timeseries-forecasting-1

October 11, 2024

1 Climate Data Time-Series

You are again moving to another role, not at *The Weather Channel*, where you are ask to create a Weather Forecasting Model.

For that, you will be using *Jena Climate* dataset recorded by the *Max Planck Institute for Biogeochemistry*.

The dataset consists of 14 features such as temperature, pressure, humidity etc, recorded **once per 10 minutes**.

Location: Weather Station, Max Planck Institute for Biogeochemistry in Jena, Germany

Time-frame Considered: **Jan 10, 2009 - December 31, 2012**

Library Imports

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import keras
```

1.0.1 1) Load your data

Your data can be found on the Deep Learning Module under a file named: climate_data_2009_2012.csv

[2]:
```
df = pd.read_csv("climate_data_2009_2012.csv")
```

1.0.2 2) Data engineering

You are given 3 lists: - titles: Display names of your columns - feature_keys: Names of the columns used as features - colors: The color to use when ploting that column's value

[3]:
```
titles = [
    "Pressure",
    "Temperature",
    "Temperature in Kelvin",
    "Temperature (dew point)",
    "Relative Humidity",
    "Saturation vapor pressure",
    "Vapor pressure",
```

```python
    "Vapor pressure deficit",
    "Specific humidity",
    "Water vapor concentration",
    "Airtight",
    "Wind speed",
    "Maximum wind speed",
    "Wind direction in degrees",
]

feature_keys = [
    "p (mbar)",
    "T (degC)",
    "Tpot (K)",
    "Tdew (degC)",
    "rh (%)",
    "VPmax (mbar)",
    "VPact (mbar)",
    "VPdef (mbar)",
    "sh (g/kg)",
    "H2OC (mmol/mol)",
    "rho (g/m**3)",
    "wv (m/s)",
    "max. wv (m/s)",
    "wd (deg)",
]

