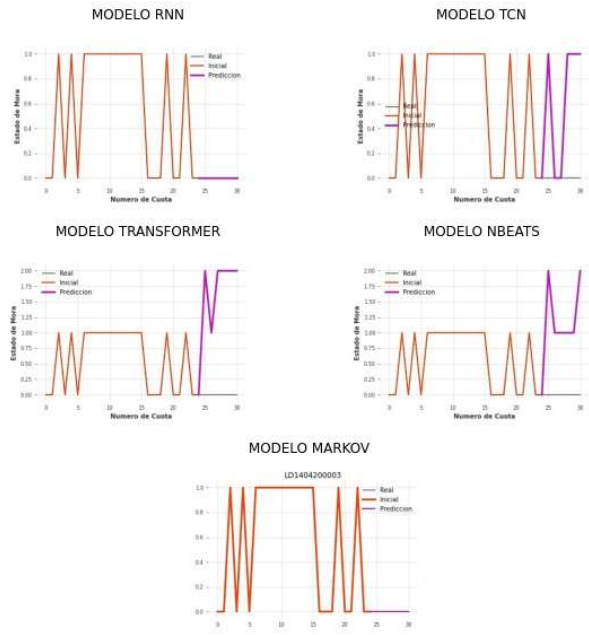
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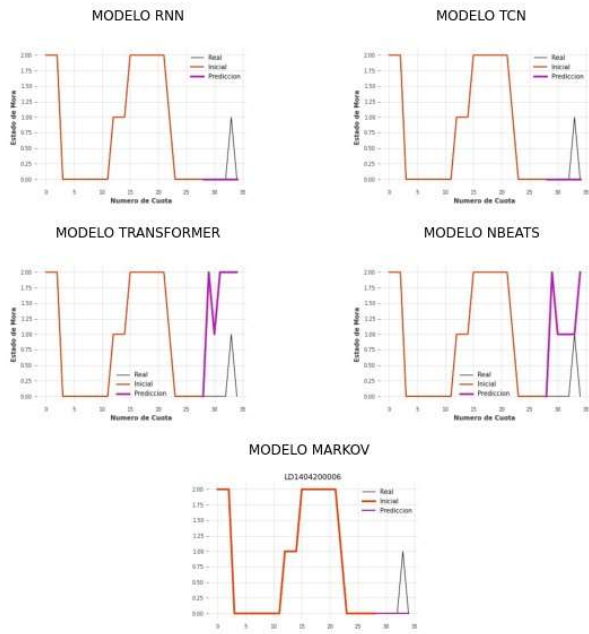
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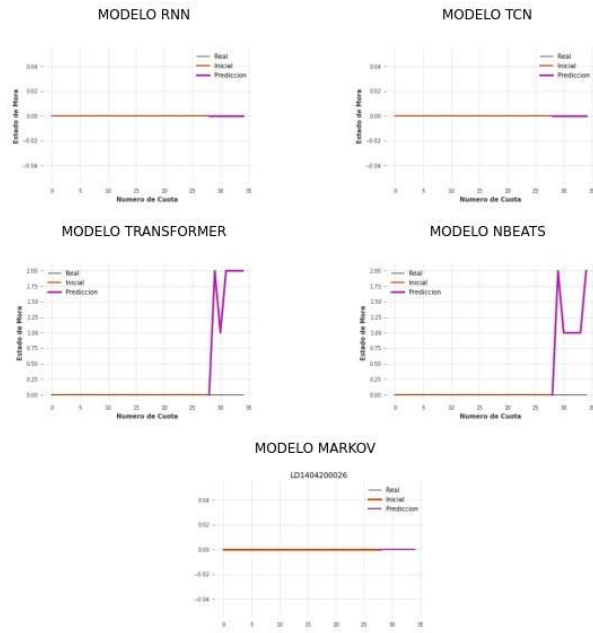
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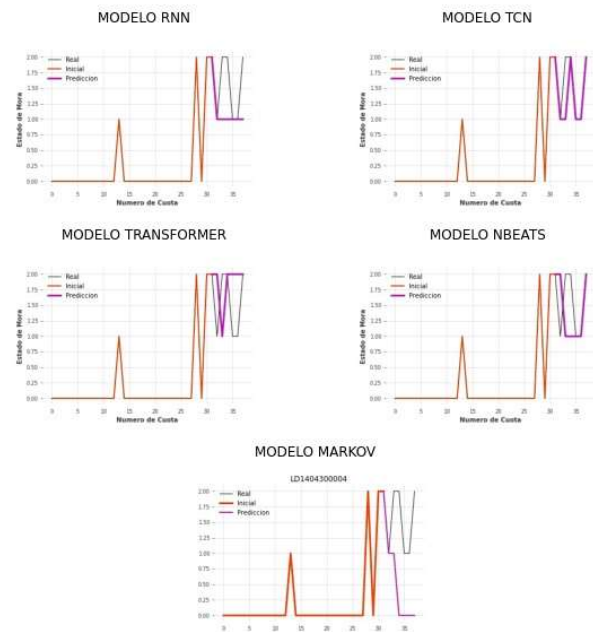
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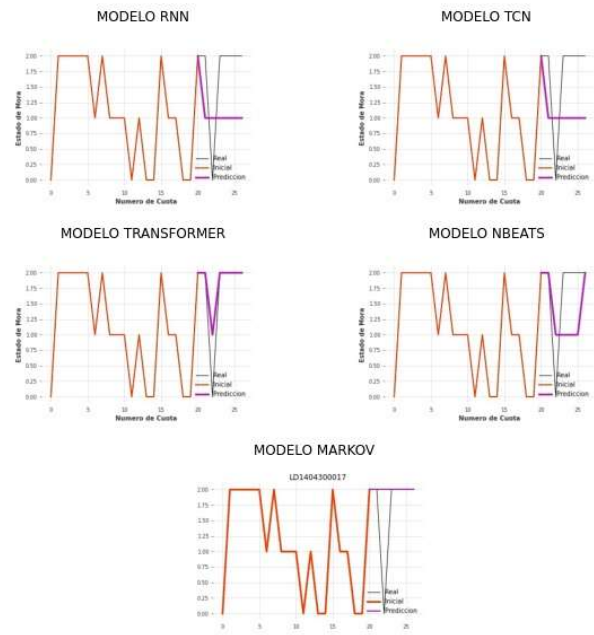
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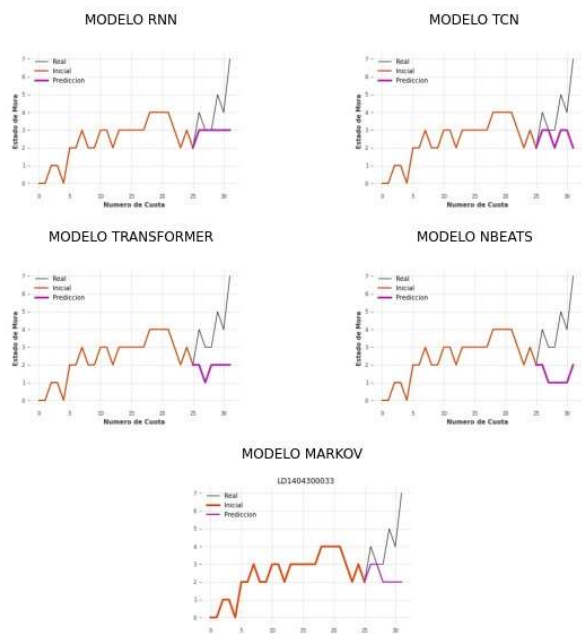
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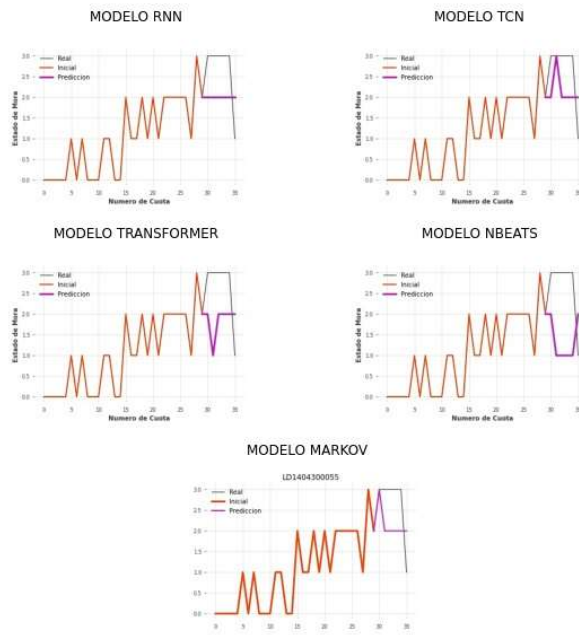


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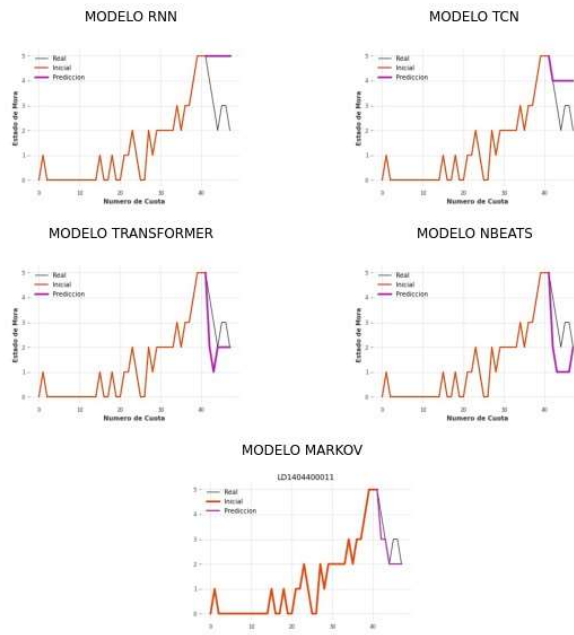
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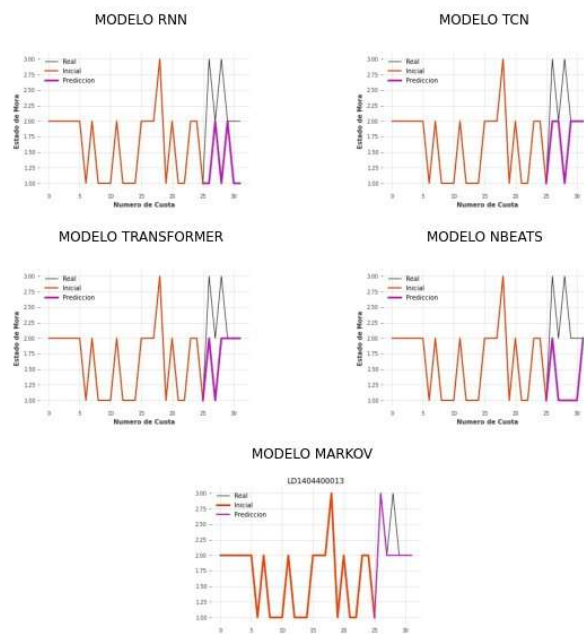
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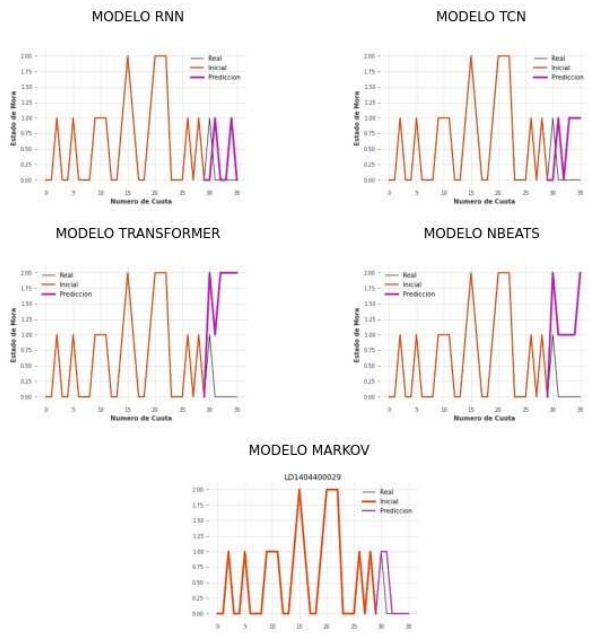
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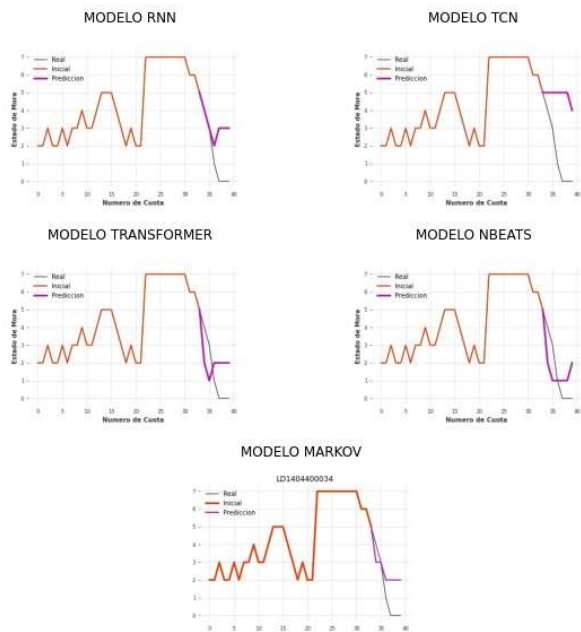
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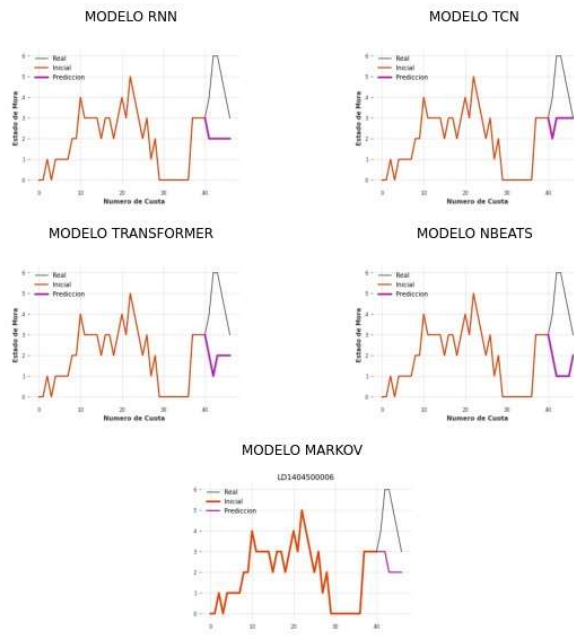
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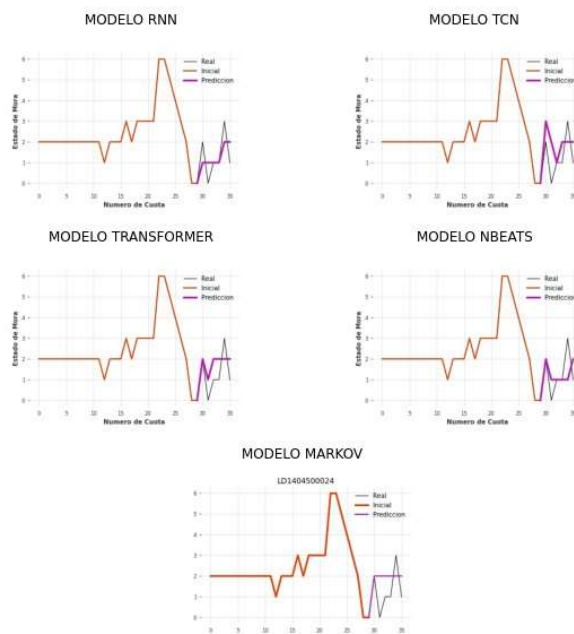
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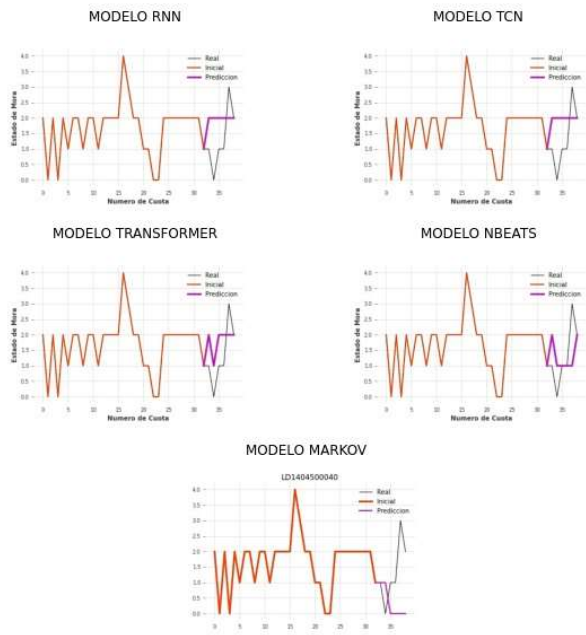
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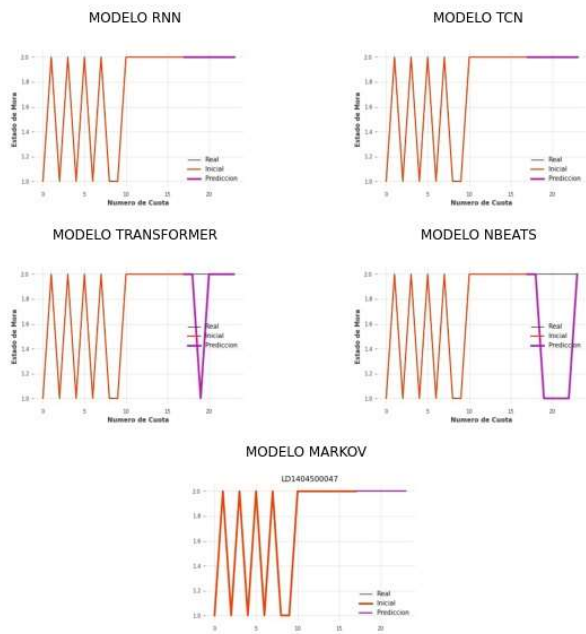
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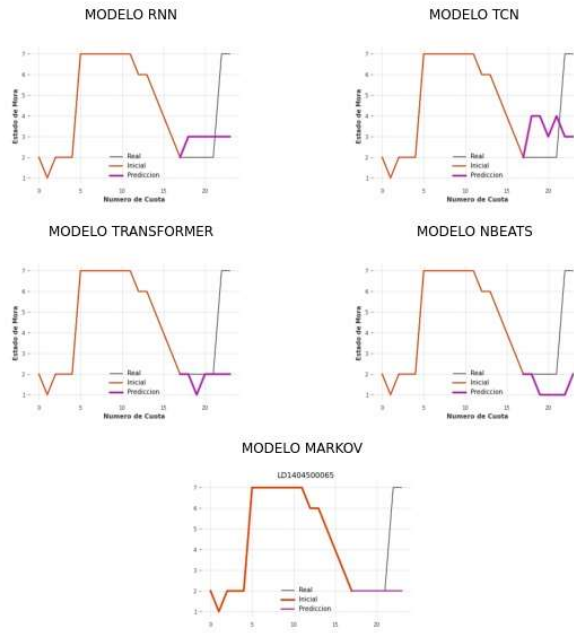
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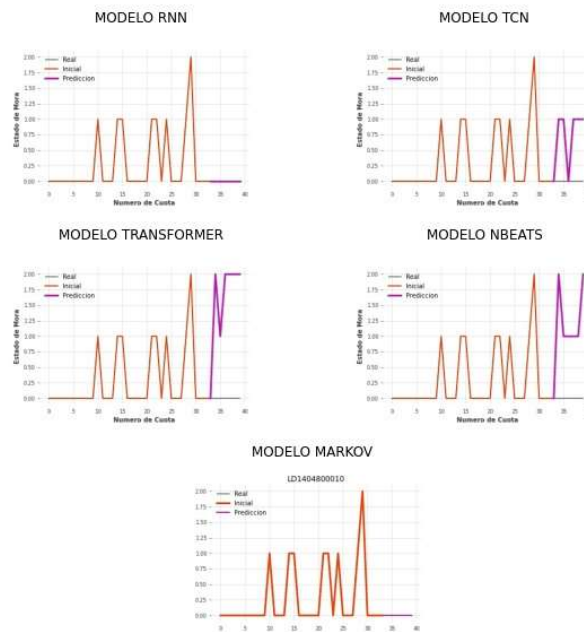
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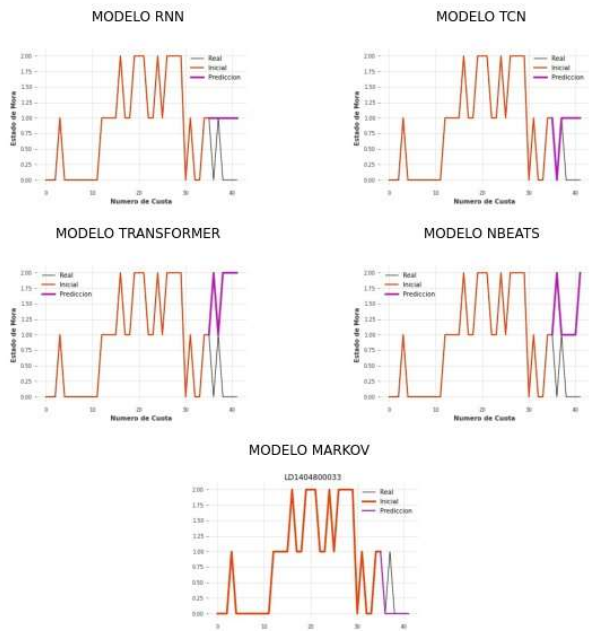
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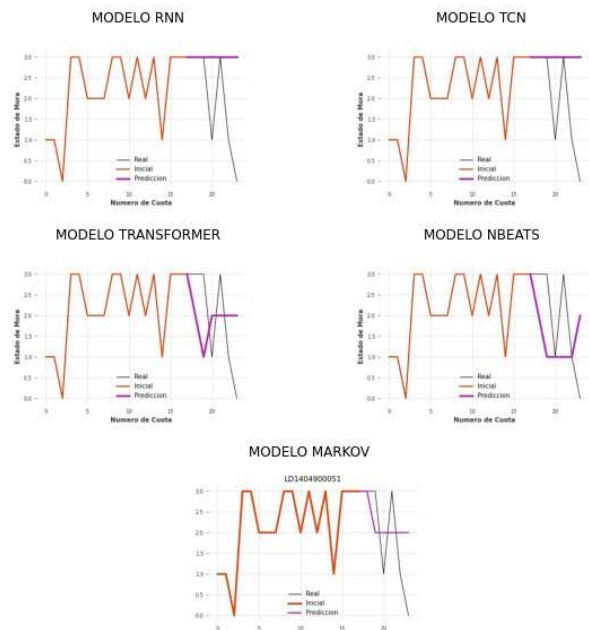
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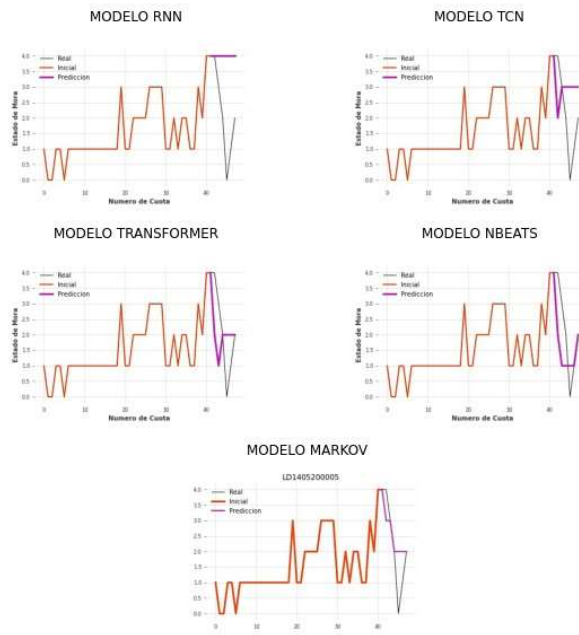
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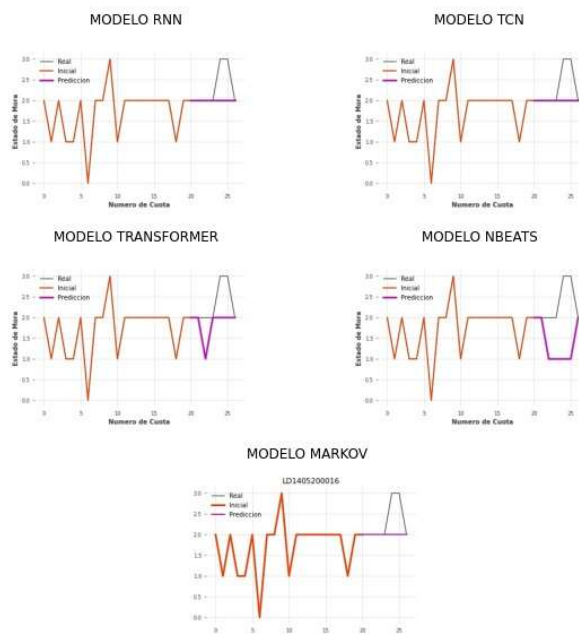
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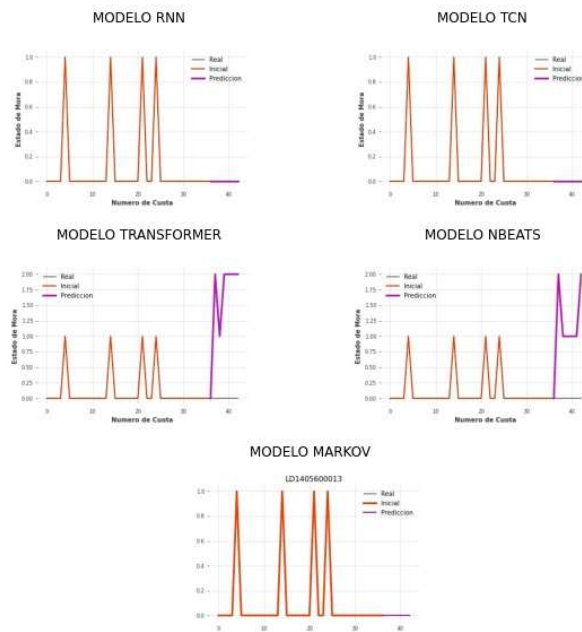




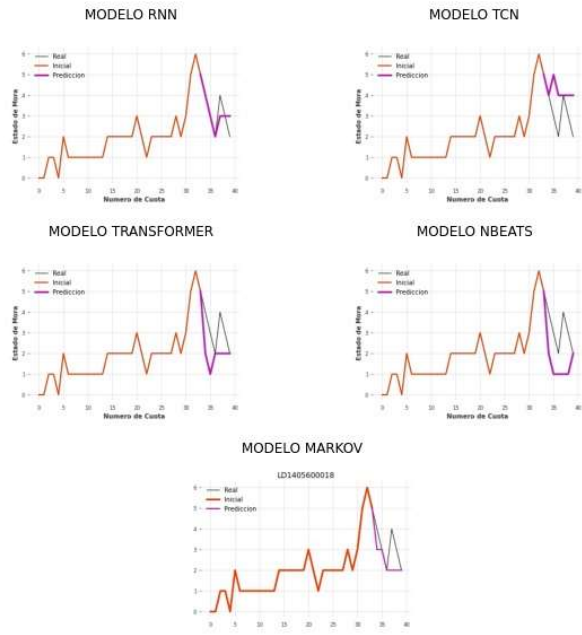
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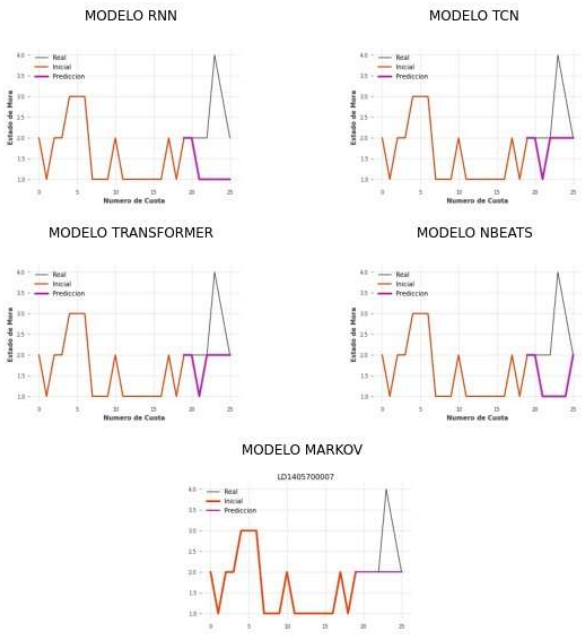
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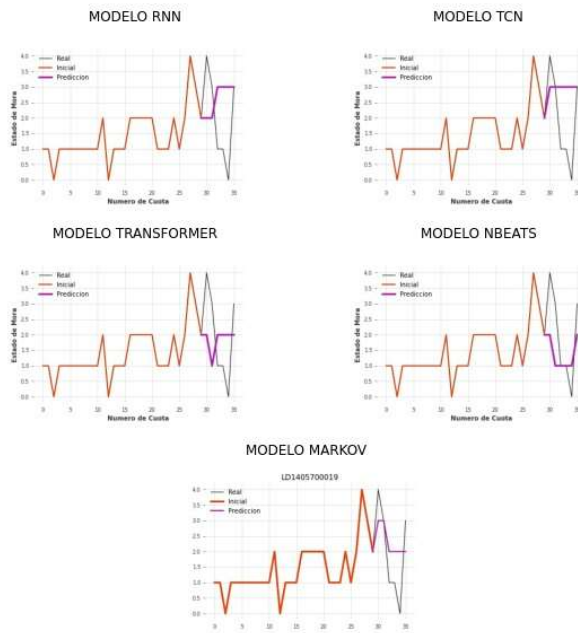
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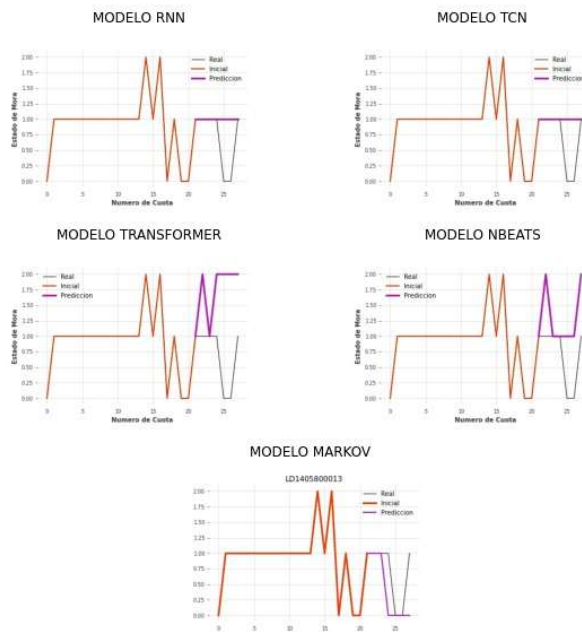
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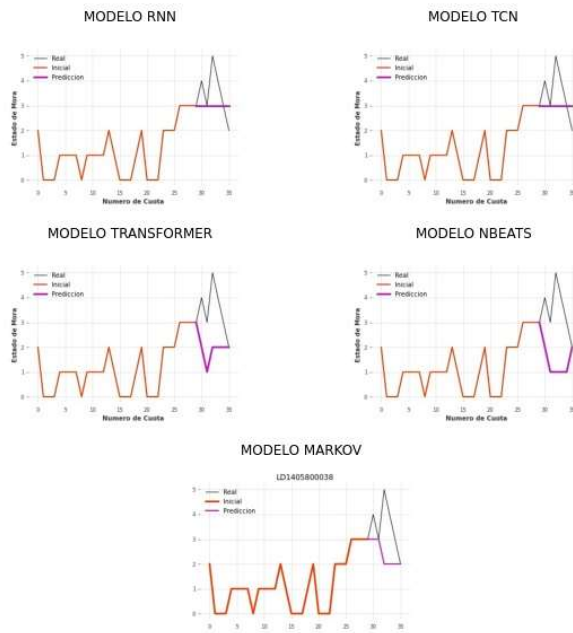
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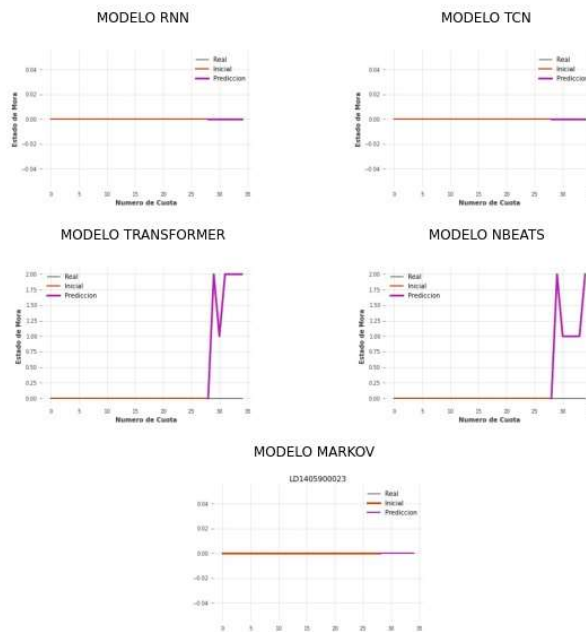
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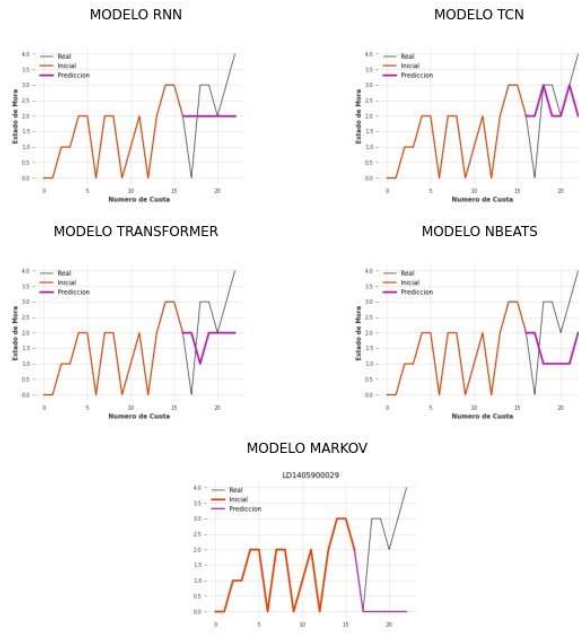
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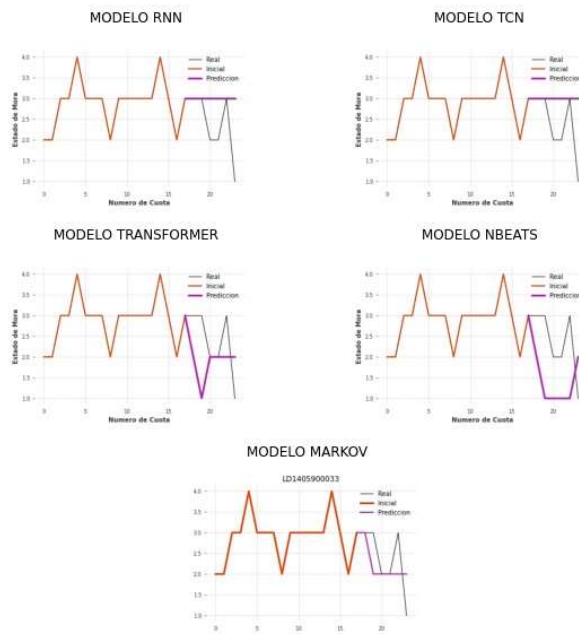
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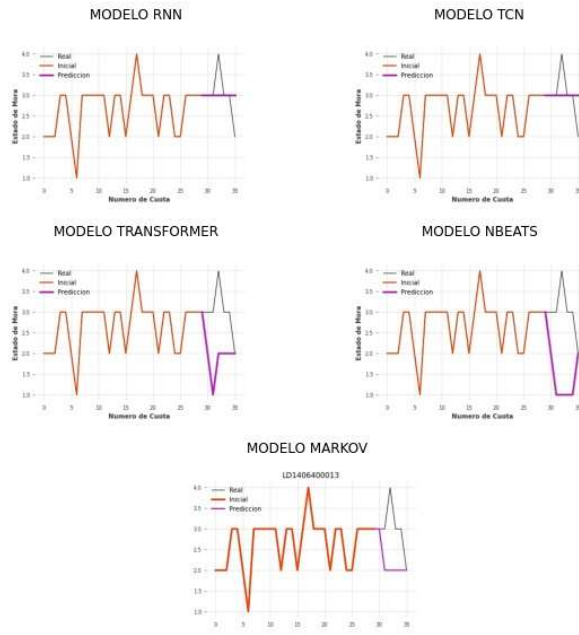
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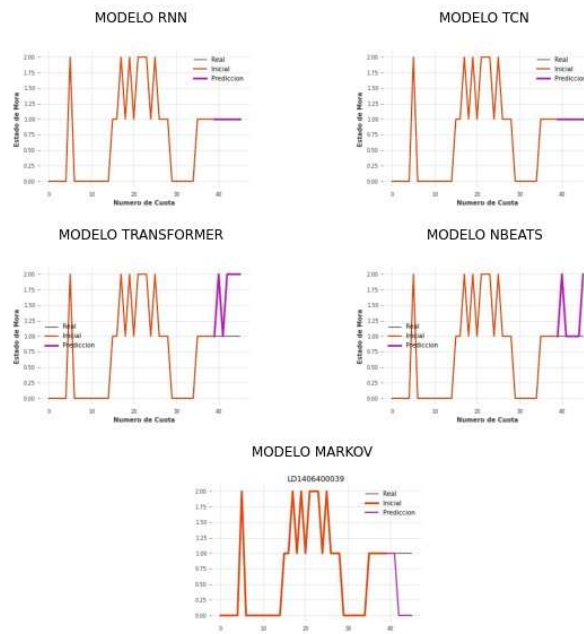
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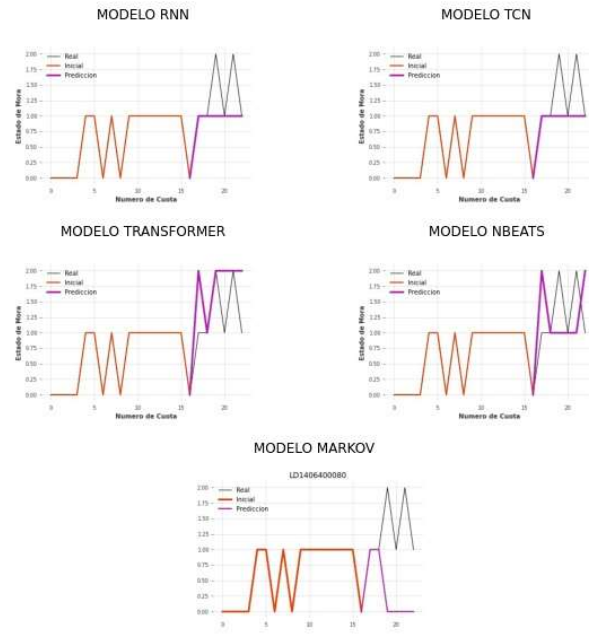
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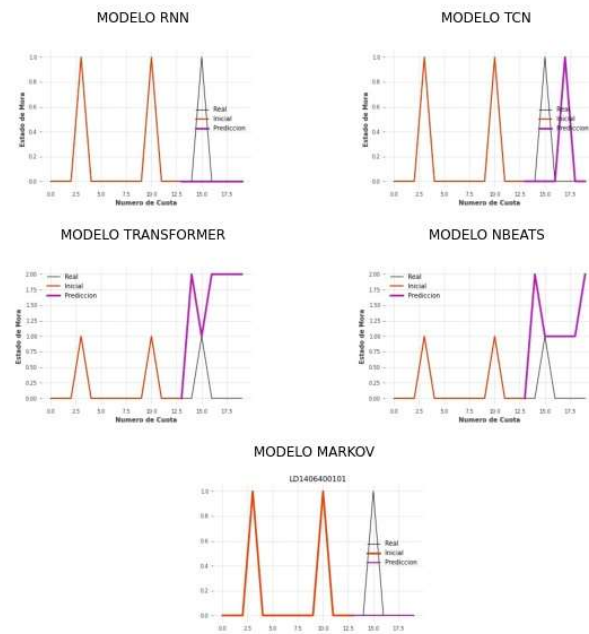
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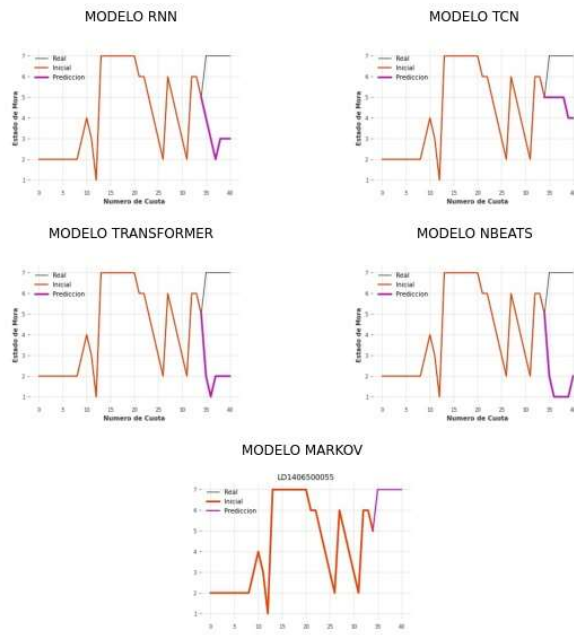
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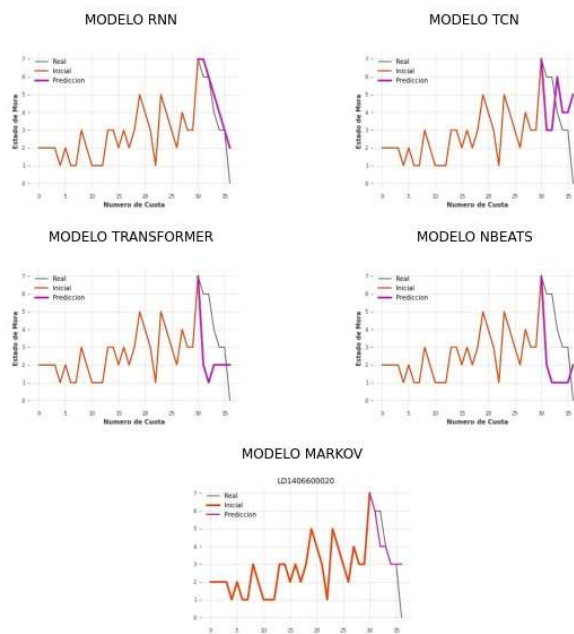
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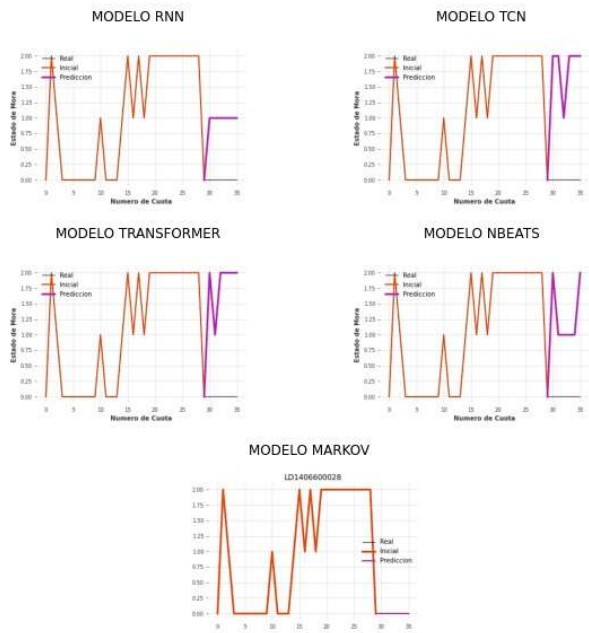


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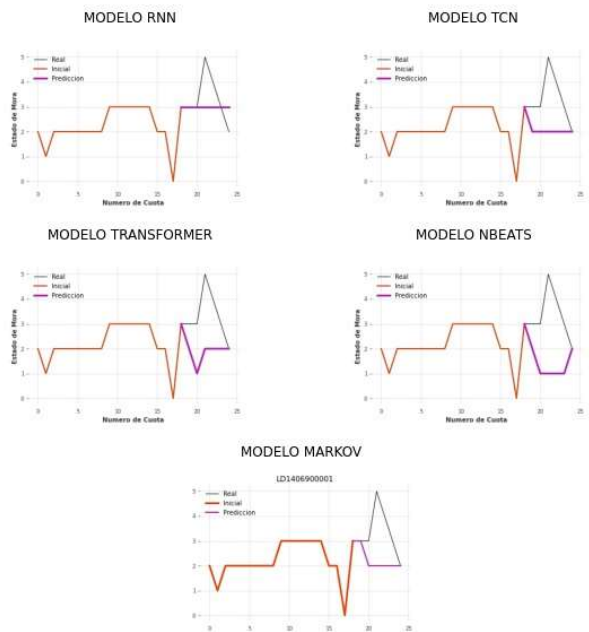




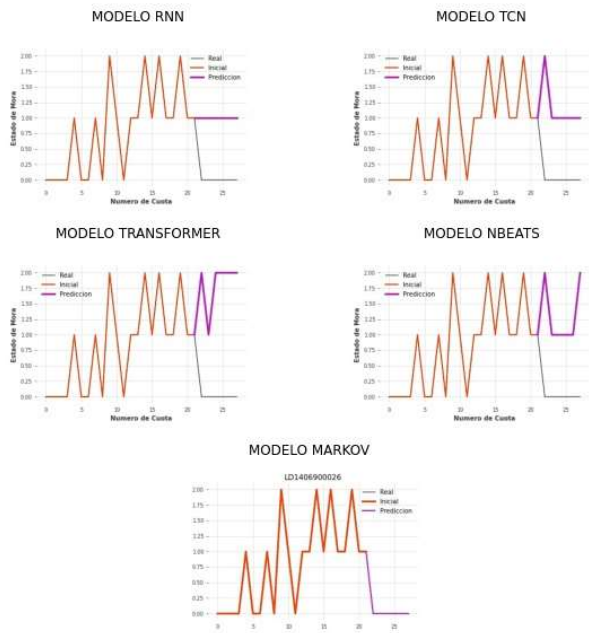
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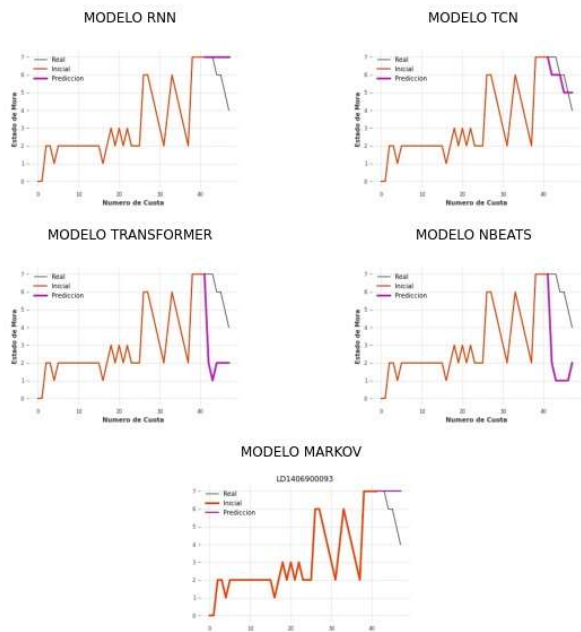
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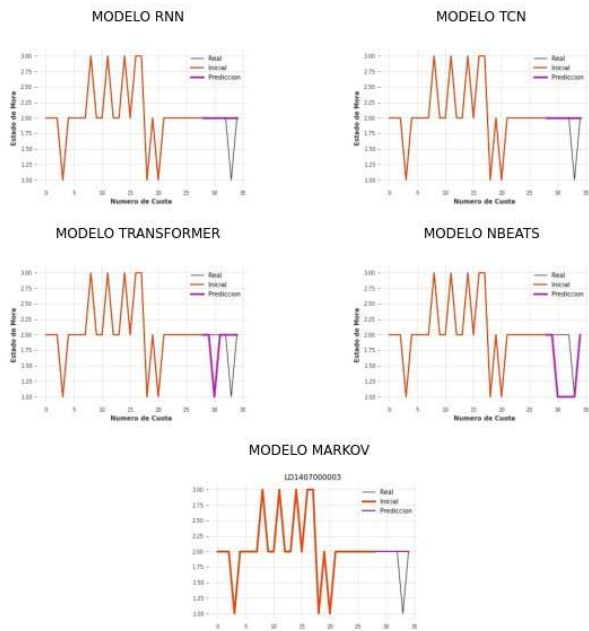
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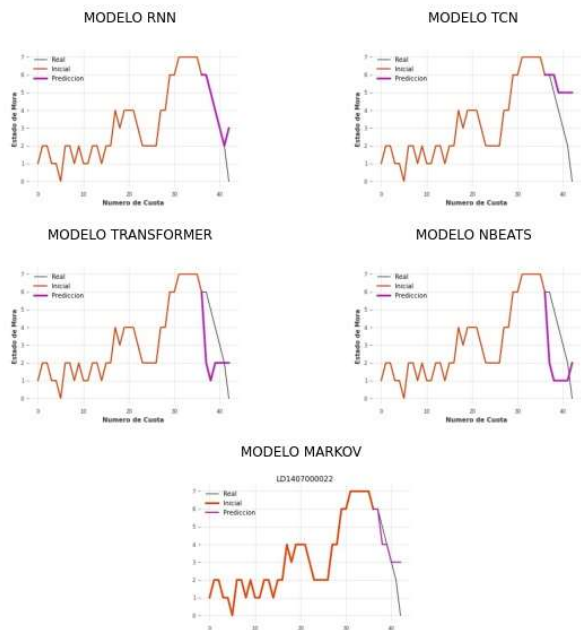
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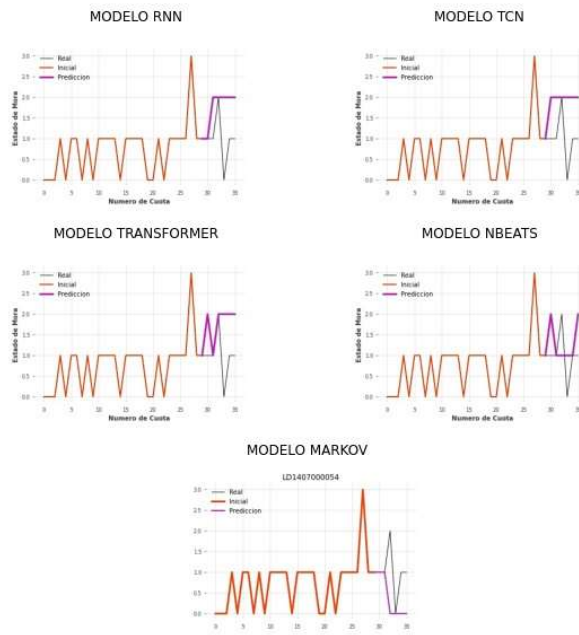
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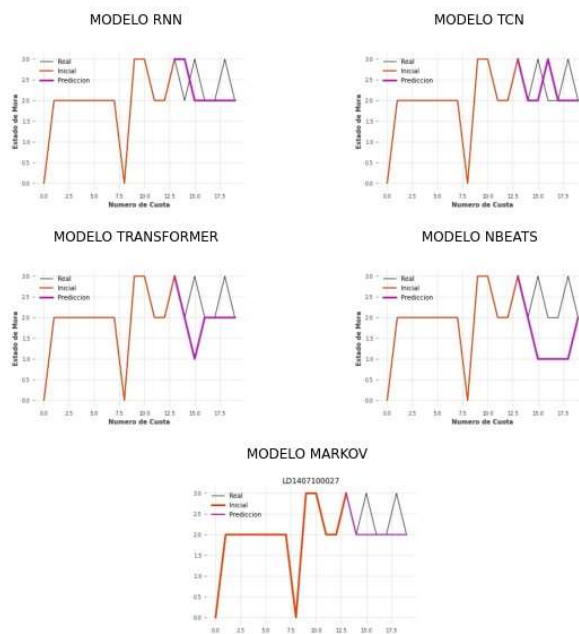
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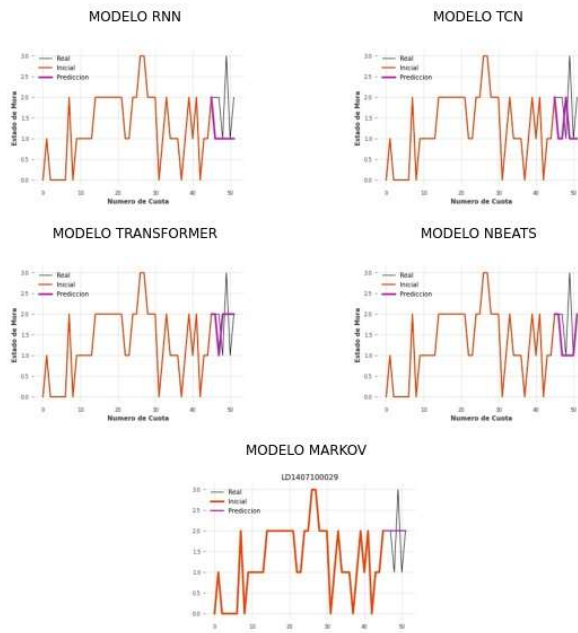
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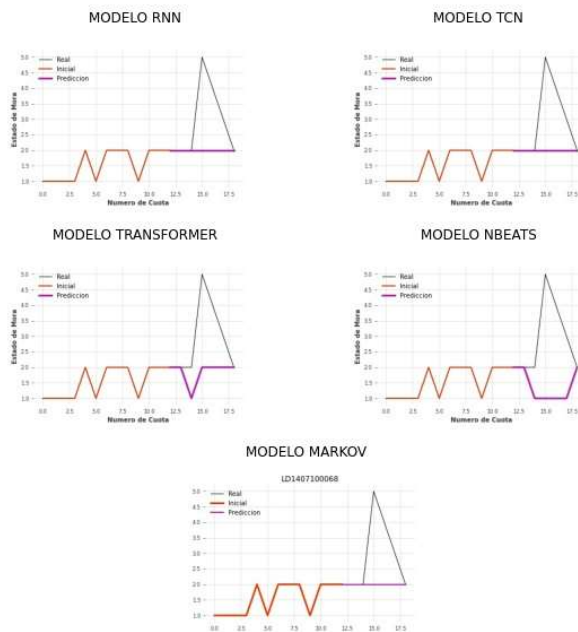
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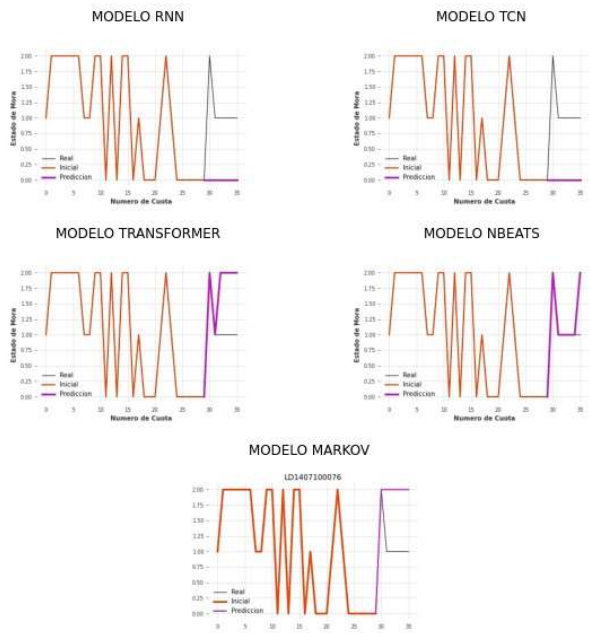
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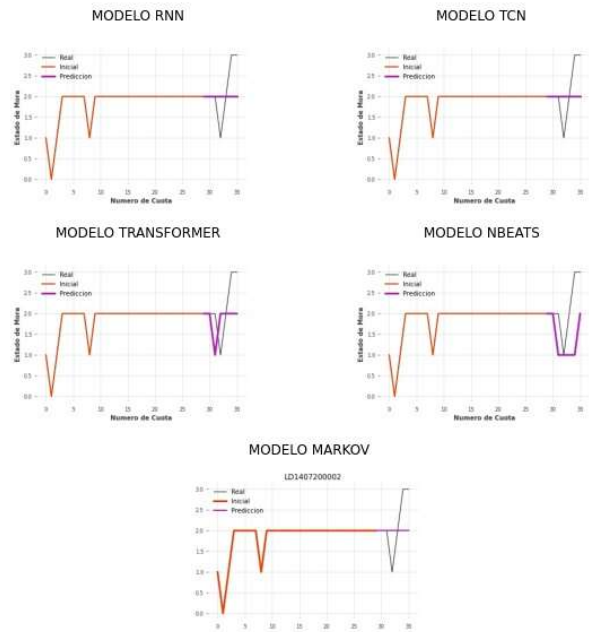
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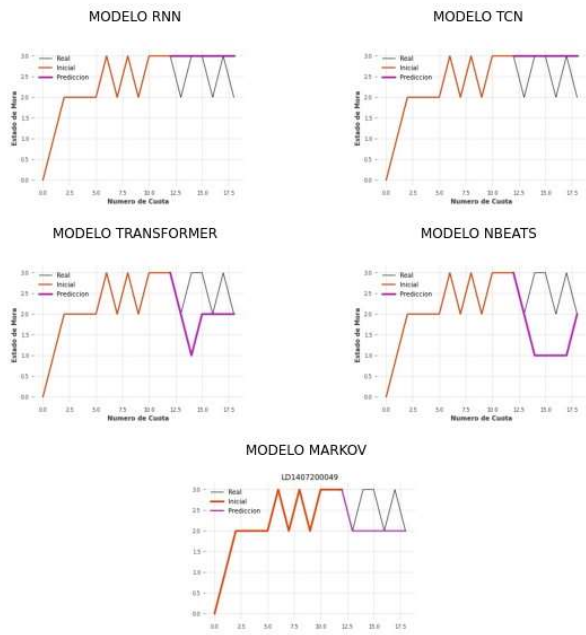
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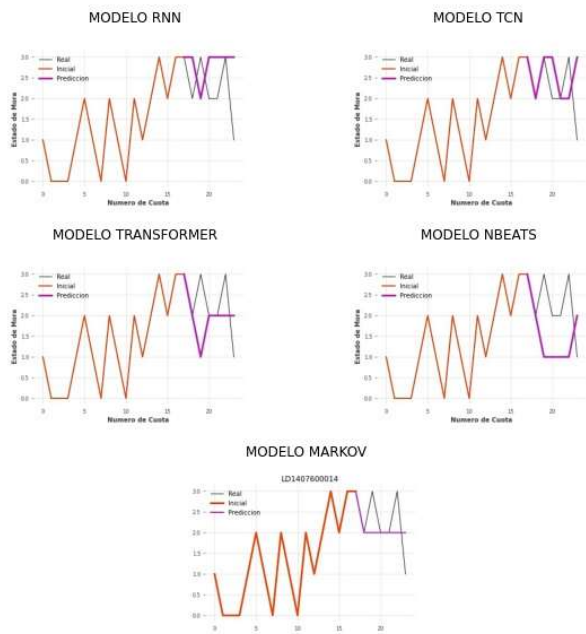
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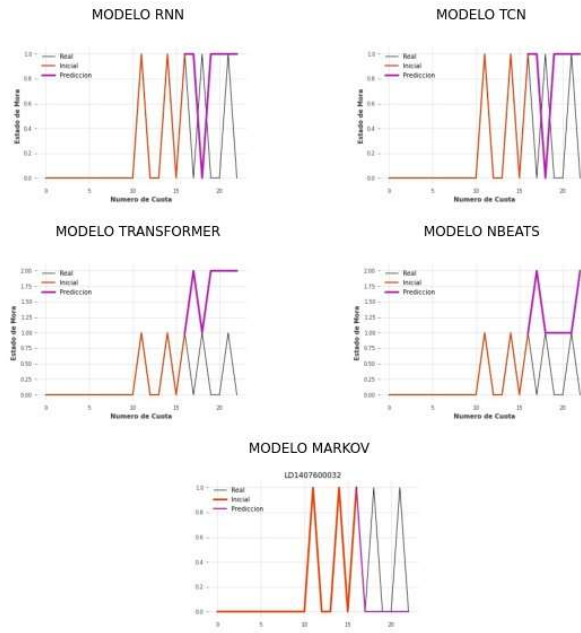
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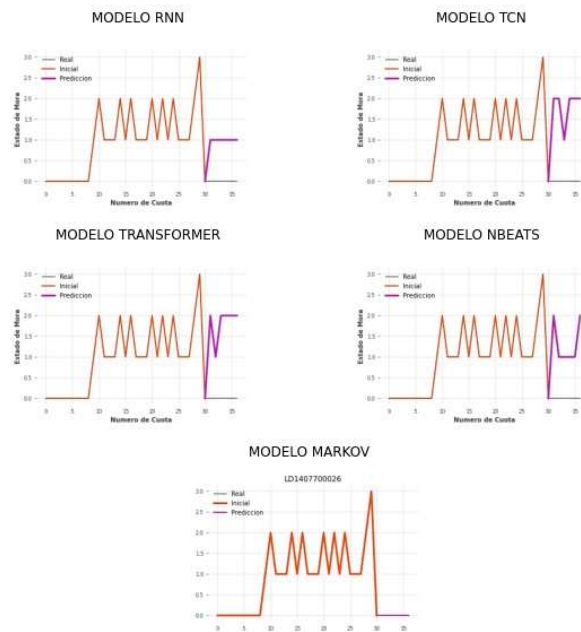
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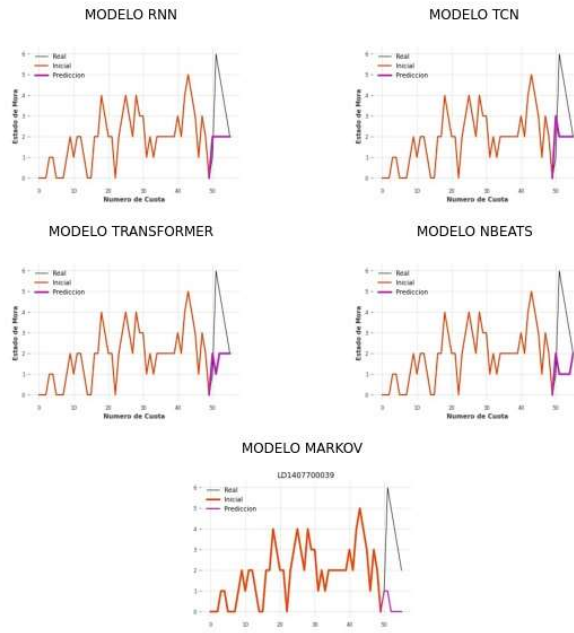


