

Actividad 3. Redes neuronales artificiales

El desarrollo de esta actividad tiene el objetivo de llevar a cabo la resolución de un problema de regresión mediante LSTM.

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Asignatura: Aprendizaje Estadístico

Considerando los datos mensuales para una serie temporal dados en serie3.csv, ajustaremos una red neuronal tipo LSTM con la cual se pretende predecir a futuro los valores de la serie.

```
In [23]: # Cargamos los datos

import pandas as pd

serie = pd.read_csv("C:/Users/witsm/Desktop/AP Estadístico/Actividades/gcd15_act
serie
```

```
Out[23]:
```

	time	series
0	0	74.967140
1	1	65.737860
2	2	66.076880
3	3	64.630300
4	4	36.858467
...
356	356	-18.678429
357	357	-22.178604
358	358	-16.731112
359	359	-28.793756
360	360	3.193465

361 rows × 2 columns

A partir de este conjunto de datos, los transformaremos en arrays y haremos la división en conjunto de entrenamiento y de prueba. Usaremos el default: 75% entrenamiento 25% prueba.

```
In [24]: # Convertimos en array cada una de las columnas del dataframe
time = serie[["time"]].to_numpy()
series = serie[["series"]].to_numpy()

# Dividimos datos en conjunto de entrenamiento y prueba (default: 75%, 25%)
split_time = int(len(time) * 0.75)

# Conjunto de entrenamiento
time_train = time[:split_time]
x_train = series[:split_time]
x_train

# Conjunto de prueba (o validación)
time_valid = time[split_time:]
x_valid = series[split_time:]
```

Modelo 1 (Capas bidireccionales, función de activación tanh)

Asignaremos parámetros adecuados según los datos para el tamaño de la ventana, el tamaño de cada batch y el proceso de la aleatorización de estos.

Cuando trabajamos con datos temporales, los dividimos en ventanas de tiempo para alimentar el modelo.

`window_size = 10` : Indica cuántas observaciones previas se usarán para predecir la siguiente. En este caso, el modelo solo tomará en cuenta las últimas 10 observaciones en lugar de usar toda la serie de datos. Es decir, cada predicción se basará en una "ventana" de 10 datos anteriores.

Ahora cada conjunto de 10 observaciones se considera una mini-serie de tiempo o "window".

`batch_size = 8` : Dividimos los datos de entrenamiento en lotes (batches). Cada batch contiene 8 miniseries de tiempo (ventanas de 10 observaciones cada una). Estos batches permiten entrenar redes neuronales de manera más eficiente y pueden utilizarse para transferir pesos entre distintas redes RNN.

`shuffle_buffer_size = 200` : Sirve para mezclar los datos antes de crear los batches. Si no se mezclaran, los primeros batches contendrían solo los datos iniciales de la serie y los últimos solo los finales, lo que podría afectar el entrenamiento. Aumentar este valor incrementa la aleatorización y evita que los batches sigan un orden fijo.

```
In [25]: window_size = 20
batch_size = 8
shuffle_buffer_size = 200
```

Crearemos una función que transforma la serie temporal en un conjunto de datos adecuado para entrenar un modelo basado en ventanas de tiempo. La idea es dividir la serie en fragmentos (ventanas) que contienen datos pasados como entrada (input) y el valor siguiente como salida (output), siguiendo un enfoque autoregresivo.

Los parámetros de la función `windowed_dataset()` son los siguientes:

`series` : Es el conjunto de datos de la serie temporal.

`window_size` : Define cuántos pasos en el tiempo se usarán como entrada.

`batch_size` : Cantidad de muestras por lote para el entrenamiento.

`shuffle_buffer` : Controla la aleatorización de las ventanas de datos.

```
In [26]: # Con esta función obtenemos los inputs y outputs que se usan en los datos, esto
# la serie retrasada en un tiempo, en t-1, y output la serie en el tiempo t, seg
# que corresponde a qué tanto "desenrollamos" nuestra neurona LSTM. Además, revo

import tensorflow as tf

def windowed_dataset(series, window_size, batch_size, shuffle_buffer):
    """Generates dataset windows

    Args:
        series (array of float) - contains the values of the time series
        window_size (int) - the number of time steps to include in the feature
        batch_size (int) - the batch size
        shuffle_buffer(int) - buffer size to use for the shuffle method

    Returns:
        dataset (TF Dataset) - TF Dataset containing time windows
    """

    # Generate a TF Dataset from the series values
    dataset = tf.data.Dataset.from_tensor_slices(series)

    # Window the data but only take those with the specified size
    #Aquí generamos las miniserias según el window_size, esto es, generamos
    #los datos como si el valor retrasado en un tiempo (shift=1) fuera el input
    #y el valor del tiempo siguiente es el output, como en un proceso autoregres
    dataset = dataset.window(window_size + 1, shift=1, drop_remainder=True)

    # Flatten the windows by putting its elements in a single batch
    #Esto solo es para que esté en formato adecuado de tensorflow
    dataset = dataset.flat_map(lambda window: window.batch(window_size + 1))

    # Create tuples with features and labels
    dataset = dataset.map(lambda window: (window[:-1], window[-1]))

    # Shuffle the windows
    dataset = dataset.shuffle(shuffle_buffer)

    # Create batches of windows
    dataset = dataset.batch(batch_size).prefetch(1)

    return dataset
```

Ahora, definiremos y ajustaremos un modelo que incluya neuronas tipo LSTM bidireccionales (la secuencia se aprende tanto hacia adelante como hacia atrás).

Organización de Capas con `tf.keras`

`tf.keras.models.Sequential` Permite organizar las capas de la red neuronal. En este caso, cada capa procesará las miniseries de tiempo de tamaño `window_size`, lo cual se logra con `tf.keras.layers.Lambda` al especificar qué tiempos se toman.

`tf.keras.layers.Bidirectional` Define que la red LSTM procesará la información en ambas direcciones (hacia el futuro y el pasado).

`tf.keras.layers.LSTM` Esta capa implementa el modelo LSTM, donde podemos definir parámetros como:

- Función de activación.
- Número de neuronas.
- Si queremos devolver secuencias completas (usando el argumento `return_sequences=True`).

Parámetros y Dimensiones

`return_sequences=True` permite que la capa devuelva la secuencia completa de salidas, lo cual es útil cuando se trabaja con varias capas LSTM.

El número 8 representa la dimensionalidad de la salida de la LSTM, es decir, el número de neuronas LSTM en la capa. En este caso, también coincide con el tamaño del batch (`batch_size`), ya que estamos analizando 8 miniseries en cada batch.

Nota Importante La capa `tf.keras.layers.LSTM` es donde se pueden experimentar con distintas funciones de activación y otros parámetros. El hecho de que la red sea bidireccional significa que se analizarán los datos en ambas direcciones (hacia el futuro y el pasado).

```
In [27]: model_tune = tf.keras.models.Sequential([
    tf.keras.layers.Lambda(lambda x: tf.expand_dims(x, axis=-1),
                           input_shape=[window_size]),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(8, return_sequences=True)),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(8)),
    tf.keras.layers.Dense(1),
    tf.keras.layers.Lambda(lambda x: x * 100.0)
])

# Imprimir el resumen del modelo
model_tune.summary()
```

```
C:\Users\witsm\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n2kfra8p0\LocalCache\local-packages\Python311\site-packages\keras\src\layers\core\lambda_layer.py:65: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
```

```
super().__init__(**kwargs)
```

Model: "sequential_3"

Layer (type)	Output Shape	Param #
lambda_6 (Lambda)	(None, 20, 1)	0
bidirectional_2 (Bidirectional)	(None, 20, 16)	640
bidirectional_3 (Bidirectional)	(None, 16)	1,600
dense_3 (Dense)	(None, 1)	17
lambda_7 (Lambda)	(None, 1)	0

Total params: 2,257 (8.82 KB)

Trainable params: 2,257 (8.82 KB)

Non-trainable params: 0 (0.00 B)

Pasamos a definir la tasa de aprendizaje. Ajustamos dinámicamente la tasa de aprendizaje (learning rate) a lo largo de los epochs. Preparamos el dataset con ventanas de tiempo, definimos un optimizador de descenso de gradiente con momentum, y usamos la pérdida de Huber para mejorar la estabilidad del entrenamiento. Finalmente, el modelo se entrena por 100 epochs, actualizando progresivamente el learning rate mediante una función exponencial.

```
In [28]: #Aquí vamos a dar el valor del Learning rate que nos da mejores resultados

# Conjunto de datos partidos en "ventanas"
dataset = windowed_dataset(series, window_size, batch_size, shuffle_buffer_size)

#Esto permite que se use la información del epoch en el que vamos (ciclo hacia a
#para actualizar la learning rate a través de alguna función, aquí en particular
#se incrementa el epoch el learning rate se hace más grande
lr_schedule = tf.keras.callbacks.LearningRateScheduler(
    lambda epoch: 1e-8 * 10**(epoch / 20))

# Initialize the optimizer
#Uso de descenso del gradiente como método para actualizar los pesos con un pará
#que acelera el descenso de gradiente en la dirección relevante
optimizer = tf.keras.optimizers.SGD(momentum=0.9)

# Set the training parameters
#La función de pérdida usada es la de Huber. Esta función de pérdida incluye una
#para cuando no estamos cerca del valor real, usando optimizer que definimos arr
model_tune.compile(loss=tf.keras.losses.Huber(), optimizer=optimizer)

# Train the model
#Ponemos a que sean 100 epochs, con learning rate que se actualiza según lr_scne
history = model_tune.fit(dataset, epochs=100, callbacks=[lr_schedule])
```





















Epoch 1/100


43/43 ————— 3s 9ms/step - loss: 49.8910 - learning_rate: 1.0000e-08


Epoch 2/100


13/43 ————— 0s 10ms/step - loss: 52.6309


```
C:\Users\witsm\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n2kfra8p0\LocalCache\local-packages\Python311\site-packages\keras\src\trainers\epoch_iterator.py:151: UserWarning: Your input ran out of data; interrupting training. Make sure that your dataset or generator can generate at least `steps_per_epoch * epochs` batches. You may need to use the `.repeat()` function when building your dataset.  
    self._interrupted_warning()
```


43/43  0s 10ms/step - loss: 50.0610 - learning_rate: 1.1220e-08
Epoch 3/100
43/43  0s 8ms/step - loss: 50.0866 - learning_rate: 1.2589e-08
Epoch 4/100
43/43  0s 10ms/step - loss: 49.0078 - learning_rate: 1.4125e-08
Epoch 5/100
43/43  0s 9ms/step - loss: 50.1339 - learning_rate: 1.5849e-08
Epoch 6/100
43/43  0s 9ms/step - loss: 48.4050 - learning_rate: 1.7783e-08
Epoch 7/100
43/43  0s 9ms/step - loss: 48.5919 - learning_rate: 1.9953e-08
Epoch 8/100
43/43  0s 9ms/step - loss: 49.0641 - learning_rate: 2.2387e-08
Epoch 9/100
43/43  0s 9ms/step - loss: 48.4950 - learning_rate: 2.5119e-08
Epoch 10/100
43/43  0s 9ms/step - loss: 47.2905 - learning_rate: 2.8184e-08
Epoch 11/100
43/43  0s 9ms/step - loss: 47.9628 - learning_rate: 3.1623e-08
Epoch 12/100
43/43  0s 9ms/step - loss: 46.4053 - learning_rate: 3.5481e-08
Epoch 13/100
43/43  0s 9ms/step - loss: 47.8150 - learning_rate: 3.9811e-08
Epoch 14/100
43/43  0s 9ms/step - loss: 45.5916 - learning_rate: 4.4668e-08
Epoch 15/100
43/43  0s 9ms/step - loss: 45.1349 - learning_rate: 5.0119e-08
Epoch 16/100
43/43  0s 8ms/step - loss: 44.6952 - learning_rate: 5.6234e-08
Epoch 17/100
43/43  0s 9ms/step - loss: 44.0242 - learning_rate: 6.3096e-08
Epoch 18/100
43/43  0s 9ms/step - loss: 43.8156 - learning_rate: 7.0795e-08
Epoch 19/100
43/43  0s 9ms/step - loss: 42.0645 - learning_rate: 7.9433e-08
Epoch 20/100
43/43  0s 9ms/step - loss: 40.9522 - learning_rate: 8.9125e-08
Epoch 21/100
43/43  0s 9ms/step - loss: 39.5984 - learning_rate: 1.0000e-07
Epoch 22/100


43/43  0s 9ms/step - loss: 38.4166 - learning_rate: 1.1220e-07
Epoch 23/100


43/43  0s 9ms/step - loss: 35.9669 - learning_rate: 1.2589e-07
Epoch 24/100


43/43  0s 9ms/step - loss: 34.9265 - learning_rate: 1.4125e-07
Epoch 25/100


43/43  0s 9ms/step - loss: 31.8579 - learning_rate: 1.5849e-07
Epoch 26/100


43/43  0s 9ms/step - loss: 30.5548 - learning_rate: 1.7783e-07
Epoch 27/100


43/43  0s 9ms/step - loss: 28.1598 - learning_rate: 1.9953e-07
Epoch 28/100


43/43  0s 9ms/step - loss: 26.1921 - learning_rate: 2.2387e-07
Epoch 29/100


43/43  0s 8ms/step - loss: 24.5319 - learning_rate: 2.5119e-07
Epoch 30/100


43/43  0s 9ms/step - loss: 21.7954 - learning_rate: 2.8184e-07
Epoch 31/100


43/43  0s 9ms/step - loss: 20.9756 - learning_rate: 3.1623e-07
Epoch 32/100


43/43  0s 9ms/step - loss: 18.4978 - learning_rate: 3.5481e-07
Epoch 33/100


43/43  0s 9ms/step - loss: 16.8910 - learning_rate: 3.9811e-07
Epoch 34/100


43/43  0s 8ms/step - loss: 16.0788 - learning_rate: 4.4668e-07
Epoch 35/100


43/43  0s 9ms/step - loss: 15.1798 - learning_rate: 5.0119e-07
Epoch 36/100


43/43  0s 9ms/step - loss: 15.1308 - learning_rate: 5.6234e-07
Epoch 37/100


43/43  0s 8ms/step - loss: 14.0054 - learning_rate: 6.3096e-07
Epoch 38/100


43/43  0s 10ms/step - loss: 13.6677 - learning_rate: 7.0795e-07
Epoch 39/100


43/43  0s 9ms/step - loss: 13.1147 - learning_rate: 7.9433e-07
Epoch 40/100


43/43  0s 8ms/step - loss: 13.2841 - learning_rate: 8.9125e-07
Epoch 41/100


43/43  0s 9ms/step - loss: 13.9031 - learning_rate: 1.0000e-06
Epoch 42/100


43/43  0s 9ms/step - loss: 13.3970 - learning_rate: 1.1220e-06
Epoch 43/100


43/43  0s 9ms/step - loss: 13.9584 - learning_rate: 1.2589e-06
Epoch 44/100


43/43  0s 9ms/step - loss: 14.0701 - learning_rate: 1.4125e-06
Epoch 45/100


43/43  0s 9ms/step - loss: 13.5108 - learning_rate: 1.5849e-06
Epoch 46/100


43/43  0s 10ms/step - loss: 12.6217 - learning_rate: 1.7783e-06
Epoch 47/100


43/43  0s 9ms/step - loss: 13.4139 - learning_rate: 1.9953e-06
Epoch 48/100


43/43  0s 9ms/step - loss: 13.4983 - learning_rate: 2.2387e-06
Epoch 49/100


43/43  0s 9ms/step - loss: 13.8699 - learning_rate: 2.5119e-06
Epoch 50/100


43/43  0s 8ms/step - loss: 13.2590 - learning_rate: 2.8184e-06
Epoch 51/100


43/43  0s 9ms/step - loss: 13.7705 - learning_rate: 3.1623e-06
Epoch 52/100


43/43  0s 9ms/step - loss: 13.5090 - learning_rate: 3.5481e-06
Epoch 53/100


43/43  0s 8ms/step - loss: 12.9583 - learning_rate: 3.9811e-06
Epoch 54/100


43/43  0s 8ms/step - loss: 11.4429 - learning_rate: 4.4668e-06
Epoch 55/100


43/43  0s 9ms/step - loss: 12.0020 - learning_rate: 5.0119e-06
Epoch 56/100


43/43  0s 9ms/step - loss: 12.5140 - learning_rate: 5.6234e-06
Epoch 57/100






















43/43  0s 9ms/step - loss: 13.0436 - learning_rate: 6.3096e-06
Epoch 58/100

43/43  0s 9ms/step - loss: 12.4870 - learning_rate: 7.0795e-06
Epoch 59/100

43/43  0s 9ms/step - loss: 12.1794 - learning_rate: 7.9433e-06
Epoch 60/100

43/43  0s 9ms/step - loss: 12.5713 - learning_rate: 8.9125e-06
Epoch 61/100

43/43  0s 9ms/step - loss: 12.5043 - learning_rate: 1.0000e-05
Epoch 62/100

43/43  0s 9ms/step - loss: 12.5907 - learning_rate: 1.1220e-05
Epoch 63/100
43/43  0s 9ms/step - loss: 11.0133 - learning_rate: 1.2589e-05
Epoch 64/100
43/43  0s 8ms/step - loss: 11.2733 - learning_rate: 1.4125e-05
Epoch 65/100
43/43  0s 9ms/step - loss: 10.8086 - learning_rate: 1.5849e-05
Epoch 66/100
43/43  0s 9ms/step - loss: 11.3063 - learning_rate: 1.7783e-05
Epoch 67/100
43/43  0s 9ms/step - loss: 10.1240 - learning_rate: 1.9953e-05
Epoch 68/100
43/43  0s 8ms/step - loss: 10.2275 - learning_rate: 2.2387e-05
Epoch 69/100
43/43  0s 8ms/step - loss: 9.9508 - learning_rate: 2.5119e-05
Epoch 70/100
43/43  0s 8ms/step - loss: 10.2994 - learning_rate: 2.8184e-05
Epoch 71/100
43/43  0s 9ms/step - loss: 9.8124 - learning_rate: 3.1623e-05
Epoch 72/100
43/43  0s 9ms/step - loss: 10.1321 - learning_rate: 3.5481e-05
Epoch 73/100
43/43  0s 8ms/step - loss: 10.1913 - learning_rate: 3.9811e-05
Epoch 74/100
43/43  0s 8ms/step - loss: 10.8014 - learning_rate: 4.4668e-05
Epoch 75/100
43/43  0s 9ms/step - loss: 10.5035 - learning_rate: 5.0119e-05
Epoch 76/100
43/43  0s 9ms/step - loss: 10.5730 - learning_rate: 5.6234e-05
Epoch 77/100
43/43  0s 10ms/step - loss: 10.9446 - learning_rate: 6.3096e-05
Epoch 78/100
43/43  0s 9ms/step - loss: 9.6581 - learning_rate: 7.0795e-05
Epoch 79/100
43/43  0s 9ms/step - loss: 10.7854 - learning_rate: 7.9433e-05
Epoch 80/100
43/43  0s 9ms/step - loss: 10.3953 - learning_rate: 8.9125e-05
Epoch 81/100
43/43  0s 9ms/step - loss: 11.0054 - learning_rate: 1.0000e-04
Epoch 82/100
43/43  0s 9ms/step - loss: 12.8055 - learning_rate: 1.1220e-04
Epoch 83/100

```

43/43 ————— 0s 9ms/step - loss: 11.5386 - learning_rate: 1.2589e-0
4
Epoch 84/100
43/43 ————— 0s 9ms/step - loss: 10.4940 - learning_rate: 1.4125e-0
4
Epoch 85/100
43/43 ————— 0s 8ms/step - loss: 11.8736 - learning_rate: 1.5849e-0
4
Epoch 86/100
43/43 ————— 0s 8ms/step - loss: 11.0038 - learning_rate: 1.7783e-0
4
Epoch 87/100
43/43 ————— 0s 9ms/step - loss: 11.1591 - learning_rate: 1.9953e-0
4
Epoch 88/100
43/43 ————— 0s 9ms/step - loss: 9.8378 - learning_rate: 2.2387e-04
Epoch 89/100
43/43 ————— 0s 9ms/step - loss: 10.3026 - learning_rate: 2.5119e-0
4
Epoch 90/100
43/43 ————— 0s 9ms/step - loss: 10.9418 - learning_rate: 2.8184e-0
4
Epoch 91/100
43/43 ————— 0s 9ms/step - loss: 13.3390 - learning_rate: 3.1623e-0
4
Epoch 92/100
43/43 ————— 0s 9ms/step - loss: 10.5089 - learning_rate: 3.5481e-0
4
Epoch 93/100
43/43 ————— 0s 9ms/step - loss: 11.8854 - learning_rate: 3.9811e-0
4
Epoch 94/100
43/43 ————— 0s 9ms/step - loss: 12.4241 - learning_rate: 4.4668e-0
4
Epoch 95/100
43/43 ————— 0s 9ms/step - loss: 12.3087 - learning_rate: 5.0119e-0
4
Epoch 96/100
43/43 ————— 0s 9ms/step - loss: 14.7410 - learning_rate: 5.6234e-0
4
Epoch 97/100
43/43 ————— 0s 9ms/step - loss: 13.5219 - learning_rate: 6.3096e-0
4
Epoch 98/100
43/43 ————— 0s 9ms/step - loss: 11.8776 - learning_rate: 7.0795e-0
4
Epoch 99/100
43/43 ————— 0s 9ms/step - loss: 12.1980 - learning_rate: 7.9433e-0
4
Epoch 100/100
43/43 ————— 0s 9ms/step - loss: 14.3358 - learning_rate: 8.9125e-0
4

```

Generamos la gráfica de la tasa de aprendizaje (learning rate) vs. la función de pérdida (loss) para identificar el valor óptimo del learning rate. Creamos un array de valores de learning rate en escala logarítmica, trazamos los valores de pérdida registrados durante el entrenamiento y usamos una escala semilogarítmica en el eje x para visualizar mejor la relación.

```

In [29]: #Gráfica entre el Learning rate y la función de pérdida, escogeríamos un valor d
#mínimo

import numpy as np
import matplotlib.pyplot as plt

# Definimos el array de tasa de aprendizaje
lrs = 1e-8 * (10 ** (np.arange(100) / 20))

# Ejemplo de valores de pérdida (esto debe ser reemplazado con los valores reales)
losses = history.history["loss"]

# Encontramos el índice del mínimo de la pérdida
min_loss_index = np.argmin(losses)

# Encontramos el valor del Learning rate asociado al mínimo de la pérdida
min_loss_lr = lrs[min_loss_index]

# Mostramos el resultado
print(f"El valor mínimo de la pérdida es {losses[min_loss_index]} y ocurre en el
# Escogemos el tamaño de la gráfica
plt.figure(figsize=(10, 6))
plt.grid(True)

# Graficamos la pérdida en escala logarítmica
plt.semilogx(lrs, history.history["loss"])

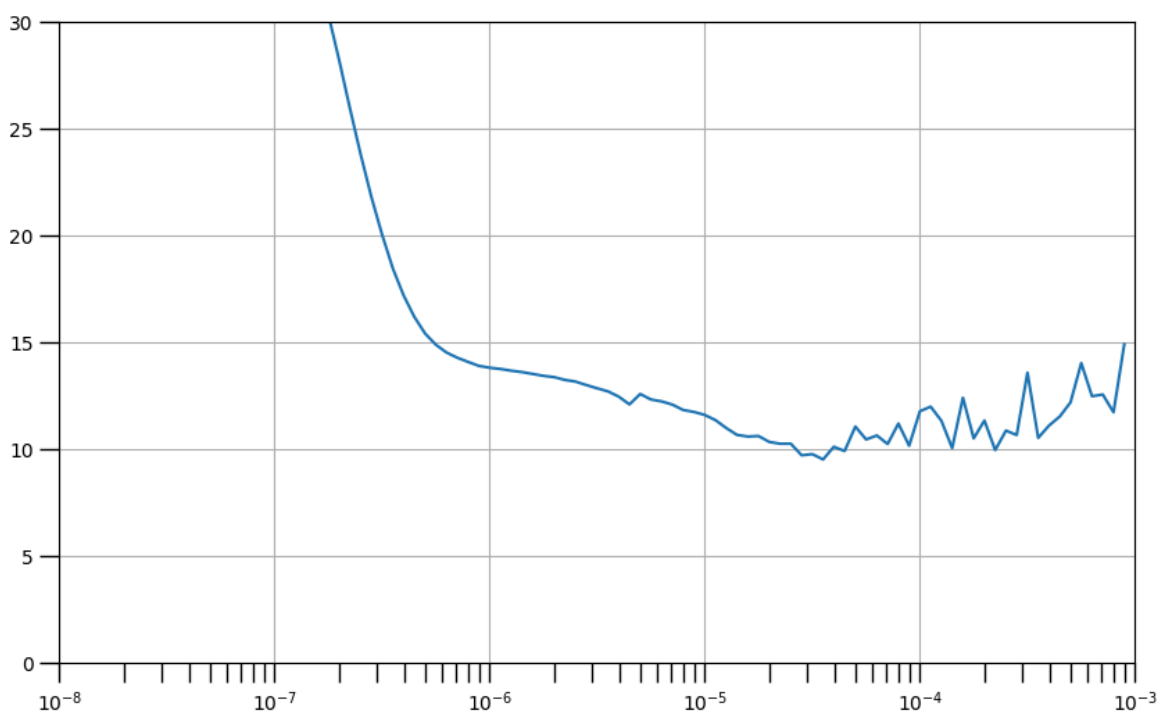
# Aumentamos el tamaño de los tickmarks
plt.tick_params('both', length=10, width=1, which='both')

# Establecemos los límites de la gráfica
plt.axis([1e-8, 1e-3, 0, 30])

```

El valor mínimo de la pérdida es 9.495048522949219 y ocurre en el learning rate de 3.5481338923357534e-05

Out[29]: (1e-08, 0.001, 0.0, 30.0)



El valor donde la pérdida es menor es cuando la tasa de aprendizaje es de aproximadamente 10^{-4} .

```
In [30]: learning_rate = min_loss_lr
```

Pasamos a construir y entrenar el modelo.

```
In [31]: # Reset states generated by Keras
tf.keras.backend.clear_session()

# Se repite lo mismo visto arriba para la construcción del modelo

# Construimos el modelo
model = tf.keras.models.Sequential([
    tf.keras.layers.Lambda(lambda x: tf.expand_dims(x, axis=-1),
                           input_shape=[None]),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(8, return_sequences=True)),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(8)),
    tf.keras.layers.Dense(1),
    tf.keras.layers.Lambda(lambda x: x * 100.0)
])

# Establecemos el optimizador (otra vez es desenso de gradiente)
optimizer = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)

# Parámetros de entrenamiento











# En este caso la función de pérdida es otra vez la de Huber, con similar compo
# el Learning rate y momentum, la métrica que se pide es el error absoluto medio
model.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer,
              metrics=["mae"])

# Entrenamos el modelo (Nuevamente se usan 100 epochs)
history = model.fit(dataset, epochs=100)
```

Epoch 1/100			
43/43	<div><div></div></div>	3s 9ms/step	loss: 13.9436 - mae: 14.4327
Epoch 2/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 10.3654 - mae: 10.8503
Epoch 3/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 11.8498 - mae: 12.3454
Epoch 4/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.8402 - mae: 10.3312
Epoch 5/100			
43/43	<div><div></div></div>	0s 8ms/step	loss: 9.2521 - mae: 9.7393
Epoch 6/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.5980 - mae: 10.0820
Epoch 7/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.9496 - mae: 10.4427
Epoch 8/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.4552 - mae: 9.9479
Epoch 9/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.4131 - mae: 9.8973
Epoch 10/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.7106 - mae: 10.1950
Epoch 11/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 10.0115 - mae: 10.5004
Epoch 12/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 10.2122 - mae: 10.7005
Epoch 13/100			
43/43	<div><div></div></div>	0s 8ms/step	loss: 9.6843 - mae: 10.1682
Epoch 14/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.8699 - mae: 10.3575
Epoch 15/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 10.0166 - mae: 10.5051
Epoch 16/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.9409 - mae: 10.4297
Epoch 17/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 10.5531 - mae: 11.0424
Epoch 18/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 10.1690 - mae: 10.6576
Epoch 19/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.1370 - mae: 9.6318
Epoch 20/100			
43/43	<div><div></div></div>	0s 8ms/step	loss: 9.1456 - mae: 9.6316
Epoch 21/100			
43/43	<div><div></div></div>	0s 8ms/step	loss: 9.8038 - mae: 10.2940
Epoch 22/100			
43/43	<div><div></div></div>	0s 8ms/step	loss: 10.1007 - mae: 10.5851
Epoch 23/100			
43/43	<div><div></div></div>	0s 8ms/step	loss: 9.8102 - mae: 10.2964
Epoch 24/100			
43/43	<div><div></div></div>	0s 8ms/step	loss: 9.9261 - mae: 10.4123
Epoch 25/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 10.2026 - mae: 10.6892
Epoch 26/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.5236 - mae: 10.0163
Epoch 27/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.0588 - mae: 9.5491
Epoch 28/100			
43/43	<div><div></div></div>	0s 8ms/step	loss: 9.6492 - mae: 10.1415
Epoch 29/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.8086 - mae: 10.2957
Epoch 30/100			
43/43	<div><div></div></div>	0s 10ms/step	loss: 10.3350 - mae: 10.8218

Epoch 31/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 10.5915 - mae: 11.0861
Epoch 32/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 10.1272 - mae: 10.6190
Epoch 33/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.4548 - mae: 9.9442
Epoch 34/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.5757 - mae: 10.0626
Epoch 35/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.9912 - mae: 9.4734
Epoch 36/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.9812 - mae: 9.4678
Epoch 37/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.0464 - mae: 9.5296
Epoch 38/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.5807 - mae: 10.0720
Epoch 39/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.5401 - mae: 10.0272
Epoch 40/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.1457 - mae: 9.6344
Epoch 41/100		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.0260 - mae: 9.5131
Epoch 42/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.7367 - mae: 10.2314
Epoch 43/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.4292 - mae: 9.9062
Epoch 44/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.2660 - mae: 8.7433
Epoch 45/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.6015 - mae: 10.0909
Epoch 46/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.5856 - mae: 10.0793
Epoch 47/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.7621 - mae: 9.2500
Epoch 48/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.4895 - mae: 9.9787
Epoch 49/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.0870 - mae: 9.5747
Epoch 50/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.7713 - mae: 10.2558
Epoch 51/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.9578 - mae: 10.4501
Epoch 52/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 10.1385 - mae: 10.6317
Epoch 53/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.5727 - mae: 10.0670
Epoch 54/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.3117 - mae: 9.7999
Epoch 55/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.7058 - mae: 10.1866
Epoch 56/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.2455 - mae: 9.7334
Epoch 57/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.5337 - mae: 10.0133
Epoch 58/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.5115 - mae: 9.9960
Epoch 59/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.8284 - mae: 10.3139
Epoch 60/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.2327 - mae: 9.7133

Epoch 61/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.8312 - mae: 9.3214
Epoch 62/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 10.0734 - mae: 10.5498
Epoch 63/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.5357 - mae: 10.0154
Epoch 64/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.6064 - mae: 10.0878
Epoch 65/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.8028 - mae: 9.2890
Epoch 66/100		
43/43	<div><div></div></div>	0s 7ms/step - loss: 9.2467 - mae: 9.7328
Epoch 67/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.0827 - mae: 9.5751
Epoch 68/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.9607 - mae: 9.4482
Epoch 69/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.6618 - mae: 9.1438
Epoch 70/100		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.2520 - mae: 9.7375
Epoch 71/100		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.4722 - mae: 9.9623
Epoch 72/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.3659 - mae: 9.8595
Epoch 73/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.6691 - mae: 10.1546
Epoch 74/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.9994 - mae: 9.4923
Epoch 75/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.9817 - mae: 9.4638
Epoch 76/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.4274 - mae: 8.9148
Epoch 77/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.7747 - mae: 10.2648
Epoch 78/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.2246 - mae: 9.7200
Epoch 79/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.5459 - mae: 10.0336
Epoch 80/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.3137 - mae: 9.7996
Epoch 81/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.5839 - mae: 9.0654
Epoch 82/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.0267 - mae: 9.5117
Epoch 83/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.1069 - mae: 9.5973
Epoch 84/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.7833 - mae: 10.2733
Epoch 85/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.2248 - mae: 9.7112
Epoch 86/100		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.6001 - mae: 10.0881
Epoch 87/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.7596 - mae: 9.2408
Epoch 88/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.7006 - mae: 9.1814
Epoch 89/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.0923 - mae: 9.5797
Epoch 90/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.1363 - mae: 9.6226