colors = [
    "blue",
    "orange",
    "green",
    "red",
    "purple",
    "brown",
    "pink",
    "gray",
    "olive",
    "cyan",
]
```

Let's look at the climate data:

[4]:
```python
df.head()
```

[4]:
```
             Date Time  p (mbar)  T (degC)  Tpot (K)  Tdew (degC)  rh (%)  \
0  01.01.2009 00:10:00    996.52     -8.02    265.40        -8.90    93.3
1  01.01.2009 00:20:00    996.57     -8.41    265.01        -9.28    93.4
2  01.01.2009 00:30:00    996.53     -8.51    264.91        -9.31    93.9
```

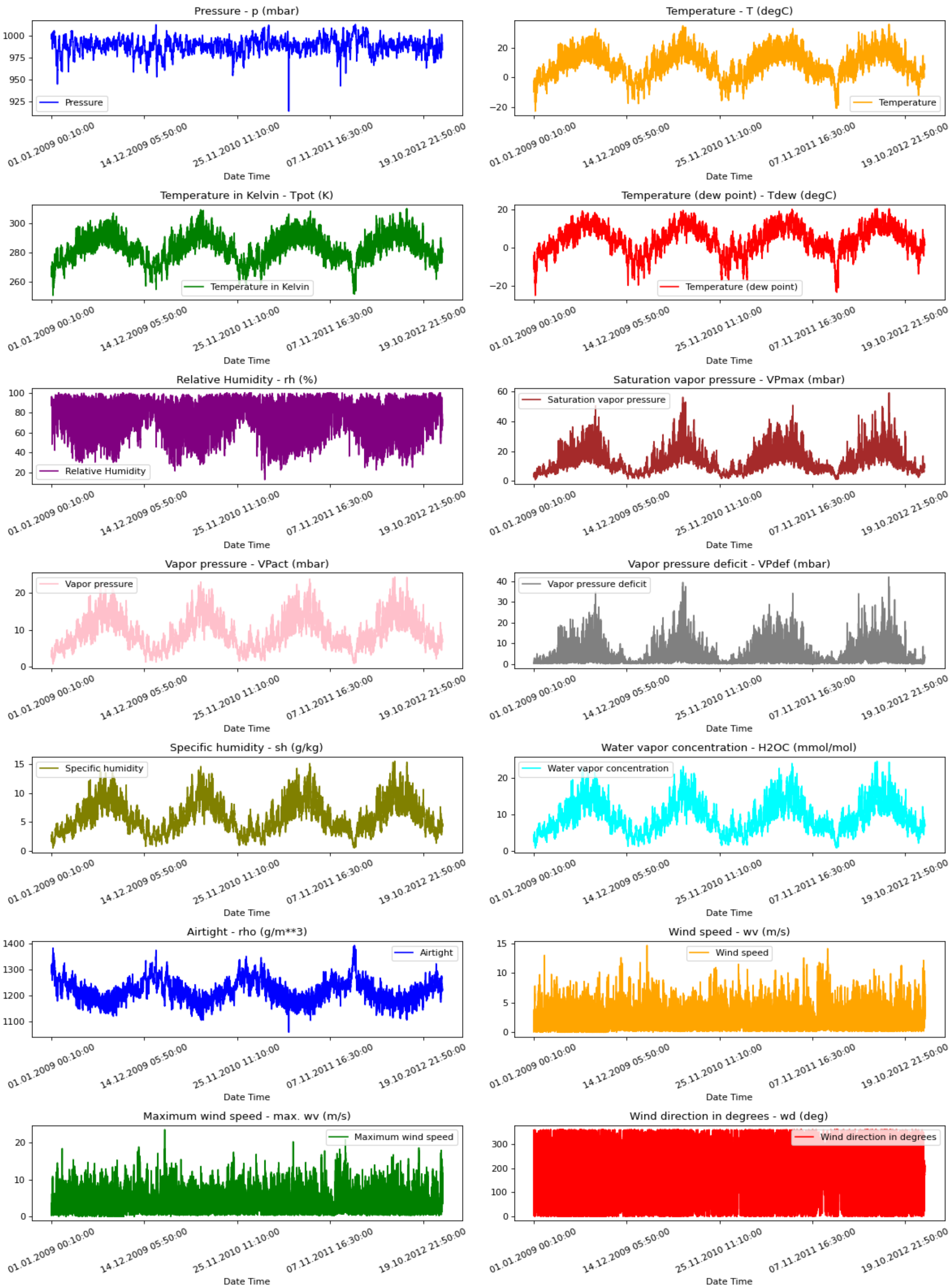
```
3  01.01.2009 00:40:00    996.51     -8.31    265.12        -9.07    94.2
4  01.01.2009 00:50:00    996.51     -8.27    265.15        -9.04    94.1

   VPmax (mbar)  VPact (mbar)  VPdef (mbar)  sh (g/kg)  H2OC (mmol/mol)  \
0          3.33          3.11          0.22       1.94             3.12
1          3.23          3.02          0.21       1.89             3.03
2          3.21          3.01          0.20       1.88             3.02
3          3.26          3.07          0.19       1.92             3.08
4          3.27          3.08          0.19       1.92             3.09