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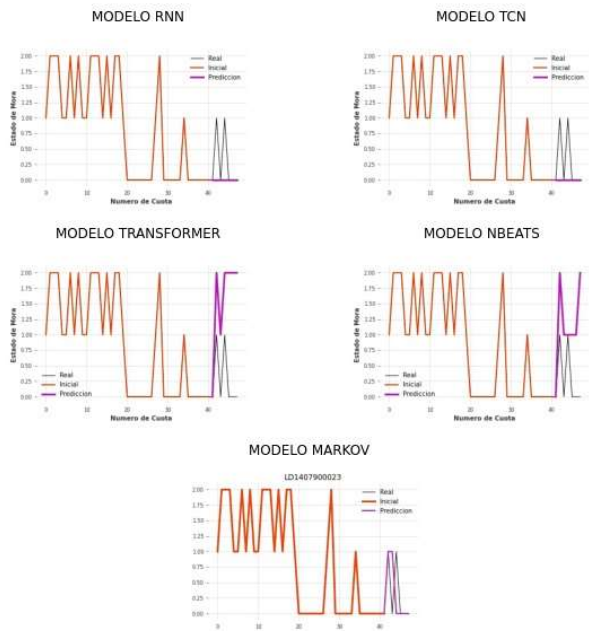
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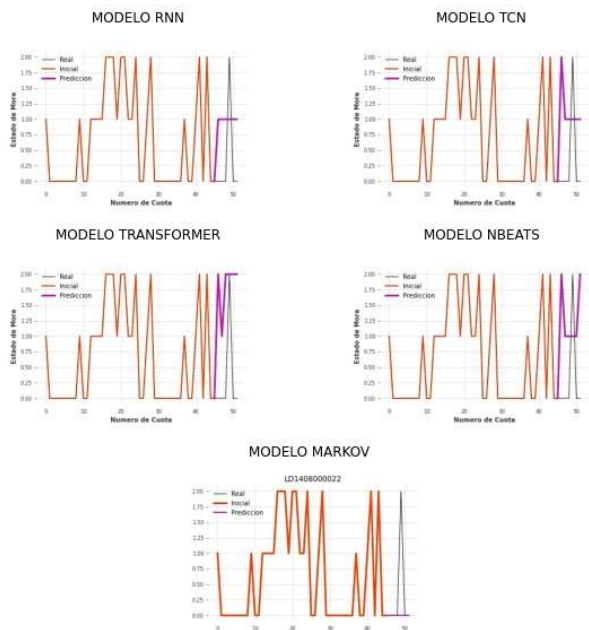
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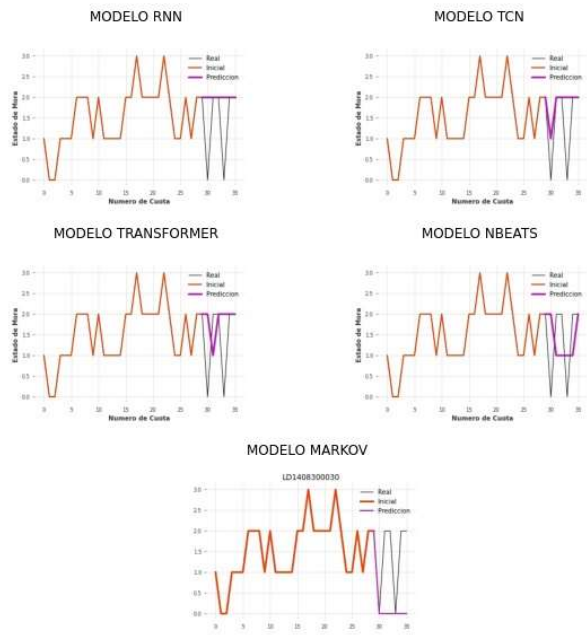
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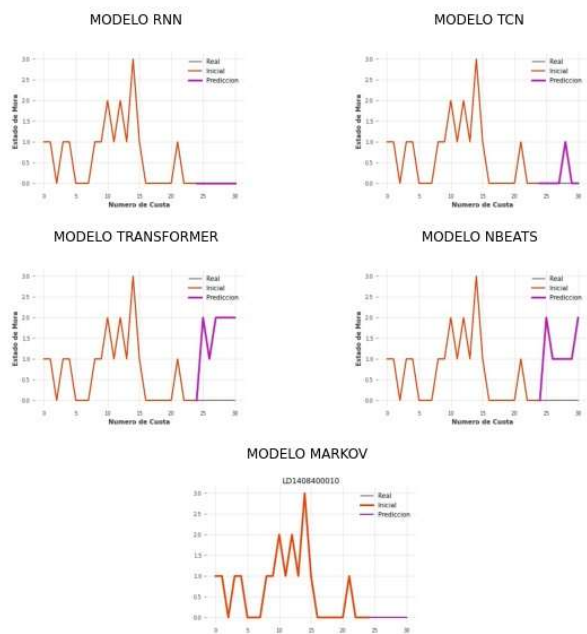
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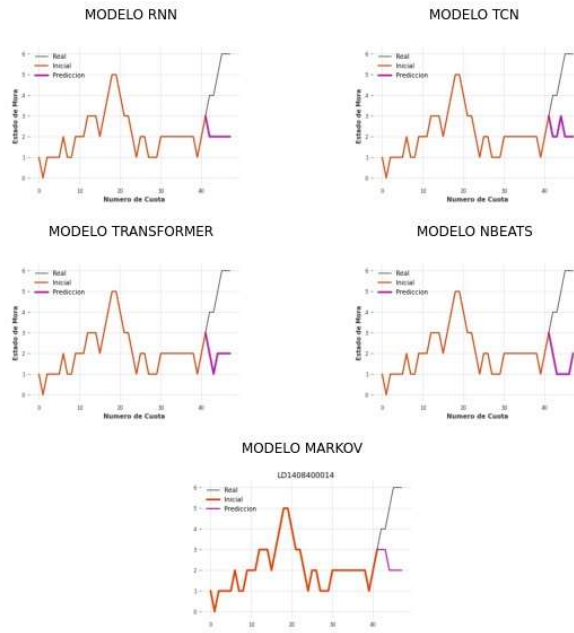
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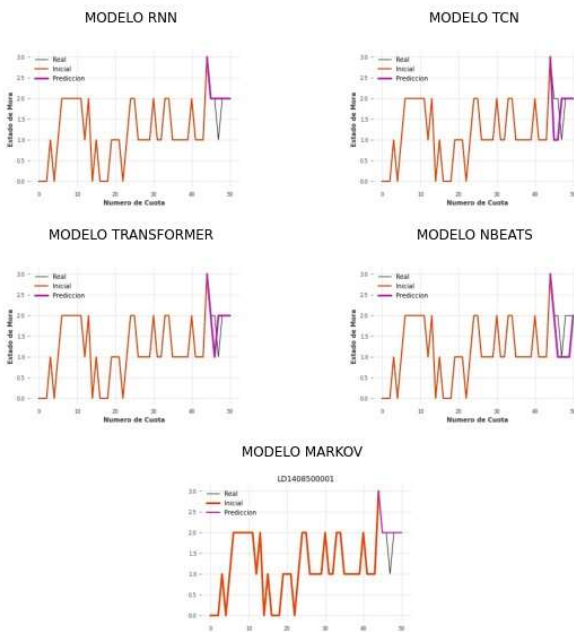
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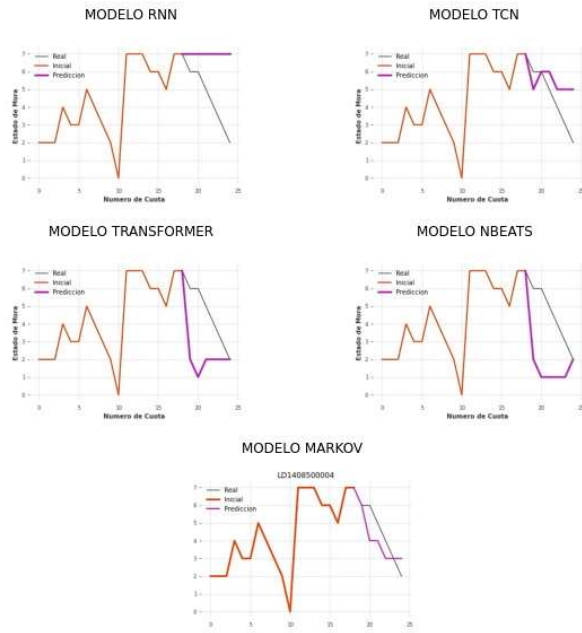
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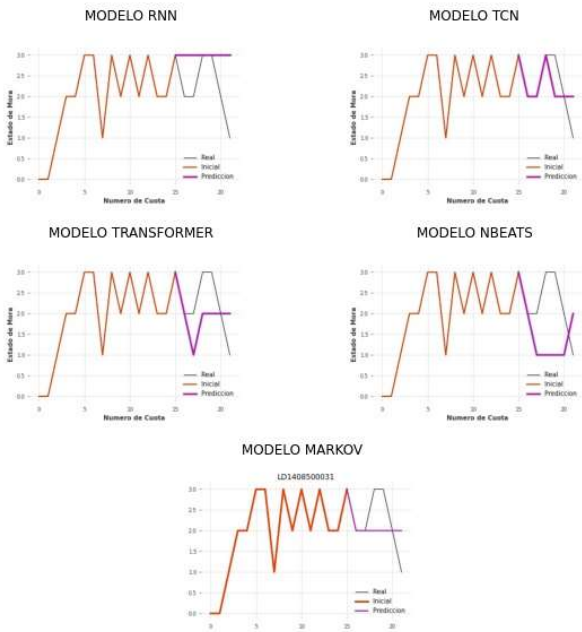
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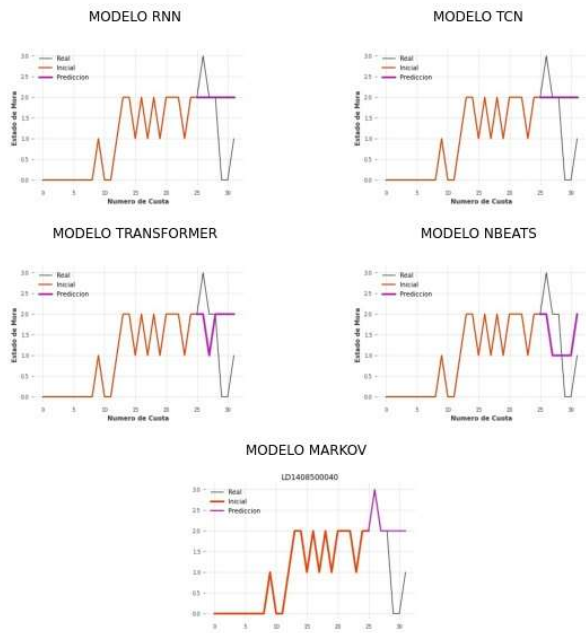
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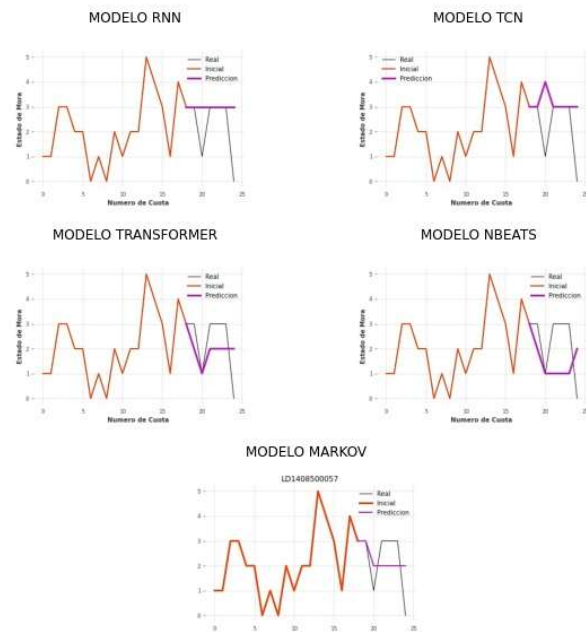
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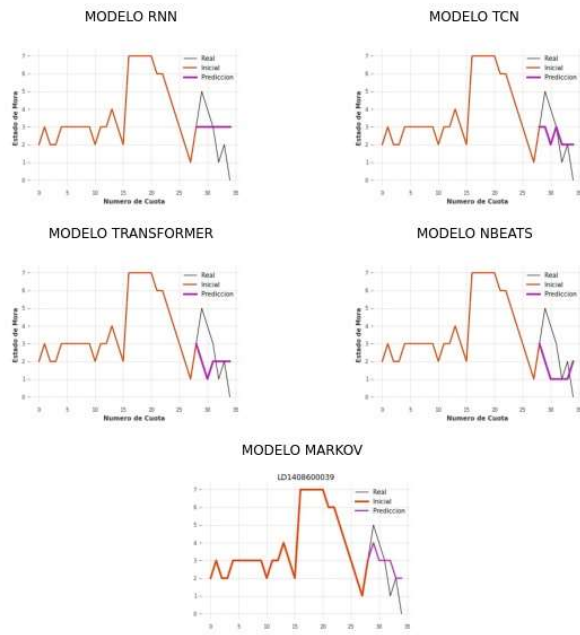
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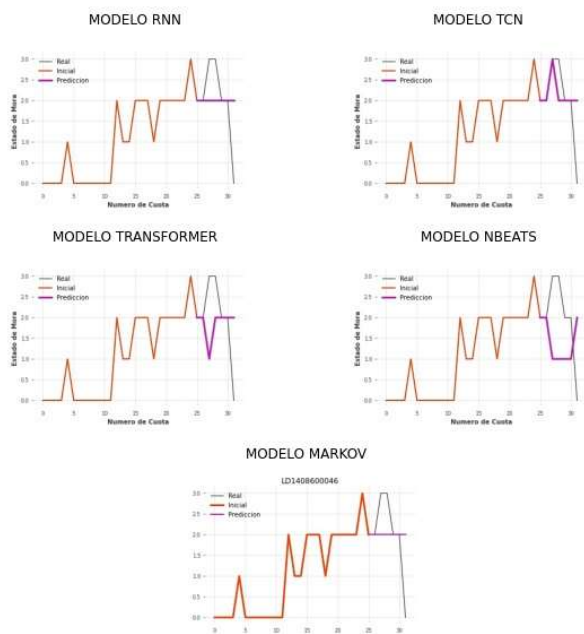
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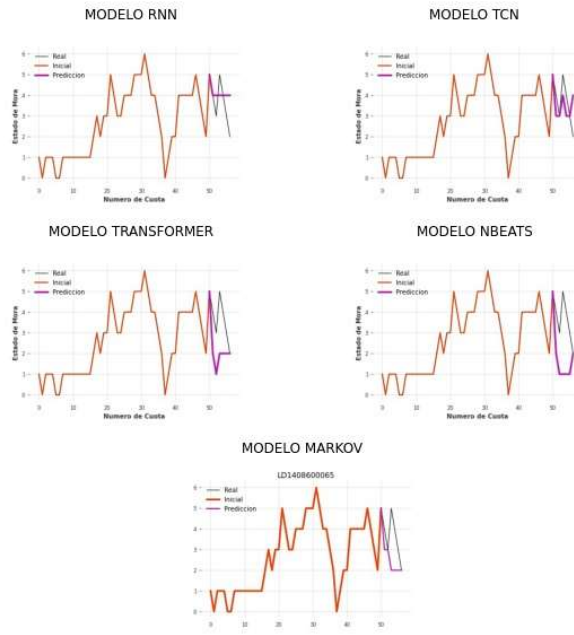
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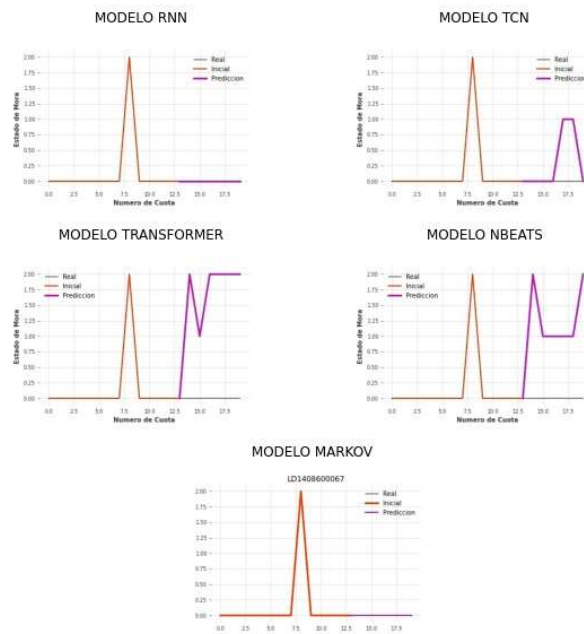
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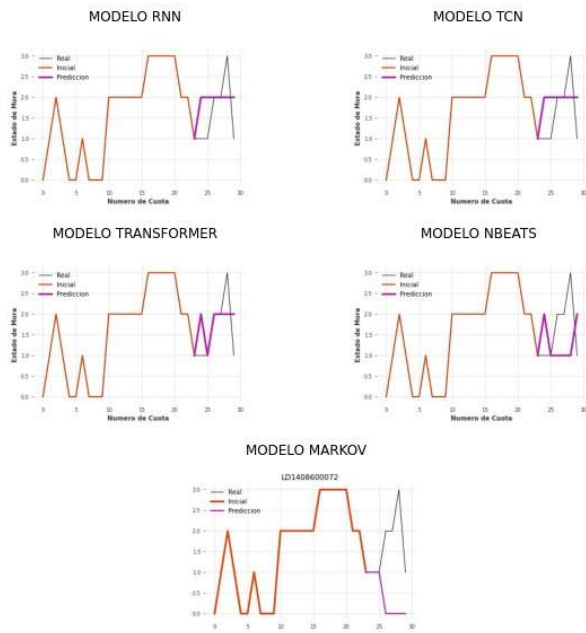


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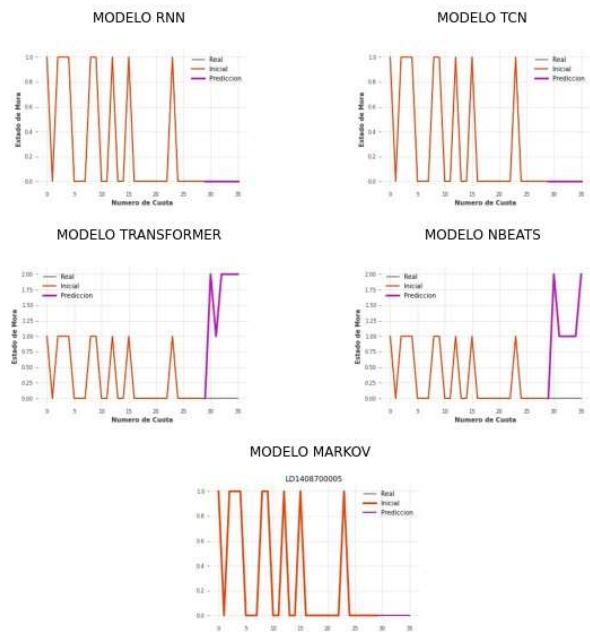




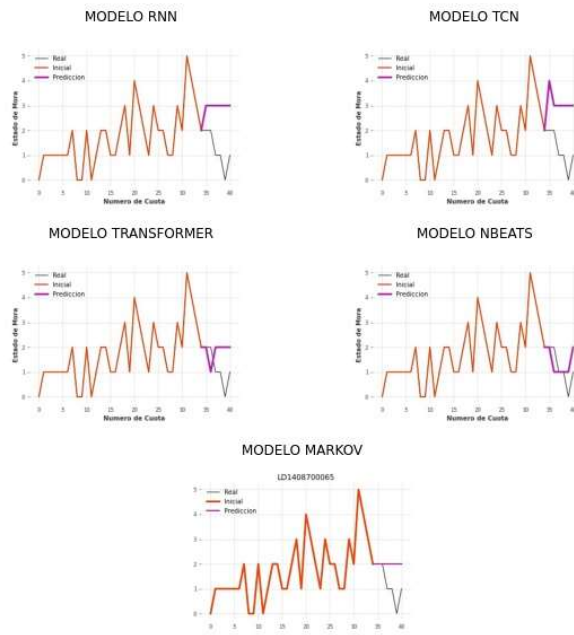
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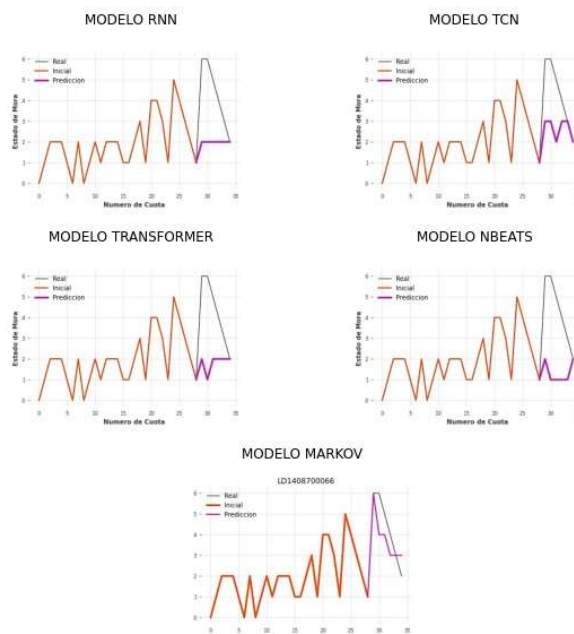
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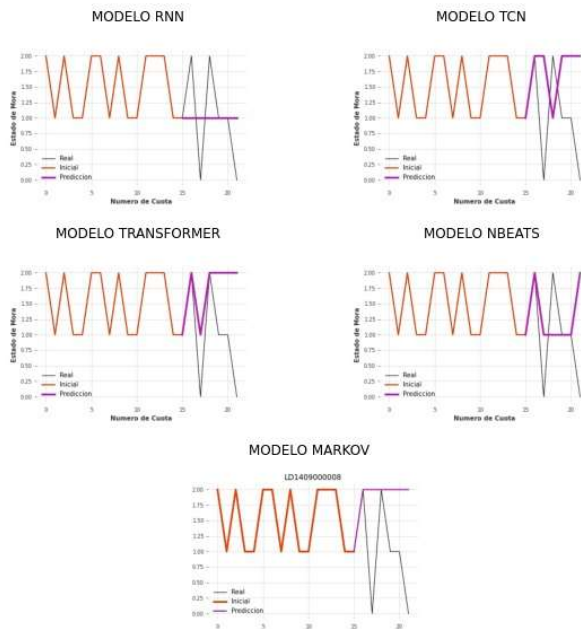
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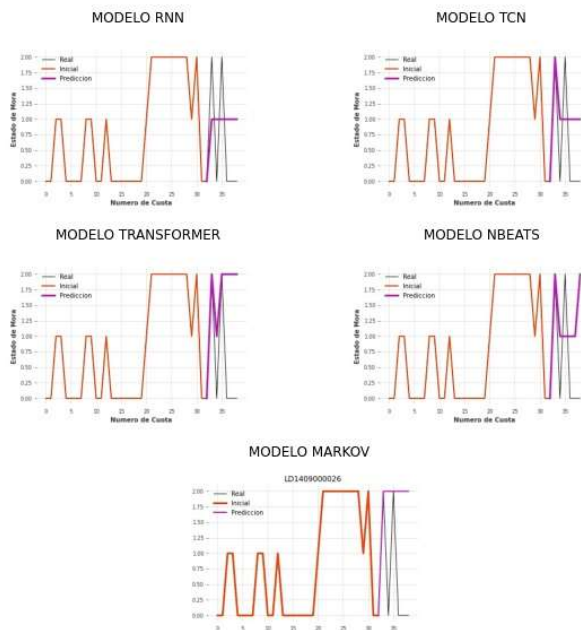
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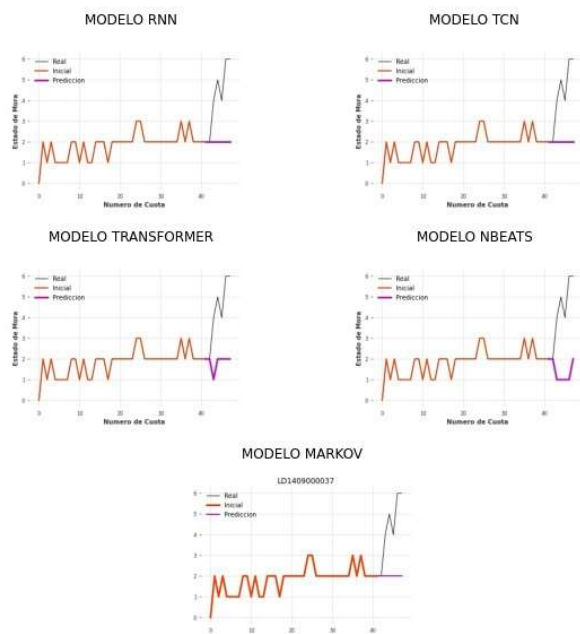
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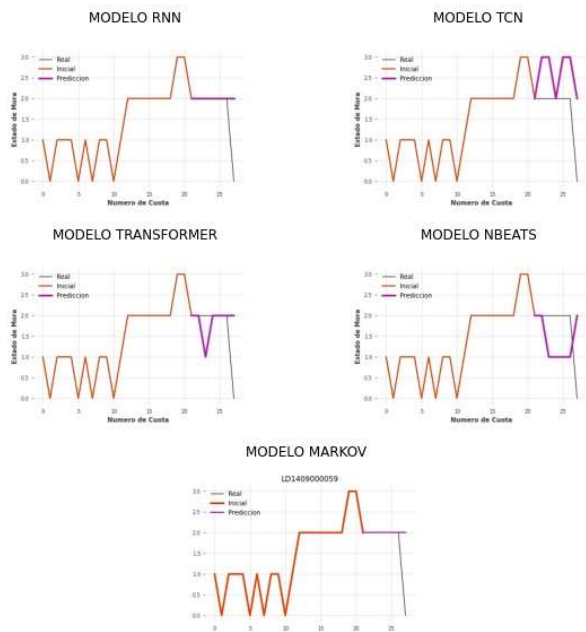
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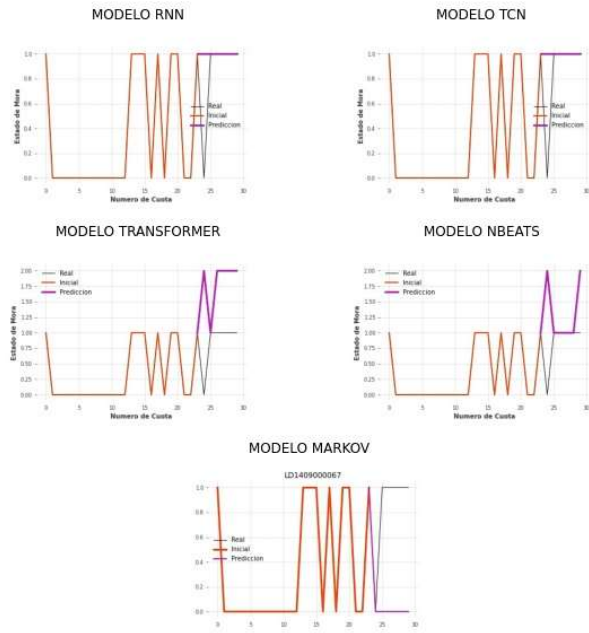
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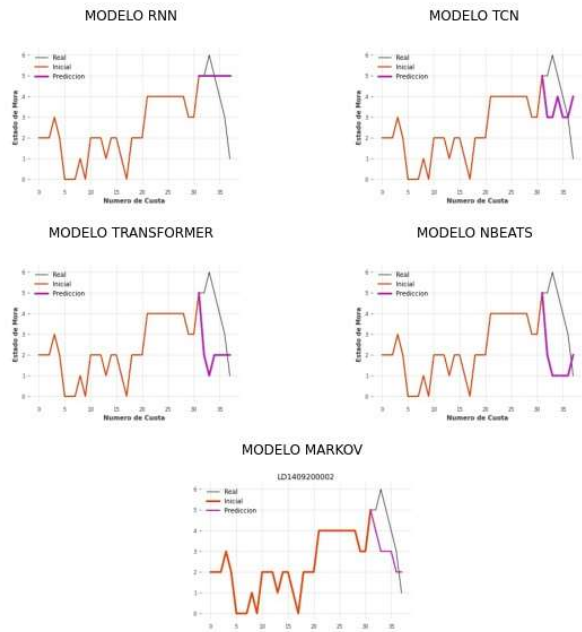
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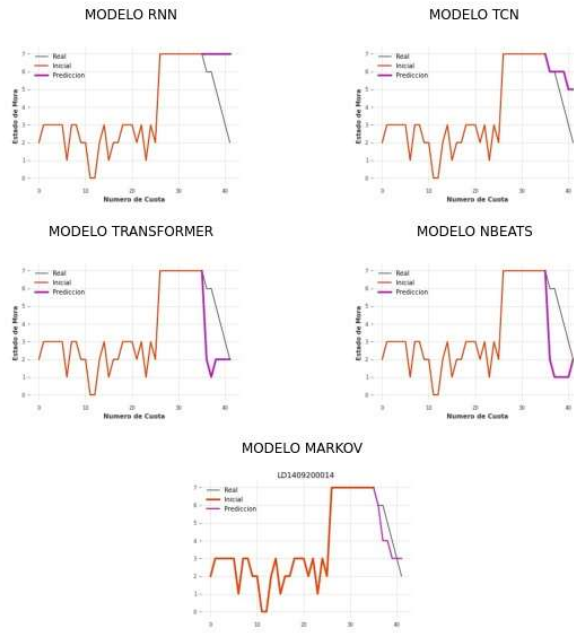
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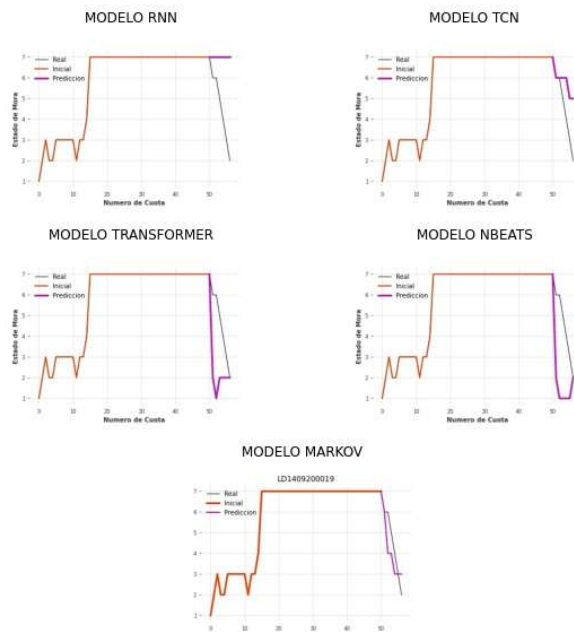
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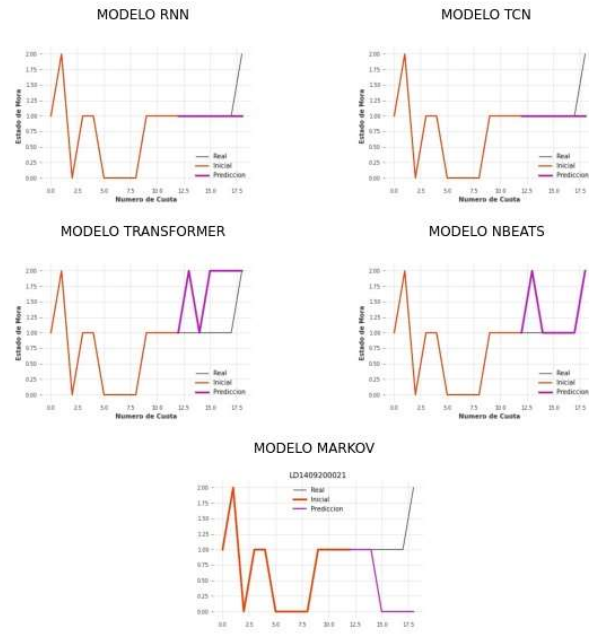
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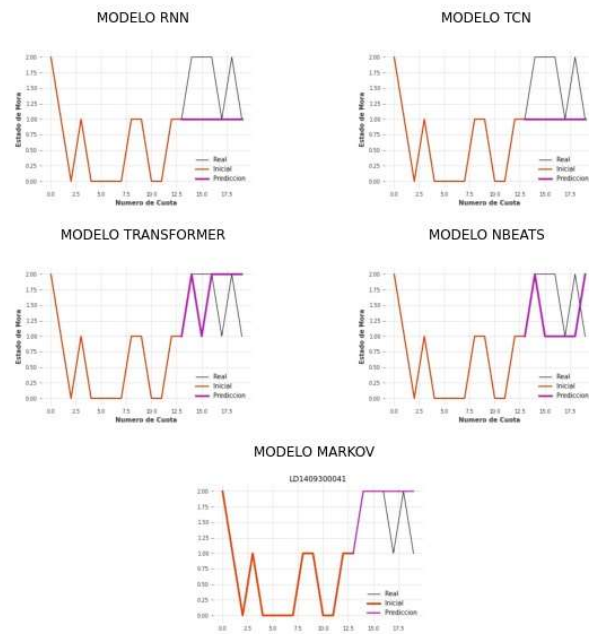
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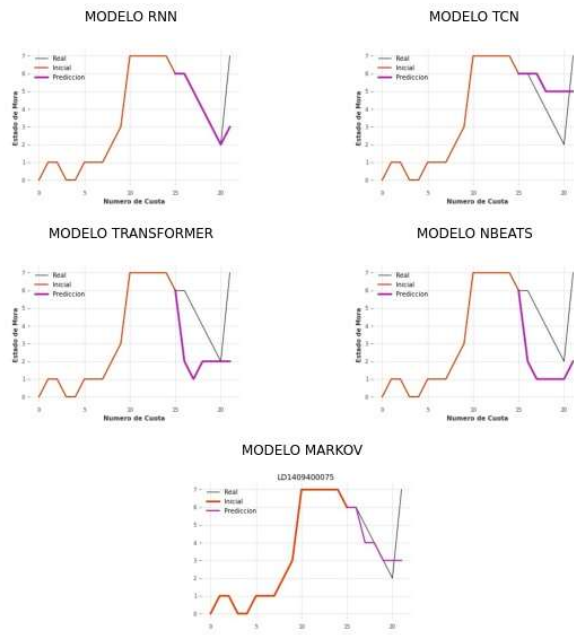


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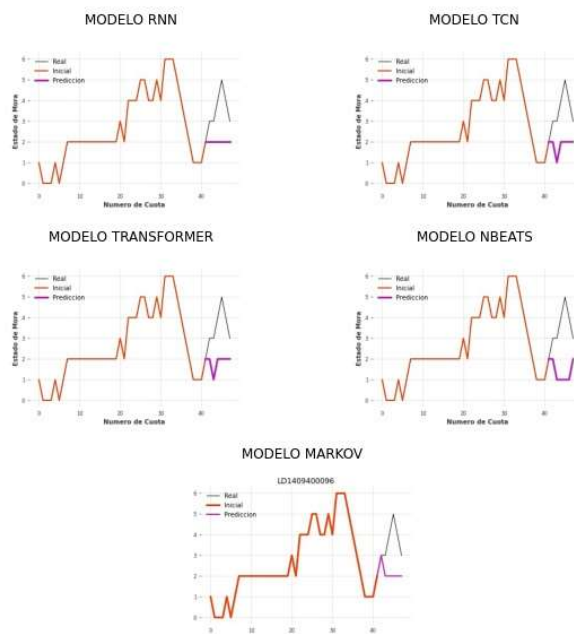




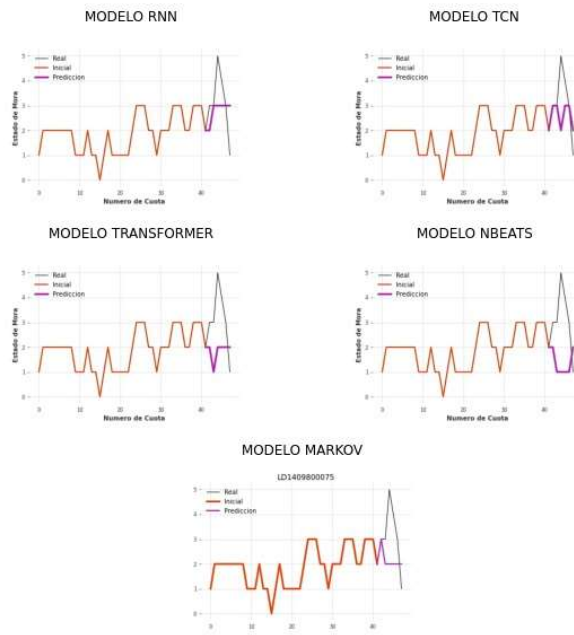
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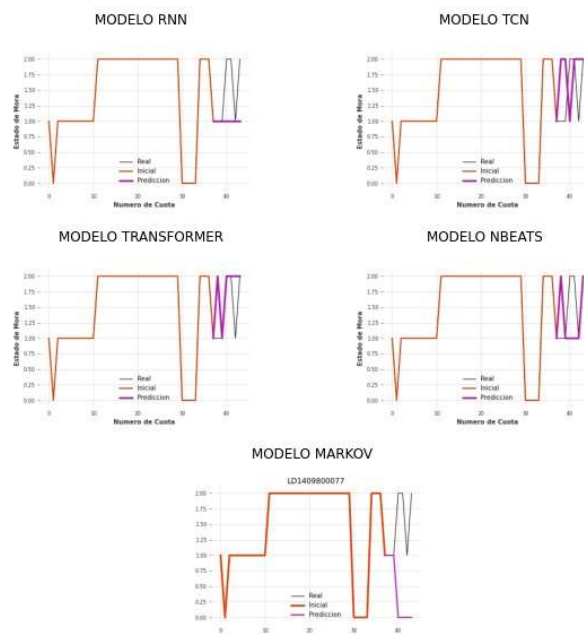
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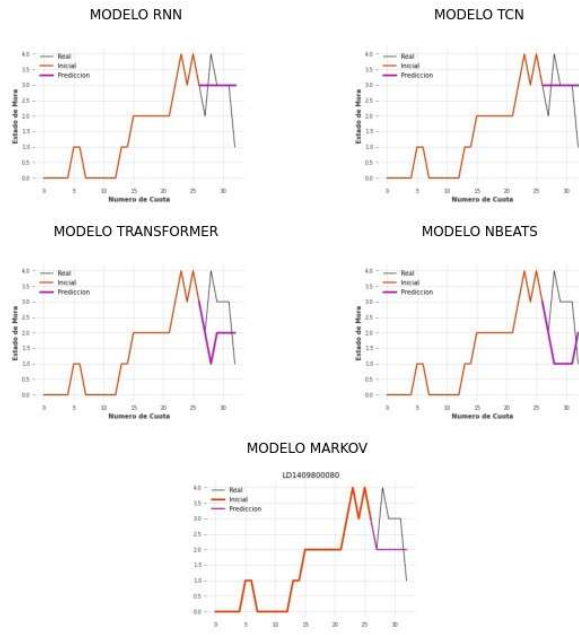
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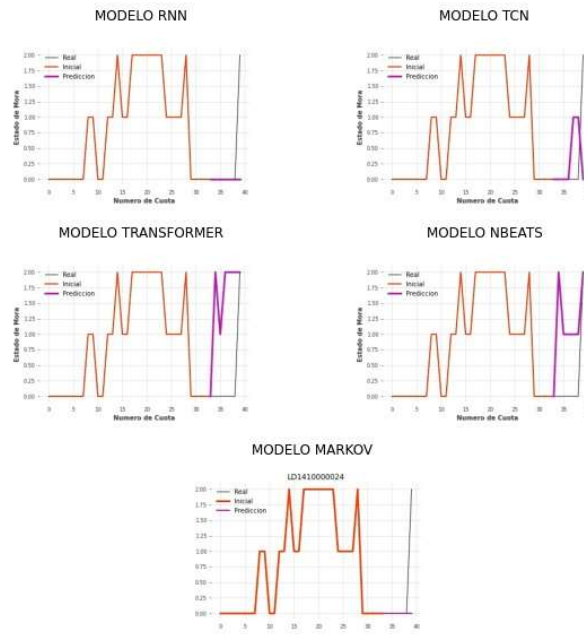
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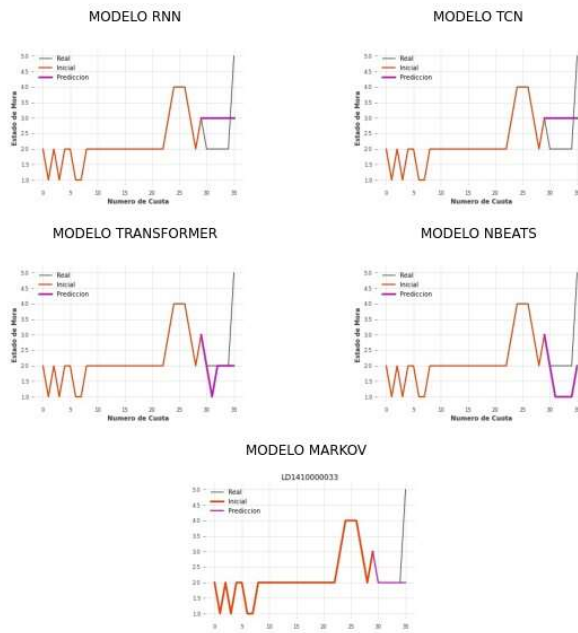
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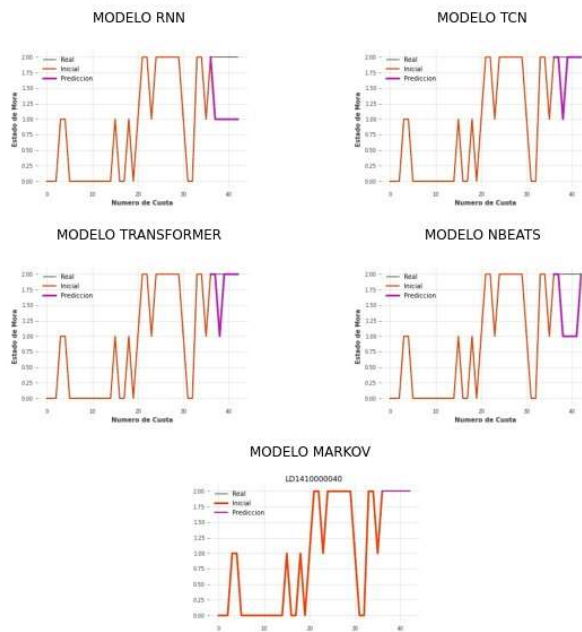
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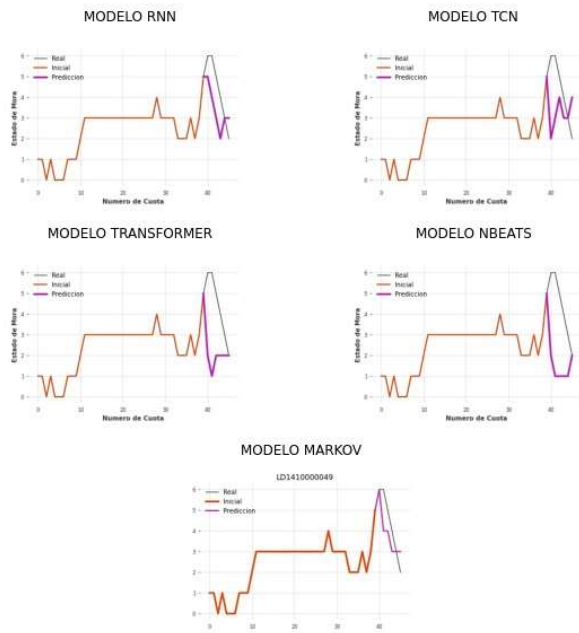
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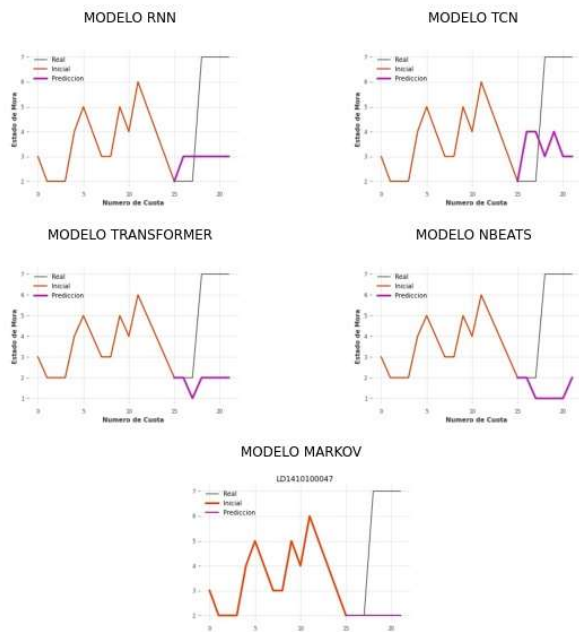
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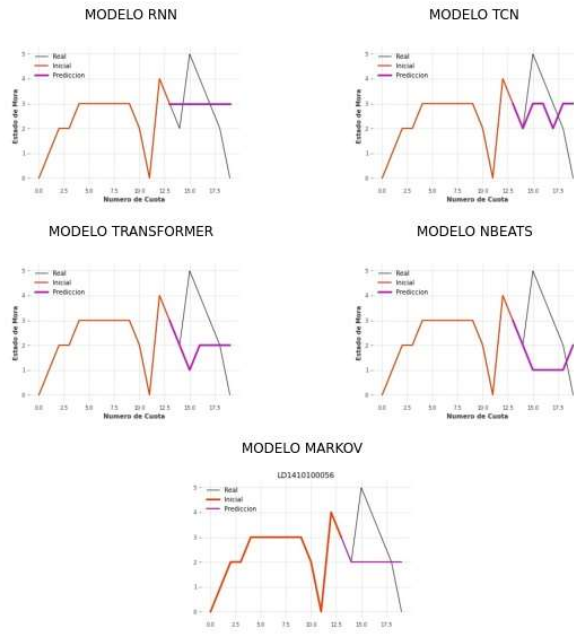
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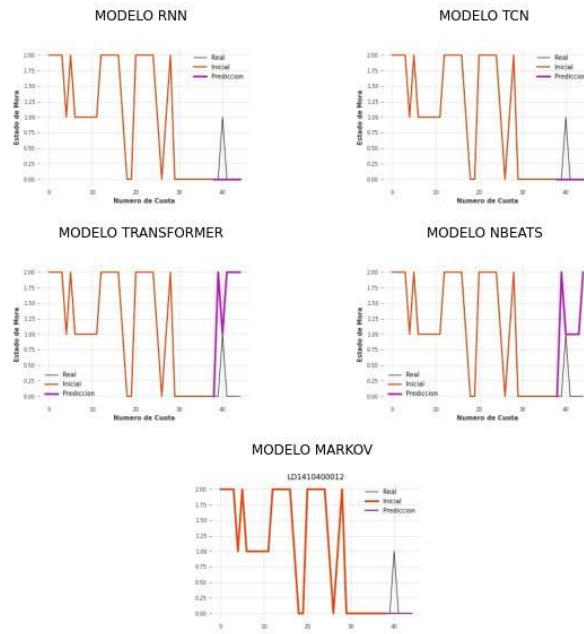
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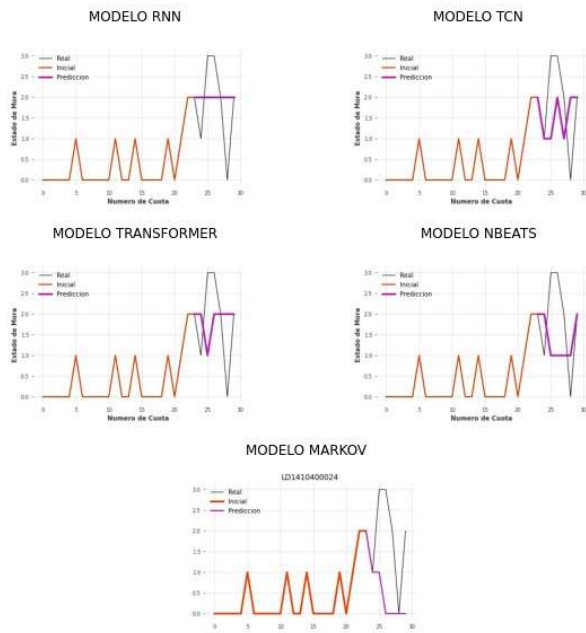
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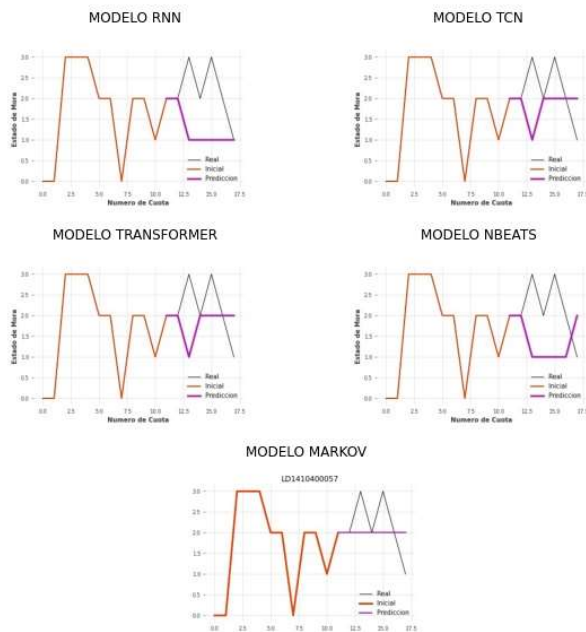
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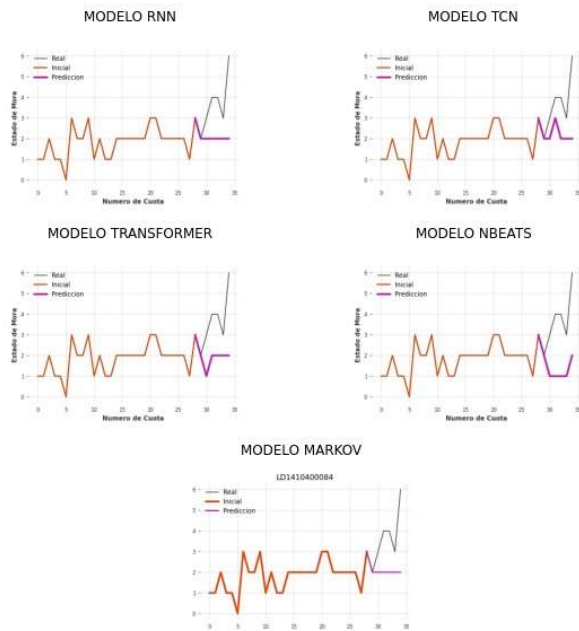
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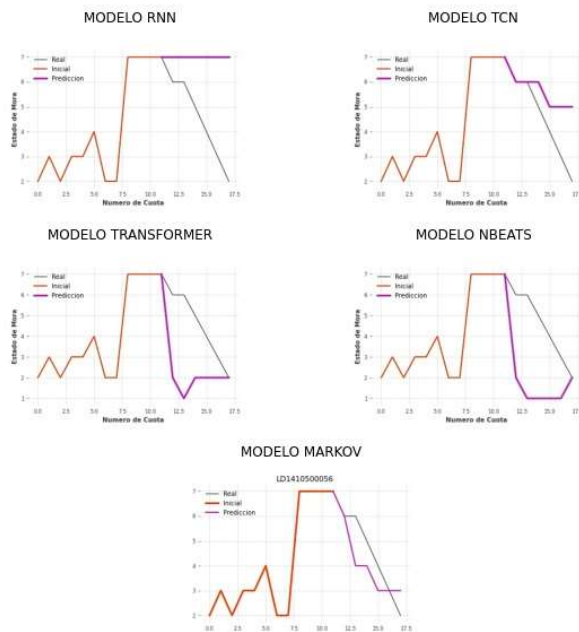
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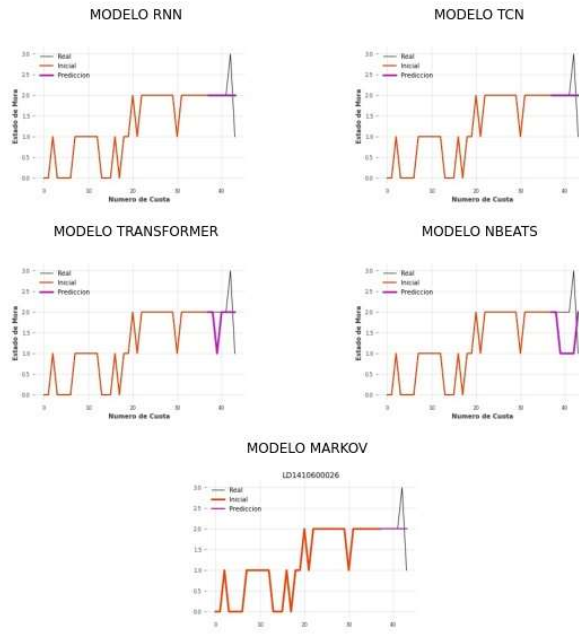


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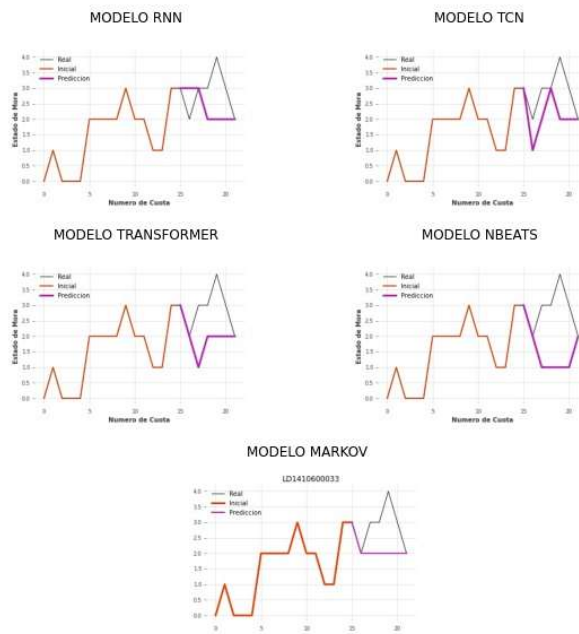




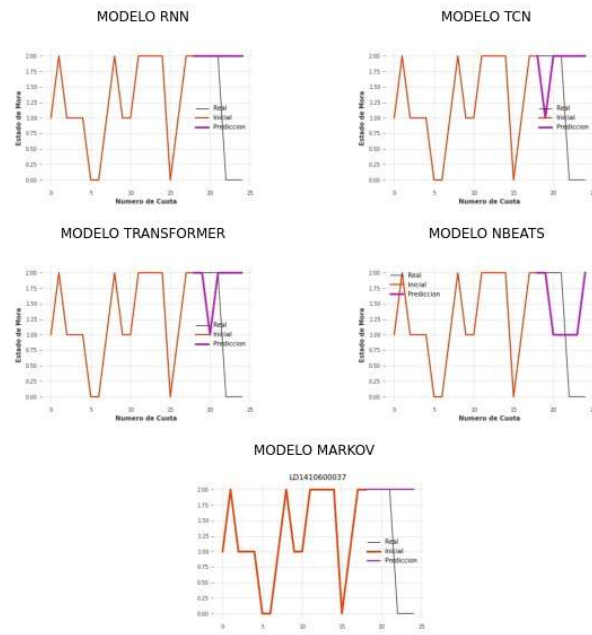
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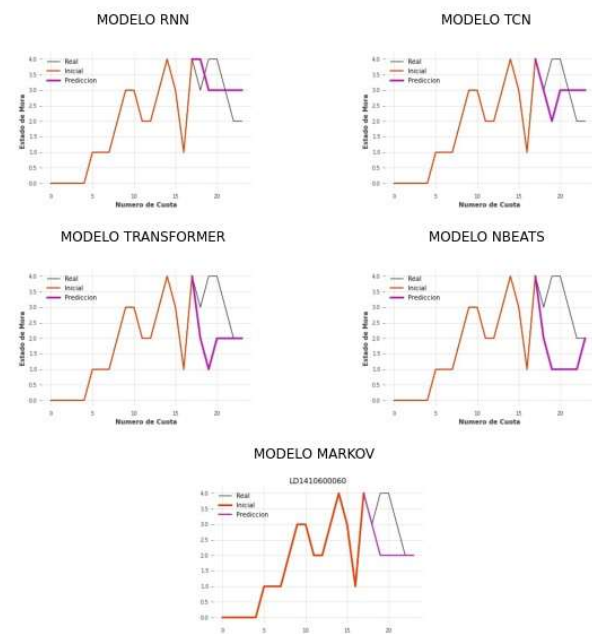
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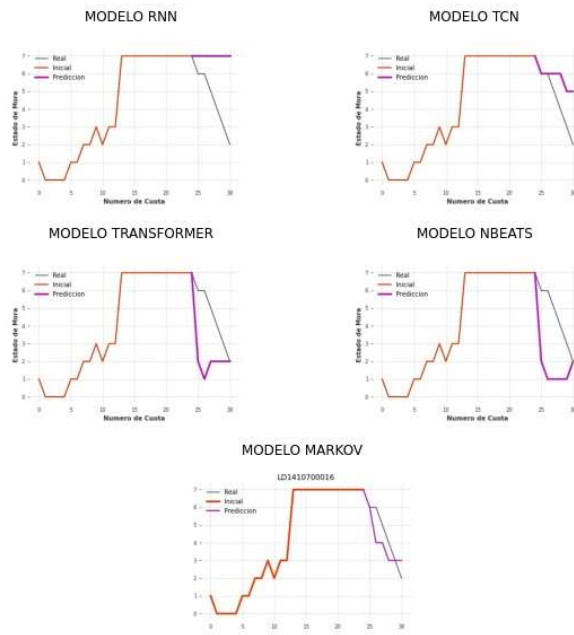
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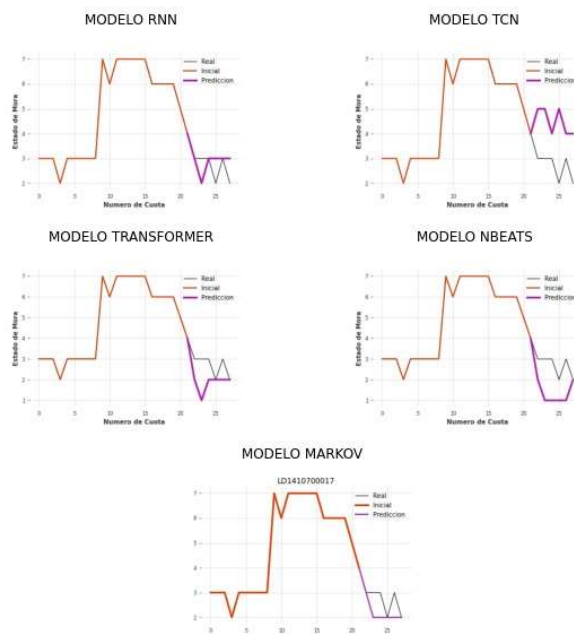
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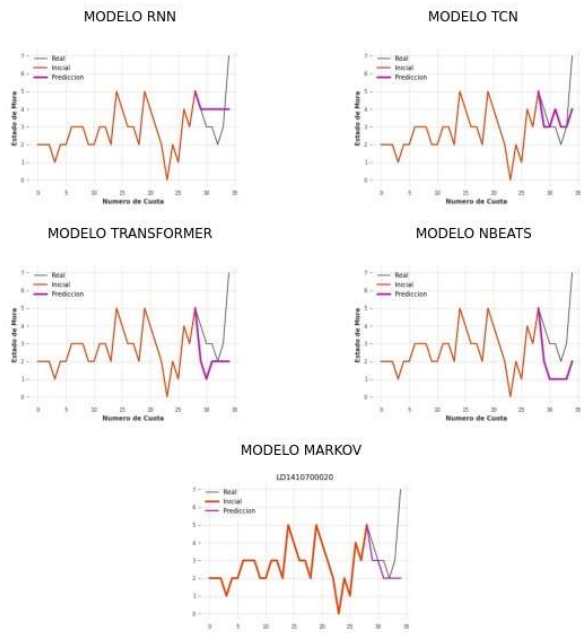
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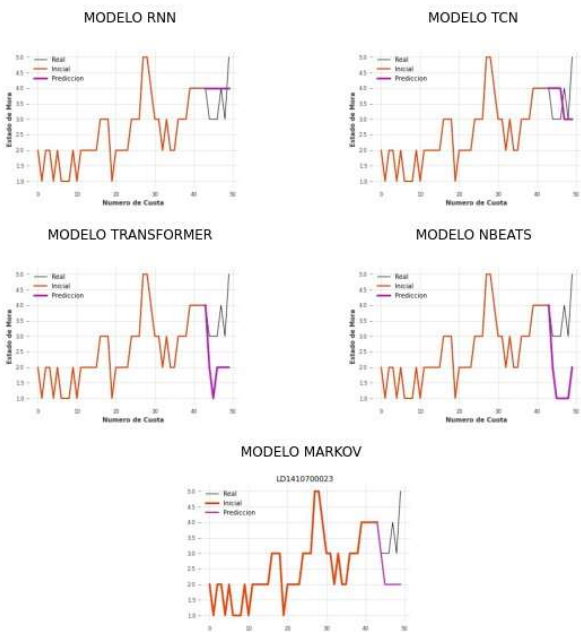
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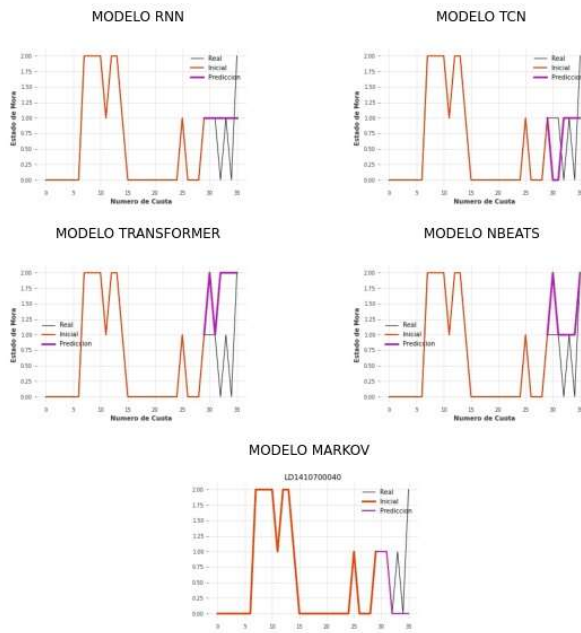
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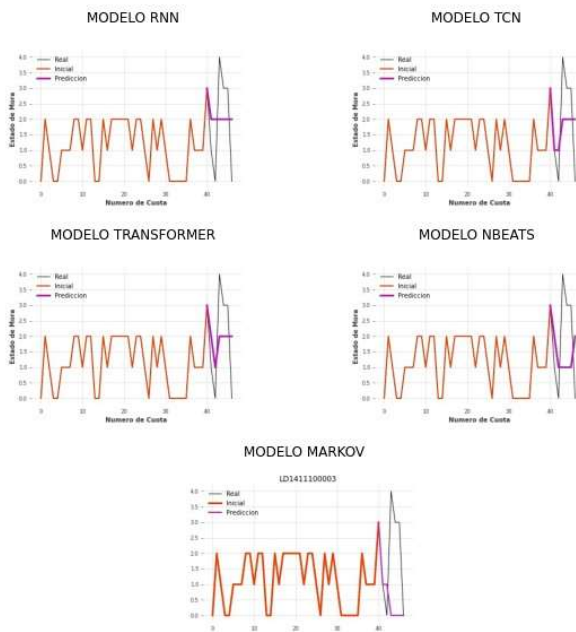
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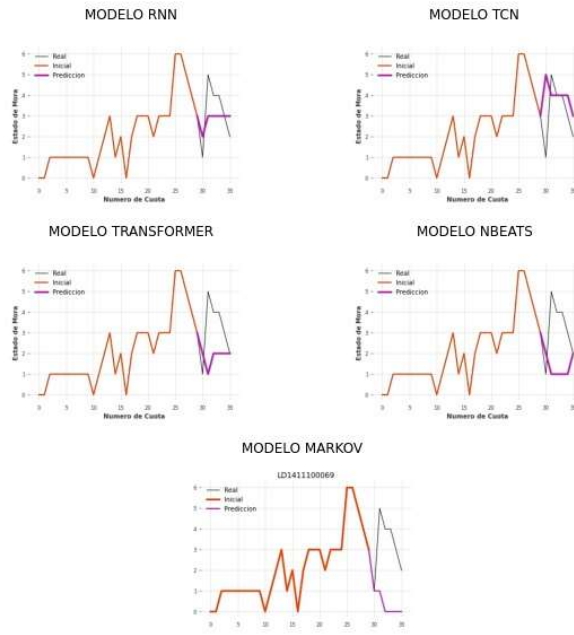
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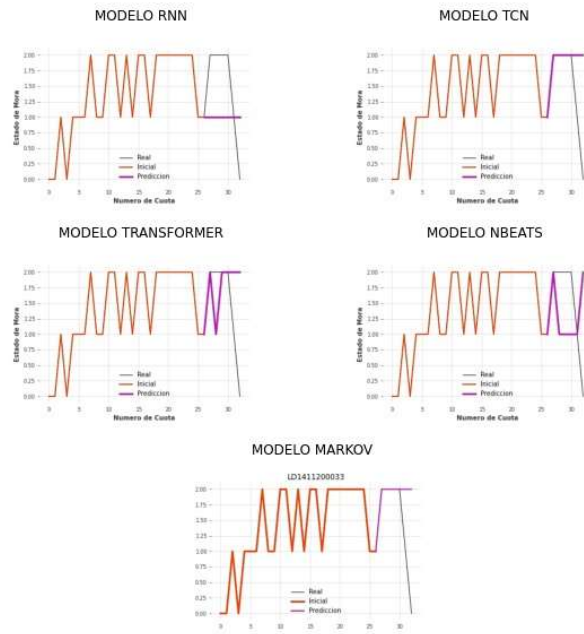
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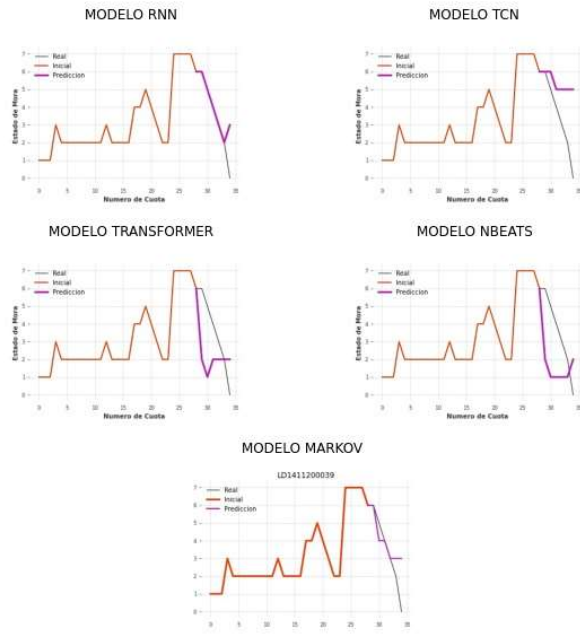
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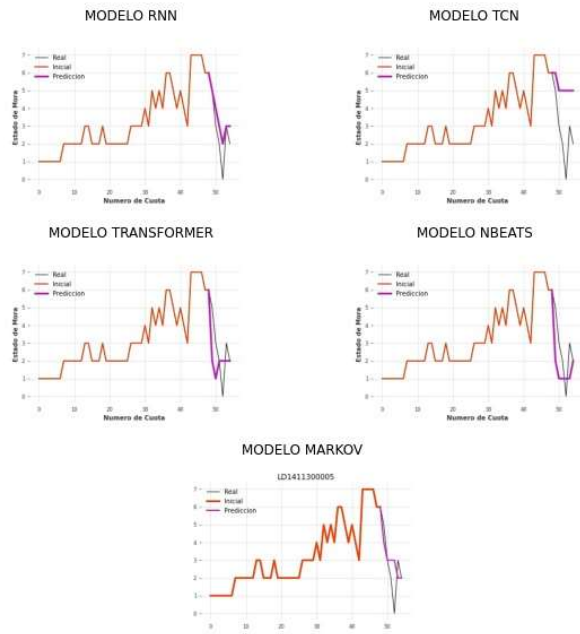
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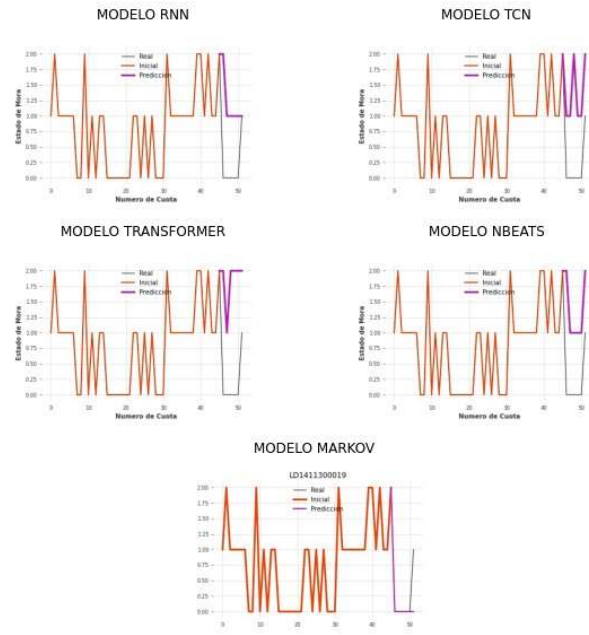
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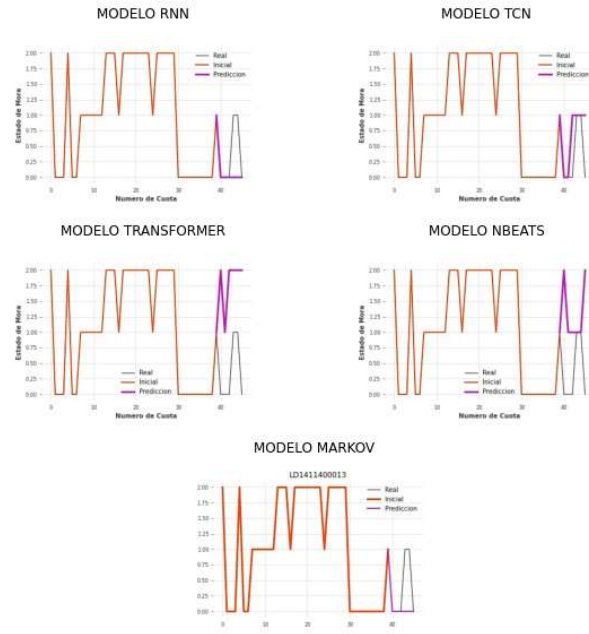
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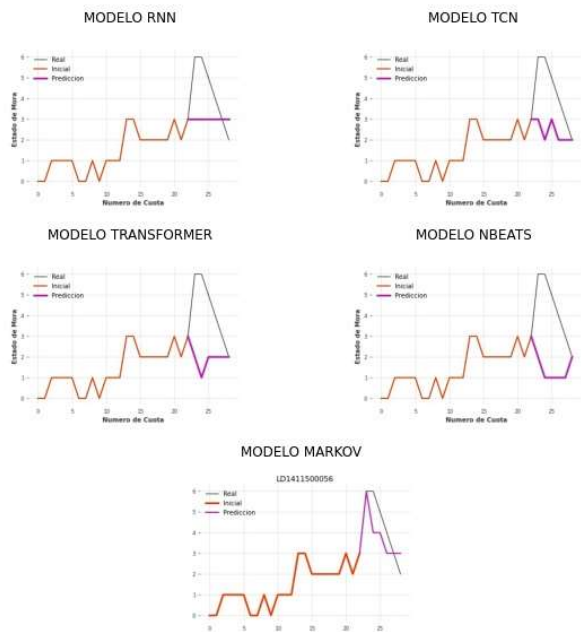