Epoch 91/100
43/43  0s 10ms/step - loss: 9.5173 - mae: 10.0083
Epoch 92/100
43/43  0s 8ms/step - loss: 8.2687 - mae: 8.7602
Epoch 93/100
43/43  0s 9ms/step - loss: 9.1181 - mae: 9.6087
Epoch 94/100
43/43  0s 9ms/step - loss: 9.2581 - mae: 9.7498
Epoch 95/100
43/43  0s 9ms/step - loss: 9.0279 - mae: 9.5169
Epoch 96/100
43/43  0s 10ms/step - loss: 9.2598 - mae: 9.7475
Epoch 97/100
43/43  0s 8ms/step - loss: 8.7155 - mae: 9.2033
Epoch 98/100
43/43  0s 9ms/step - loss: 10.1251 - mae: 10.6199
Epoch 99/100
43/43  0s 8ms/step - loss: 8.8179 - mae: 9.3006
Epoch 100/100
43/43  0s 9ms/step - loss: 9.4271 - mae: 9.9143

```
In [32]: import matplotlib.pyplot as plt

# Entrenamos el modelo
history = model.fit(dataset, epochs=100)

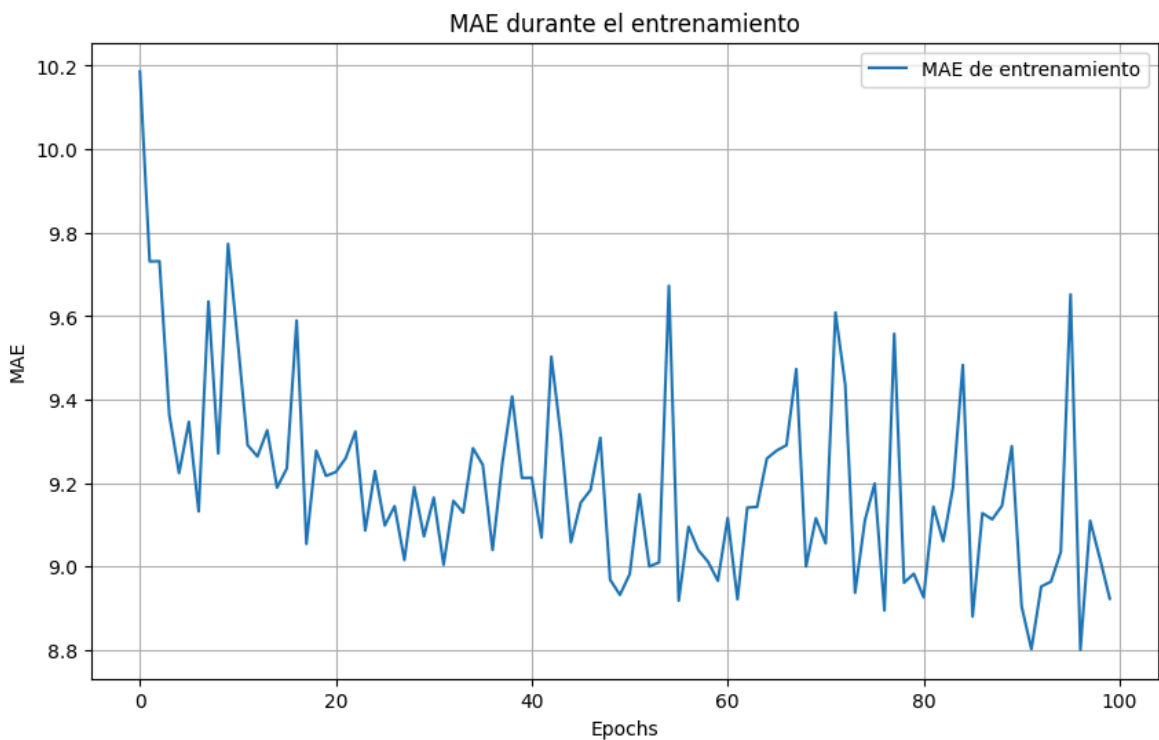
# Graficamos el MAE durante el entrenamiento
plt.figure(figsize=(10, 6))
plt.plot(history.history['mae'], label='MAE de entrenamiento')
plt.xlabel('Epochs')
plt.ylabel('MAE')
plt.title('MAE durante el entrenamiento')
plt.legend()
plt.grid(True)
plt.show()
```

Epoch 1/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 10.2811 - mae: 10.7741
Epoch 2/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 10.3380 - mae: 10.8299
Epoch 3/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.0425 - mae: 9.5272
Epoch 4/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.6093 - mae: 9.0896
Epoch 5/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.7125 - mae: 9.1998
Epoch 6/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.0634 - mae: 9.5482
Epoch 7/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.1154 - mae: 8.6012
Epoch 8/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.9419 - mae: 9.4285
Epoch 9/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.7289 - mae: 9.2175
Epoch 10/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 10.0155 - mae: 10.5053
Epoch 11/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.1748 - mae: 9.6670
Epoch 12/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.4633 - mae: 8.9484
Epoch 13/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.1037 - mae: 9.6000
Epoch 14/100		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.5324 - mae: 9.0213
Epoch 15/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.7828 - mae: 9.2662
Epoch 16/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.3037 - mae: 8.7905
Epoch 17/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.5784 - mae: 10.0682
Epoch 18/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.8558 - mae: 9.3437
Epoch 19/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.8978 - mae: 9.3859
Epoch 20/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.8249 - mae: 9.3165
Epoch 21/100		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.1653 - mae: 8.6504
Epoch 22/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.9529 - mae: 9.4379
Epoch 23/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.1499 - mae: 9.6363
Epoch 24/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.7106 - mae: 9.1979
Epoch 25/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.2686 - mae: 9.7602
Epoch 26/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.6096 - mae: 9.0995
Epoch 27/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.3168 - mae: 9.8063
Epoch 28/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.3509 - mae: 8.8432
Epoch 29/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.1051 - mae: 9.5947
Epoch 30/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.3951 - mae: 8.8843

Epoch 31/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.0329 - mae: 9.5212
Epoch 32/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.5201 - mae: 9.0033
Epoch 33/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.1993 - mae: 9.6830
Epoch 34/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.2426 - mae: 9.7313
Epoch 35/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.0249 - mae: 9.5077
Epoch 36/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.8738 - mae: 9.3581
Epoch 37/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.5640 - mae: 9.0489
Epoch 38/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.7846 - mae: 9.2716
Epoch 39/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.6315 - mae: 10.1120
Epoch 40/100		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.4061 - mae: 9.8928
Epoch 41/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.5167 - mae: 10.0050
Epoch 42/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.2262 - mae: 8.7075
Epoch 43/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.9428 - mae: 9.4285
Epoch 44/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.8528 - mae: 9.3423
Epoch 45/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.7074 - mae: 9.1970
Epoch 46/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.0021 - mae: 9.4896
Epoch 47/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.8770 - mae: 9.3675
Epoch 48/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.6937 - mae: 10.1804
Epoch 49/100		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.5573 - mae: 9.0416
Epoch 50/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 7.9811 - mae: 8.4599
Epoch 51/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.5766 - mae: 9.0620
Epoch 52/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.1223 - mae: 8.6064
Epoch 53/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.9508 - mae: 9.4389
Epoch 54/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.7825 - mae: 9.2675
Epoch 55/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.3981 - mae: 9.8918
Epoch 56/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.3075 - mae: 8.7999
Epoch 57/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.3254 - mae: 9.8169
Epoch 58/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.2753 - mae: 9.7657
Epoch 59/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.8371 - mae: 9.3267
Epoch 60/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.1897 - mae: 8.6791

Epoch 61/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.4090 - mae: 8.8982
Epoch 62/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.0778 - mae: 9.5676
Epoch 63/100		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.7882 - mae: 9.2837
Epoch 64/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.1390 - mae: 9.6269
Epoch 65/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.2394 - mae: 9.7203
Epoch 66/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.4459 - mae: 8.9315
Epoch 67/100		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.2944 - mae: 8.7784
Epoch 68/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.8226 - mae: 9.3083
Epoch 69/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.0273 - mae: 9.5099
Epoch 70/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.5757 - mae: 9.0623
Epoch 71/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.9724 - mae: 9.4647
Epoch 72/100		
43/43	<div><div></div></div>	1s 10ms/step - loss: 8.4953 - mae: 8.9839
Epoch 73/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.4920 - mae: 9.9818
Epoch 74/100		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.6091 - mae: 9.0981
Epoch 75/100		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.5263 - mae: 9.0149
Epoch 76/100		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.3119 - mae: 9.8062
Epoch 77/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.1612 - mae: 9.6415
Epoch 78/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.5117 - mae: 10.0040
Epoch 79/100		
43/43	<div><div></div></div>	1s 11ms/step - loss: 8.6651 - mae: 9.1534
Epoch 80/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.0436 - mae: 8.5318
Epoch 81/100		
43/43	<div><div></div></div>	1s 12ms/step - loss: 8.1361 - mae: 8.6197
Epoch 82/100		
43/43	<div><div></div></div>	1s 11ms/step - loss: 8.4538 - mae: 8.9410
Epoch 83/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.8537 - mae: 9.3351
Epoch 84/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.6298 - mae: 9.1159
Epoch 85/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 10.3497 - mae: 10.8348
Epoch 86/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.4532 - mae: 8.9371
Epoch 87/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.8200 - mae: 9.3071
Epoch 88/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.3094 - mae: 9.8003
Epoch 89/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.1606 - mae: 9.6522
Epoch 90/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.8575 - mae: 9.3492

Epoch 91/100
43/43 ————— 0s 9ms/step - loss: 8.7028 - mae: 9.1901
 Epoch 92/100
43/43 ————— 0s 9ms/step - loss: 7.6934 - mae: 8.1749
 Epoch 93/100
43/43 ————— 0s 8ms/step - loss: 8.7170 - mae: 9.2063
 Epoch 94/100
43/43 ————— 0s 9ms/step - loss: 8.7584 - mae: 9.2469
 Epoch 95/100
43/43 ————— 0s 8ms/step - loss: 8.6423 - mae: 9.1269
 Epoch 96/100
43/43 ————— 0s 8ms/step - loss: 9.3110 - mae: 9.7978
 Epoch 97/100
43/43 ————— 0s 8ms/step - loss: 8.5419 - mae: 9.0292
 Epoch 98/100
43/43 ————— 0s 8ms/step - loss: 8.6870 - mae: 9.1705
 Epoch 99/100
43/43 ————— 0s 8ms/step - loss: 8.9352 - mae: 9.4180
 Epoch 100/100
43/43 ————— 0s 8ms/step - loss: 8.6349 - mae: 9.1233



En el conjunto de datos de entrenamiento, vemos que cuando llegamos a los 19 epochs, al siguiente se dispara el MAE (error absoluto medio). A partir de ahí, va oscilando entre un MAE de 8 y 10. Aun así, el mínimo MAE lo encontramos en el epoch número 88, donde MAE = 8.7 aproximadamente.

Tras entrenar el modelo, vamos a generar una serie de batches (lotes) de ventanas para hacer predicciones con el conjunto de prueba.

```
In [33]: # Función para obtener la predicción, depende del modelo, de los datos y repite
# las ventanas, lo nuevo es que se agrega la instrucción model.predict para obtener

def model_forecast(model, series, window_size, batch_size):
    """Uses an input model to generate predictions on data windows

    Args:
```

```

    model (TF Keras Model) - model that accepts data windows
    series (array of float) - contains the values of the time series
    window_size (int) - the number of time steps to include in the window
    batch_size (int) - the batch size

Returns:
    forecast (numpy array) - array containing predictions
"""

# Generate a TF Dataset from the series values
dataset = tf.data.Dataset.from_tensor_slices(series)

# Window the data but only take those with the specified size
dataset = dataset.window(window_size, shift=1, drop_remainder=True)

# Flatten the windows by putting its elements in a single batch
dataset = dataset.flat_map(lambda w: w.batch(window_size))

# Create batches of windows
dataset = dataset.batch(batch_size).prefetch(1)

# Get predictions on the entire dataset
forecast = model.predict(dataset)

return forecast

```

```

In [34]: # Reduce the original series
forecast_series = series[split_time-window_size:-1]

# Use helper function to generate predictions
forecast = model_forecast(model, forecast_series, window_size, batch_size)

# Drop single dimensional axis
results = forecast.squeeze()

# Plot the results
#!pip install sktime

###Función para graficar la serie
def plot_series(time, series, format="-", start=0, end=None):
    """
    Visualizes time series data

    Args:
        time (array of int) - contains the time steps
        series (array of int) - contains the measurements for each time step
        format - line style when plotting the graph
        start - first time step to plot
        end - last time step to plot
    """

    # Setup dimensions of the graph figure
    plt.figure(figsize=(10, 6))

    if type(series) is tuple:

        for series_num in series:
            # Plot the time series data
            plt.plot(time[start:end], series_num[start:end], format)

```

```

else:
    # Plot the time series data
    plt.plot(time[start:end], series[start:end], format)

    # Label the x-axis
    plt.xlabel("Time")

    # Label the y-axis
    plt.ylabel("Value")

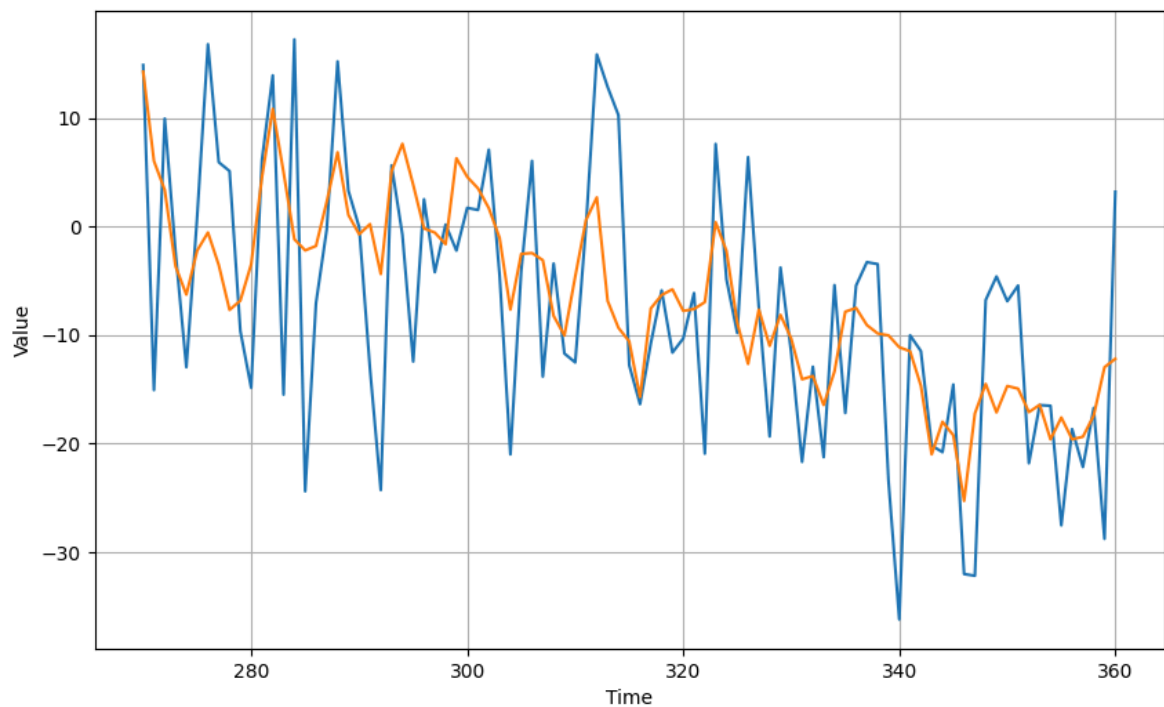
    # Overlay a grid on the graph
    plt.grid(True)

    # Draw the graph on screen
    plt.show()

plot_series(time_valid, (x_valid, results))
#forecast
#results

```

12/12 ————— 1s 32ms/step



Por último, obtenemos las métricas para evaluar la eficiencia del modelo.

```

In [35]: # x_valid
# Para que x_valid esté en el mismo formato que la predicción
x_valid2 = x_valid.squeeze()
x_valid2

```

```
Out[35]: array([ 14.875337 , -15.083143 ,  9.938342 , -2.389687 ,
-12.973386 ,  0.89959204, 16.790596 ,  5.918337 ,
 5.0980177 , -9.653136 , -14.864826 ,  6.151402 ,
13.9227705 , -15.502678 , 17.237041 , -24.412893 ,
-7.0761514 , -0.23827216, 15.209916 ,  3.2935126 ,
-0.08122346, -13.130011 , -24.29365 ,  5.6261144 ,
-0.7672408 , -12.453617 ,  2.5027041 , -4.219022 ,
 0.17031917, -2.225154 ,  1.7100499 ,  1.5186958 ,
 7.0729337 , -4.4963007 , -21.009016 , -4.09663 ,
 6.039252 , -13.840237 , -3.4223225 , -11.713942 ,
-12.535112 ,  0.06632458, 15.854162 , 12.855601 ,
10.254787 , -12.789963 , -16.38047 , -10.772573 ,
-5.8957353 , -11.625951 , -10.323335 , -6.14045 ,
-20.940508 ,  7.6024313 , -4.860177 , -9.821379 ,
 6.381103 , -7.4833755 , -19.3588 , -3.786452 ,
-11.659864 , -21.69707 , -12.93525 , -21.263632 ,
-5.407106 , -17.192017 , -5.4549766 , -3.2933528 ,
-3.4706848 , -23.437248 , -36.222202 , -10.033036 ,
-11.487732 , -20.19395 , -20.803679 , -14.571516 ,
-32.039146 , -32.196083 , -6.7844405 , -4.6139674 ,
-6.8909254 , -5.4464426 , -21.823406 , -16.469288 ,
-16.527561 , -27.549814 , -18.678429 , -22.178604 ,
-16.731112 , -28.793756 ,  3.1934652 ])
```

```
In [36]: # Calculamos MSE (Error cuadrático medio) y el MAE (Error absoluto medio)

# Calculamos la métrica sobre el conjunto de prueba (validación)
print(tf.keras.metrics.MSE(x_valid2, results).numpy())
print(tf.keras.metrics.MAE(x_valid2, results).numpy())
```

```
90.84448
7.161354
```

- MSE (Error Cuadrático Medio = 90.84448):

Esto indica que, en promedio, el cuadrado del error entre las predicciones y los valores reales es 90.84. Como el MSE eleva los errores al cuadrado, penaliza fuertemente los errores grandes. Un MSE alto sugiere que hay errores significativos en algunas predicciones.

- MAE (Error Absoluto Medio = 7.161354):

Esto muestra que, en promedio, las predicciones están a 7.16 unidades de los valores reales. A diferencia del MSE, el MAE es más fácil de interpretar porque está en la misma escala que tus datos originales y no exagera los errores grandes.

Modelo 2 (Capas no bidireccionales, función de activación softsign)

Ahora, repetimos el ajuste del modelo original pero variando la función de activación de tanh a softsign y sin usar aprendizaje bidireccional y compararemos las predicciones.

```
In [59]: import tensorflow as tf
```



```

model_tune = tf.keras.models.Sequential([
    tf.keras.layers.Lambda(lambda x: tf.expand_dims(x, axis=-1), input_shape=[wind
    tf.keras.layers.LSTM(8, return_sequences=True, activation='softsign'),
    tf.keras.layers.LSTM(8, activation='softsign'),
    tf.keras.layers.Dense(1, activation='softsign'),
    tf.keras.layers.Lambda(lambda x: x * 100.0)
])
#Aquí vamos a dar el valor del Learning rate que nos da mejores resultados

# Conjunto de datos partidos en "ventanas"
dataset = windowed_dataset(series, window_size, batch_size, shuffle_buffer_size)

#Esto permite que se use la información del epoch en el que vamos (ciclo hacia a
#para actualizar la Learning rate a través de alguna función, aquí en particular
#se incrementa el epoch el Learning rate se hace más grande
lr_schedule = tf.keras.callbacks.LearningRateScheduler(
    lambda epoch: 1e-8 * 10**(epoch / 20))

# Initialize the optimizer
#Uso de descenso del gradiente como método para actualizar los pesos con un pará
#que acelera el descenso de gradiente en la dirección relevante
optimizer = tf.keras.optimizers.SGD(momentum=0.9)

# Set the training parameters
#La función de pérdida usada es la de Huber. Esta función de pérdida incluye una
#para cuando no estamos cerca del valor real, usando optimizer que definimos arr
model_tune.compile(loss=tf.keras.losses.Huber(), optimizer=optimizer)

# Train the model
#Ponemos a que sean 100 epochs, con Learning rate que se actualiza según lr_scne
history = model_tune.fit(dataset, epochs=100, callbacks=[lr_schedule])

# Definimos el array de tasa de aprendizaje
lrs = 1e-8 * (10 ** (np.arange(100) / 20))

# Ejemplo de valores de pérdida (esto debe ser reemplazado con los valores reales)
losses = history.history["loss"]

# Encontramos el índice del mínimo de la pérdida
min_loss_index = np.argmin(losses)

# Encontramos el valor del Learning rate asociado al mínimo de la pérdida
min_loss_lr = lrs[min_loss_index]
learning_rate = min_loss_lr

# Reset states generated by Keras
tf.keras.backend.clear_session()

# Se repite lo mismo visto arriba para la construcción del modelo

# Construimos el modelo
model = model_tune = tf.keras.models.Sequential([
    tf.keras.layers.Lambda(lambda x: tf.expand_dims(x, axis=-1), input_shape=[wind
    tf.keras.layers.LSTM(8, return_sequences=True, activation='softsign'),
    tf.keras.layers.LSTM(8, activation='softsign'),
    tf.keras.layers.Dense(1, activation='softsign'),
    tf.keras.layers.Lambda(lambda x: x * 100.0)
])

# Establecemos el optimizador (otra vez es descenso de gradiente)

```

```
optimizer = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)

# Parámetros de entrenamiento

# En este caso la función de pérdida es otra vez la de Huber, con similar compo
# el learning rate y momentum, la métrica que se pide es el error absoluto medio
model.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer,
              metrics=["mae"])

# Entrenamos el modelo (Nuevamente se usan 100 epochs)
history = model.fit(dataset, epochs=100)
```

Epoch 1/100
43/43  2s 6ms/step - loss: 24.2442 - learning_rate: 1.0000e-08

Epoch 2/100
43/43  0s 6ms/step - loss: 23.4801 - learning_rate: 1.1220e-08

Epoch 3/100
43/43  0s 6ms/step - loss: 22.2930 - learning_rate: 1.2589e-08

Epoch 4/100
43/43  0s 7ms/step - loss: 24.3730 - learning_rate: 1.4125e-08

Epoch 5/100
43/43  0s 6ms/step - loss: 24.2277 - learning_rate: 1.5849e-08

Epoch 6/100
43/43  0s 6ms/step - loss: 23.2999 - learning_rate: 1.7783e-08

Epoch 7/100
43/43  0s 6ms/step - loss: 23.3990 - learning_rate: 1.9953e-08

Epoch 8/100
43/43  0s 6ms/step - loss: 23.3502 - learning_rate: 2.2387e-08

Epoch 9/100
43/43  0s 6ms/step - loss: 22.3654 - learning_rate: 2.5119e-08

Epoch 10/100
43/43  0s 6ms/step - loss: 22.7522 - learning_rate: 2.8184e-08

Epoch 11/100
43/43  0s 6ms/step - loss: 22.6993 - learning_rate: 3.1623e-08

Epoch 12/100
43/43  0s 6ms/step - loss: 22.4715 - learning_rate: 3.5481e-08

Epoch 13/100
43/43  0s 6ms/step - loss: 23.6765 - learning_rate: 3.9811e-08

Epoch 14/100
43/43  0s 6ms/step - loss: 21.3196 - learning_rate: 4.4668e-08

Epoch 15/100
43/43  0s 7ms/step - loss: 21.6324 - learning_rate: 5.0119e-08


Epoch 16/100
43/43  0s 7ms/step - loss: 21.7894 - learning_rate: 5.6234e-08


Epoch 17/100
43/43  0s 6ms/step - loss: 21.2321 - learning_rate: 6.3096e-08


Epoch 18/100
43/43  0s 6ms/step - loss: 20.4785 - learning_rate: 7.0795e-08


Epoch 19/100
43/43  0s 6ms/step - loss: 20.2709 - learning_rate: 7.9433e-08


Epoch 20/100
43/43  0s 6ms/step - loss: 20.0192 - learning_rate: 8.9125e-08


Epoch 21/100
43/43  0s 6ms/step - loss: 20.7139 - learning_rate: 1.0000e-07


Epoch 22/100
43/43  0s 6ms/step - loss: 19.5973 - learning_rate: 1.1220e-07


Epoch 23/100
43/43  0s 6ms/step - loss: 19.2903 - learning_rate: 1.2589e-07


Epoch 24/100
43/43  0s 6ms/step - loss: 18.8720 - learning_rate: 1.4125e-07


Epoch 25/100
43/43  0s 6ms/step - loss: 16.7828 - learning_rate: 1.5849e-07


Epoch 26/100
43/43  0s 6ms/step - loss: 15.9941 - learning_rate: 1.7783e-07


Epoch 27/100
43/43  0s 6ms/step - loss: 16.3670 - learning_rate: 1.9953e-07


Epoch 28/100
43/43  0s 6ms/step - loss: 16.3810 - learning_rate: 2.2387e-07


Epoch 29/100
43/43  0s 6ms/step - loss: 15.3645 - learning_rate: 2.5119e-07


Epoch 30/100
43/43  0s 6ms/step - loss: 16.1092 - learning_rate: 2.8184e-07


Epoch 31/100
43/43  0s 6ms/step - loss: 17.1478 - learning_rate: 3.1623e-07


Epoch 32/100
43/43  0s 6ms/step - loss: 15.1524 - learning_rate: 3.5481e-07


Epoch 33/100
43/43  0s 6ms/step - loss: 15.2679 - learning_rate: 3.9811e-07


Epoch 34/100
43/43  0s 7ms/step - loss: 15.8760 - learning_rate: 4.4668e-07


Epoch 35/100
43/43  0s 6ms/step - loss: 16.2433 - learning_rate: 5.0119e-07


Epoch 36/100
43/43  0s 6ms/step - loss: 15.4990 - learning_rate: 5.6234e-07


Epoch 37/100
43/43  0s 6ms/step - loss: 15.2590 - learning_rate: 6.3096e-07


Epoch 38/100
43/43  0s 6ms/step - loss: 14.3359 - learning_rate: 7.0795e-07


Epoch 39/100
43/43  0s 6ms/step - loss: 14.8397 - learning_rate: 7.9433e-07


Epoch 40/100
43/43  0s 7ms/step - loss: 14.4525 - learning_rate: 8.9125e-07


Epoch 41/100
43/43  0s 6ms/step - loss: 13.4133 - learning_rate: 1.0000e-06


Epoch 42/100
43/43  0s 6ms/step - loss: 14.7478 - learning_rate: 1.1220e-06


Epoch 43/100
43/43  0s 6ms/step - loss: 14.4455 - learning_rate: 1.2589e-06


Epoch 44/100
43/43  0s 6ms/step - loss: 14.3509 - learning_rate: 1.4125e-06


Epoch 45/100
43/43  0s 6ms/step - loss: 15.7272 - learning_rate: 1.5849e-06


Epoch 46/100
43/43  0s 7ms/step - loss: 13.8861 - learning_rate: 1.7783e-06


Epoch 47/100
43/43  0s 7ms/step - loss: 13.9535 - learning_rate: 1.9953e-06


Epoch 48/100
43/43  0s 6ms/step - loss: 12.9911 - learning_rate: 2.2387e-06


Epoch 49/100
43/43  0s 6ms/step - loss: 11.8050 - learning_rate: 2.5119e-06


Epoch 50/100
43/43  0s 7ms/step - loss: 13.7738 - learning_rate: 2.8184e-06


Epoch 51/100
43/43  0s 6ms/step - loss: 11.9747 - learning_rate: 3.1623e-06


Epoch 52/100
43/43  0s 6ms/step - loss: 12.5475 - learning_rate: 3.5481e-06


Epoch 53/100
43/43  0s 6ms/step - loss: 12.7652 - learning_rate: 3.9811e-06


Epoch 54/100
43/43  0s 6ms/step - loss: 12.4765 - learning_rate: 4.4668e-06


Epoch 55/100
43/43  0s 6ms/step - loss: 12.7345 - learning_rate: 5.0119e-06


Epoch 56/100
43/43  0s 6ms/step - loss: 12.9330 - learning_rate: 5.6234e-06


Epoch 57/100
43/43  0s 6ms/step - loss: 12.3912 - learning_rate: 6.3096e-06


Epoch 58/100
43/43  0s 7ms/step - loss: 11.6905 - learning_rate: 7.0795e-06


Epoch 59/100
43/43  0s 6ms/step - loss: 11.6481 - learning_rate: 7.9433e-06


Epoch 60/100
43/43  0s 6ms/step - loss: 11.4474 - learning_rate: 8.9125e-06


Epoch 61/100
43/43  0s 6ms/step - loss: 11.3874 - learning_rate: 1.0000e-05


Epoch 62/100
43/43  0s 6ms/step - loss: 11.0772 - learning_rate: 1.1220e-05


Epoch 63/100
43/43  0s 6ms/step - loss: 12.3083 - learning_rate: 1.2589e-05


Epoch 64/100
43/43  0s 6ms/step - loss: 12.0643 - learning_rate: 1.4125e-05


Epoch 65/100
43/43  0s 6ms/step - loss: 11.1969 - learning_rate: 1.5849e-05


Epoch 66/100
43/43  0s 6ms/step - loss: 11.5840 - learning_rate: 1.7783e-05


Epoch 67/100
43/43  0s 6ms/step - loss: 11.6766 - learning_rate: 1.9953e-05


Epoch 68/100
43/43  0s 6ms/step - loss: 11.6329 - learning_rate: 2.2387e-05


Epoch 69/100
43/43  0s 6ms/step - loss: 11.2728 - learning_rate: 2.5119e-05


Epoch 70/100
43/43  0s 6ms/step - loss: 10.6884 - learning_rate: 2.8184e-05


Epoch 71/100
43/43  0s 6ms/step - loss: 11.2220 - learning_rate: 3.1623e-05


Epoch 72/100
43/43  0s 6ms/step - loss: 11.4785 - learning_rate: 3.5481e-05


Epoch 73/100
43/43  0s 7ms/step - loss: 11.2295 - learning_rate: 3.9811e-05


Epoch 74/100
43/43  0s 6ms/step - loss: 10.7281 - learning_rate: 4.4668e-05


Epoch 75/100
43/43  0s 6ms/step - loss: 10.4909 - learning_rate: 5.0119e-05

Epoch 76/100
43/43  0s 6ms/step - loss: 10.3509 - learning_rate: 5.6234e-05

Epoch 77/100
43/43  0s 6ms/step - loss: 10.4129 - learning_rate: 6.3096e-05






















Epoch 78/100
43/43  0s 6ms/step - loss: 10.3898 - learning_rate: 7.0795e-05

Epoch 79/100
43/43  0s 6ms/step - loss: 11.0131 - learning_rate: 7.9433e-05

Epoch 80/100
43/43  0s 6ms/step - loss: 9.6667 - learning_rate: 8.9125e-05

Epoch 81/100

```

43/43  0s 6ms/step - loss: 9.8251 - learning_rate: 1.0000e-04
Epoch 82/100
43/43  0s 6ms/step - loss: 10.1864 - learning_rate: 1.1220e-04
Epoch 83/100
43/43  0s 6ms/step - loss: 9.7746 - learning_rate: 1.2589e-04
Epoch 84/100
43/43  0s 6ms/step - loss: 10.2401 - learning_rate: 1.4125e-04
Epoch 85/100
43/43  0s 6ms/step - loss: 10.4307 - learning_rate: 1.5849e-04
Epoch 86/100
43/43  0s 6ms/step - loss: 11.5307 - learning_rate: 1.7783e-04
Epoch 87/100
43/43  0s 6ms/step - loss: 12.2665 - learning_rate: 1.9953e-04
Epoch 88/100
43/43  0s 6ms/step - loss: 10.3097 - learning_rate: 2.2387e-04
Epoch 89/100
43/43  0s 6ms/step - loss: 10.5441 - learning_rate: 2.5119e-04
Epoch 90/100
43/43  0s 6ms/step - loss: 9.6756 - learning_rate: 2.8184e-04
Epoch 91/100
43/43  0s 6ms/step - loss: 9.8348 - learning_rate: 3.1623e-04
Epoch 92/100
43/43  0s 6ms/step - loss: 10.5982 - learning_rate: 3.5481e-04
Epoch 93/100
43/43  0s 6ms/step - loss: 12.3785 - learning_rate: 3.9811e-04
Epoch 94/100
43/43  0s 6ms/step - loss: 10.2422 - learning_rate: 4.4668e-04
Epoch 95/100
43/43  0s 6ms/step - loss: 11.1095 - learning_rate: 5.0119e-04
Epoch 96/100
43/43  0s 6ms/step - loss: 10.9621 - learning_rate: 5.6234e-04
Epoch 97/100
43/43  0s 6ms/step - loss: 11.4795 - learning_rate: 6.3096e-04
Epoch 98/100
43/43  0s 6ms/step - loss: 10.7324 - learning_rate: 7.0795e-04
Epoch 99/100
43/43  0s 6ms/step - loss: 11.1101 - learning_rate: 7.9433e-04
Epoch 100/100
43/43  0s 6ms/step - loss: 10.8373 - learning_rate: 8.9125e-04
El valor mínimo de la pérdida es 9.690518379211426 y ocurre en el learning rate d
e 0.0001122018454301963
Epoch 1/100
43/43  2s 7ms/step - loss: 14.7128 - mae: 15.2079
Epoch 2/100

```

43/43	<div></div>	0s	6ms/step	-	loss: 11.7113	-	mae: 12.2027
Epoch 3/100							
43/43	<div></div>	0s	6ms/step	-	loss: 10.5680	-	mae: 11.0596
Epoch 4/100							
43/43	<div></div>	0s	6ms/step	-	loss: 10.8742	-	mae: 11.3623
Epoch 5/100							
43/43	<div></div>	0s	6ms/step	-	loss: 10.6574	-	mae: 11.1494
Epoch 6/100							
43/43	<div></div>	0s	7ms/step	-	loss: 10.4117	-	mae: 10.8994
Epoch 7/100							
43/43	<div></div>	0s	6ms/step	-	loss: 10.7834	-	mae: 11.2726
Epoch 8/100							
43/43	<div></div>	0s	6ms/step	-	loss: 9.7434	-	mae: 10.2375
Epoch 9/100							
43/43	<div></div>	0s	6ms/step	-	loss: 10.6759	-	mae: 11.1625
Epoch 10/100							
43/43	<div></div>	0s	6ms/step	-	loss: 10.6377	-	mae: 11.1278
Epoch 11/100							
43/43	<div></div>	0s	6ms/step	-	loss: 11.0362	-	mae: 11.5300
Epoch 12/100							
43/43	<div></div>	0s	6ms/step	-	loss: 10.5924	-	mae: 11.0780
Epoch 13/100							
43/43	<div></div>	0s	6ms/step	-	loss: 10.7305	-	mae: 11.2197
Epoch 14/100							
43/43	<div></div>	0s	6ms/step	-	loss: 10.7543	-	mae: 11.2454
Epoch 15/100							
43/43	<div></div>	0s	6ms/step	-	loss: 12.5669	-	mae: 13.0600
Epoch 16/100							
43/43	<div></div>	0s	6ms/step	-	loss: 10.0357	-	mae: 10.5244
Epoch 17/100							
43/43	<div></div>	0s	6ms/step	-	loss: 10.3350	-	mae: 10.8247
Epoch 18/100							
43/43	<div></div>	0s	6ms/step	-	loss: 9.8268	-	mae: 10.3193
Epoch 19/100							
43/43	<div></div>	0s	6ms/step	-	loss: 10.0354	-	mae: 10.5264
Epoch 20/100							
43/43	<div></div>	0s	7ms/step	-	loss: 9.0344	-	mae: 9.5227
Epoch 21/100							
43/43	<div></div>	0s	6ms/step	-	loss: 9.8423	-	mae: 10.3313
Epoch 22/100							
43/43	<div></div>	0s	6ms/step	-	loss: 10.5968	-	mae: 11.0935
Epoch 23/100							
43/43	<div></div>	0s	6ms/step	-	loss: 10.2640	-	mae: 10.7454
Epoch 24/100							
43/43	<div></div>	0s	6ms/step	-	loss: 9.7751	-	mae: 10.2681
Epoch 25/100							
43/43	<div></div>	0s	7ms/step	-	loss: 9.8953	-	mae: 10.3758
Epoch 26/100							
43/43	<div></div>	0s	7ms/step	-	loss: 10.4960	-	mae: 10.9884
Epoch 27/100							
43/43	<div></div>	0s	6ms/step	-	loss: 10.4012	-	mae: 10.8781
Epoch 28/100							
43/43	<div></div>	0s	6ms/step	-	loss: 12.3326	-	mae: 12.8303
Epoch 29/100							
43/43	<div></div>	0s	6ms/step	-	loss: 10.3219	-	mae: 10.8157
Epoch 30/100							
43/43	<div></div>	0s	7ms/step	-	loss: 10.2186	-	mae: 10.7031
Epoch 31/100							
43/43	<div></div>	0s	6ms/step	-	loss: 9.1418	-	mae: 9.6351
Epoch 32/100							