   rho (g/m**3)  wv (m/s)  max. wv (m/s)  wd (deg)
0       1307.75      1.03           1.75     152.3
1       1309.80      0.72           1.50     136.1
2       1310.24      0.19           0.63     171.6
3       1309.19      0.34           0.50     198.0
4       1309.00      0.32           0.63     214.3
```

Define a function to show a plot of each column (using the respective color)

[5]:
```python
def show_raw_visualization(data, date_time_key):
    time_data = data[date_time_key]
    fig, axes = plt.subplots(
        nrows=7, ncols=2, figsize=(15, 20), dpi=80, facecolor="w", edgecolor="k"
    )
    for i in range(len(feature_keys)):
        key = feature_keys[i]
        c = colors[i % (len(colors))]
        t_data = data[key]
        t_data.index = time_data
        t_data.head()
        ax = t_data.plot(
            ax=axes[i // 2, i % 2],
            color=c,
            title="{} - {}".format(titles[i], key),
            rot=25,
        )
        ax.legend([titles[i]])
    plt.tight_layout()
```

Display each column in a plot using above funciton:

[6]:
```python
show_raw_visualization(df, "Date Time")
```



As you can see we have lots of data, this can be a challenge when we train our model, to resolve that we will reduce the resolution of our data, instead of having a climate signal each 10 minutes, we will have it each hour

- Add a new column to your dataframe with the Date Time information
- Name that column FormatedDateTime
- Convert that column into date time data type
- Set that column as the dataframe index
- Regroup data to be each 1 hour instead of each 10 minutes
- Save the grouped data into a dataframe called df_resampled
- Remove the FormatedDateTime as the index.
- Show the top 5 rows of df_resampled

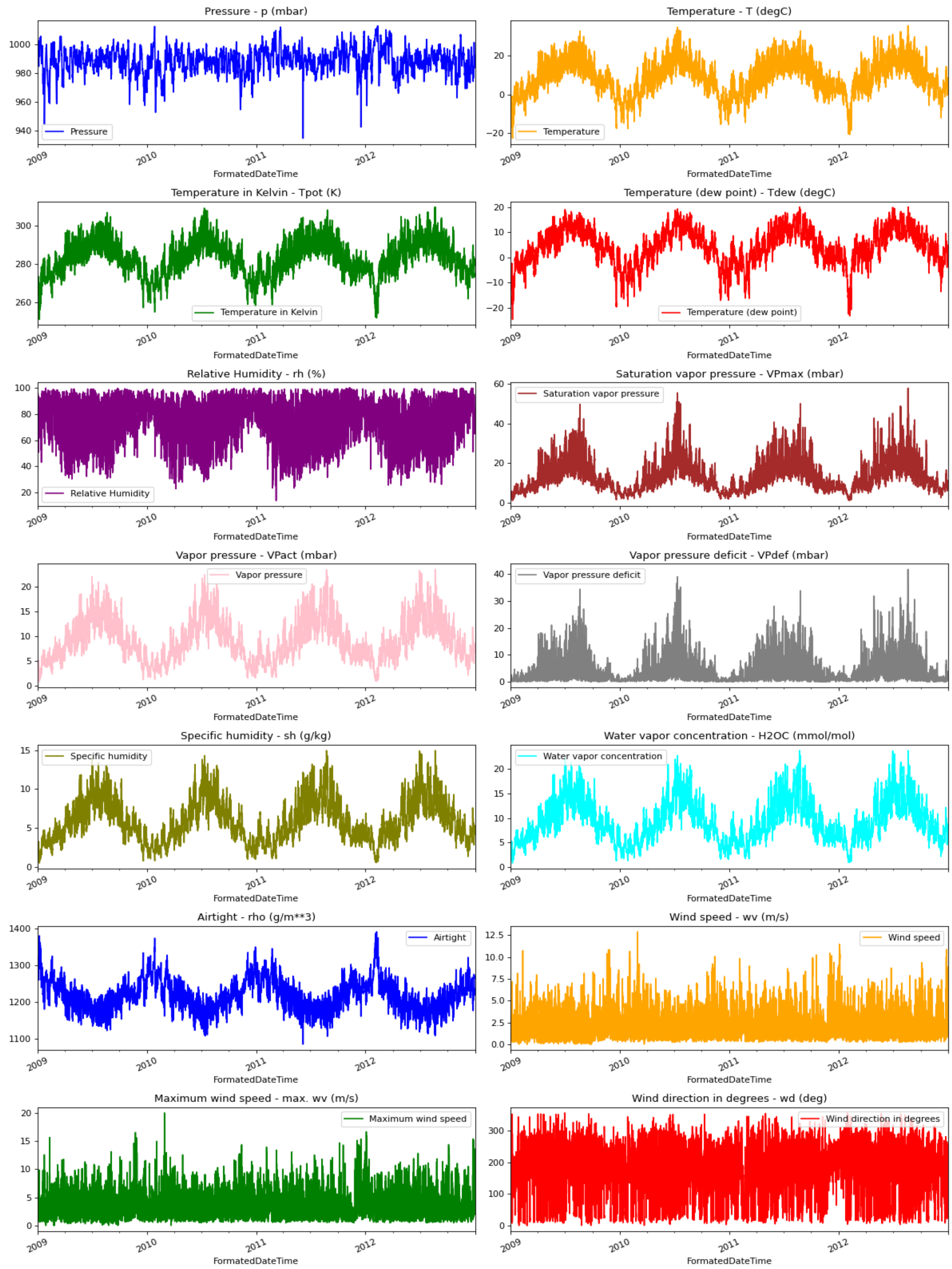
[7]:
```
df['FormatedDateTime'] = pd.to_datetime(df['Date Time'], format='%d.%m.%Y %H:%M:
↪%S')
df = df.set_index('FormatedDateTime')
df_resampled = df[feature_keys].resample('H').mean()
df_resampled = df_resampled.reset_index()