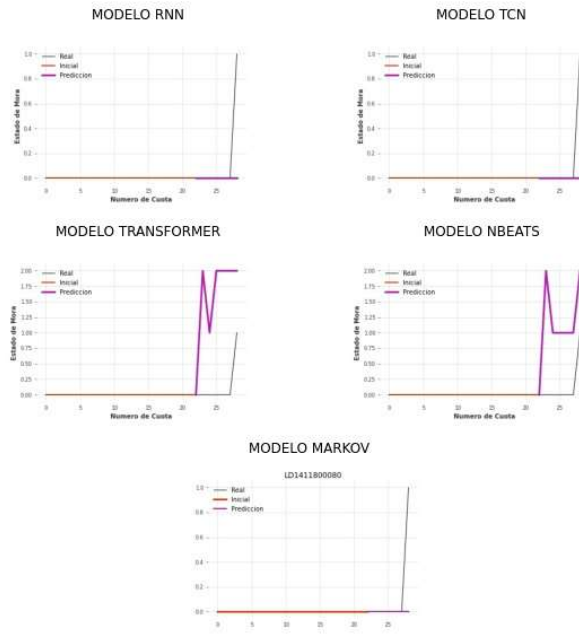
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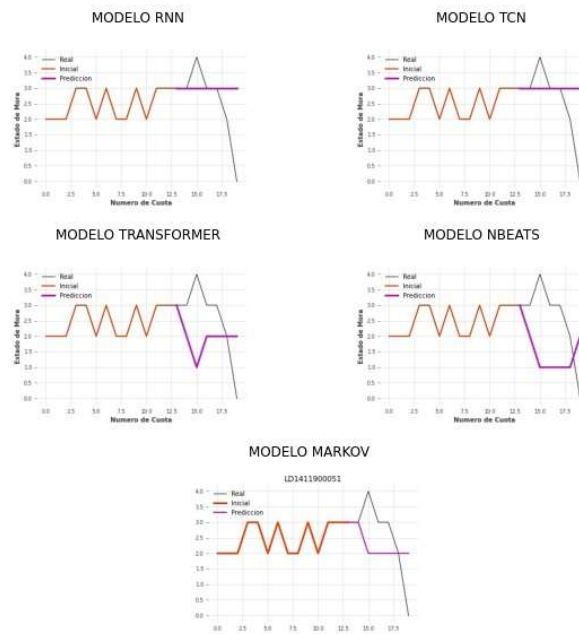
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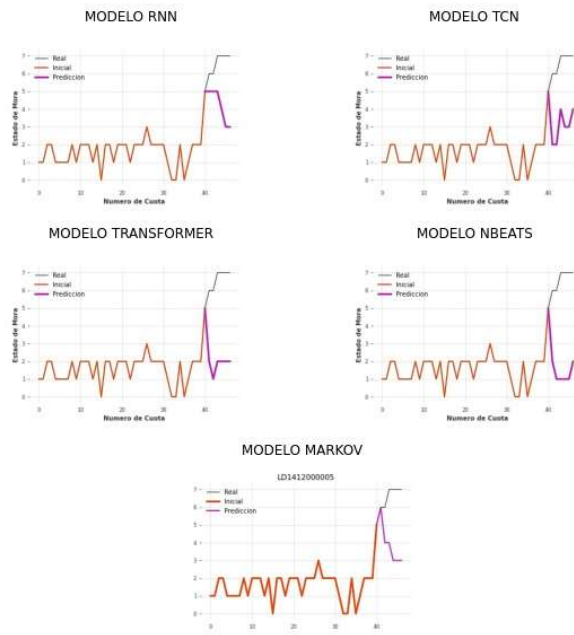
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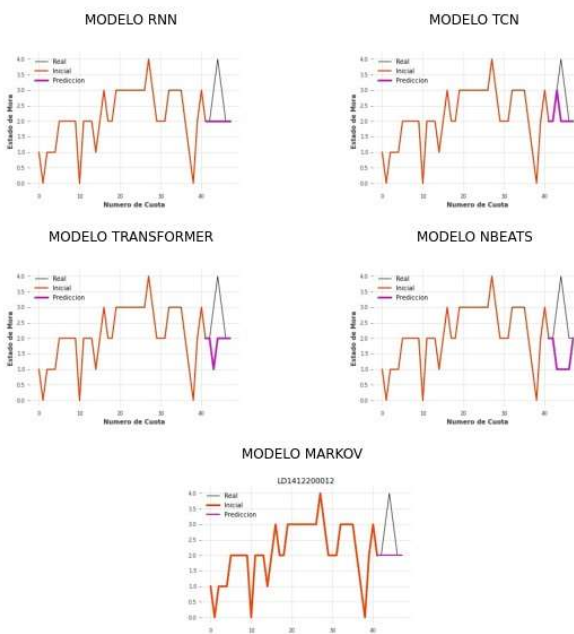
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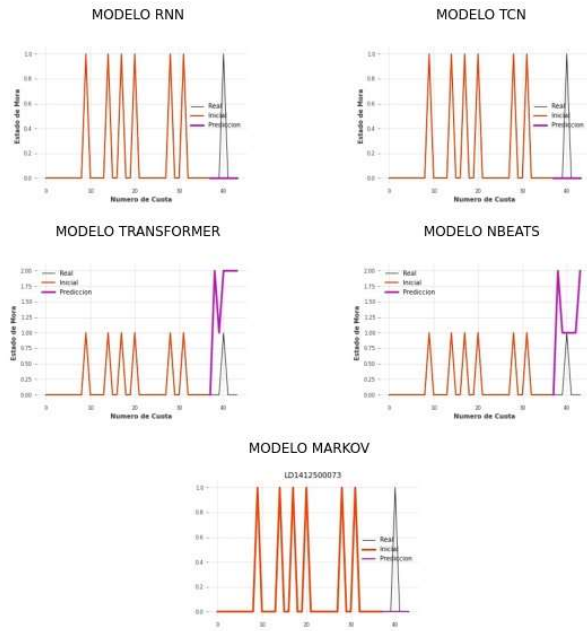
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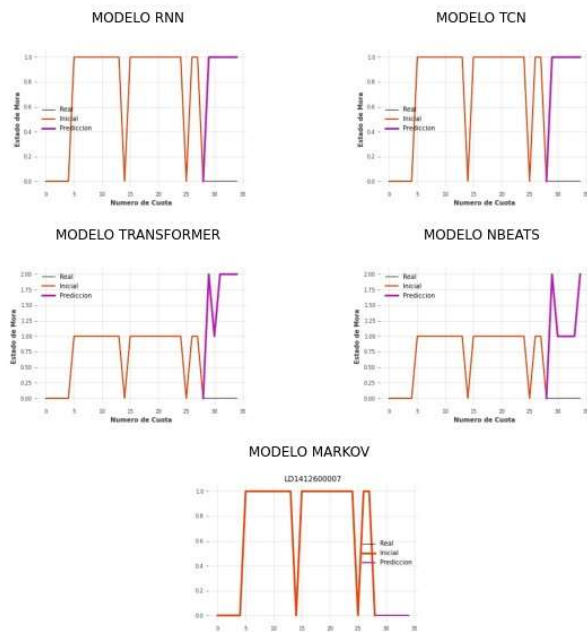
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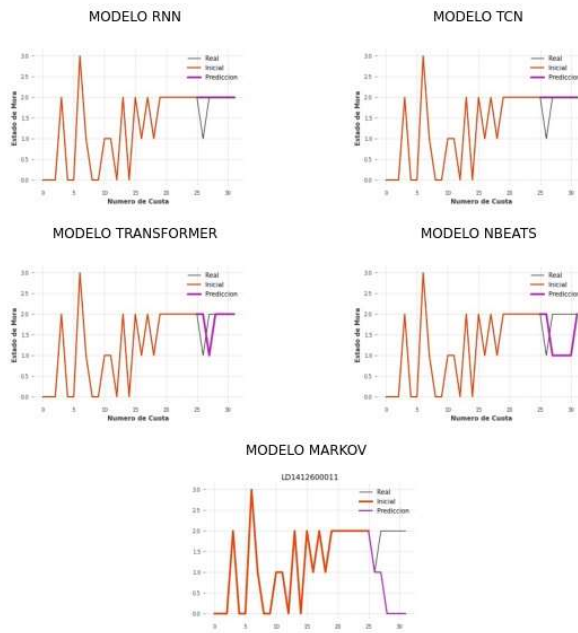
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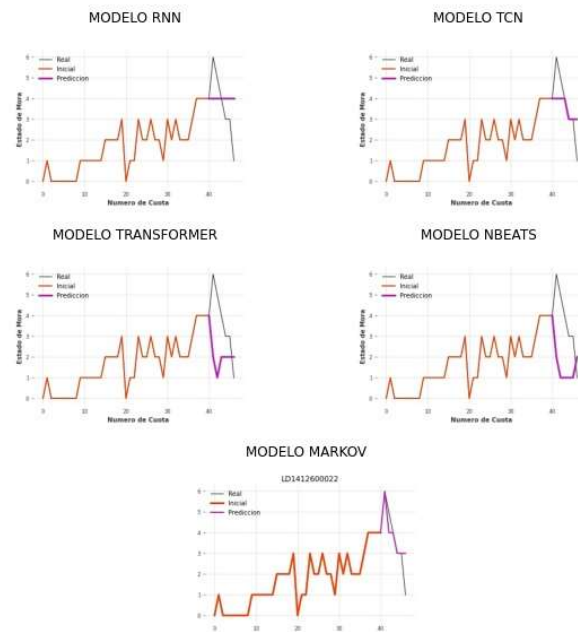
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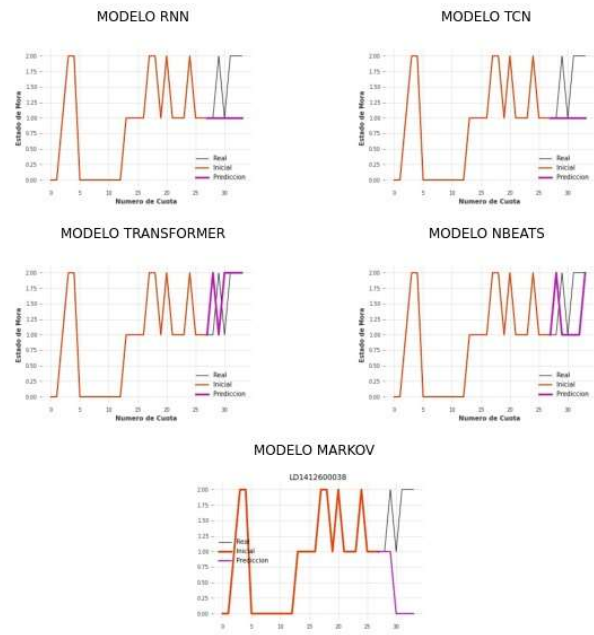
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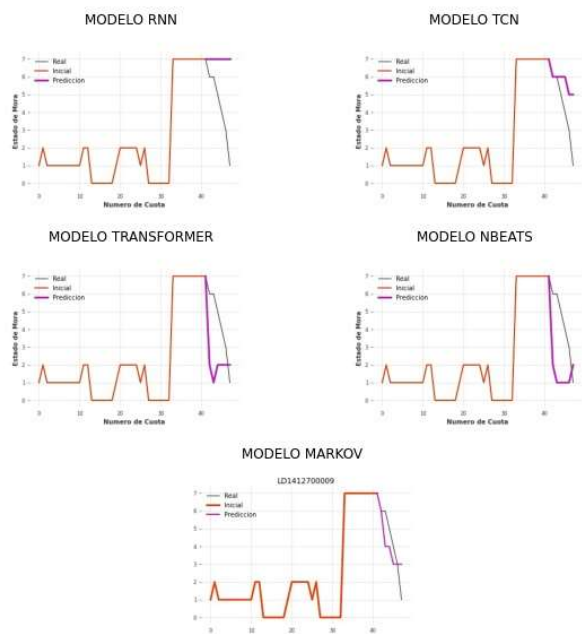
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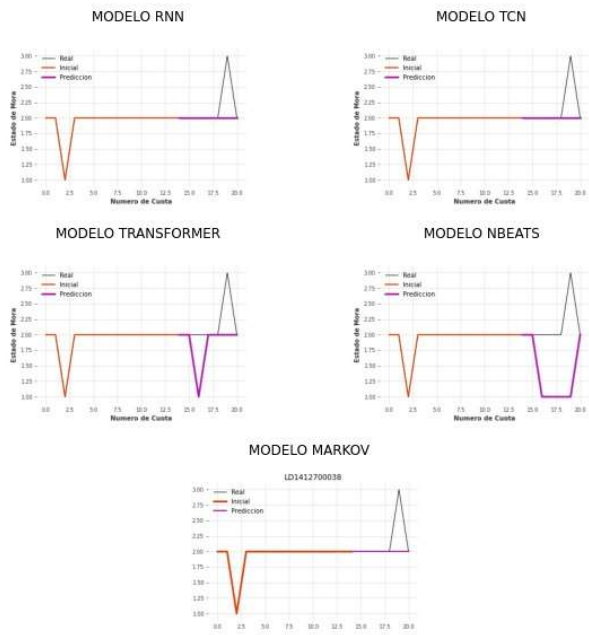
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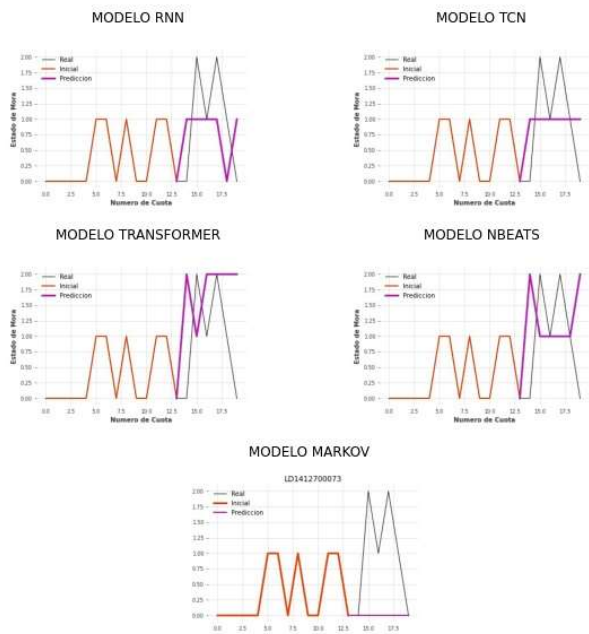
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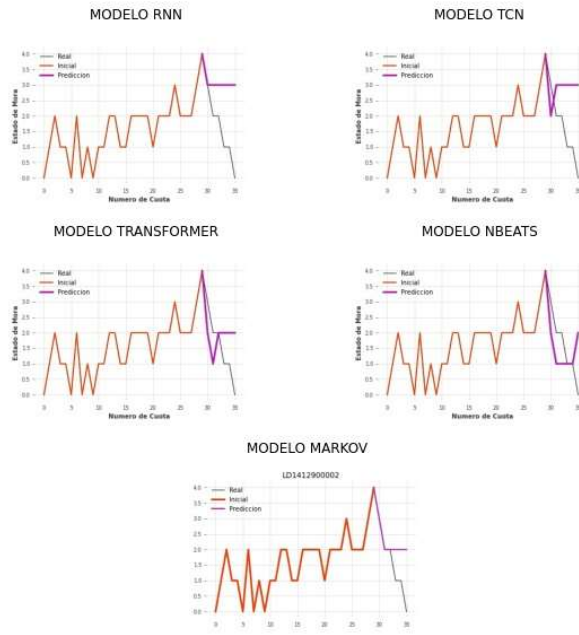
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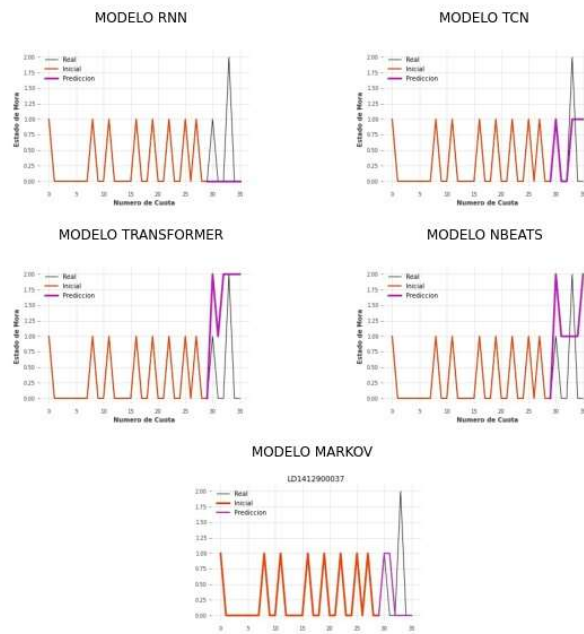
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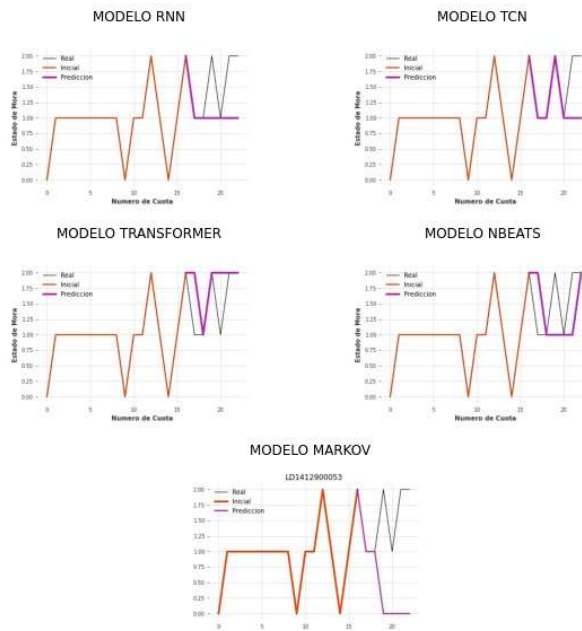


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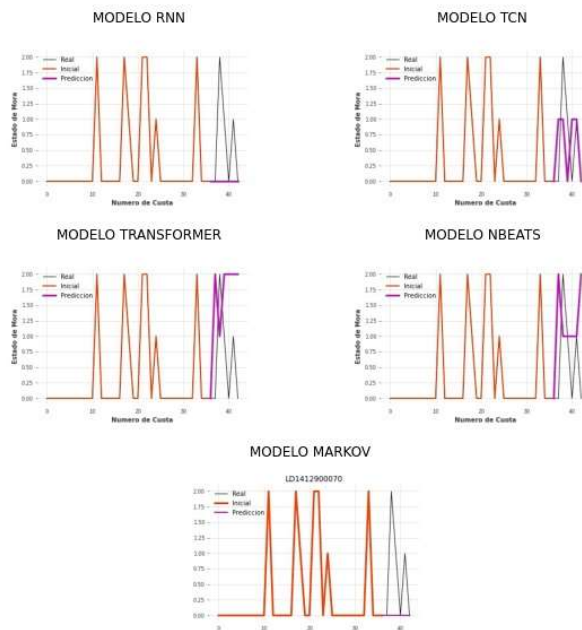




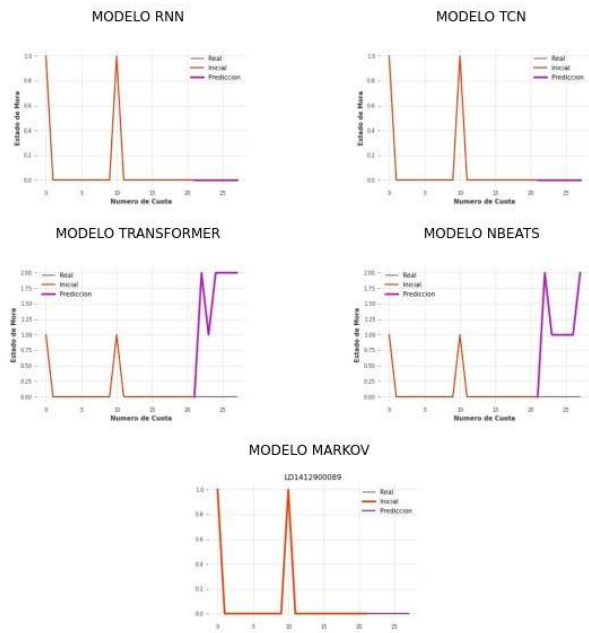
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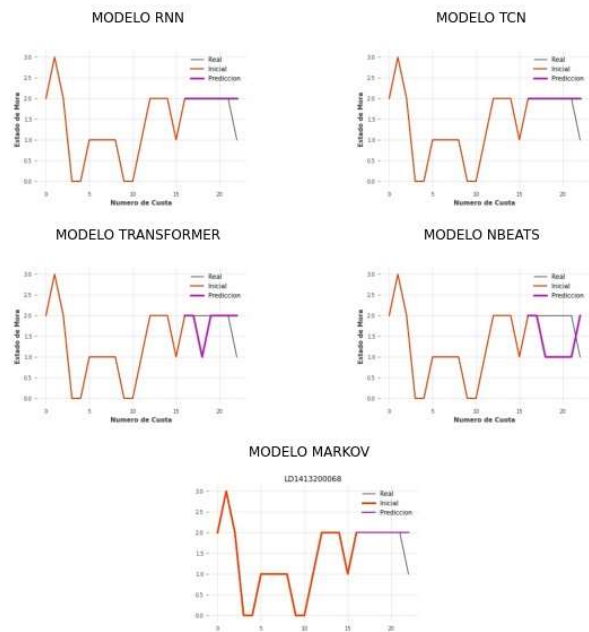
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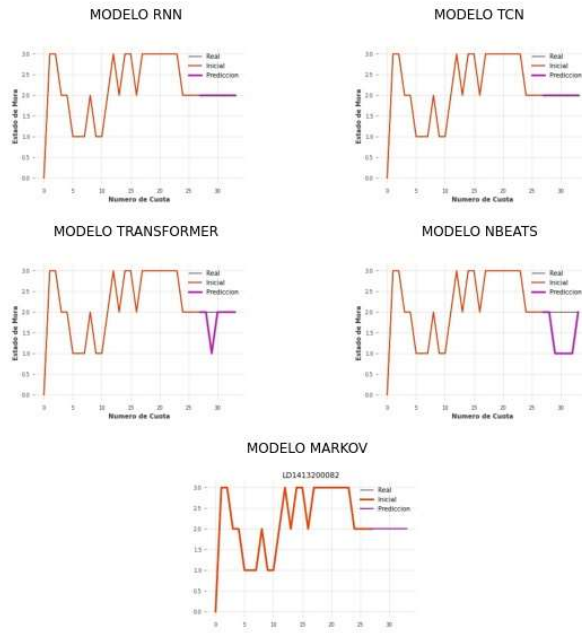
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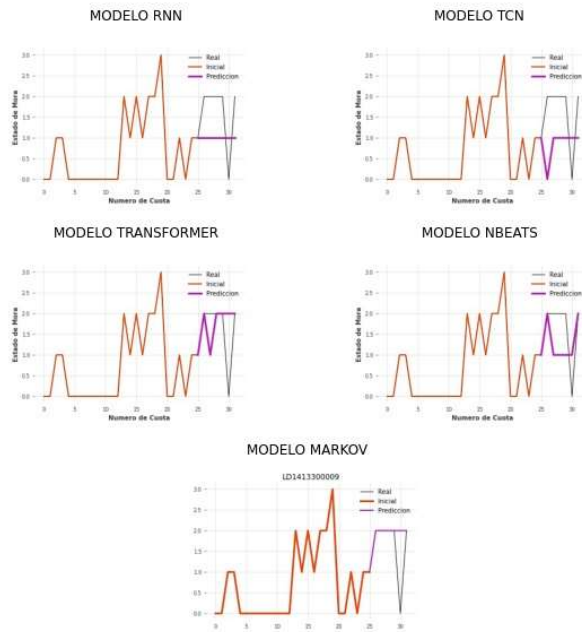
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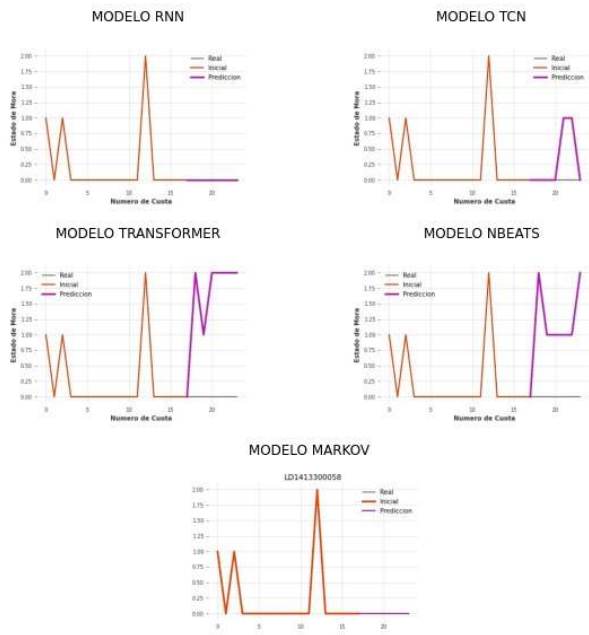
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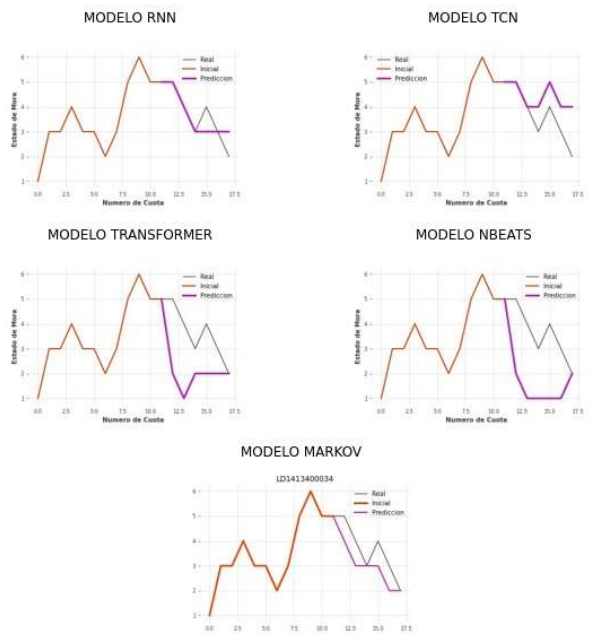
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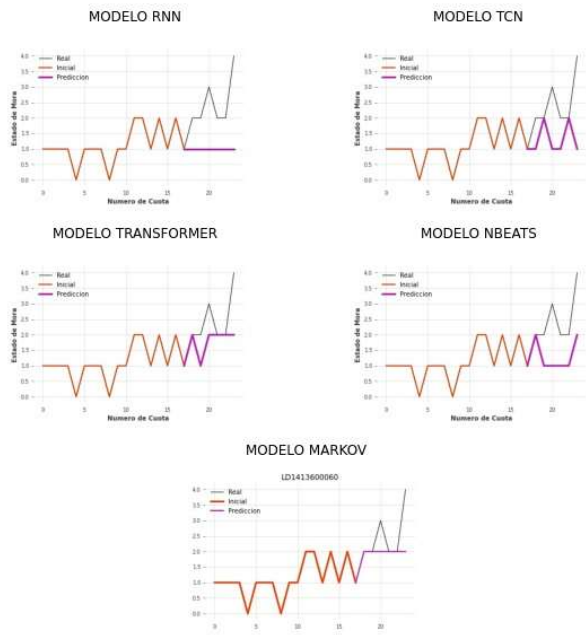
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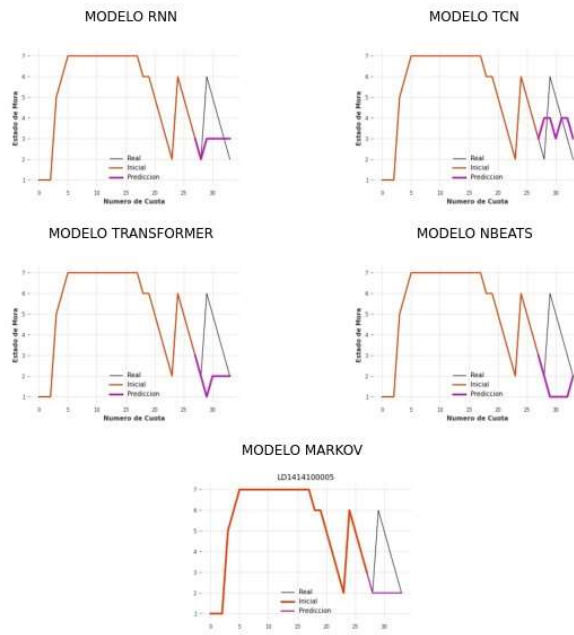
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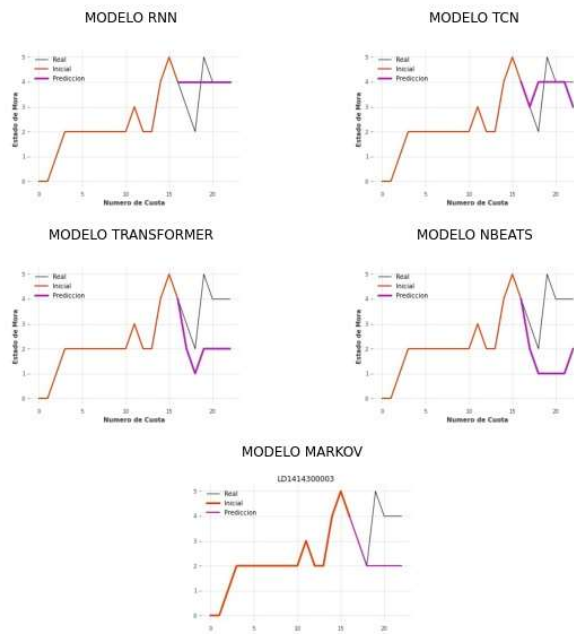
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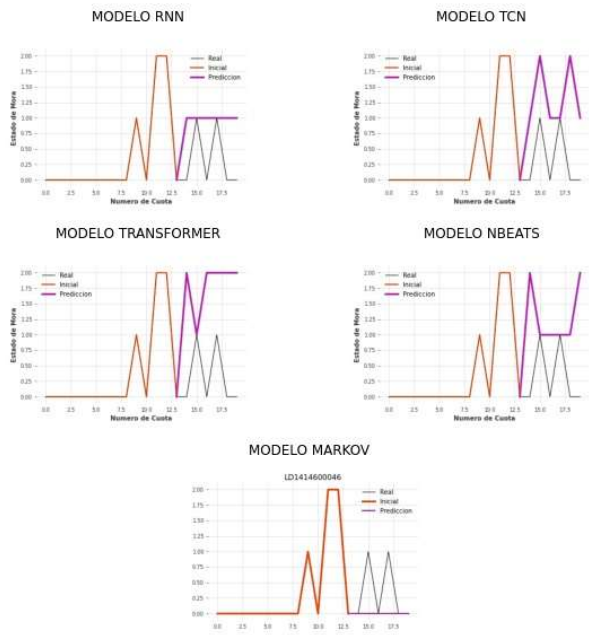
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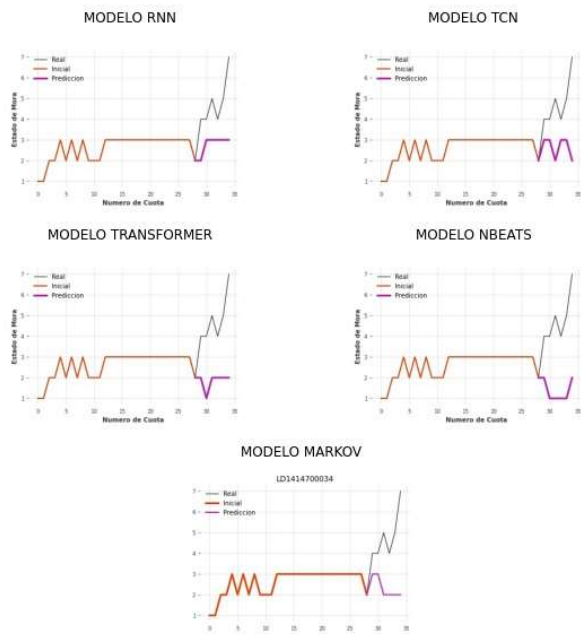
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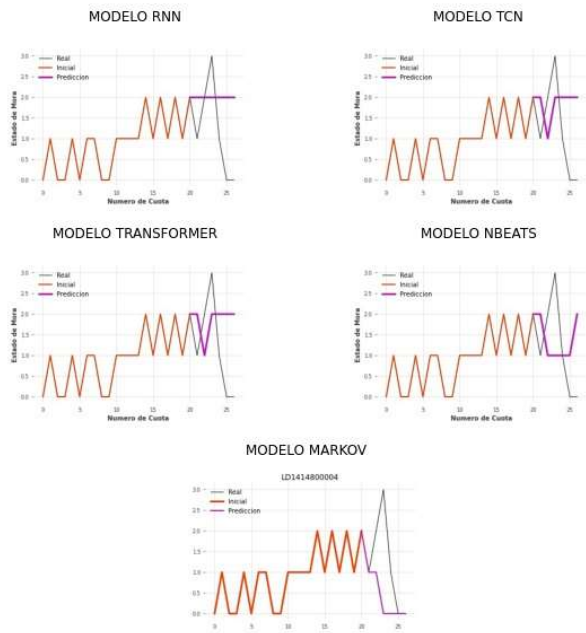
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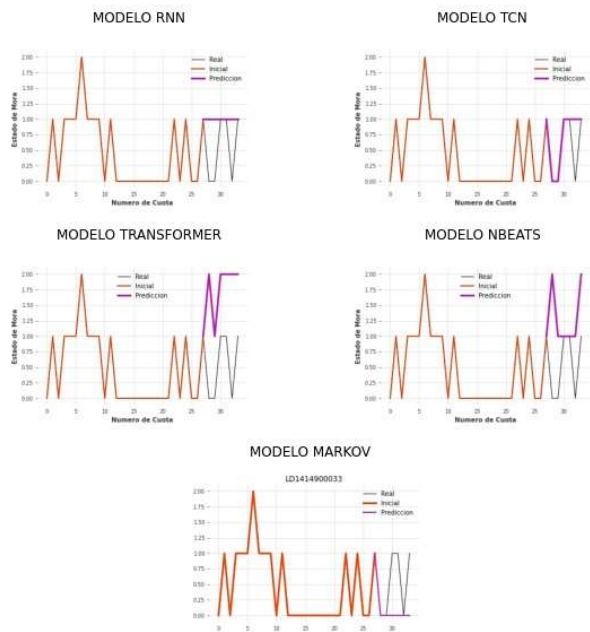
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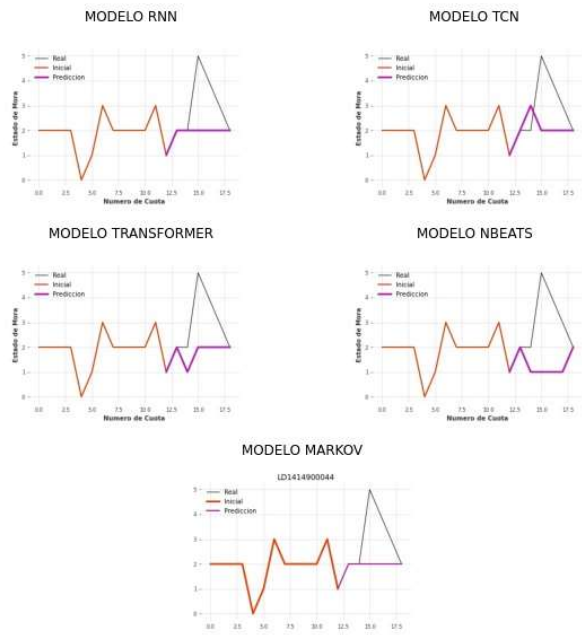


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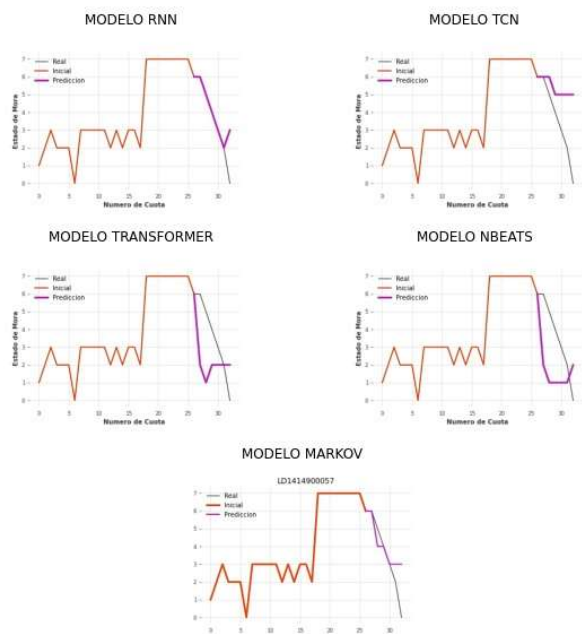




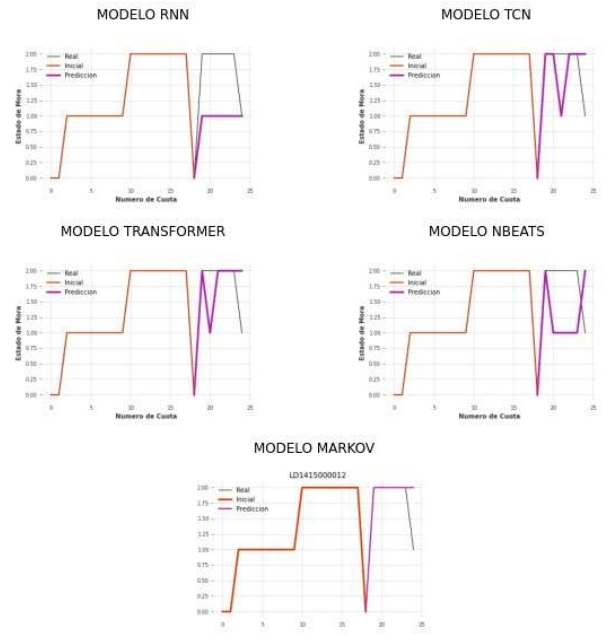
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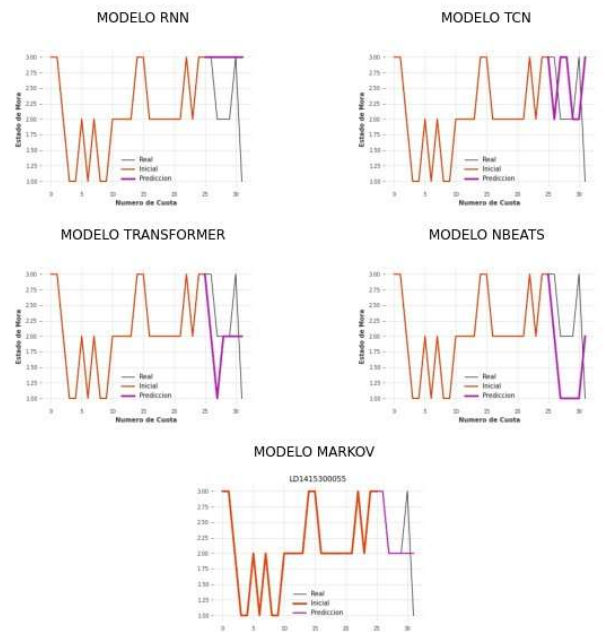
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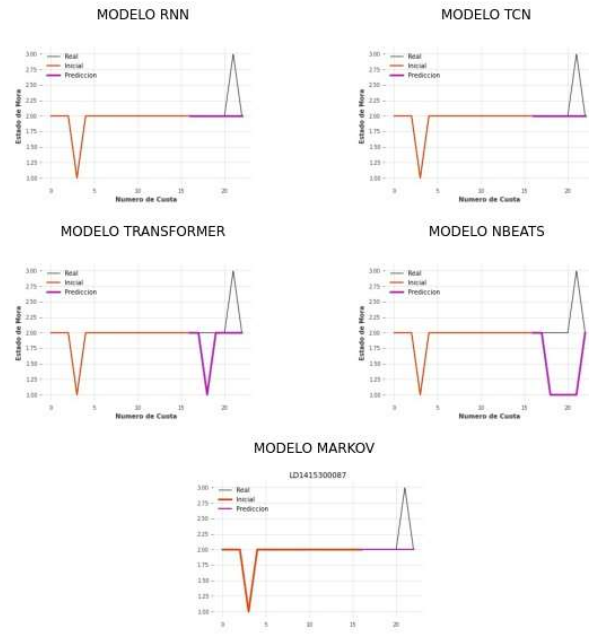
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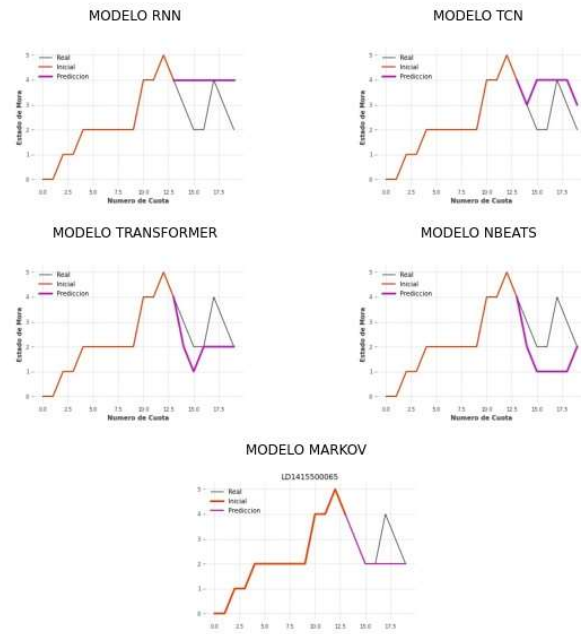
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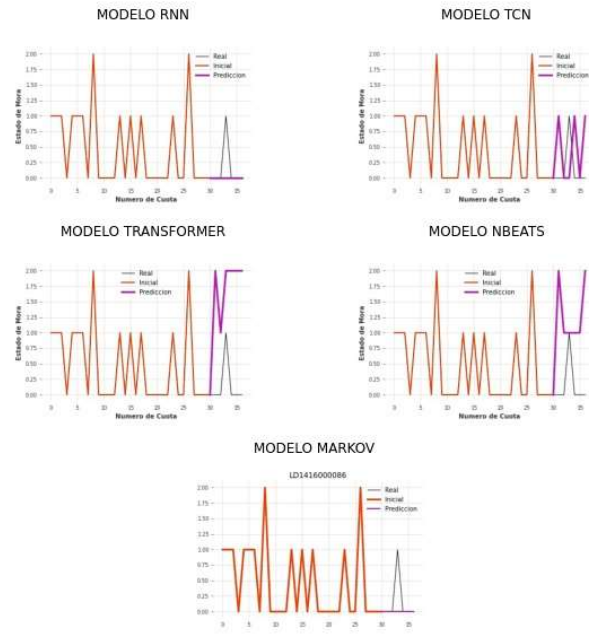
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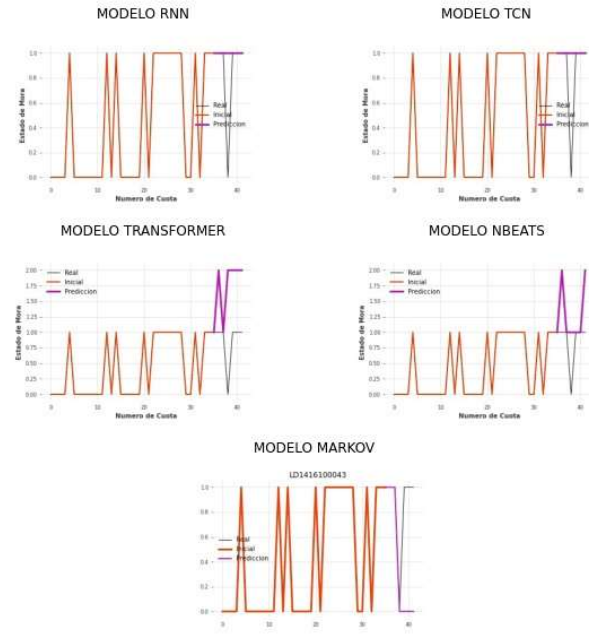
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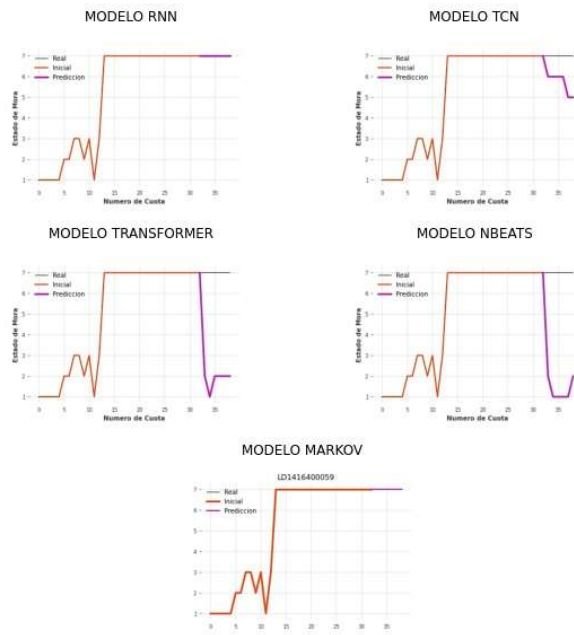
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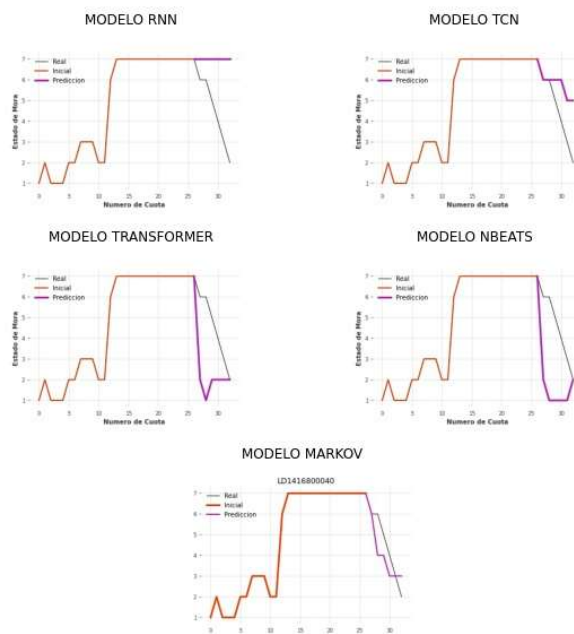
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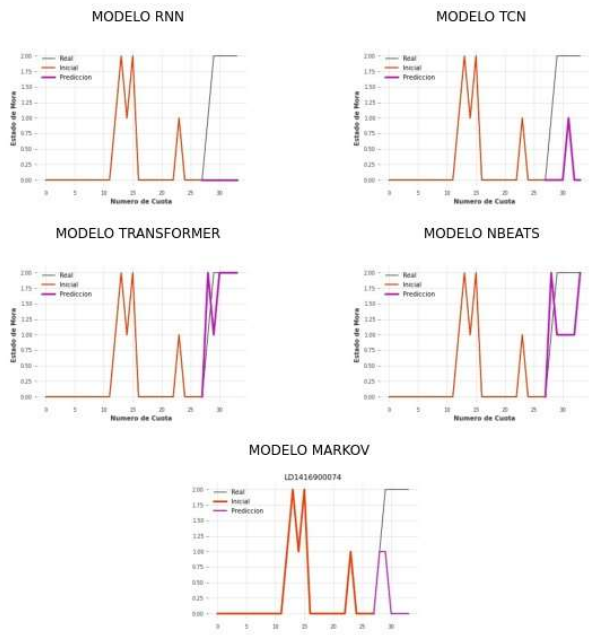
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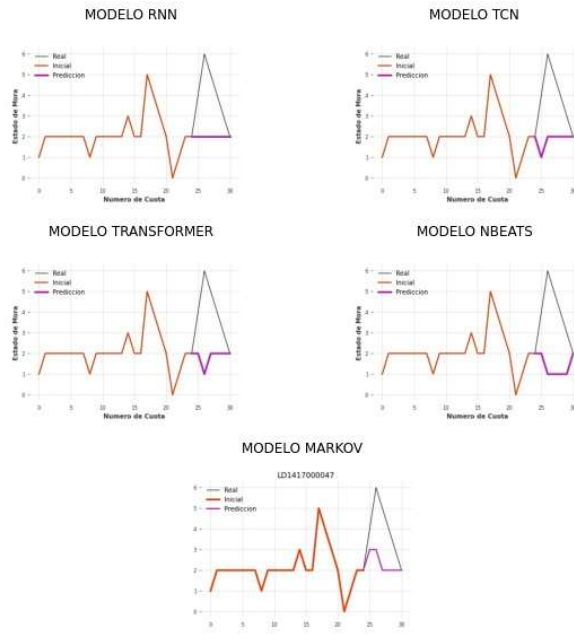
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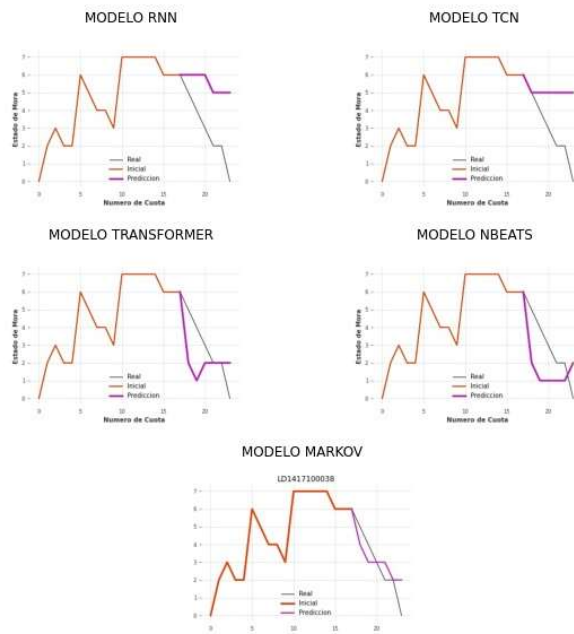
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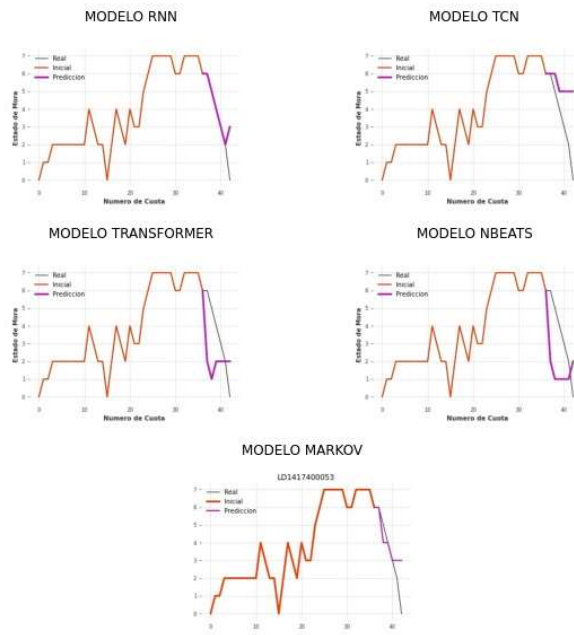
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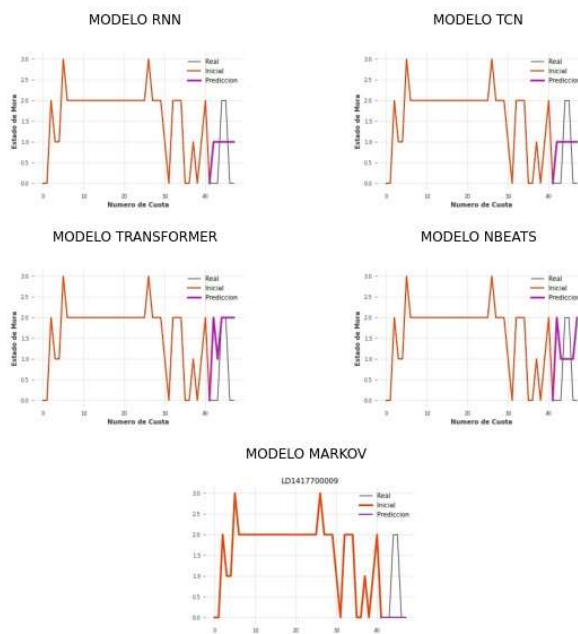
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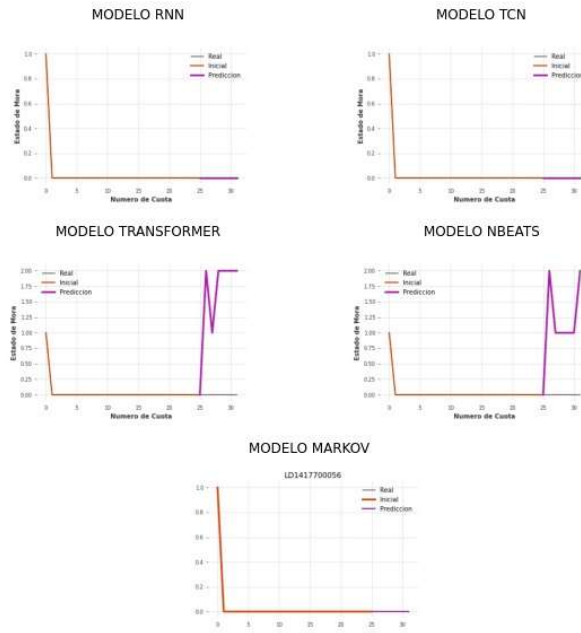


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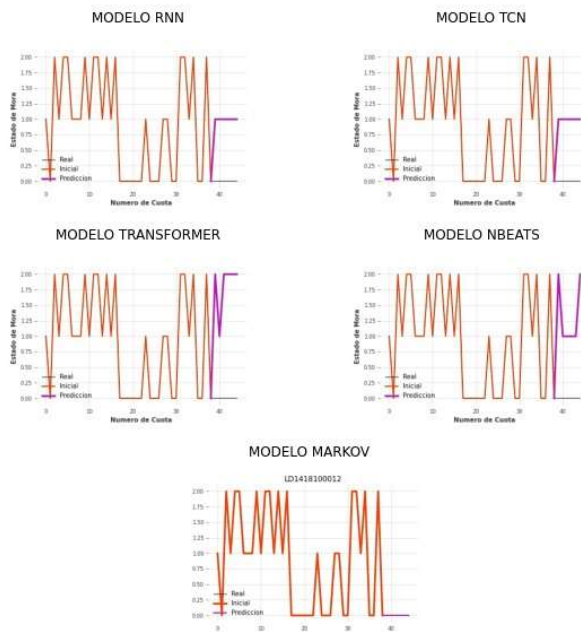