43/43	0s	6ms/step	-	loss: 11.5757	-	mae: 12.0721
Epoch 33/100						
43/43	0s	6ms/step	-	loss: 9.5623	-	mae: 10.0468
Epoch 34/100						
43/43	0s	6ms/step	-	loss: 9.2869	-	mae: 9.7739
Epoch 35/100						
43/43	0s	7ms/step	-	loss: 9.7864	-	mae: 10.2800
Epoch 36/100						
43/43	0s	6ms/step	-	loss: 9.9831	-	mae: 10.4776
Epoch 37/100						
43/43	0s	6ms/step	-	loss: 10.1276	-	mae: 10.6145
Epoch 38/100						
43/43	0s	6ms/step	-	loss: 9.7601	-	mae: 10.2445
Epoch 39/100						
43/43	0s	6ms/step	-	loss: 9.9971	-	mae: 10.4899
Epoch 40/100						
43/43	0s	7ms/step	-	loss: 9.8845	-	mae: 10.3688
Epoch 41/100						
43/43	0s	6ms/step	-	loss: 9.7282	-	mae: 10.2200
Epoch 42/100						
43/43	0s	6ms/step	-	loss: 10.1706	-	mae: 10.6596
Epoch 43/100						
43/43	0s	6ms/step	-	loss: 10.4950	-	mae: 10.9755
Epoch 44/100						
43/43	0s	6ms/step	-	loss: 9.5812	-	mae: 10.0652
Epoch 45/100						
43/43	0s	6ms/step	-	loss: 10.5831	-	mae: 11.0763
Epoch 46/100						
43/43	0s	6ms/step	-	loss: 9.4364	-	mae: 9.9219
Epoch 47/100						
43/43	0s	6ms/step	-	loss: 9.3935	-	mae: 9.8822
Epoch 48/100						
43/43	0s	6ms/step	-	loss: 9.3470	-	mae: 9.8361
Epoch 49/100						
43/43	0s	6ms/step	-	loss: 10.0667	-	mae: 10.5549
Epoch 50/100						
43/43	0s	7ms/step	-	loss: 10.0048	-	mae: 10.4993
Epoch 51/100						
43/43	0s	6ms/step	-	loss: 9.1907	-	mae: 9.6760
Epoch 52/100						
43/43	0s	7ms/step	-	loss: 9.5484	-	mae: 10.0334
Epoch 53/100						
43/43	0s	7ms/step	-	loss: 9.2549	-	mae: 9.7450
Epoch 54/100						
43/43	0s	8ms/step	-	loss: 9.6334	-	mae: 10.1212
Epoch 55/100						
43/43	0s	6ms/step	-	loss: 9.9266	-	mae: 10.4177
Epoch 56/100						
43/43	0s	6ms/step	-	loss: 10.6427	-	mae: 11.1350
Epoch 57/100						
43/43	0s	7ms/step	-	loss: 9.5474	-	mae: 10.0408
Epoch 58/100						
43/43	0s	7ms/step	-	loss: 9.7871	-	mae: 10.2767
Epoch 59/100						
43/43	0s	7ms/step	-	loss: 9.8700	-	mae: 10.3586
Epoch 60/100						
43/43	0s	7ms/step	-	loss: 9.0839	-	mae: 9.5742
Epoch 61/100						
43/43	0s	7ms/step	-	loss: 9.8099	-	mae: 10.3033
Epoch 62/100						

43/43	<div></div>	0s	7ms/step	-	loss: 9.3400	-	mae: 9.8329
Epoch 63/100							
43/43	<div></div>	0s	7ms/step	-	loss: 9.9029	-	mae: 10.3920
Epoch 64/100							
43/43	<div></div>	0s	6ms/step	-	loss: 9.7483	-	mae: 10.2333
Epoch 65/100							
43/43	<div></div>	0s	7ms/step	-	loss: 9.8479	-	mae: 10.3270
Epoch 66/100							
43/43	<div></div>	0s	6ms/step	-	loss: 10.4493	-	mae: 10.9389
Epoch 67/100							
43/43	<div></div>	0s	7ms/step	-	loss: 9.8081	-	mae: 10.2988
Epoch 68/100							
43/43	<div></div>	0s	6ms/step	-	loss: 10.3739	-	mae: 10.8672
Epoch 69/100							
43/43	<div></div>	0s	6ms/step	-	loss: 9.7856	-	mae: 10.2724
Epoch 70/100							
43/43	<div></div>	0s	6ms/step	-	loss: 9.8167	-	mae: 10.3019
Epoch 71/100							
43/43	<div></div>	0s	7ms/step	-	loss: 9.6304	-	mae: 10.1101
Epoch 72/100							
43/43	<div></div>	0s	7ms/step	-	loss: 10.5035	-	mae: 10.9942
Epoch 73/100							
43/43	<div></div>	0s	7ms/step	-	loss: 10.1591	-	mae: 10.6454
Epoch 74/100							
43/43	<div></div>	0s	6ms/step	-	loss: 9.2215	-	mae: 9.7090
Epoch 75/100							
43/43	<div></div>	0s	7ms/step	-	loss: 9.6022	-	mae: 10.0943
Epoch 76/100							
43/43	<div></div>	0s	7ms/step	-	loss: 9.5825	-	mae: 10.0697
Epoch 77/100							
43/43	<div></div>	0s	6ms/step	-	loss: 9.1305	-	mae: 9.6174
Epoch 78/100							
43/43	<div></div>	0s	7ms/step	-	loss: 9.9297	-	mae: 10.4244
Epoch 79/100							
43/43	<div></div>	0s	7ms/step	-	loss: 10.4565	-	mae: 10.9446
Epoch 80/100							
43/43	<div></div>	0s	7ms/step	-	loss: 9.6935	-	mae: 10.1824
Epoch 81/100							
43/43	<div></div>	0s	7ms/step	-	loss: 9.6015	-	mae: 10.0929
Epoch 82/100							
43/43	<div></div>	0s	7ms/step	-	loss: 10.1047	-	mae: 10.5974
Epoch 83/100							
43/43	<div></div>	0s	7ms/step	-	loss: 9.4125	-	mae: 9.9061
Epoch 84/100							
43/43	<div></div>	0s	7ms/step	-	loss: 10.0075	-	mae: 10.4995
Epoch 85/100							
43/43	<div></div>	0s	6ms/step	-	loss: 9.1470	-	mae: 9.6373
Epoch 86/100							
43/43	<div></div>	0s	7ms/step	-	loss: 9.5955	-	mae: 10.0780
Epoch 87/100							
43/43	<div></div>	0s	7ms/step	-	loss: 9.2578	-	mae: 9.7458
Epoch 88/100							
43/43	<div></div>	0s	7ms/step	-	loss: 9.3732	-	mae: 9.8627
Epoch 89/100							
43/43	<div></div>	0s	7ms/step	-	loss: 9.7748	-	mae: 10.2645
Epoch 90/100							
43/43	<div></div>	0s	6ms/step	-	loss: 9.4323	-	mae: 9.9204
Epoch 91/100							
43/43	<div></div>	0s	6ms/step	-	loss: 9.1048	-	mae: 9.5902
Epoch 92/100							

```

43/43 ————— 0s 7ms/step - loss: 10.1791 - mae: 10.6673
Epoch 93/100
43/43 ————— 0s 6ms/step - loss: 9.4687 - mae: 9.9635
Epoch 94/100
43/43 ————— 0s 6ms/step - loss: 9.6430 - mae: 10.1314
Epoch 95/100
43/43 ————— 0s 6ms/step - loss: 9.7891 - mae: 10.2731
Epoch 96/100
43/43 ————— 0s 7ms/step - loss: 9.0784 - mae: 9.5638
Epoch 97/100
43/43 ————— 0s 6ms/step - loss: 10.2142 - mae: 10.7030
Epoch 98/100
43/43 ————— 0s 6ms/step - loss: 9.2216 - mae: 9.7044
Epoch 99/100
43/43 ————— 0s 7ms/step - loss: 9.9452 - mae: 10.4367
Epoch 100/100
43/43 ————— 0s 7ms/step - loss: 9.0464 - mae: 9.5292

```

```

In [60]: # Reduce the original series
forecast_series = series[split_time-window_size:-1]

# Use helper function to generate predictions
forecast = model_forecast(model, forecast_series, window_size, batch_size)

# Drop single dimensional axis
results = forecast.squeeze()

# Plot the results
#!pip install sktime

###Función para graficar la serie
def plot_series(time, series, format="-", start=0, end=None):
    """
    Visualizes time series data

    Args:
        time (array of int) - contains the time steps
        series (array of int) - contains the measurements for each time step
        format - line style when plotting the graph
        start - first time step to plot
        end - last time step to plot
    """

    # Setup dimensions of the graph figure
    plt.figure(figsize=(10, 6))

    if type(series) is tuple:

        for series_num in series:

            # Plot the time series data
            plt.plot(time[start:end], series_num[start:end], format)

    else:

        # Plot the time series data
        plt.plot(time[start:end], series[start:end], format)

    # Label the x-axis
    plt.xlabel("Time")

    # Label the y-axis

```

```

plt.ylabel("Value")

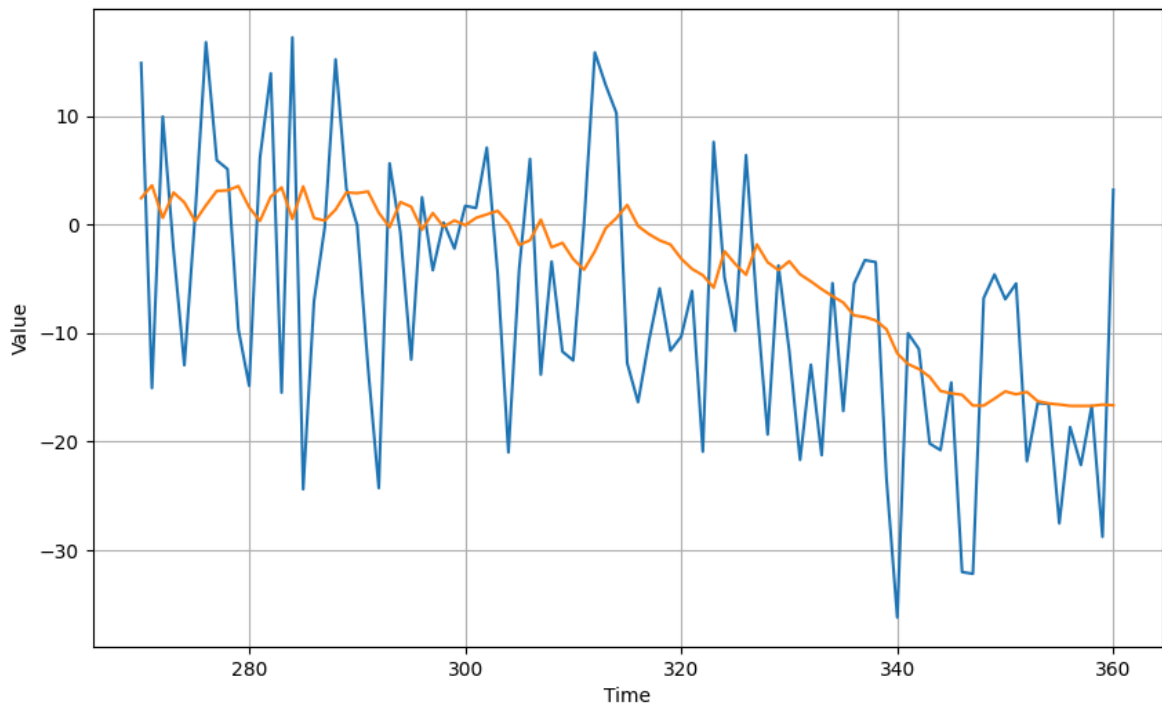
# Overlay a grid on the graph
plt.grid(True)

# Draw the graph on screen
plt.show()

plot_series(time_valid, (x_valid, results))
#forecast
#results

```

12/12 ————— 0s 19ms/step



```

In [61]: x_valid2 = x_valid.squeeze()

# Calculamos la métrica sobre el conjunto de prueba (validación)
print(tf.keras.metrics.MSE(x_valid2, results).numpy())
print(tf.keras.metrics.MAE(x_valid2, results).numpy())

```

122.25438

8.913031

En el Modelo 2 obtenemos peores métricas, lo que quiere decir que los datos de prueba se ajustan peor que en el modelo 1.

Métricas:

MSE

Modelo 1: 90.84448

Modelo 2: 122.25438

MAE

Modelo 1: 7.161354

Modelo 3 (Capas bidireccionales, función de activación softsign)

Esta vez, repetiremos el ajuste del modelo del punto anterior, pero usando aprendizaje bidireccional y compararemos las predicciones.

```
In [63]: import tensorflow as tf

model_tune = tf.keras.models.Sequential([
    tf.keras.layers.Lambda(lambda x: tf.expand_dims(x, axis=-1), input_shape=[wind
    tf.keras.layers.LSTM(8, return_sequences=True, activation='tanh'),
    tf.keras.layers.LSTM(8, activation='tanh'),
    tf.keras.layers.Dense(1, activation='relu'),
    tf.keras.layers.Lambda(lambda x: x * 100.0)
])

#Aquí vamos a dar el valor del learning rate que nos da mejores resultados

# Conjunto de datos partidos en "ventanas"
dataset = windowed_dataset(series, window_size, batch_size, shuffle_buffer_size)

#Esto permite que se use la información del epoch en el que vamos (ciclo hacia a
#para actualizar la learning rate a través de alguna función, aquí en particular
#se incrementa el epoch el learning rate se hace más grande
lr_schedule = tf.keras.callbacks.LearningRateScheduler(
    lambda epoch: 1e-8 * 10**(epoch / 20))

# Initialize the optimizer
#Uso de descenso del gradiente como método para actualizar los pesos con un pará
#que acelera el descenso de gradiente en la dirección relevante
optimizer = tf.keras.optimizers.SGD(momentum=0.9)

# Set the training parameters
#La función de pérdida usada es la de Huber. Esta función de pérdida incluye una
#para cuando no estamos cerca del valor real, usando optimizer que definimos arr
model_tune.compile(loss=tf.keras.losses.Huber(), optimizer=optimizer)

# Train the model
#Ponemos a que sean 100 epochs, con learning rate que se actualiza según lr_scne
history = model_tune.fit(dataset, epochs=100, callbacks=[lr_schedule])

# Definimos el array de tasa de aprendizaje
lrs = 1e-8 * (10 ** (np.arange(100) / 20))

# Ejemplo de valores de pérdida (esto debe ser reemplazado con los valores reales)
losses = history.history["loss"]

# Encontramos el índice del mínimo de la pérdida
min_loss_index = np.argmin(losses)

# Encontramos el valor del learning rate asociado al mínimo de la pérdida
min_loss_lr = lrs[min_loss_index]
learning_rate = min_loss_lr

# Reset states generated by Keras
```

```

tf.keras.backend.clear_session()

# Se repite lo mismo visto arriba para la construcción del modelo

# Construimos el modelo
model = tf.keras.models.Sequential([
    tf.keras.layers.Lambda(lambda x: tf.expand_dims(x, axis=-1), input_shape=[wind
    tf.keras.layers.LSTM(8, return_sequences=True, activation='tanh'),
    tf.keras.layers.LSTM(8, activation='tanh'),
    tf.keras.layers.Dense(1, activation='relu'),
    tf.keras.layers.Lambda(lambda x: x * 100.0)
])


# Establecemos el optimizador (otra vez es desenso de gradiente)
optimizer = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)


# Parámetros de entrenamiento


# En este caso la función de pérdida es otra vez la de Huber, con similar compo
# el learning rate y momentum, la métrica que se pide es el error absoluto medio
model.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer,
              metrics=["mae"])


# Entrenamos el modelo (Nuevamente se usan 100 epochs)
history = model.fit(dataset, epochs=100)


```


Epoch 1/100
43/43  2s 6ms/step - loss: 26.1389 - learning_rate: 1.0000e-08


Epoch 2/100
43/43  0s 6ms/step - loss: 25.2504 - learning_rate: 1.1220e-08


Epoch 3/100
43/43  0s 6ms/step - loss: 24.8634 - learning_rate: 1.2589e-08


Epoch 4/100
43/43  0s 6ms/step - loss: 26.1236 - learning_rate: 1.4125e-08


Epoch 5/100
43/43  0s 6ms/step - loss: 25.4804 - learning_rate: 1.5849e-08


Epoch 6/100
43/43  0s 6ms/step - loss: 25.8417 - learning_rate: 1.7783e-08


Epoch 7/100
43/43  0s 6ms/step - loss: 26.2560 - learning_rate: 1.9953e-08


Epoch 8/100
43/43  0s 6ms/step - loss: 25.0220 - learning_rate: 2.2387e-08


Epoch 9/100
43/43  0s 6ms/step - loss: 23.6238 - learning_rate: 2.5119e-08


Epoch 10/100
43/43  0s 6ms/step - loss: 25.8320 - learning_rate: 2.8184e-08


Epoch 11/100
43/43  0s 6ms/step - loss: 24.9279 - learning_rate: 3.1623e-08


Epoch 12/100
43/43  0s 5ms/step - loss: 26.6621 - learning_rate: 3.5481e-08


Epoch 13/100
43/43  0s 6ms/step - loss: 24.9240 - learning_rate: 3.9811e-08


Epoch 14/100
43/43  0s 6ms/step - loss: 25.6285 - learning_rate: 4.4668e-08


Epoch 15/100
43/43  0s 6ms/step - loss: 25.3987 - learning_rate: 5.0119e-08

Epoch 16/100
43/43  0s 6ms/step - loss: 24.6523 - learning_rate: 5.6234e-08

Epoch 17/100
43/43  0s 6ms/step - loss: 24.1675 - learning_rate: 6.3096e-08


Epoch 18/100
43/43  0s 6ms/step - loss: 25.7462 - learning_rate: 7.0795e-08

Epoch 19/100
43/43  0s 6ms/step - loss: 25.1072 - learning_rate: 7.9433e-08

Epoch 20/100
43/43  0s 6ms/step - loss: 25.9578 - learning_rate: 8.9125e-08

Epoch 21/100
43/43  0s 6ms/step - loss: 25.0423 - learning_rate: 1.0000e-07

Epoch 22/100
43/43  0s 6ms/step - loss: 25.2840 - learning_rate: 1.1220e-07

Epoch 23/100
43/43  0s 6ms/step - loss: 24.3596 - learning_rate: 1.2589e-07

Epoch 24/100
43/43  0s 6ms/step - loss: 24.2584 - learning_rate: 1.4125e-07

Epoch 25/100
43/43  0s 6ms/step - loss: 25.3035 - learning_rate: 1.5849e-07

Epoch 26/100
43/43  0s 6ms/step - loss: 25.9233 - learning_rate: 1.7783e-07

Epoch 27/100
43/43  0s 6ms/step - loss: 24.7453 - learning_rate: 1.9953e-07

Epoch 28/100
43/43  0s 6ms/step - loss: 26.2247 - learning_rate: 2.2387e-07

Epoch 29/100
43/43  0s 6ms/step - loss: 26.3812 - learning_rate: 2.5119e-07

Epoch 30/100
43/43  0s 6ms/step - loss: 25.2256 - learning_rate: 2.8184e-07

Epoch 31/100
43/43  0s 6ms/step - loss: 26.4368 - learning_rate: 3.1623e-07

Epoch 32/100
43/43  0s 6ms/step - loss: 26.3589 - learning_rate: 3.5481e-07

Epoch 33/100
43/43  0s 6ms/step - loss: 24.7455 - learning_rate: 3.9811e-07


Epoch 34/100
43/43  0s 6ms/step - loss: 24.6790 - learning_rate: 4.4668e-07

Epoch 35/100
43/43  0s 6ms/step - loss: 25.9207 - learning_rate: 5.0119e-07


Epoch 36/100
43/43  0s 6ms/step - loss: 25.7845 - learning_rate: 5.6234e-07


Epoch 37/100
43/43  0s 6ms/step - loss: 25.2574 - learning_rate: 6.3096e-07


Epoch 38/100
43/43  0s 7ms/step - loss: 26.4746 - learning_rate: 7.0795e-07


Epoch 39/100
43/43  0s 6ms/step - loss: 25.6635 - learning_rate: 7.9433e-07


Epoch 40/100
43/43  0s 6ms/step - loss: 24.8265 - learning_rate: 8.9125e-07


Epoch 41/100
43/43  0s 5ms/step - loss: 25.0109 - learning_rate: 1.0000e-06


Epoch 42/100
43/43  0s 6ms/step - loss: 24.3257 - learning_rate: 1.1220e-06


Epoch 43/100
43/43  0s 6ms/step - loss: 25.5041 - learning_rate: 1.2589e-06


Epoch 44/100
43/43  0s 6ms/step - loss: 24.6451 - learning_rate: 1.4125e-06


Epoch 45/100
43/43  0s 6ms/step - loss: 24.7485 - learning_rate: 1.5849e-06


Epoch 46/100
43/43  0s 6ms/step - loss: 25.0150 - learning_rate: 1.7783e-06


Epoch 47/100
43/43  0s 6ms/step - loss: 25.2525 - learning_rate: 1.9953e-06


Epoch 48/100
43/43  0s 6ms/step - loss: 25.9250 - learning_rate: 2.2387e-06


Epoch 49/100
43/43  0s 6ms/step - loss: 24.6741 - learning_rate: 2.5119e-06


Epoch 50/100
43/43  0s 6ms/step - loss: 24.9575 - learning_rate: 2.8184e-06


Epoch 51/100
43/43  0s 6ms/step - loss: 25.1101 - learning_rate: 3.1623e-06


Epoch 52/100
43/43  0s 6ms/step - loss: 24.7410 - learning_rate: 3.5481e-06


Epoch 53/100
43/43  0s 6ms/step - loss: 24.9662 - learning_rate: 3.9811e-06


Epoch 54/100
43/43  0s 6ms/step - loss: 25.5952 - learning_rate: 4.4668e-06


Epoch 55/100
43/43  0s 6ms/step - loss: 25.0202 - learning_rate: 5.0119e-06


Epoch 56/100
43/43  0s 6ms/step - loss: 25.3501 - learning_rate: 5.6234e-06


Epoch 57/100
43/43  0s 5ms/step - loss: 24.8627 - learning_rate: 6.3096e-06


Epoch 58/100
43/43  0s 5ms/step - loss: 25.0126 - learning_rate: 7.0795e-06


Epoch 59/100
43/43  0s 6ms/step - loss: 25.1933 - learning_rate: 7.9433e-06

Epoch 60/100
43/43  0s 6ms/step - loss: 24.8333 - learning_rate: 8.9125e-06


Epoch 61/100
43/43  0s 6ms/step - loss: 25.7486 - learning_rate: 1.0000e-05


Epoch 62/100
43/43  0s 6ms/step - loss: 24.9791 - learning_rate: 1.1220e-05


Epoch 63/100
43/43  0s 6ms/step - loss: 24.1896 - learning_rate: 1.2589e-05


Epoch 64/100
43/43  0s 6ms/step - loss: 25.3074 - learning_rate: 1.4125e-05

Epoch 65/100
43/43  0s 6ms/step - loss: 25.2220 - learning_rate: 1.5849e-05

Epoch 66/100
43/43  0s 6ms/step - loss: 23.9334 - learning_rate: 1.7783e-05


Epoch 67/100
43/43  0s 6ms/step - loss: 24.8757 - learning_rate: 1.9953e-05


Epoch 68/100
43/43  0s 6ms/step - loss: 24.5937 - learning_rate: 2.2387e-05


Epoch 69/100
43/43  0s 6ms/step - loss: 26.4503 - learning_rate: 2.5119e-05


Epoch 70/100
43/43  0s 6ms/step - loss: 25.0789 - learning_rate: 2.8184e-05

Epoch 71/100
43/43  0s 6ms/step - loss: 25.3033 - learning_rate: 3.1623e-05


Epoch 72/100
43/43  0s 6ms/step - loss: 24.1996 - learning_rate: 3.5481e-05

Epoch 73/100
43/43  0s 6ms/step - loss: 24.2337 - learning_rate: 3.9811e-05


Epoch 74/100
43/43  0s 6ms/step - loss: 24.4025 - learning_rate: 4.4668e-05


Epoch 75/100
43/43  0s 6ms/step - loss: 25.2083 - learning_rate: 5.0119e-05


Epoch 76/100
43/43  0s 6ms/step - loss: 25.2668 - learning_rate: 5.6234e-05


Epoch 77/100
43/43  0s 6ms/step - loss: 25.2199 - learning_rate: 6.3096e-05


Epoch 78/100
43/43  0s 6ms/step - loss: 24.6166 - learning_rate: 7.0795e-05


Epoch 79/100
43/43  0s 7ms/step - loss: 24.5056 - learning_rate: 7.9433e-05


Epoch 80/100
43/43  0s 6ms/step - loss: 24.9256 - learning_rate: 8.9125e-05


Epoch 81/100
43/43  0s 6ms/step - loss: 25.3833 - learning_rate: 1.0000e-04


Epoch 82/100
43/43  0s 6ms/step - loss: 24.9789 - learning_rate: 1.1220e-04


Epoch 83/100
43/43  0s 6ms/step - loss: 25.6933 - learning_rate: 1.2589e-04


Epoch 84/100
43/43  0s 6ms/step - loss: 24.7213 - learning_rate: 1.4125e-04


Epoch 85/100
43/43  0s 6ms/step - loss: 24.9035 - learning_rate: 1.5849e-04


Epoch 86/100
43/43  0s 6ms/step - loss: 25.4046 - learning_rate: 1.7783e-04


Epoch 87/100
43/43  0s 6ms/step - loss: 25.6980 - learning_rate: 1.9953e-04


Epoch 88/100
43/43  0s 6ms/step - loss: 23.9709 - learning_rate: 2.2387e-04


Epoch 89/100
43/43  0s 5ms/step - loss: 25.0095 - learning_rate: 2.5119e-04


Epoch 90/100
43/43  0s 6ms/step - loss: 24.7488 - learning_rate: 2.8184e-04


Epoch 91/100
43/43  0s 6ms/step - loss: 23.7962 - learning_rate: 3.1623e-04


Epoch 92/100
43/43  0s 6ms/step - loss: 24.7146 - learning_rate: 3.5481e-04


Epoch 93/100
43/43  0s 6ms/step - loss: 25.0281 - learning_rate: 3.9811e-04


Epoch 94/100
43/43  0s 6ms/step - loss: 24.9249 - learning_rate: 4.4668e-04


Epoch 95/100
43/43  0s 6ms/step - loss: 25.6964 - learning_rate: 5.0119e-04

Epoch 96/100
43/43  0s 6ms/step - loss: 25.2191 - learning_rate: 5.6234e-04

Epoch 97/100
43/43  0s 5ms/step - loss: 25.3830 - learning_rate: 6.3096e-04

Epoch 98/100
43/43  0s 6ms/step - loss: 23.9953 - learning_rate: 7.0795e-04

Epoch 99/100
43/43  0s 6ms/step - loss: 24.3295 - learning_rate: 7.9433e-04

Epoch 100/100
43/43  0s 6ms/step - loss: 27.1388 - learning_rate: 8.9125e-04

Epoch 1/100			
43/43	<div><div></div></div>	2s 6ms/step	loss: 24.5813 - mae: 25.0786
Epoch 2/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.1058 - mae: 25.6042
Epoch 3/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.9702 - mae: 25.4669
Epoch 4/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.3855 - mae: 25.8822
Epoch 5/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.0537 - mae: 24.5497
Epoch 6/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 23.9073 - mae: 24.4042
Epoch 7/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.3080 - mae: 25.8041
Epoch 8/100			
43/43	<div><div></div></div>	0s 5ms/step	loss: 25.9027 - mae: 26.3994
Epoch 9/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.1605 - mae: 25.6572
Epoch 10/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 26.4451 - mae: 26.9410
Epoch 11/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.6426 - mae: 26.1401
Epoch 12/100			
43/43	<div><div></div></div>	0s 5ms/step	loss: 25.8203 - mae: 26.3163
Epoch 13/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.6808 - mae: 26.1784
Epoch 14/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.7137 - mae: 26.2105
Epoch 15/100			
43/43	<div><div></div></div>	0s 7ms/step	loss: 25.7524 - mae: 26.2484
Epoch 16/100			
43/43	<div><div></div></div>	0s 7ms/step	loss: 25.5901 - mae: 26.0859
Epoch 17/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 26.5185 - mae: 27.0137
Epoch 18/100			
43/43	<div><div></div></div>	0s 5ms/step	loss: 24.7393 - mae: 25.2348
Epoch 19/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.5050 - mae: 25.0016
Epoch 20/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.2008 - mae: 25.6978
Epoch 21/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 23.6940 - mae: 24.1893
Epoch 22/100			
43/43	<div><div></div></div>	0s 5ms/step	loss: 24.9174 - mae: 25.4142
Epoch 23/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 26.0121 - mae: 26.5100
Epoch 24/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 26.0708 - mae: 26.5685
Epoch 25/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.2186 - mae: 25.7145
Epoch 26/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.2019 - mae: 25.6992
Epoch 27/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.7260 - mae: 26.2220
Epoch 28/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.8410 - mae: 26.3380
Epoch 29/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.4933 - mae: 25.9900
Epoch 30/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 26.4533 - mae: 26.9496

Epoch 31/100			
43/43	<div><div></div></div>	0s 7ms/step	loss: 25.4091 - mae: 25.9046
Epoch 32/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.8106 - mae: 25.3086
Epoch 33/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.2230 - mae: 24.7197
Epoch 34/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.6050 - mae: 26.1012
Epoch 35/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.0577 - mae: 25.5548
Epoch 36/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.8093 - mae: 25.3072
Epoch 37/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.4763 - mae: 24.9729
Epoch 38/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.8982 - mae: 26.3945
Epoch 39/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.4169 - mae: 24.9122
Epoch 40/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.3402 - mae: 24.8373
Epoch 41/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.7242 - mae: 26.2219
Epoch 42/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.5950 - mae: 26.0915
Epoch 43/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.2940 - mae: 24.7926
Epoch 44/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.6883 - mae: 26.1848
Epoch 45/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.8112 - mae: 25.3085
Epoch 46/100			
43/43	<div><div></div></div>	0s 5ms/step	loss: 25.6732 - mae: 26.1702
Epoch 47/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.0710 - mae: 25.5684
Epoch 48/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.2499 - mae: 25.7455
Epoch 49/100			
43/43	<div><div></div></div>	0s 5ms/step	loss: 24.7686 - mae: 25.2651
Epoch 50/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.8502 - mae: 25.3469
Epoch 51/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.7762 - mae: 25.2727
Epoch 52/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.2115 - mae: 25.7071
Epoch 53/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.0805 - mae: 25.5770
Epoch 54/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.9536 - mae: 25.4507
Epoch 55/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.1309 - mae: 25.6275
Epoch 56/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.3301 - mae: 24.8273
Epoch 57/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.0512 - mae: 25.5476
Epoch 58/100			
43/43	<div><div></div></div>	0s 5ms/step	loss: 26.3512 - mae: 26.8486
Epoch 59/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 26.1103 - mae: 26.6049
Epoch 60/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.7940 - mae: 25.2895

Epoch 61/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 26.0247 - mae: 26.5215
Epoch 62/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.3985 - mae: 24.8952
Epoch 63/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.8183 - mae: 26.3143
Epoch 64/100			
43/43	<div><div></div></div>	0s 7ms/step	loss: 24.6867 - mae: 25.1841
Epoch 65/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 23.7192 - mae: 24.2150
Epoch 66/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.8010 - mae: 25.2946
Epoch 67/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.7312 - mae: 25.2289
Epoch 68/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.5636 - mae: 26.0611
Epoch 69/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.7450 - mae: 26.2419
Epoch 70/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 23.7497 - mae: 24.2472
Epoch 71/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.5894 - mae: 26.0851
Epoch 72/100			
43/43	<div><div></div></div>	0s 8ms/step	loss: 24.5530 - mae: 25.0506
Epoch 73/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.2109 - mae: 25.7080
Epoch 74/100			
43/43	<div><div></div></div>	0s 7ms/step	loss: 25.9484 - mae: 26.4451
Epoch 75/100			
43/43	<div><div></div></div>	0s 7ms/step	loss: 24.6912 - mae: 25.1885
Epoch 76/100			
43/43	<div><div></div></div>	0s 7ms/step	loss: 25.1798 - mae: 25.6768
Epoch 77/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.5568 - mae: 25.0542
Epoch 78/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.2015 - mae: 24.6988
Epoch 79/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.4544 - mae: 25.9526
Epoch 80/100			
43/43	<div><div></div></div>	0s 7ms/step	loss: 25.4957 - mae: 25.9933
Epoch 81/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.9805 - mae: 26.4762
Epoch 82/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.4914 - mae: 24.9883
Epoch 83/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.4639 - mae: 24.9598
Epoch 84/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 24.7910 - mae: 25.2886
Epoch 85/100			
43/43	<div><div></div></div>	0s 7ms/step	loss: 26.4664 - mae: 26.9646
Epoch 86/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.7476 - mae: 26.2436
Epoch 87/100			
43/43	<div><div></div></div>	0s 8ms/step	loss: 25.5706 - mae: 26.0671
Epoch 88/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 24.9256 - mae: 25.4223
Epoch 89/100			
43/43	<div><div></div></div>	0s 7ms/step	loss: 23.5043 - mae: 24.0013
Epoch 90/100			
43/43	<div><div></div></div>	0s 6ms/step	loss: 25.1044 - mae: 25.6007

```

Epoch 91/100
43/43 ————— 0s 6ms/step - loss: 23.4791 - mae: 23.9740
Epoch 92/100
43/43 ————— 0s 6ms/step - loss: 25.4492 - mae: 25.9458
Epoch 93/100
43/43 ————— 0s 6ms/step - loss: 24.7616 - mae: 25.2580
Epoch 94/100
43/43 ————— 0s 8ms/step - loss: 24.2880 - mae: 24.7848
Epoch 95/100
43/43 ————— 0s 8ms/step - loss: 25.8020 - mae: 26.3005
Epoch 96/100
43/43 ————— 0s 9ms/step - loss: 25.9427 - mae: 26.4388
Epoch 97/100
43/43 ————— 0s 8ms/step - loss: 25.5192 - mae: 26.0145
Epoch 98/100
43/43 ————— 0s 9ms/step - loss: 25.0187 - mae: 25.5168
Epoch 99/100
43/43 ————— 0s 9ms/step - loss: 24.8071 - mae: 25.3030
Epoch 100/100
43/43 ————— 0s 10ms/step - loss: 25.9905 - mae: 26.4877

```

```

In [64]: # Reduce the original series
forecast_series = series[split_time-window_size:-1]

# Use helper function to generate predictions
forecast = model_forecast(model, forecast_series, window_size, batch_size)

# Drop single dimensional axis
results = forecast.squeeze()

x_valid2 = x_valid.squeeze()

# Calculamos la métrica sobre el conjunto de prueba (validación)
print(tf.keras.metrics.MSE(x_valid2, results).numpy())
print(tf.keras.metrics.MAE(x_valid2, results).numpy())

```

```

12/12 ————— 0s 19ms/step
200.42162
11.5769205

```

Podemos ver que el Modelo 3 es bastante peor que los dos anteriores, ya que los datos de prueba se ajustan peor, pues tanto el MAE como el MSAE son más altos.