df_resampled.head()
```

```
<ipython-input-7-e61db8939877>:3: FutureWarning: 'H' is deprecated and will be
removed in a future version, please use 'h' instead.
  df_resampled = df[feature_keys].resample('H').mean()
```

[7]:
```
     FormatedDateTime    p (mbar)  T (degC)    Tpot (K)  Tdew (degC)  \
0 2009-01-01 00:00:00  996.528000 -8.304000  265.118000    -9.120000
1 2009-01-01 01:00:00  996.525000 -8.065000  265.361667    -8.861667
2 2009-01-01 02:00:00  996.745000 -8.763333  264.645000    -9.610000
3 2009-01-01 03:00:00  996.986667 -8.896667  264.491667    -9.786667
4 2009-01-01 04:00:00  997.158333 -9.348333  264.026667   -10.345000

      rh (%)  VPmax (mbar)  VPact (mbar)  VPdef (mbar)  sh (g/kg)  \
0  93.780000      3.260000      3.058000      0.202000   1.910000
1  93.933333      3.323333      3.121667      0.201667   1.951667
2  93.533333      3.145000      2.940000      0.201667   1.836667
3  93.200000      3.111667      2.898333      0.210000   1.811667
4  92.383333      3.001667      2.775000      0.231667   1.733333

   H2OC (mmol/mol)  rho (g/m**3)  wv (m/s)  max. wv (m/s)    wd (deg)
0         3.068000   1309.196000  0.520000       1.002000  174.460000
1         3.133333   1307.981667  0.316667       0.711667  172.416667
2         2.950000   1311.816667  0.248333       0.606667  196.816667
3         2.906667   1312.813333  0.176667       0.606667  157.083333
4         2.780000   1315.355000  0.290000       0.670000  150.093333
```

Let's look at our fields again

[8]:
```
show_raw_visualization(df_resampled, "FormatedDateTime")
```



1.0.3 3) Data Split: Train and Evaluation datasets.

- We are tracking data from past 120 timestamps (120 hours = 5 days).

- This data will be used to predict the temperature after 12 timestamps (12 hours).
- Since every feature has values with varying ranges, we do normalization to confine feature values to a range of [0, 1] before training a neural network.
- We do this by subtracting the mean and dividing by the standard deviation of each feature in the *normalize* function
- The model is shown data for first 5 days i.e. 120 observations, that are sampled every hour.
- The temperature after 12 hours observation will be used as a label.

[9]:
```
# 70% of the data will be used for training, the rest for testing
split_fraction = 0.7
# The number of samples is the number of rows in the data
number_of_samples = df_resampled.shape[0]
# The size in rows of the split dataset
train_split = int(split_fraction * int(number_of_samples))

# Number of samples in the past used to predict the future
past = 120
# Number of samples in the future to predict (the value in the 72nd hour is our␣
↪label)
future = 12
# Learning rate parameter for the Adam optimizer
learning_rate = 0.001
# Batch size for the model training
batch_size = 256
# Number of epochs for the model training
epochs = 10