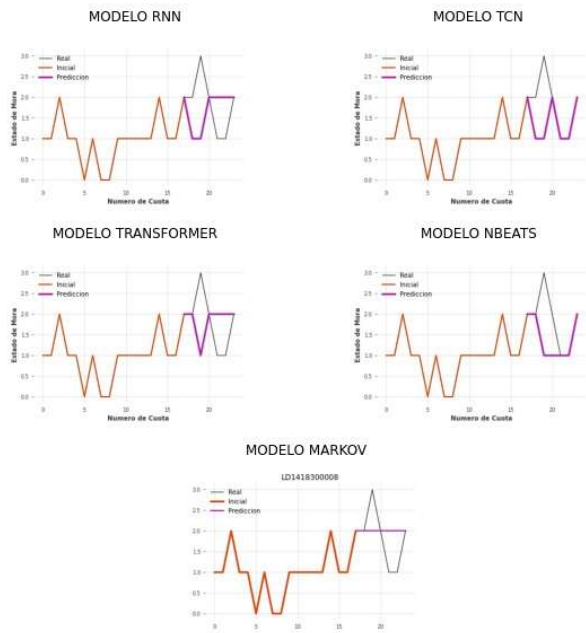
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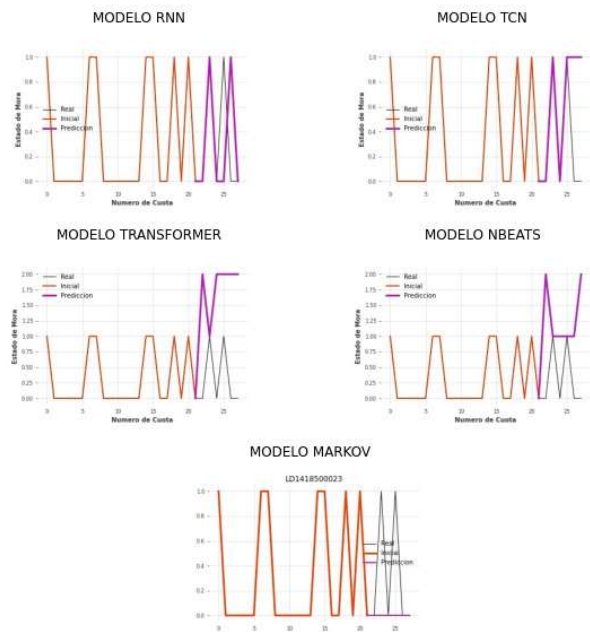
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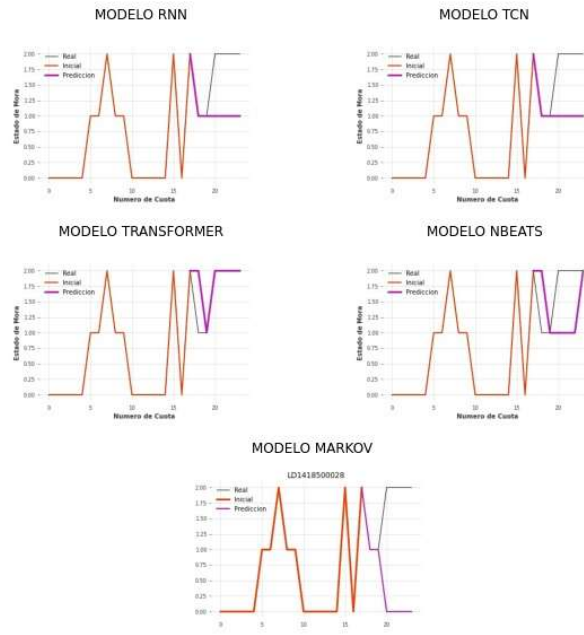
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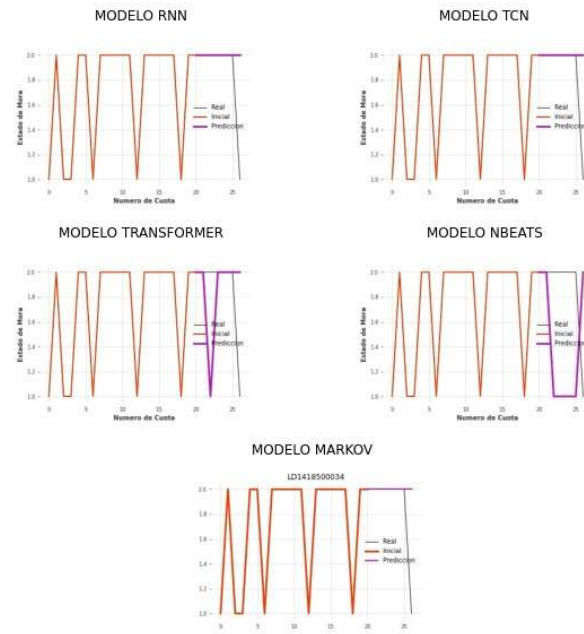
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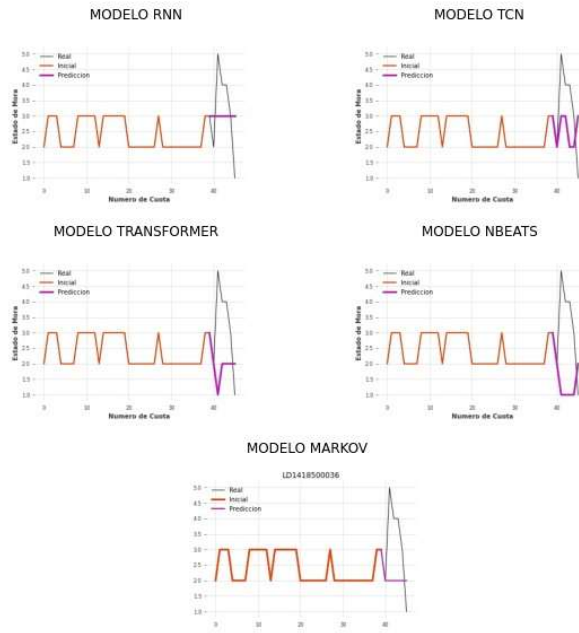
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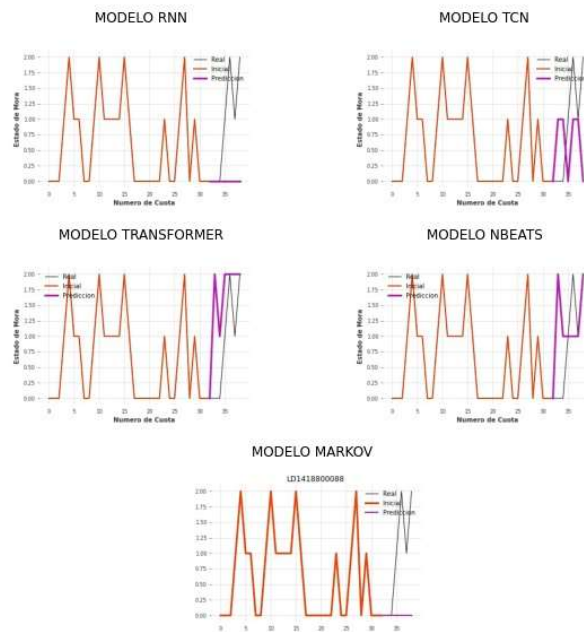
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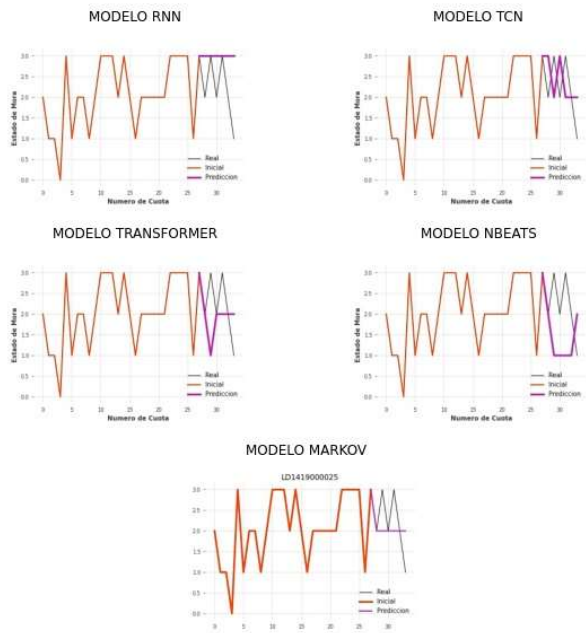
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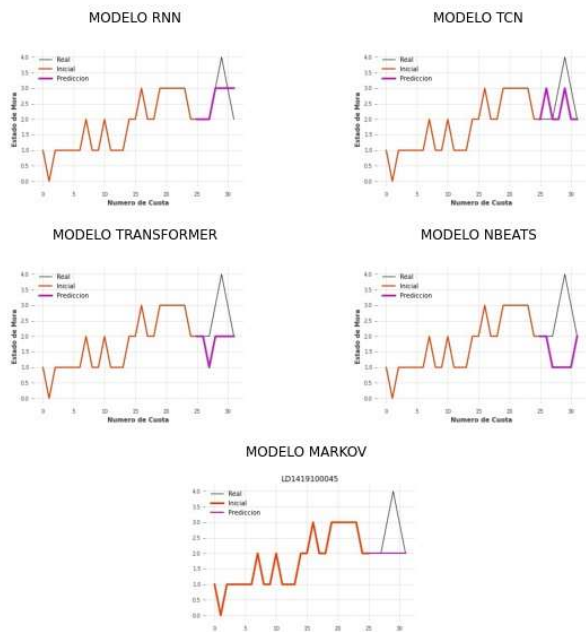
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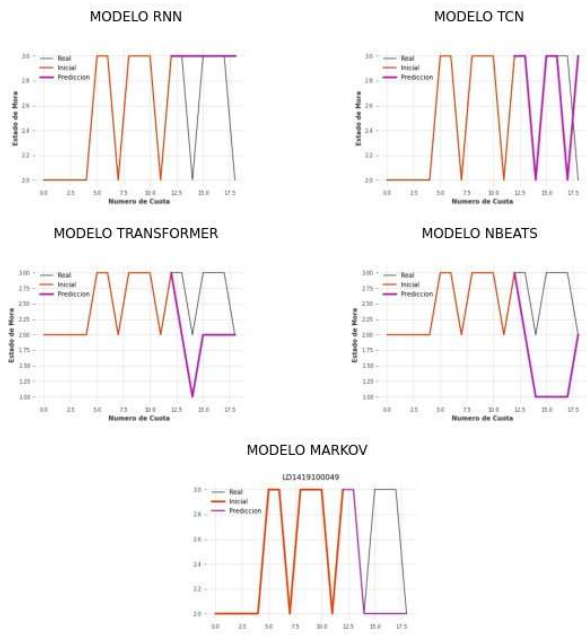
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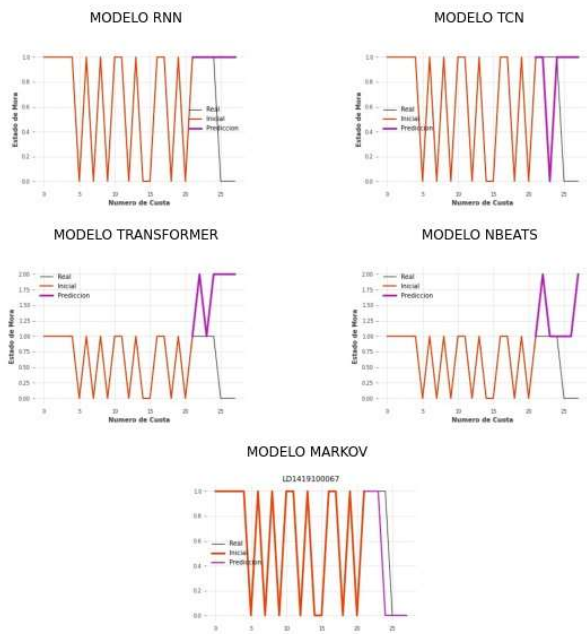
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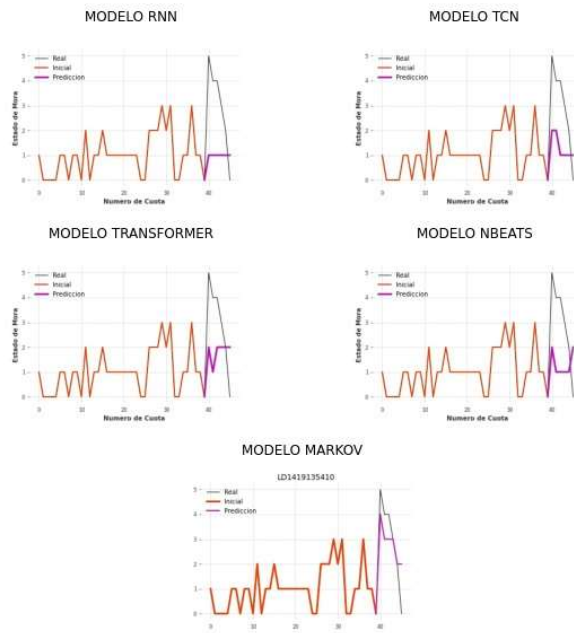
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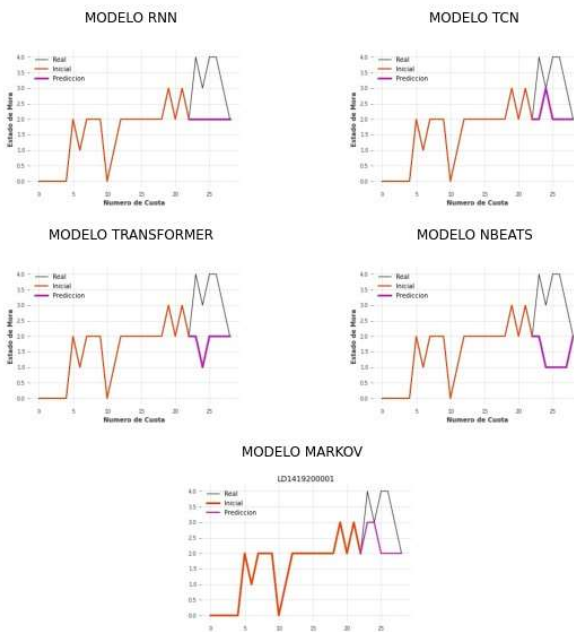
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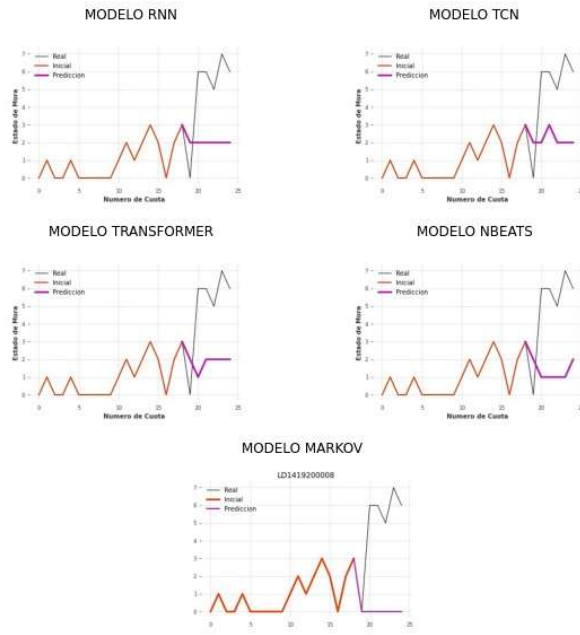
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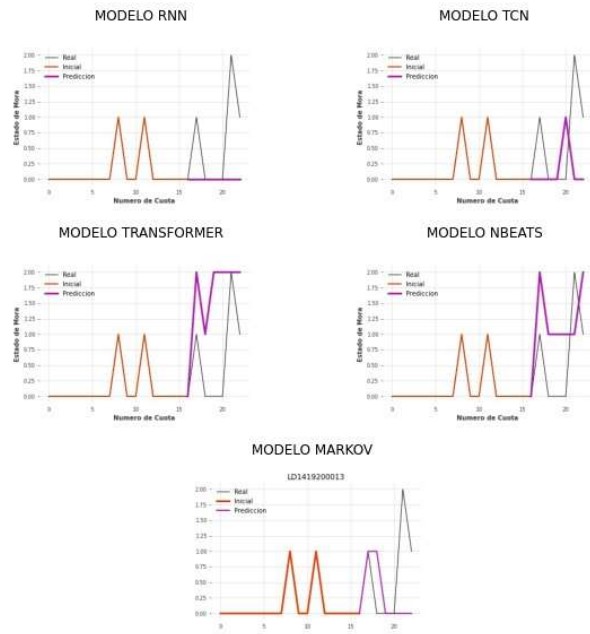
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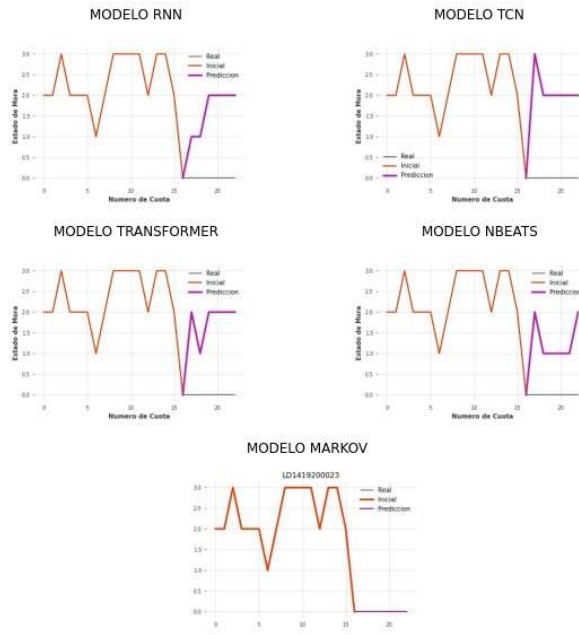


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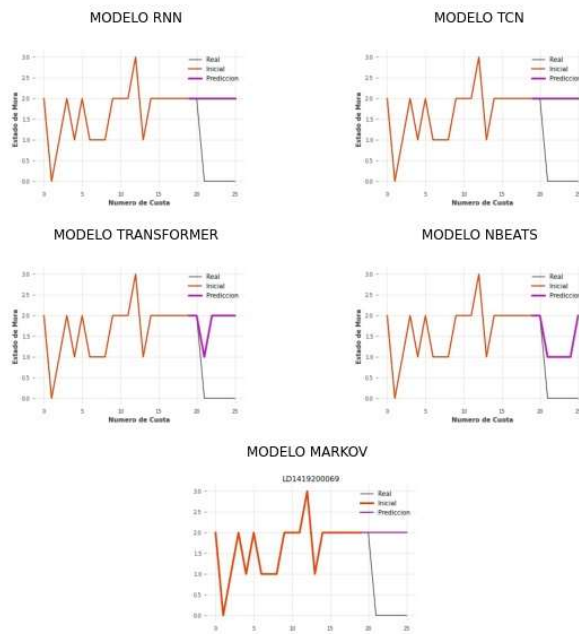




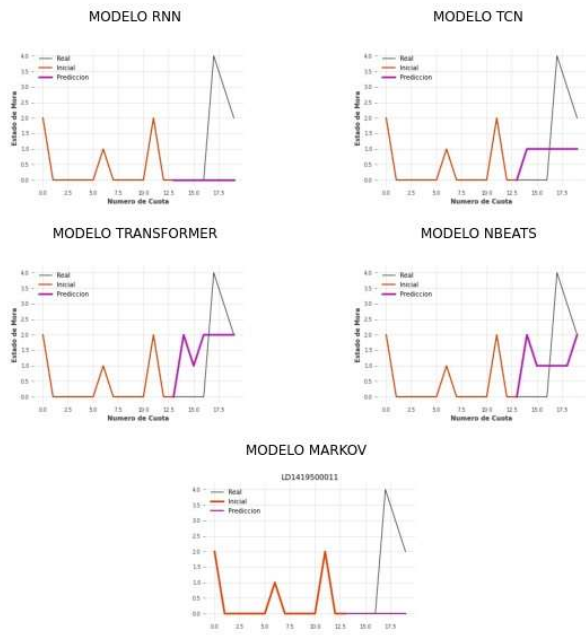
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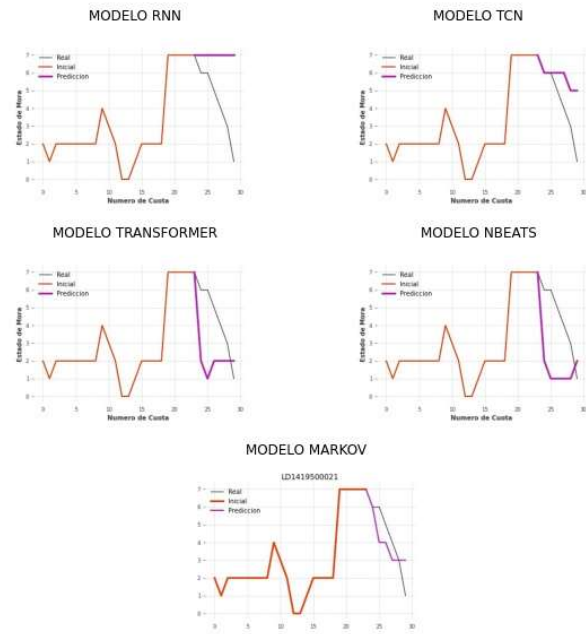
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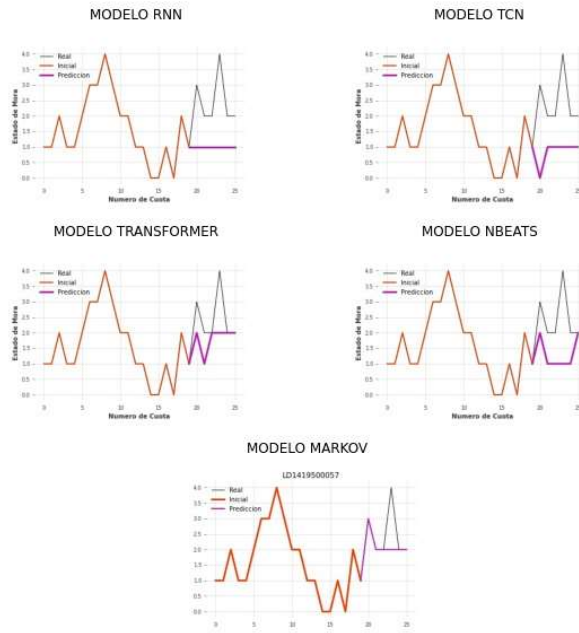
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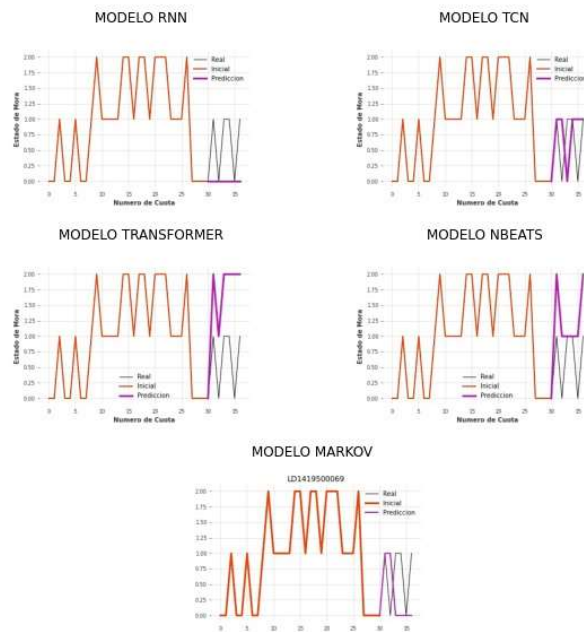
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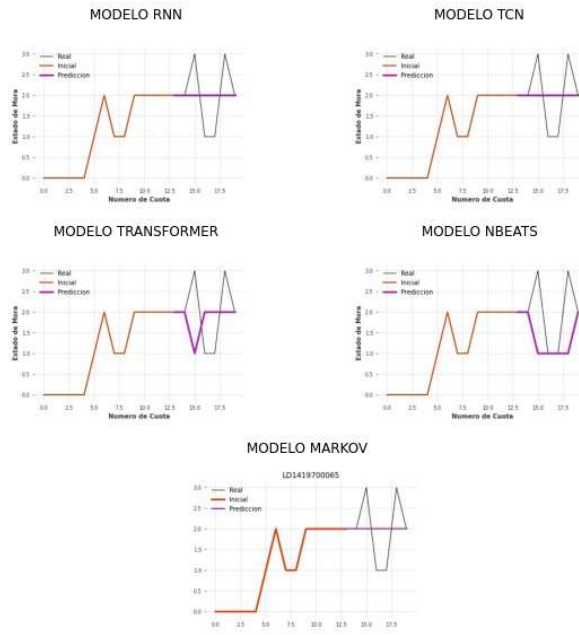
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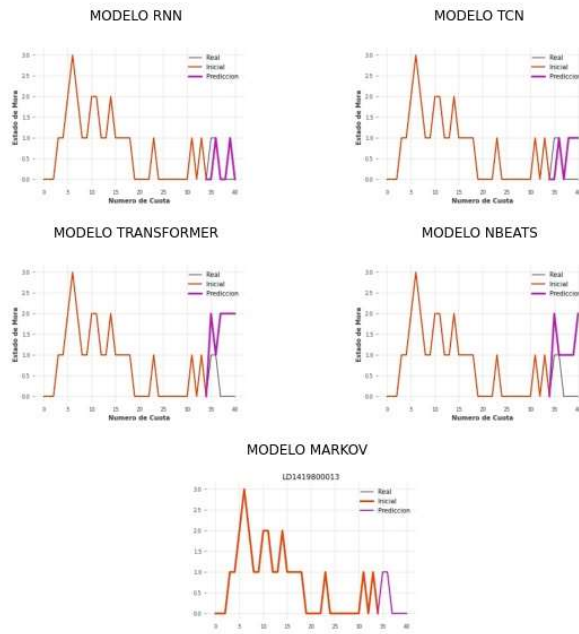
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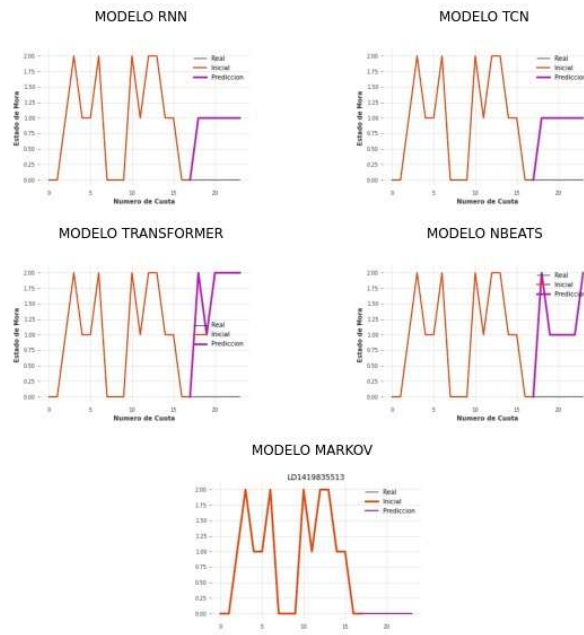
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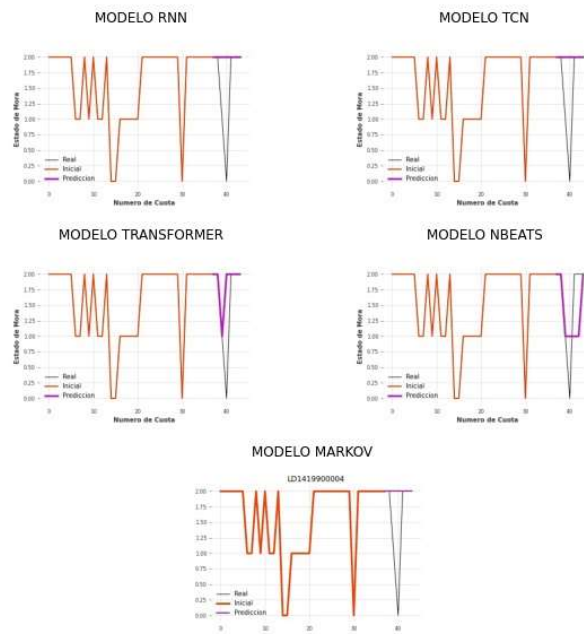
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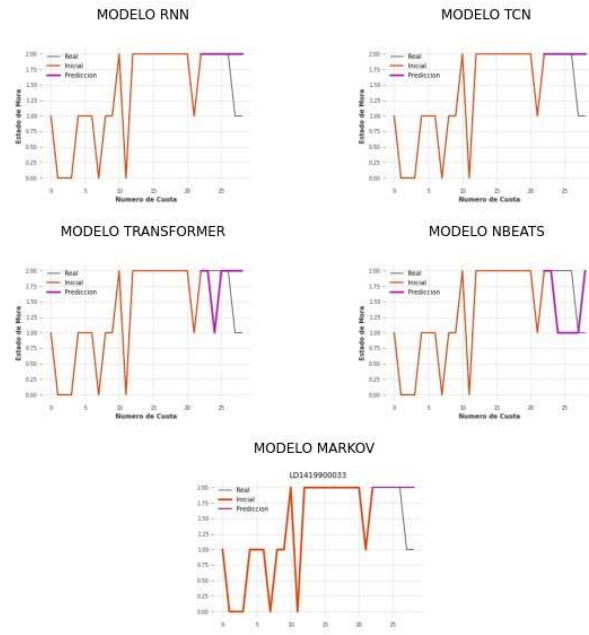
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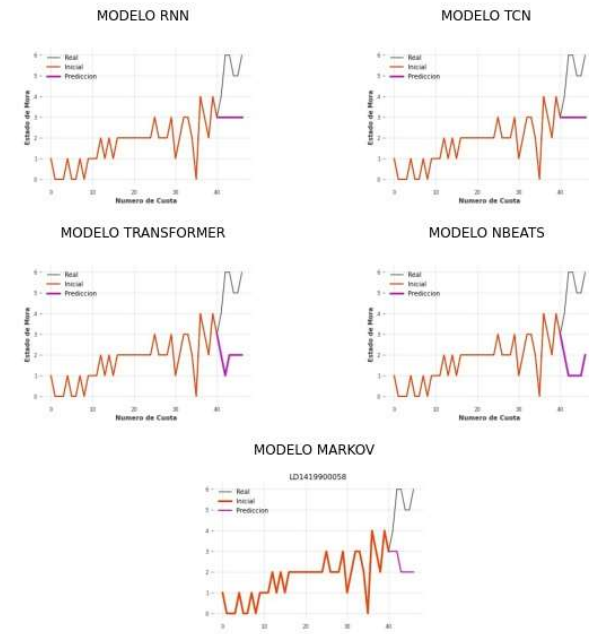
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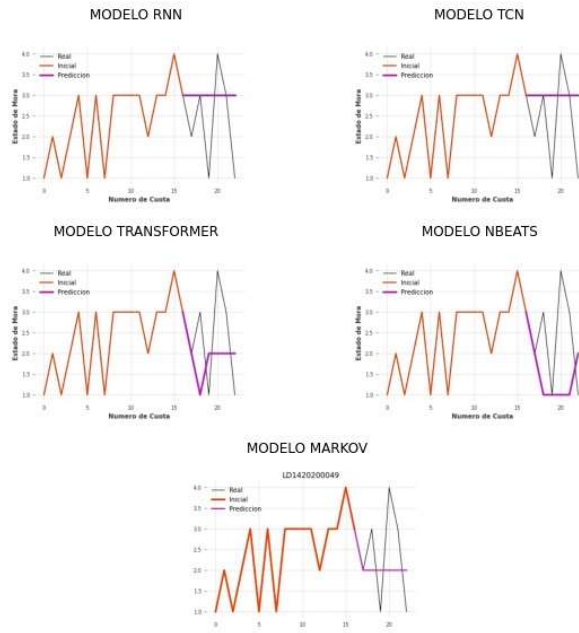
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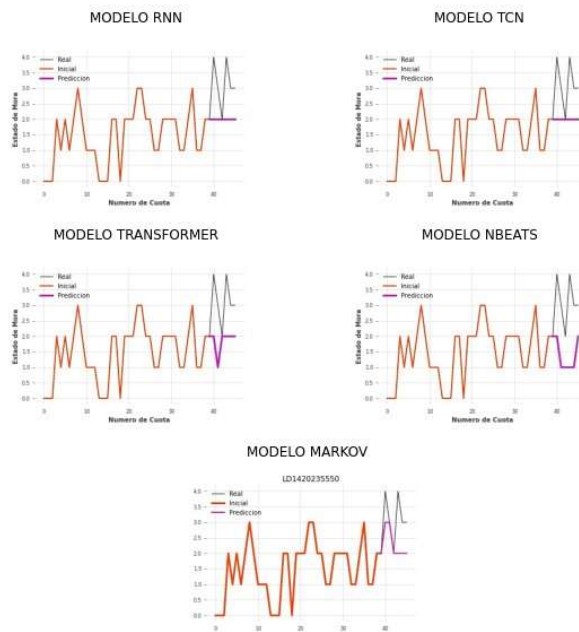
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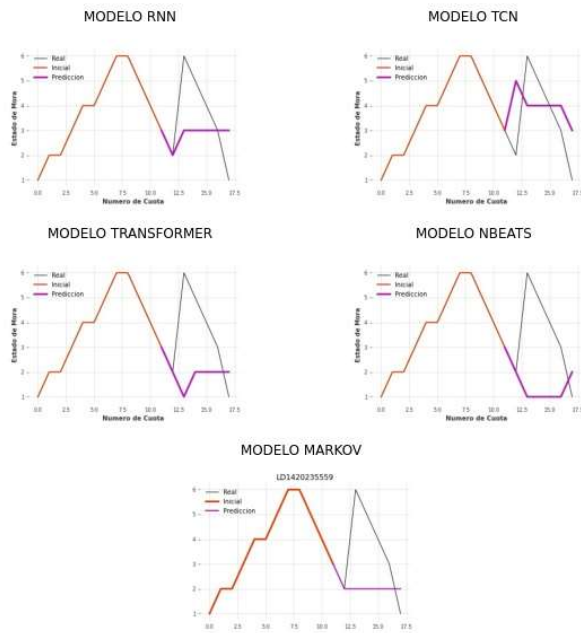
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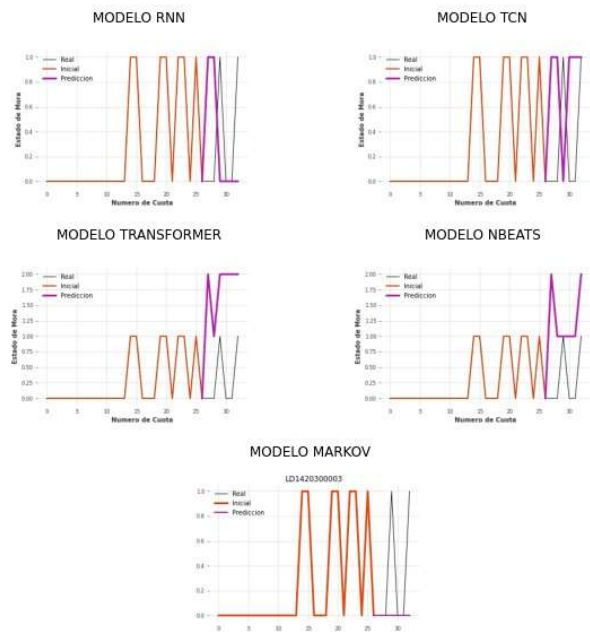
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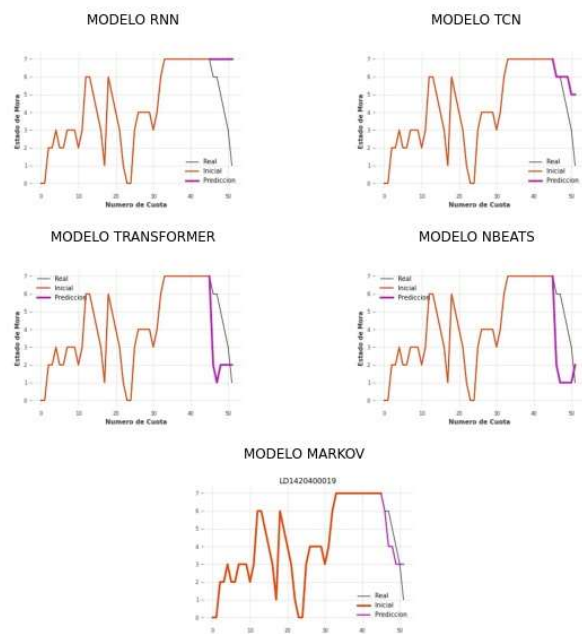




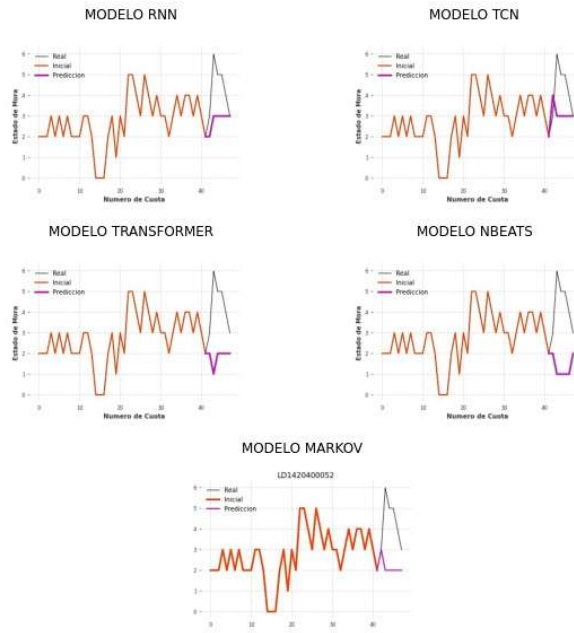
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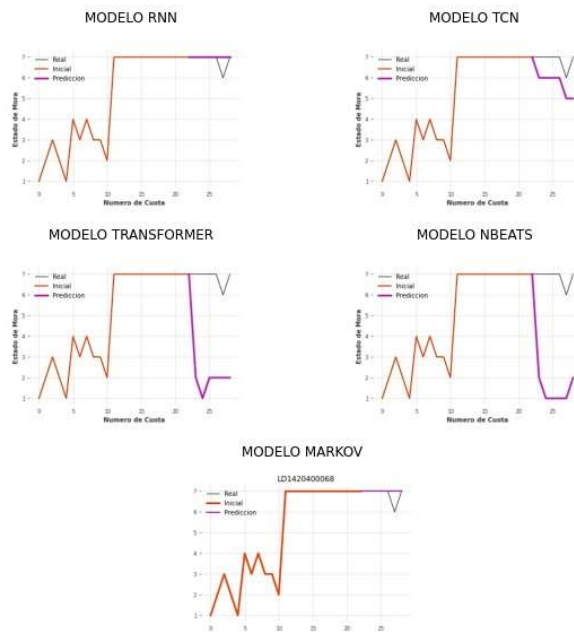
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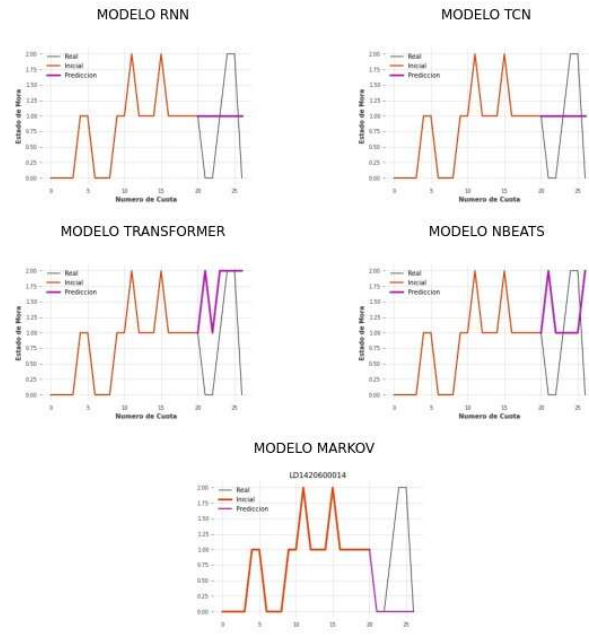
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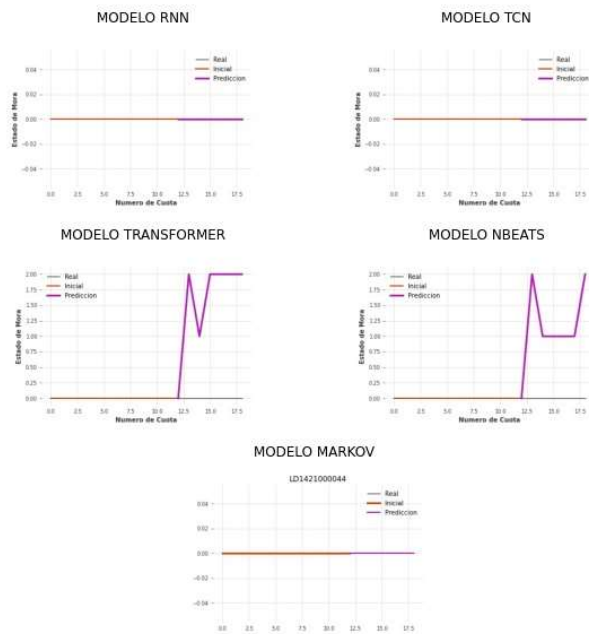
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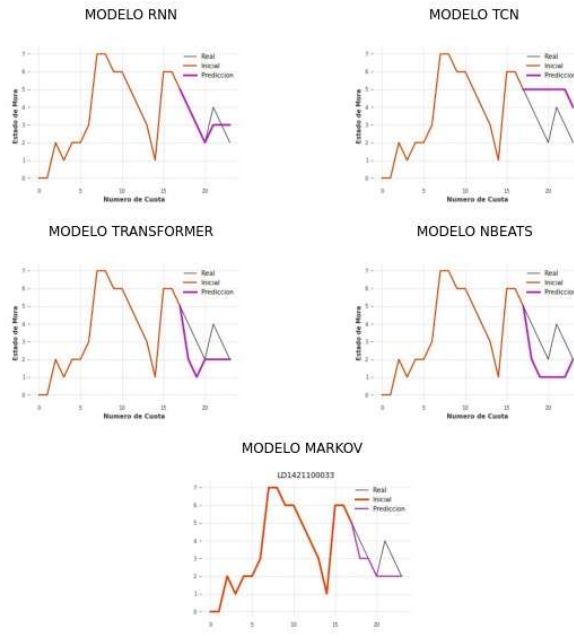
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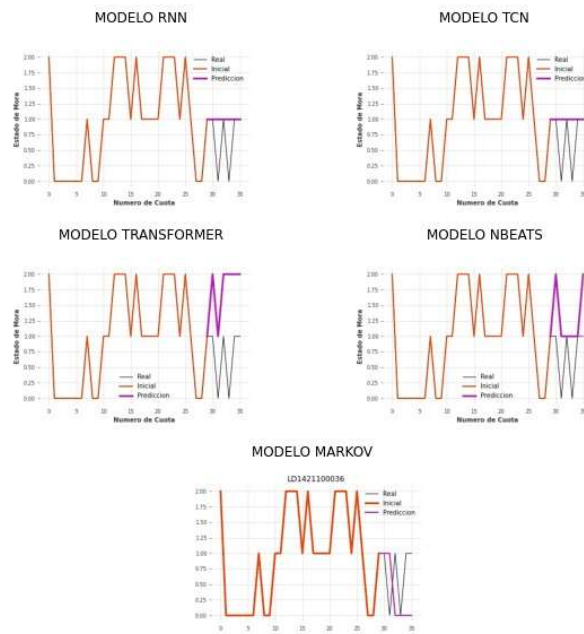
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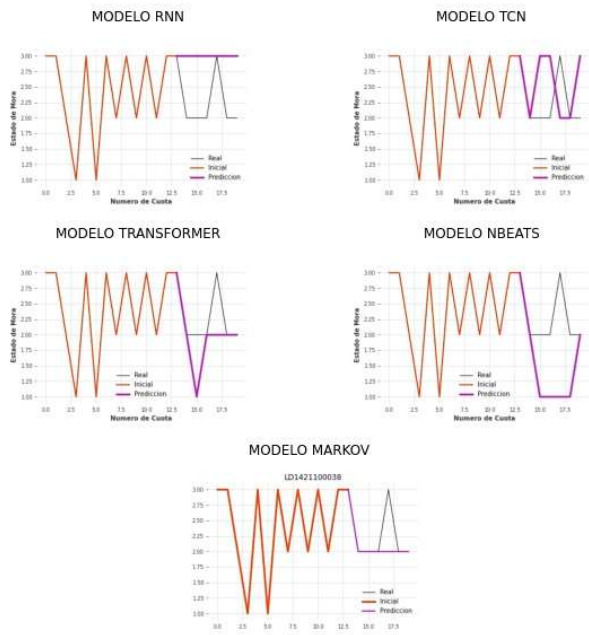
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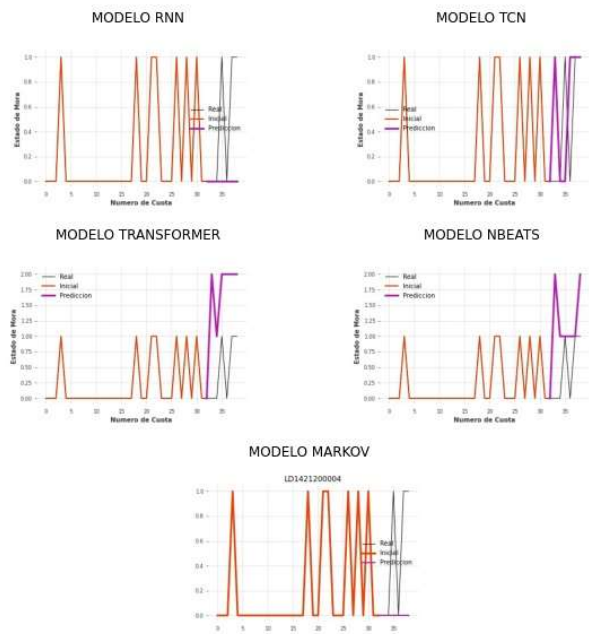
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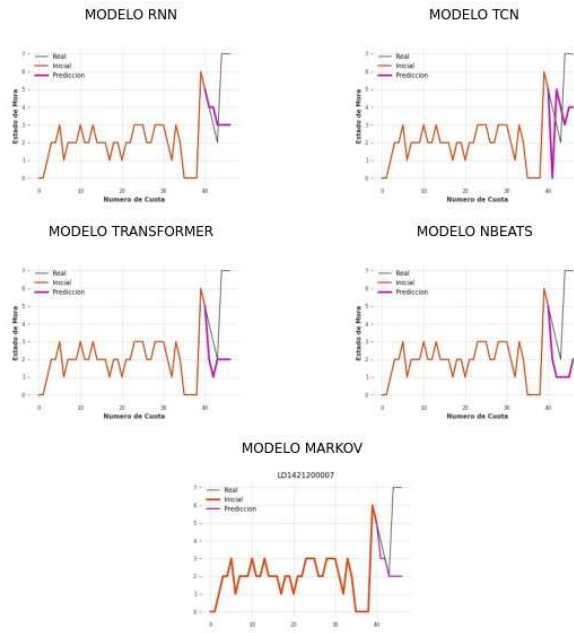
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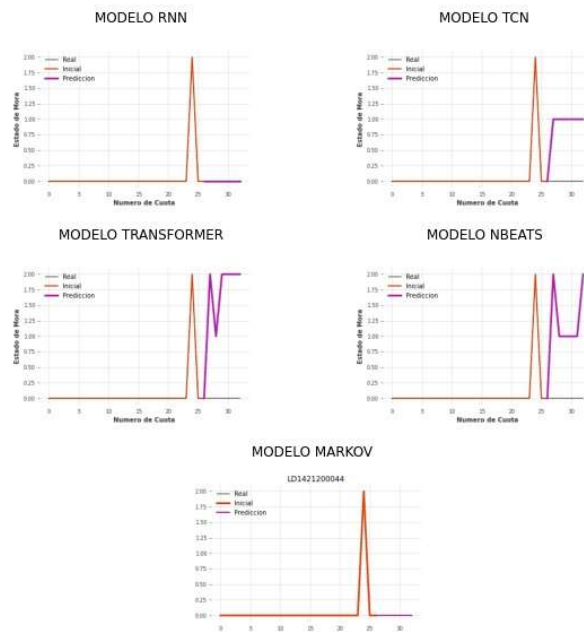
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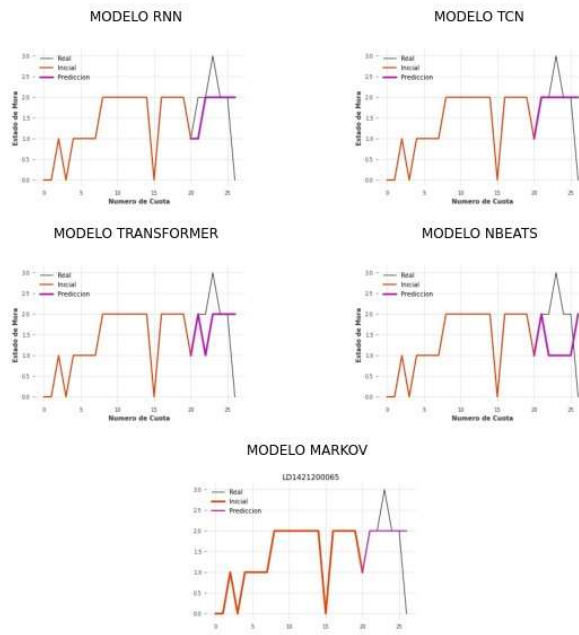
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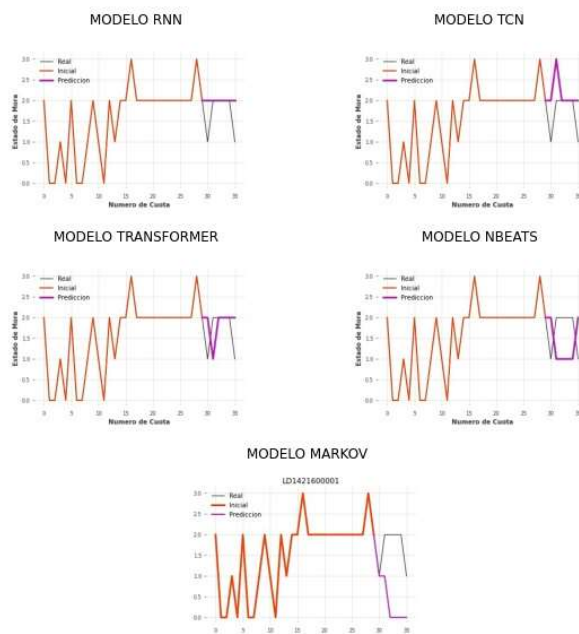
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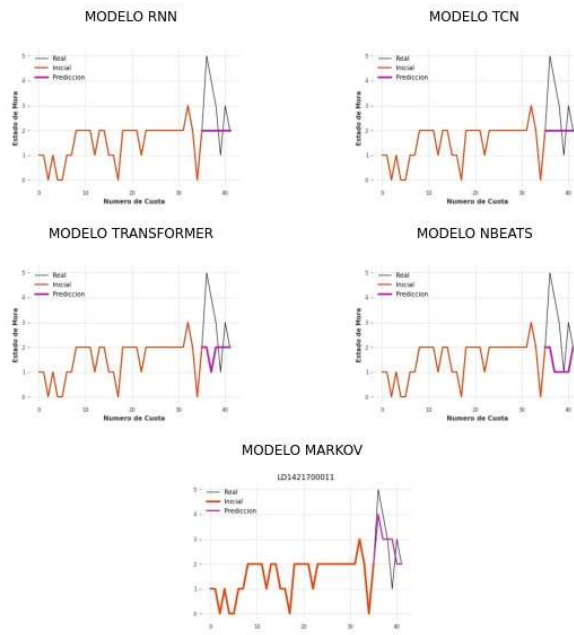
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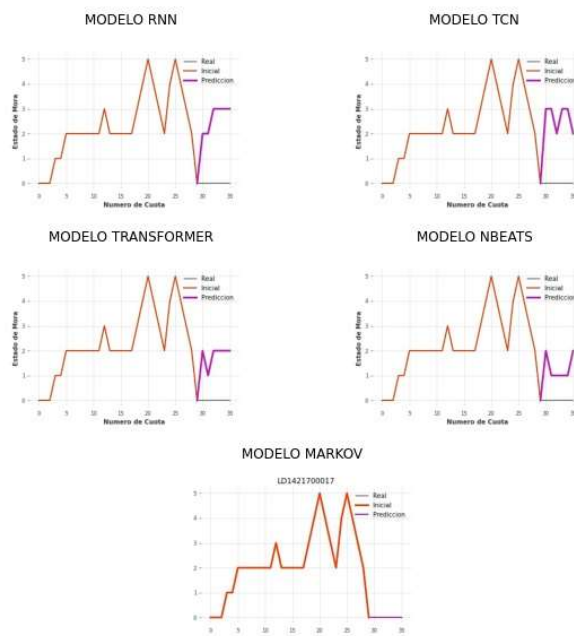
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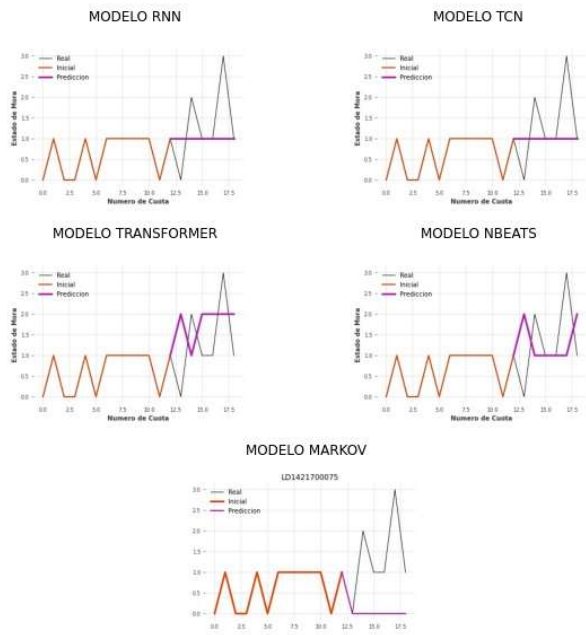


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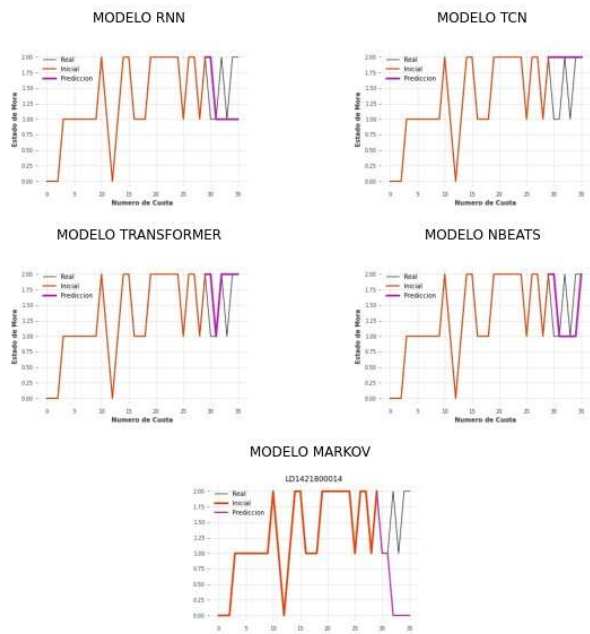




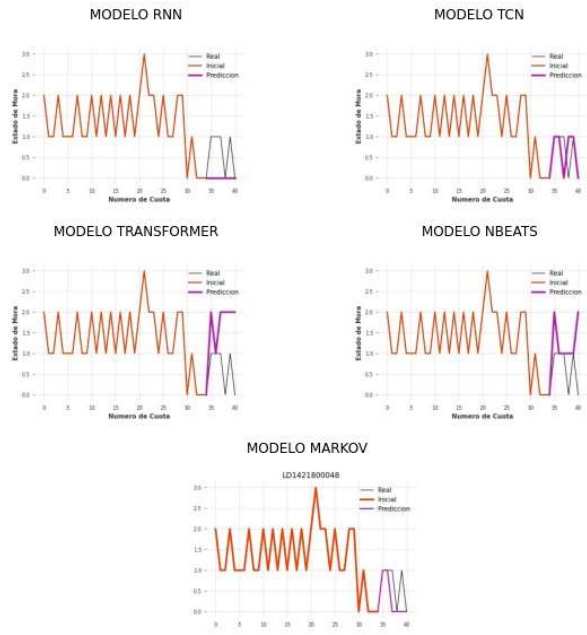
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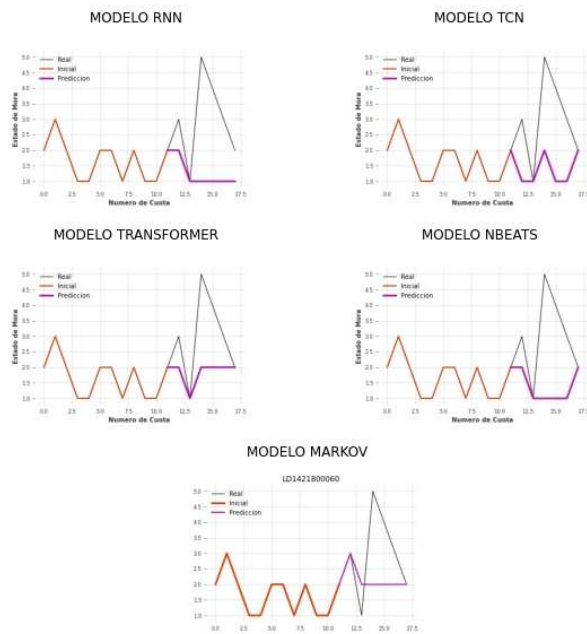
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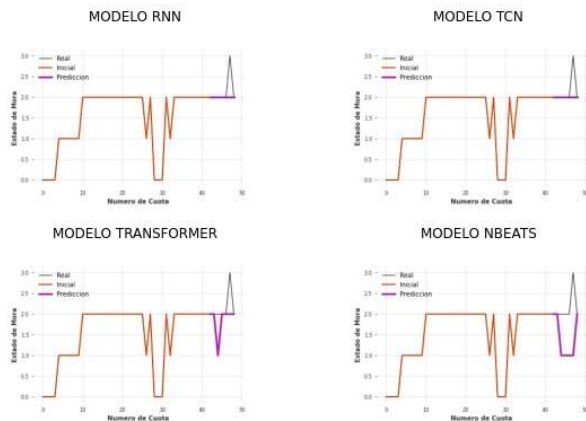
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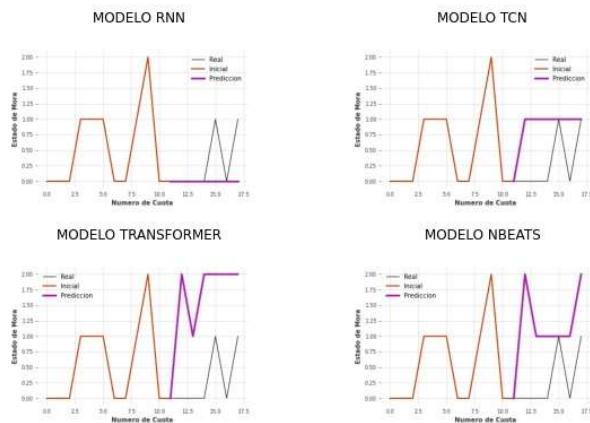
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MODELO MARKOV



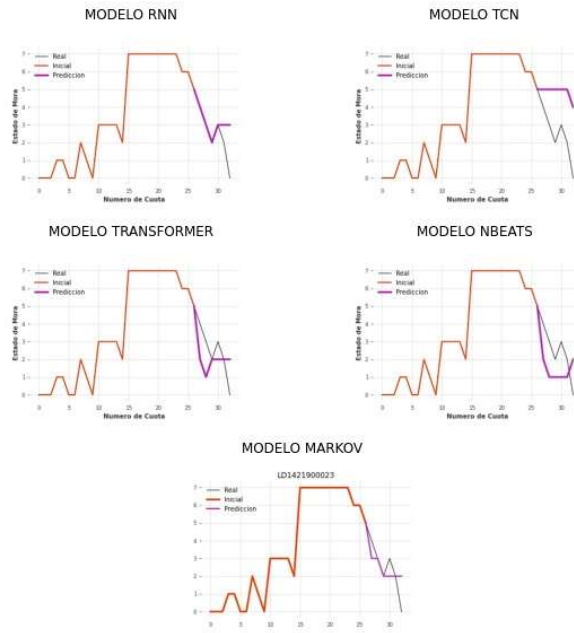
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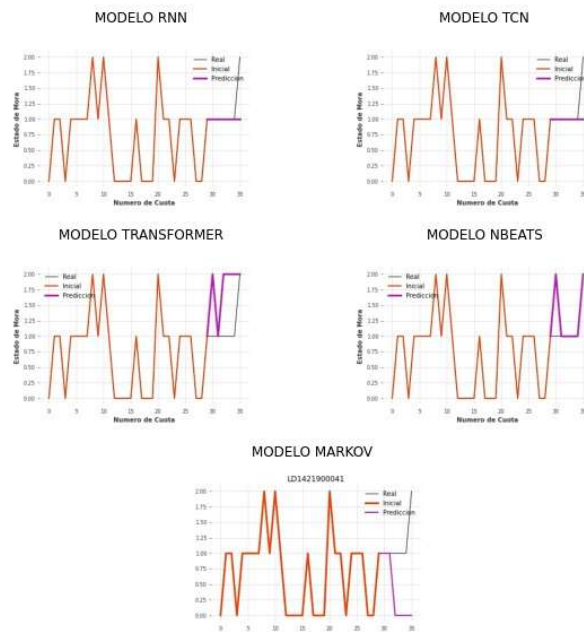
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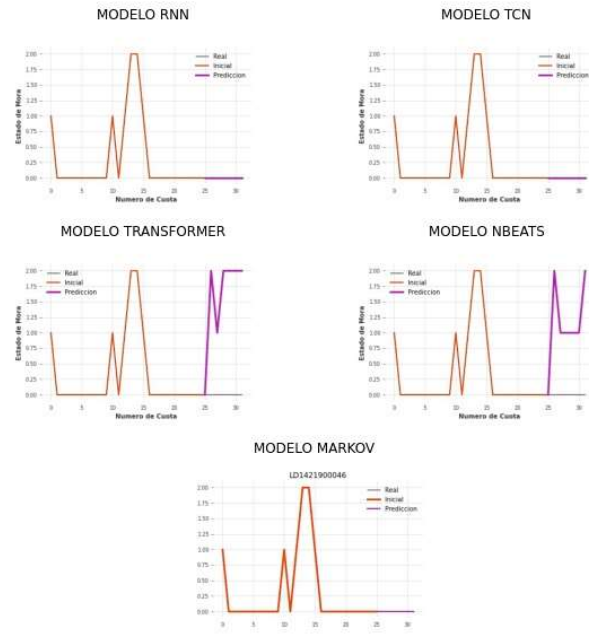
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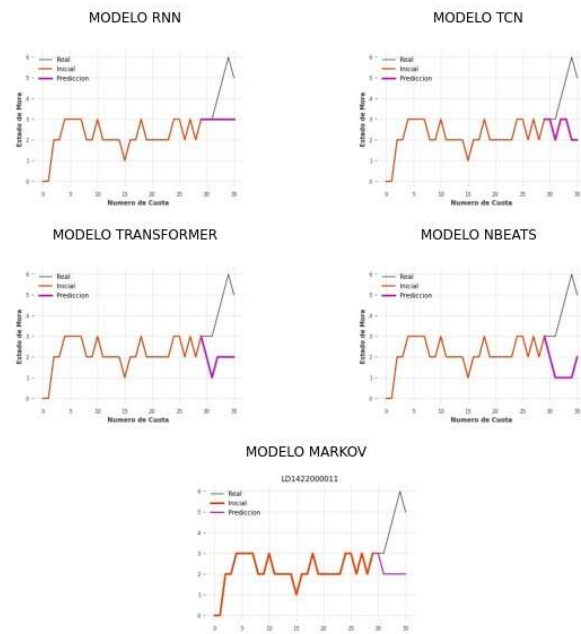
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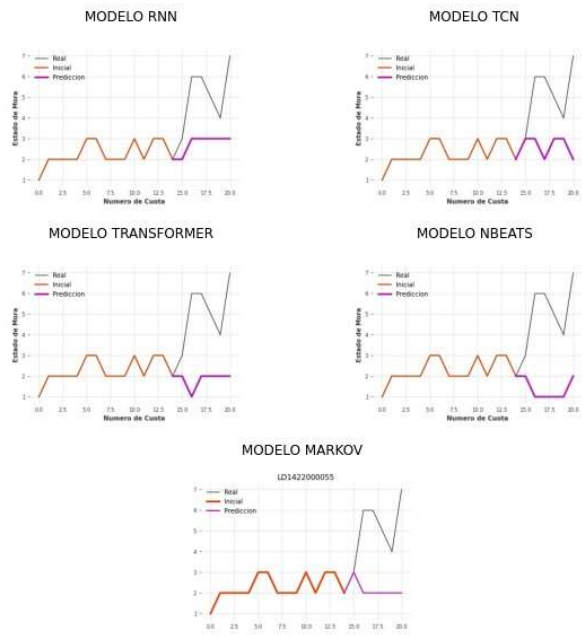
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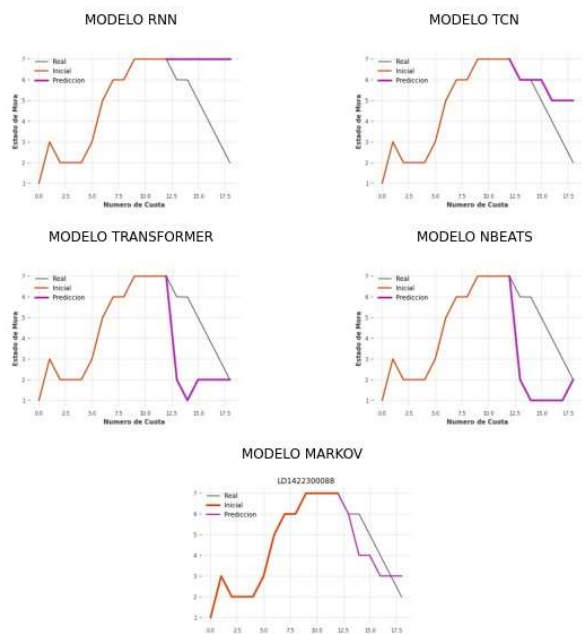
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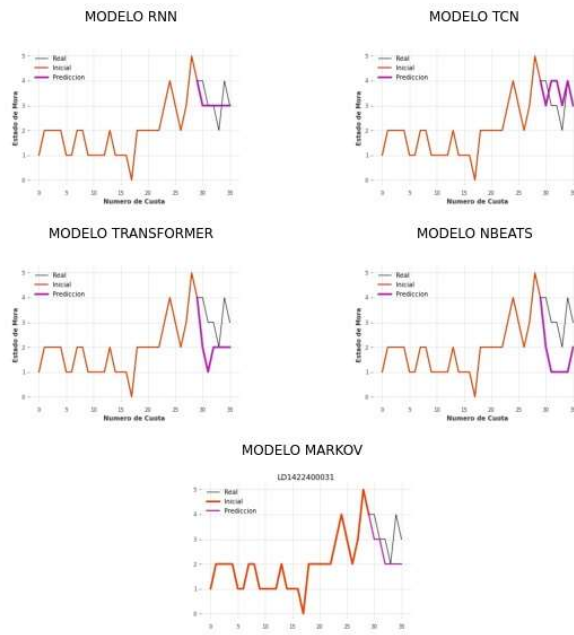
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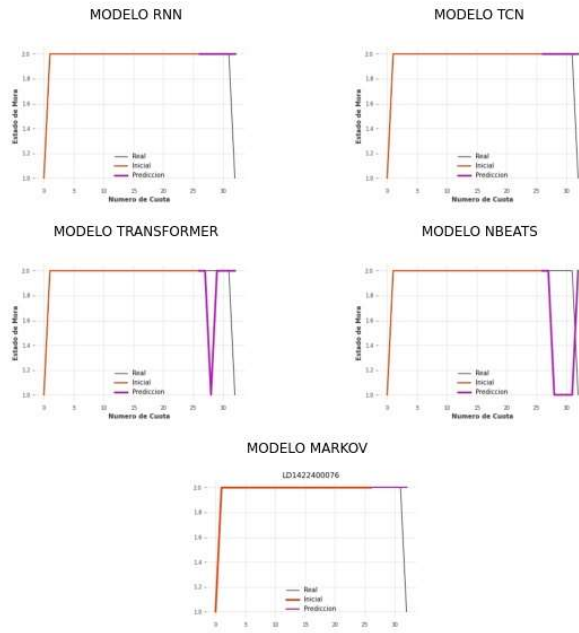
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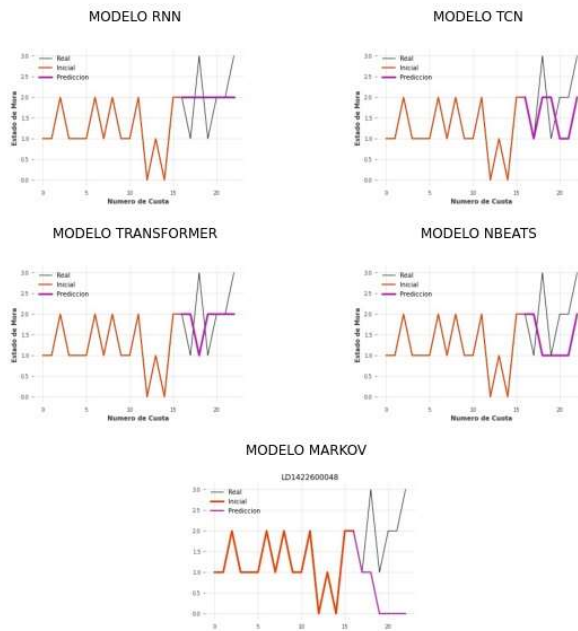


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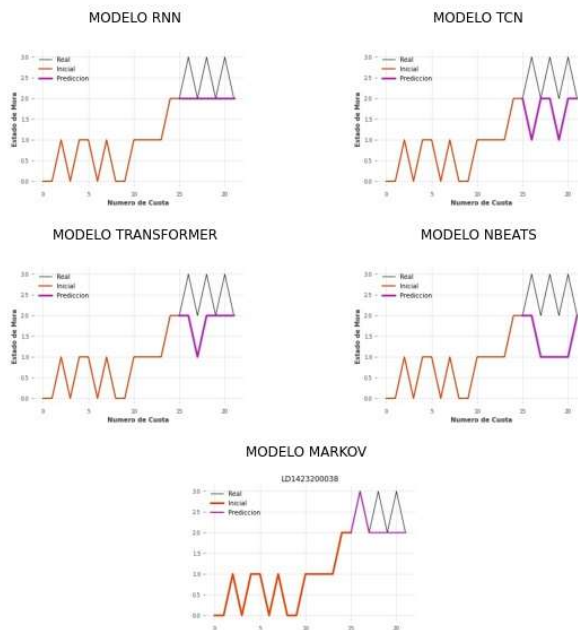