Métricas:

MSE

Modelo 1: 90.84448

Modelo 2: 122.25438

Modelo 3: 200.42162

MAE

Modelo 1: 7.161354

Modelo 2: 8.913031

Modelo 4 (Capas no bidireccionales, función de activación tanh)

Ahora, repetiremos el ajuste del modelo del modelo original, pero sin capas bidireccionales y compararemos las predicciones.

```
In [65]: import tensorflow as tf

model_tune = tf.keras.models.Sequential([
    tf.keras.layers.Lambda(lambda x: tf.expand_dims(x, axis=-1), input_shape=[wind
    tf.keras.layers.LSTM(8, return_sequences=True, activation='tanh'),
    tf.keras.layers.LSTM(8, activation='tanh'),
    tf.keras.layers.Dense(1, activation='relu'),
    tf.keras.layers.Lambda(lambda x: x * 100.0)
])

#Aquí vamos a dar el valor del Learning rate que nos da mejores resultados

# Conjunto de datos partidos en "ventanas"
dataset = windowed_dataset(series, window_size, batch_size, shuffle_buffer_size)

#Esto permite que se use la información del epoch en el que vamos (ciclo hacia a
#para actualizar la Learning rate a través de alguna función, aquí en particular
#se incrementa el epoch el Learning rate se hace más grande
lr_schedule = tf.keras.callbacks.LearningRateScheduler(
    lambda epoch: 1e-8 * 10**(epoch / 20))

# Initialize the optimizer
#Uso de descenso del gradiente como método para actualizar los pesos con un pará
#que acelera el descenso de gradiente en la dirección relevante
optimizer = tf.keras.optimizers.SGD(momentum=0.9)

# Set the training parameters
#La función de pérdida usada es la de Huber. Esta función de pérdida incluye una
#para cuando no estamos cerca del valor real, usando optimizer que definimos arr
model_tune.compile(loss=tf.keras.losses.Huber(), optimizer=optimizer)

# Train the model
#Ponemos a que sean 100 epochs, con Learning rate que se actualiza según lr_scne
history = model_tune.fit(dataset, epochs=100, callbacks=[lr_schedule])

# Definimos el array de tasa de aprendizaje
lrs = 1e-8 * (10 ** (np.arange(100) / 20))

# Ejemplo de valores de pérdida (esto debe ser reemplazado con los valores reales)
losses = history.history["loss"]

# Encontramos el índice del mínimo de la pérdida
min_loss_index = np.argmin(losses)

# Encontramos el valor del Learning rate asociado al mínimo de la pérdida
min_loss_lr = lrs[min_loss_index]
learning_rate = min_loss_lr

# Reset states generated by Keras
```



```

tf.keras.backend.clear_session()

# Se repite lo mismo visto arriba para la construcción del modelo

# Construimos el modelo
model = tf.keras.models.Sequential([
    tf.keras.layers.Lambda(lambda x: tf.expand_dims(x, axis=-1), input_shape=[wind
    tf.keras.layers.LSTM(8, return_sequences=True, activation='tanh'),
    tf.keras.layers.LSTM(8, activation='tanh'),
    tf.keras.layers.Dense(1, activation='relu'),
    tf.keras.layers.Lambda(lambda x: x * 100.0)
])


# Establecemos el optimizador (otra vez es desenso de gradiente)
optimizer = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)


# Parámetros de entrenamiento


# En este caso la función de pérdida es otra vez la de Huber, con similar compo
# el learning rate y momentum, la métrica que se pide es el error absoluto medio
model.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer,
              metrics=["mae"])


# Entrenamos el modelo (Nuevamente se usan 100 epochs)
history = model.fit(dataset, epochs=100)


```


Epoch 1/100
43/43  2s 6ms/step - loss: 18.8461 - learning_rate: 1.0000e-08


Epoch 2/100
43/43  0s 6ms/step - loss: 18.1648 - learning_rate: 1.1220e-08


Epoch 3/100
43/43  0s 6ms/step - loss: 17.3166 - learning_rate: 1.2589e-08


Epoch 4/100
43/43  0s 6ms/step - loss: 18.2186 - learning_rate: 1.4125e-08


Epoch 5/100
43/43  0s 6ms/step - loss: 17.7151 - learning_rate: 1.5849e-08


Epoch 6/100
43/43  0s 6ms/step - loss: 17.0227 - learning_rate: 1.7783e-08


Epoch 7/100
43/43  0s 6ms/step - loss: 16.6711 - learning_rate: 1.9953e-08


Epoch 8/100
43/43  0s 6ms/step - loss: 16.1398 - learning_rate: 2.2387e-08


Epoch 9/100
43/43  0s 6ms/step - loss: 16.0275 - learning_rate: 2.5119e-08


Epoch 10/100
43/43  0s 6ms/step - loss: 15.8726 - learning_rate: 2.8184e-08


Epoch 11/100
43/43  0s 6ms/step - loss: 15.6128 - learning_rate: 3.1623e-08


Epoch 12/100
43/43  0s 6ms/step - loss: 14.2974 - learning_rate: 3.5481e-08


Epoch 13/100
43/43  0s 6ms/step - loss: 14.0094 - learning_rate: 3.9811e-08


Epoch 14/100
43/43  0s 6ms/step - loss: 14.4608 - learning_rate: 4.4668e-08


Epoch 15/100
43/43  0s 6ms/step - loss: 12.8065 - learning_rate: 5.0119e-08


Epoch 16/100
43/43  0s 6ms/step - loss: 14.0111 - learning_rate: 5.6234e-08


Epoch 17/100
43/43  0s 6ms/step - loss: 12.6600 - learning_rate: 6.3096e-08


Epoch 18/100
43/43  0s 6ms/step - loss: 12.8982 - learning_rate: 7.0795e-08


Epoch 19/100
43/43  0s 6ms/step - loss: 12.8153 - learning_rate: 7.9433e-08


Epoch 20/100
43/43  0s 6ms/step - loss: 12.5494 - learning_rate: 8.9125e-08


Epoch 21/100
43/43  0s 6ms/step - loss: 12.3114 - learning_rate: 1.0000e-07


Epoch 22/100
43/43  0s 6ms/step - loss: 12.9391 - learning_rate: 1.1220e-07


Epoch 23/100
43/43  0s 6ms/step - loss: 12.3442 - learning_rate: 1.2589e-07


Epoch 24/100
43/43  0s 6ms/step - loss: 12.9822 - learning_rate: 1.4125e-07


Epoch 25/100
43/43  0s 7ms/step - loss: 11.4807 - learning_rate: 1.5849e-07


Epoch 26/100
43/43  0s 8ms/step - loss: 11.7031 - learning_rate: 1.7783e-07


Epoch 27/100
43/43  0s 7ms/step - loss: 12.3591 - learning_rate: 1.9953e-07


Epoch 28/100
43/43  0s 7ms/step - loss: 11.9551 - learning_rate: 2.2387e-07


Epoch 29/100
43/43  0s 7ms/step - loss: 11.6774 - learning_rate: 2.5119e-07


Epoch 30/100
43/43  0s 7ms/step - loss: 11.9666 - learning_rate: 2.8184e-07


Epoch 31/100
43/43  0s 7ms/step - loss: 11.6021 - learning_rate: 3.1623e-07


Epoch 32/100
43/43  0s 7ms/step - loss: 12.0587 - learning_rate: 3.5481e-07


Epoch 33/100
43/43  0s 7ms/step - loss: 12.1473 - learning_rate: 3.9811e-07


Epoch 34/100
43/43  0s 7ms/step - loss: 12.5433 - learning_rate: 4.4668e-07


Epoch 35/100
43/43  0s 7ms/step - loss: 12.0613 - learning_rate: 5.0119e-07


Epoch 36/100
43/43  0s 7ms/step - loss: 11.2821 - learning_rate: 5.6234e-07


Epoch 37/100
43/43  0s 7ms/step - loss: 11.3182 - learning_rate: 6.3096e-07


Epoch 38/100
43/43  0s 6ms/step - loss: 11.3331 - learning_rate: 7.0795e-07


Epoch 39/100
43/43  0s 7ms/step - loss: 11.7006 - learning_rate: 7.9433e-07


Epoch 40/100
43/43  0s 6ms/step - loss: 10.0455 - learning_rate: 8.9125e-07


Epoch 41/100
43/43  0s 7ms/step - loss: 10.2087 - learning_rate: 1.0000e-06


Epoch 42/100
43/43  0s 7ms/step - loss: 9.7991 - learning_rate: 1.1220e-06


Epoch 43/100
43/43  0s 7ms/step - loss: 11.3281 - learning_rate: 1.2589e-06


Epoch 44/100
43/43  0s 6ms/step - loss: 10.7669 - learning_rate: 1.4125e-06


Epoch 45/100
43/43  0s 7ms/step - loss: 10.5910 - learning_rate: 1.5849e-06


Epoch 46/100
43/43  0s 7ms/step - loss: 10.2546 - learning_rate: 1.7783e-06


Epoch 47/100
43/43  0s 6ms/step - loss: 10.3014 - learning_rate: 1.9953e-06


Epoch 48/100
43/43  0s 6ms/step - loss: 11.2328 - learning_rate: 2.2387e-06


Epoch 49/100
43/43  0s 6ms/step - loss: 10.4791 - learning_rate: 2.5119e-06


Epoch 50/100
43/43  0s 6ms/step - loss: 9.5278 - learning_rate: 2.8184e-06


Epoch 51/100
43/43  0s 6ms/step - loss: 10.3388 - learning_rate: 3.1623e-06


Epoch 52/100
43/43  0s 6ms/step - loss: 9.1898 - learning_rate: 3.5481e-06


Epoch 53/100
43/43  0s 6ms/step - loss: 10.1096 - learning_rate: 3.9811e-06


Epoch 54/100
43/43  0s 7ms/step - loss: 10.2749 - learning_rate: 4.4668e-06


Epoch 55/100
43/43  0s 6ms/step - loss: 10.3730 - learning_rate: 5.0119e-06


Epoch 56/100
43/43  0s 6ms/step - loss: 9.9820 - learning_rate: 5.6234e-06


Epoch 57/100
43/43  0s 6ms/step - loss: 10.2576 - learning_rate: 6.3096e-06




















Epoch 58/100
43/43  0s 6ms/step - loss: 10.2129 - learning_rate: 7.0795e-06























Epoch 59/100
43/43  0s 6ms/step - loss: 9.6284 - learning_rate: 7.9433e-06

Epoch 60/100
43/43  0s 6ms/step - loss: 10.1848 - learning_rate: 8.9125e-06































Epoch 61/100
43/43  0s 6ms/step - loss: 10.2990 - learning_rate: 1.0000e-05

Epoch 62/100
43/43  0s 6ms/step - loss: 10.1700 - learning_rate: 1.1220e-06

5
Epoch 63/100
43/43  0s 6ms/step - loss: 9.8889 - learning_rate: 1.2589e-05
Epoch 64/100
43/43  0s 6ms/step - loss: 9.6460 - learning_rate: 1.4125e-05
Epoch 65/100
43/43  0s 6ms/step - loss: 9.9368 - learning_rate: 1.5849e-05
Epoch 66/100
43/43  0s 6ms/step - loss: 9.9978 - learning_rate: 1.7783e-05
Epoch 67/100
43/43  0s 6ms/step - loss: 10.4472 - learning_rate: 1.9953e-05
5
Epoch 68/100
43/43  0s 6ms/step - loss: 9.7442 - learning_rate: 2.2387e-05
Epoch 69/100
43/43  0s 6ms/step - loss: 10.3375 - learning_rate: 2.5119e-05
5
Epoch 70/100
43/43  0s 6ms/step - loss: 10.7381 - learning_rate: 2.8184e-05
5
Epoch 71/100
43/43  0s 6ms/step - loss: 10.6683 - learning_rate: 3.1623e-05
5
Epoch 72/100
43/43  0s 6ms/step - loss: 10.9443 - learning_rate: 3.5481e-05
5
Epoch 73/100
43/43  0s 6ms/step - loss: 10.4606 - learning_rate: 3.9811e-05
5
Epoch 74/100
43/43  0s 6ms/step - loss: 10.0789 - learning_rate: 4.4668e-05
5
Epoch 75/100
43/43  0s 6ms/step - loss: 10.7290 - learning_rate: 5.0119e-05
5
Epoch 76/100
43/43  0s 6ms/step - loss: 10.3211 - learning_rate: 5.6234e-05
5
Epoch 77/100
43/43  0s 6ms/step - loss: 10.7727 - learning_rate: 6.3096e-05
5
Epoch 78/100
43/43  0s 6ms/step - loss: 10.5987 - learning_rate: 7.0795e-05
5
Epoch 79/100
43/43  0s 6ms/step - loss: 10.6715 - learning_rate: 7.9433e-05
5
Epoch 80/100
43/43  0s 6ms/step - loss: 9.9418 - learning_rate: 8.9125e-05
Epoch 81/100
43/43  0s 6ms/step - loss: 10.0236 - learning_rate: 1.0000e-04
4
Epoch 82/100
43/43  0s 6ms/step - loss: 10.2930 - learning_rate: 1.1220e-04
4
Epoch 83/100
43/43  0s 6ms/step - loss: 11.0452 - learning_rate: 1.2589e-04
4
Epoch 84/100
43/43  0s 6ms/step - loss: 10.1826 - learning_rate: 1.4125e-04

4
Epoch 85/100
43/43  0s 6ms/step - loss: 9.5261 - learning_rate: 1.5849e-04
Epoch 86/100
43/43  0s 6ms/step - loss: 10.0025 - learning_rate: 1.7783e-04
4
Epoch 87/100
43/43  0s 6ms/step - loss: 11.9670 - learning_rate: 1.9953e-04
4
Epoch 88/100
43/43  0s 6ms/step - loss: 10.1965 - learning_rate: 2.2387e-04
4
Epoch 89/100
43/43  0s 6ms/step - loss: 12.2081 - learning_rate: 2.5119e-04
4
Epoch 90/100
43/43  0s 6ms/step - loss: 11.2422 - learning_rate: 2.8184e-04
4
Epoch 91/100
43/43  0s 6ms/step - loss: 15.3763 - learning_rate: 3.1623e-04
4
Epoch 92/100
43/43  0s 6ms/step - loss: 10.6453 - learning_rate: 3.5481e-04
4
Epoch 93/100
43/43  0s 6ms/step - loss: 10.8564 - learning_rate: 3.9811e-04
4
Epoch 94/100
43/43  0s 6ms/step - loss: 10.9312 - learning_rate: 4.4668e-04
4
Epoch 95/100
43/43  0s 6ms/step - loss: 10.4106 - learning_rate: 5.0119e-04
4
Epoch 96/100
43/43  0s 6ms/step - loss: 12.0417 - learning_rate: 5.6234e-04
4
Epoch 97/100
43/43  0s 6ms/step - loss: 11.5762 - learning_rate: 6.3096e-04
4
Epoch 98/100
43/43  0s 6ms/step - loss: 11.9801 - learning_rate: 7.0795e-04
4
Epoch 99/100
43/43  0s 6ms/step - loss: 12.3684 - learning_rate: 7.9433e-04
4
Epoch 100/100
43/43  0s 6ms/step - loss: 17.2264 - learning_rate: 8.9125e-04
4
Epoch 1/100
43/43  2s 6ms/step - loss: 17.3013 - mae: 17.7960
Epoch 2/100
43/43  0s 6ms/step - loss: 11.4140 - mae: 11.9030
Epoch 3/100
43/43  0s 6ms/step - loss: 11.1987 - mae: 11.6916
Epoch 4/100
43/43  0s 6ms/step - loss: 10.3758 - mae: 10.8576
Epoch 5/100
43/43  0s 6ms/step - loss: 9.9475 - mae: 10.4377
Epoch 6/100
43/43  0s 6ms/step - loss: 10.8001 - mae: 11.2894

Epoch 7/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 11.0429 - mae: 11.5293
Epoch 8/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 11.2700 - mae: 11.7633
Epoch 9/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 9.8915 - mae: 10.3824
Epoch 10/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 9.9733 - mae: 10.4582
Epoch 11/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 11.0082 - mae: 11.4918
Epoch 12/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 10.1788 - mae: 10.6682
Epoch 13/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 10.1008 - mae: 10.5892
Epoch 14/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 10.1181 - mae: 10.6061
Epoch 15/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 9.9612 - mae: 10.4487
Epoch 16/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 10.6339 - mae: 11.1232
Epoch 17/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 10.2677 - mae: 10.7500
Epoch 18/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 9.5136 - mae: 10.0043
Epoch 19/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 9.9527 - mae: 10.4336
Epoch 20/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 10.0296 - mae: 10.5179
Epoch 21/100		
43/43	<div><div></div></div>	0s 7ms/step - loss: 9.4861 - mae: 9.9581
Epoch 22/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 9.6790 - mae: 10.1668
Epoch 23/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 9.3169 - mae: 9.8076
Epoch 24/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 9.3816 - mae: 9.8621
Epoch 25/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 8.9231 - mae: 9.4005
Epoch 26/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 9.2830 - mae: 9.7639
Epoch 27/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 10.3046 - mae: 10.7847
Epoch 28/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 9.3040 - mae: 9.7928
Epoch 29/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 9.6202 - mae: 10.1056
Epoch 30/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 9.7873 - mae: 10.2672
Epoch 31/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 9.7167 - mae: 10.2038
Epoch 32/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 9.4299 - mae: 9.9185
Epoch 33/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 9.8510 - mae: 10.3397
Epoch 34/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 9.6904 - mae: 10.1783
Epoch 35/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 9.2091 - mae: 9.6896
Epoch 36/100		
43/43	<div><div></div></div>	0s 6ms/step - loss: 8.9814 - mae: 9.4630

Epoch 37/100
43/43  0s 6ms/step - loss: 9.1416 - mae: 9.6348
Epoch 38/100
43/43  0s 6ms/step - loss: 9.2719 - mae: 9.7519
Epoch 39/100
43/43  0s 6ms/step - loss: 9.7753 - mae: 10.2623
Epoch 40/100
43/43  0s 6ms/step - loss: 9.3383 - mae: 9.8149
Epoch 41/100
43/43  0s 8ms/step - loss: 9.4363 - mae: 9.9267
Epoch 42/100
43/43  0s 7ms/step - loss: 9.1692 - mae: 9.6637
Epoch 43/100
43/43  0s 6ms/step - loss: 10.0476 - mae: 10.5387
Epoch 44/100
43/43  0s 6ms/step - loss: 9.3073 - mae: 9.7909
Epoch 45/100
43/43  0s 6ms/step - loss: 9.9773 - mae: 10.4625
Epoch 46/100
43/43  0s 7ms/step - loss: 10.1951 - mae: 10.6823
Epoch 47/100
43/43  0s 6ms/step - loss: 10.0389 - mae: 10.5218
Epoch 48/100
43/43  0s 7ms/step - loss: 9.7482 - mae: 10.2328
Epoch 49/100
43/43  0s 6ms/step - loss: 9.5882 - mae: 10.0784
Epoch 50/100
43/43  0s 7ms/step - loss: 9.5582 - mae: 10.0453
Epoch 51/100
43/43  0s 7ms/step - loss: 9.8811 - mae: 10.3672
Epoch 52/100
43/43  0s 6ms/step - loss: 9.3308 - mae: 9.8166
Epoch 53/100
43/43  0s 6ms/step - loss: 9.7934 - mae: 10.2828
Epoch 54/100
43/43  0s 7ms/step - loss: 9.2486 - mae: 9.7372
Epoch 55/100
43/43  0s 7ms/step - loss: 9.4040 - mae: 9.8888
Epoch 56/100
43/43  0s 7ms/step - loss: 9.3959 - mae: 9.8860
Epoch 57/100
43/43  0s 7ms/step - loss: 9.3732 - mae: 9.8604
Epoch 58/100
43/43  0s 7ms/step - loss: 9.3751 - mae: 9.8610
Epoch 59/100
43/43  0s 7ms/step - loss: 9.9446 - mae: 10.4278
Epoch 60/100
43/43  0s 6ms/step - loss: 9.4147 - mae: 9.8981
Epoch 61/100
43/43  0s 6ms/step - loss: 9.5269 - mae: 10.0144
Epoch 62/100
43/43  0s 6ms/step - loss: 9.2933 - mae: 9.7802
Epoch 63/100
43/43  0s 8ms/step - loss: 9.4189 - mae: 9.9015
Epoch 64/100
43/43  0s 7ms/step - loss: 10.0072 - mae: 10.4945
Epoch 65/100
43/43  0s 6ms/step - loss: 9.2250 - mae: 9.7140
Epoch 66/100
43/43  0s 6ms/step - loss: 8.9105 - mae: 9.3969

Epoch 67/100			
43/43	<div></div>	0s 6ms/step	loss: 9.2766 - mae: 9.7660
Epoch 68/100			
43/43	<div></div>	0s 6ms/step	loss: 9.9076 - mae: 10.3986
Epoch 69/100			
43/43	<div></div>	0s 6ms/step	loss: 9.5010 - mae: 9.9848
Epoch 70/100			
43/43	<div></div>	0s 6ms/step	loss: 9.4488 - mae: 9.9309
Epoch 71/100			
43/43	<div></div>	0s 6ms/step	loss: 9.4924 - mae: 9.9823
Epoch 72/100			
43/43	<div></div>	0s 6ms/step	loss: 9.6542 - mae: 10.1379
Epoch 73/100			
43/43	<div></div>	0s 7ms/step	loss: 9.3203 - mae: 9.8072
Epoch 74/100			
43/43	<div></div>	0s 6ms/step	loss: 10.0586 - mae: 10.5471
Epoch 75/100			
43/43	<div></div>	0s 6ms/step	loss: 9.3886 - mae: 9.8772
Epoch 76/100			
43/43	<div></div>	0s 6ms/step	loss: 9.9043 - mae: 10.3883
Epoch 77/100			
43/43	<div></div>	0s 7ms/step	loss: 9.5862 - mae: 10.0701
Epoch 78/100			
43/43	<div></div>	0s 6ms/step	loss: 9.0002 - mae: 9.4931
Epoch 79/100			
43/43	<div></div>	0s 6ms/step	loss: 9.6321 - mae: 10.1271
Epoch 80/100			
43/43	<div></div>	0s 7ms/step	loss: 9.2293 - mae: 9.7085
Epoch 81/100			
43/43	<div></div>	0s 7ms/step	loss: 9.2459 - mae: 9.7275
Epoch 82/100			
43/43	<div></div>	0s 6ms/step	loss: 9.0975 - mae: 9.5864
Epoch 83/100			
43/43	<div></div>	0s 7ms/step	loss: 9.4294 - mae: 9.9226
Epoch 84/100			
43/43	<div></div>	0s 6ms/step	loss: 9.2111 - mae: 9.6990
Epoch 85/100			
43/43	<div></div>	0s 6ms/step	loss: 9.4661 - mae: 9.9538
Epoch 86/100			
43/43	<div></div>	0s 7ms/step	loss: 10.2806 - mae: 10.7710
Epoch 87/100			
43/43	<div></div>	0s 6ms/step	loss: 9.2419 - mae: 9.7297
Epoch 88/100			
43/43	<div></div>	0s 6ms/step	loss: 9.2789 - mae: 9.7696
Epoch 89/100			
43/43	<div></div>	0s 6ms/step	loss: 9.3731 - mae: 9.8601
Epoch 90/100			
43/43	<div></div>	0s 7ms/step	loss: 9.5639 - mae: 10.0527
Epoch 91/100			
43/43	<div></div>	0s 6ms/step	loss: 9.5485 - mae: 10.0325
Epoch 92/100			
43/43	<div></div>	0s 6ms/step	loss: 9.0998 - mae: 9.5881
Epoch 93/100			
43/43	<div></div>	0s 6ms/step	loss: 9.3962 - mae: 9.8814
Epoch 94/100			
43/43	<div></div>	0s 6ms/step	loss: 8.8060 - mae: 9.2961
Epoch 95/100			
43/43	<div></div>	0s 7ms/step	loss: 9.8214 - mae: 10.3101
Epoch 96/100			
43/43	<div></div>	0s 7ms/step	loss: 9.9921 - mae: 10.4758

```

Epoch 97/100
43/43 ————— 0s 7ms/step - loss: 9.7791 - mae: 10.2712
Epoch 98/100
43/43 ————— 0s 7ms/step - loss: 9.7671 - mae: 10.2587
Epoch 99/100
43/43 ————— 0s 7ms/step - loss: 9.2778 - mae: 9.7602
Epoch 100/100
43/43 ————— 0s 8ms/step - loss: 10.0112 - mae: 10.4940

```

```

In [66]: # Reduce the original series
forecast_series = series[split_time-window_size:-1]

# Use helper function to generate predictions
forecast = model_forecast(model, forecast_series, window_size, batch_size)

# Drop single dimensional axis
results = forecast.squeeze()

x_valid2 = x_valid.squeeze()

# Calculamos la métrica sobre el conjunto de prueba (validación)
print(tf.keras.metrics.MSE(x_valid2, results).numpy())
print(tf.keras.metrics.MAE(x_valid2, results).numpy())

```

```

12/12 ————— 0s 17ms/step
200.74113
11.611933

```

Obtenemos resultados igual de malos que en el Modelo 3.

Métricas:

MSE

Modelo 1: 90.84448

Modelo 2: 122.25438

Modelo 3: 200.42162

Modelo 4: 200.74113

MAE

Modelo 1: 7.161354

Modelo 2: 8.913031

Modelo 3: 11.5769205

Modelo 4: 11.611933

Modelo 5 (Modelo 1 con 300 epochs)

```

In [48]: model_tune = tf.keras.models.Sequential([
    tf.keras.layers.Lambda(lambda x: tf.expand_dims(x, axis=-1),
        input_shape=[window_size]),

```

```

    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(8, return_sequences=True))
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(8)),
    tf.keras.layers.Dense(1),
    tf.keras.layers.Lambda(lambda x: x * 100.0)
])

```

In [49]: *#Aquí vamos a dar el valor del Learning rate que nos da mejores resultados*

```

# Conjunto de datos partidos en "ventanas"
dataset = windowed_dataset(series, window_size, batch_size, shuffle_buffer_size)


#Esto permite que se use la información del epoch en el que vamos (ciclo hacia a
#para actualizar la Learning rate a través de alguna función, aquí en particular
#se incrementa el epoch el Learning rate se hace más grande
lr_schedule = tf.keras.callbacks.LearningRateScheduler(
    lambda epoch: 1e-8 * 10**(epoch / 20))


# Initialize the optimizer
#Uso de descenso del gradiente como método para actualizar los pesos con un pará
#que acelera el descenso de gradiente en la dirección relevante
optimizer = tf.keras.optimizers.SGD(momentum=0.9)


# Set the training parameters
#La función de pérdida usada es la de Huber. Esta función de pérdida incluye una
#para cuando no estamos cerca del valor real, usando optimizer que definimos arr
model_tune.compile(loss=tf.keras.losses.Huber(), optimizer=optimizer)


# Train the model
#Ponemos a que sean 300 epochs, con Learning rate que se actualiza según lr_scne
history = model_tune.fit(dataset, epochs=300, callbacks=[lr_schedule])


```


Epoch 1/300
43/43  3s 9ms/step - loss: 28.1931 - learning_rate: 1.0000e-08


Epoch 2/300
43/43  0s 9ms/step - loss: 29.3745 - learning_rate: 1.1220e-08


Epoch 3/300
43/43  0s 9ms/step - loss: 28.2501 - learning_rate: 1.2589e-08


Epoch 4/300
43/43  0s 9ms/step - loss: 28.1482 - learning_rate: 1.4125e-08


Epoch 5/300
43/43  0s 8ms/step - loss: 27.0111 - learning_rate: 1.5849e-08


Epoch 6/300
43/43  0s 9ms/step - loss: 27.6514 - learning_rate: 1.7783e-08


Epoch 7/300
43/43  0s 9ms/step - loss: 26.6663 - learning_rate: 1.9953e-08


Epoch 8/300
43/43  0s 9ms/step - loss: 28.0894 - learning_rate: 2.2387e-08


Epoch 9/300
43/43  0s 9ms/step - loss: 26.1826 - learning_rate: 2.5119e-08


Epoch 10/300
43/43  0s 9ms/step - loss: 26.8503 - learning_rate: 2.8184e-08


Epoch 11/300
43/43  0s 9ms/step - loss: 26.8309 - learning_rate: 3.1623e-08


Epoch 12/300
43/43  0s 10ms/step - loss: 26.3015 - learning_rate: 3.5481e-08


Epoch 13/300
43/43  0s 9ms/step - loss: 26.1185 - learning_rate: 3.9811e-08


Epoch 14/300
43/43  0s 9ms/step - loss: 24.4207 - learning_rate: 4.4668e-08


Epoch 15/300
43/43  0s 9ms/step - loss: 24.0081 - learning_rate: 5.0119e-08


Epoch 16/300
43/43  0s 9ms/step - loss: 23.2332 - learning_rate: 5.6234e-08


Epoch 17/300
43/43  0s 9ms/step - loss: 22.6521 - learning_rate: 6.3096e-08


Epoch 18/300
43/43  0s 9ms/step - loss: 21.9881 - learning_rate: 7.0795e-08


Epoch 19/300
43/43  0s 9ms/step - loss: 21.0935 - learning_rate: 7.9433e-08


Epoch 20/300
43/43  0s 9ms/step - loss: 20.9077 - learning_rate: 8.9125e-08


Epoch 21/300
43/43  0s 9ms/step - loss: 19.7702 - learning_rate: 1.0000e-07


Epoch 22/300
43/43  0s 8ms/step - loss: 19.0968 - learning_rate: 1.1220e-07


Epoch 23/300
43/43  0s 8ms/step - loss: 19.1317 - learning_rate: 1.2589e-07


Epoch 24/300
43/43  0s 9ms/step - loss: 17.4572 - learning_rate: 1.4125e-07


Epoch 25/300
43/43  0s 9ms/step - loss: 16.6812 - learning_rate: 1.5849e-07


Epoch 26/300
43/43  0s 8ms/step - loss: 16.1364 - learning_rate: 1.7783e-07


Epoch 27/300
43/43  0s 9ms/step - loss: 16.7073 - learning_rate: 1.9953e-07


Epoch 28/300
43/43  0s 9ms/step - loss: 16.2240 - learning_rate: 2.2387e-07


Epoch 29/300
43/43  0s 8ms/step - loss: 14.7370 - learning_rate: 2.5119e-07


Epoch 30/300
43/43  0s 9ms/step - loss: 14.3253 - learning_rate: 2.8184e-07


Epoch 31/300
43/43  0s 9ms/step - loss: 12.7855 - learning_rate: 3.1623e-07


Epoch 32/300
43/43  0s 10ms/step - loss: 14.4204 - learning_rate: 3.5481e-07


Epoch 33/300
43/43  0s 9ms/step - loss: 12.8690 - learning_rate: 3.9811e-07


Epoch 34/300
43/43  0s 9ms/step - loss: 12.8229 - learning_rate: 4.4668e-07


Epoch 35/300
43/43  0s 8ms/step - loss: 13.1302 - learning_rate: 5.0119e-07


Epoch 36/300
43/43  0s 9ms/step - loss: 13.1263 - learning_rate: 5.6234e-07


Epoch 37/300
43/43  0s 9ms/step - loss: 12.0709 - learning_rate: 6.3096e-07


Epoch 38/300
43/43  0s 9ms/step - loss: 12.3130 - learning_rate: 7.0795e-07


Epoch 39/300
43/43  0s 9ms/step - loss: 12.3761 - learning_rate: 7.9433e-07


Epoch 40/300
43/43  0s 9ms/step - loss: 12.0536 - learning_rate: 8.9125e-07


Epoch 41/300
43/43  0s 9ms/step - loss: 11.7713 - learning_rate: 1.0000e-06


Epoch 42/300
43/43  0s 9ms/step - loss: 11.8207 - learning_rate: 1.1220e-06


Epoch 43/300
43/43  0s 8ms/step - loss: 10.8305 - learning_rate: 1.2589e-06


Epoch 44/300
43/43  0s 9ms/step - loss: 11.4879 - learning_rate: 1.4125e-06


Epoch 45/300
43/43  0s 9ms/step - loss: 10.6115 - learning_rate: 1.5849e-06


Epoch 46/300
43/43  0s 9ms/step - loss: 11.5082 - learning_rate: 1.7783e-06


Epoch 47/300
43/43  0s 9ms/step - loss: 10.9844 - learning_rate: 1.9953e-06


Epoch 48/300
43/43  0s 8ms/step - loss: 11.0296 - learning_rate: 2.2387e-06


Epoch 49/300
43/43  0s 9ms/step - loss: 10.5929 - learning_rate: 2.5119e-06


Epoch 50/300
43/43  0s 9ms/step - loss: 11.1991 - learning_rate: 2.8184e-06


Epoch 51/300
43/43  0s 8ms/step - loss: 10.5574 - learning_rate: 3.1623e-06


Epoch 52/300
43/43  0s 9ms/step - loss: 10.3819 - learning_rate: 3.5481e-06


Epoch 53/300
43/43  0s 8ms/step - loss: 9.8645 - learning_rate: 3.9811e-06


Epoch 54/300
43/43  0s 9ms/step - loss: 10.1178 - learning_rate: 4.4668e-06


Epoch 55/300
43/43  0s 9ms/step - loss: 9.5448 - learning_rate: 5.0119e-06


Epoch 56/300
43/43  0s 9ms/step - loss: 9.6180 - learning_rate: 5.6234e-06


Epoch 57/300
43/43  0s 9ms/step - loss: 9.9099 - learning_rate: 6.3096e-06


Epoch 58/300
43/43  0s 9ms/step - loss: 9.4822 - learning_rate: 7.0795e-06

























Epoch 59/300
43/43  0s 9ms/step - loss: 9.2269 - learning_rate: 7.9433e-06


Epoch 60/300
43/43  0s 8ms/step - loss: 10.0574 - learning_rate: 8.9125e-06


Epoch 61/300
43/43  0s 8ms/step - loss: 9.3719 - learning_rate: 1.0000e-05


Epoch 62/300
43/43  0s 9ms/step - loss: 9.5730 - learning_rate: 1.1220e-05


Epoch 63/300
43/43  0s 9ms/step - loss: 8.8027 - learning_rate: 1.2589e-05


Epoch 64/300
43/43  0s 9ms/step - loss: 8.7391 - learning_rate: 1.4125e-05
Epoch 65/300
43/43  0s 8ms/step - loss: 9.8515 - learning_rate: 1.5849e-05
Epoch 66/300
43/43  0s 8ms/step - loss: 9.0321 - learning_rate: 1.7783e-05
Epoch 67/300
43/43  0s 9ms/step - loss: 9.6318 - learning_rate: 1.9953e-05
Epoch 68/300
43/43  0s 9ms/step - loss: 9.2384 - learning_rate: 2.2387e-05
Epoch 69/300
43/43  0s 10ms/step - loss: 9.3742 - learning_rate: 2.5119e-05
Epoch 70/300
43/43  0s 9ms/step - loss: 9.6681 - learning_rate: 2.8184e-05
Epoch 71/300
43/43  0s 9ms/step - loss: 9.3461 - learning_rate: 3.1623e-05
Epoch 72/300
43/43  0s 8ms/step - loss: 10.4588 - learning_rate: 3.5481e-05
Epoch 73/300
43/43  0s 9ms/step - loss: 9.4502 - learning_rate: 3.9811e-05
Epoch 74/300
43/43  0s 9ms/step - loss: 10.5546 - learning_rate: 4.4668e-05
Epoch 75/300
43/43  0s 9ms/step - loss: 10.5258 - learning_rate: 5.0119e-05
Epoch 76/300
43/43  0s 9ms/step - loss: 9.8366 - learning_rate: 5.6234e-05
Epoch 77/300
43/43  0s 9ms/step - loss: 10.2663 - learning_rate: 6.3096e-05
Epoch 78/300
43/43  0s 8ms/step - loss: 9.5190 - learning_rate: 7.0795e-05
Epoch 79/300
43/43  0s 9ms/step - loss: 9.7780 - learning_rate: 7.9433e-05
Epoch 80/300
43/43  0s 9ms/step - loss: 9.9450 - learning_rate: 8.9125e-05
Epoch 81/300
43/43  0s 8ms/step - loss: 9.5255 - learning_rate: 1.0000e-04
Epoch 82/300
43/43  0s 9ms/step - loss: 14.6696 - learning_rate: 1.1220e-04
Epoch 83/300
43/43  0s 9ms/step - loss: 10.6811 - learning_rate: 1.2589e-04
Epoch 84/300
43/43  0s 9ms/step - loss: 10.6123 - learning_rate: 1.4125e-04
Epoch 85/300
43/43  0s 9ms/step - loss: 11.5651 - learning_rate: 1.5849e-04
Epoch 86/300
43/43  0s 10ms/step - loss: 10.7440 - learning_rate: 1.7783e-04
Epoch 87/300
43/43  0s 9ms/step - loss: 11.3558 - learning_rate: 1.9953e-04
Epoch 88/300