# Another way to normalize the data (all columns in the same range)
def normalize(data, train_split):
    data_mean = data[:train_split].mean(axis=0)
    data_std = data[:train_split].std(axis=0)
    return (data - data_mean) / data_std
```

- Let's select the following parameters as our features:
  - Pressure, Temperature, Saturation vapor pressure, Vapor pressure deficit, Specific humidity, Airtight, Wind speed
- Set the column FormatedDateTime as the index of our dataframe.
  - This is important since now, FormatedDateTime is used as our datetime field and not as a Feature field
- Normalize all fields
- Generate two datasets:
  - train_data: Train dataset with our normalized fields
  - val_data: Validation dataset

[10]:
```
print(
    "The selected parameters are:",
    ", ".join([titles[i] for i in [0, 1, 5, 7, 8, 10, 11]]),
)
selected_features = [feature_keys[i] for i in [0, 1, 5, 7, 8, 10, 11]]
features = df_resampled[selected_features]
features.index = df_resampled["FormatedDateTime"]
print(features.head())

features = normalize(features.values, train_split)
features = pd.DataFrame(features)
print(features.head())

train_data = features.loc[0 : train_split - 1]
val_data = features.loc[train_split:]
```

```
The selected parameters are: Pressure, Temperature, Saturation vapor pressure,
Vapor pressure deficit, Specific humidity, Airtight, Wind speed
                      p (mbar)  T (degC)  VPmax (mbar)  VPdef (mbar)  \
FormatedDateTime
2009-01-01 00:00:00  996.528000 -8.304000      3.260000      0.202000
2009-01-01 01:00:00  996.525000 -8.065000      3.323333      0.201667
2009-01-01 02:00:00  996.745000 -8.763333      3.145000      0.201667
2009-01-01 03:00:00  996.986667 -8.896667      3.111667      0.210000
2009-01-01 04:00:00  997.158333 -9.348333      3.001667      0.231667

                     sh (g/kg)  rho (g/m**3)  wv (m/s)
FormatedDateTime
2009-01-01 00:00:00   1.910000   1309.196000  0.520000
2009-01-01 01:00:00   1.951667   1307.981667  0.316667
2009-01-01 02:00:00   1.836667   1311.816667  0.248333
2009-01-01 03:00:00   1.811667   1312.813333  0.176667
2009-01-01 04:00:00   1.733333   1315.355000  0.290000
          0         1         2         3         4         5         6
0  0.988366 -1.936957 -1.314750 -0.797292 -1.472751  2.198783 -1.116409
1  0.988002 -1.909978 -1.306369 -0.797363 -1.457136  2.169559 -1.256715
2  1.014643 -1.988807 -1.329968 -0.797363 -1.500234  2.261854 -1.303867
3  1.043907 -2.003858 -1.334379 -0.795594 -1.509604  2.285840 -1.353320
4  1.064694 -2.054843 -1.348935 -0.790994 -1.538961  2.347009 -1.275116
```

Now, here we need to set our Label Dataset.

- We want to use the last 5 days of data, to predict the next 12 hours
- This means that our label starts at the 12th hour after the history data.
  - [……………………. .]
  - ——Start——>
- And it will end at the end of our train dataset size.
  - <——— Train ———> <— Test —>

– [……………………………………….|……….]
– ———-End———->

[11]:
```
start = past + future
end = start + train_split

x_train = train_data[[i for i in range(7)]].values
y_train = features.iloc[start:end][[1]]