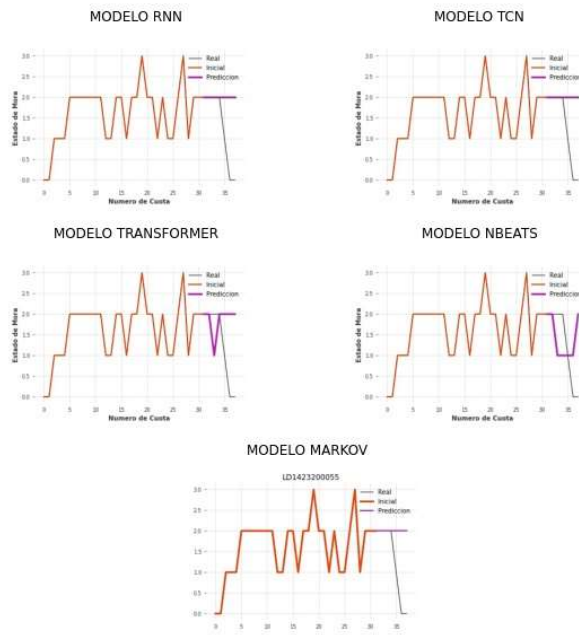
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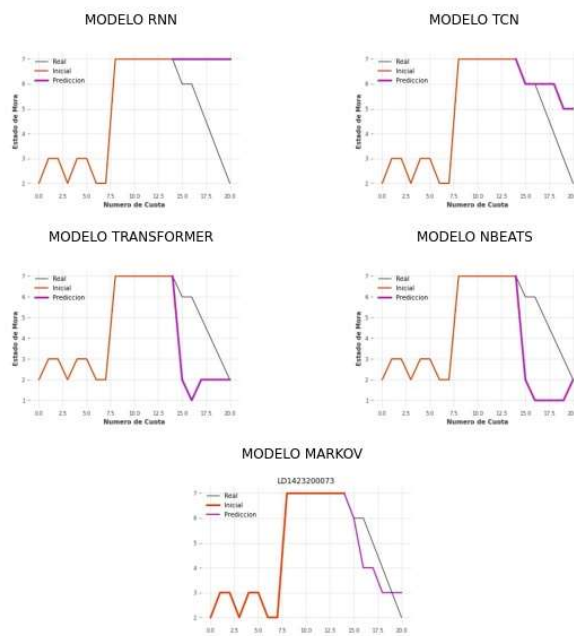
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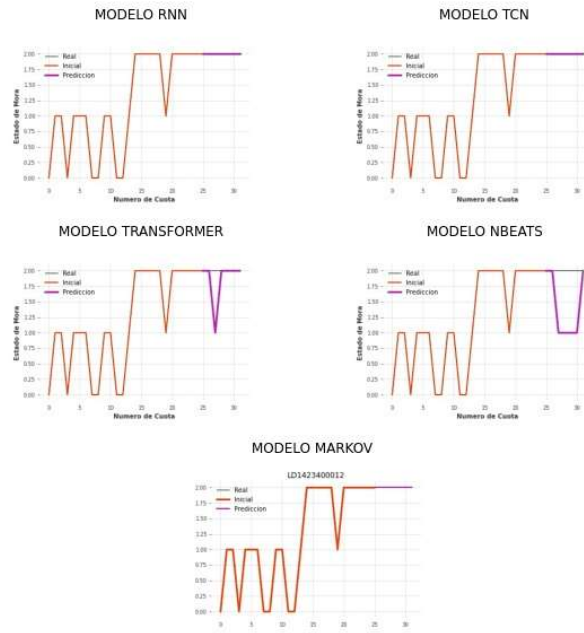
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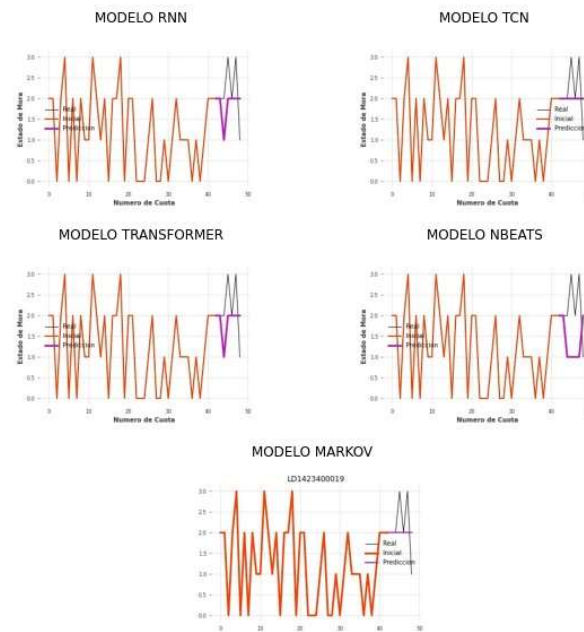
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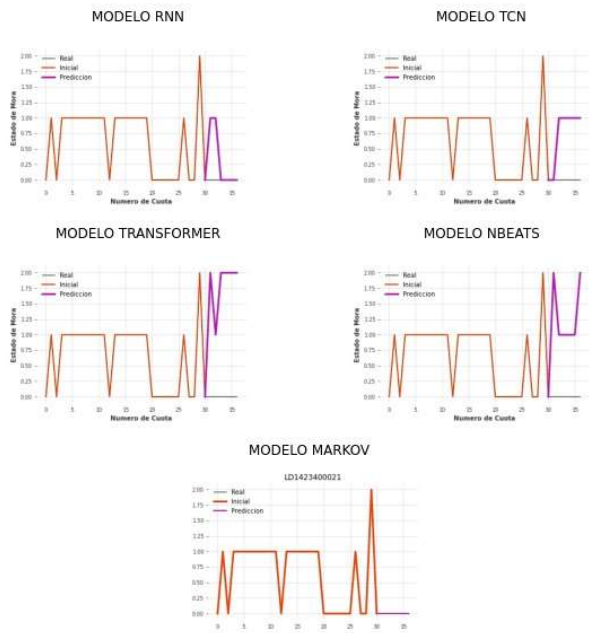
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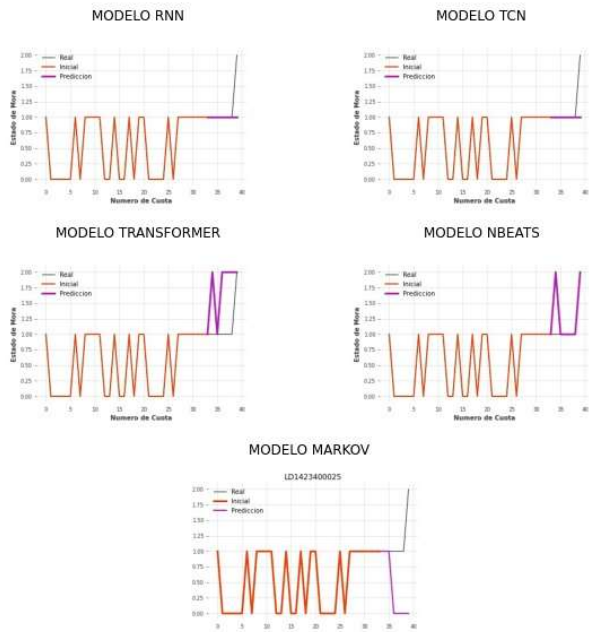
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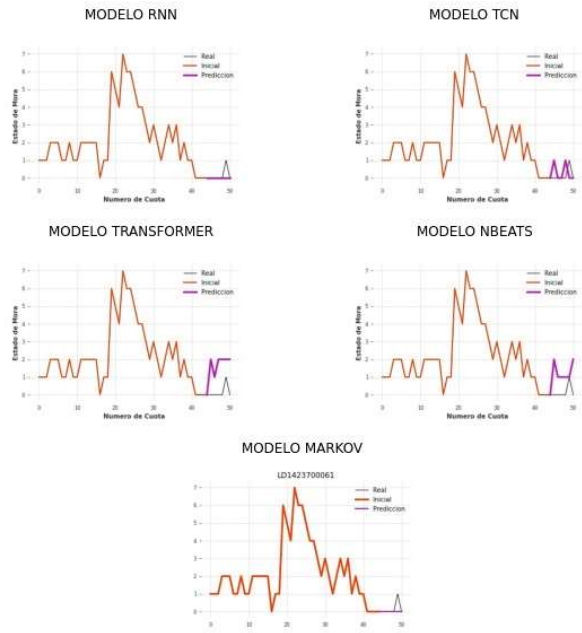
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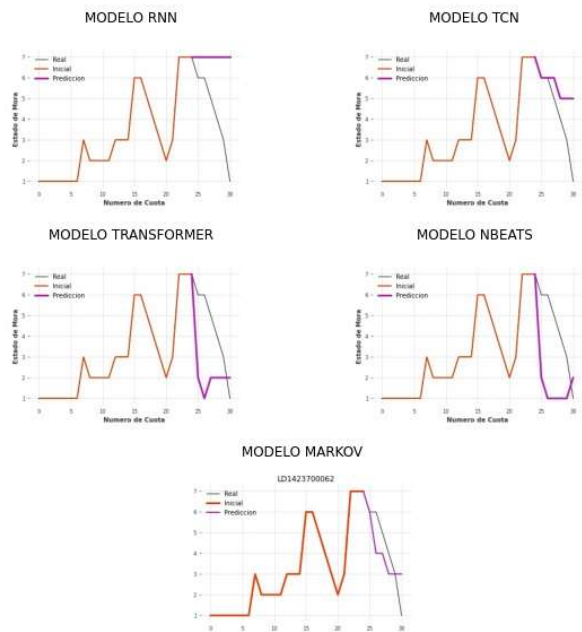
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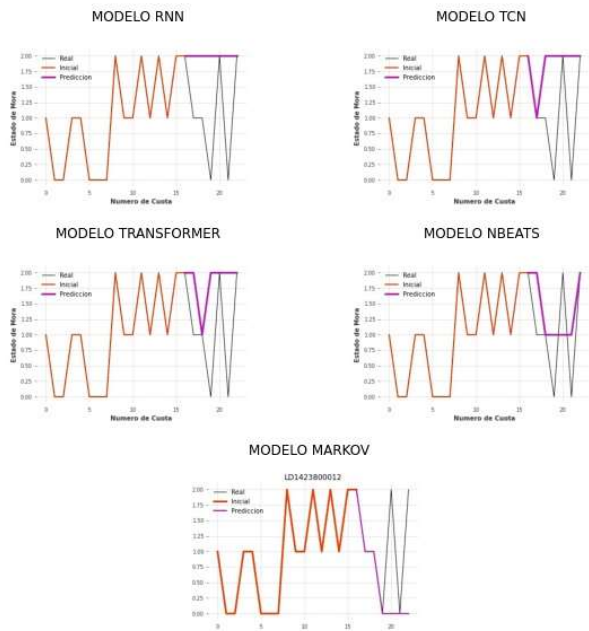
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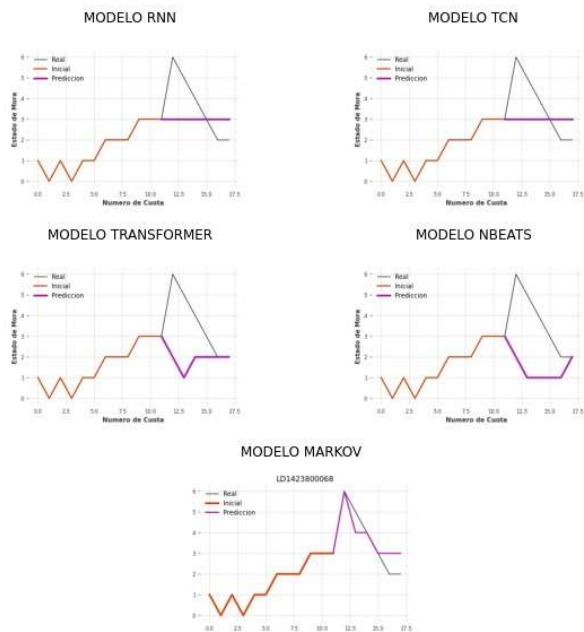
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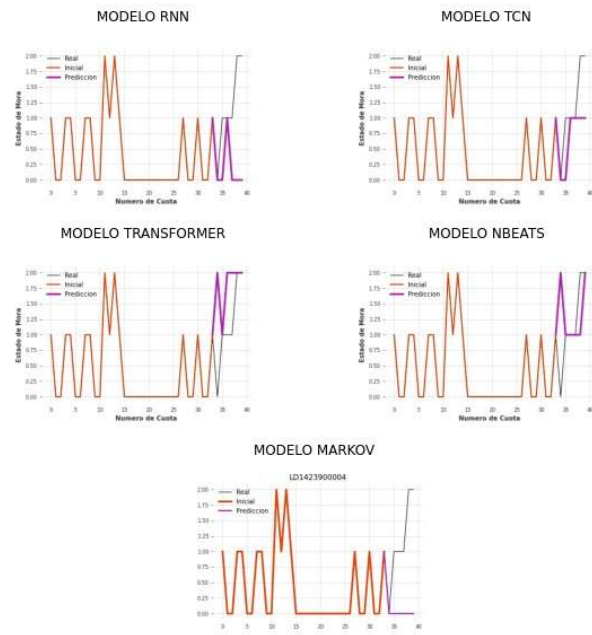
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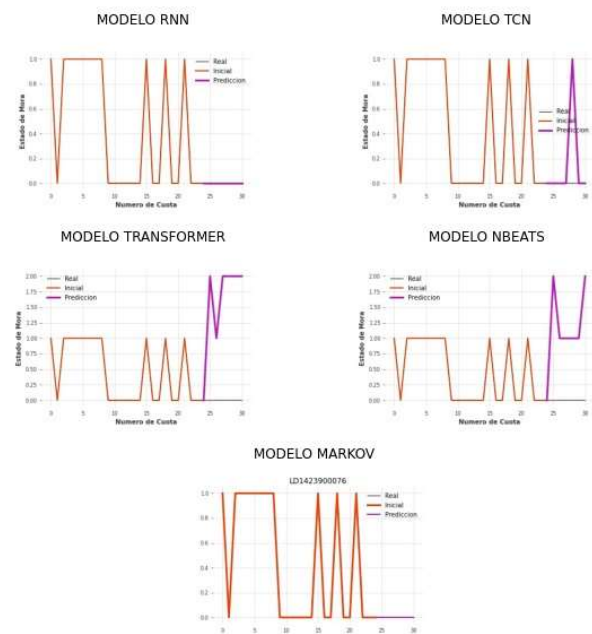
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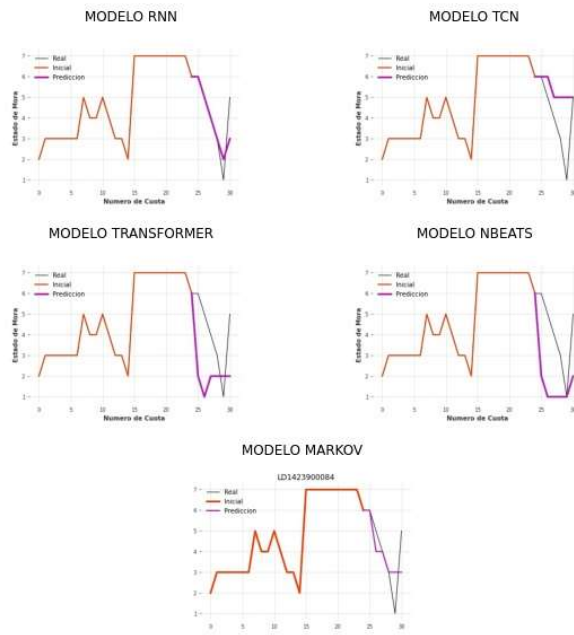
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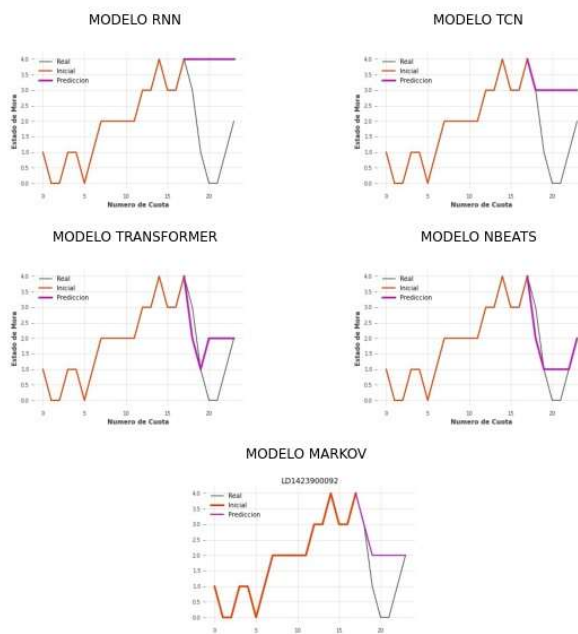
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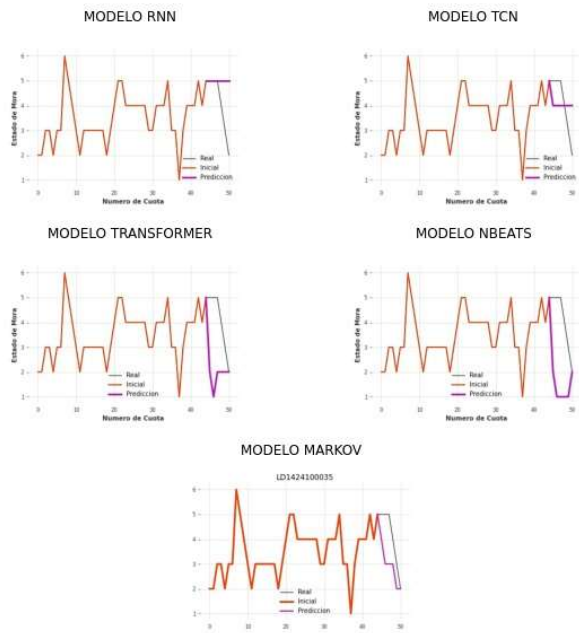


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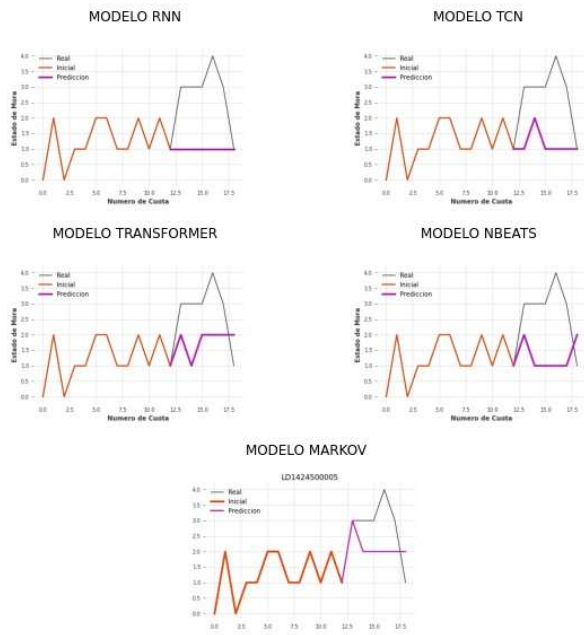
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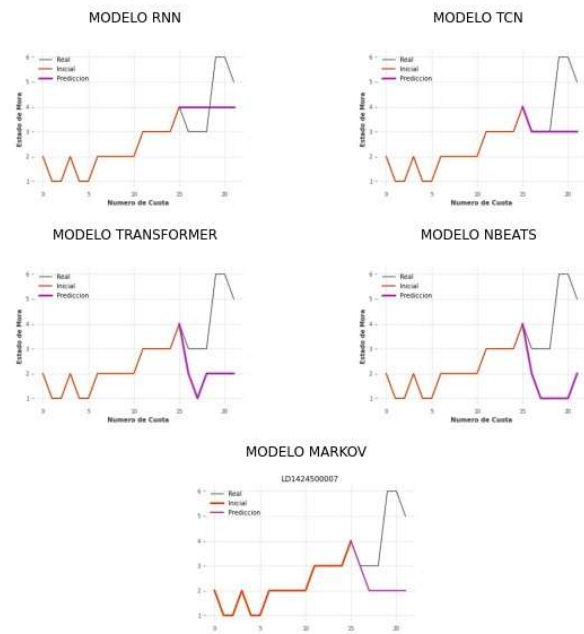
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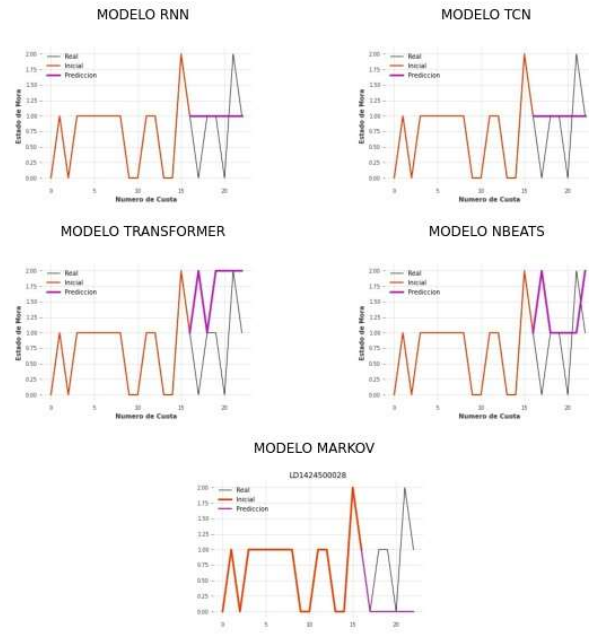
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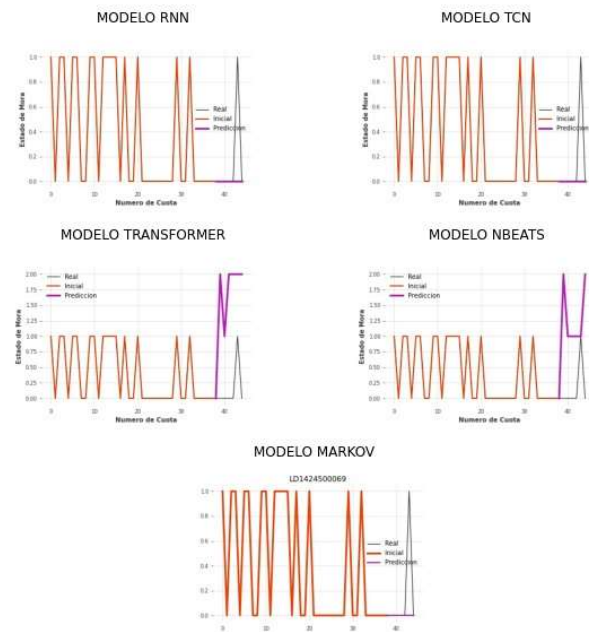
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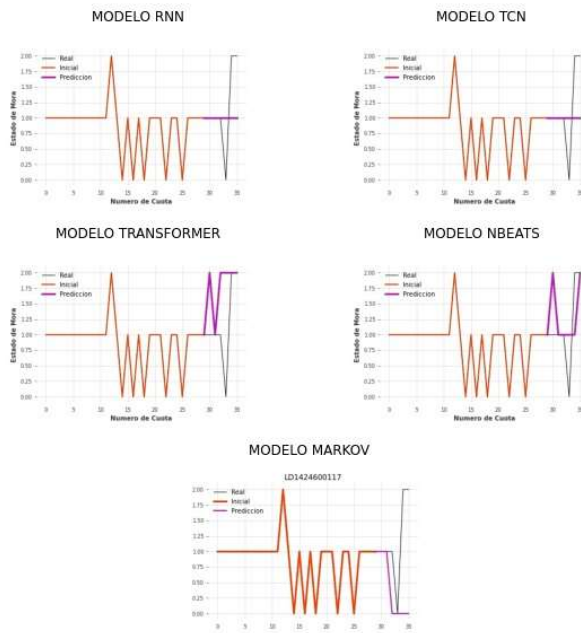
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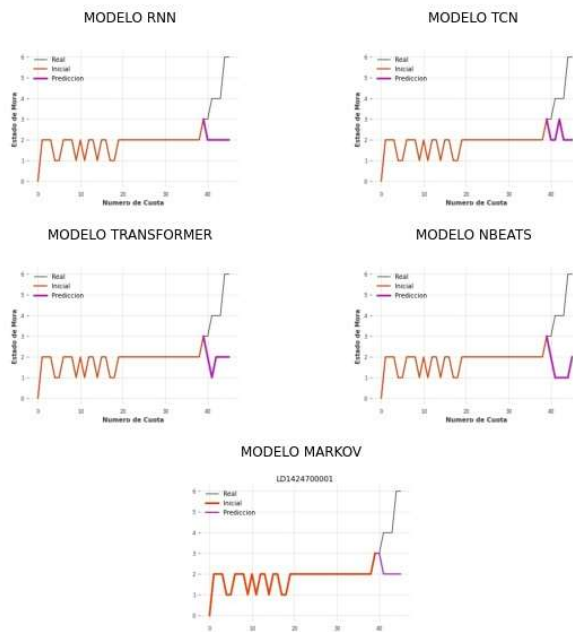
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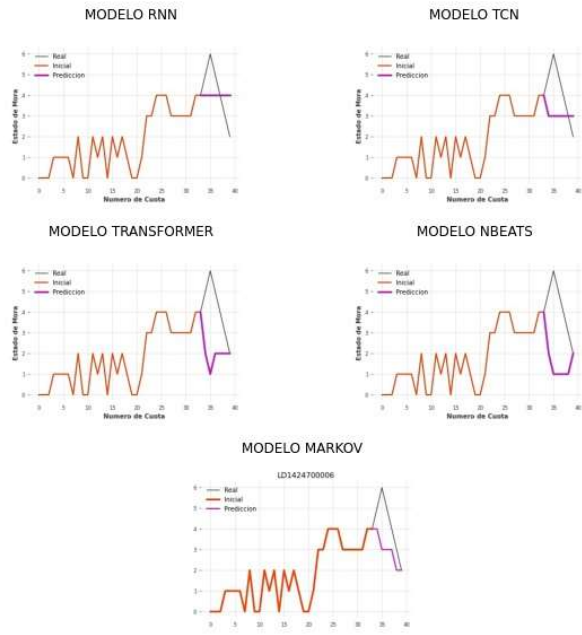
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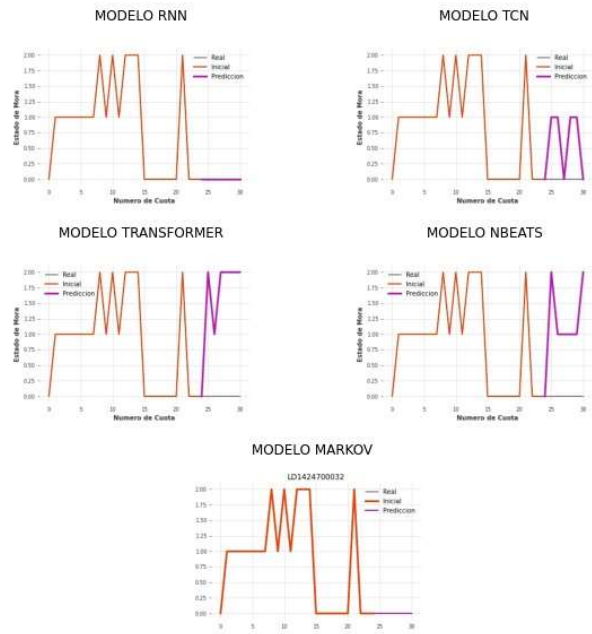
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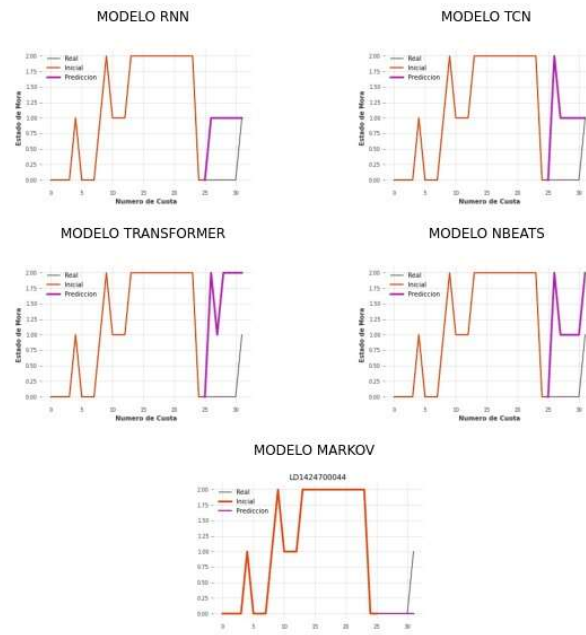
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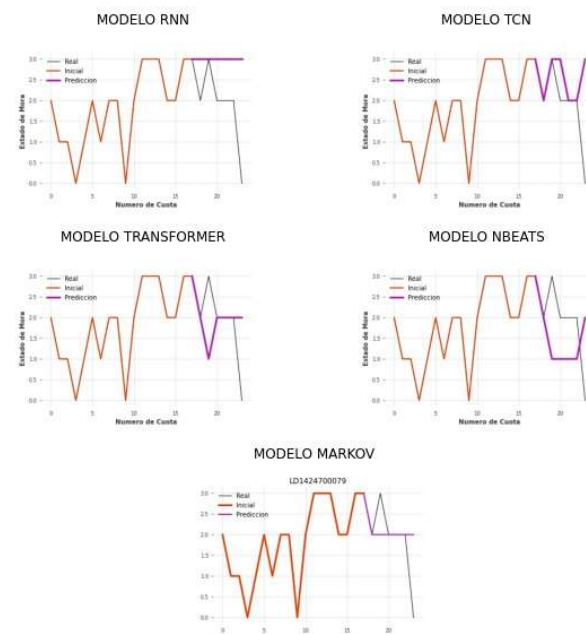
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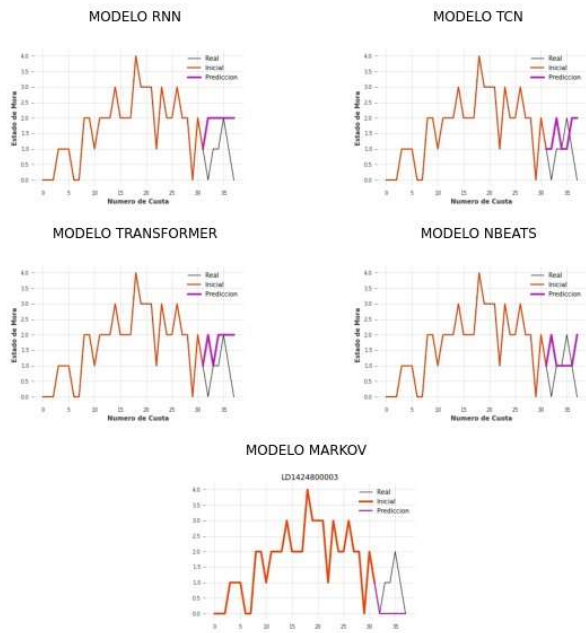
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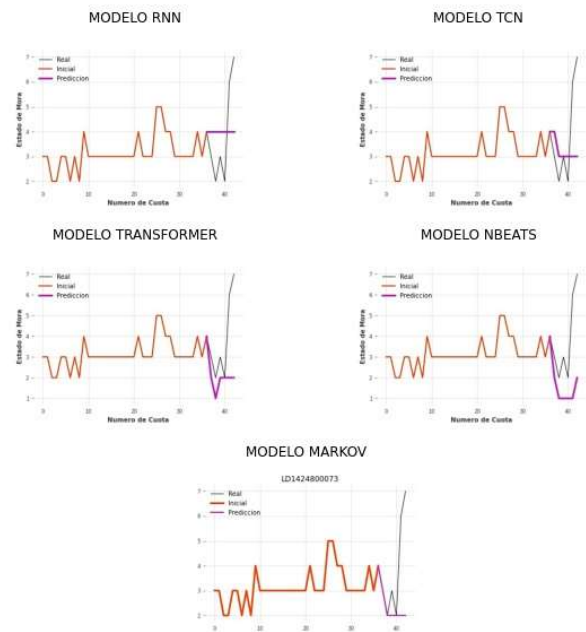
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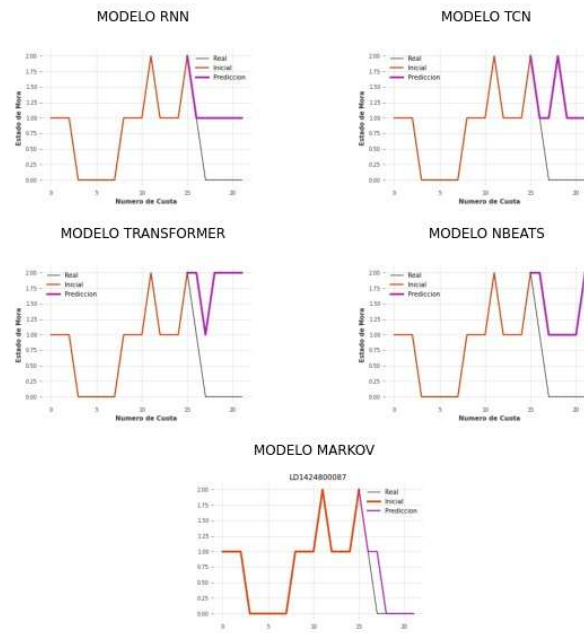
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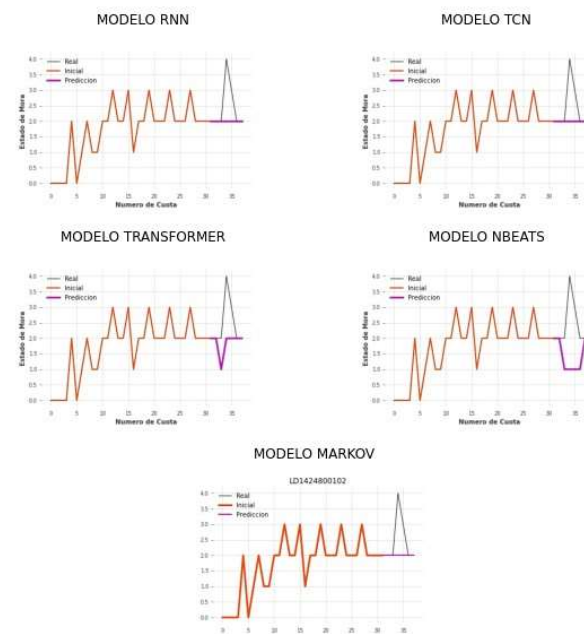
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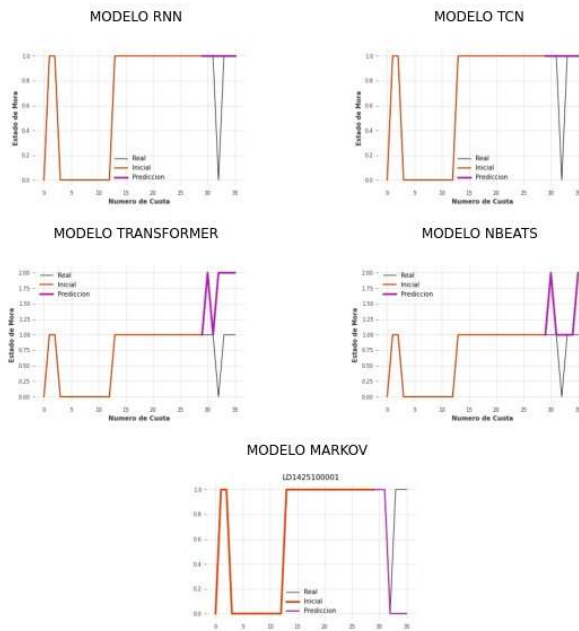


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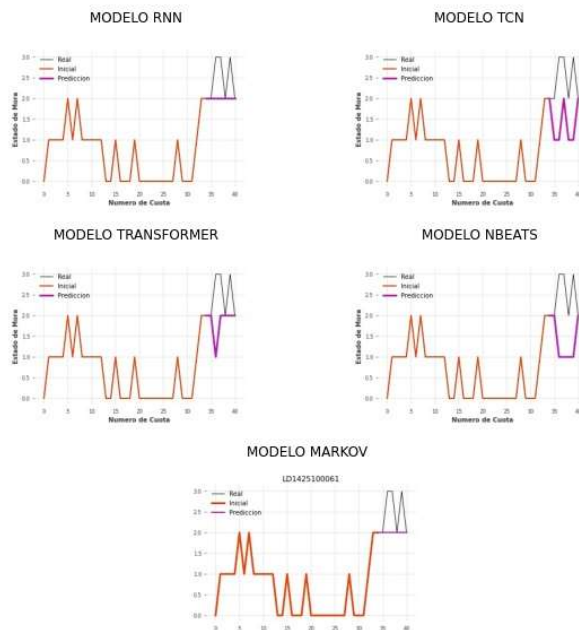




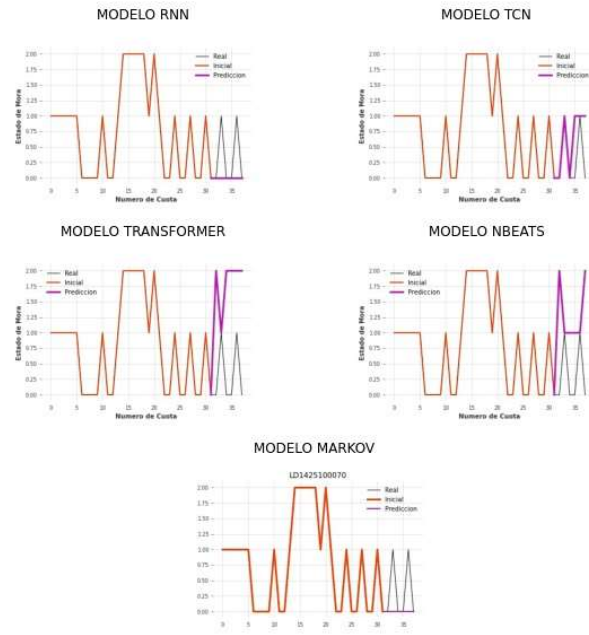
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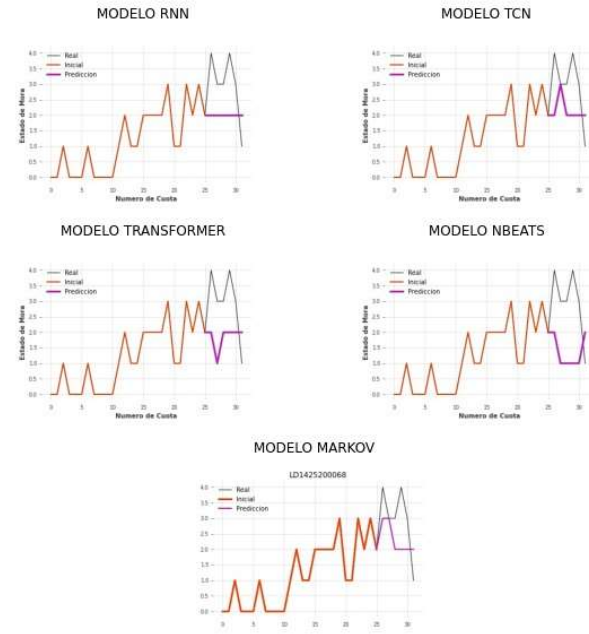
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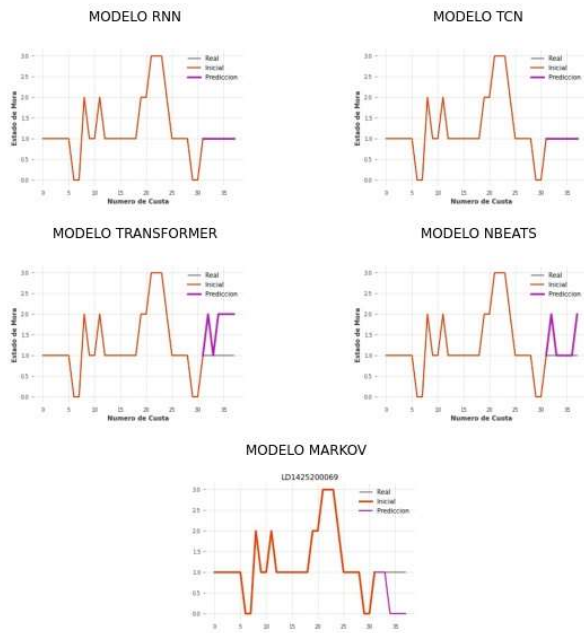
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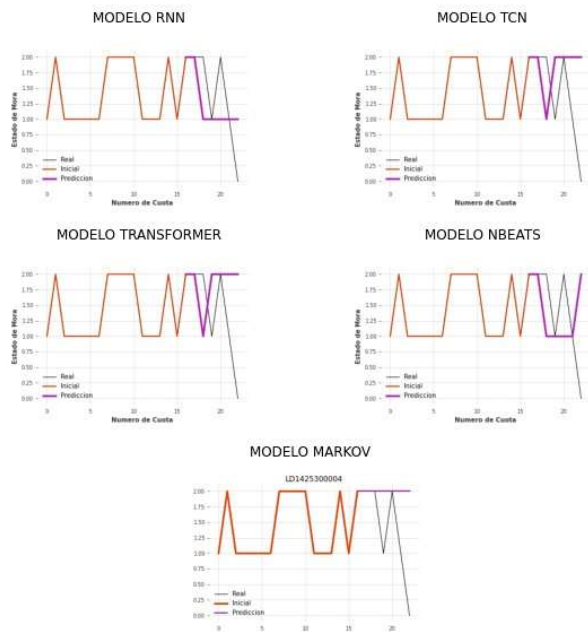
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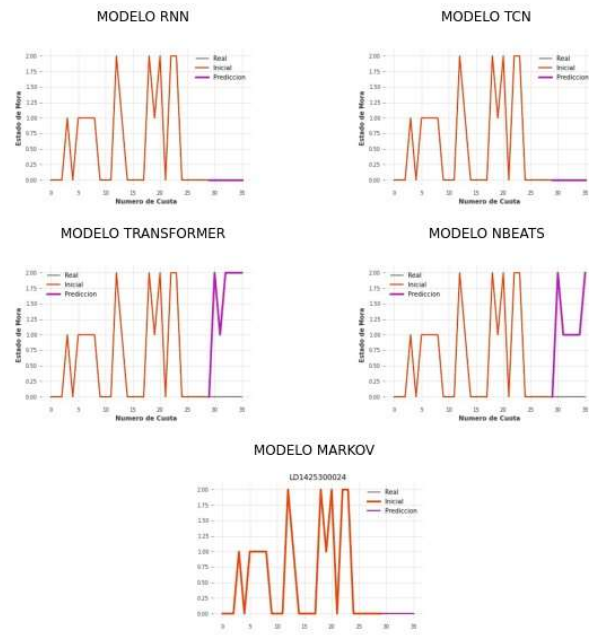
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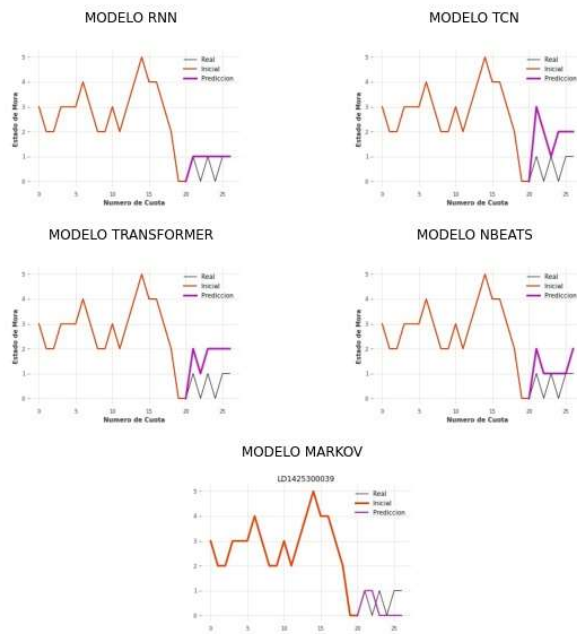
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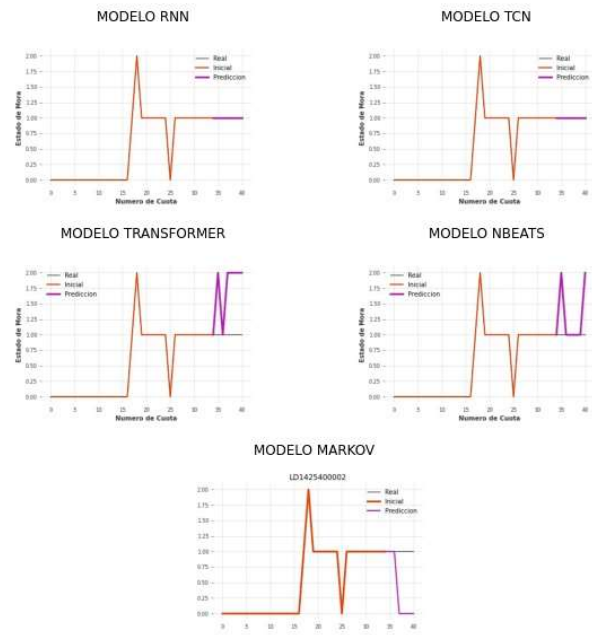
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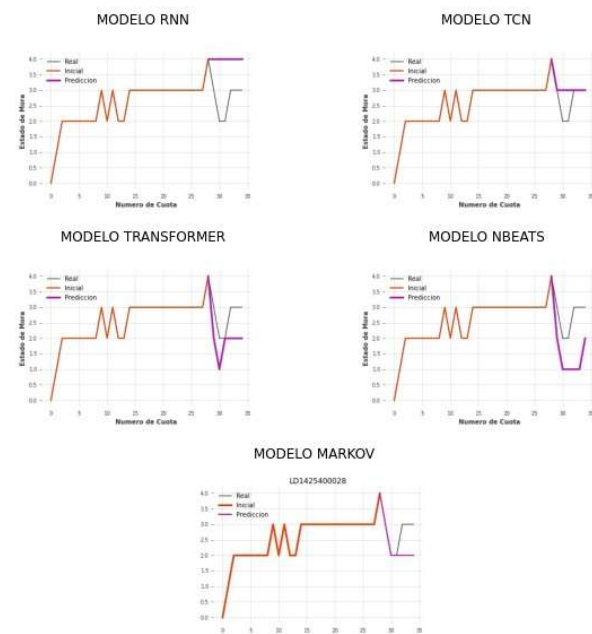
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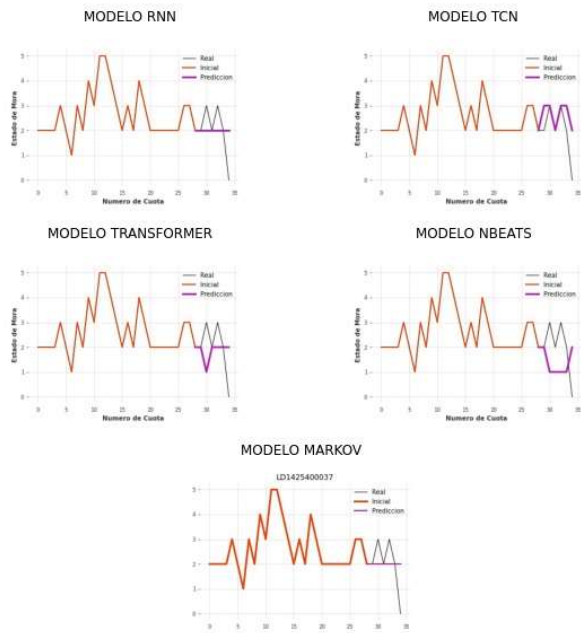
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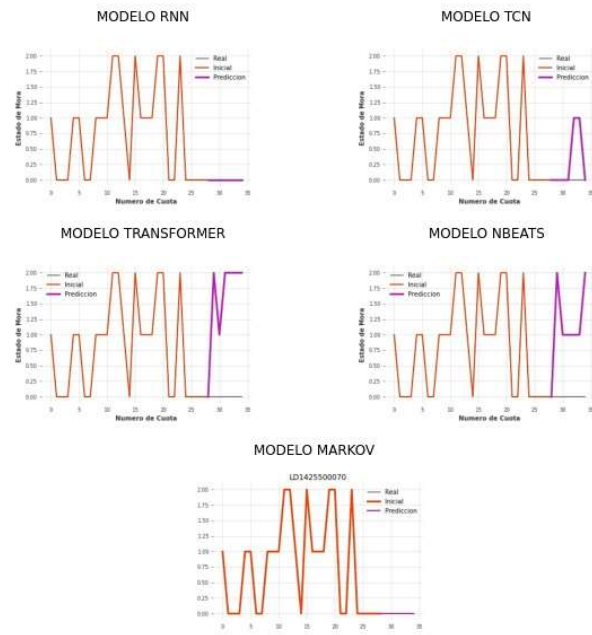
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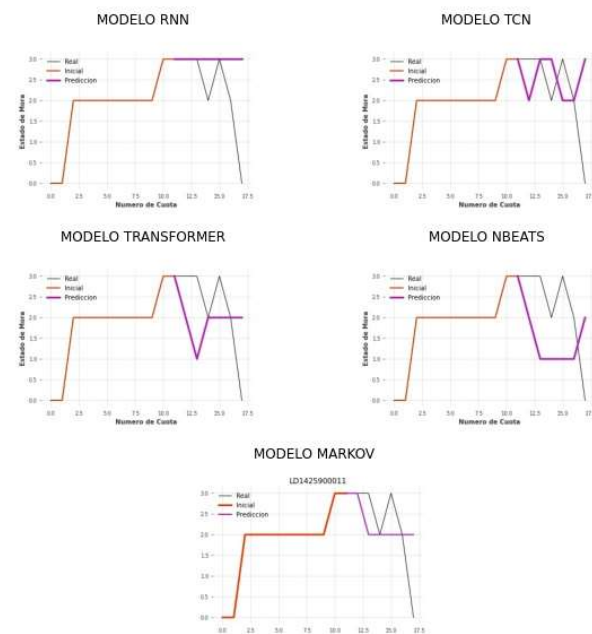
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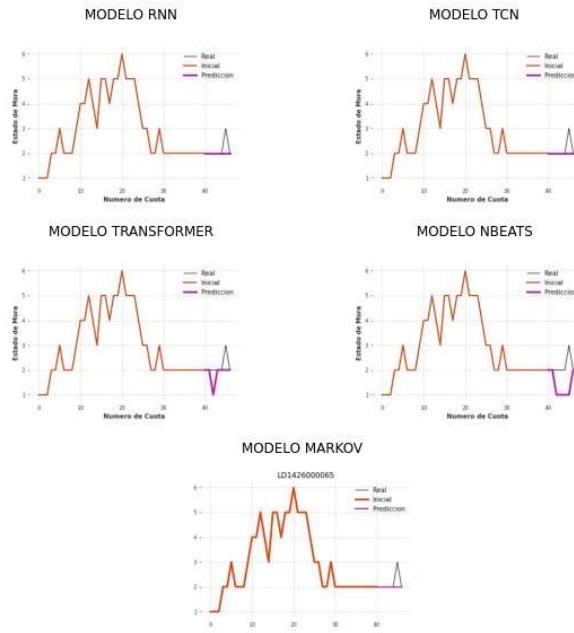
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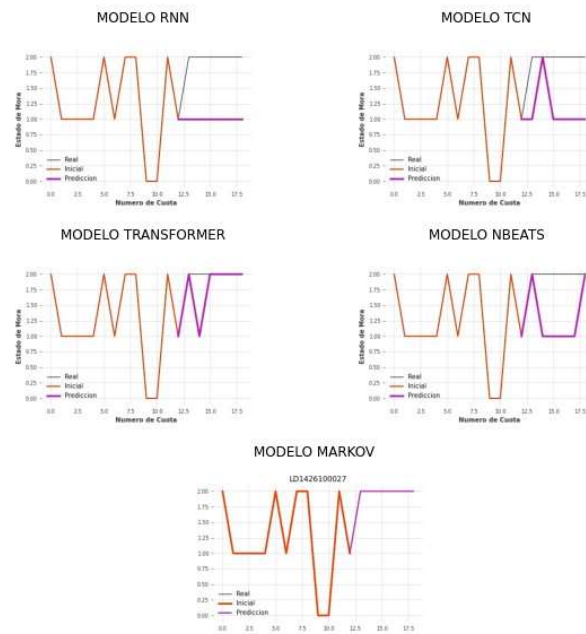
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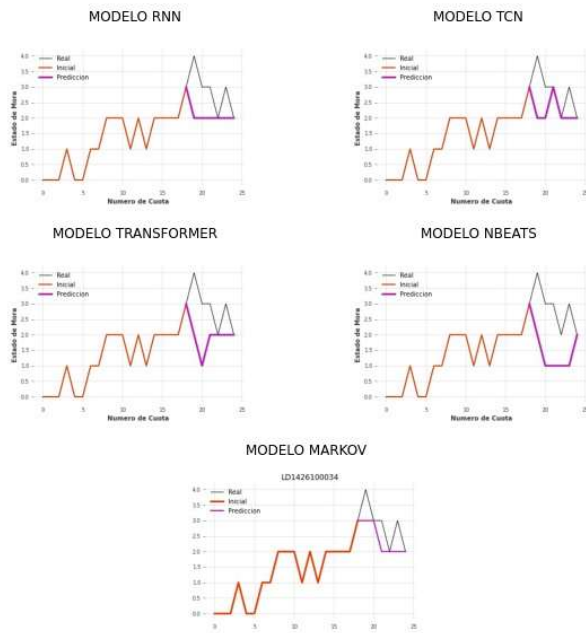


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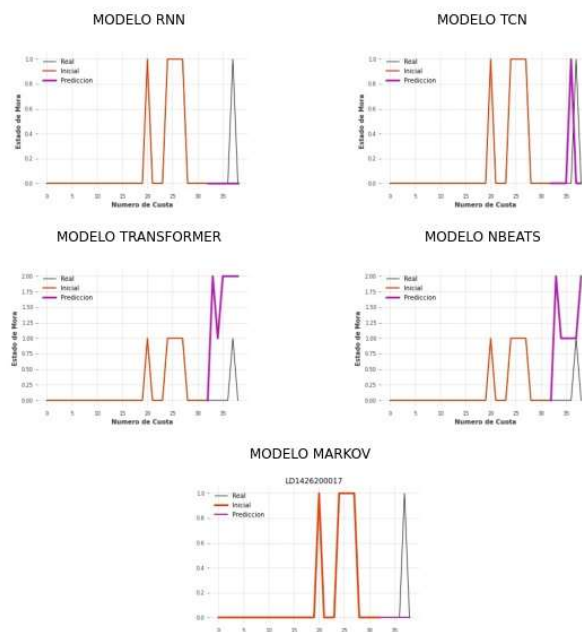




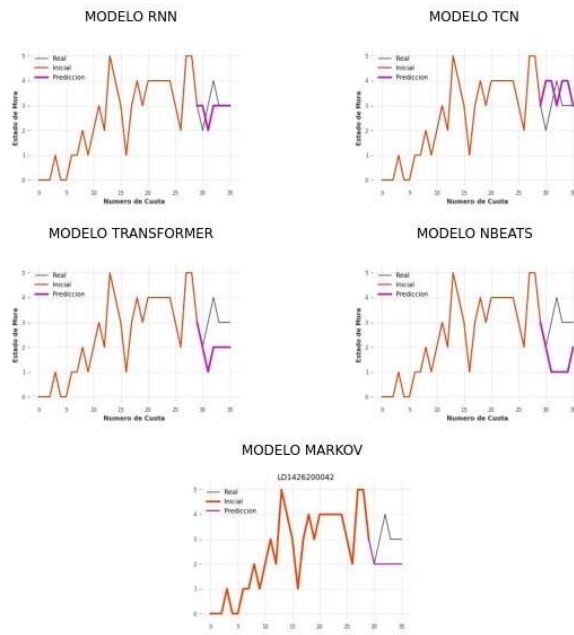
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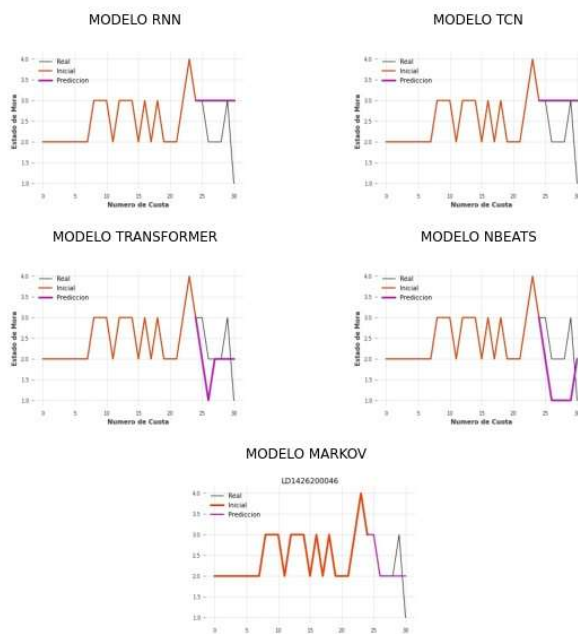
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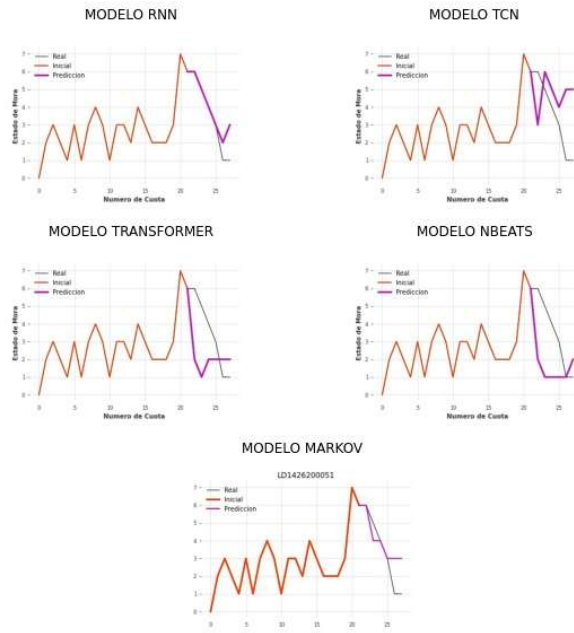
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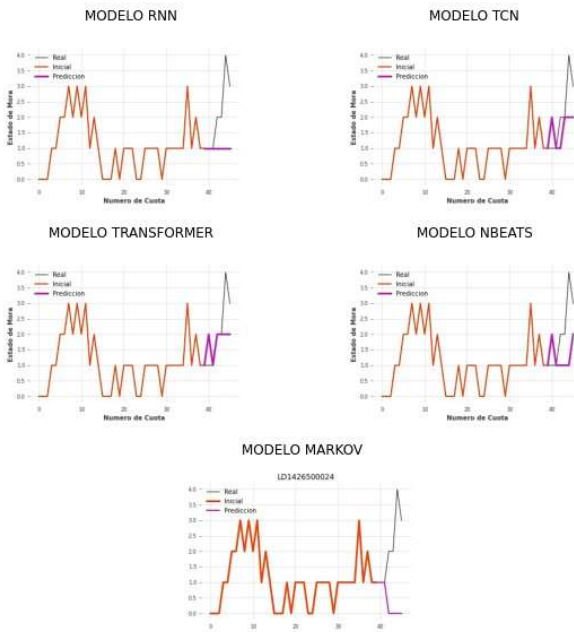
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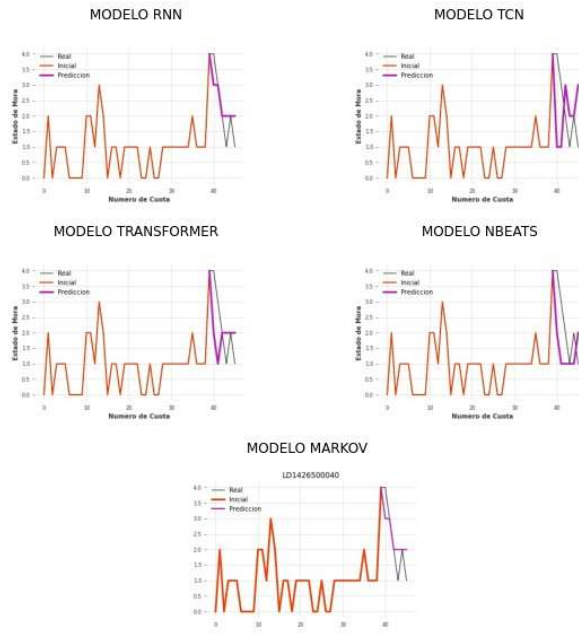
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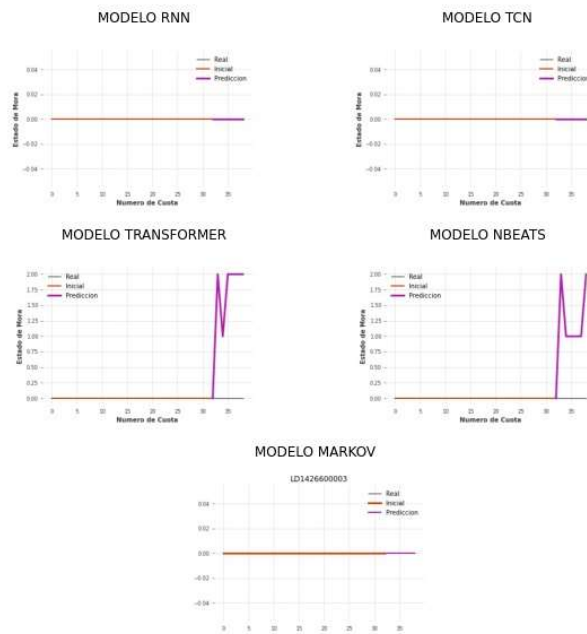
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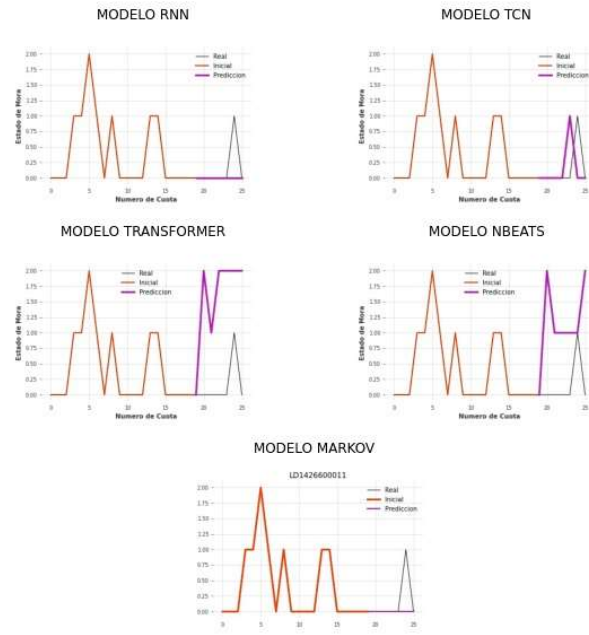
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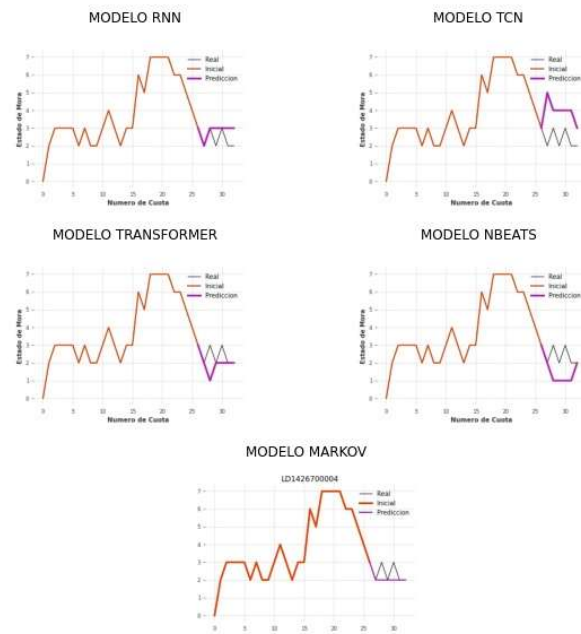
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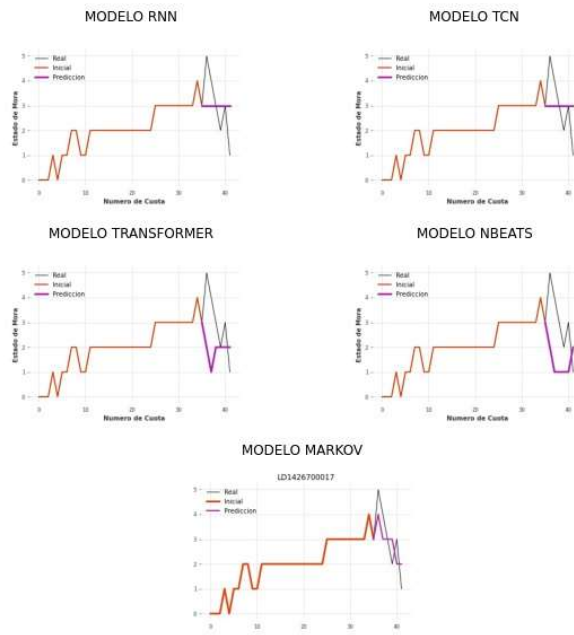
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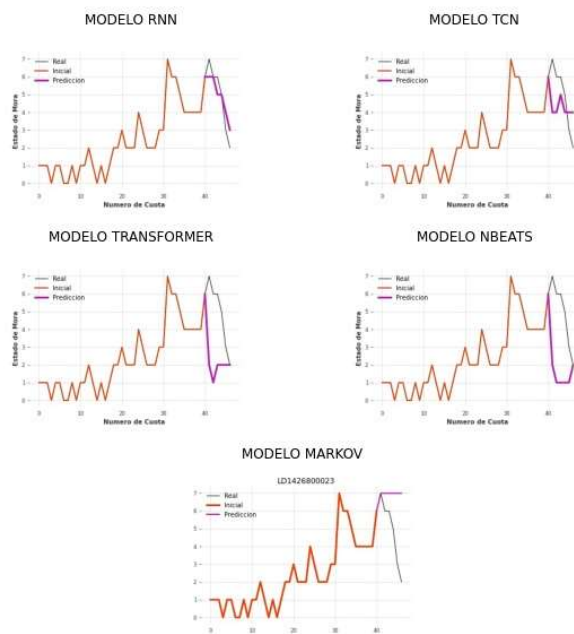
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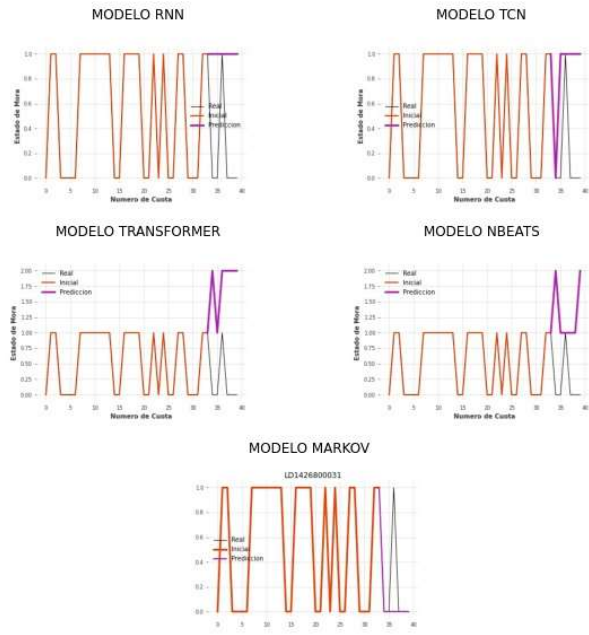
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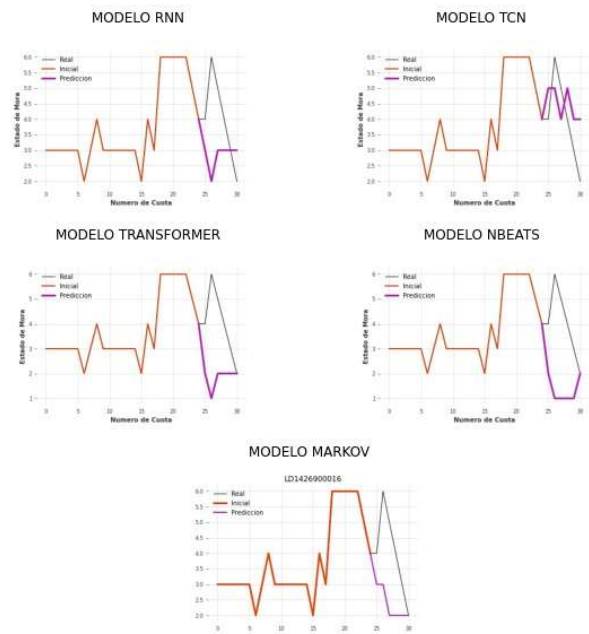
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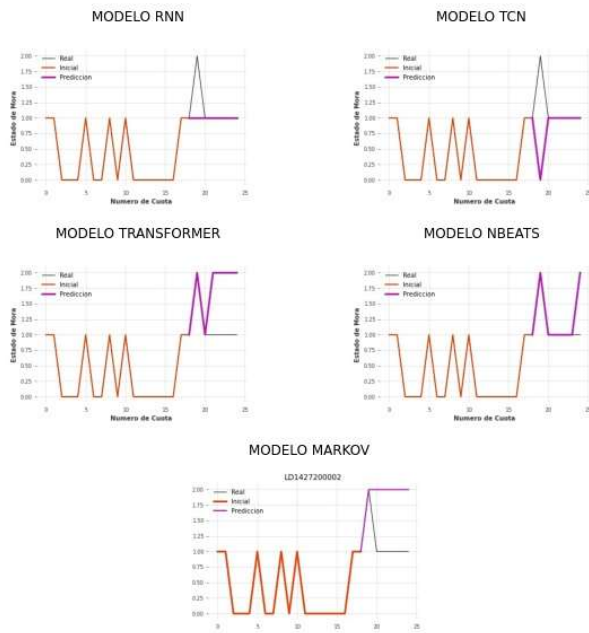
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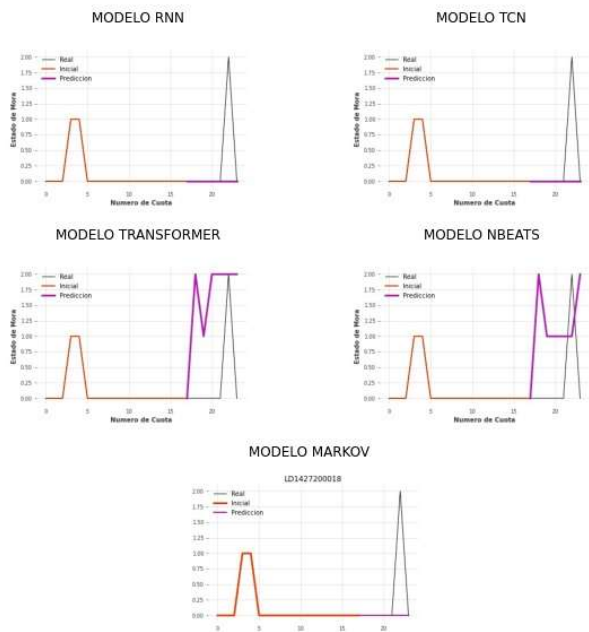
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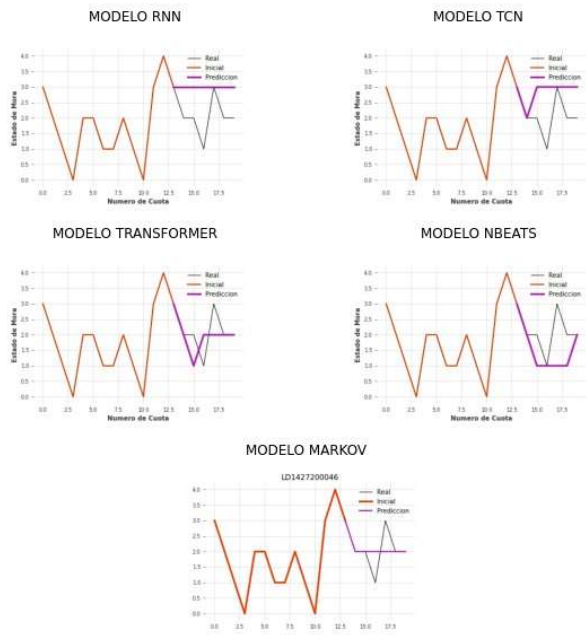