43/43  0s 9ms/step - loss: 9.4736 - learning_rate: 2.2387e-04
Epoch 89/300


43/43  0s 9ms/step - loss: 10.0665 - learning_rate: 2.5119e-04
Epoch 90/300


43/43  0s 9ms/step - loss: 12.3265 - learning_rate: 2.8184e-04
Epoch 91/300


43/43  0s 8ms/step - loss: 10.5215 - learning_rate: 3.1623e-04
Epoch 92/300


43/43  0s 9ms/step - loss: 11.9618 - learning_rate: 3.5481e-04
Epoch 93/300


43/43  0s 9ms/step - loss: 11.4972 - learning_rate: 3.9811e-04
Epoch 94/300


43/43  0s 9ms/step - loss: 11.5586 - learning_rate: 4.4668e-04
Epoch 95/300


43/43  0s 9ms/step - loss: 12.3933 - learning_rate: 5.0119e-04
Epoch 96/300


43/43  0s 8ms/step - loss: 12.7450 - learning_rate: 5.6234e-04
Epoch 97/300


43/43  0s 9ms/step - loss: 13.3838 - learning_rate: 6.3096e-04
Epoch 98/300


43/43  0s 8ms/step - loss: 11.4946 - learning_rate: 7.0795e-04
Epoch 99/300


43/43  0s 8ms/step - loss: 13.2036 - learning_rate: 7.9433e-04
Epoch 100/300


43/43  0s 8ms/step - loss: 11.5553 - learning_rate: 8.9125e-04
Epoch 101/300


43/43  0s 9ms/step - loss: 11.6279 - learning_rate: 0.0010
Epoch 102/300


43/43  0s 9ms/step - loss: 16.4929 - learning_rate: 0.0011
Epoch 103/300


43/43  0s 9ms/step - loss: 13.7857 - learning_rate: 0.0013
Epoch 104/300


43/43  0s 8ms/step - loss: 12.8430 - learning_rate: 0.0014
Epoch 105/300


43/43  0s 9ms/step - loss: 16.4250 - learning_rate: 0.0016
Epoch 106/300


43/43  0s 9ms/step - loss: 14.5620 - learning_rate: 0.0018
Epoch 107/300


43/43  0s 9ms/step - loss: 17.0005 - learning_rate: 0.0020
Epoch 108/300


43/43  0s 9ms/step - loss: 13.9269 - learning_rate: 0.0022
Epoch 109/300


43/43  0s 9ms/step - loss: 15.2191 - learning_rate: 0.0025
Epoch 110/300


43/43  0s 9ms/step - loss: 29.3000 - learning_rate: 0.0028
Epoch 111/300


43/43  0s 9ms/step - loss: 16.9176 - learning_rate: 0.0032
Epoch 112/300


43/43  0s 9ms/step - loss: 23.7796 - learning_rate: 0.0035
Epoch 113/300


43/43  0s 9ms/step - loss: 21.2006 - learning_rate: 0.0040
Epoch 114/300


43/43  0s 9ms/step - loss: 17.9735 - learning_rate: 0.0045
Epoch 115/300


43/43  0s 8ms/step - loss: 26.3414 - learning_rate: 0.0050
Epoch 116/300


43/43  0s 9ms/step - loss: 31.2172 - learning_rate: 0.0056
Epoch 117/300


43/43  0s 9ms/step - loss: 85.1496 - learning_rate: 0.0063
Epoch 118/300


43/43  0s 9ms/step - loss: 104.3421 - learning_rate: 0.0071
Epoch 119/300


43/43  0s 9ms/step - loss: 114.8178 - learning_rate: 0.0079
Epoch 120/300


43/43  0s 8ms/step - loss: 48.1101 - learning_rate: 0.0089
Epoch 121/300


43/43  0s 8ms/step - loss: 77.1315 - learning_rate: 0.0100
Epoch 122/300


43/43  0s 8ms/step - loss: 65.7176 - learning_rate: 0.0112
Epoch 123/300


43/43  0s 9ms/step - loss: 61.9318 - learning_rate: 0.0126
Epoch 124/300


43/43  0s 9ms/step - loss: 168.9651 - learning_rate: 0.0141
Epoch 125/300


43/43  0s 9ms/step - loss: 183.1717 - learning_rate: 0.0158
Epoch 126/300


43/43  0s 9ms/step - loss: 177.2868 - learning_rate: 0.0178
Epoch 127/300


43/43  0s 8ms/step - loss: 119.2953 - learning_rate: 0.0200
Epoch 128/300


43/43  0s 9ms/step - loss: 117.3120 - learning_rate: 0.0224
Epoch 129/300


43/43  0s 9ms/step - loss: 101.9693 - learning_rate: 0.0251
Epoch 130/300


43/43  0s 9ms/step - loss: 148.9558 - learning_rate: 0.0282
Epoch 131/300


43/43  0s 8ms/step - loss: 210.5111 - learning_rate: 0.0316
Epoch 132/300


43/43  0s 8ms/step - loss: 291.2883 - learning_rate: 0.0355
Epoch 133/300


43/43  0s 8ms/step - loss: 208.7988 - learning_rate: 0.0398
Epoch 134/300


43/43  0s 8ms/step - loss: 270.1143 - learning_rate: 0.0447
Epoch 135/300


43/43  0s 10ms/step - loss: 334.1456 - learning_rate: 0.0501
Epoch 136/300


43/43  0s 9ms/step - loss: 300.3108 - learning_rate: 0.0562
Epoch 137/300


43/43  0s 9ms/step - loss: 488.1733 - learning_rate: 0.0631
Epoch 138/300


43/43  0s 8ms/step - loss: 630.6548 - learning_rate: 0.0708
Epoch 139/300


43/43  0s 9ms/step - loss: 952.5734 - learning_rate: 0.0794
Epoch 140/300


43/43  0s 9ms/step - loss: 925.0166 - learning_rate: 0.0891
Epoch 141/300


43/43  0s 9ms/step - loss: 690.3282 - learning_rate: 0.1000
Epoch 142/300


43/43  0s 9ms/step - loss: 1133.6462 - learning_rate: 0.1122
Epoch 143/300


43/43  0s 9ms/step - loss: 1172.8704 - learning_rate: 0.1259
Epoch 144/300


43/43  0s 10ms/step - loss: 1409.6646 - learning_rate: 0.1413
Epoch 145/300


43/43  0s 8ms/step - loss: 2406.2542 - learning_rate: 0.1585
Epoch 146/300


43/43  0s 9ms/step - loss: 2852.8562 - learning_rate: 0.1778
Epoch 147/300


43/43  0s 10ms/step - loss: 1706.3550 - learning_rate: 0.1995
Epoch 148/300


43/43  1s 11ms/step - loss: 1096.8768 - learning_rate: 0.2239
Epoch 149/300


43/43  0s 10ms/step - loss: 1308.7451 - learning_rate: 0.2512
Epoch 150/300


43/43  0s 9ms/step - loss: 1709.1527 - learning_rate: 0.2818
Epoch 151/300


43/43  0s 10ms/step - loss: 1760.1178 - learning_rate: 0.3162
Epoch 152/300


43/43  0s 10ms/step - loss: 1857.9910 - learning_rate: 0.3548
Epoch 153/300


43/43  0s 10ms/step - loss: 3935.6218 - learning_rate: 0.3981
Epoch 154/300


43/43  0s 9ms/step - loss: 2622.9766 - learning_rate: 0.4467
Epoch 155/300


43/43  0s 9ms/step - loss: 4293.0298 - learning_rate: 0.5012
Epoch 156/300


43/43  0s 9ms/step - loss: 5935.9561 - learning_rate: 0.5623
Epoch 157/300


43/43  0s 10ms/step - loss: 6287.9878 - learning_rate: 0.6310
Epoch 158/300


43/43  0s 9ms/step - loss: 5858.7021 - learning_rate: 0.7079
Epoch 159/300


43/43  0s 9ms/step - loss: 2053.4153 - learning_rate: 0.7943
Epoch 160/300


43/43  0s 9ms/step - loss: 7198.5518 - learning_rate: 0.8913
Epoch 161/300


43/43  0s 9ms/step - loss: 7115.3242 - learning_rate: 1.0000
Epoch 162/300


43/43  0s 9ms/step - loss: 5908.0854 - learning_rate: 1.1220
Epoch 163/300


43/43  0s 9ms/step - loss: 6513.8389 - learning_rate: 1.2589
Epoch 164/300


43/43  0s 9ms/step - loss: 15487.2275 - learning_rate: 1.4125
Epoch 165/300


43/43  0s 8ms/step - loss: 21916.0664 - learning_rate: 1.5849
Epoch 166/300


43/43  0s 9ms/step - loss: 18110.6289 - learning_rate: 1.7783
Epoch 167/300

43/43  0s 9ms/step - loss: 20839.2598 - learning_rate: 1.9953
Epoch 168/300

43/43  0s 9ms/step - loss: 40411.1055 - learning_rate: 2.2387
Epoch 169/300


43/43  0s 8ms/step - loss: 35317.7617 - learning_rate: 2.5119
Epoch 170/300


43/43  0s 9ms/step - loss: 31720.1426 - learning_rate: 2.8184
Epoch 171/300


43/43  0s 9ms/step - loss: 32609.7910 - learning_rate: 3.1623
Epoch 172/300


43/43 ————— 0s 9ms/step - loss: 56905.9727 - learning_rate: 3.5481
Epoch 173/300
43/43 ————— 0s 9ms/step - loss: 54614.8164 - learning_rate: 3.9811
Epoch 174/300
43/43 ————— 0s 9ms/step - loss: 62559.3594 - learning_rate: 4.4668
Epoch 175/300
43/43 ————— 0s 9ms/step - loss: 71996.3828 - learning_rate: 5.0119
Epoch 176/300
43/43 ————— 0s 8ms/step - loss: 44021.0430 - learning_rate: 5.6234
Epoch 177/300
43/43 ————— 0s 9ms/step - loss: 74362.4844 - learning_rate: 6.3096
Epoch 178/300
43/43 ————— 0s 8ms/step - loss: 415673.8125 - learning_rate: 7.0795
Epoch 179/300
43/43 ————— 0s 9ms/step - loss: 761643.0000 - learning_rate: 7.9433
Epoch 180/300
43/43 ————— 0s 9ms/step - loss: 1203888.1250 - learning_rate: 8.9125
Epoch 181/300
43/43 ————— 0s 9ms/step - loss: 628199.1250 - learning_rate: 10.0000
Epoch 182/300
43/43 ————— 0s 9ms/step - loss: 739791.8750 - learning_rate: 11.2202
Epoch 183/300
43/43 ————— 0s 9ms/step - loss: 1043523.3125 - learning_rate: 12.5893
Epoch 184/300
43/43 ————— 0s 9ms/step - loss: 440683.0312 - learning_rate: 14.1254
Epoch 185/300
43/43 ————— 0s 9ms/step - loss: 446871.2500 - learning_rate: 15.8489
Epoch 186/300
43/43 ————— 0s 9ms/step - loss: 1002477.0000 - learning_rate: 17.7828
Epoch 187/300
43/43 ————— 0s 8ms/step - loss: 1925381.8750 - learning_rate: 19.9526
Epoch 188/300
43/43 ————— 0s 9ms/step - loss: 859388.6250 - learning_rate: 22.3872
Epoch 189/300
43/43 ————— 0s 8ms/step - loss: 1624523.2500 - learning_rate: 25.1189
Epoch 190/300
43/43 ————— 0s 9ms/step - loss: 2259431.0000 - learning_rate: 28.1838
Epoch 191/300
43/43 ————— 0s 9ms/step - loss: 1510500.8750 - learning_rate: 31.6228
Epoch 192/300
43/43 ————— 0s 10ms/step - loss: 2125333.0000 - learning_rate: 35.4813
Epoch 193/300
43/43 ————— 0s 10ms/step - loss: 1471295.0000 - learning_rate: 39.8107
Epoch 194/300


43/43 ————— 1s 11ms/step - loss: 2215386.0000 - learning_rate: 44.6684
Epoch 195/300
43/43 ————— 0s 9ms/step - loss: 4390655.5000 - learning_rate: 50.1187
Epoch 196/300
43/43 ————— 0s 9ms/step - loss: 5040729.0000 - learning_rate: 56.2341
Epoch 197/300
43/43 ————— 1s 11ms/step - loss: 2902520.5000 - learning_rate: 63.0957
Epoch 198/300
43/43 ————— 0s 9ms/step - loss: 5471350.5000 - learning_rate: 70.7946
Epoch 199/300
43/43 ————— 1s 11ms/step - loss: 3531622.5000 - learning_rate: 79.4328
Epoch 200/300
43/43 ————— 1s 12ms/step - loss: 4260089.5000 - learning_rate: 89.1251
Epoch 201/300
43/43 ————— 1s 11ms/step - loss: 6685639.5000 - learning_rate: 100.0000
Epoch 202/300
43/43 ————— 1s 12ms/step - loss: 6088729.0000 - learning_rate: 112.2018
Epoch 203/300
43/43 ————— 1s 15ms/step - loss: 11361024.0000 - learning_rate: 125.8925
Epoch 204/300
43/43 ————— 1s 16ms/step - loss: 12746171.0000 - learning_rate: 141.2538
Epoch 205/300
43/43 ————— 1s 15ms/step - loss: 8357888.0000 - learning_rate: 158.4893
Epoch 206/300
43/43 ————— 1s 11ms/step - loss: 11697764.0000 - learning_rate: 177.8279
Epoch 207/300
43/43 ————— 1s 12ms/step - loss: 9149957.0000 - learning_rate: 199.5262
Epoch 208/300
43/43 ————— 1s 13ms/step - loss: 7353246.5000 - learning_rate: 223.8721
Epoch 209/300
43/43 ————— 1s 11ms/step - loss: 23921998.0000 - learning_rate: 251.1886
Epoch 210/300
43/43 ————— 1s 10ms/step - loss: 25938516.0000 - learning_rate: 281.8383
Epoch 211/300
43/43 ————— 1s 11ms/step - loss: 23011370.0000 - learning_rate: 316.2278
Epoch 212/300
43/43 ————— 1s 11ms/step - loss: 26483398.0000 - learning_rate: 354.8134
Epoch 213/300
43/43 ————— 1s 13ms/step - loss: 19733372.0000 - learning_rate: 398.1072
Epoch 214/300


43/43  1s 13ms/step - loss: 24480420.0000 - learning_rate: 44
6.6836
Epoch 215/300


43/43  1s 13ms/step - loss: 23768118.0000 - learning_rate: 50
1.1872
Epoch 216/300


43/43  1s 12ms/step - loss: 37529044.0000 - learning_rate: 56
2.3413
Epoch 217/300


43/43  1s 12ms/step - loss: 20994846.0000 - learning_rate: 63
0.9573
Epoch 218/300


43/43  1s 14ms/step - loss: 70497656.0000 - learning_rate: 70
7.9458
Epoch 219/300


43/43  1s 13ms/step - loss: 113184928.0000 - learning_rate: 7
94.3282
Epoch 220/300


43/43  1s 11ms/step - loss: 114917296.0000 - learning_rate: 8
91.2509
Epoch 221/300


43/43  0s 10ms/step - loss: 90841256.0000 - learning_rate: 10
00.0000
Epoch 222/300


43/43  0s 10ms/step - loss: 42656260.0000 - learning_rate: 11
22.0184
Epoch 223/300


43/43  1s 14ms/step - loss: 75517456.0000 - learning_rate: 12
58.9254
Epoch 224/300


43/43  1s 11ms/step - loss: 76066496.0000 - learning_rate: 14
12.5376
Epoch 225/300


43/43  1s 11ms/step - loss: 99995720.0000 - learning_rate: 15
84.8932
Epoch 226/300


43/43  0s 10ms/step - loss: 94766344.0000 - learning_rate: 17
78.2794
Epoch 227/300


43/43  0s 10ms/step - loss: 112679192.0000 - learning_rate: 1
995.2623
Epoch 228/300


43/43  0s 10ms/step - loss: 122792096.0000 - learning_rate: 2
238.7212
Epoch 229/300


43/43  1s 12ms/step - loss: 219495136.0000 - learning_rate: 2
511.8865
Epoch 230/300


43/43  1s 11ms/step - loss: 214595856.0000 - learning_rate: 2
818.3828
Epoch 231/300


43/43  0s 10ms/step - loss: 127575088.0000 - learning_rate: 3
162.2776
Epoch 232/300


43/43  0s 10ms/step - loss: 203931600.0000 - learning_rate: 3
548.1338
Epoch 233/300


43/43  1s 13ms/step - loss: 222508320.0000 - learning_rate: 3
981.0718
Epoch 234/300


43/43  1s 11ms/step - loss: 131779872.0000 - learning_rate: 4
466.8359
Epoch 235/300


43/43  1s 11ms/step - loss: 362233344.0000 - learning_rate: 5
011.8726
Epoch 236/300


43/43  1s 11ms/step - loss: 282465920.0000 - learning_rate: 5
623.4131
Epoch 237/300


43/43  0s 10ms/step - loss: 252849792.0000 - learning_rate: 6
309.5732
Epoch 238/300


43/43  1s 11ms/step - loss: 390113536.0000 - learning_rate: 7
079.4580
Epoch 239/300


43/43  1s 11ms/step - loss: 714055424.0000 - learning_rate: 7
943.2822
Epoch 240/300


43/43  1s 12ms/step - loss: 548783936.0000 - learning_rate: 8
912.5098
Epoch 241/300


43/43  1s 12ms/step - loss: 476639232.0000 - learning_rate: 1
0000.0000
Epoch 242/300


43/43  1s 11ms/step - loss: 528598720.0000 - learning_rate: 1
1220.1846
Epoch 243/300


43/43  1s 11ms/step - loss: 1056415744.0000 - learning_rate:
12589.2539
Epoch 244/300


43/43  1s 12ms/step - loss: 805391744.0000 - learning_rate: 1
4125.3750
Epoch 245/300


43/43  0s 10ms/step - loss: 982615168.0000 - learning_rate: 1
5848.9316
Epoch 246/300


43/43  1s 11ms/step - loss: 547379264.0000 - learning_rate: 1
7782.7949
Epoch 247/300


43/43  1s 11ms/step - loss: 679488448.0000 - learning_rate: 1
9952.6230
Epoch 248/300


43/43  1s 13ms/step - loss: 774156864.0000 - learning_rate: 2
2387.2109
Epoch 249/300


43/43  0s 11ms/step - loss: 1257949696.0000 - learning_rate:
25118.8652
Epoch 250/300


43/43  1s 13ms/step - loss: 1126430592.0000 - learning_rate:
28183.8301
Epoch 251/300


43/43  1s 13ms/step - loss: 1606570880.0000 - learning_rate:
31622.7773
Epoch 252/300


43/43  1s 11ms/step - loss: 1388650880.0000 - learning_rate:
35481.3398
Epoch 253/300


43/43  1s 11ms/step - loss: 1774989440.0000 - learning_rate:
39810.7188
Epoch 254/300


43/43  0s 11ms/step - loss: 2820595456.0000 - learning_rate:
44668.3594
Epoch 255/300


43/43  0s 10ms/step - loss: 1535620096.0000 - learning_rate:
50118.7227
Epoch 256/300


43/43  0s 10ms/step - loss: 2081064832.0000 - learning_rate:
56234.1328
Epoch 257/300


43/43  1s 11ms/step - loss: 3105193472.0000 - learning_rate:
63095.7344
Epoch 258/300


43/43  0s 11ms/step - loss: 4918697472.0000 - learning_rate:
70794.5781
Epoch 259/300


43/43  0s 10ms/step - loss: 3700700928.0000 - learning_rate:
79432.8203
Epoch 260/300


43/43  0s 11ms/step - loss: 3000319744.0000 - learning_rate:
89125.0938
Epoch 261/300


43/43  1s 11ms/step - loss: 5841334784.0000 - learning_rate:
100000.0000
Epoch 262/300


43/43  1s 11ms/step - loss: 6100281344.0000 - learning_rate:
112201.8438
Epoch 263/300


43/43  1s 11ms/step - loss: 5010114560.0000 - learning_rate:
125892.5391
Epoch 264/300


43/43  1s 12ms/step - loss: 12450372608.0000 - learning_rate:
141253.7500
Epoch 265/300


43/43  1s 12ms/step - loss: 6705346560.0000 - learning_rate:
158489.3125
Epoch 266/300


43/43  1s 11ms/step - loss: 8860326912.0000 - learning_rate:
177827.9375
Epoch 267/300


43/43  1s 11ms/step - loss: 7978790912.0000 - learning_rate:
199526.2344
Epoch 268/300


43/43  1s 11ms/step - loss: 11054258176.0000 - learning_rate:
223872.1094
Epoch 269/300

43/43  1s 11ms/step - loss: 15532723200.0000 - learning_rate:
251188.6406
Epoch 270/300

43/43  1s 12ms/step - loss: 15419382784.0000 - learning_rate:
281838.2812
Epoch 271/300

43/43  0s 10ms/step - loss: 16690487296.0000 - learning_rate:
316227.7812
Epoch 272/300

43/43  0s 11ms/step - loss: 18667954176.0000 - learning_rate:
354813.3750
Epoch 273/300

43/43  0s 10ms/step - loss: 21436454912.0000 - learning_rate:
398107.1562
Epoch 274/300

43/43 ————— 0s 11ms/step - loss: 22264016896.0000 - learning_rate: 446683.5938
Epoch 275/300

43/43 ————— 1s 11ms/step - loss: 21148803072.0000 - learning_rate: 501187.2188
Epoch 276/300

43/43 ————— 1s 11ms/step - loss: 20573440000.0000 - learning_rate: 562341.3125
Epoch 277/300

43/43 ————— 1s 11ms/step - loss: 67714015232.0000 - learning_rate: 630957.3750
Epoch 278/300

43/43 ————— 1s 11ms/step - loss: 28564013056.0000 - learning_rate: 707945.8125
Epoch 279/300

43/43 ————— 1s 11ms/step - loss: 31719139328.0000 - learning_rate: 794328.2500
Epoch 280/300

43/43 ————— 1s 11ms/step - loss: 29030479872.0000 - learning_rate: 891250.9375
Epoch 281/300

43/43 ————— 0s 10ms/step - loss: 71124295680.0000 - learning_rate: 1000000.0000
Epoch 282/300

43/43 ————— 1s 11ms/step - loss: 71868276736.0000 - learning_rate: 1122018.5000
Epoch 283/300

43/43 ————— 1s 11ms/step - loss: 54683521024.0000 - learning_rate: 1258925.3750
Epoch 284/300

43/43 ————— 0s 11ms/step - loss: 80719028224.0000 - learning_rate: 1412537.5000
Epoch 285/300

43/43 ————— 0s 11ms/step - loss: 81146773504.0000 - learning_rate: 1584893.2500
Epoch 286/300

43/43 ————— 0s 11ms/step - loss: 107755274240.0000 - learning_rate: 1778279.3750
Epoch 287/300

43/43 ————— 1s 12ms/step - loss: 128643522560.0000 - learning_rate: 1995262.3750
Epoch 288/300

43/43 ————— 0s 10ms/step - loss: 190114906112.0000 - learning_rate: 2238721.2500
Epoch 289/300

43/43 ————— 0s 10ms/step - loss: 112017637376.0000 - learning_rate: 2511886.5000
Epoch 290/300

43/43 ————— 0s 11ms/step - loss: 165668372480.0000 - learning_rate: 2818383.0000
Epoch 291/300

43/43 ————— 0s 10ms/step - loss: 186881867776.0000 - learning_rate: 3162277.7500
Epoch 292/300

43/43 ————— 0s 10ms/step - loss: 360523923456.0000 - learning_rate: 3548134.0000
Epoch 293/300

43/43 ————— 1s 11ms/step - loss: 126893768704.0000 - learning_rate: 3981071.7500
Epoch 294/300


```

43/43 ————— 1s 11ms/step - loss: 415992217600.0000 - learning_rate: 4466836.0000
Epoch 295/300
43/43 ————— 1s 10ms/step - loss: 355278520320.0000 - learning_rate: 5011872.5000
Epoch 296/300
43/43 ————— 0s 10ms/step - loss: 879325675520.0000 - learning_rate: 5623413.5000
Epoch 297/300
43/43 ————— 0s 10ms/step - loss: 673913307136.0000 - learning_rate: 6309573.5000
Epoch 298/300
43/43 ————— 1s 11ms/step - loss: 474887356416.0000 - learning_rate: 7079458.0000
Epoch 299/300
43/43 ————— 1s 10ms/step - loss: 748463128576.0000 - learning_rate: 7943282.5000
Epoch 300/300
43/43 ————— 1s 11ms/step - loss: 290839560192.0000 - learning_rate: 8912509.0000

```

In [50]: *#Gráfica entre el Learning rate y la función de pérdida, escogeríamos un valor d*
#mínimo

```

import numpy as np
import matplotlib.pyplot as plt

# Definimos el array de tasa de aprendizaje
lrs = 1e-8 * (10 ** (np.arange(300) / 20))

# Ejemplo de valores de pérdida (esto debe ser reemplazado con los valores reales)
losses = history.history["loss"]

# Encontramos el índice del mínimo de la pérdida
min_loss_index = np.argmin(losses)

# Encontramos el valor del Learning rate asociado al mínimo de la pérdida
min_loss_lr = lrs[min_loss_index]

# Mostramos el resultado
print(f"El valor mínimo de la pérdida es {losses[min_loss_index]} y ocurre en el")
# Escogemos el tamaño de la gráfica
plt.figure(figsize=(10, 6))
plt.grid(True)

# Graficamos la pérdida en escala logarítmica
plt.semilogx(lrs, history.history["loss"])

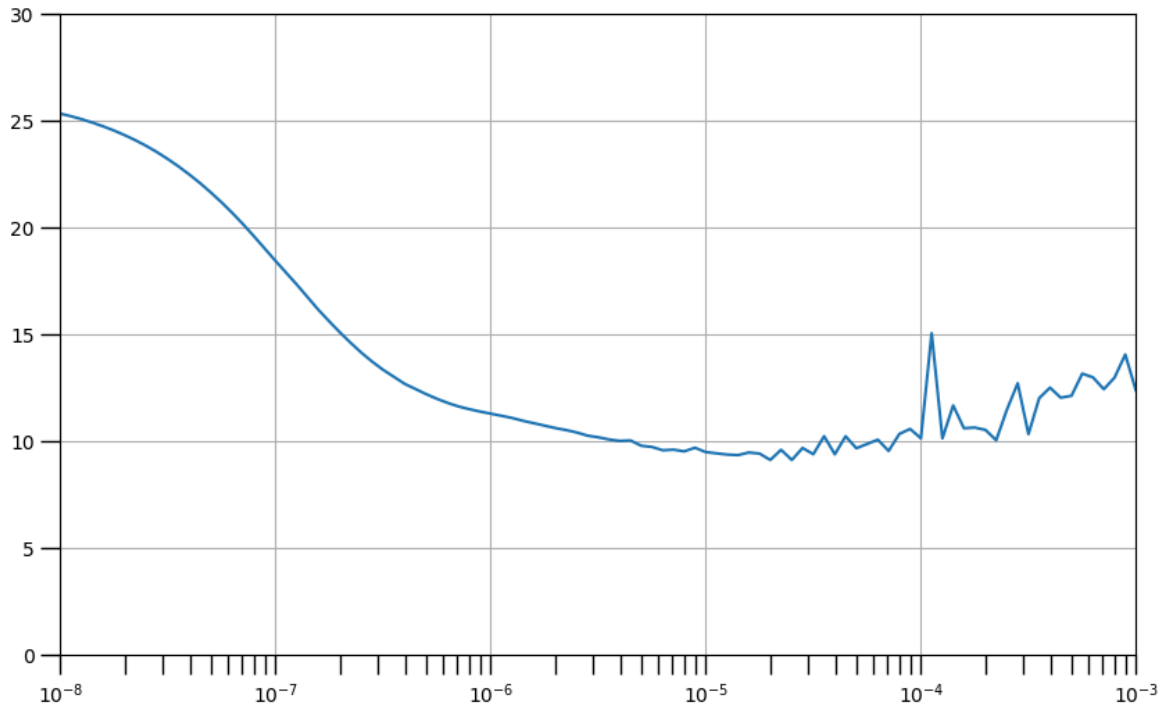
# Aumentamos el tamaño de los tickmarks
plt.tick_params('both', length=10, width=1, which='both')

# Establecemos los límites de la gráfica
plt.axis([1e-8, 1e-3, 0, 30])

```

El valor mínimo de la pérdida es 9.095111846923828 y ocurre en el learning rate de 2.5118864315095798e-05

Out[50]: (1e-08, 0.001, 0.0, 30.0)



```
In [51]: learning_rate = min_loss_lr

# Reset states generated by Keras
tf.keras.backend.clear_session()

# Se repite lo mismo visto arriba para la construcción del modelo

# Construimos el modelo
model = tf.keras.models.Sequential([
    tf.keras.layers.Lambda(lambda x: tf.expand_dims(x, axis=-1),
                           input_shape=[None]),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(8, return_sequences=True)),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(8)),
    tf.keras.layers.Dense(1),
    tf.keras.layers.Lambda(lambda x: x * 100.0)
])

# Establecemos el optimizador (otra vez es desenso de gradiente)
optimizer = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)

# Parámetros de entrenamiento

# En este caso la función de pérdida es otra vez la de Huber, con similar compo
# el learning rate y momentum, la métrica que se pide es el error absoluto medio
model.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer,
              metrics=["mae"])

# Entrenamos el modelo (Nuevamente se usan 300 epochs)
history = model.fit(dataset, epochs=300)
```