step = 1
sequence_length = past
```

The *timeseries_dataset_from_array* function takes in a sequence of data-points gathered at equal intervals, along with time series parameters such as length of the sequences/windows, spacing between two sequence/windows, etc., to produce batches of sub-timeseries inputs and targets sampled from the main timeseries.

- Input data (hour features) = x_train
- The **corresponding** value of the temperature 12 hours into the future = y_train
- Since we want to use 5 days of data to predict the future temperature then: sequence_length = 120
- Since we want to sample every hour then: sampling_rate = 1
- Let's use a common batch size of 256 (variable above)

[12]:
```
dataset_train = keras.preprocessing.timeseries_dataset_from_array(
    x_train,
    y_train,
    sequence_length=sequence_length,
    sampling_rate=step,
    batch_size=batch_size,
)
```

Now let's prepare our validation dataset:

- The validation dataset must not contain the last 120+12 rows as we won't have label data for those records, hence these rows must be subtracted from the end of the data.
- The validation label dataset must start from 120+12 after train_split, hence we must add past + future to label_start.

[13]:
```
x_end = len(val_data) - past - future

label_start = train_split + past + future

x_val = val_data.iloc[:x_end][[i for i in range(7)]].values
y_val = features.iloc[label_start:][[1]]

dataset_val = keras.preprocessing.timeseries_dataset_from_array(
    x_val,
    y_val,
```

```
    sequence_length=sequence_length,
    sampling_rate=step,
    batch_size=batch_size,
)


for batch in dataset_train.take(1):
    inputs, targets = batch

print("Input shape:", inputs.numpy().shape)
print("Target shape:", targets.numpy().shape)
```

```
Input shape: (256, 120, 7)
Target shape: (256, 1)
```

1.0.4 4) Define and Compile your model:

- An input layer
- A Long Short-Term Memory Hidden Layer with 32 units. LSTM is a type of recurrent neural network layer that is well-suited for time series data.
- An output Dense Layer (Linear Activation function)

[14]:
```
inputs = keras.layers.Input(shape=(inputs.shape[1], inputs.shape[2]))
lstm_out = keras.layers.LSTM(32)(inputs)
outputs = keras.layers.Dense(1)(lstm_out)

model = keras.Model(inputs=inputs, outputs=outputs)
model.compile(optimizer=keras.optimizers.Adam(learning_rate=learning_rate),␣
 ↪loss="mse")
model.summary()
```

```
Model: "functional"


 Layer (type)                    Output Shape                              ␣
↪Param #

 input_layer (InputLayer)        (None, 120, 7)                              ␣
↪  0

 lstm (LSTM)                     (None, 32)                                ␣
↪5,120

 dense (Dense)                   (None, 1)                                   ␣
↪ 33
```

Total params: 5,153 (20.13 KB)

Trainable params: 5,153 (20.13 KB)

Non-trainable params: 0 (0.00 B)

1.0.5 5) Train your model:

Specify the file path where the model's weights will be saved with: `path_checkpoint = "model_checkpoint.weights.h5"`

We want to add a callback to stop training when a monitored metric stops improving: `es_callback = keras.callbacks.EarlyStopping(monitor="val_loss", min_delta=0, patience=5)`

Train the model using Fit

[15]:
```
path_checkpoint = "model_checkpoint.weights.h5"
es_callback = keras.callbacks.EarlyStopping(monitor="val_loss", min_delta=0,␣
↪patience=5)

modelckpt_callback = keras.callbacks.ModelCheckpoint(
    monitor="val_loss",
    filepath=path_checkpoint,
    verbose=1,
    save_weights_only=True,
    save_best_only=True,
)