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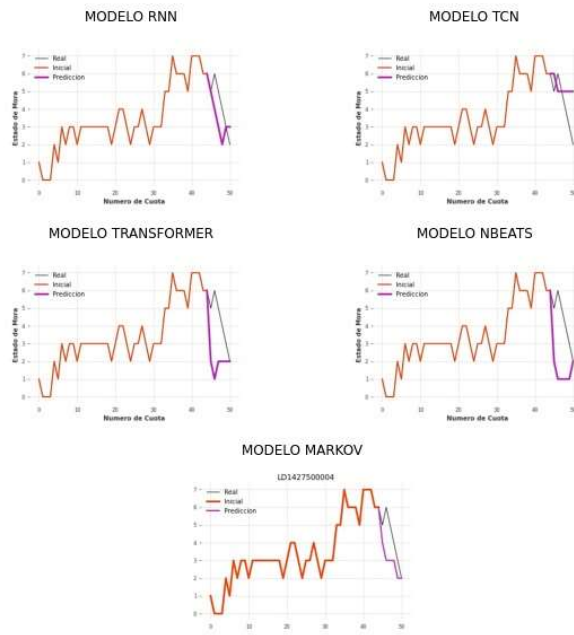
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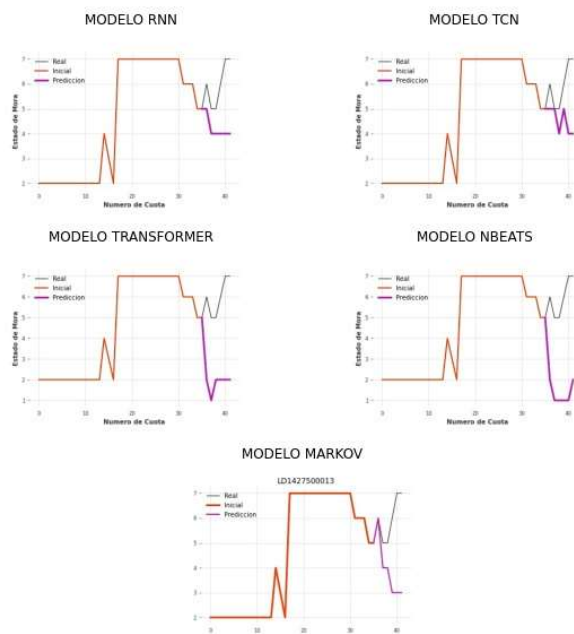
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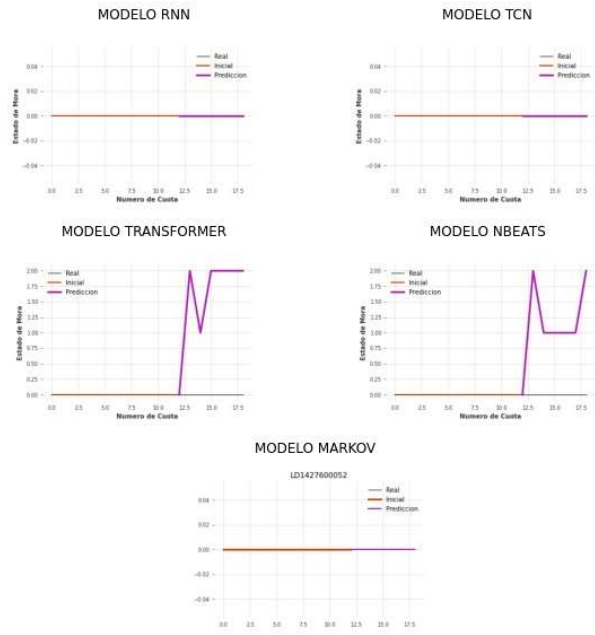
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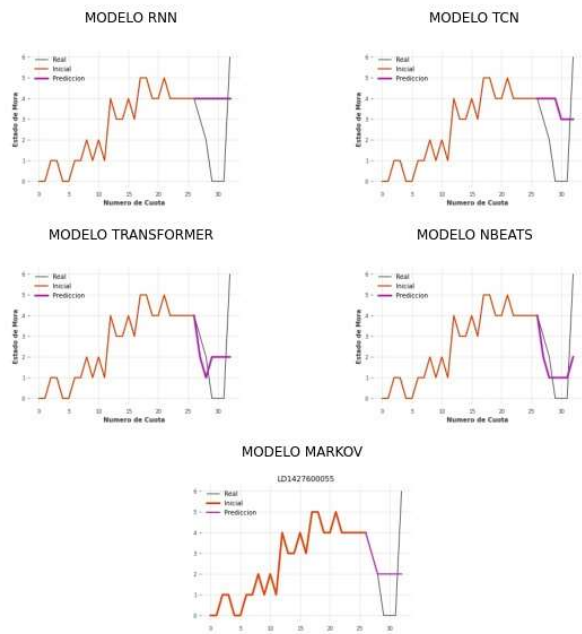
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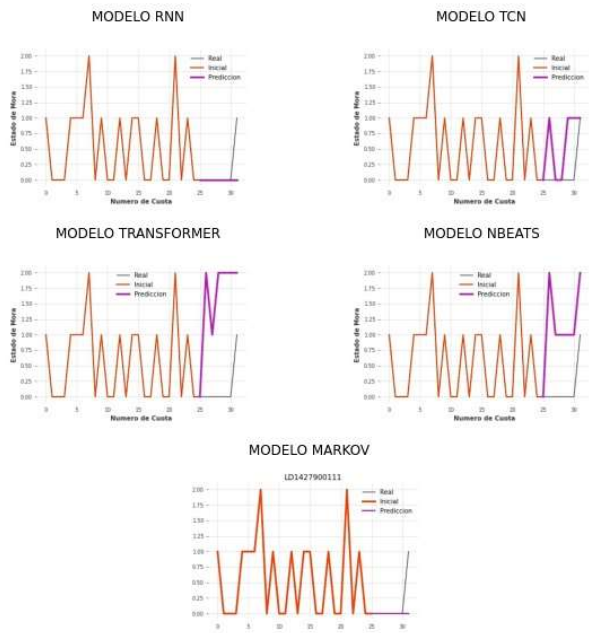
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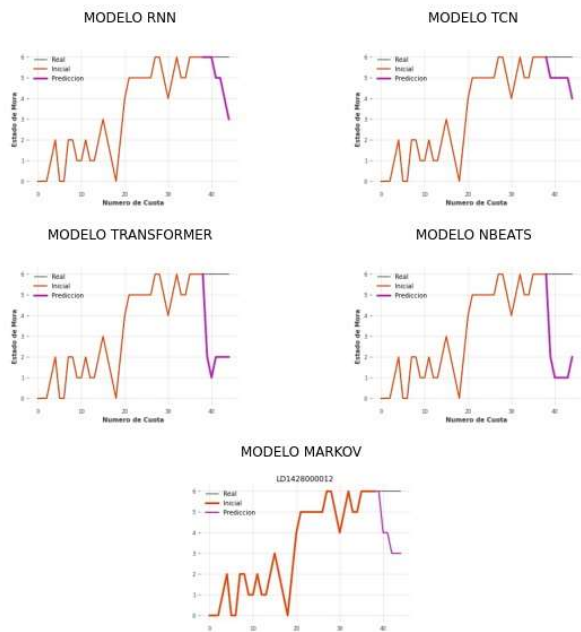
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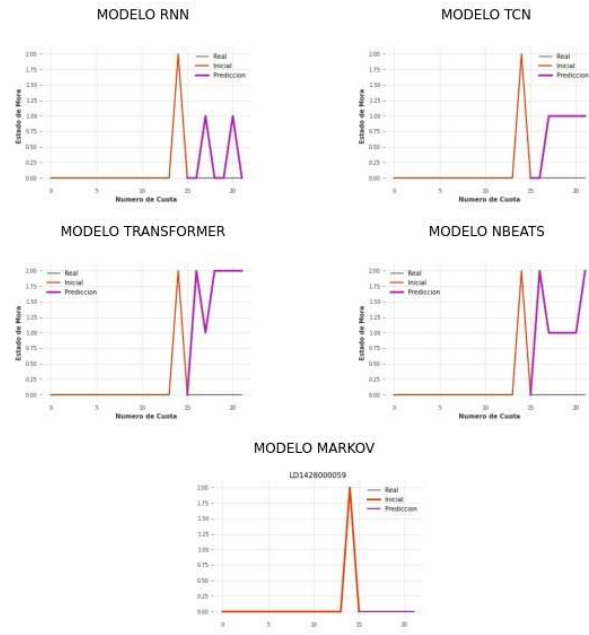
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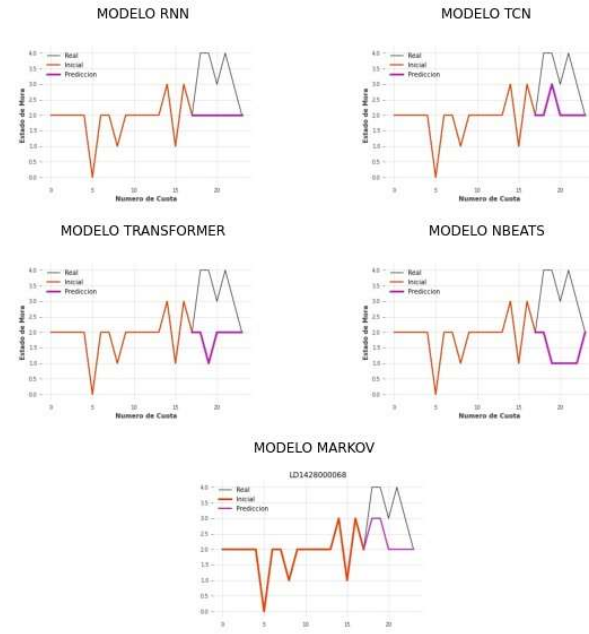
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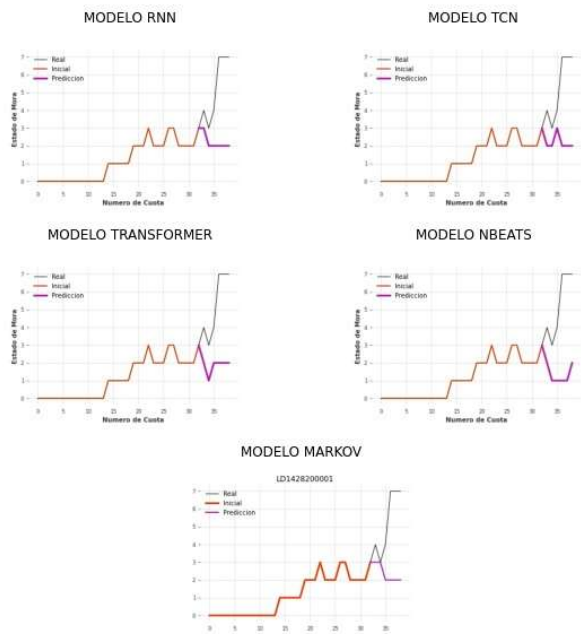
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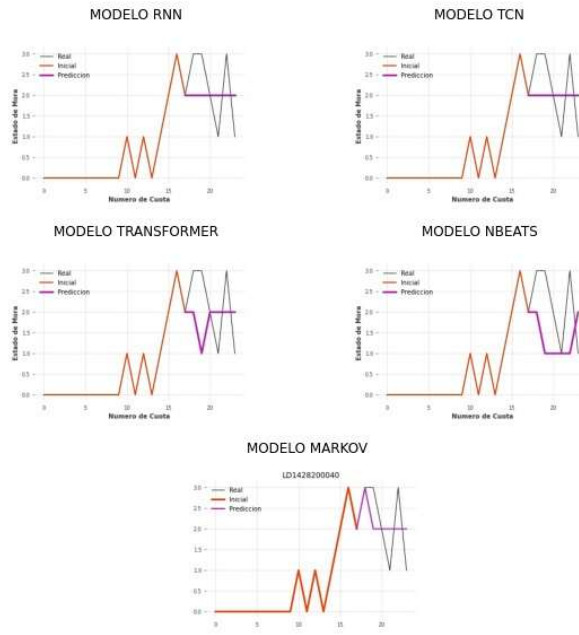
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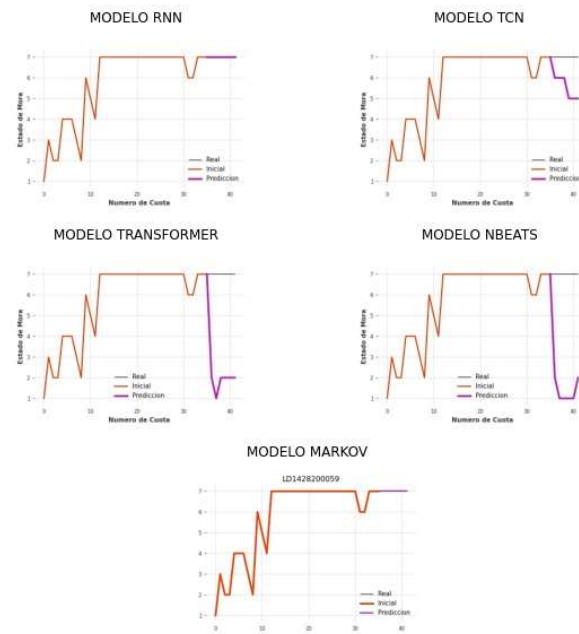
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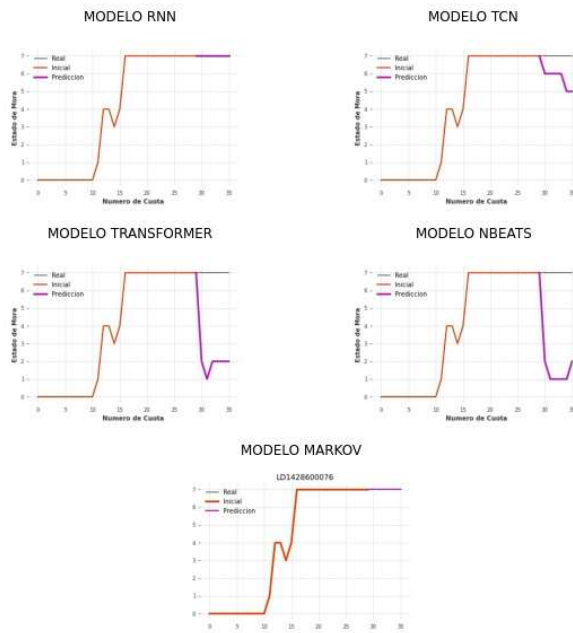
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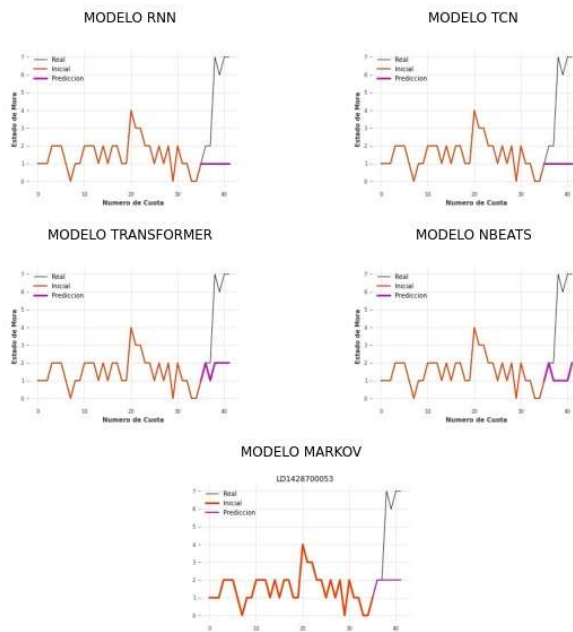
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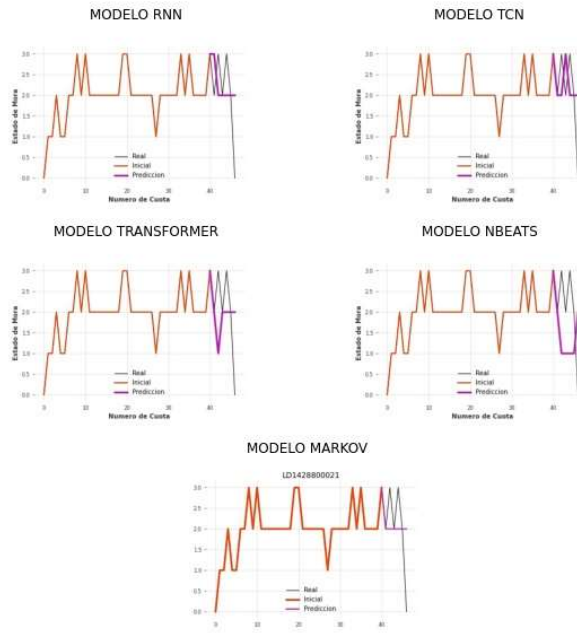


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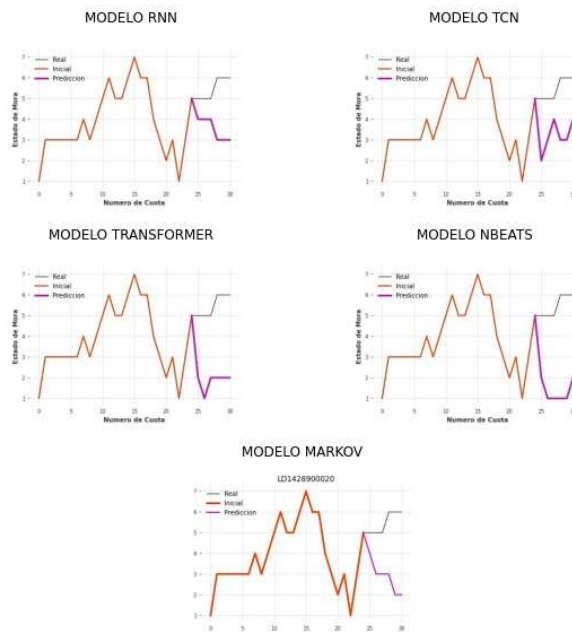




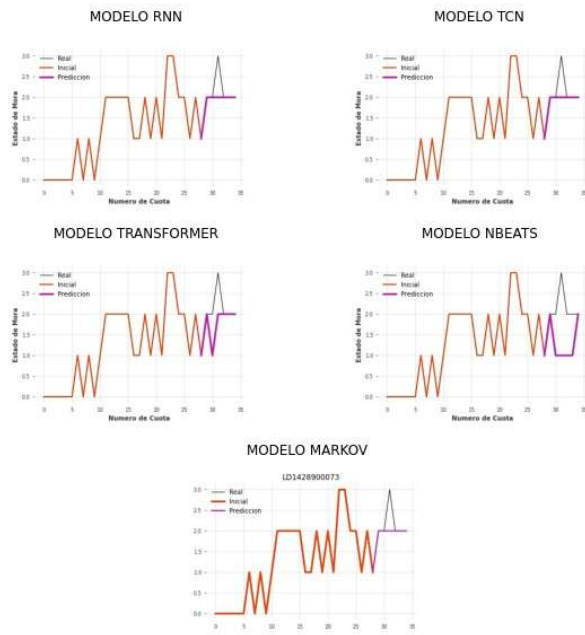
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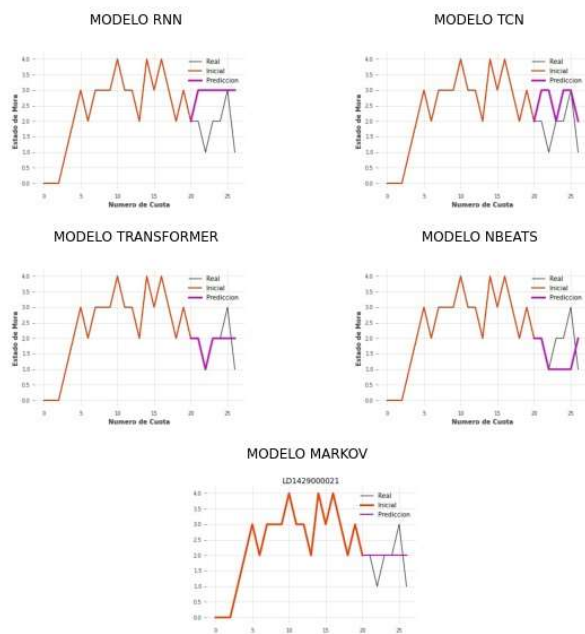
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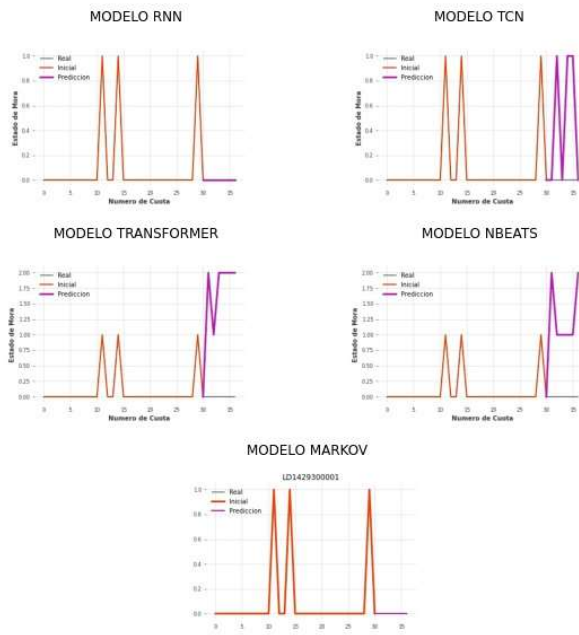
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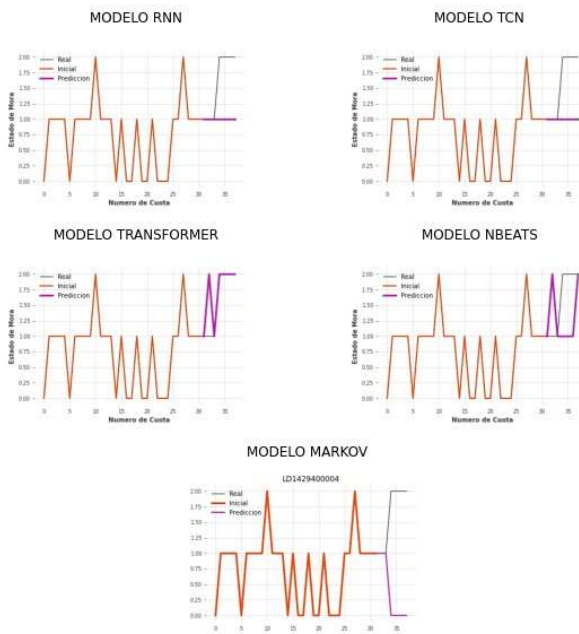
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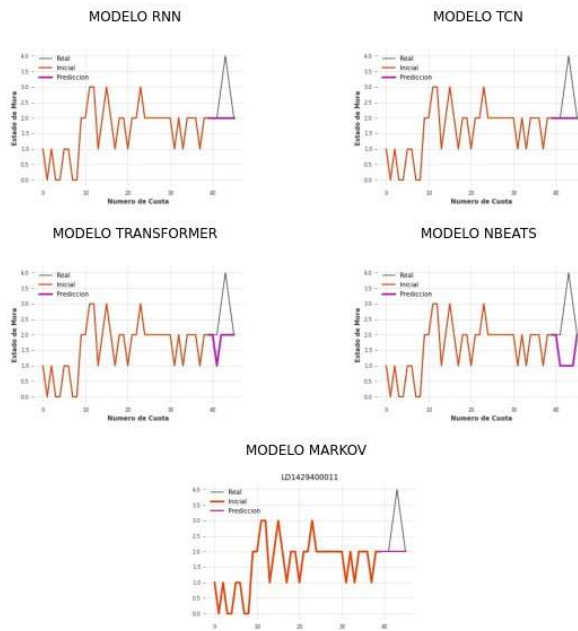
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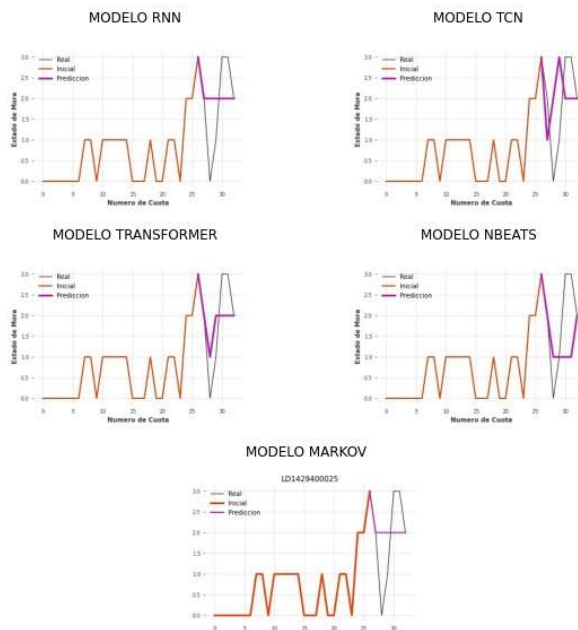
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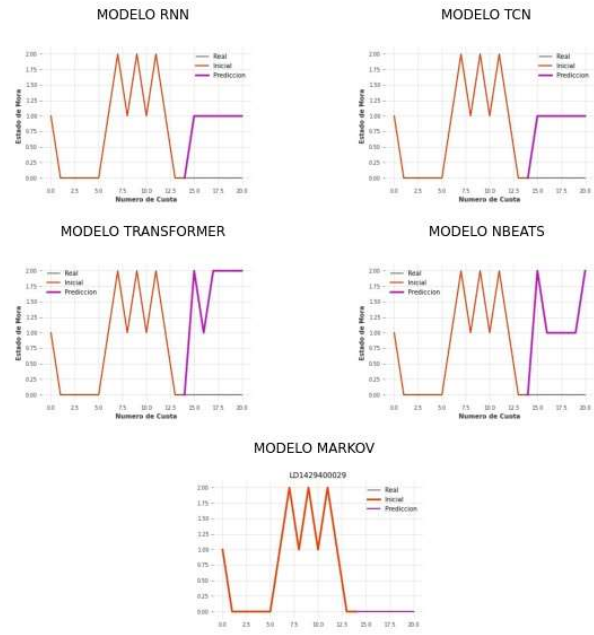
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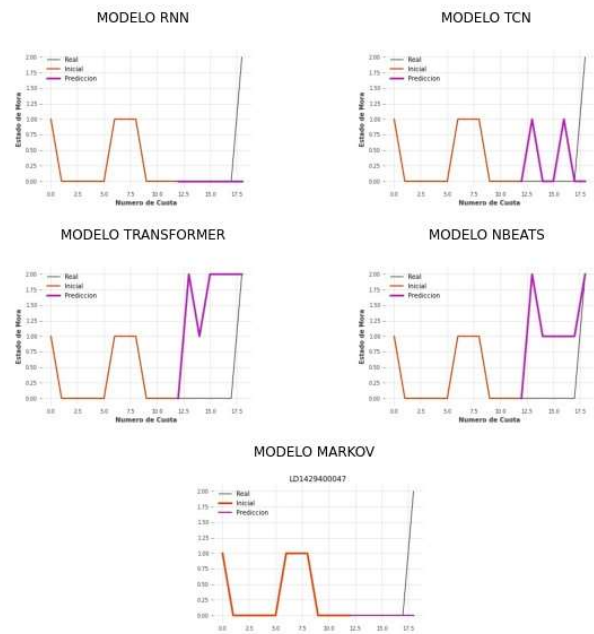
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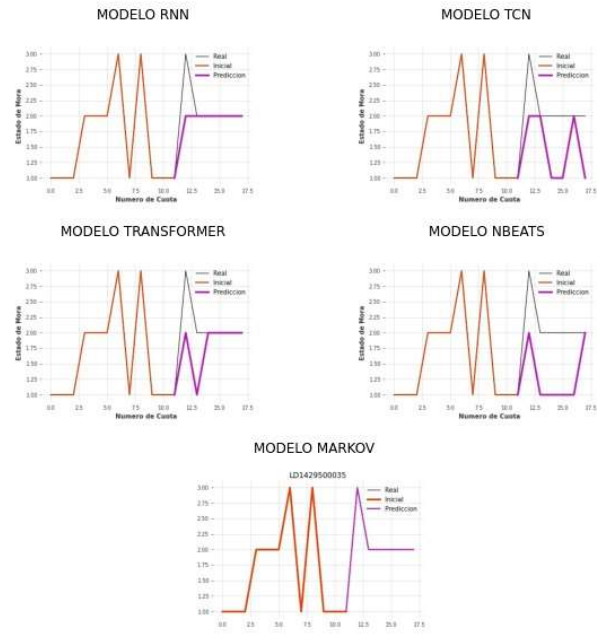
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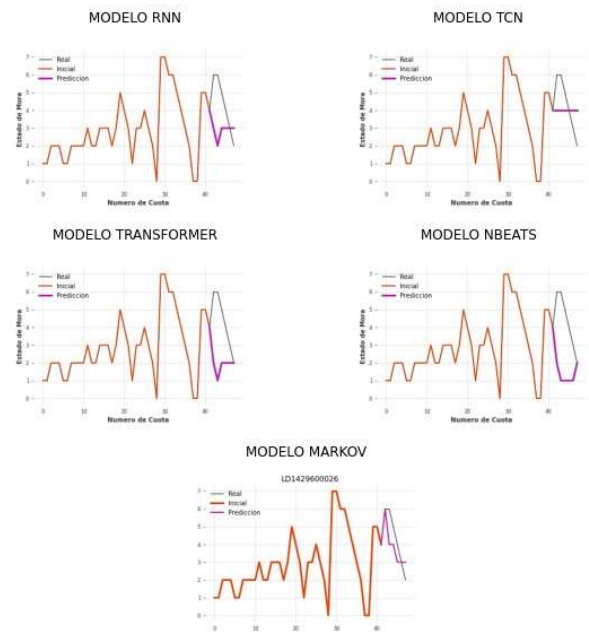
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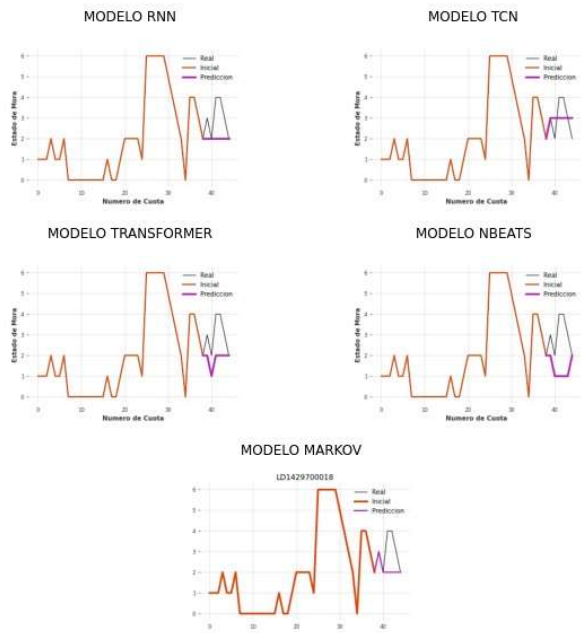
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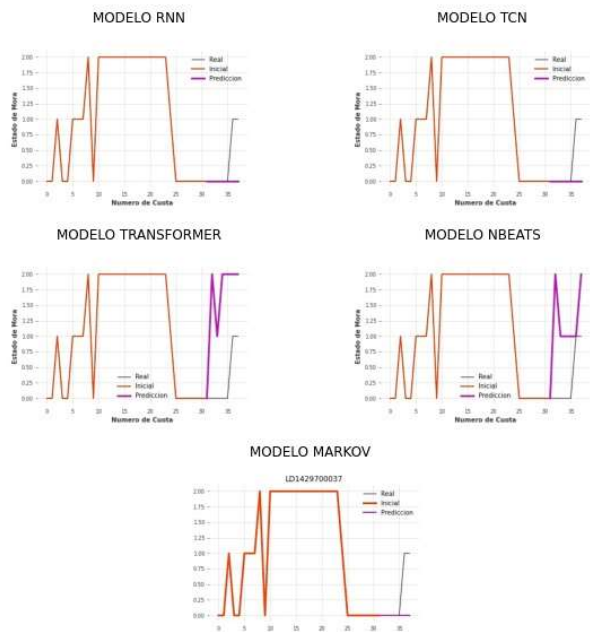
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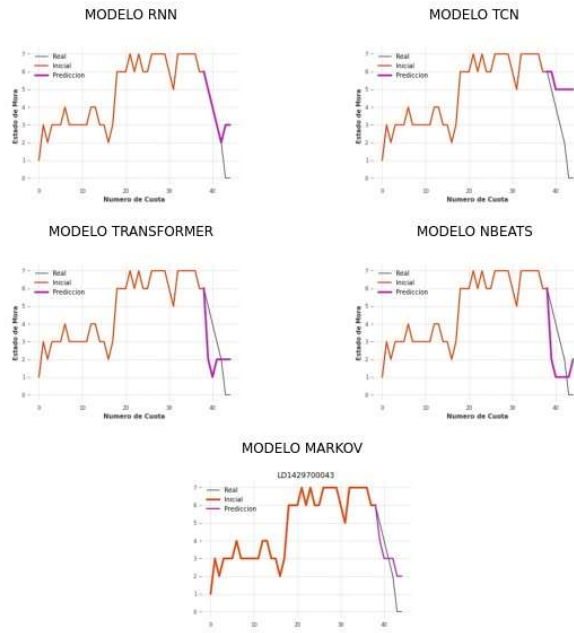
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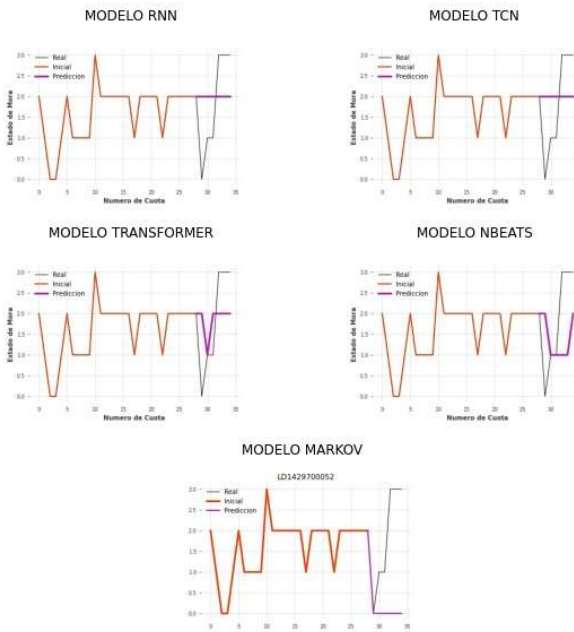
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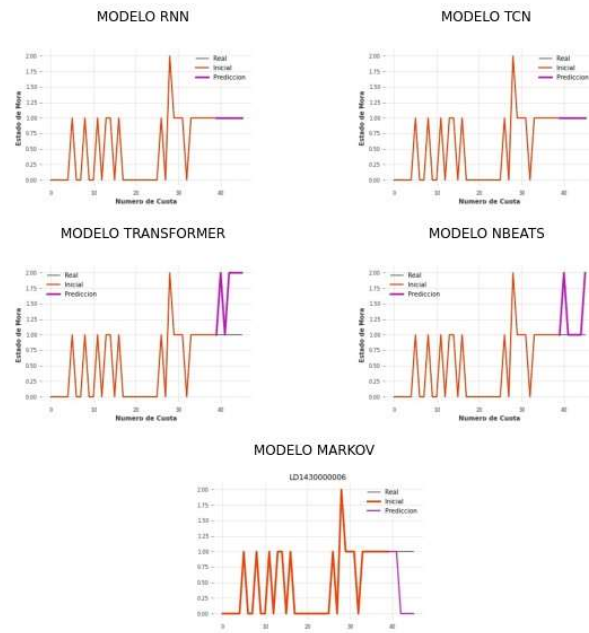


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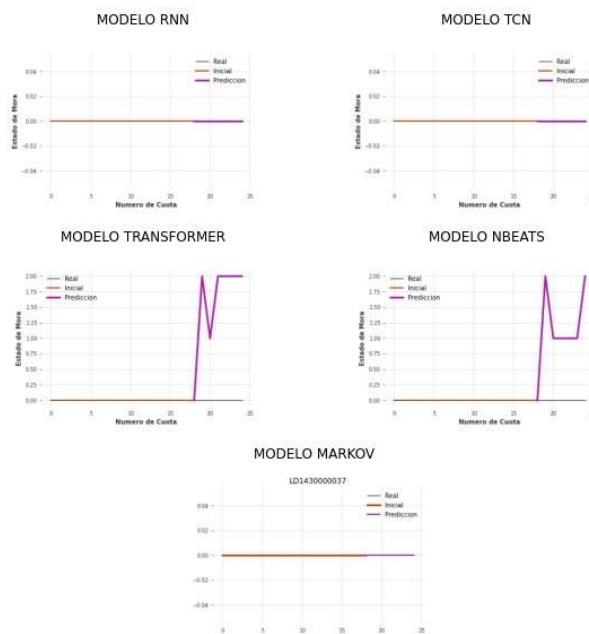




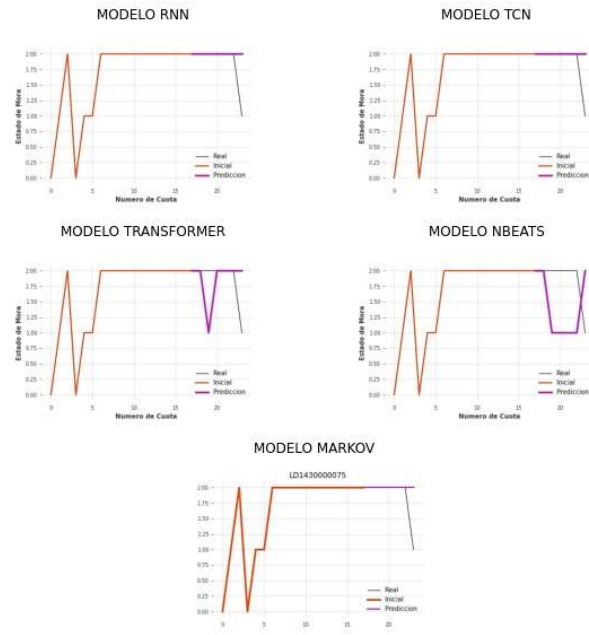
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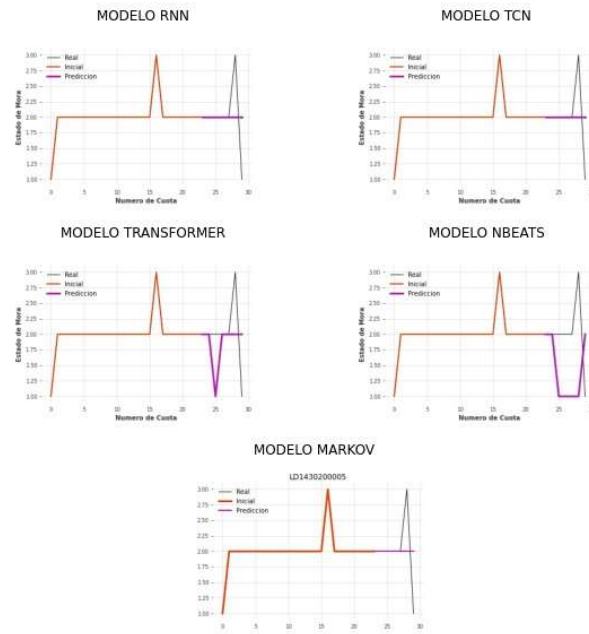
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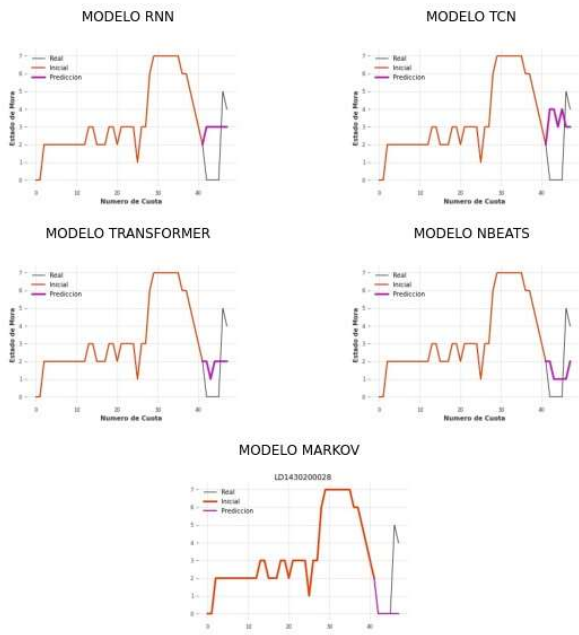
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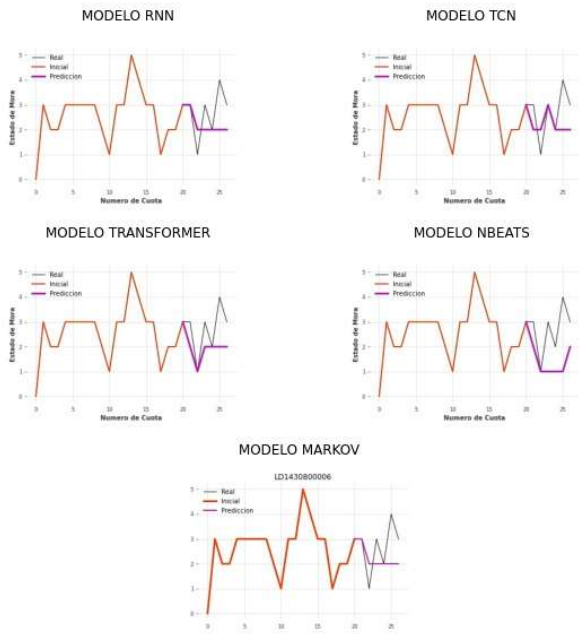
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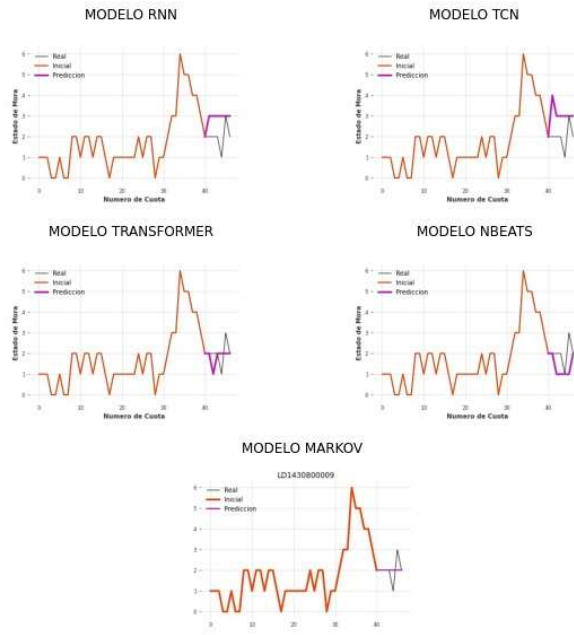
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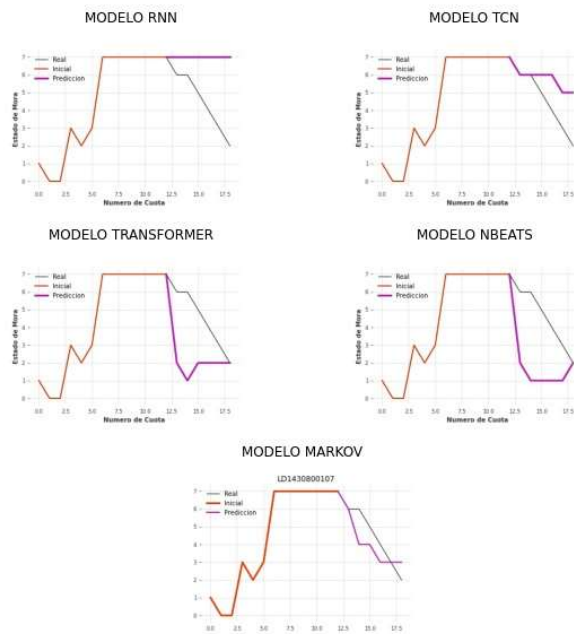
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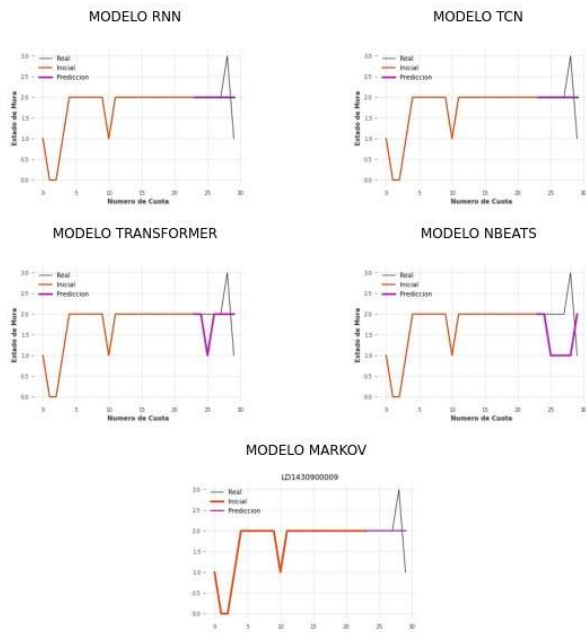
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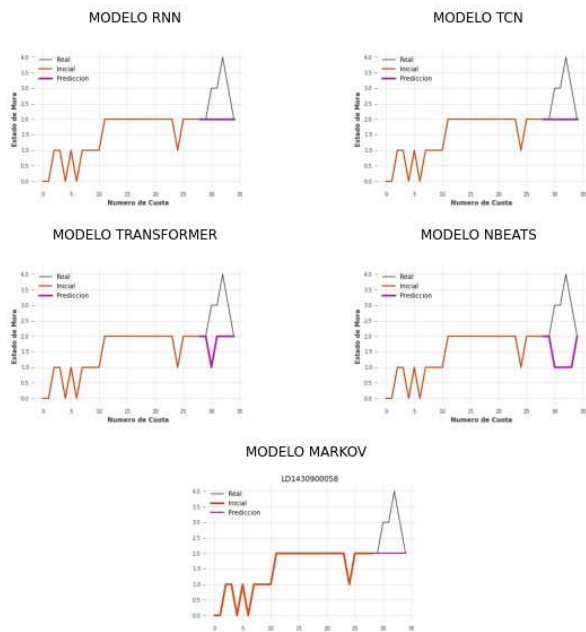
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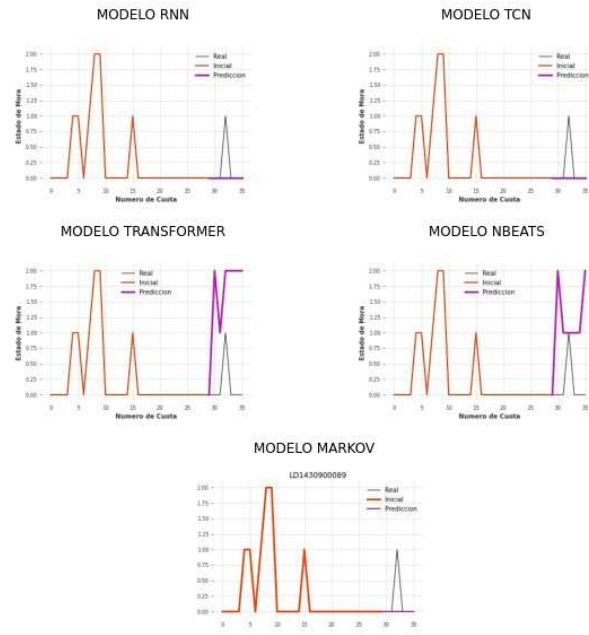
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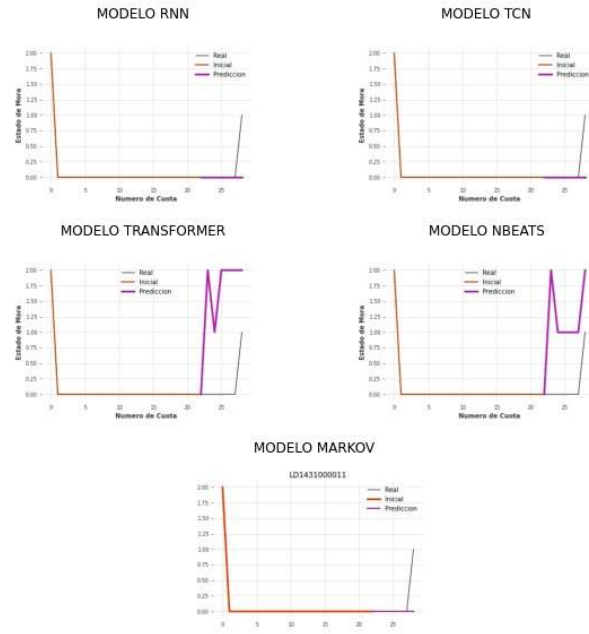
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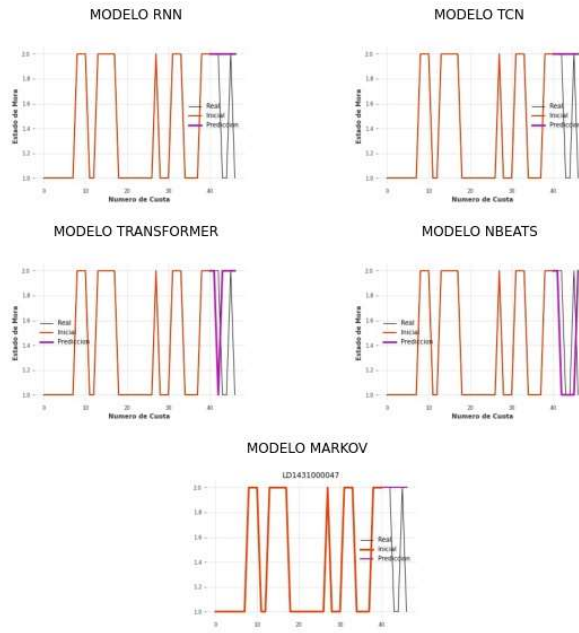
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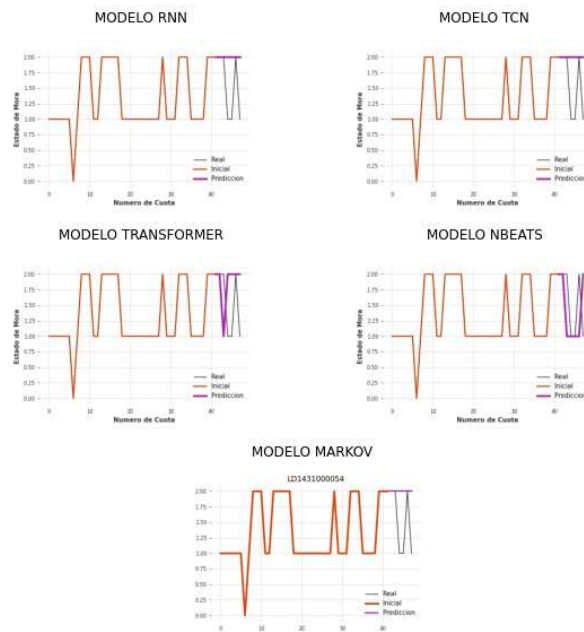
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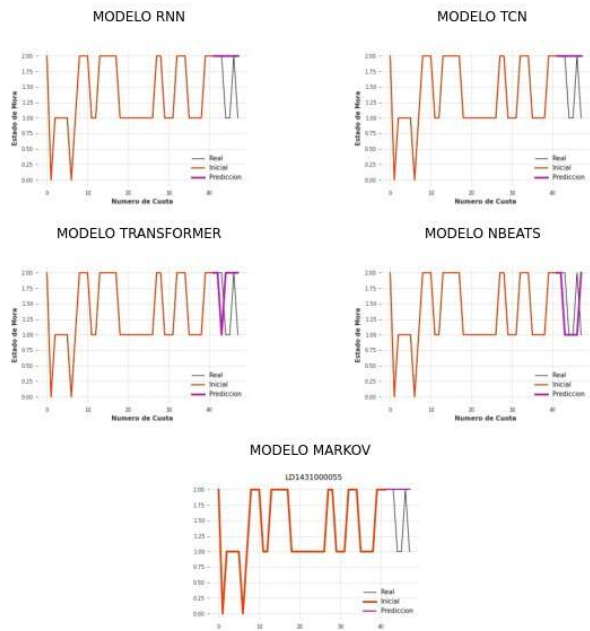
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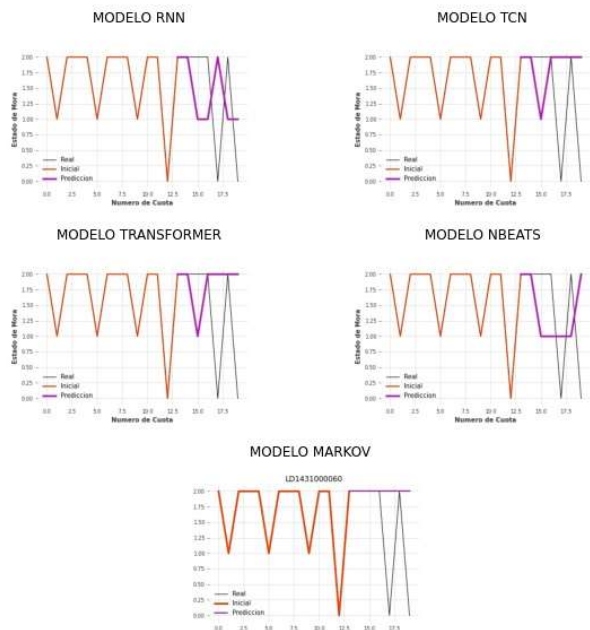
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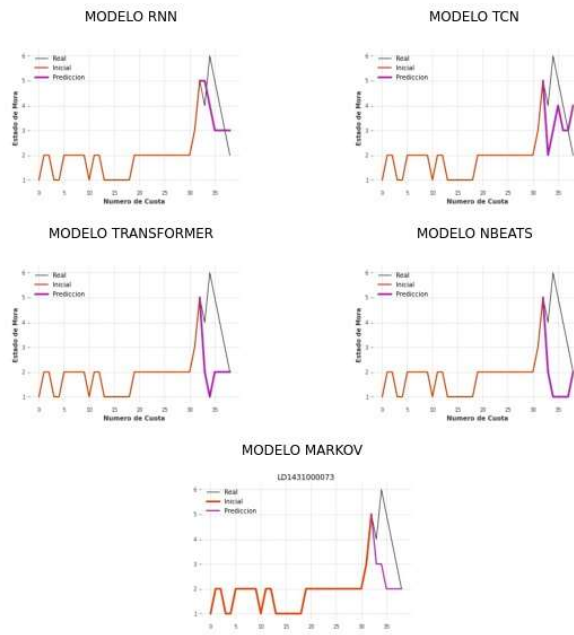


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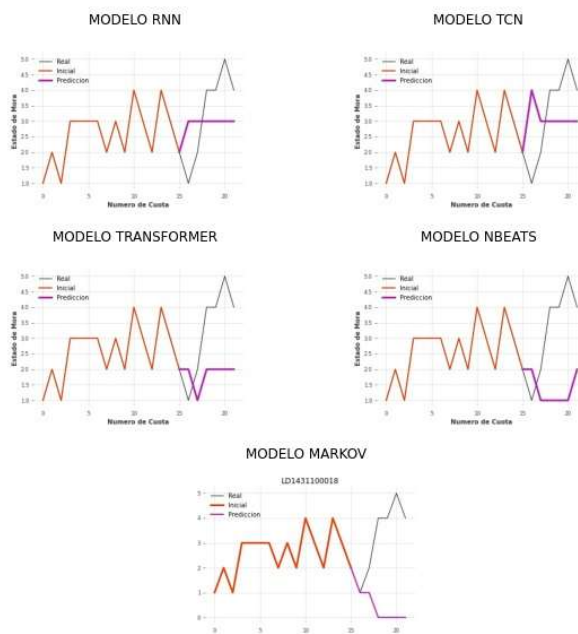