Epoch 1/300		
43/43	<div><div></div></div>	3s 8ms/step - loss: 16.7256 - mae: 17.2217
Epoch 2/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 11.0217 - mae: 11.5147
Epoch 3/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 10.7720 - mae: 11.2569
Epoch 4/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.3057 - mae: 9.7908
Epoch 5/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 11.0215 - mae: 11.5179
Epoch 6/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.2567 - mae: 9.7527
Epoch 7/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.7432 - mae: 10.2351
Epoch 8/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 10.4530 - mae: 10.9299
Epoch 9/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.3035 - mae: 9.7919
Epoch 10/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.8029 - mae: 10.2986
Epoch 11/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.5544 - mae: 9.0459
Epoch 12/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.6412 - mae: 10.1257
Epoch 13/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.4321 - mae: 9.9251
Epoch 14/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 10.0887 - mae: 10.5814
Epoch 15/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.6999 - mae: 10.1865
Epoch 16/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.5293 - mae: 10.0225
Epoch 17/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.4985 - mae: 9.9891
Epoch 18/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.5375 - mae: 10.0232
Epoch 19/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.4942 - mae: 9.9791
Epoch 20/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.8160 - mae: 9.3036
Epoch 21/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.2847 - mae: 9.7782
Epoch 22/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.1327 - mae: 9.6170
Epoch 23/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.7027 - mae: 9.1910
Epoch 24/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.2256 - mae: 9.7095
Epoch 25/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.9778 - mae: 9.4657
Epoch 26/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 10.1578 - mae: 10.6419
Epoch 27/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.1133 - mae: 9.5942
Epoch 28/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 10.7783 - mae: 11.2720
Epoch 29/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.9862 - mae: 9.4729
Epoch 30/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.5427 - mae: 10.0363

Epoch 31/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.6712 - mae: 10.1676
Epoch 32/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.9134 - mae: 10.4042
Epoch 33/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.8488 - mae: 9.3396
Epoch 34/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.4356 - mae: 9.9158
Epoch 35/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.4833 - mae: 9.9707
Epoch 36/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.5776 - mae: 9.0653
Epoch 37/300			
43/43	<div><div></div></div>	0s 8ms/step	loss: 8.5331 - mae: 9.0223
Epoch 38/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.2388 - mae: 9.7279
Epoch 39/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.7447 - mae: 10.2347
Epoch 40/300			
43/43	<div><div></div></div>	0s 10ms/step	loss: 9.0735 - mae: 9.5642
Epoch 41/300			
43/43	<div><div></div></div>	0s 10ms/step	loss: 8.8570 - mae: 9.3445
Epoch 42/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.3818 - mae: 9.8747
Epoch 43/300			
43/43	<div><div></div></div>	0s 8ms/step	loss: 9.4445 - mae: 9.9381
Epoch 44/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 10.0245 - mae: 10.5062
Epoch 45/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.1252 - mae: 9.6125
Epoch 46/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.6184 - mae: 10.1098
Epoch 47/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.7819 - mae: 9.2699
Epoch 48/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.3844 - mae: 9.8701
Epoch 49/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.5622 - mae: 9.0536
Epoch 50/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.2939 - mae: 9.7889
Epoch 51/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.2716 - mae: 9.7622
Epoch 52/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 7.9851 - mae: 8.4685
Epoch 53/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.3304 - mae: 8.8218
Epoch 54/300			
43/43	<div><div></div></div>	0s 11ms/step	loss: 9.1212 - mae: 9.6138
Epoch 55/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.8548 - mae: 9.3488
Epoch 56/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.9853 - mae: 9.4757
Epoch 57/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.8648 - mae: 9.3471
Epoch 58/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.4554 - mae: 9.9504
Epoch 59/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.8991 - mae: 9.3914
Epoch 60/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.1030 - mae: 9.5940

Epoch 61/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.3310 - mae: 8.8118
Epoch 62/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.0823 - mae: 9.5734
Epoch 63/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.2938 - mae: 9.7814
Epoch 64/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.1684 - mae: 9.6520
Epoch 65/300		
43/43	<div><div></div></div>	1s 13ms/step - loss: 8.8647 - mae: 9.3439
Epoch 66/300		
43/43	<div><div></div></div>	1s 15ms/step - loss: 9.6411 - mae: 10.1298
Epoch 67/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.1017 - mae: 9.5863
Epoch 68/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.4533 - mae: 9.9396
Epoch 69/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 10.2603 - mae: 10.7472
Epoch 70/300		
43/43	<div><div></div></div>	0s 11ms/step - loss: 8.6045 - mae: 9.0903
Epoch 71/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.7119 - mae: 9.1971
Epoch 72/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.6198 - mae: 9.1046
Epoch 73/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.6770 - mae: 10.1662
Epoch 74/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.8838 - mae: 9.3688
Epoch 75/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.2539 - mae: 9.7361
Epoch 76/300		
43/43	<div><div></div></div>	0s 11ms/step - loss: 9.3305 - mae: 9.8165
Epoch 77/300		
43/43	<div><div></div></div>	0s 11ms/step - loss: 8.9569 - mae: 9.4472
Epoch 78/300		
43/43	<div><div></div></div>	1s 11ms/step - loss: 8.9054 - mae: 9.3949
Epoch 79/300		
43/43	<div><div></div></div>	1s 11ms/step - loss: 8.5872 - mae: 9.0795
Epoch 80/300		
43/43	<div><div></div></div>	1s 11ms/step - loss: 8.3420 - mae: 8.8286
Epoch 81/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.9363 - mae: 9.4210
Epoch 82/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.5411 - mae: 10.0217
Epoch 83/300		
43/43	<div><div></div></div>	1s 11ms/step - loss: 9.1815 - mae: 9.6763
Epoch 84/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.7964 - mae: 9.2816
Epoch 85/300		
43/43	<div><div></div></div>	1s 12ms/step - loss: 9.4128 - mae: 9.9005
Epoch 86/300		
43/43	<div><div></div></div>	1s 11ms/step - loss: 9.6386 - mae: 10.1225
Epoch 87/300		
43/43	<div><div></div></div>	1s 12ms/step - loss: 8.4282 - mae: 8.9088
Epoch 88/300		
43/43	<div><div></div></div>	1s 15ms/step - loss: 8.2073 - mae: 8.6949
Epoch 89/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.9735 - mae: 9.4466
Epoch 90/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.3630 - mae: 8.8468

Epoch 91/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.9173 - mae: 9.4056
Epoch 92/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.3377 - mae: 8.8276
Epoch 93/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.0080 - mae: 9.4949
Epoch 94/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.9426 - mae: 10.4283
Epoch 95/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.4840 - mae: 8.9665
Epoch 96/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.5884 - mae: 9.0705
Epoch 97/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.3071 - mae: 9.7983
Epoch 98/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.0433 - mae: 8.5306
Epoch 99/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.9907 - mae: 9.4854
Epoch 100/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.7882 - mae: 9.2786
Epoch 101/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.5189 - mae: 10.0148
Epoch 102/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.5854 - mae: 9.0773
Epoch 103/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.7552 - mae: 9.2383
Epoch 104/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.1798 - mae: 9.6694
Epoch 105/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.5915 - mae: 10.0747
Epoch 106/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.3743 - mae: 9.8622
Epoch 107/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 10.0117 - mae: 10.4963
Epoch 108/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.2252 - mae: 8.7123
Epoch 109/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.2751 - mae: 8.7688
Epoch 110/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.5715 - mae: 10.0596
Epoch 111/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.7947 - mae: 9.2837
Epoch 112/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.0350 - mae: 9.5253
Epoch 113/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.5391 - mae: 9.0221
Epoch 114/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.9327 - mae: 9.4128
Epoch 115/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.6977 - mae: 9.1866
Epoch 116/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.4201 - mae: 8.9013
Epoch 117/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.9236 - mae: 9.4093
Epoch 118/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.0091 - mae: 9.4991
Epoch 119/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.6705 - mae: 9.1576
Epoch 120/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.1137 - mae: 9.5997

Epoch 121/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.7744 - mae: 9.2614
Epoch 122/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.3860 - mae: 8.8626
Epoch 123/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.0473 - mae: 9.5392
Epoch 124/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.4316 - mae: 8.9162
Epoch 125/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.9077 - mae: 9.3999
Epoch 126/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 10.4485 - mae: 10.9380
Epoch 127/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.4221 - mae: 8.9046
Epoch 128/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.7790 - mae: 9.2674
Epoch 129/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.3058 - mae: 9.7903
Epoch 130/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.2955 - mae: 9.7830
Epoch 131/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.4037 - mae: 8.8952
Epoch 132/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.9248 - mae: 9.4140
Epoch 133/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.1302 - mae: 9.6178
Epoch 134/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.3942 - mae: 9.8842
Epoch 135/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.0075 - mae: 9.4904
Epoch 136/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.8319 - mae: 10.3183
Epoch 137/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.8081 - mae: 9.2973
Epoch 138/300		
43/43	<div><div></div></div>	0s 11ms/step - loss: 9.0682 - mae: 9.5537
Epoch 139/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.5251 - mae: 9.0106
Epoch 140/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.9375 - mae: 9.4326
Epoch 141/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.0099 - mae: 9.5018
Epoch 142/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.8928 - mae: 9.3762
Epoch 143/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.7049 - mae: 9.1964
Epoch 144/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.8272 - mae: 9.3065
Epoch 145/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.2659 - mae: 9.7568
Epoch 146/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.2146 - mae: 9.7039
Epoch 147/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.7985 - mae: 9.2798
Epoch 148/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.7628 - mae: 9.2492
Epoch 149/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.9431 - mae: 9.4275
Epoch 150/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.3140 - mae: 9.8082

Epoch 151/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.1939 - mae: 8.6754
Epoch 152/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.9194 - mae: 9.4043
Epoch 153/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.8719 - mae: 9.3606
Epoch 154/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.7911 - mae: 9.2854
Epoch 155/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.4874 - mae: 9.9726
Epoch 156/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.9723 - mae: 9.4615
Epoch 157/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.8464 - mae: 9.3324
Epoch 158/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.7056 - mae: 9.1924
Epoch 159/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.6580 - mae: 9.1485
Epoch 160/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.7613 - mae: 9.2431
Epoch 161/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.8386 - mae: 9.3234
Epoch 162/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.3970 - mae: 9.8909
Epoch 163/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.1649 - mae: 9.6551
Epoch 164/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.5421 - mae: 9.0250
Epoch 165/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.6513 - mae: 9.1352
Epoch 166/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.9949 - mae: 9.4829
Epoch 167/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.0461 - mae: 8.5338
Epoch 168/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.8295 - mae: 9.3152
Epoch 169/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.1851 - mae: 9.6804
Epoch 170/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.9344 - mae: 9.4279
Epoch 171/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.3586 - mae: 8.8404
Epoch 172/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.4189 - mae: 8.9060
Epoch 173/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.3089 - mae: 9.7921
Epoch 174/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.7830 - mae: 9.2717
Epoch 175/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.8656 - mae: 8.3460
Epoch 176/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.6147 - mae: 9.1006
Epoch 177/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.3929 - mae: 9.8738
Epoch 178/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.5012 - mae: 8.9889
Epoch 179/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.1970 - mae: 9.6815
Epoch 180/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.0419 - mae: 9.5317

Epoch 181/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.0458 - mae: 9.5338
Epoch 182/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.5663 - mae: 9.0571
Epoch 183/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.0192 - mae: 9.4960
Epoch 184/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.6509 - mae: 9.1373
Epoch 185/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.1428 - mae: 9.6286
Epoch 186/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.3642 - mae: 9.8558
Epoch 187/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.1641 - mae: 8.6553
Epoch 188/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.7633 - mae: 9.2482
Epoch 189/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.7015 - mae: 9.1825
Epoch 190/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.0343 - mae: 9.5189
Epoch 191/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.4500 - mae: 9.9393
Epoch 192/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.4383 - mae: 8.9280
Epoch 193/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.0571 - mae: 9.5414
Epoch 194/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 7.9985 - mae: 8.4867
Epoch 195/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.6877 - mae: 9.1651
Epoch 196/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.5539 - mae: 9.0310
Epoch 197/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.0667 - mae: 8.5529
Epoch 198/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.2937 - mae: 8.7772
Epoch 199/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.5678 - mae: 9.0557
Epoch 200/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.8388 - mae: 9.3239
Epoch 201/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.1759 - mae: 9.6608
Epoch 202/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.3197 - mae: 9.8065
Epoch 203/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.9642 - mae: 9.4534
Epoch 204/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.6214 - mae: 9.1097
Epoch 205/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.4996 - mae: 8.9880
Epoch 206/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.9875 - mae: 9.4770
Epoch 207/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.9893 - mae: 9.4744
Epoch 208/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.0423 - mae: 8.5343
Epoch 209/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.9426 - mae: 9.4176
Epoch 210/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.9836 - mae: 8.4736

Epoch 211/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.3335 - mae: 8.8157
Epoch 212/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.5421 - mae: 9.0300
Epoch 213/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.6738 - mae: 9.1599
Epoch 214/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.3990 - mae: 8.8787
Epoch 215/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.7244 - mae: 9.2159
Epoch 216/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.1487 - mae: 8.6437
Epoch 217/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.0697 - mae: 8.5547
Epoch 218/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.1686 - mae: 9.6555
Epoch 219/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.5566 - mae: 9.0458
Epoch 220/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.0886 - mae: 8.5801
Epoch 221/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.0956 - mae: 9.5892
Epoch 222/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.2886 - mae: 8.7697
Epoch 223/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.4482 - mae: 8.9269
Epoch 224/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.6320 - mae: 9.1219
Epoch 225/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.4465 - mae: 8.9274
Epoch 226/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.2602 - mae: 9.7487
Epoch 227/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.4377 - mae: 8.9191
Epoch 228/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.9388 - mae: 9.4316
Epoch 229/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.7539 - mae: 9.2449
Epoch 230/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.1360 - mae: 9.6285
Epoch 231/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.6702 - mae: 9.1467
Epoch 232/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.2732 - mae: 9.7592
Epoch 233/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.3564 - mae: 8.8453
Epoch 234/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.5397 - mae: 10.0295
Epoch 235/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.3200 - mae: 8.8059
Epoch 236/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.8832 - mae: 9.3721
Epoch 237/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 7.8495 - mae: 8.3320
Epoch 238/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.1254 - mae: 8.6177
Epoch 239/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.7420 - mae: 9.2290
Epoch 240/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.1828 - mae: 8.6622

Epoch 241/300		
43/43	<div></div>	0s 9ms/step - loss: 8.4206 - mae: 8.9020
Epoch 242/300		
43/43	<div></div>	0s 9ms/step - loss: 8.4368 - mae: 8.9196
Epoch 243/300		
43/43	<div></div>	0s 9ms/step - loss: 8.9593 - mae: 9.4492
Epoch 244/300		
43/43	<div></div>	0s 9ms/step - loss: 8.0966 - mae: 8.5796
Epoch 245/300		
43/43	<div></div>	0s 9ms/step - loss: 8.6183 - mae: 9.0994
Epoch 246/300		
43/43	<div></div>	0s 10ms/step - loss: 7.9291 - mae: 8.4203
Epoch 247/300		
43/43	<div></div>	0s 9ms/step - loss: 8.3541 - mae: 8.8397
Epoch 248/300		
43/43	<div></div>	0s 9ms/step - loss: 8.7193 - mae: 9.2089
Epoch 249/300		
43/43	<div></div>	0s 9ms/step - loss: 8.6871 - mae: 9.1783
Epoch 250/300		
43/43	<div></div>	0s 9ms/step - loss: 8.5921 - mae: 9.0821
Epoch 251/300		
43/43	<div></div>	0s 9ms/step - loss: 8.6300 - mae: 9.1216
Epoch 252/300		
43/43	<div></div>	0s 9ms/step - loss: 8.6249 - mae: 9.1169
Epoch 253/300		
43/43	<div></div>	0s 9ms/step - loss: 9.1327 - mae: 9.6197
Epoch 254/300		
43/43	<div></div>	0s 10ms/step - loss: 8.5446 - mae: 9.0352
Epoch 255/300		
43/43	<div></div>	0s 10ms/step - loss: 8.9753 - mae: 9.4623
Epoch 256/300		
43/43	<div></div>	0s 9ms/step - loss: 8.6216 - mae: 9.1062
Epoch 257/300		
43/43	<div></div>	1s 11ms/step - loss: 8.4341 - mae: 8.9250
Epoch 258/300		
43/43	<div></div>	0s 9ms/step - loss: 8.7803 - mae: 9.2615
Epoch 259/300		
43/43	<div></div>	0s 9ms/step - loss: 8.3669 - mae: 8.8505
Epoch 260/300		
43/43	<div></div>	0s 10ms/step - loss: 8.9940 - mae: 9.4857
Epoch 261/300		
43/43	<div></div>	0s 9ms/step - loss: 9.3384 - mae: 9.8214
Epoch 262/300		
43/43	<div></div>	0s 9ms/step - loss: 9.4585 - mae: 9.9435
Epoch 263/300		
43/43	<div></div>	0s 9ms/step - loss: 8.0142 - mae: 8.5041
Epoch 264/300		
43/43	<div></div>	0s 9ms/step - loss: 8.4876 - mae: 8.9771
Epoch 265/300		
43/43	<div></div>	0s 9ms/step - loss: 10.1345 - mae: 10.6257
Epoch 266/300		
43/43	<div></div>	0s 9ms/step - loss: 8.6522 - mae: 9.1305
Epoch 267/300		
43/43	<div></div>	0s 9ms/step - loss: 8.9245 - mae: 9.4117
Epoch 268/300		
43/43	<div></div>	0s 9ms/step - loss: 8.6818 - mae: 9.1667
Epoch 269/300		
43/43	<div></div>	0s 9ms/step - loss: 8.5967 - mae: 9.0853
Epoch 270/300		
43/43	<div></div>	0s 8ms/step - loss: 8.3813 - mae: 8.8692

Epoch 271/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.6813 - mae: 9.1628
Epoch 272/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.7068 - mae: 8.1914
Epoch 273/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.4620 - mae: 9.9516
Epoch 274/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.1742 - mae: 8.6599
Epoch 275/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.4430 - mae: 8.9300
Epoch 276/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.6539 - mae: 9.1478
Epoch 277/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.4185 - mae: 8.9088
Epoch 278/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.7074 - mae: 9.1960
Epoch 279/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.7406 - mae: 9.2316
Epoch 280/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.4830 - mae: 8.9688
Epoch 281/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.6578 - mae: 9.1408
Epoch 282/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.1976 - mae: 8.6857
Epoch 283/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.3140 - mae: 8.7947
Epoch 284/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.8871 - mae: 8.3755
Epoch 285/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.0915 - mae: 8.5801
Epoch 286/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.0962 - mae: 9.5816
Epoch 287/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 7.9892 - mae: 8.4737
Epoch 288/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.0163 - mae: 8.4991
Epoch 289/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.4526 - mae: 8.9400
Epoch 290/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.6898 - mae: 9.1732
Epoch 291/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.9102 - mae: 9.3987
Epoch 292/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.4565 - mae: 8.9313
Epoch 293/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.3520 - mae: 8.8363
Epoch 294/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.1563 - mae: 9.6514
Epoch 295/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.8759 - mae: 9.3574
Epoch 296/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.5649 - mae: 9.0486
Epoch 297/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.1640 - mae: 8.6509
Epoch 298/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.5141 - mae: 9.0006
Epoch 299/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.4451 - mae: 8.9261
Epoch 300/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.1529 - mae: 9.6444

```
In [53]: import matplotlib.pyplot as plt

# Entrenamos el modelo
history = model.fit(dataset, epochs=300)

# Graficamos el MAE durante el entrenamiento
plt.figure(figsize=(10, 6))
plt.plot(history.history['mae'], label='MAE de entrenamiento')
plt.xlabel('Epochs')
plt.ylabel('MAE')
plt.title('MAE durante el entrenamiento')
plt.legend()
plt.grid(True)
plt.show()
```

Epoch 1/300			
43/43	<div><div></div></div>	0s 9ms/step	- loss: 8.5215 - mae: 9.0038
Epoch 2/300			
43/43	<div><div></div></div>	0s 9ms/step	- loss: 8.9077 - mae: 9.3871
Epoch 3/300			
43/43	<div><div></div></div>	0s 8ms/step	- loss: 7.9177 - mae: 8.3938
Epoch 4/300			
43/43	<div><div></div></div>	0s 9ms/step	- loss: 7.7419 - mae: 8.2189
Epoch 5/300			
43/43	<div><div></div></div>	0s 8ms/step	- loss: 8.1282 - mae: 8.6163
Epoch 6/300			
43/43	<div><div></div></div>	0s 8ms/step	- loss: 8.9876 - mae: 9.4820
Epoch 7/300			
43/43	<div><div></div></div>	0s 8ms/step	- loss: 8.6021 - mae: 9.0956
Epoch 8/300			
43/43	<div><div></div></div>	0s 8ms/step	- loss: 8.9550 - mae: 9.4427
Epoch 9/300			
43/43	<div><div></div></div>	0s 8ms/step	- loss: 8.3225 - mae: 8.8074
Epoch 10/300			
43/43	<div><div></div></div>	0s 9ms/step	- loss: 8.3389 - mae: 8.8245
Epoch 11/300			
43/43	<div><div></div></div>	0s 8ms/step	- loss: 9.0192 - mae: 9.5024
Epoch 12/300			
43/43	<div><div></div></div>	0s 8ms/step	- loss: 8.2730 - mae: 8.7580
Epoch 13/300			
43/43	<div><div></div></div>	0s 8ms/step	- loss: 7.7439 - mae: 8.2261
Epoch 14/300			
43/43	<div><div></div></div>	0s 9ms/step	- loss: 7.9014 - mae: 8.3844
Epoch 15/300			
43/43	<div><div></div></div>	0s 8ms/step	- loss: 8.7278 - mae: 9.2198
Epoch 16/300			
43/43	<div><div></div></div>	0s 9ms/step	- loss: 8.8118 - mae: 9.2970
Epoch 17/300			
43/43	<div><div></div></div>	0s 9ms/step	- loss: 8.6859 - mae: 9.1698
Epoch 18/300			
43/43	<div><div></div></div>	0s 8ms/step	- loss: 8.5959 - mae: 9.0854
Epoch 19/300			
43/43	<div><div></div></div>	0s 9ms/step	- loss: 9.0610 - mae: 9.5521
Epoch 20/300			
43/43	<div><div></div></div>	0s 8ms/step	- loss: 8.0376 - mae: 8.5195
Epoch 21/300			
43/43	<div><div></div></div>	0s 9ms/step	- loss: 8.1080 - mae: 8.5912
Epoch 22/300			
43/43	<div><div></div></div>	0s 9ms/step	- loss: 8.5786 - mae: 9.0576
Epoch 23/300			
43/43	<div><div></div></div>	0s 10ms/step	- loss: 9.0366 - mae: 9.5134
Epoch 24/300			
43/43	<div><div></div></div>	0s 9ms/step	- loss: 8.2945 - mae: 8.7884
Epoch 25/300			
43/43	<div><div></div></div>	0s 9ms/step	- loss: 8.7303 - mae: 9.2147
Epoch 26/300			
43/43	<div><div></div></div>	0s 8ms/step	- loss: 9.0099 - mae: 9.5039
Epoch 27/300			
43/43	<div><div></div></div>	0s 8ms/step	- loss: 8.3081 - mae: 8.7963
Epoch 28/300			
43/43	<div><div></div></div>	0s 8ms/step	- loss: 8.5504 - mae: 9.0427
Epoch 29/300			
43/43	<div><div></div></div>	0s 9ms/step	- loss: 8.9196 - mae: 9.4095
Epoch 30/300			
43/43	<div><div></div></div>	0s 9ms/step	- loss: 8.9830 - mae: 9.4720

Epoch 31/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.9633 - mae: 9.4498
Epoch 32/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.3479 - mae: 8.8310
Epoch 33/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.6253 - mae: 9.1180
Epoch 34/300			
43/43	<div><div></div></div>	0s 8ms/step	loss: 8.4152 - mae: 8.9072
Epoch 35/300			
43/43	<div><div></div></div>	0s 8ms/step	loss: 8.2810 - mae: 8.7696
Epoch 36/300			
43/43	<div><div></div></div>	0s 8ms/step	loss: 8.0530 - mae: 8.5304
Epoch 37/300			
43/43	<div><div></div></div>	0s 8ms/step	loss: 8.2580 - mae: 8.7496
Epoch 38/300			
43/43	<div><div></div></div>	0s 8ms/step	loss: 8.7684 - mae: 9.2566
Epoch 39/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.6554 - mae: 9.1433
Epoch 40/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.2063 - mae: 8.6975
Epoch 41/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.6238 - mae: 9.1066
Epoch 42/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.2138 - mae: 8.6980
Epoch 43/300			
43/43	<div><div></div></div>	0s 8ms/step	loss: 8.2819 - mae: 8.7616
Epoch 44/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.5959 - mae: 9.0788
Epoch 45/300			
43/43	<div><div></div></div>	0s 8ms/step	loss: 8.4664 - mae: 8.9508
Epoch 46/300			
43/43	<div><div></div></div>	0s 8ms/step	loss: 8.8663 - mae: 9.3529
Epoch 47/300			
43/43	<div><div></div></div>	0s 8ms/step	loss: 8.4843 - mae: 8.9732
Epoch 48/300			
43/43	<div><div></div></div>	0s 8ms/step	loss: 8.4886 - mae: 8.9720
Epoch 49/300			
43/43	<div><div></div></div>	0s 8ms/step	loss: 8.0754 - mae: 8.5637
Epoch 50/300			
43/43	<div><div></div></div>	0s 10ms/step	loss: 8.5033 - mae: 8.9869
Epoch 51/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.9265 - mae: 9.4096
Epoch 52/300			
43/43	<div><div></div></div>	0s 8ms/step	loss: 8.0056 - mae: 8.4930
Epoch 53/300			
43/43	<div><div></div></div>	0s 10ms/step	loss: 9.0059 - mae: 9.4957
Epoch 54/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.0284 - mae: 8.5128
Epoch 55/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.1858 - mae: 8.6770
Epoch 56/300			
43/43	<div><div></div></div>	0s 8ms/step	loss: 9.2428 - mae: 9.7344
Epoch 57/300			
43/43	<div><div></div></div>	0s 8ms/step	loss: 8.4275 - mae: 8.9095
Epoch 58/300			
43/43	<div><div></div></div>	0s 8ms/step	loss: 8.8500 - mae: 9.3409
Epoch 59/300			
43/43	<div><div></div></div>	0s 8ms/step	loss: 8.4274 - mae: 8.9100
Epoch 60/300			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.0198 - mae: 8.5051

Epoch 61/300		
43/43	<div></div>	0s 8ms/step - loss: 8.7501 - mae: 9.2403
Epoch 62/300		
43/43	<div></div>	0s 9ms/step - loss: 8.2689 - mae: 8.7544
Epoch 63/300		
43/43	<div></div>	0s 8ms/step - loss: 8.5705 - mae: 9.0549
Epoch 64/300		
43/43	<div></div>	0s 9ms/step - loss: 7.7347 - mae: 8.2194
Epoch 65/300		
43/43	<div></div>	0s 10ms/step - loss: 8.5950 - mae: 9.0833
Epoch 66/300		
43/43	<div></div>	0s 9ms/step - loss: 8.2564 - mae: 8.7403
Epoch 67/300		
43/43	<div></div>	0s 9ms/step - loss: 8.4825 - mae: 8.9674
Epoch 68/300		
43/43	<div></div>	0s 9ms/step - loss: 9.1203 - mae: 9.6092
Epoch 69/300		
43/43	<div></div>	0s 9ms/step - loss: 7.9257 - mae: 8.4159
Epoch 70/300		
43/43	<div></div>	0s 8ms/step - loss: 8.6984 - mae: 9.1864
Epoch 71/300		
43/43	<div></div>	0s 9ms/step - loss: 8.3573 - mae: 8.8500
Epoch 72/300		
43/43	<div></div>	0s 9ms/step - loss: 8.2700 - mae: 8.7575
Epoch 73/300		
43/43	<div></div>	0s 9ms/step - loss: 8.2266 - mae: 8.7187
Epoch 74/300		
43/43	<div></div>	0s 9ms/step - loss: 8.8171 - mae: 9.2901
Epoch 75/300		
43/43	<div></div>	0s 10ms/step - loss: 8.9165 - mae: 9.4027
Epoch 76/300		
43/43	<div></div>	0s 9ms/step - loss: 7.5389 - mae: 8.0157
Epoch 77/300		
43/43	<div></div>	0s 9ms/step - loss: 8.5759 - mae: 9.0606
Epoch 78/300		
43/43	<div></div>	0s 9ms/step - loss: 8.1881 - mae: 8.6632
Epoch 79/300		
43/43	<div></div>	0s 9ms/step - loss: 8.4182 - mae: 8.9066
Epoch 80/300		
43/43	<div></div>	0s 9ms/step - loss: 9.3907 - mae: 9.8817
Epoch 81/300		
43/43	<div></div>	0s 9ms/step - loss: 8.3524 - mae: 8.8378
Epoch 82/300		
43/43	<div></div>	0s 9ms/step - loss: 8.4344 - mae: 8.9156
Epoch 83/300		
43/43	<div></div>	0s 9ms/step - loss: 8.9521 - mae: 9.4382
Epoch 84/300		
43/43	<div></div>	0s 9ms/step - loss: 8.6413 - mae: 9.1249
Epoch 85/300		
43/43	<div></div>	0s 10ms/step - loss: 8.4266 - mae: 8.9182
Epoch 86/300		
43/43	<div></div>	0s 9ms/step - loss: 8.1470 - mae: 8.6325
Epoch 87/300		
43/43	<div></div>	0s 9ms/step - loss: 8.1057 - mae: 8.5923
Epoch 88/300		
43/43	<div></div>	0s 9ms/step - loss: 8.6836 - mae: 9.1733
Epoch 89/300		
43/43	<div></div>	0s 10ms/step - loss: 8.7285 - mae: 9.2168
Epoch 90/300		
43/43	<div></div>	0s 8ms/step - loss: 7.9006 - mae: 8.3856

Epoch 91/300			
43/43	<div></div>	0s 8ms/step	loss: 8.1685 - mae: 8.6533
Epoch 92/300			
43/43	<div></div>	0s 8ms/step	loss: 8.2867 - mae: 8.7693
Epoch 93/300			
43/43	<div></div>	0s 8ms/step	loss: 8.8022 - mae: 9.2950
Epoch 94/300			
43/43	<div></div>	0s 9ms/step	loss: 8.2025 - mae: 8.6904
Epoch 95/300			
43/43	<div></div>	0s 9ms/step	loss: 8.0863 - mae: 8.5660
Epoch 96/300			
43/43	<div></div>	0s 9ms/step	loss: 8.5894 - mae: 9.0797
Epoch 97/300			
43/43	<div></div>	0s 9ms/step	loss: 8.5714 - mae: 9.0620
Epoch 98/300			
43/43	<div></div>	0s 9ms/step	loss: 8.2462 - mae: 8.7296
Epoch 99/300			
43/43	<div></div>	0s 10ms/step	loss: 8.1363 - mae: 8.6085
Epoch 100/300			
43/43	<div></div>	0s 9ms/step	loss: 8.3394 - mae: 8.8300
Epoch 101/300			
43/43	<div></div>	0s 9ms/step	loss: 8.5890 - mae: 9.0727
Epoch 102/300			
43/43	<div></div>	0s 9ms/step	loss: 8.8060 - mae: 9.2897
Epoch 103/300			
43/43	<div></div>	0s 9ms/step	loss: 9.1319 - mae: 9.6146
Epoch 104/300			
43/43	<div></div>	0s 9ms/step	loss: 8.1365 - mae: 8.6157
Epoch 105/300			
43/43	<div></div>	0s 9ms/step	loss: 8.5710 - mae: 9.0490
Epoch 106/300			
43/43	<div></div>	0s 10ms/step	loss: 9.0859 - mae: 9.5815
Epoch 107/300			
43/43	<div></div>	0s 9ms/step	loss: 9.4309 - mae: 9.9149
Epoch 108/300			
43/43	<div></div>	1s 12ms/step	loss: 8.8909 - mae: 9.3767
Epoch 109/300			
43/43	<div></div>	1s 12ms/step	loss: 8.0168 - mae: 8.4988
Epoch 110/300			
43/43	<div></div>	0s 9ms/step	loss: 8.3655 - mae: 8.8470
Epoch 111/300			
43/43	<div></div>	1s 12ms/step	loss: 8.2335 - mae: 8.7206
Epoch 112/300			
43/43	<div></div>	0s 9ms/step	loss: 7.4212 - mae: 7.9020
Epoch 113/300			
43/43	<div></div>	0s 9ms/step	loss: 7.8749 - mae: 8.3615
Epoch 114/300			
43/43	<div></div>	0s 10ms/step	loss: 8.7640 - mae: 9.2529
Epoch 115/300			
43/43	<div></div>	0s 9ms/step	loss: 7.9531 - mae: 8.4282
Epoch 116/300			
43/43	<div></div>	0s 9ms/step	loss: 8.3973 - mae: 8.8788
Epoch 117/300			
43/43	<div></div>	0s 8ms/step	loss: 8.2587 - mae: 8.7476
Epoch 118/300			
43/43	<div></div>	0s 8ms/step	loss: 8.3142 - mae: 8.7964
Epoch 119/300			
43/43	<div></div>	0s 9ms/step	loss: 7.9866 - mae: 8.4556
Epoch 120/300			
43/43	<div></div>	0s 10ms/step	loss: 8.2408 - mae: 8.7257

Epoch 121/300		
43/43	<div></div>	0s 9ms/step - loss: 8.6260 - mae: 9.1096
Epoch 122/300		
43/43	<div></div>	0s 8ms/step - loss: 8.6198 - mae: 9.1001
Epoch 123/300		
43/43	<div></div>	0s 8ms/step - loss: 9.0425 - mae: 9.5322
Epoch 124/300		
43/43	<div></div>	0s 8ms/step - loss: 7.6191 - mae: 8.1083
Epoch 125/300		
43/43	<div></div>	0s 9ms/step - loss: 8.0641 - mae: 8.5421
Epoch 126/300		
43/43	<div></div>	1s 12ms/step - loss: 8.6546 - mae: 9.1433
Epoch 127/300		
43/43	<div></div>	0s 10ms/step - loss: 8.6467 - mae: 9.1317
Epoch 128/300		
43/43	<div></div>	0s 10ms/step - loss: 8.3298 - mae: 8.8092
Epoch 129/300		
43/43	<div></div>	0s 9ms/step - loss: 8.1628 - mae: 8.6488
Epoch 130/300		
43/43	<div></div>	0s 10ms/step - loss: 8.5412 - mae: 9.0309
Epoch 131/300		
43/43	<div></div>	0s 10ms/step - loss: 8.3650 - mae: 8.8539
Epoch 132/300		
43/43	<div></div>	0s 9ms/step - loss: 8.1765 - mae: 8.6571
Epoch 133/300		
43/43	<div></div>	0s 8ms/step - loss: 7.4493 - mae: 7.9280
Epoch 134/300		
43/43	<div></div>	0s 9ms/step - loss: 8.3226 - mae: 8.8105
Epoch 135/300		
43/43	<div></div>	0s 10ms/step - loss: 7.5530 - mae: 8.0371
Epoch 136/300		
43/43	<div></div>	0s 10ms/step - loss: 8.1982 - mae: 8.6847
Epoch 137/300		
43/43	<div></div>	1s 12ms/step - loss: 8.6284 - mae: 9.1155
Epoch 138/300		
43/43	<div></div>	0s 10ms/step - loss: 8.7797 - mae: 9.2677
Epoch 139/300		
43/43	<div></div>	0s 9ms/step - loss: 7.8762 - mae: 8.3608
Epoch 140/300		
43/43	<div></div>	0s 9ms/step - loss: 8.1874 - mae: 8.6669
Epoch 141/300		
43/43	<div></div>	0s 9ms/step - loss: 8.3404 - mae: 8.8262
Epoch 142/300		
43/43	<div></div>	0s 10ms/step - loss: 7.6990 - mae: 8.1753
Epoch 143/300		
43/43	<div></div>	0s 9ms/step - loss: 7.7205 - mae: 8.2057
Epoch 144/300		
43/43	<div></div>	0s 10ms/step - loss: 8.2072 - mae: 8.6891
Epoch 145/300		
43/43	<div></div>	0s 10ms/step - loss: 7.7757 - mae: 8.2608
Epoch 146/300		
43/43	<div></div>	1s 11ms/step - loss: 8.5170 - mae: 9.0037
Epoch 147/300		
43/43	<div></div>	0s 10ms/step - loss: 8.0899 - mae: 8.5755
Epoch 148/300		
43/43	<div></div>	0s 10ms/step - loss: 9.1377 - mae: 9.6168
Epoch 149/300		
43/43	<div></div>	0s 9ms/step - loss: 8.0903 - mae: 8.5716
Epoch 150/300		
43/43	<div></div>	0s 9ms/step - loss: 8.2423 - mae: 8.7310

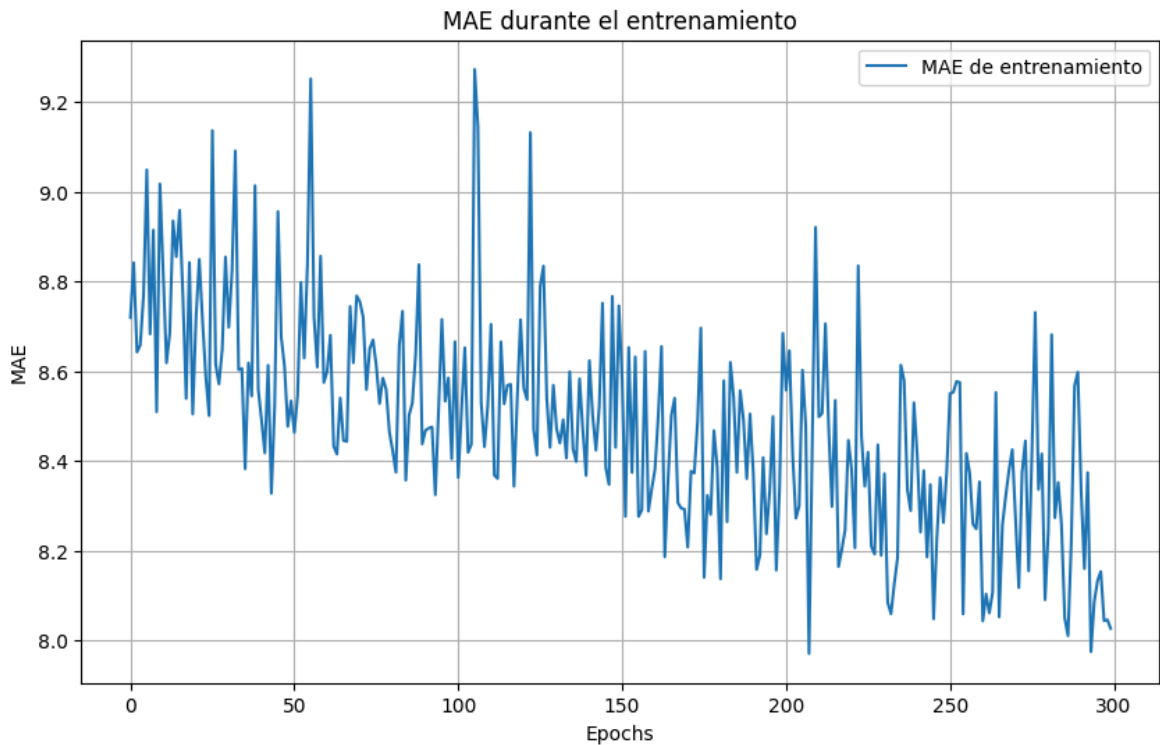
Epoch 151/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.2659 - mae: 8.7538
Epoch 152/300		
43/43	<div><div></div></div>	1s 11ms/step - loss: 8.1529 - mae: 8.6335
Epoch 153/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.5427 - mae: 9.0274
Epoch 154/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.7571 - mae: 8.2414
Epoch 155/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.7199 - mae: 9.1998
Epoch 156/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 7.7725 - mae: 8.2556
Epoch 157/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.3226 - mae: 8.8100
Epoch 158/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 7.8921 - mae: 8.3722
Epoch 159/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.9290 - mae: 8.4121
Epoch 160/300		
43/43	<div><div></div></div>	1s 11ms/step - loss: 8.1131 - mae: 8.5921
Epoch 161/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.4260 - mae: 8.9125
Epoch 162/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.4971 - mae: 8.9832
Epoch 163/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.8006 - mae: 9.2910
Epoch 164/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.8900 - mae: 8.3738
Epoch 165/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.3083 - mae: 8.7937
Epoch 166/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.2418 - mae: 9.7299
Epoch 167/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.5963 - mae: 9.0867
Epoch 168/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.3098 - mae: 8.7914
Epoch 169/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.1396 - mae: 8.6304
Epoch 170/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.6994 - mae: 8.1770
Epoch 171/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.0131 - mae: 8.4953
Epoch 172/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.5859 - mae: 8.0731
Epoch 173/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.0590 - mae: 8.5438
Epoch 174/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.2343 - mae: 8.7188
Epoch 175/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.4479 - mae: 8.9292
Epoch 176/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.0342 - mae: 8.5049
Epoch 177/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.3272 - mae: 8.8128
Epoch 178/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.0979 - mae: 8.5863
Epoch 179/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.9839 - mae: 8.4616
Epoch 180/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.5180 - mae: 9.0033

Epoch 181/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.8215 - mae: 8.2956
Epoch 182/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.6030 - mae: 9.0895
Epoch 183/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.2103 - mae: 8.6874
Epoch 184/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 7.9376 - mae: 8.4198
Epoch 185/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.3761 - mae: 8.8668
Epoch 186/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.6855 - mae: 8.1726
Epoch 187/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.3738 - mae: 8.8592
Epoch 188/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 7.6222 - mae: 8.0996
Epoch 189/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 7.6800 - mae: 8.1636
Epoch 190/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.0988 - mae: 8.5837
Epoch 191/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.6393 - mae: 9.1257
Epoch 192/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.3118 - mae: 7.7889
Epoch 193/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.0170 - mae: 8.5052
Epoch 194/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.6121 - mae: 9.0940
Epoch 195/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 7.6104 - mae: 8.0892
Epoch 196/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.7685 - mae: 8.2592
Epoch 197/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.1969 - mae: 8.6817
Epoch 198/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 7.6829 - mae: 8.1636
Epoch 199/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.8480 - mae: 8.3202
Epoch 200/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.0775 - mae: 8.5605
Epoch 201/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.9456 - mae: 9.4380
Epoch 202/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.1397 - mae: 8.6218
Epoch 203/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 7.4969 - mae: 7.9769
Epoch 204/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.8391 - mae: 8.3239
Epoch 205/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.8758 - mae: 8.3600
Epoch 206/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.6729 - mae: 9.1573
Epoch 207/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.6022 - mae: 9.0904
Epoch 208/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.0641 - mae: 8.5496
Epoch 209/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.1070 - mae: 8.5923
Epoch 210/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.7305 - mae: 9.2112

Epoch 211/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.1776 - mae: 8.6628
Epoch 212/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 7.9347 - mae: 8.4242
Epoch 213/300		
43/43	<div><div></div></div>	1s 11ms/step - loss: 7.7881 - mae: 8.2759
Epoch 214/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.1189 - mae: 8.6076
Epoch 215/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.6900 - mae: 8.1765
Epoch 216/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.8044 - mae: 9.2977
Epoch 217/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.2594 - mae: 8.7488
Epoch 218/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.3585 - mae: 8.8394
Epoch 219/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 7.9171 - mae: 8.3969
Epoch 220/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.2983 - mae: 8.7840
Epoch 221/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.1325 - mae: 8.6111
Epoch 222/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.4248 - mae: 7.8921
Epoch 223/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.2096 - mae: 9.6999
Epoch 224/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.6227 - mae: 8.1054
Epoch 225/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.4015 - mae: 7.8893
Epoch 226/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.1596 - mae: 8.6463
Epoch 227/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.1635 - mae: 8.6488
Epoch 228/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.7805 - mae: 8.2654
Epoch 229/300		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.8780 - mae: 9.3648
Epoch 230/300		
43/43	<div><div></div></div>	1s 11ms/step - loss: 8.1644 - mae: 8.6458
Epoch 231/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.3192 - mae: 8.7972
Epoch 232/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.4213 - mae: 7.9042
Epoch 233/300		
43/43	<div><div></div></div>	1s 12ms/step - loss: 8.1365 - mae: 8.6235
Epoch 234/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.8369 - mae: 8.3113
Epoch 235/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.1935 - mae: 8.6711
Epoch 236/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.3365 - mae: 9.8268
Epoch 237/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.2347 - mae: 8.7273
Epoch 238/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 7.9251 - mae: 8.4154
Epoch 239/300		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.7047 - mae: 9.1892
Epoch 240/300		
43/43	<div><div></div></div>	0s 10ms/step - loss: 8.0079 - mae: 8.4928

Epoch 241/300		
43/43	<div></div>	0s 10ms/step - loss: 8.4450 - mae: 8.9332
Epoch 242/300		
43/43	<div></div>	0s 9ms/step - loss: 7.6324 - mae: 8.1231
Epoch 243/300		
43/43	<div></div>	0s 8ms/step - loss: 7.8839 - mae: 8.3686
Epoch 244/300		
43/43	<div></div>	0s 10ms/step - loss: 8.2077 - mae: 8.6794
Epoch 245/300		
43/43	<div></div>	0s 8ms/step - loss: 7.3140 - mae: 7.7882
Epoch 246/300		
43/43	<div></div>	0s 9ms/step - loss: 7.5898 - mae: 8.0633
Epoch 247/300		
43/43	<div></div>	0s 8ms/step - loss: 8.1601 - mae: 8.6433
Epoch 248/300		
43/43	<div></div>	0s 8ms/step - loss: 8.2052 - mae: 8.6902
Epoch 249/300		
43/43	<div></div>	0s 10ms/step - loss: 7.7290 - mae: 8.2125
Epoch 250/300		
43/43	<div></div>	0s 10ms/step - loss: 8.0554 - mae: 8.5426
Epoch 251/300		
43/43	<div></div>	0s 9ms/step - loss: 8.5872 - mae: 9.0755
Epoch 252/300		
43/43	<div></div>	0s 9ms/step - loss: 8.1184 - mae: 8.6099
Epoch 253/300		
43/43	<div></div>	0s 9ms/step - loss: 8.0706 - mae: 8.5578
Epoch 254/300		
43/43	<div></div>	0s 8ms/step - loss: 8.3087 - mae: 8.8008
Epoch 255/300		
43/43	<div></div>	0s 8ms/step - loss: 7.2819 - mae: 7.7695
Epoch 256/300		
43/43	<div></div>	0s 9ms/step - loss: 7.9350 - mae: 8.4191
Epoch 257/300		
43/43	<div></div>	0s 9ms/step - loss: 7.9571 - mae: 8.4413
Epoch 258/300		
43/43	<div></div>	0s 9ms/step - loss: 8.1874 - mae: 8.6665
Epoch 259/300		
43/43	<div></div>	0s 8ms/step - loss: 7.8160 - mae: 8.2986
Epoch 260/300		
43/43	<div></div>	0s 9ms/step - loss: 7.8802 - mae: 8.3673
Epoch 261/300		
43/43	<div></div>	0s 9ms/step - loss: 7.4784 - mae: 7.9554
Epoch 262/300		
43/43	<div></div>	0s 11ms/step - loss: 8.2786 - mae: 8.7628
Epoch 263/300		
43/43	<div></div>	0s 9ms/step - loss: 7.3793 - mae: 7.8548
Epoch 264/300		
43/43	<div></div>	0s 9ms/step - loss: 7.8936 - mae: 8.3817
Epoch 265/300		
43/43	<div></div>	0s 9ms/step - loss: 9.2686 - mae: 9.7593
Epoch 266/300		
43/43	<div></div>	1s 9ms/step - loss: 8.3585 - mae: 8.8378
Epoch 267/300		
43/43	<div></div>	0s 9ms/step - loss: 7.9953 - mae: 8.4695
Epoch 268/300		
43/43	<div></div>	0s 9ms/step - loss: 7.9759 - mae: 8.4527
Epoch 269/300		
43/43	<div></div>	0s 9ms/step - loss: 7.9781 - mae: 8.4676
Epoch 270/300		
43/43	<div></div>	0s 9ms/step - loss: 7.5677 - mae: 8.0492

Epoch 271/300			
43/43	<div></div>	0s 9ms/step	loss: 7.9848 - mae: 8.4747
Epoch 272/300			
43/43	<div></div>	0s 8ms/step	loss: 7.6896 - mae: 8.1731
Epoch 273/300			
43/43	<div></div>	0s 9ms/step	loss: 8.3870 - mae: 8.8798
Epoch 274/300			
43/43	<div></div>	0s 9ms/step	loss: 8.5594 - mae: 9.0443
Epoch 275/300			
43/43	<div></div>	0s 9ms/step	loss: 8.2361 - mae: 8.7129
Epoch 276/300			
43/43	<div></div>	0s 9ms/step	loss: 8.5265 - mae: 8.9997
Epoch 277/300			
43/43	<div></div>	0s 9ms/step	loss: 8.4444 - mae: 8.9365
Epoch 278/300			
43/43	<div></div>	1s 11ms/step	loss: 6.9088 - mae: 7.3854
Epoch 279/300			
43/43	<div></div>	0s 10ms/step	loss: 8.4789 - mae: 8.9705
Epoch 280/300			
43/43	<div></div>	0s 9ms/step	loss: 7.6284 - mae: 8.1076
Epoch 281/300			
43/43	<div></div>	0s 9ms/step	loss: 7.5773 - mae: 8.0602
Epoch 282/300			
43/43	<div></div>	0s 9ms/step	loss: 8.7731 - mae: 9.2581
Epoch 283/300			
43/43	<div></div>	0s 9ms/step	loss: 7.5537 - mae: 8.0295
Epoch 284/300			
43/43	<div></div>	0s 9ms/step	loss: 8.1156 - mae: 8.5903
Epoch 285/300			
43/43	<div></div>	0s 9ms/step	loss: 8.0697 - mae: 8.5567
Epoch 286/300			
43/43	<div></div>	0s 9ms/step	loss: 8.2612 - mae: 8.7428
Epoch 287/300			
43/43	<div></div>	0s 9ms/step	loss: 8.2047 - mae: 8.6904
Epoch 288/300			
43/43	<div></div>	0s 10ms/step	loss: 8.1768 - mae: 8.6645
Epoch 289/300			
43/43	<div></div>	0s 9ms/step	loss: 8.3893 - mae: 8.8770
Epoch 290/300			
43/43	<div></div>	0s 9ms/step	loss: 8.4324 - mae: 8.9220
Epoch 291/300			
43/43	<div></div>	0s 9ms/step	loss: 7.9126 - mae: 8.4029
Epoch 292/300			
43/43	<div></div>	0s 10ms/step	loss: 7.3082 - mae: 7.7821
Epoch 293/300			
43/43	<div></div>	0s 10ms/step	loss: 8.3675 - mae: 8.8525
Epoch 294/300			
43/43	<div></div>	0s 10ms/step	loss: 7.4984 - mae: 7.9823
Epoch 295/300			
43/43	<div></div>	0s 10ms/step	loss: 7.8307 - mae: 8.3008
Epoch 296/300			
43/43	<div></div>	0s 9ms/step	loss: 7.5758 - mae: 8.0563
Epoch 297/300			
43/43	<div></div>	0s 10ms/step	loss: 8.1582 - mae: 8.6408
Epoch 298/300			
43/43	<div></div>	0s 10ms/step	loss: 8.2516 - mae: 8.7312
Epoch 299/300			
43/43	<div></div>	0s 9ms/step	loss: 7.6584 - mae: 8.1396
Epoch 300/300			
43/43	<div></div>	0s 9ms/step	loss: 7.6550 - mae: 8.1329



```
In [54]: def model_forecast(model, series, window_size, batch_size):
        """Uses an input model to generate predictions on data windows

        Args:
            model (TF Keras Model) - model that accepts data windows
            series (array of float) - contains the values of the time series
            window_size (int) - the number of time steps to include in the window
            batch_size (int) - the batch size

        Returns:
            forecast (numpy array) - array containing predictions
        """

        # Generate a TF Dataset from the series values
        dataset = tf.data.Dataset.from_tensor_slices(series)

        # Window the data but only take those with the specified size
        dataset = dataset.window(window_size, shift=1, drop_remainder=True)

        # Flatten the windows by putting its elements in a single batch
        dataset = dataset.flat_map(lambda w: w.batch(window_size))

        # Create batches of windows
        dataset = dataset.batch(batch_size).prefetch(1)

        # Get predictions on the entire dataset
        forecast = model.predict(dataset)

        return forecast
```

```
In [55]: # Reduce the original series
forecast_series = series[split_time-window_size:-1]

# Use helper function to generate predictions
forecast = model_forecast(model, forecast_series, window_size, batch_size)
```



```

# Drop single dimensional axis
results = forecast.squeeze()

# Plot the results
#!pip install sktime

###Función para graficar la serie
def plot_series(time, series, format="-", start=0, end=None):
    """
    Visualizes time series data

    Args:
        time (array of int) - contains the time steps
        series (array of int) - contains the measurements for each time step
        format - line style when plotting the graph
        start - first time step to plot
        end - last time step to plot
    """

    # Setup dimensions of the graph figure
    plt.figure(figsize=(10, 6))

    if type(series) is tuple:

        for series_num in series:
            # Plot the time series data
            plt.plot(time[start:end], series_num[start:end], format)

    else:
        # Plot the time series data
        plt.plot(time[start:end], series[start:end], format)

    # Label the x-axis
    plt.xlabel("Time")

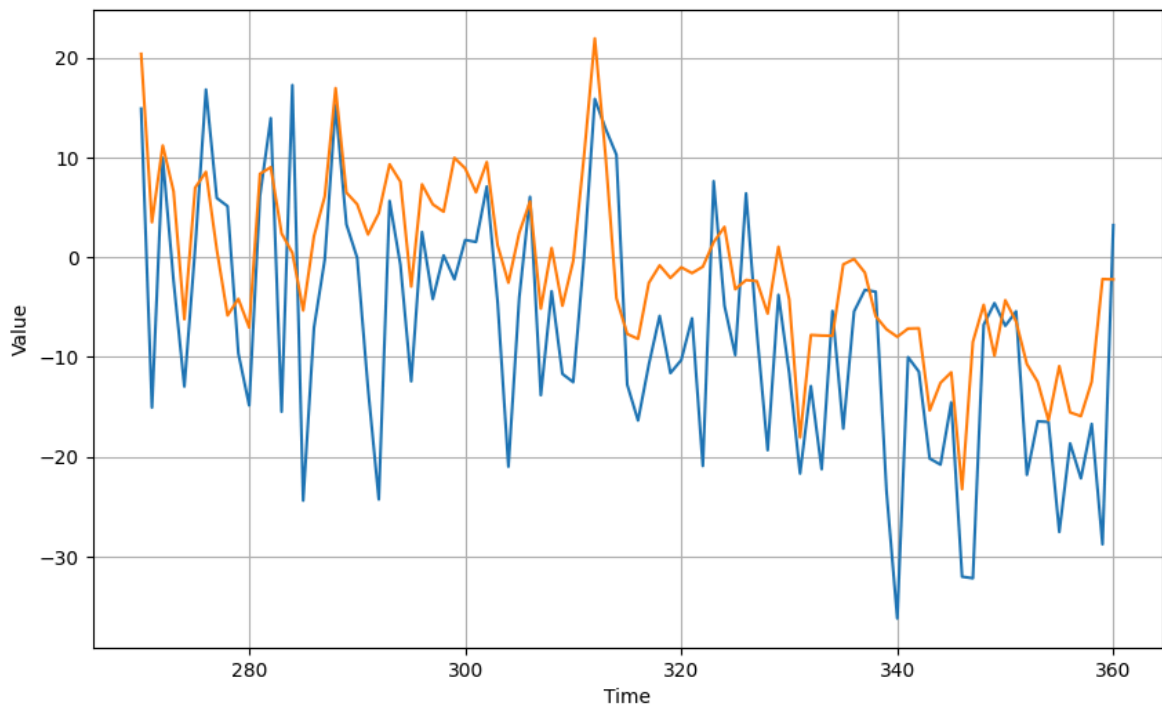
    # Label the y-axis
    plt.ylabel("Value")

    # Overlay a grid on the graph
    plt.grid(True)

    # Draw the graph on screen
    plt.show()

plot_series(time_valid, (x_valid, results))
#forecast
#results

```



```
In [56]: x_valid2 = x_valid.squeeze()
# Calculamos la métrica sobre el conjunto de prueba (validación)
print(tf.keras.metrics.MSE(x_valid2, results).numpy())
print(tf.keras.metrics.MAE(x_valid2, results).numpy())
```

105.09526

8.217949

Comparación con el modelo original

Observamos que la tasa de aprendizaje y la pérdida sigue siendo la misma independientemente del número de epochs.

En cambio, las métricas del modelo original son mejores. Esto puede deberse a que, a veces, al aumentar los epochs, el modelo puede sobreajustarse, aprendiendo demasiado de los datos de entrenamiento y perdiendo capacidad de generalización.

Diferencias de hiperparámetros

En los modelos anteriores, hemos obtenido las siguientes métricas de MAE:

Modelo 1 (capas bidireccionales, función de activación tanh): 7.161354

Modelo 2 (capas NO bidireccionales, función de activación softsign): 8.913031

Modelo 3 (capas bidireccionales, función de activación softsign): 11.5769205

Modelo 4 (capas NO bidireccionales, función de activación tanh): 11.611933

Conclusión

Al comparar capas bidireccionales y no bidireccionales, los modelos con capas bidireccionales generalmente muestran un mejor rendimiento. El Modelo 1 es

significativamente mejor que el Modelo 2, lo que sugiere que las capas bidireccionales ayudan a capturar mejor la información secuencial en los datos.

Respecto a las funciones de activación, tanh parece ser superior a softsign. El Modelo 1 con tanh supera al Modelo 3 con softsign, lo cual indica que tanh es más efectiva en este caso para las capas LSTM, independientemente de si son bidireccionales o no.

En resumen, la combinación de capas bidireccionales con la función de activación tanh ofrece el mejor rendimiento general. Los modelos que utilizan softsign y capas no bidireccionales tienden a tener un rendimiento inferior, como se observa en los Modelos 3 y 4.

Modelo 6 (tasa de aprendizaje no óptima)

```
In [69]: model_tune = tf.keras.models.Sequential([
    tf.keras.layers.Lambda(lambda x: tf.expand_dims(x, axis=-1),
                           input_shape=[window_size]),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(8, return_sequences=True)),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(8)),
    tf.keras.layers.Dense(1),
    tf.keras.layers.Lambda(lambda x: x * 100.0)
])

#Aquí vamos a dar el valor del Learning rate que nos da mejores resultados

# Conjunto de datos partidos en "ventanas"
dataset = windowed_dataset(series, window_size, batch_size, shuffle_buffer_size)

#Esto permite que se use la información del epoch en el que vamos (ciclo hacia a
#para actualizar la Learning rate a través de alguna función, aquí en particular
#se incrementa el epoch el Learning rate se hace más grande
lr_schedule = tf.keras.callbacks.LearningRateScheduler(
    lambda epoch: 1e-8 * 10**(epoch / 20))

# Initialize the optimizer
#Uso de descenso del gradiente como método para actualizar los pesos con un pará
#que acelera el descenso de gradiente en la dirección relevante
optimizer = tf.keras.optimizers.SGD(momentum=0.9)

# Set the training parameters
#La función de pérdida usada es la de Huber. Esta función de pérdida incluye una
#para cuando no estamos cerca del valor real, usando optimizer que definimos arr
model_tune.compile(loss=tf.keras.losses.Huber(), optimizer=optimizer)

# Train the model
#Ponemos a que sean 100 epochs, con Learning rate que se actualiza según lr_scne
history = model_tune.fit(dataset, epochs=100, callbacks=[lr_schedule])

# Ponemos una tasa de aprendizaje no óptima
learning_rate = 1e-07

# Reset states generated by Keras
tf.keras.backend.clear_session()

# Se repite lo mismo visto arriba para la construcción del modelo
```

```

# Construimos el modelo
model = tf.keras.models.Sequential([
    tf.keras.layers.Lambda(lambda x: tf.expand_dims(x, axis=-1),
                            input_shape=[None]),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(8, return_sequences=True)),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(8)),
    tf.keras.layers.Dense(1),
    tf.keras.layers.Lambda(lambda x: x * 100.0)
])

# Establecemos el optimizador (otra vez es desenso de gradiente)
optimizer = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)

# Parámetros de entrenamiento

# En este caso la función de pérdida es otra vez la de Huber, con similar compo
# el learning rate y momentum, la métrica que se pide es el error absoluto medio
model.compile(loss=tf.keras.losses.Huber(),
              optimizer=optimizer,
              metrics=["mae"])

# Entrenamos el modelo (Nuevamente se usan 100 epochs)
history = model.fit(dataset, epochs=100)
import matplotlib.pyplot as plt

# Graficamos el MAE durante el entrenamiento
plt.figure(figsize=(10, 6))
plt.plot(history.history['mae'], label='MAE de entrenamiento')
plt.xlabel('Epochs')
plt.ylabel('MAE')
plt.title('MAE durante el entrenamiento')
plt.legend()
plt.grid(True)
plt.show()

def model_forecast(model, series, window_size, batch_size):
    """Uses an input model to generate predictions on data windows

    Args:
        model (TF Keras Model) - model that accepts data windows
        series (array of float) - contains the values of the time series
        window_size (int) - the number of time steps to include in the window
        batch_size (int) - the batch size

    Returns:
        forecast (numpy array) - array containing predictions
    """

    # Generate a TF Dataset from the series values
    dataset = tf.data.Dataset.from_tensor_slices(series)

    # Window the data but only take those with the specified size
    dataset = dataset.window(window_size, shift=1, drop_remainder=True)

    # Flatten the windows by putting its elements in a single batch
    dataset = dataset.flat_map(lambda w: w.batch(window_size))

    # Create batches of windows
    dataset = dataset.batch(batch_size).prefetch(1)

```

```
# Get predictions on the entire dataset
forecast = model.predict(dataset)


return forecast


# Reduce the original series
forecast_series = series[split_time-window_size:-1]


# Use helper function to generate predictions
forecast = model_forecast(model, forecast_series, window_size, batch_size)


# Drop single dimensional axis
results = forecast.squeeze()


x_valid2 = x_valid.squeeze()
# Calculamos la métrica sobre el conjunto de prueba (validación)
print(tf.keras.metrics.MSE(x_valid2, results).numpy())
print(tf.keras.metrics.MAE(x_valid2, results).numpy())
```