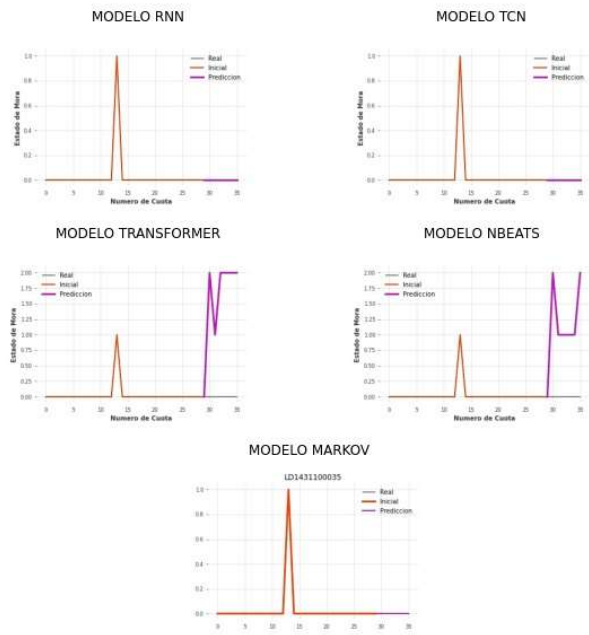
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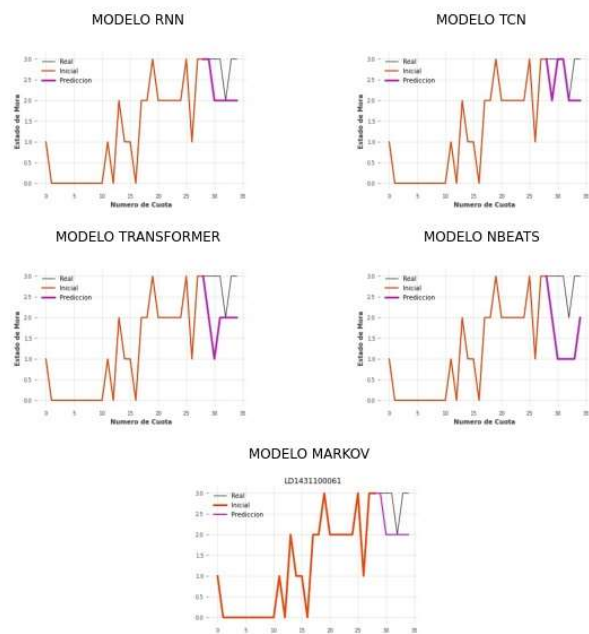
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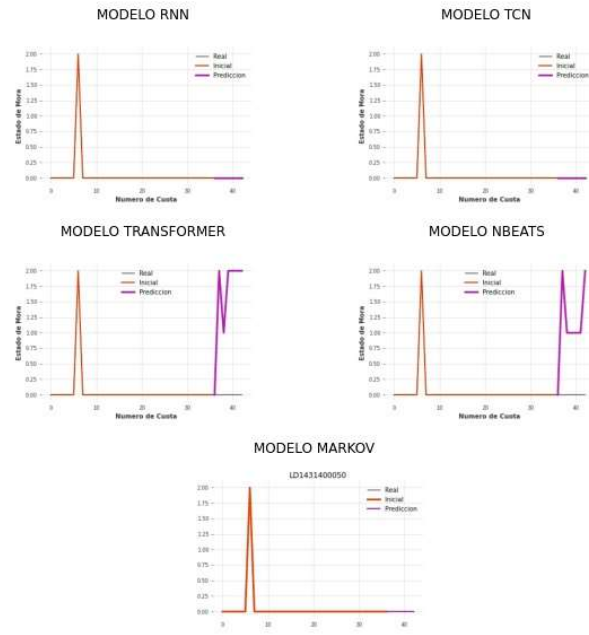
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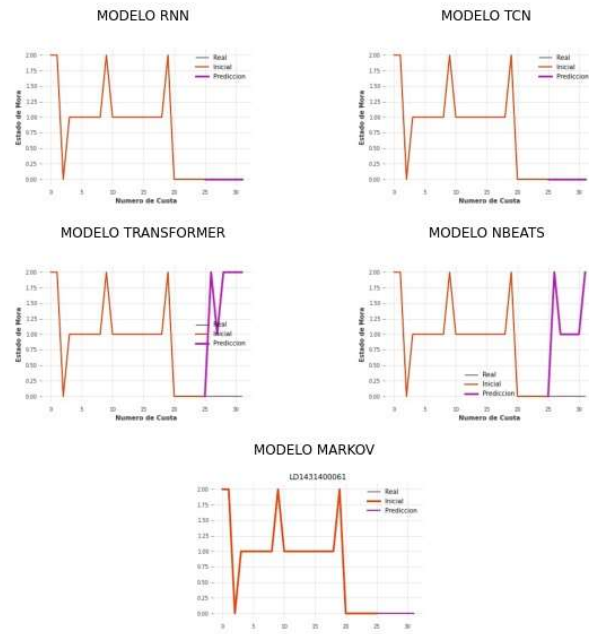
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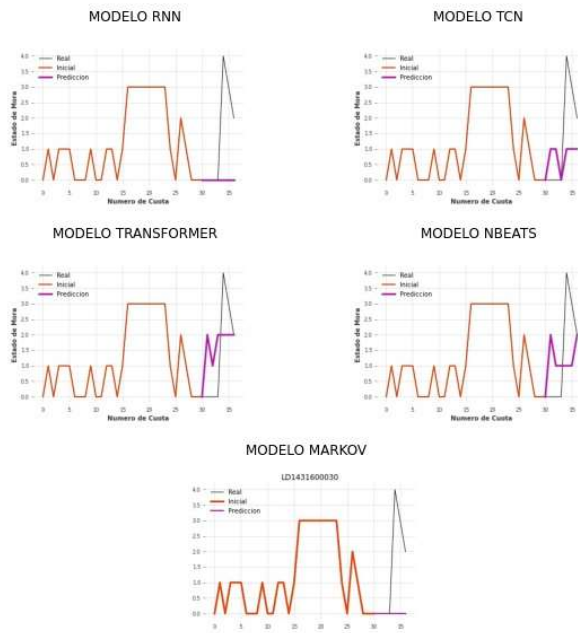
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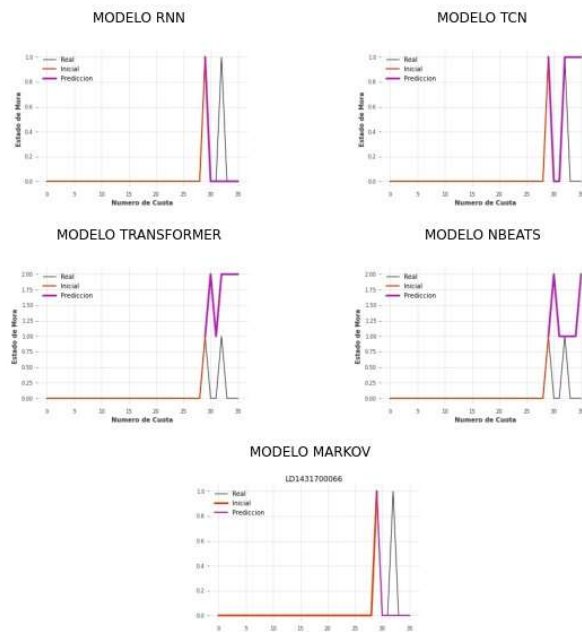
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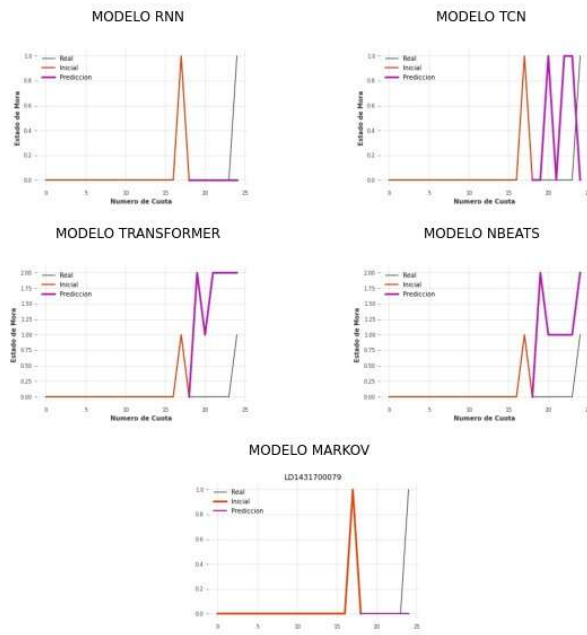
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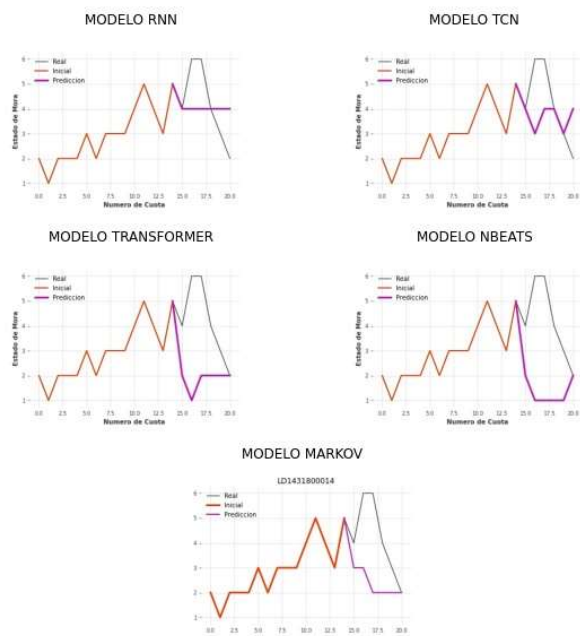
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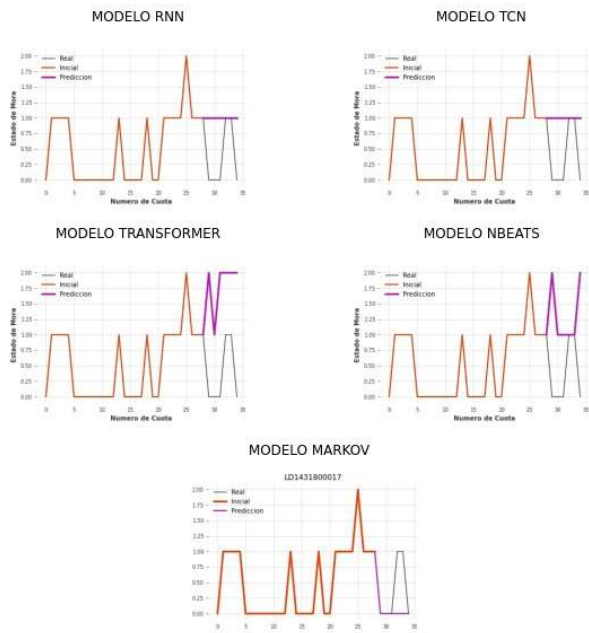
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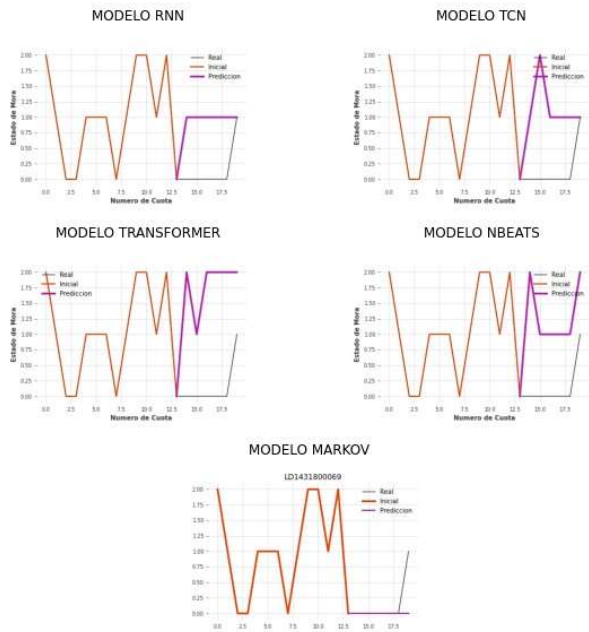
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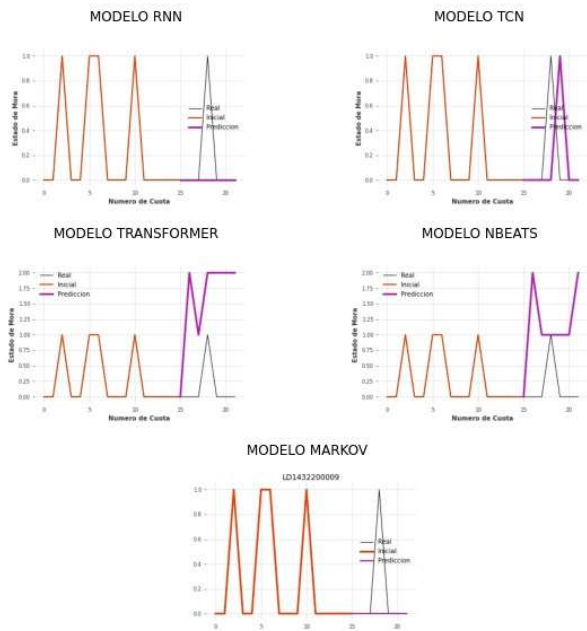
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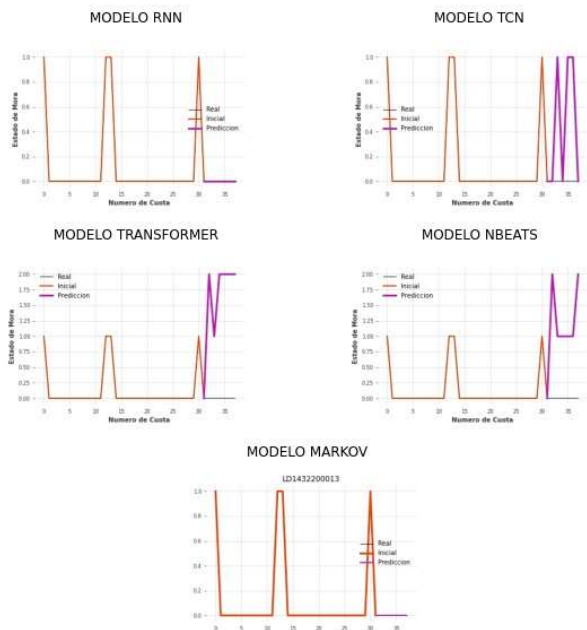
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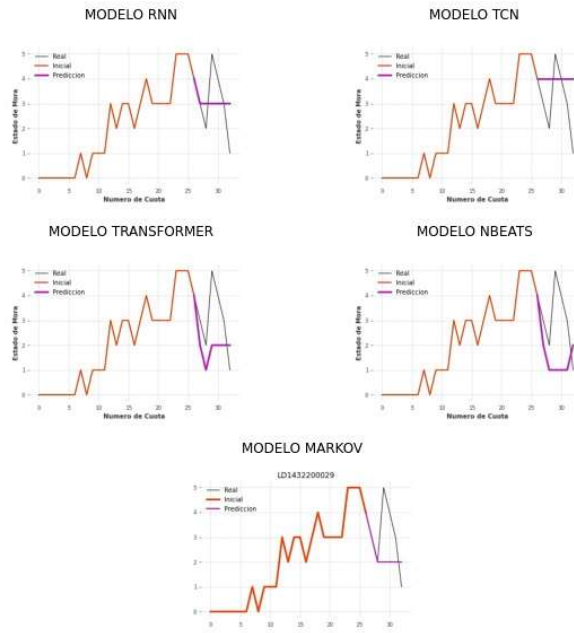
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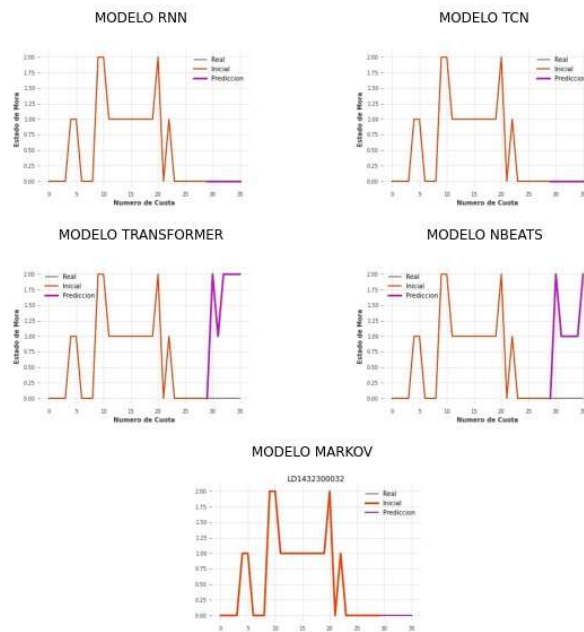
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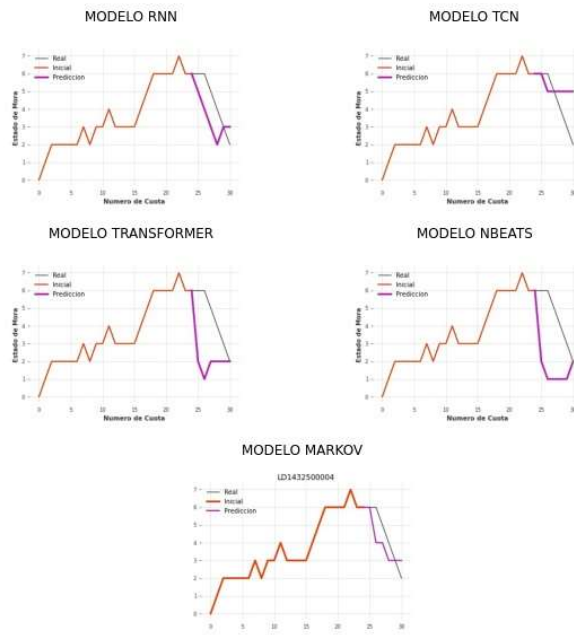


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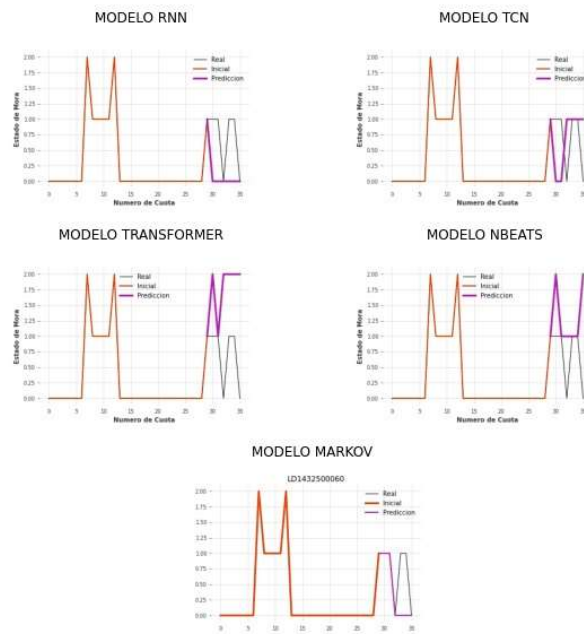




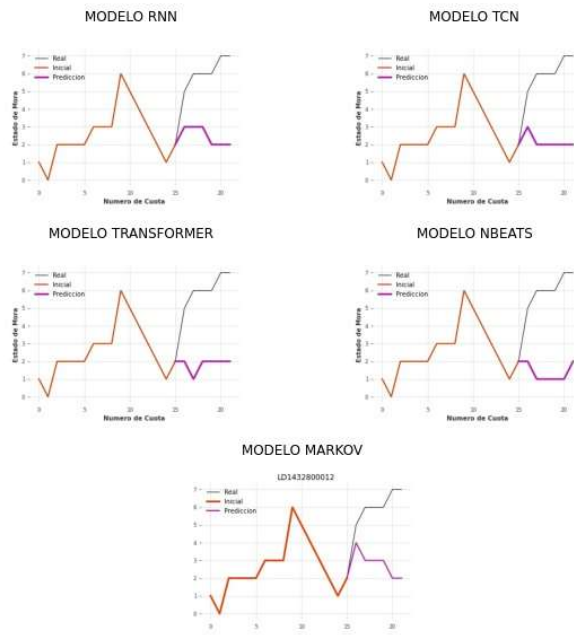
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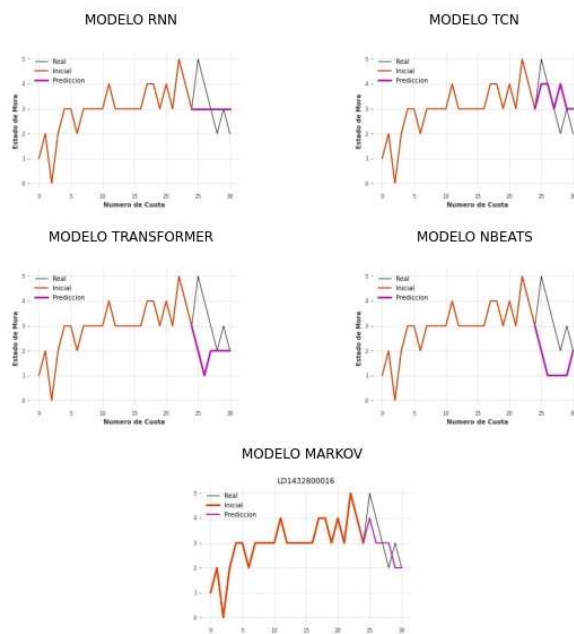
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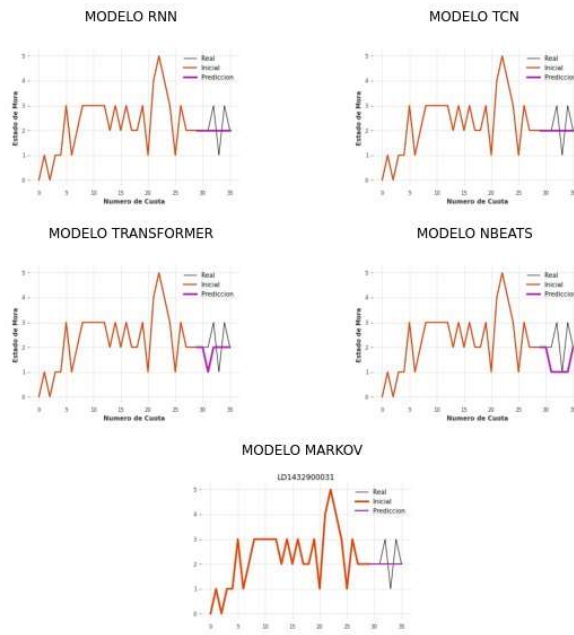
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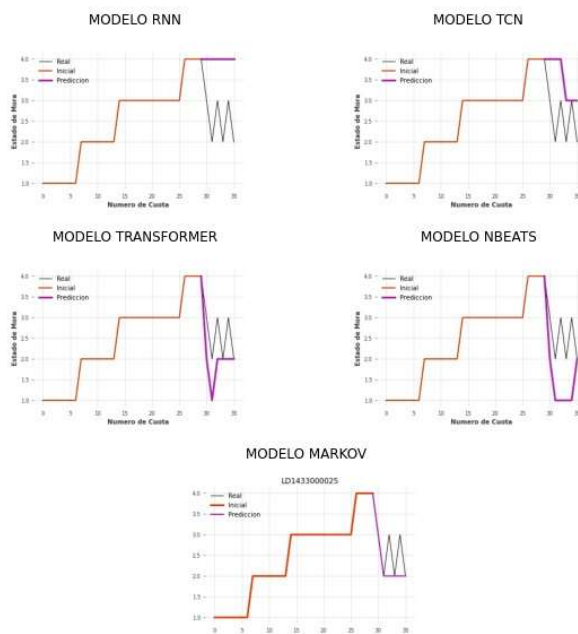
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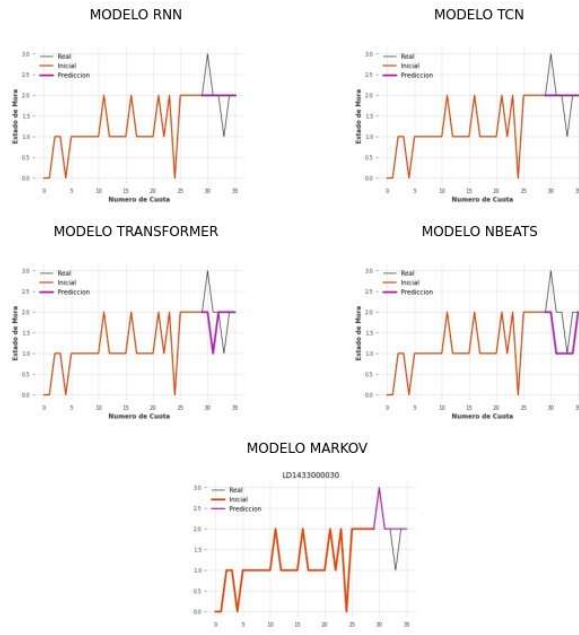
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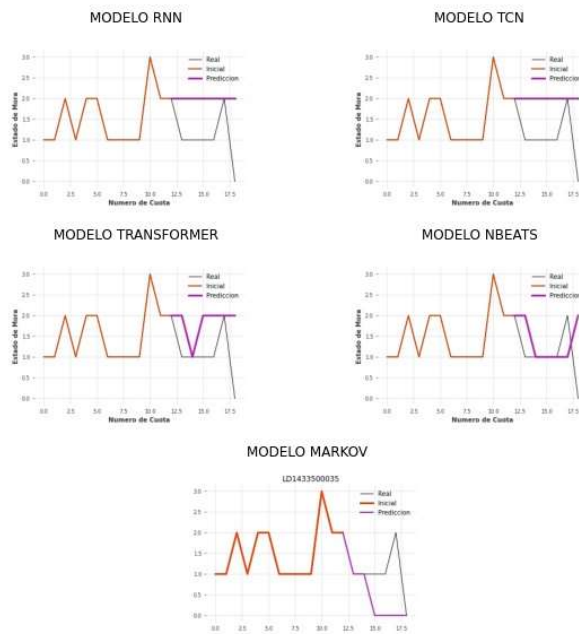
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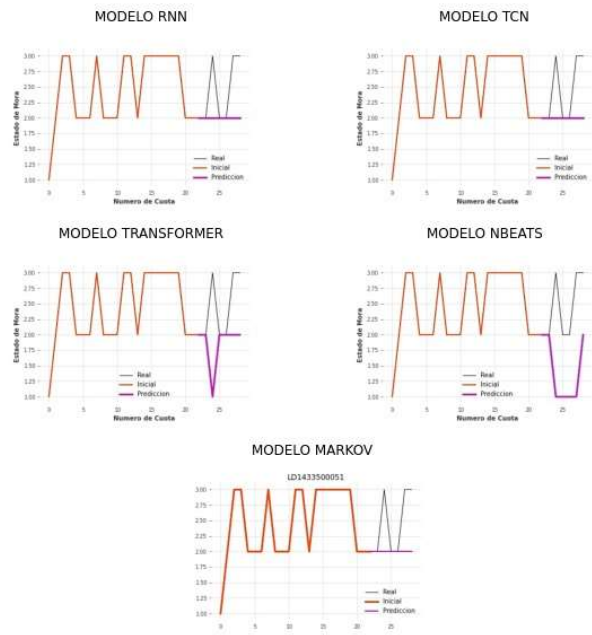
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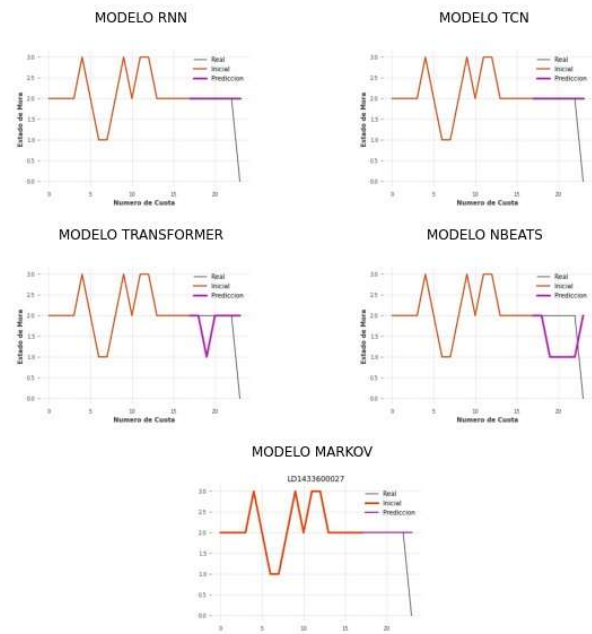
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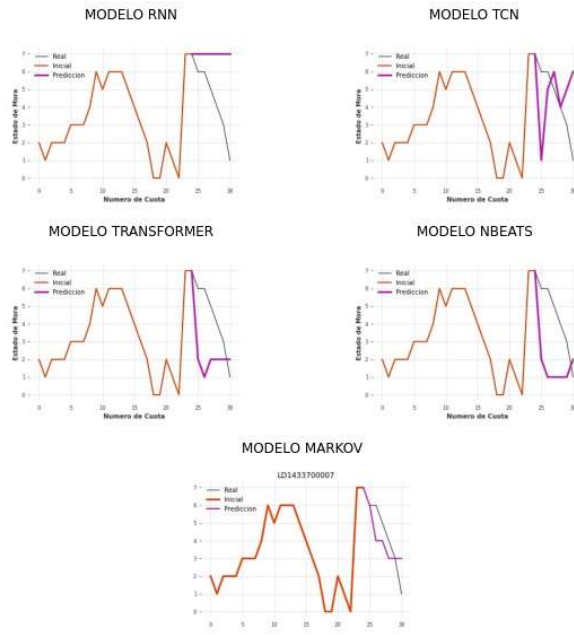
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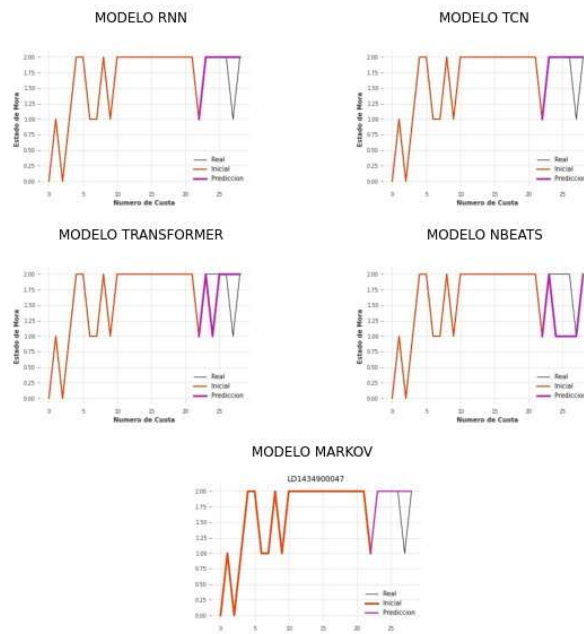
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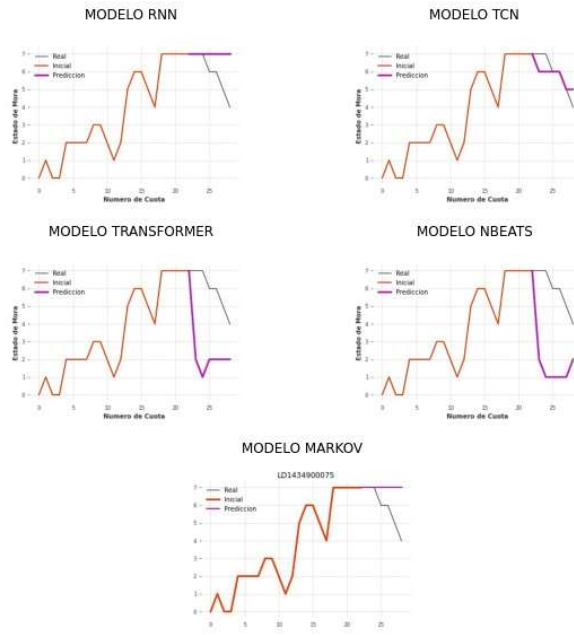
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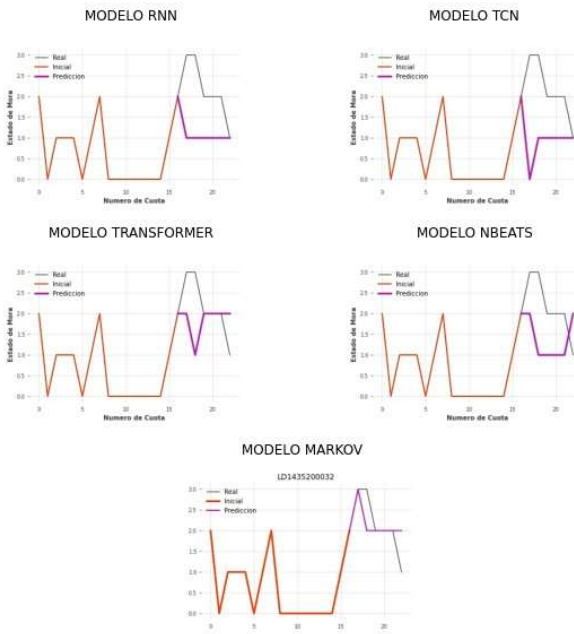
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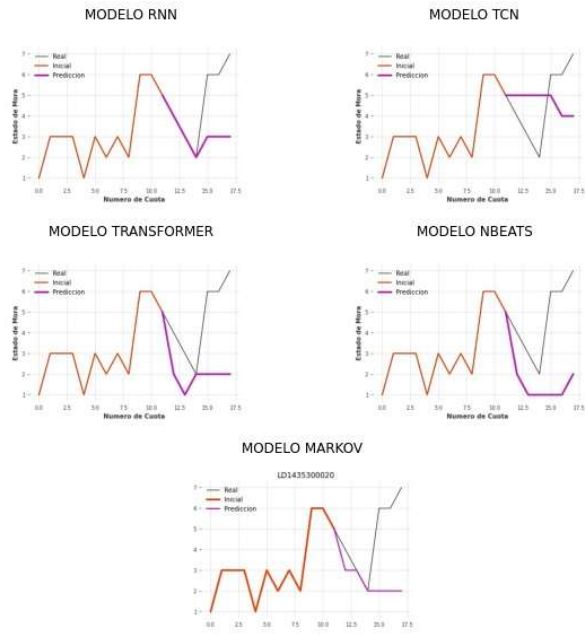
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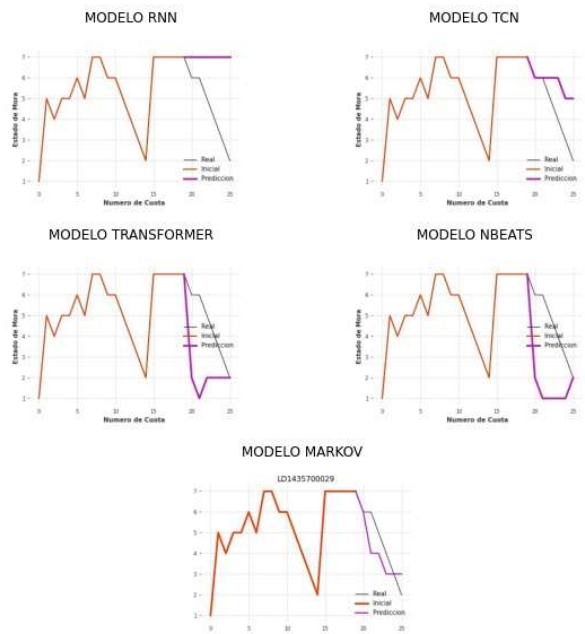
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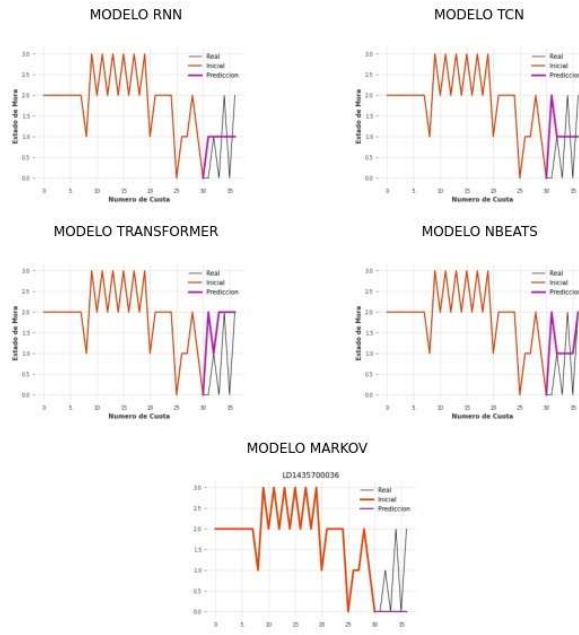


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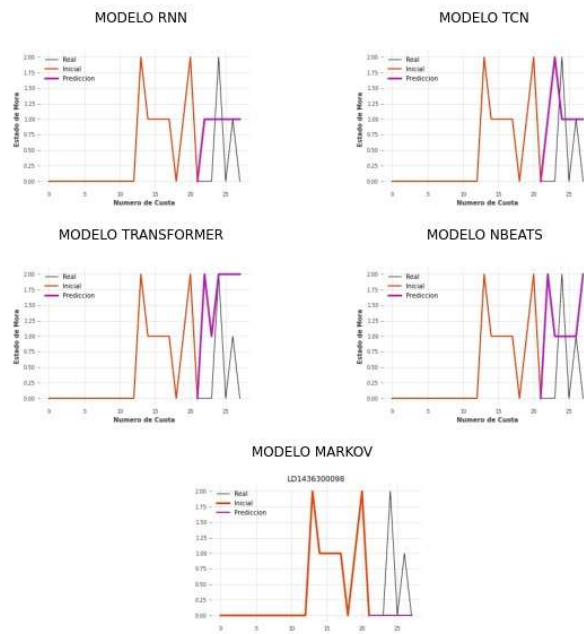




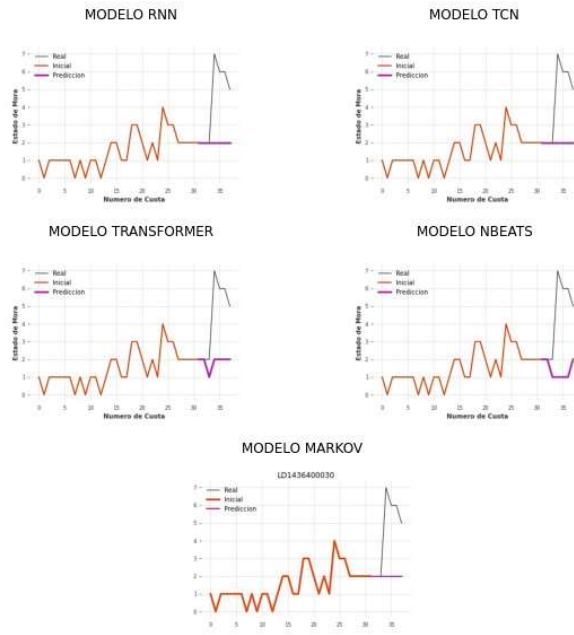
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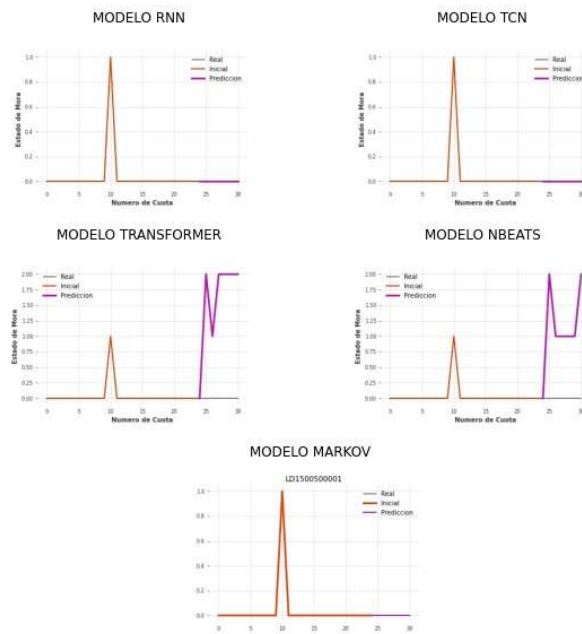
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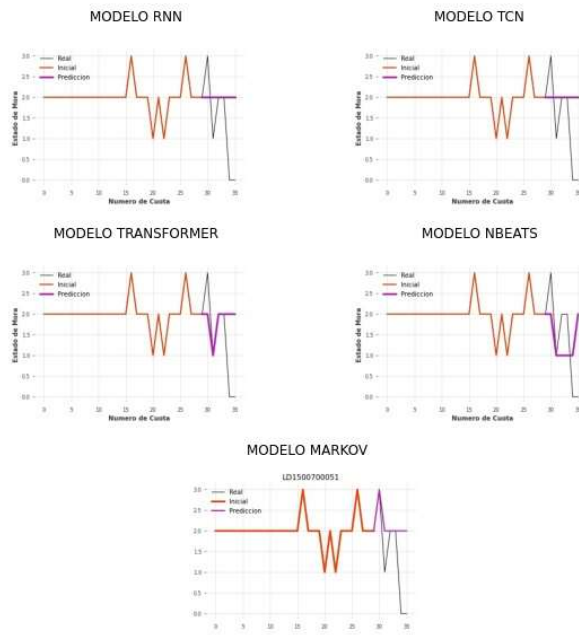
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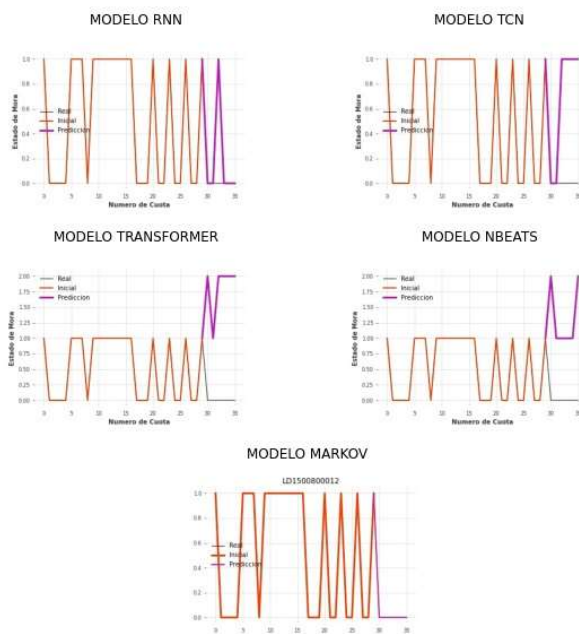
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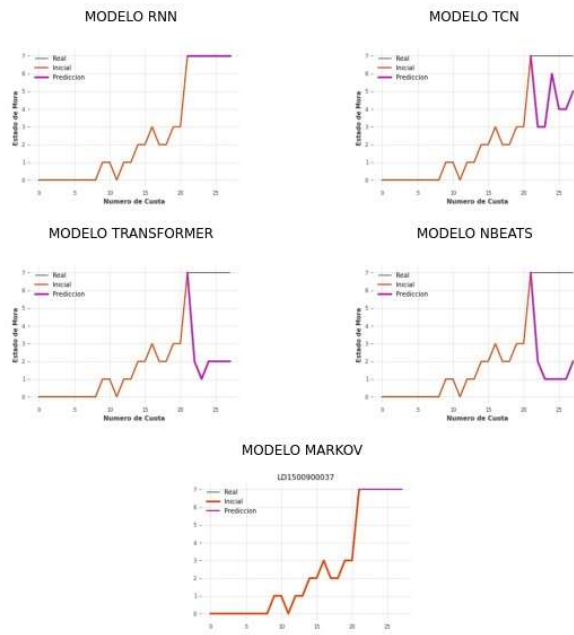
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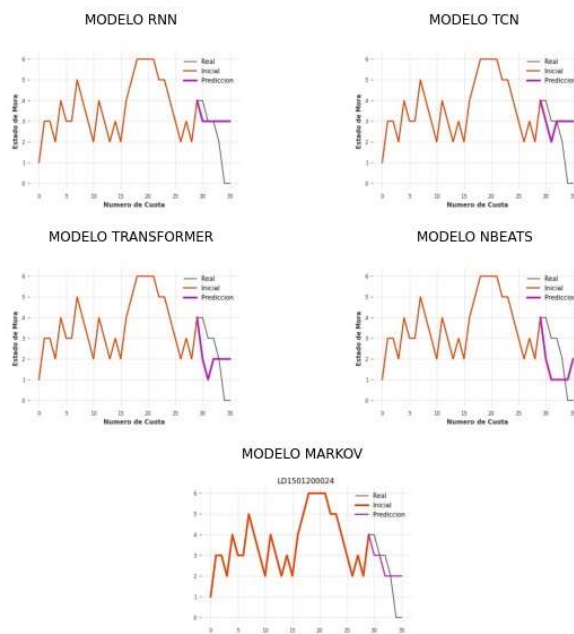
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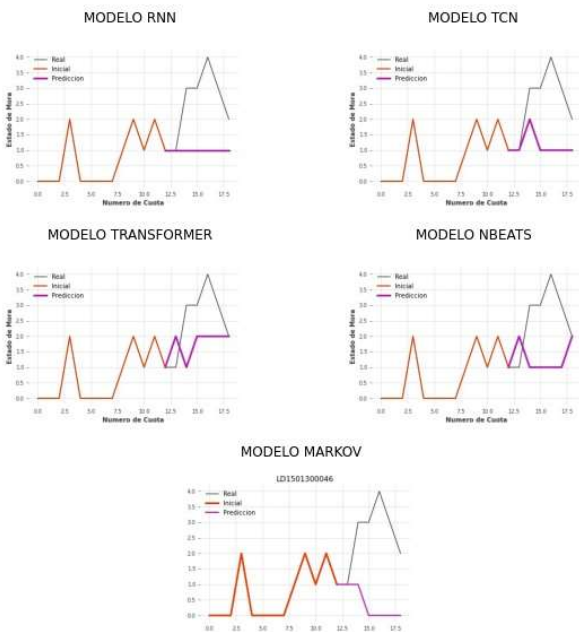
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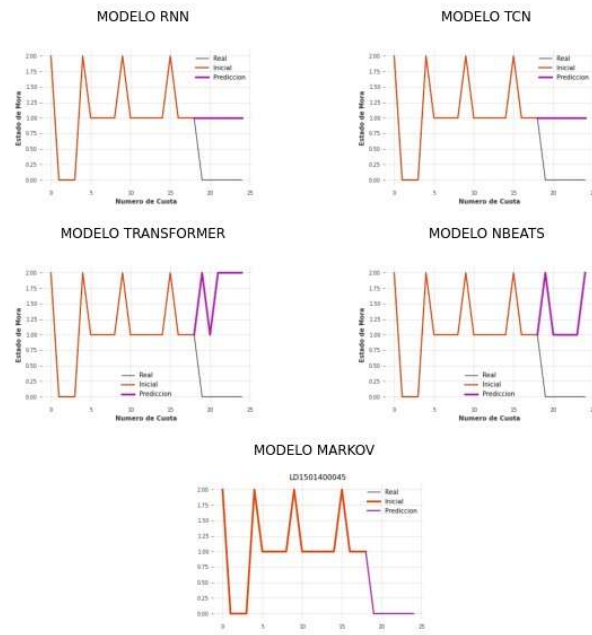
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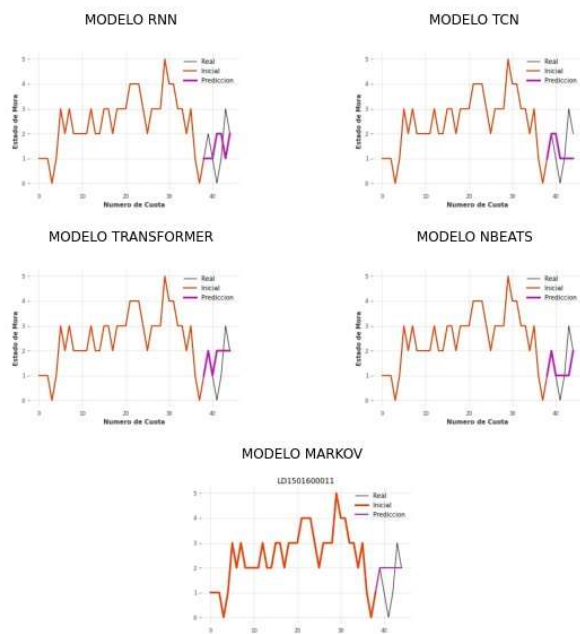
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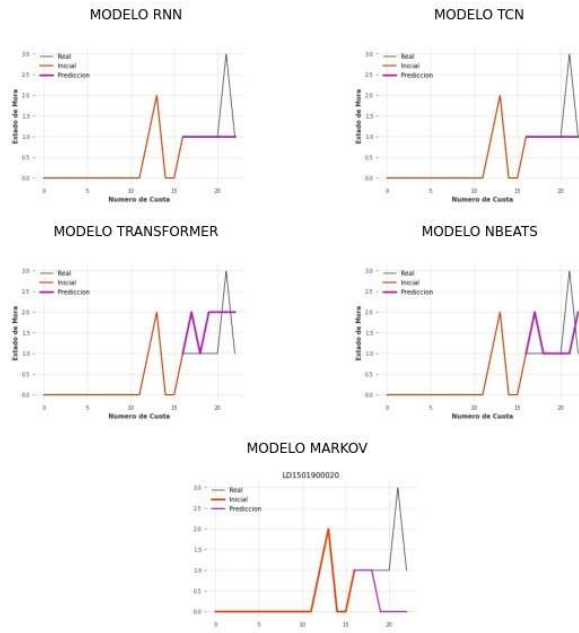
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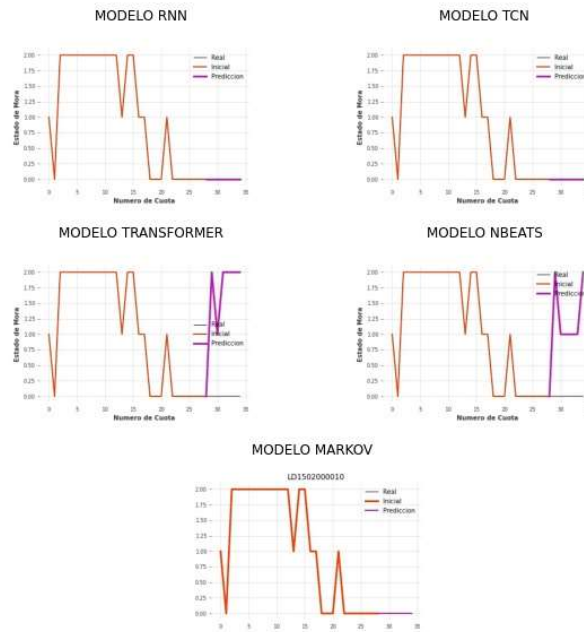
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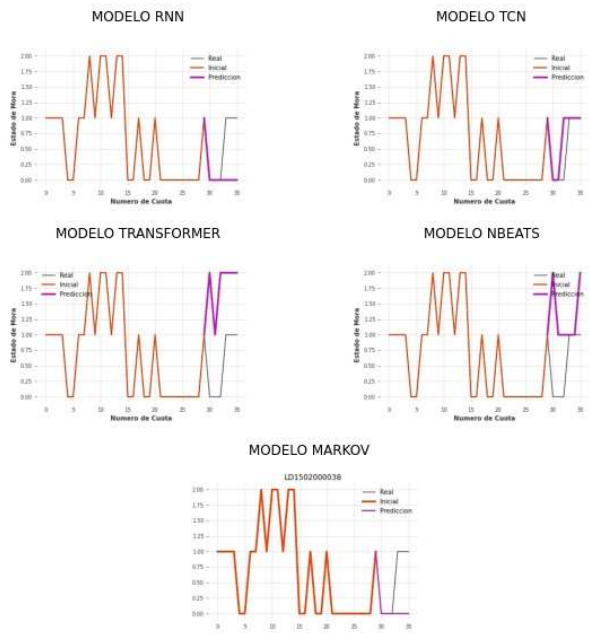
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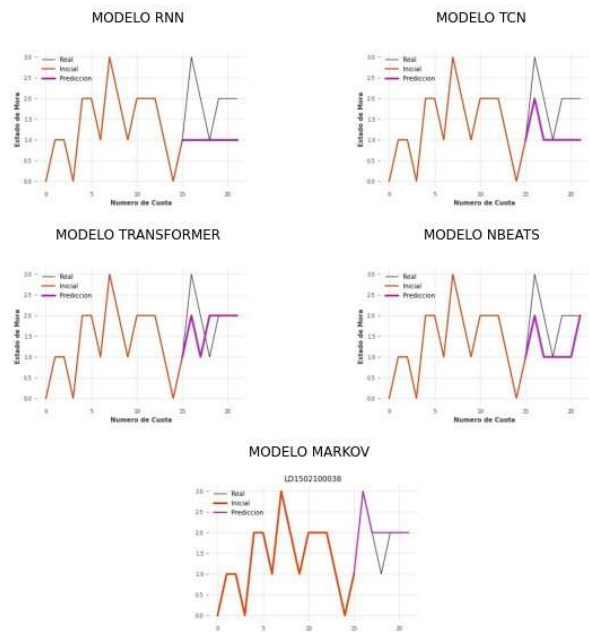
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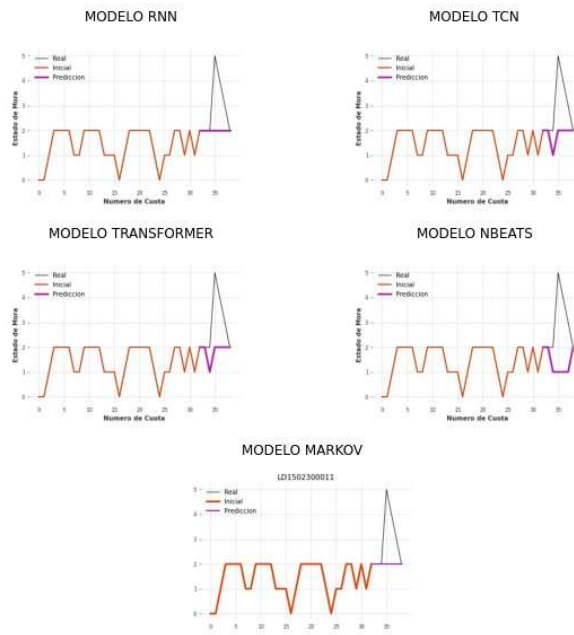


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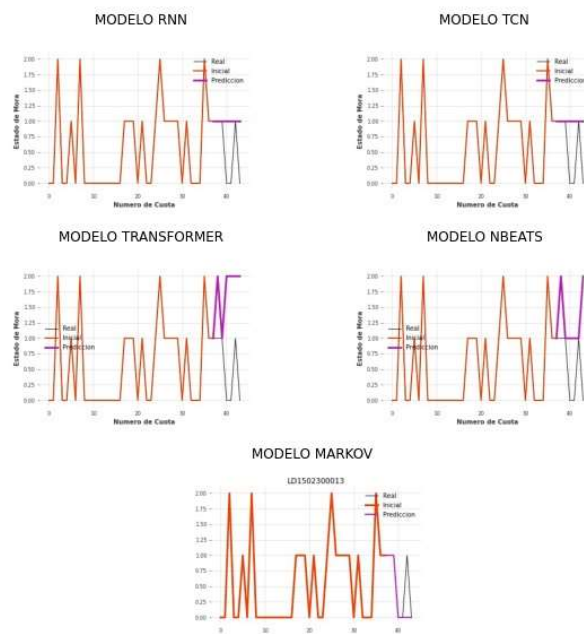




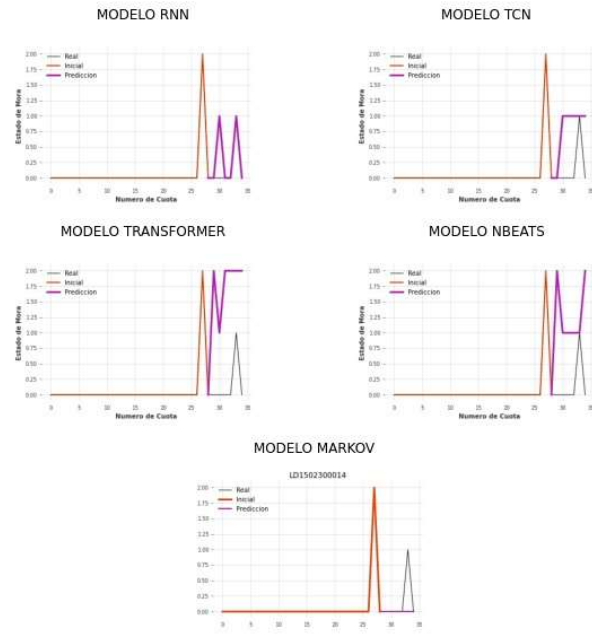
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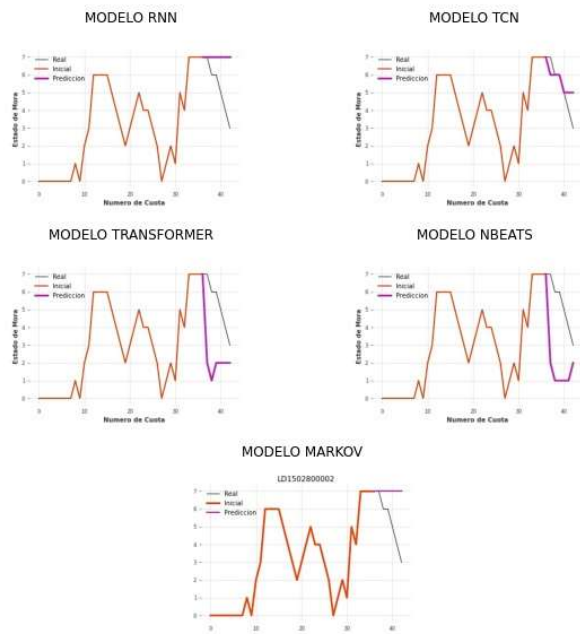
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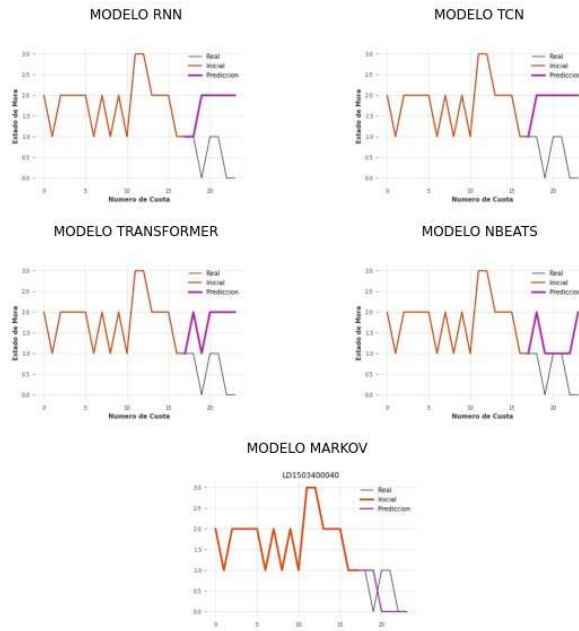
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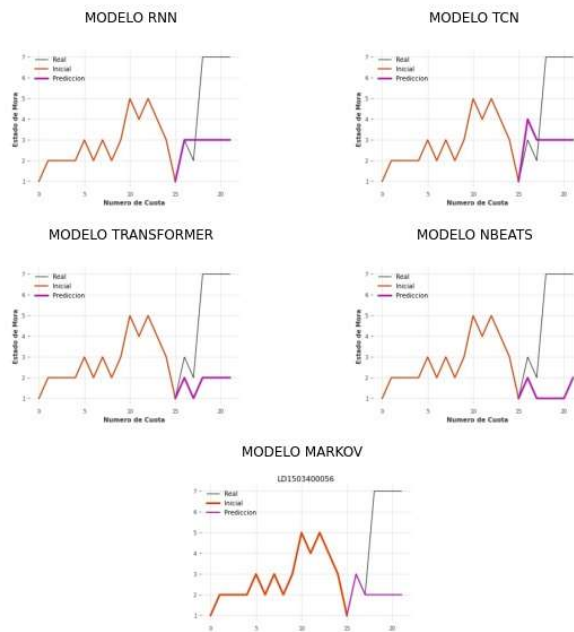
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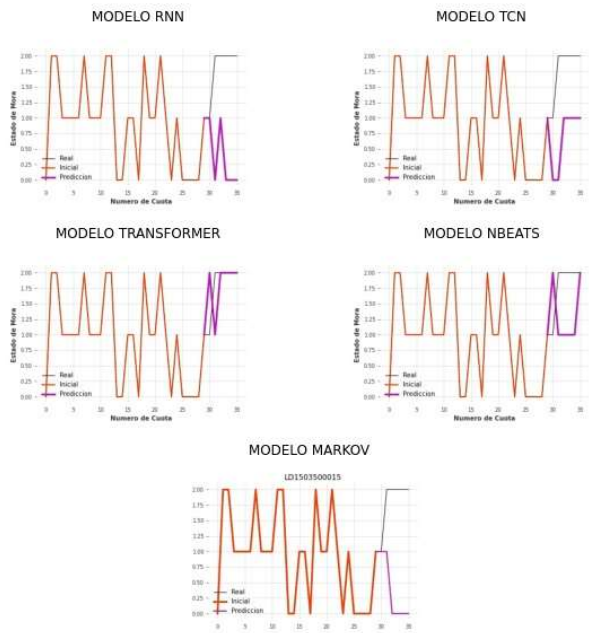
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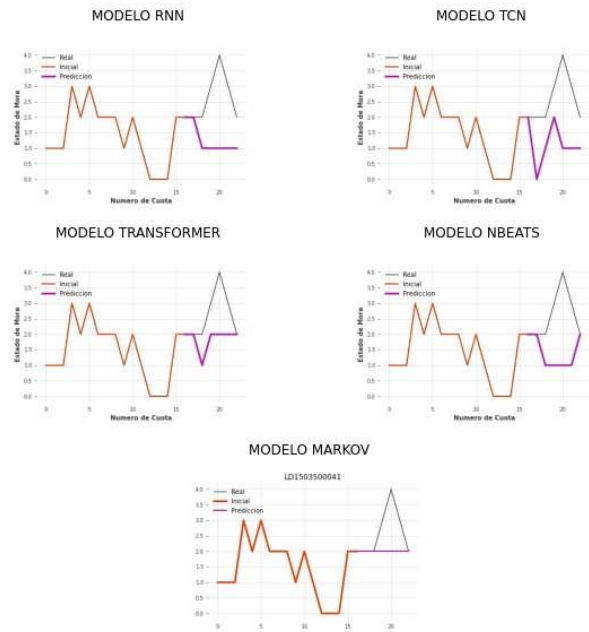
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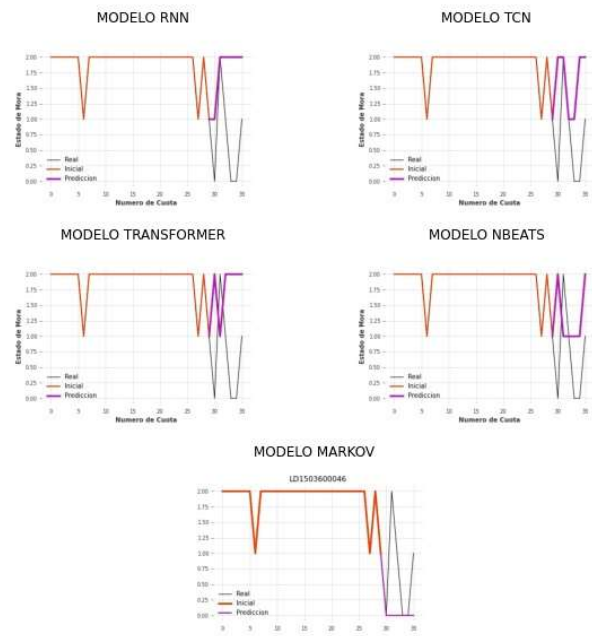
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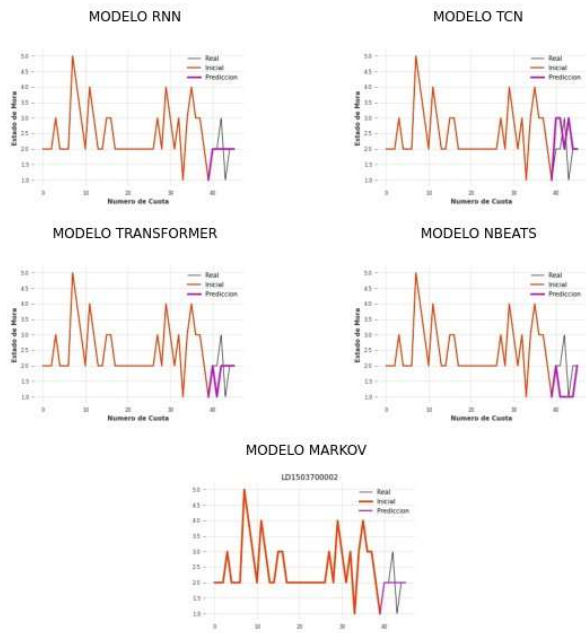
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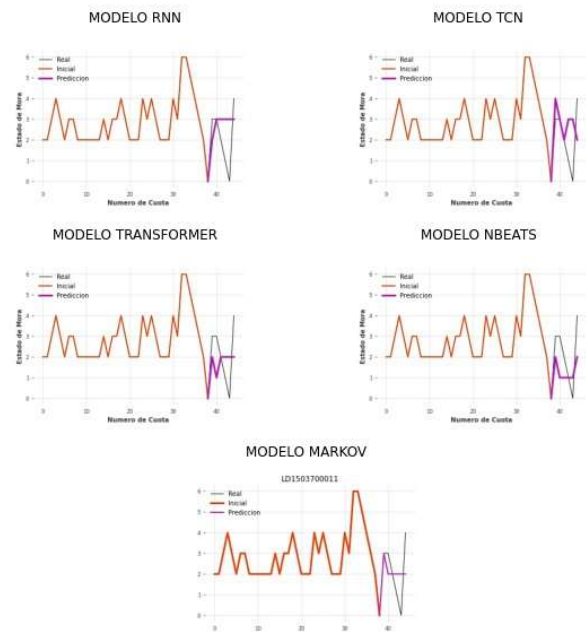
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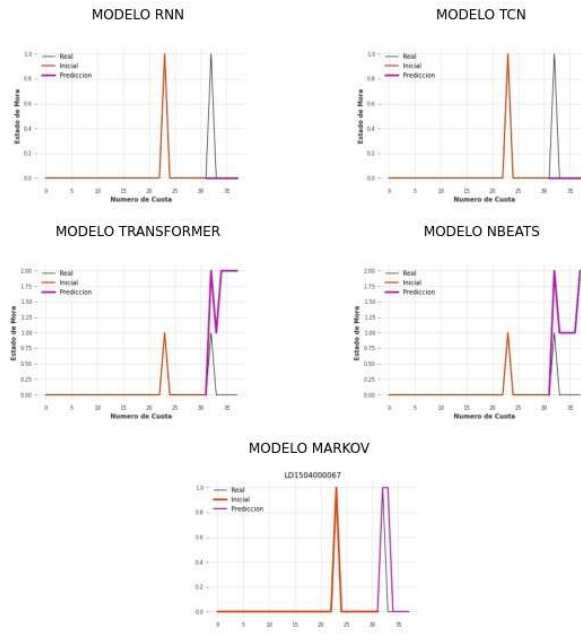
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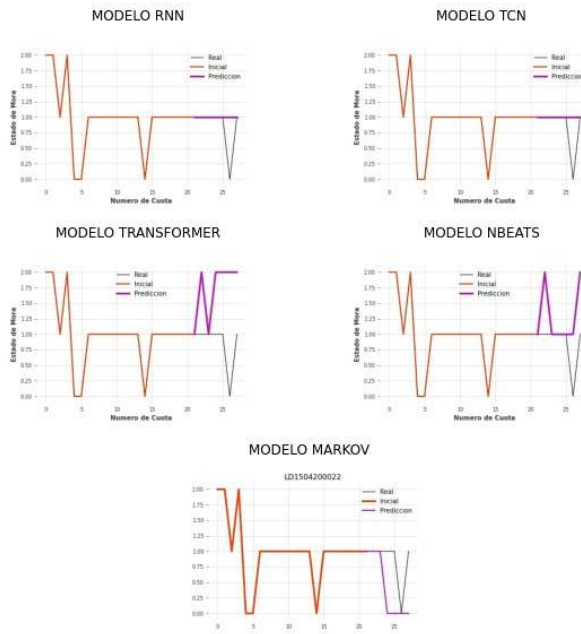
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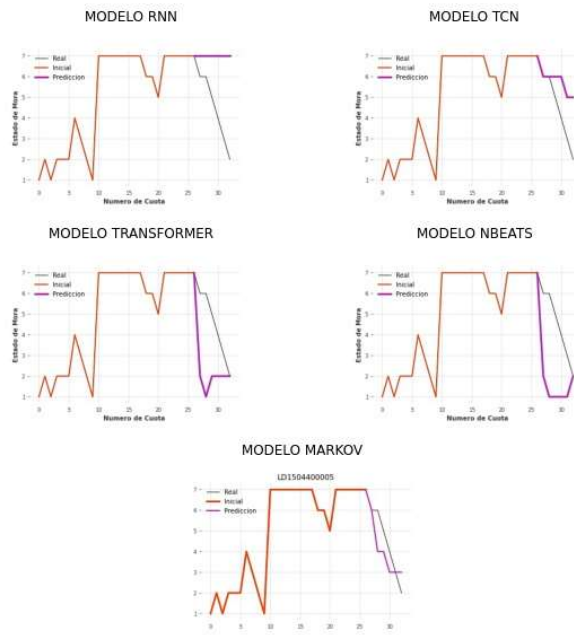
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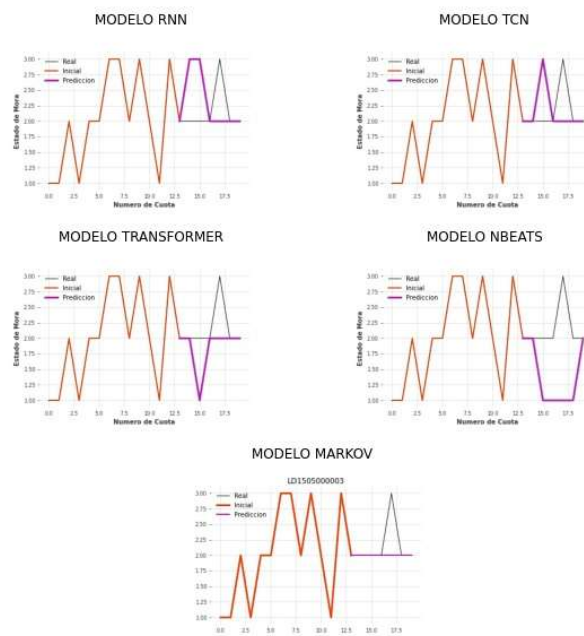
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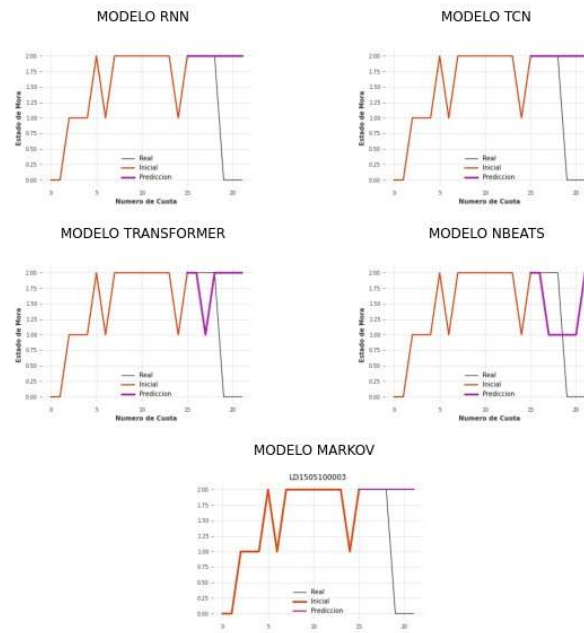


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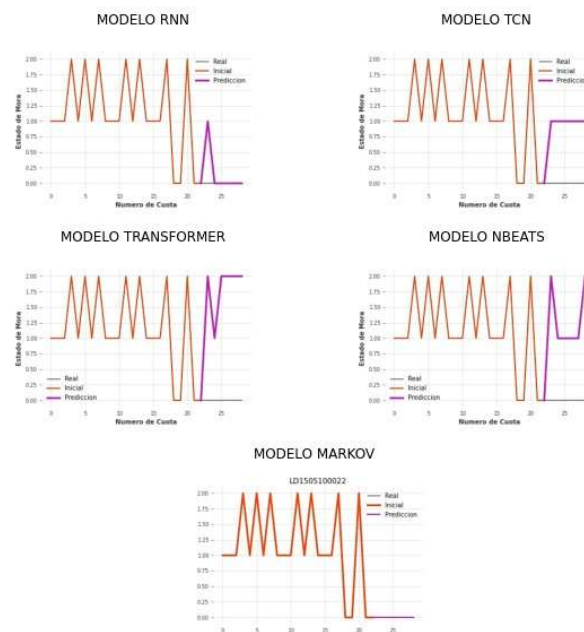




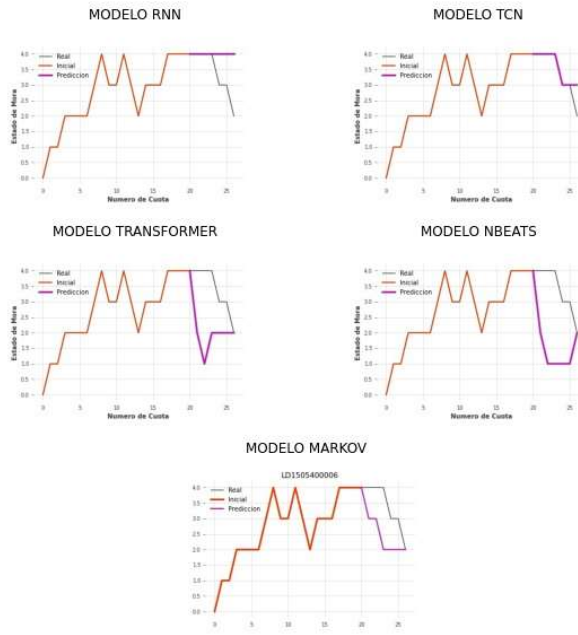
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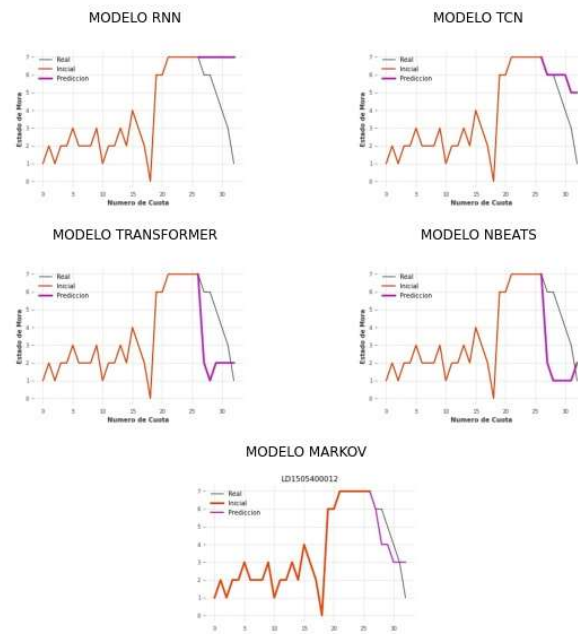
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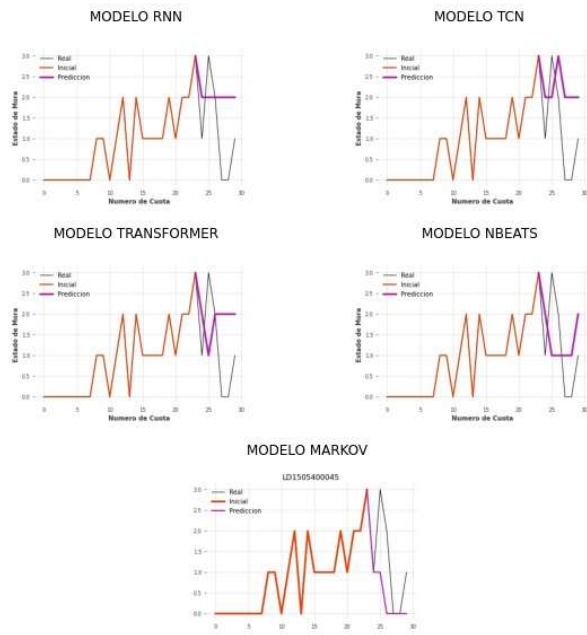
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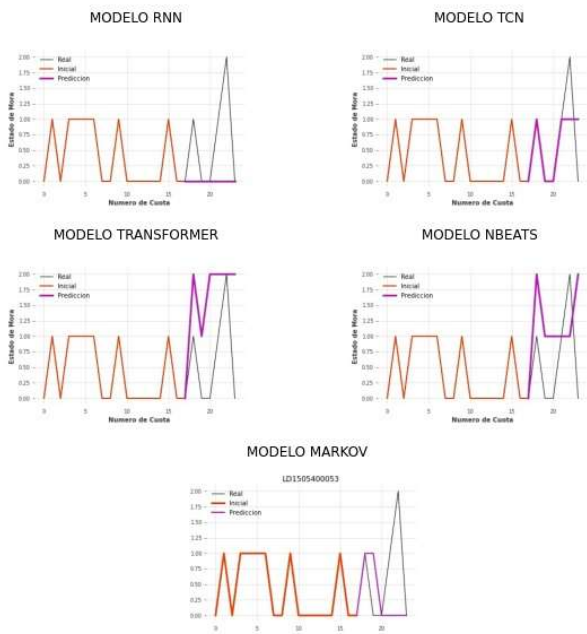
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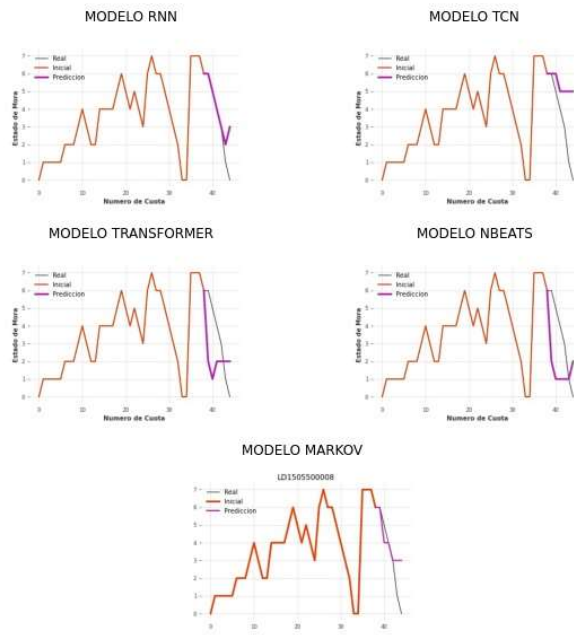
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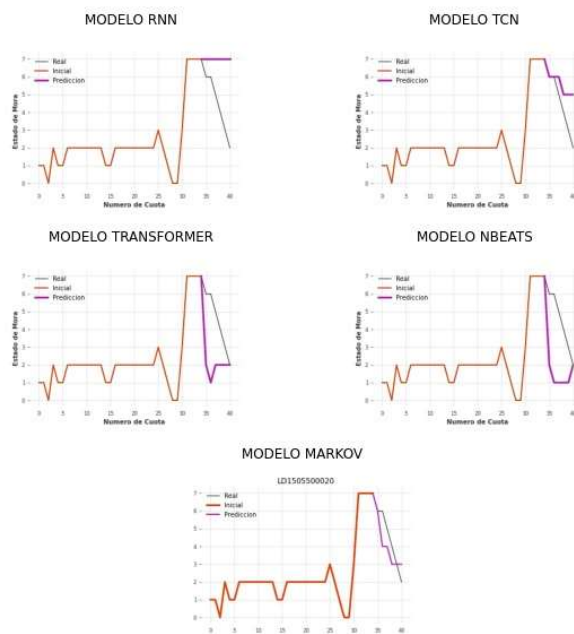
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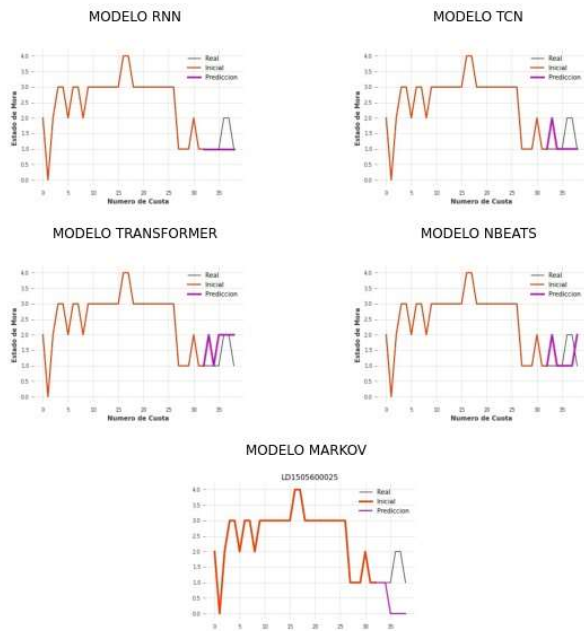
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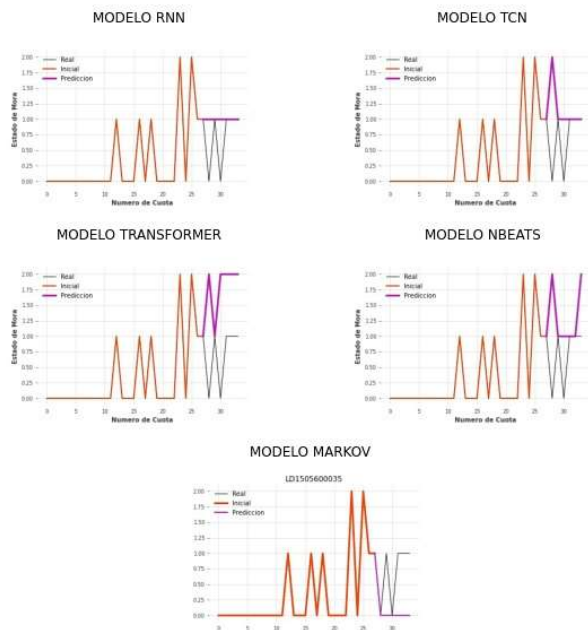
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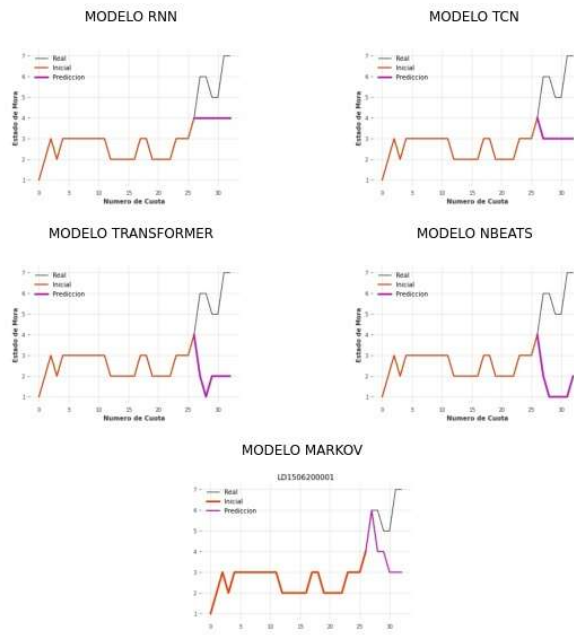
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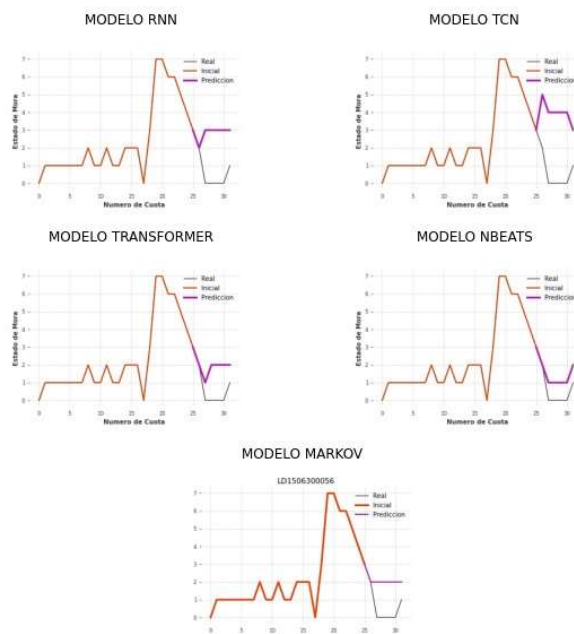
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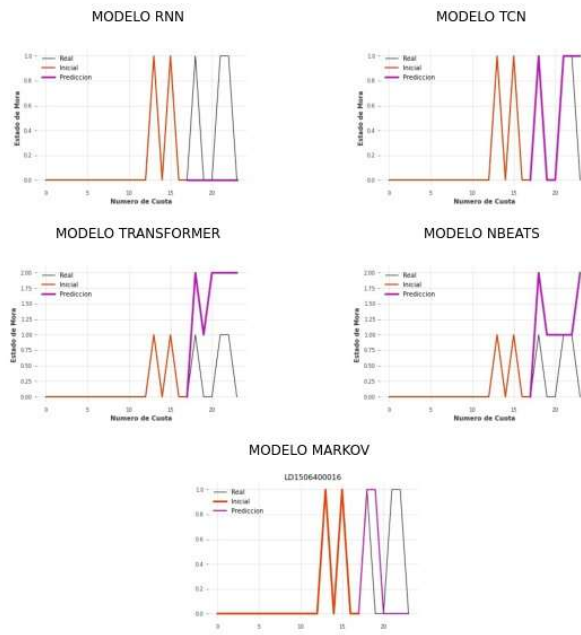
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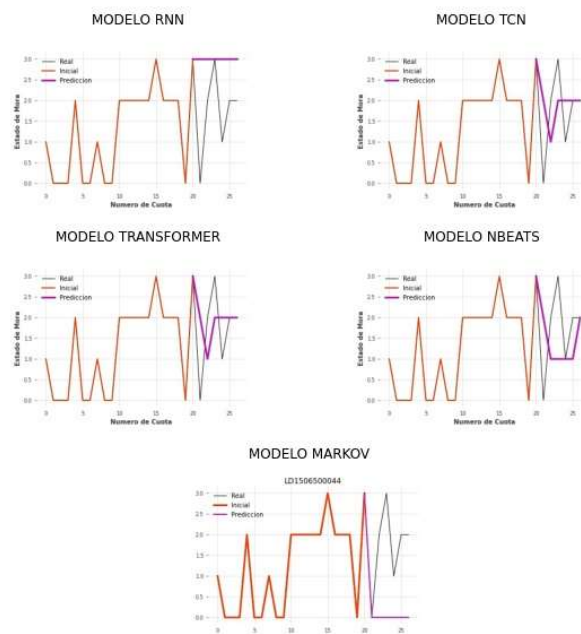
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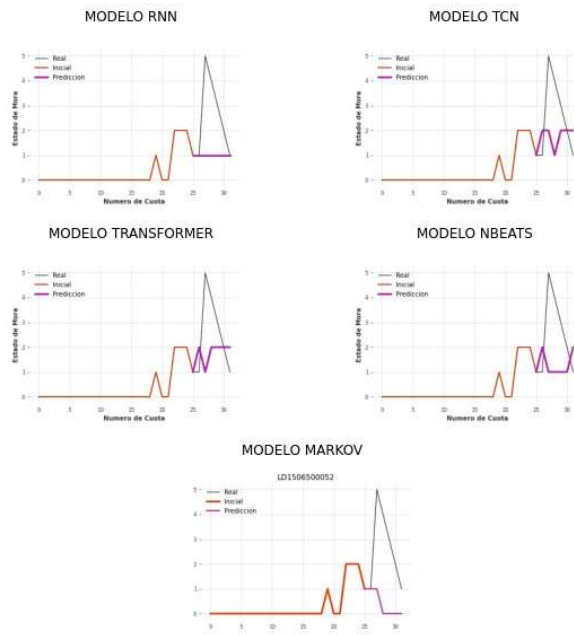
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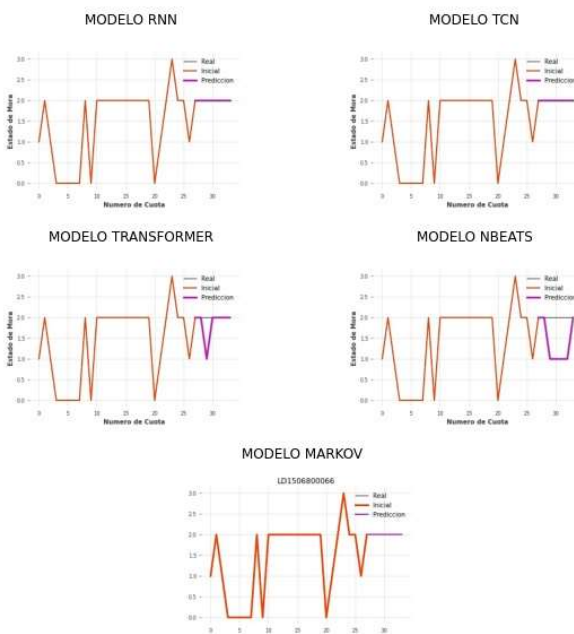
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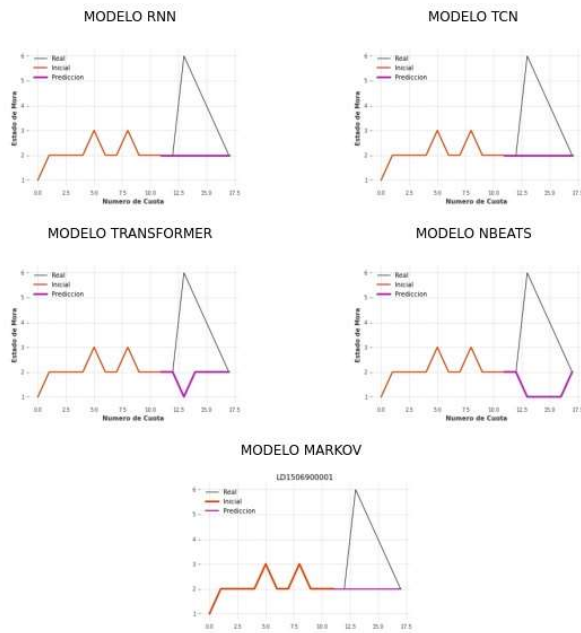


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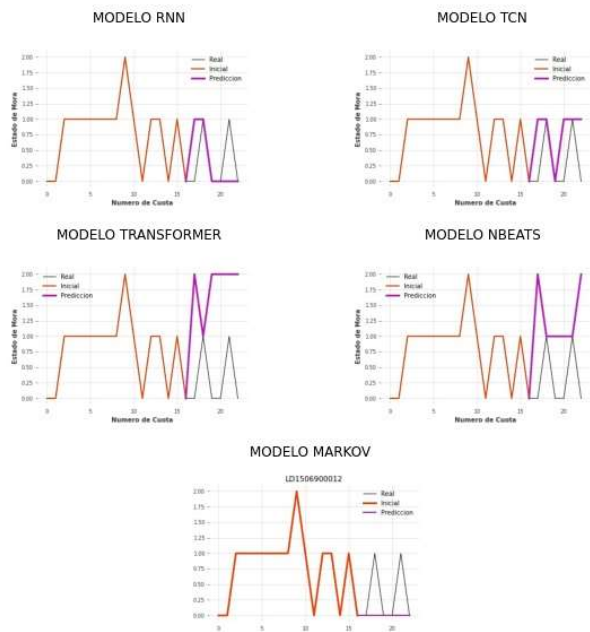




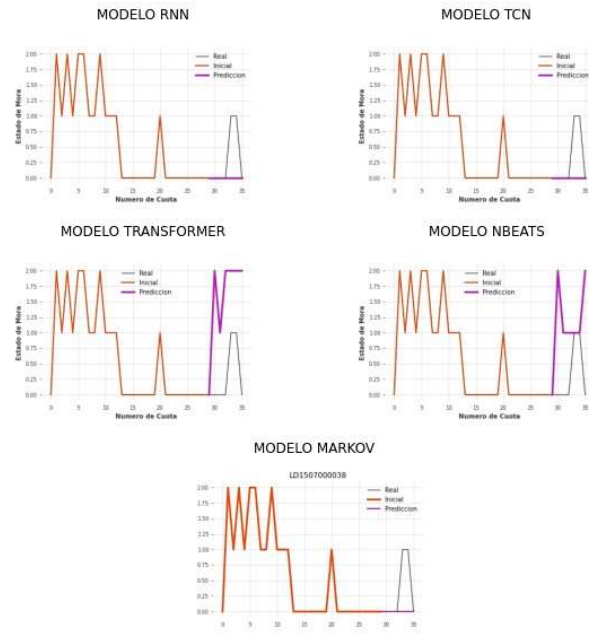
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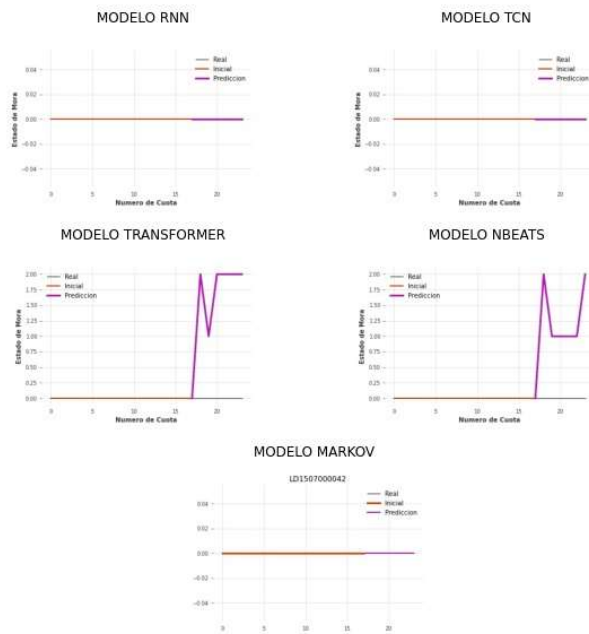
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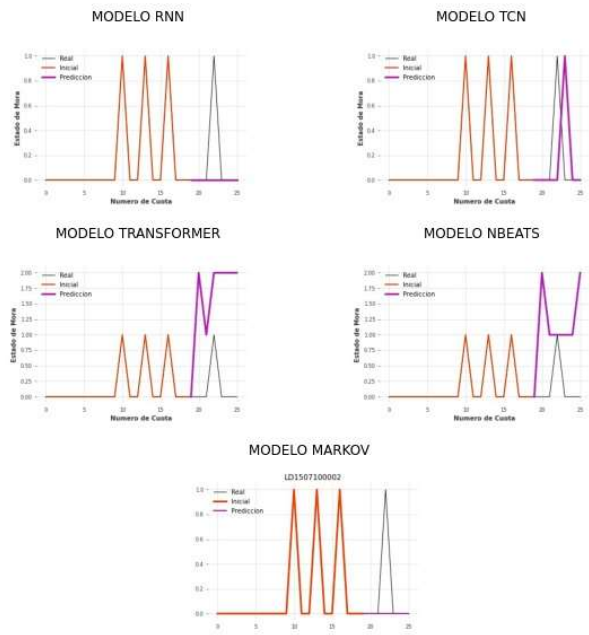
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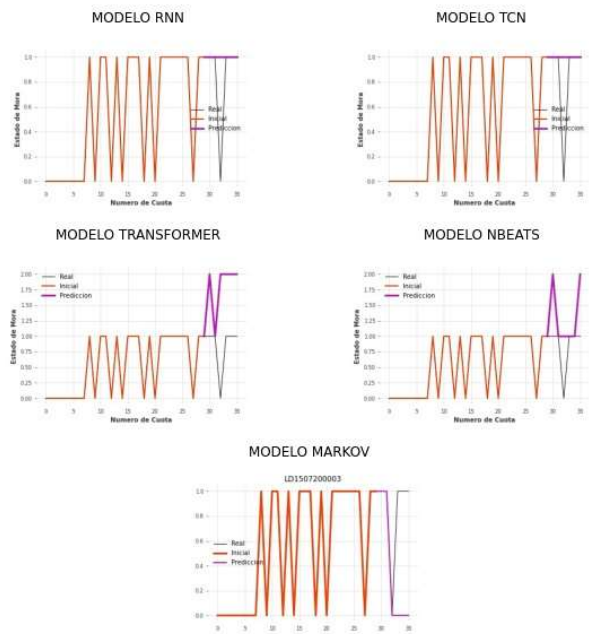
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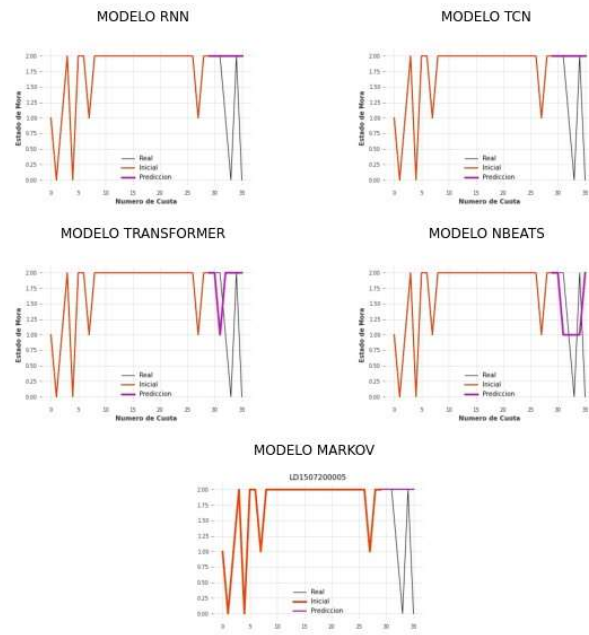
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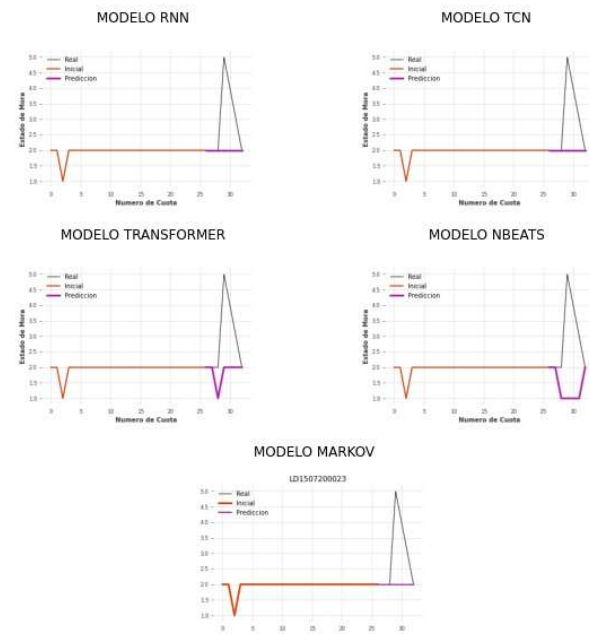
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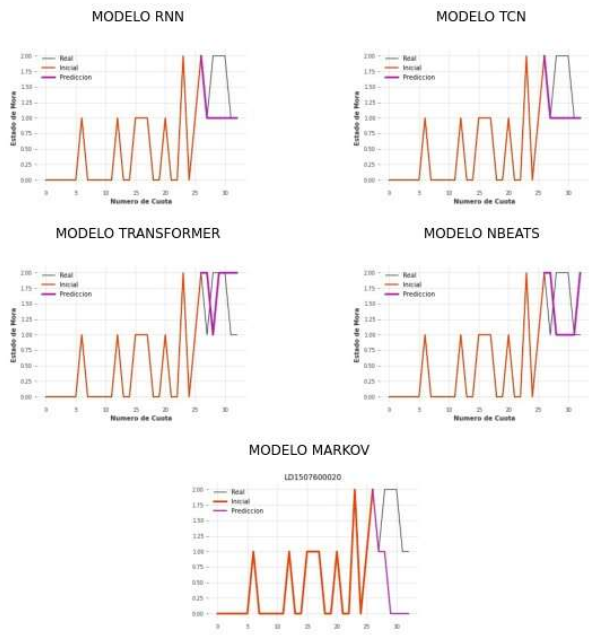
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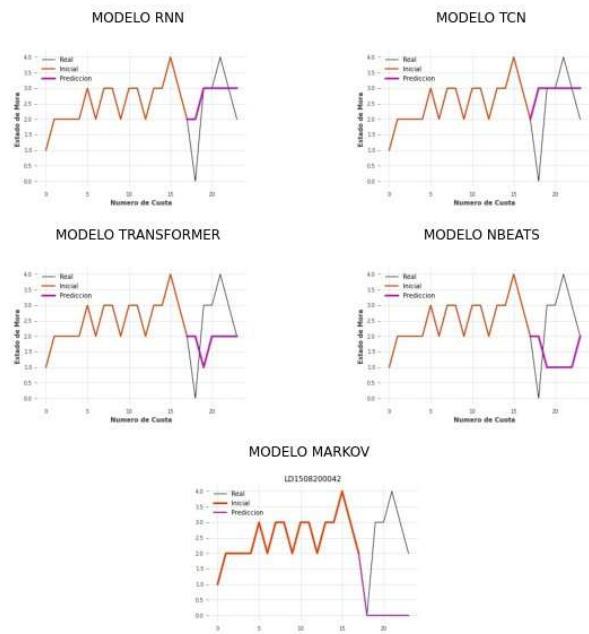
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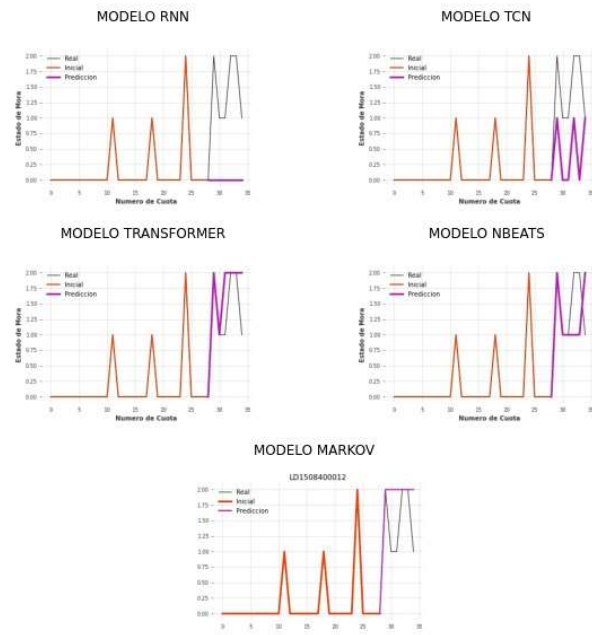
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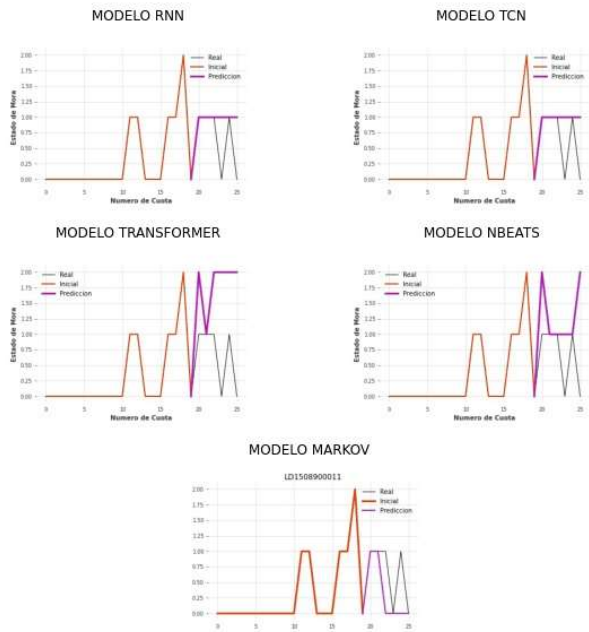
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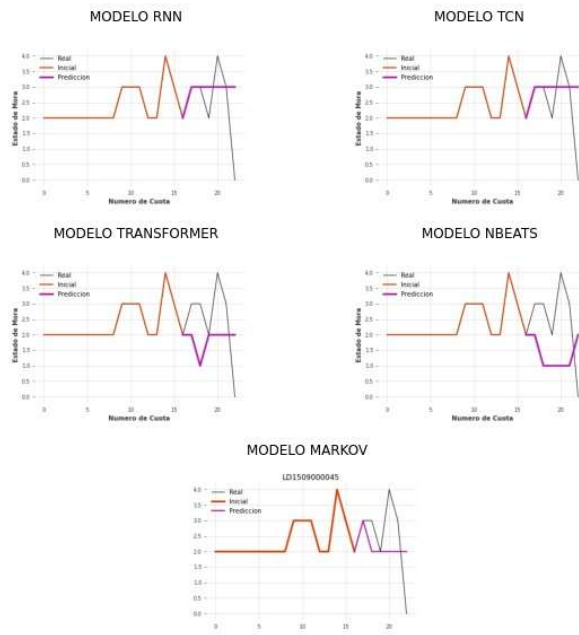
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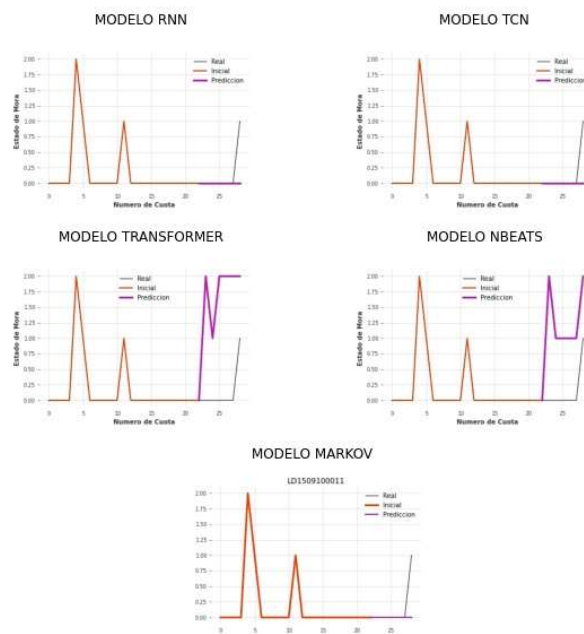
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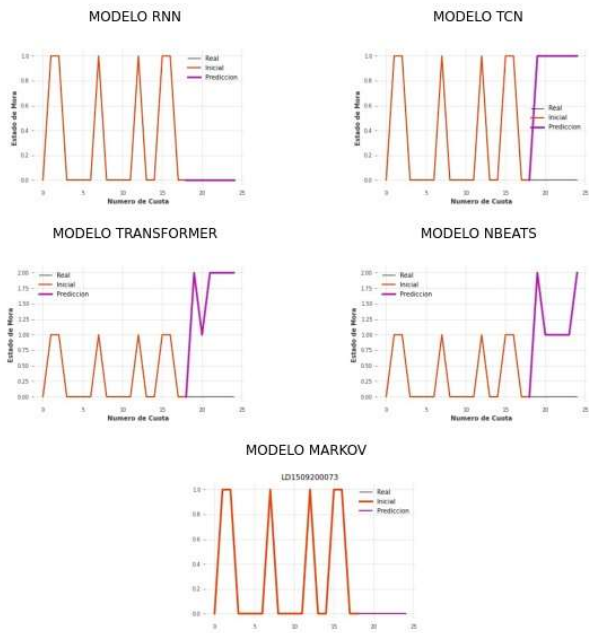


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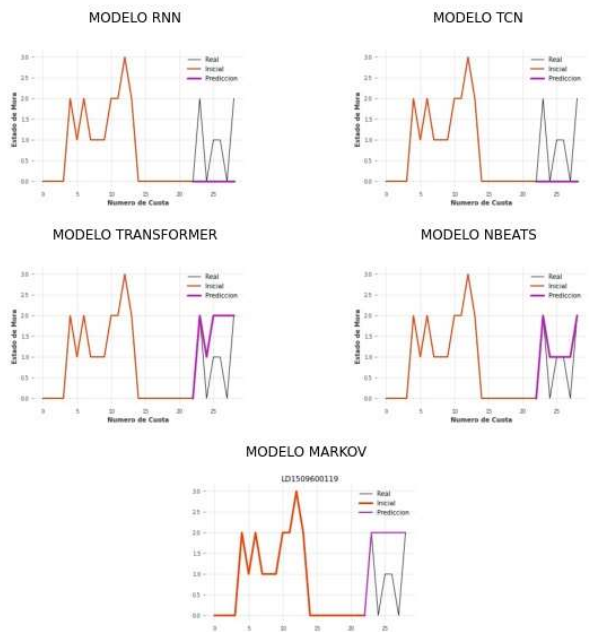




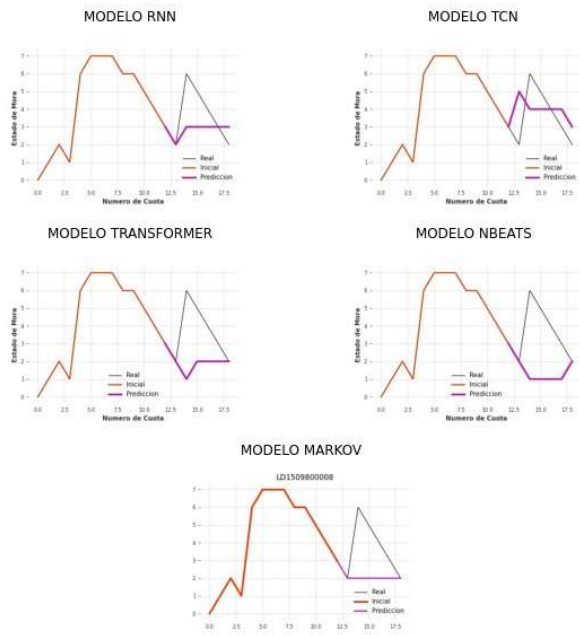
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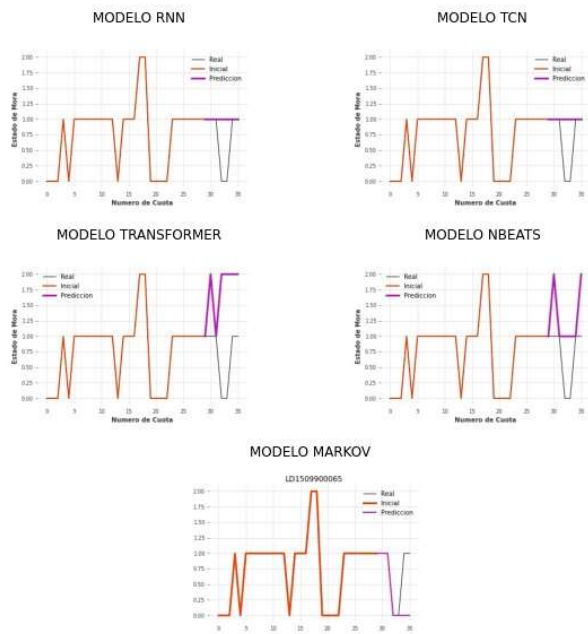
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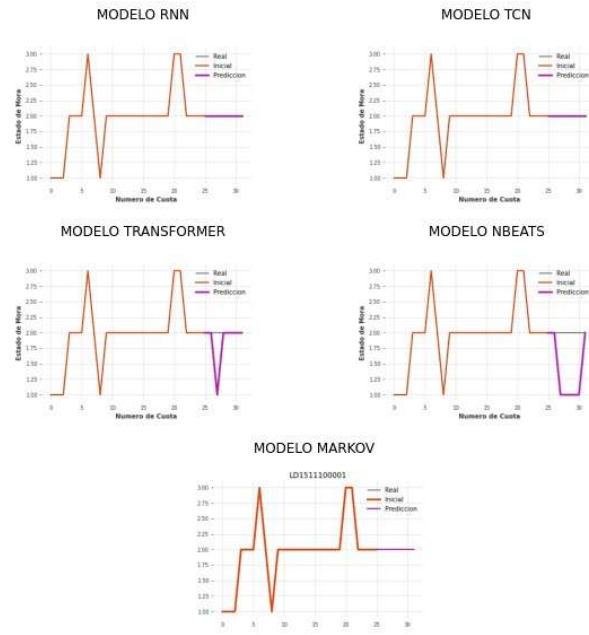
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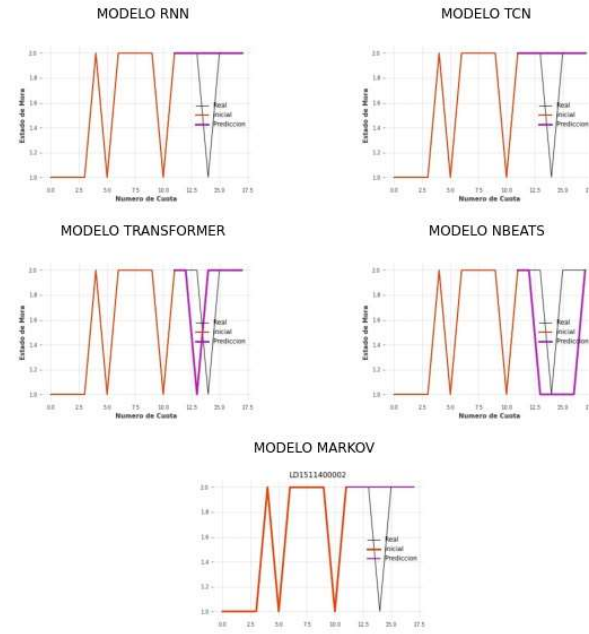
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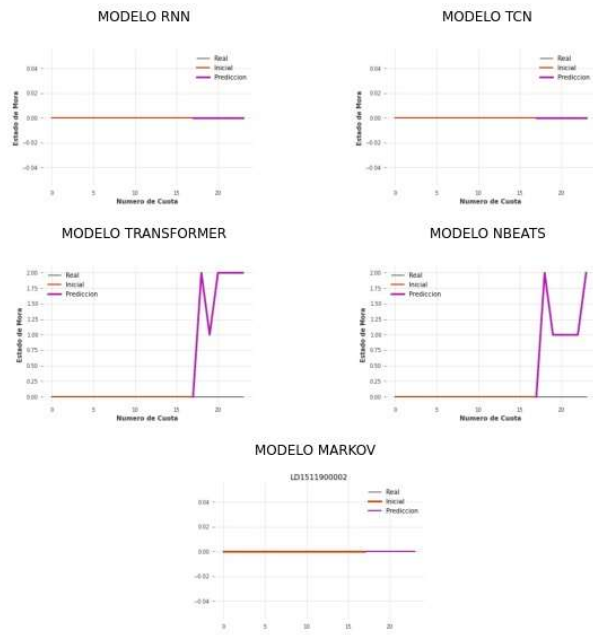
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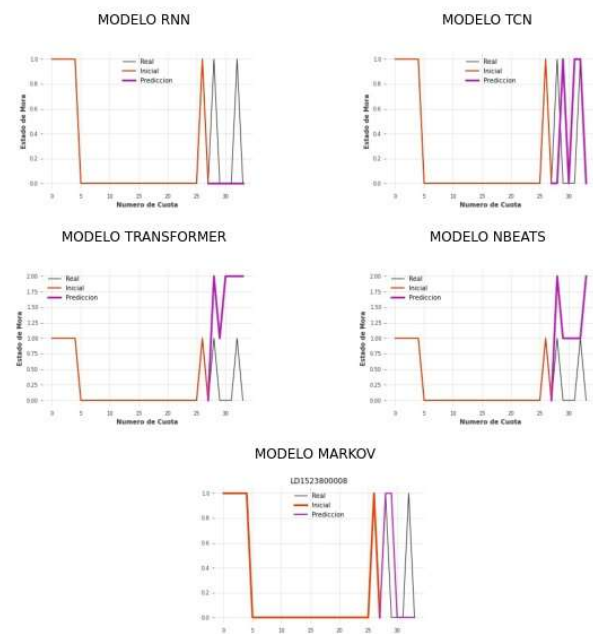
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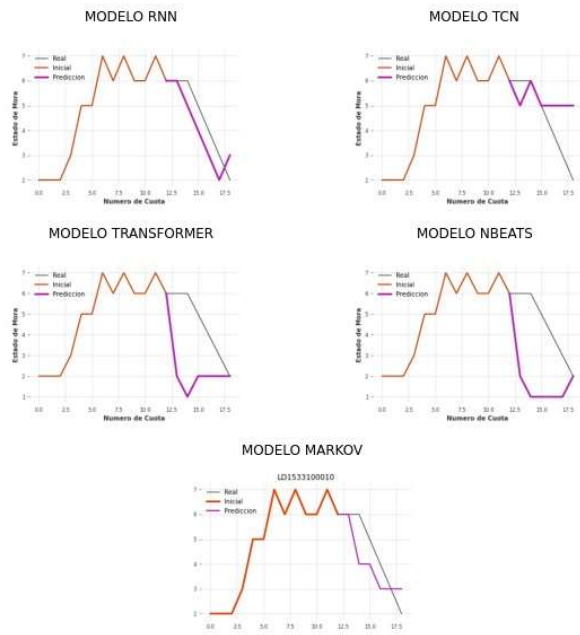
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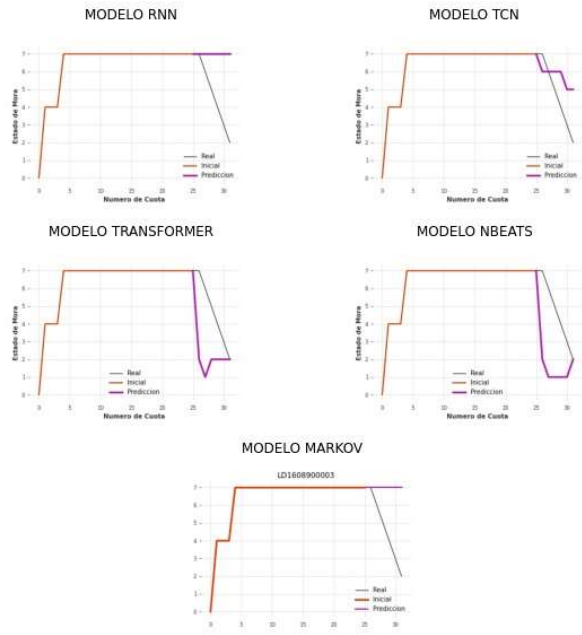
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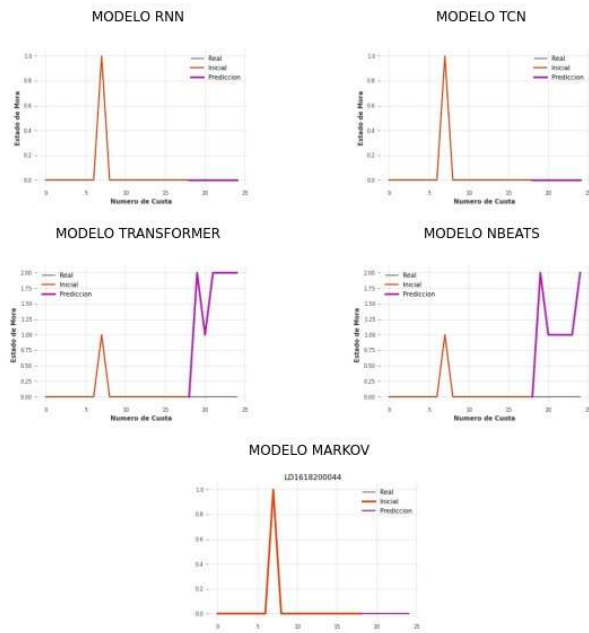
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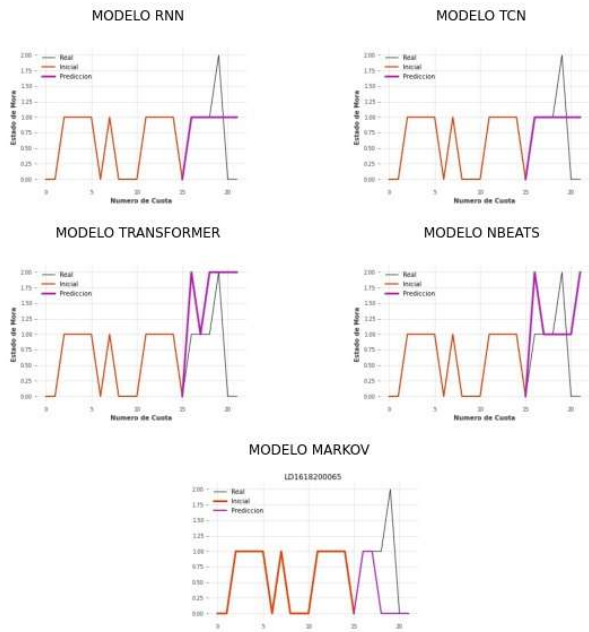
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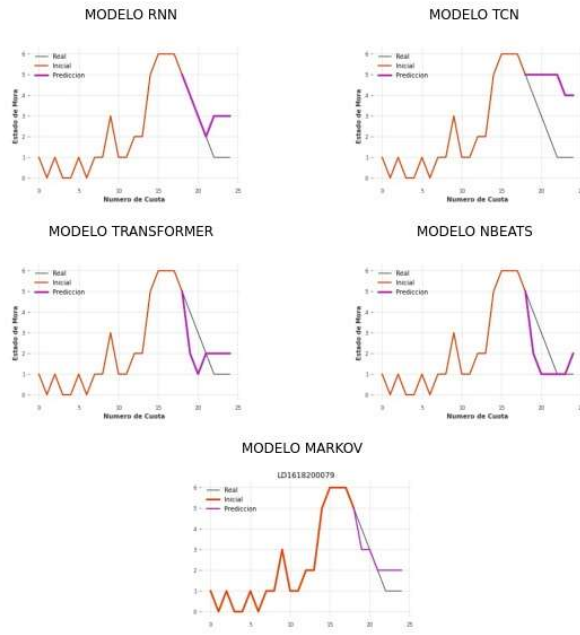


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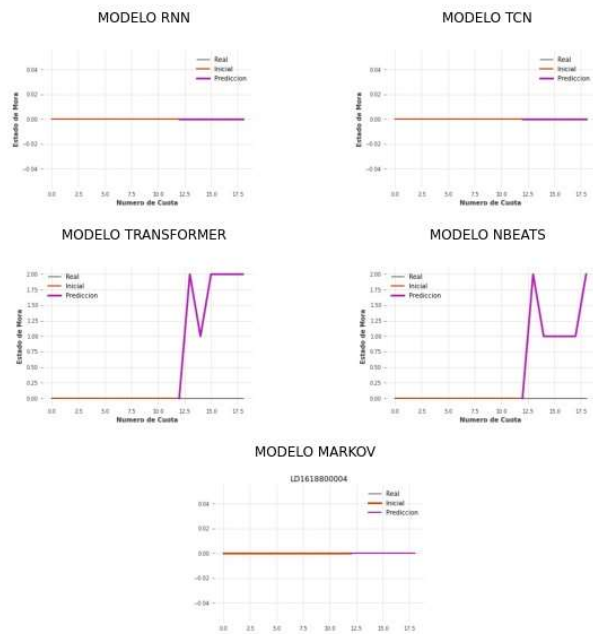




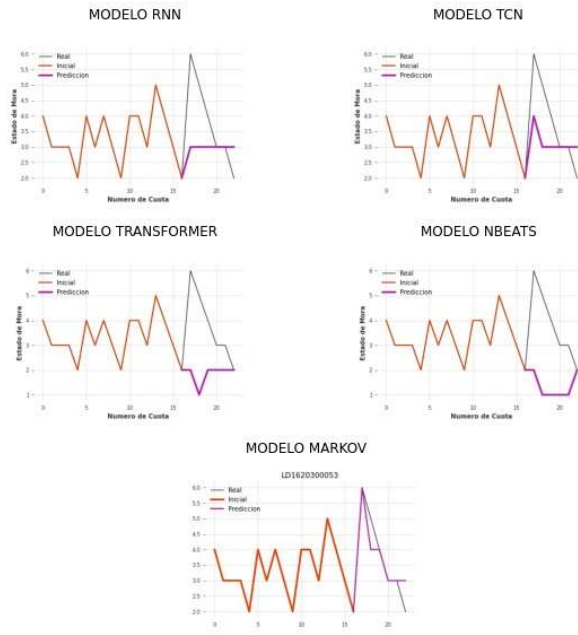
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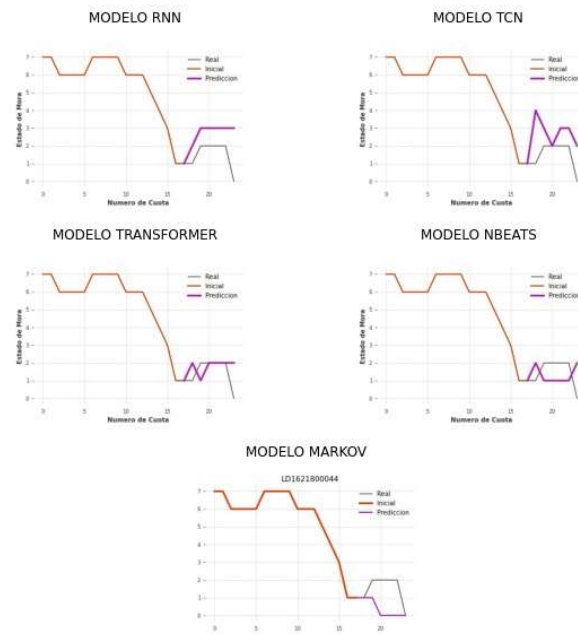
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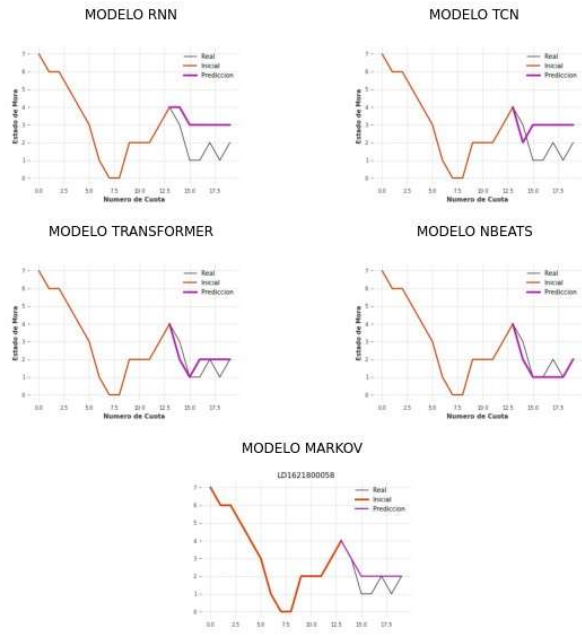
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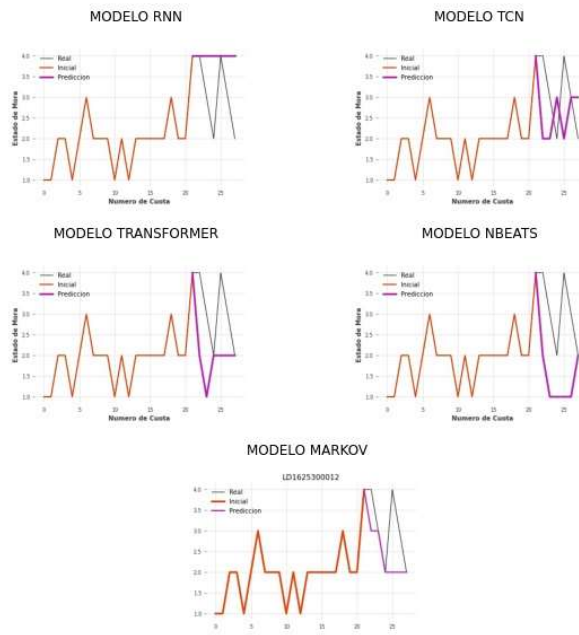
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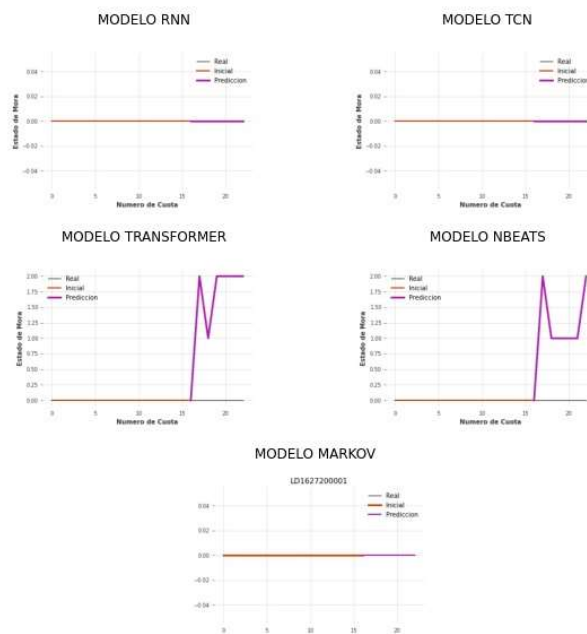
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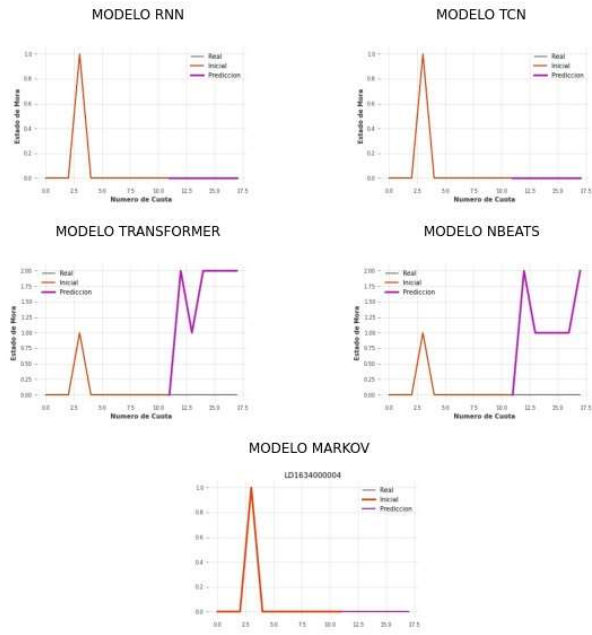
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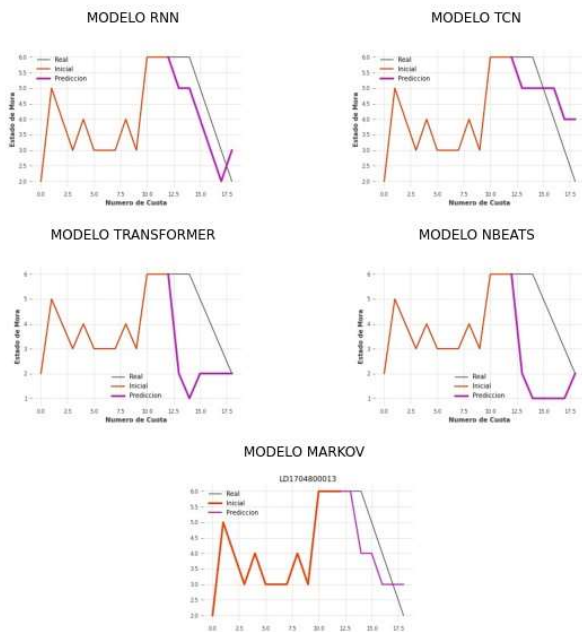
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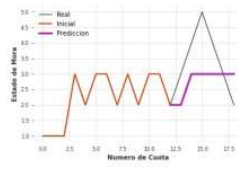


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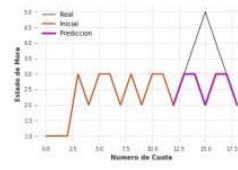


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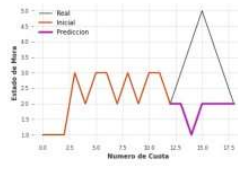
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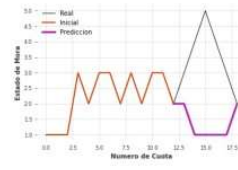
MODELO TCN



MODELO TRANSFORMER



MODELO NBEATS



MODELO MARKOV