Epoch 1/100
43/43  3s 8ms/step - loss: 55.4139 - learning_rate: 1.0000e-08


Epoch 2/100
43/43  0s 9ms/step - loss: 55.4674 - learning_rate: 1.1220e-08


Epoch 3/100
43/43  0s 9ms/step - loss: 54.4896 - learning_rate: 1.2589e-08


Epoch 4/100
43/43  0s 9ms/step - loss: 57.0525 - learning_rate: 1.4125e-08


Epoch 5/100
43/43  0s 9ms/step - loss: 55.0224 - learning_rate: 1.5849e-08


Epoch 6/100
43/43  0s 9ms/step - loss: 54.1567 - learning_rate: 1.7783e-08


Epoch 7/100
43/43  0s 9ms/step - loss: 53.7357 - learning_rate: 1.9953e-08


Epoch 8/100
43/43  0s 8ms/step - loss: 54.6260 - learning_rate: 2.2387e-08


Epoch 9/100
43/43  0s 9ms/step - loss: 54.5460 - learning_rate: 2.5119e-08


Epoch 10/100
43/43  0s 9ms/step - loss: 53.5617 - learning_rate: 2.8184e-08


Epoch 11/100
43/43  0s 9ms/step - loss: 52.6253 - learning_rate: 3.1623e-08


Epoch 12/100
43/43  0s 9ms/step - loss: 51.4476 - learning_rate: 3.5481e-08


Epoch 13/100
43/43  0s 9ms/step - loss: 53.0597 - learning_rate: 3.9811e-08


Epoch 14/100
43/43  0s 9ms/step - loss: 51.5664 - learning_rate: 4.4668e-08


Epoch 15/100
43/43  0s 9ms/step - loss: 51.2848 - learning_rate: 5.0119e-08


Epoch 16/100
43/43  0s 8ms/step - loss: 50.0089 - learning_rate: 5.6234e-08


Epoch 17/100
43/43  0s 9ms/step - loss: 48.6233 - learning_rate: 6.3096e-08


Epoch 18/100
43/43  0s 9ms/step - loss: 48.5276 - learning_rate: 7.0795e-08


Epoch 19/100
43/43  0s 8ms/step - loss: 45.9701 - learning_rate: 7.9433e-08


Epoch 20/100
43/43  0s 9ms/step - loss: 45.0897 - learning_rate: 8.9125e-08


Epoch 21/100
43/43  0s 8ms/step - loss: 43.3009 - learning_rate: 1.0000e-07


Epoch 22/100
43/43  0s 9ms/step - loss: 41.8146 - learning_rate: 1.1220e-07


Epoch 23/100
43/43  0s 8ms/step - loss: 38.6752 - learning_rate: 1.2589e-07


Epoch 24/100
43/43  0s 8ms/step - loss: 36.2607 - learning_rate: 1.4125e-07


Epoch 25/100
43/43  0s 9ms/step - loss: 34.1316 - learning_rate: 1.5849e-07


Epoch 26/100
43/43  0s 9ms/step - loss: 31.6423 - learning_rate: 1.7783e-07


Epoch 27/100
43/43  0s 9ms/step - loss: 29.8527 - learning_rate: 1.9953e-07


Epoch 28/100
43/43  0s 9ms/step - loss: 26.5554 - learning_rate: 2.2387e-07


Epoch 29/100
43/43  0s 10ms/step - loss: 23.6684 - learning_rate: 2.5119e-07


Epoch 30/100
43/43  0s 10ms/step - loss: 21.2355 - learning_rate: 2.8184e-07


Epoch 31/100
43/43  0s 10ms/step - loss: 18.8368 - learning_rate: 3.1623e-07


Epoch 32/100
43/43  0s 8ms/step - loss: 16.8955 - learning_rate: 3.5481e-07


Epoch 33/100
43/43  0s 9ms/step - loss: 16.4561 - learning_rate: 3.9811e-07


Epoch 34/100
43/43  0s 9ms/step - loss: 14.3800 - learning_rate: 4.4668e-07


Epoch 35/100
43/43  0s 10ms/step - loss: 13.9138 - learning_rate: 5.0119e-07


Epoch 36/100
43/43  0s 9ms/step - loss: 14.0168 - learning_rate: 5.6234e-07


Epoch 37/100
43/43  0s 9ms/step - loss: 12.6066 - learning_rate: 6.3096e-07


Epoch 38/100
43/43  0s 10ms/step - loss: 12.2452 - learning_rate: 7.0795e-07


Epoch 39/100
43/43  0s 8ms/step - loss: 11.2863 - learning_rate: 7.9433e-07


Epoch 40/100
43/43  0s 9ms/step - loss: 11.5364 - learning_rate: 8.9125e-07


Epoch 41/100
43/43  0s 8ms/step - loss: 11.9768 - learning_rate: 1.0000e-06


Epoch 42/100
43/43  0s 9ms/step - loss: 11.0809 - learning_rate: 1.1220e-06


Epoch 43/100
43/43  0s 9ms/step - loss: 11.4212 - learning_rate: 1.2589e-06


Epoch 44/100
43/43  0s 9ms/step - loss: 10.9555 - learning_rate: 1.4125e-06


Epoch 45/100
43/43  0s 9ms/step - loss: 10.5052 - learning_rate: 1.5849e-06


Epoch 46/100
43/43  0s 8ms/step - loss: 10.9076 - learning_rate: 1.7783e-06


Epoch 47/100
43/43  0s 9ms/step - loss: 11.3230 - learning_rate: 1.9953e-06


Epoch 48/100
43/43  0s 9ms/step - loss: 11.1525 - learning_rate: 2.2387e-06


Epoch 49/100
43/43  0s 9ms/step - loss: 10.6582 - learning_rate: 2.5119e-06


Epoch 50/100
43/43  0s 8ms/step - loss: 11.0365 - learning_rate: 2.8184e-06


Epoch 51/100
43/43  0s 8ms/step - loss: 10.9628 - learning_rate: 3.1623e-06


Epoch 52/100
43/43  1s 11ms/step - loss: 10.2420 - learning_rate: 3.5481e-06


Epoch 53/100
43/43  0s 10ms/step - loss: 9.6740 - learning_rate: 3.9811e-06


Epoch 54/100
43/43  1s 11ms/step - loss: 9.7487 - learning_rate: 4.4668e-06


Epoch 55/100
43/43  0s 10ms/step - loss: 9.8402 - learning_rate: 5.0119e-06


Epoch 56/100
43/43  0s 10ms/step - loss: 10.5095 - learning_rate: 5.6234e-06


Epoch 57/100
43/43  0s 9ms/step - loss: 10.7550 - learning_rate: 6.3096e-06


Epoch 58/100
43/43  0s 11ms/step - loss: 9.7876 - learning_rate: 7.0795e-06


Epoch 59/100
43/43  0s 10ms/step - loss: 9.6052 - learning_rate: 7.9433e-06


Epoch 60/100
43/43  0s 10ms/step - loss: 9.8331 - learning_rate: 8.9125e-06


Epoch 61/100
43/43  0s 10ms/step - loss: 9.7488 - learning_rate: 1.0000e-05


Epoch 62/100
43/43  0s 10ms/step - loss: 9.0683 - learning_rate: 1.1220e-05


Epoch 63/100
43/43  0s 10ms/step - loss: 9.8502 - learning_rate: 1.2589e-05


Epoch 64/100
43/43  0s 10ms/step - loss: 9.2113 - learning_rate: 1.4125e-05


Epoch 65/100
43/43  0s 10ms/step - loss: 9.3878 - learning_rate: 1.5849e-05


Epoch 66/100
43/43  0s 9ms/step - loss: 9.1566 - learning_rate: 1.7783e-05


Epoch 67/100
43/43  1s 10ms/step - loss: 9.2013 - learning_rate: 1.9953e-05


Epoch 68/100
43/43  0s 9ms/step - loss: 10.1364 - learning_rate: 2.2387e-05


Epoch 69/100
43/43  0s 10ms/step - loss: 10.2438 - learning_rate: 2.5119e-05


Epoch 70/100
43/43  0s 9ms/step - loss: 8.9068 - learning_rate: 2.8184e-05


Epoch 71/100
43/43  0s 10ms/step - loss: 9.2138 - learning_rate: 3.1623e-05


Epoch 72/100
43/43  0s 10ms/step - loss: 10.0635 - learning_rate: 3.5481e-05


Epoch 73/100
43/43  1s 11ms/step - loss: 9.7320 - learning_rate: 3.9811e-05


Epoch 74/100
43/43  0s 10ms/step - loss: 12.1039 - learning_rate: 4.4668e-05


Epoch 75/100
43/43  0s 10ms/step - loss: 9.5325 - learning_rate: 5.0119e-05


Epoch 76/100
43/43  0s 9ms/step - loss: 10.8573 - learning_rate: 5.6234e-05





















Epoch 77/100
43/43  0s 11ms/step - loss: 9.0571 - learning_rate: 6.3096e-05

Epoch 78/100
43/43  0s 10ms/step - loss: 9.8378 - learning_rate: 7.0795e-05

Epoch 79/100
43/43  1s 11ms/step - loss: 9.6393 - learning_rate: 7.9433e-05

Epoch 80/100
43/43  0s 10ms/step - loss: 9.5677 - learning_rate: 8.9125e-05

Epoch 81/100
43/43  0s 10ms/step - loss: 9.8556 - learning_rate: 1.0000e-05

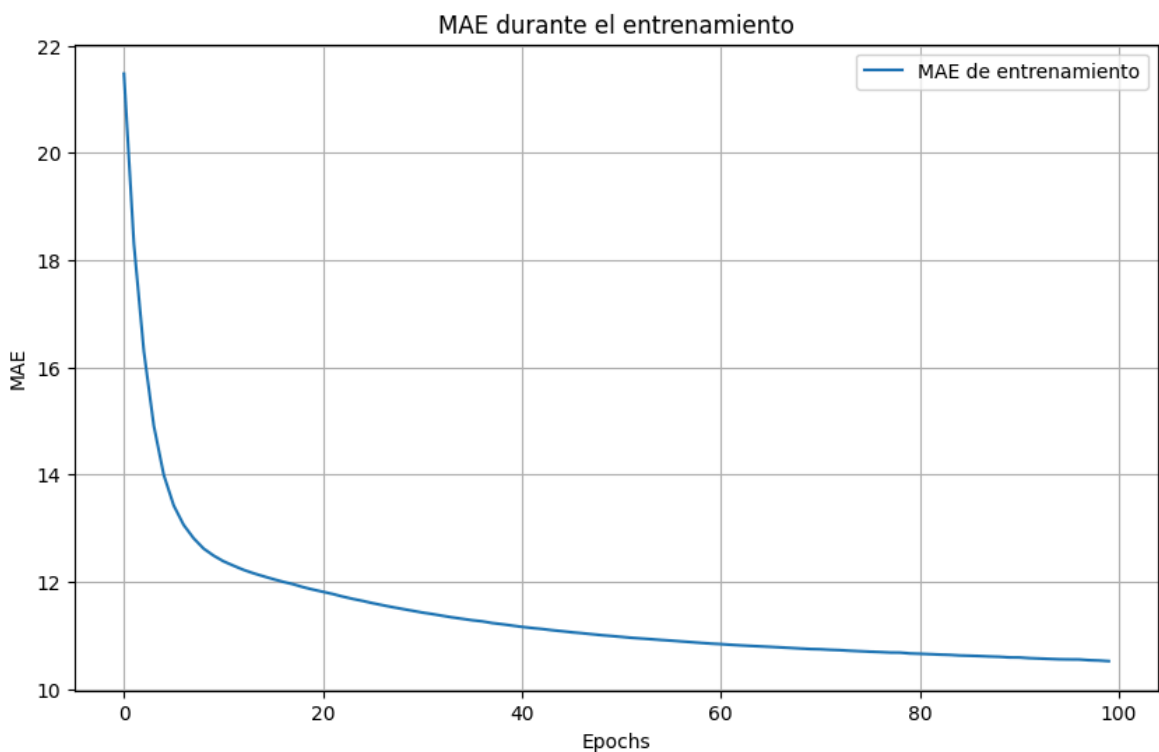
4
Epoch 82/100
43/43  0s 10ms/step - loss: 9.5464 - learning_rate: 1.1220e-04
4
Epoch 83/100
43/43  0s 10ms/step - loss: 10.0026 - learning_rate: 1.2589e-04
Epoch 84/100
43/43  0s 10ms/step - loss: 10.0442 - learning_rate: 1.4125e-04
Epoch 85/100
43/43  0s 10ms/step - loss: 10.5549 - learning_rate: 1.5849e-04
Epoch 86/100
43/43  0s 10ms/step - loss: 12.4813 - learning_rate: 1.7783e-04
Epoch 87/100
43/43  0s 10ms/step - loss: 10.1467 - learning_rate: 1.9953e-04
Epoch 88/100
43/43  0s 10ms/step - loss: 9.9074 - learning_rate: 2.2387e-04
4
Epoch 89/100
43/43  0s 10ms/step - loss: 12.6158 - learning_rate: 2.5119e-04
Epoch 90/100
43/43  0s 10ms/step - loss: 13.6954 - learning_rate: 2.8184e-04
Epoch 91/100
43/43  0s 10ms/step - loss: 12.5510 - learning_rate: 3.1623e-04
Epoch 92/100
43/43  0s 10ms/step - loss: 10.7054 - learning_rate: 3.5481e-04
Epoch 93/100
43/43  0s 11ms/step - loss: 11.6825 - learning_rate: 3.9811e-04
Epoch 94/100
43/43  0s 9ms/step - loss: 12.5201 - learning_rate: 4.4668e-04
4
Epoch 95/100
43/43  1s 12ms/step - loss: 12.7296 - learning_rate: 5.0119e-04
Epoch 96/100
43/43  0s 10ms/step - loss: 11.5685 - learning_rate: 5.6234e-04
Epoch 97/100
43/43  0s 10ms/step - loss: 11.3033 - learning_rate: 6.3096e-04
Epoch 98/100
43/43  0s 9ms/step - loss: 13.2455 - learning_rate: 7.0795e-04
4
Epoch 99/100
43/43  1s 10ms/step - loss: 14.7219 - learning_rate: 7.9433e-04
Epoch 100/100
43/43  0s 10ms/step - loss: 16.0606 - learning_rate: 8.9125e-04
Epoch 1/100
43/43  3s 9ms/step - loss: 23.2292 - mae: 23.7250

Epoch 2/100			
43/43	<div></div>	0s 10ms/step	loss: 19.0067 - mae: 19.5008
Epoch 3/100			
43/43	<div></div>	1s 11ms/step	loss: 16.3748 - mae: 16.8714
Epoch 4/100			
43/43	<div></div>	0s 10ms/step	loss: 13.9217 - mae: 14.4128
Epoch 5/100			
43/43	<div></div>	0s 10ms/step	loss: 13.5646 - mae: 14.0503
Epoch 6/100			
43/43	<div></div>	0s 10ms/step	loss: 12.5648 - mae: 13.0555
Epoch 7/100			
43/43	<div></div>	0s 10ms/step	loss: 11.6964 - mae: 12.1911
Epoch 8/100			
43/43	<div></div>	0s 10ms/step	loss: 11.7946 - mae: 12.2907
Epoch 9/100			
43/43	<div></div>	1s 10ms/step	loss: 11.4144 - mae: 11.9039
Epoch 10/100			
43/43	<div></div>	0s 10ms/step	loss: 11.5895 - mae: 12.0738
Epoch 11/100			
43/43	<div></div>	0s 10ms/step	loss: 11.4275 - mae: 11.9199
Epoch 12/100			
43/43	<div></div>	0s 10ms/step	loss: 11.3186 - mae: 11.8087
Epoch 13/100			
43/43	<div></div>	1s 11ms/step	loss: 11.0468 - mae: 11.5337
Epoch 14/100			
43/43	<div></div>	0s 10ms/step	loss: 10.9271 - mae: 11.4100
Epoch 15/100			
43/43	<div></div>	0s 10ms/step	loss: 10.2344 - mae: 10.7223
Epoch 16/100			
43/43	<div></div>	0s 9ms/step	loss: 10.5362 - mae: 11.0228
Epoch 17/100			
43/43	<div></div>	1s 10ms/step	loss: 10.4261 - mae: 10.9048
Epoch 18/100			
43/43	<div></div>	0s 10ms/step	loss: 11.3712 - mae: 11.8607
Epoch 19/100			
43/43	<div></div>	0s 10ms/step	loss: 10.7738 - mae: 11.2641
Epoch 20/100			
43/43	<div></div>	0s 10ms/step	loss: 10.5129 - mae: 11.0033
Epoch 21/100			
43/43	<div></div>	0s 10ms/step	loss: 10.9722 - mae: 11.4646
Epoch 22/100			
43/43	<div></div>	0s 10ms/step	loss: 10.5049 - mae: 10.9959
Epoch 23/100			
43/43	<div></div>	0s 10ms/step	loss: 10.8963 - mae: 11.3882
Epoch 24/100			
43/43	<div></div>	0s 10ms/step	loss: 10.8183 - mae: 11.3073
Epoch 25/100			
43/43	<div></div>	1s 11ms/step	loss: 10.5922 - mae: 11.0856
Epoch 26/100			
43/43	<div></div>	0s 10ms/step	loss: 10.2239 - mae: 10.7133
Epoch 27/100			
43/43	<div></div>	0s 10ms/step	loss: 10.3739 - mae: 10.8618
Epoch 28/100			
43/43	<div></div>	0s 10ms/step	loss: 9.8257 - mae: 10.3188
Epoch 29/100			
43/43	<div></div>	1s 10ms/step	loss: 10.5638 - mae: 11.0506
Epoch 30/100			
43/43	<div></div>	0s 10ms/step	loss: 10.1028 - mae: 10.5924
Epoch 31/100			
43/43	<div></div>	1s 10ms/step	loss: 10.6987 - mae: 11.1861

Epoch 32/100			
43/43	<div></div>	0s 10ms/step	loss: 10.1111 - mae: 10.6027
Epoch 33/100			
43/43	<div></div>	0s 10ms/step	loss: 10.8271 - mae: 11.3181
Epoch 34/100			
43/43	<div></div>	0s 10ms/step	loss: 10.2992 - mae: 10.7871
Epoch 35/100			
43/43	<div></div>	1s 10ms/step	loss: 11.6442 - mae: 12.1327
Epoch 36/100			
43/43	<div></div>	0s 10ms/step	loss: 10.4146 - mae: 10.9028
Epoch 37/100			
43/43	<div></div>	0s 10ms/step	loss: 9.9233 - mae: 10.4116
Epoch 38/100			
43/43	<div></div>	0s 10ms/step	loss: 10.7891 - mae: 11.2793
Epoch 39/100			
43/43	<div></div>	0s 10ms/step	loss: 9.7780 - mae: 10.2642
Epoch 40/100			
43/43	<div></div>	0s 10ms/step	loss: 9.6203 - mae: 10.1072
Epoch 41/100			
43/43	<div></div>	0s 10ms/step	loss: 10.7203 - mae: 11.2079
Epoch 42/100			
43/43	<div></div>	0s 10ms/step	loss: 10.1349 - mae: 10.6237
Epoch 43/100			
43/43	<div></div>	0s 10ms/step	loss: 9.9632 - mae: 10.4482
Epoch 44/100			
43/43	<div></div>	0s 10ms/step	loss: 10.4349 - mae: 10.9198
Epoch 45/100			
43/43	<div></div>	1s 10ms/step	loss: 10.2527 - mae: 10.7371
Epoch 46/100			
43/43	<div></div>	0s 10ms/step	loss: 9.6307 - mae: 10.1168
Epoch 47/100			
43/43	<div></div>	0s 10ms/step	loss: 10.0904 - mae: 10.5703
Epoch 48/100			
43/43	<div></div>	0s 10ms/step	loss: 10.7935 - mae: 11.2836
Epoch 49/100			
43/43	<div></div>	0s 11ms/step	loss: 10.0097 - mae: 10.4979
Epoch 50/100			
43/43	<div></div>	0s 10ms/step	loss: 10.5996 - mae: 11.0848
Epoch 51/100			
43/43	<div></div>	1s 11ms/step	loss: 10.1291 - mae: 10.6166
Epoch 52/100			
43/43	<div></div>	0s 10ms/step	loss: 10.5031 - mae: 10.9929
Epoch 53/100			
43/43	<div></div>	1s 10ms/step	loss: 10.4858 - mae: 10.9718
Epoch 54/100			
43/43	<div></div>	0s 10ms/step	loss: 10.6411 - mae: 11.1312
Epoch 55/100			
43/43	<div></div>	0s 10ms/step	loss: 9.7229 - mae: 10.2067
Epoch 56/100			
43/43	<div></div>	0s 10ms/step	loss: 9.7538 - mae: 10.2406
Epoch 57/100			
43/43	<div></div>	1s 10ms/step	loss: 9.5334 - mae: 10.0187
Epoch 58/100			
43/43	<div></div>	0s 10ms/step	loss: 10.4489 - mae: 10.9356
Epoch 59/100			
43/43	<div></div>	0s 10ms/step	loss: 10.7492 - mae: 11.2362
Epoch 60/100			
43/43	<div></div>	0s 10ms/step	loss: 10.0486 - mae: 10.5378
Epoch 61/100			
43/43	<div></div>	1s 11ms/step	loss: 10.6865 - mae: 11.1756

Epoch 62/100			
43/43	<div></div>	1s 11ms/step	loss: 10.2048 - mae: 10.6914
Epoch 63/100			
43/43	<div></div>	0s 10ms/step	loss: 10.0114 - mae: 10.5043
Epoch 64/100			
43/43	<div></div>	1s 11ms/step	loss: 10.4634 - mae: 10.9525
Epoch 65/100			
43/43	<div></div>	1s 11ms/step	loss: 9.8839 - mae: 10.3719
Epoch 66/100			
43/43	<div></div>	1s 11ms/step	loss: 10.1171 - mae: 10.6076
Epoch 67/100			
43/43	<div></div>	0s 10ms/step	loss: 10.7204 - mae: 11.2064
Epoch 68/100			
43/43	<div></div>	0s 10ms/step	loss: 9.6101 - mae: 10.0929
Epoch 69/100			
43/43	<div></div>	0s 10ms/step	loss: 10.3595 - mae: 10.8504
Epoch 70/100			
43/43	<div></div>	1s 10ms/step	loss: 9.7195 - mae: 10.2126
Epoch 71/100			
43/43	<div></div>	0s 10ms/step	loss: 9.6631 - mae: 10.1511
Epoch 72/100			
43/43	<div></div>	0s 10ms/step	loss: 10.1400 - mae: 10.6311
Epoch 73/100			
43/43	<div></div>	0s 10ms/step	loss: 10.2462 - mae: 10.7374
Epoch 74/100			
43/43	<div></div>	0s 10ms/step	loss: 10.1813 - mae: 10.6732
Epoch 75/100			
43/43	<div></div>	1s 11ms/step	loss: 10.7890 - mae: 11.2769
Epoch 76/100			
43/43	<div></div>	0s 10ms/step	loss: 10.0478 - mae: 10.5392
Epoch 77/100			
43/43	<div></div>	1s 11ms/step	loss: 10.0469 - mae: 10.5394
Epoch 78/100			
43/43	<div></div>	0s 10ms/step	loss: 9.7987 - mae: 10.2882
Epoch 79/100			
43/43	<div></div>	1s 11ms/step	loss: 9.8814 - mae: 10.3714
Epoch 80/100			
43/43	<div></div>	0s 10ms/step	loss: 9.5360 - mae: 10.0302
Epoch 81/100			
43/43	<div></div>	1s 10ms/step	loss: 10.0913 - mae: 10.5790
Epoch 82/100			
43/43	<div></div>	0s 10ms/step	loss: 9.5782 - mae: 10.0693
Epoch 83/100			
43/43	<div></div>	0s 10ms/step	loss: 9.7594 - mae: 10.2476
Epoch 84/100			
43/43	<div></div>	0s 11ms/step	loss: 9.7055 - mae: 10.1964
Epoch 85/100			
43/43	<div></div>	0s 10ms/step	loss: 10.1613 - mae: 10.6513
Epoch 86/100			
43/43	<div></div>	0s 10ms/step	loss: 9.8786 - mae: 10.3690
Epoch 87/100			
43/43	<div></div>	0s 10ms/step	loss: 9.5726 - mae: 10.0630
Epoch 88/100			
43/43	<div></div>	0s 11ms/step	loss: 9.8783 - mae: 10.3686
Epoch 89/100			
43/43	<div></div>	0s 10ms/step	loss: 10.0154 - mae: 10.5105
Epoch 90/100			
43/43	<div></div>	0s 10ms/step	loss: 10.9081 - mae: 11.4008
Epoch 91/100			
43/43	<div></div>	0s 10ms/step	loss: 10.0329 - mae: 10.5276

Epoch 92/100
43/43 ————— **1s** 11ms/step - loss: 9.5601 - mae: 10.0524
 Epoch 93/100
43/43 ————— **0s** 10ms/step - loss: 10.2469 - mae: 10.7342
 Epoch 94/100
43/43 ————— **1s** 10ms/step - loss: 10.2366 - mae: 10.7230
 Epoch 95/100
43/43 ————— **1s** 11ms/step - loss: 9.5681 - mae: 10.0630
 Epoch 96/100
43/43 ————— **0s** 10ms/step - loss: 9.8151 - mae: 10.3094
 Epoch 97/100
43/43 ————— **1s** 11ms/step - loss: 10.2356 - mae: 10.7304
 Epoch 98/100
43/43 ————— **0s** 10ms/step - loss: 9.9394 - mae: 10.4295
 Epoch 99/100
43/43 ————— **0s** 11ms/step - loss: 10.0843 - mae: 10.5785
 Epoch 100/100
43/43 ————— **0s** 10ms/step - loss: 9.8666 - mae: 10.3633



12/12 ————— **1s** 33ms/step
 169.58095
 10.626108

Resultados:

MSE: 169.58095

MAE: 10.626108

Observamos que al inicio el MAE es demasiado grande (22 aprox.), pero a medida que aumentan los epochs este error va disminuyendo.

Predecir hasta tiempo = 400

Eligiremos el modelo 1 ya que es el que tiene mejores métricas.

```

In [70]: learning_rate = min_loss_lr

# Construcción del modelo
tf.keras.backend.clear_session()
model = tf.keras.models.Sequential([
    tf.keras.layers.Lambda(lambda x: tf.expand_dims(x, axis=-1), input_shape=[No
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(8, return_sequences=True))
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(8)),
    tf.keras.layers.Dense(1),
    tf.keras.layers.Lambda(lambda x: x * 100.0)
])

# Compilación del modelo
optimizer = tf.keras.optimizers.SGD(learning_rate=learning_rate, momentum=0.9)
model.compile(loss=tf.keras.losses.Huber(), optimizer=optimizer, metrics=["mae"])

# Entrenamiento del modelo
history = model.fit(dataset, epochs=100)

# Visualización del MAE durante el entrenamiento
plt.figure(figsize=(10, 6))
plt.plot(history.history['mae'], label='MAE de entrenamiento')
plt.xlabel('Epochs')
plt.ylabel('MAE')
plt.title('MAE durante el entrenamiento')
plt.legend()
plt.grid(True)
plt.show()

# Función para predicciones futuras hasta el tiempo 400
def forecast_future(model, series, window_size, future_steps):
    last_window = series[-window_size:]
    future_forecast = []

    for _ in range(future_steps):
        input_window = np.expand_dims(last_window, axis=0)
        pred = model.predict(input_window)[0, 0]
        future_forecast.append(pred)
        last_window = np.append(last_window[1:], pred)

    return np.array(future_forecast)

# Definimos la cantidad de pasos futuros a predecir (hasta tiempo 400)
future_steps = 400 - len(series) # 400 - 361 = 39































# Predicciones futuras
future_forecast = forecast_future(model, series.squeeze(), window_size, future_s











# Visualización de la serie original con las predicciones futuras
future_time = np.arange(len(series), len(series) + future_steps)
plt.figure(figsize=(12, 6))
plt.plot(time, series, label='Serie original')
plt.plot(future_time, future_forecast, label='Predicciones futuras', linestyle='
plt.xlabel('Tiempo')
plt.ylabel('Valor')
plt.title('Predicciones futuras hasta el tiempo 400')
plt.legend()
plt.grid(True)
plt.show()

```

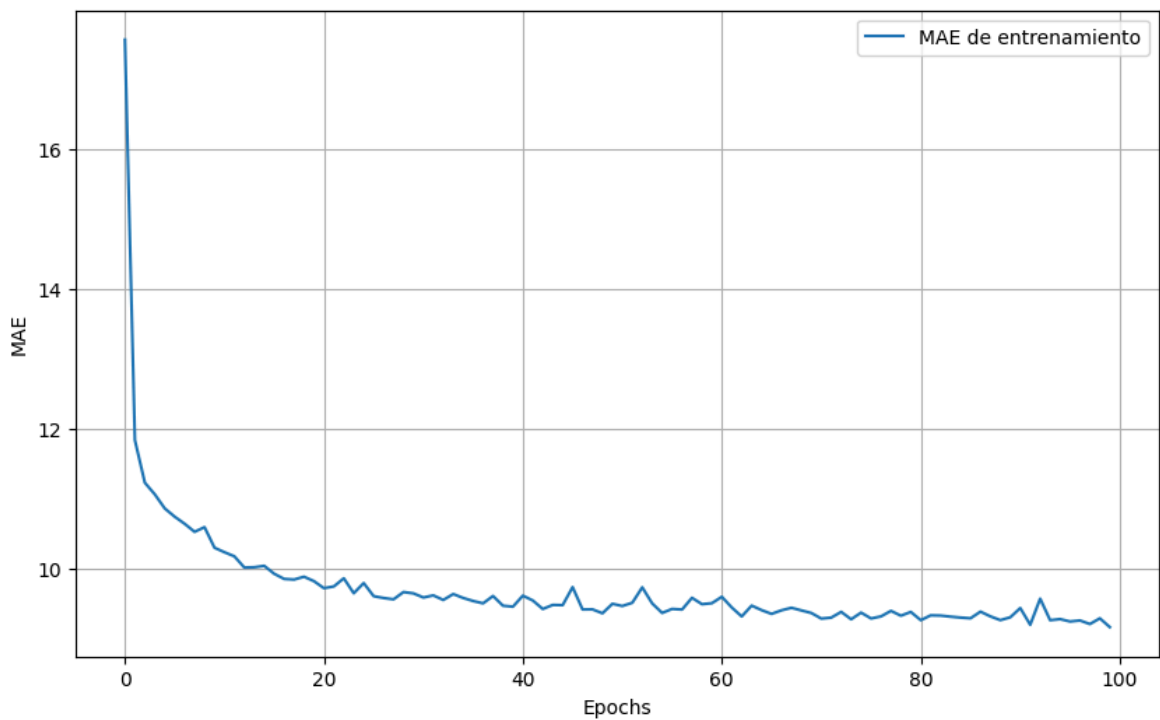
Epoch 1/100		
43/43	<div><div></div></div>	3s 8ms/step - loss: 24.3212 - mae: 24.8178
Epoch 2/100		
43/43	<div><div></div></div>	0s 10ms/step - loss: 11.3655 - mae: 11.8575
Epoch 3/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 10.9409 - mae: 11.4329
Epoch 4/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 10.8483 - mae: 11.3448
Epoch 5/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.9814 - mae: 10.4754
Epoch 6/100		
43/43	<div><div></div></div>	0s 10ms/step - loss: 10.5607 - mae: 11.0497
Epoch 7/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 10.4109 - mae: 10.8992
Epoch 8/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 10.3224 - mae: 10.8188
Epoch 9/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 10.4834 - mae: 10.9742
Epoch 10/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.7971 - mae: 10.2824
Epoch 11/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.2804 - mae: 9.7701
Epoch 12/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.4242 - mae: 9.9113
Epoch 13/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.2159 - mae: 9.7089
Epoch 14/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.8738 - mae: 9.3657
Epoch 15/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 10.1698 - mae: 10.6609
Epoch 16/100		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.2787 - mae: 9.7639
Epoch 17/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.2592 - mae: 9.7551
Epoch 18/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.1559 - mae: 9.6353
Epoch 19/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 8.5099 - mae: 8.9917
Epoch 20/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.4515 - mae: 9.9355
Epoch 21/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.1431 - mae: 9.6349
Epoch 22/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 8.7559 - mae: 9.2454
Epoch 23/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.0454 - mae: 9.5347
Epoch 24/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.1924 - mae: 9.6758
Epoch 25/100		
43/43	<div><div></div></div>	0s 10ms/step - loss: 9.2205 - mae: 9.7103
Epoch 26/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 9.6613 - mae: 10.1510
Epoch 27/100		
43/43	<div><div></div></div>	0s 8ms/step - loss: 10.1529 - mae: 10.6442
Epoch 28/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.2812 - mae: 9.7675
Epoch 29/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.0410 - mae: 9.5294
Epoch 30/100		
43/43	<div><div></div></div>	0s 9ms/step - loss: 9.3929 - mae: 9.8846

Epoch 31/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.1441 - mae: 9.6349
Epoch 32/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.1641 - mae: 9.6549
Epoch 33/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.3611 - mae: 9.8516
Epoch 34/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.5355 - mae: 9.0215
Epoch 35/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.4887 - mae: 9.9784
Epoch 36/100			
43/43	<div><div></div></div>	0s 10ms/step	loss: 9.3795 - mae: 9.8653
Epoch 37/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.5790 - mae: 9.0640
Epoch 38/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.8442 - mae: 9.3295
Epoch 39/100			
43/43	<div><div></div></div>	0s 10ms/step	loss: 9.1817 - mae: 9.6603
Epoch 40/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.1370 - mae: 9.6192
Epoch 41/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.9740 - mae: 9.4687
Epoch 42/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.8087 - mae: 9.2893
Epoch 43/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.8631 - mae: 9.3532
Epoch 44/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.7709 - mae: 9.2549
Epoch 45/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.3538 - mae: 9.8438
Epoch 46/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.3065 - mae: 9.8021
Epoch 47/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 8.6134 - mae: 9.1006
Epoch 48/100			
43/43	<div><div></div></div>	0s 9ms/step	loss: 9.1293 - mae: 9.6125
Epoch 49/100			
43/43	<div><div></div></div>	0s 8ms/step	loss: 8.7385 - mae: 9.2258
Epoch 50/100			
43/43	<div><div></div></div>	1s 11ms/step	loss: 10.0644 - mae: 10.5572
Epoch 51/100			
43/43	<div><div></div></div>	0s 11ms/step	loss: 9.2141 - mae: 9.7087
Epoch 52/100			
43/43	<div><div></div></div>	1s 13ms/step	loss: 9.0774 - mae: 9.5589
Epoch 53/100			
43/43	<div><div></div></div>	1s 15ms/step	loss: 9.6699 - mae: 10.1629
Epoch 54/100			
43/43	<div><div></div></div>	1s 12ms/step	loss: 8.1172 - mae: 8.5993
Epoch 55/100			
43/43	<div><div></div></div>	1s 12ms/step	loss: 9.2641 - mae: 9.7498
Epoch 56/100			
43/43	<div><div></div></div>	1s 11ms/step	loss: 9.6964 - mae: 10.1822
Epoch 57/100			
43/43	<div><div></div></div>	0s 10ms/step	loss: 9.4723 - mae: 9.9659
Epoch 58/100			
43/43	<div><div></div></div>	0s 10ms/step	loss: 9.2708 - mae: 9.7630
Epoch 59/100			
43/43	<div><div></div></div>	1s 12ms/step	loss: 8.5688 - mae: 9.0563
Epoch 60/100			
43/43	<div><div></div></div>	1s 11ms/step	loss: 9.0946 - mae: 9.5837

Epoch 61/100
43/43  0s 10ms/step - loss: 8.7543 - mae: 9.2349
Epoch 62/100
43/43  0s 9ms/step - loss: 9.0081 - mae: 9.4970
Epoch 63/100
43/43  0s 9ms/step - loss: 8.9480 - mae: 9.4313
Epoch 64/100
43/43  0s 9ms/step - loss: 9.7424 - mae: 10.2322
Epoch 65/100
43/43  0s 9ms/step - loss: 9.0237 - mae: 9.5154
Epoch 66/100
43/43  0s 8ms/step - loss: 8.6593 - mae: 9.1474
Epoch 67/100
43/43  0s 9ms/step - loss: 9.2620 - mae: 9.7450
Epoch 68/100
43/43  0s 9ms/step - loss: 9.2506 - mae: 9.7391
Epoch 69/100
43/43  0s 9ms/step - loss: 9.2692 - mae: 9.7609
Epoch 70/100
43/43  0s 10ms/step - loss: 8.8666 - mae: 9.3513
Epoch 71/100
43/43  0s 9ms/step - loss: 9.4042 - mae: 9.8932
Epoch 72/100
43/43  0s 9ms/step - loss: 8.4124 - mae: 8.9004
Epoch 73/100
43/43  0s 9ms/step - loss: 9.1048 - mae: 9.5872
Epoch 74/100
43/43  0s 8ms/step - loss: 9.4718 - mae: 9.9559
Epoch 75/100
43/43  0s 9ms/step - loss: 9.4386 - mae: 9.9245
Epoch 76/100
43/43  0s 10ms/step - loss: 9.0515 - mae: 9.5334
Epoch 77/100
43/43  0s 9ms/step - loss: 9.1099 - mae: 9.5963
Epoch 78/100
43/43  0s 9ms/step - loss: 8.7255 - mae: 9.2187
Epoch 79/100
43/43  0s 8ms/step - loss: 8.4947 - mae: 8.9819
Epoch 80/100
43/43  0s 8ms/step - loss: 9.2182 - mae: 9.7058
Epoch 81/100
43/43  0s 9ms/step - loss: 9.3098 - mae: 9.7982
Epoch 82/100
43/43  0s 8ms/step - loss: 9.3294 - mae: 9.8143
Epoch 83/100
43/43  0s 9ms/step - loss: 8.7490 - mae: 9.2362
Epoch 84/100
43/43  0s 9ms/step - loss: 9.2728 - mae: 9.7586
Epoch 85/100
43/43  0s 9ms/step - loss: 8.8127 - mae: 9.2968
Epoch 86/100
43/43  0s 9ms/step - loss: 8.9729 - mae: 9.4620
Epoch 87/100
43/43  0s 9ms/step - loss: 9.0967 - mae: 9.5872
Epoch 88/100
43/43  0s 9ms/step - loss: 8.8108 - mae: 9.3045
Epoch 89/100
43/43  0s 8ms/step - loss: 8.7692 - mae: 9.2493
Epoch 90/100
43/43  0s 9ms/step - loss: 8.8138 - mae: 9.2940

Epoch 91/100
43/43  0s 9ms/step - loss: 9.0981 - mae: 9.5910
Epoch 92/100
43/43  0s 9ms/step - loss: 9.0077 - mae: 9.4988
Epoch 93/100
43/43  0s 9ms/step - loss: 9.0360 - mae: 9.5233
Epoch 94/100
43/43  0s 9ms/step - loss: 9.2914 - mae: 9.7831
Epoch 95/100
43/43  0s 9ms/step - loss: 8.8462 - mae: 9.3399
Epoch 96/100
43/43  0s 9ms/step - loss: 8.9416 - mae: 9.4302
Epoch 97/100
43/43  0s 9ms/step - loss: 8.3040 - mae: 8.7937
Epoch 98/100
43/43  0s 9ms/step - loss: 9.2208 - mae: 9.7115
Epoch 99/100
43/43  0s 9ms/step - loss: 9.0936 - mae: 9.5836
Epoch 100/100
43/43  0s 10ms/step - loss: 8.4822 - mae: 8.9745

MAE durante el entrenamiento



1/1	0s	375ms/step
1/1	0s	31ms/step
1/1	0s	34ms/step
1/1	0s	32ms/step
1/1	0s	32ms/step
1/1	0s	31ms/step
1/1	0s	33ms/step
1/1	0s	32ms/step
1/1	0s	38ms/step
1/1	0s	30ms/step
1/1	0s	33ms/step
1/1	0s	31ms/step
1/1	0s	38ms/step
1/1	0s	39ms/step
1/1	0s	32ms/step
1/1	0s	31ms/step
1/1	0s	30ms/step
1/1	0s	32ms/step
1/1	0s	30ms/step
1/1	0s	32ms/step
1/1	0s	31ms/step
1/1	0s	30ms/step
1/1	0s	41ms/step
1/1	0s	32ms/step
1/1	0s	30ms/step
1/1	0s	33ms/step
1/1	0s	32ms/step
1/1	0s	32ms/step
1/1	0s	39ms/step
1/1	0s	32ms/step
1/1	0s	31ms/step
1/1	0s	31ms/step
1/1	0s	30ms/step
1/1	0s	37ms/step
1/1	0s	31ms/step
1/1	0s	31ms/step
1/1	0s	34ms/step
1/1	0s	31ms/step
1/1	0s	32ms/step