history = model.fit(
    dataset_train,
    epochs=epochs,
    validation_data=dataset_val,
    callbacks=[es_callback, modelckpt_callback],
)
```

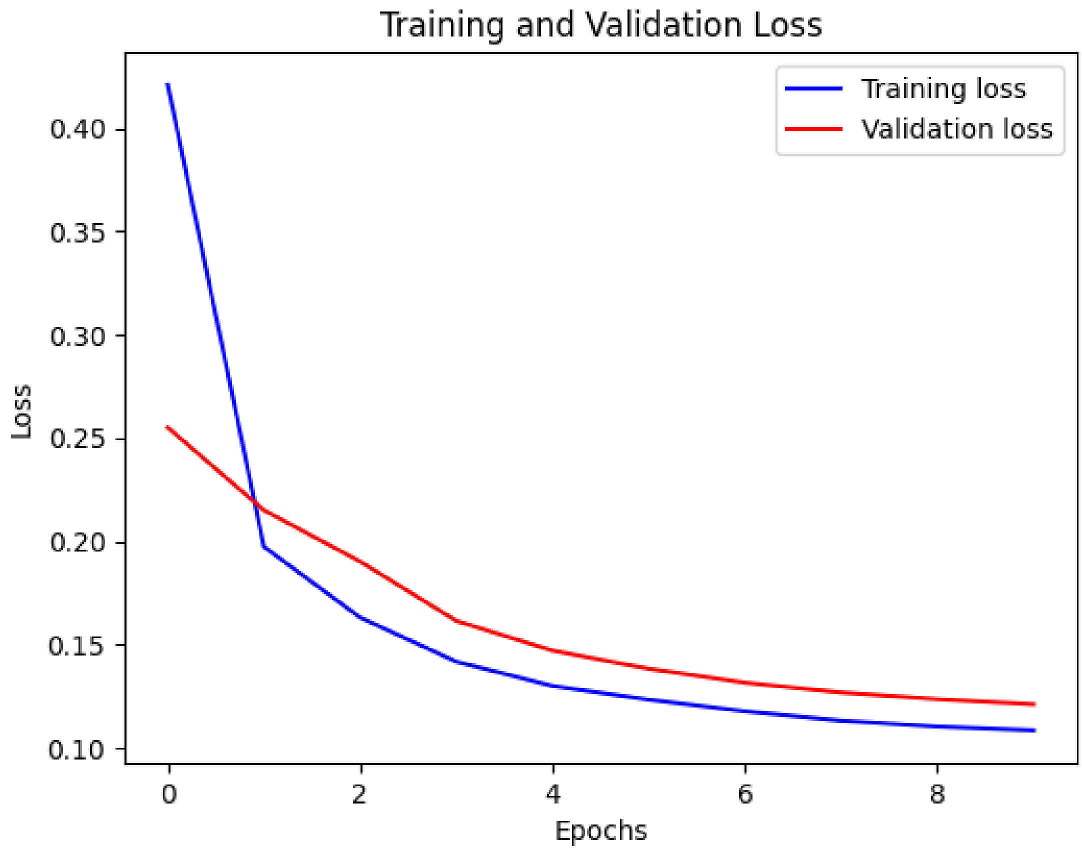
```
Epoch 1/10
96/96              0s 109ms/step -
loss: 0.7310
Epoch 1: val_loss improved from inf to 0.25503, saving model to
model_checkpoint.weights.h5
96/96              18s 144ms/step -
loss: 0.7278 - val_loss: 0.2550
Epoch 2/10
96/96              0s 114ms/step -
loss: 0.2128
Epoch 2: val_loss improved from 0.25503 to 0.21500, saving model to
model_checkpoint.weights.h5
```

```
96/96            14s 145ms/step -
loss: 0.2127 - val_loss: 0.2150
Epoch 3/10
96/96            0s 116ms/step -
loss: 0.1676
Epoch 3: val_loss improved from 0.21500 to 0.19015, saving model to
model_checkpoint.weights.h5
96/96            14s 147ms/step -
loss: 0.1676 - val_loss: 0.1902
Epoch 4/10
96/96            0s 115ms/step -
loss: 0.1460
Epoch 4: val_loss improved from 0.19015 to 0.16143, saving model to
model_checkpoint.weights.h5
96/96            14s 146ms/step -
loss: 0.1460 - val_loss: 0.1614
Epoch 5/10
96/96            0s 113ms/step -
loss: 0.1318
Epoch 5: val_loss improved from 0.16143 to 0.14703, saving model to
model_checkpoint.weights.h5
96/96            14s 145ms/step -
loss: 0.1317 - val_loss: 0.1470
Epoch 6/10
95/96            0s 121ms/step -
loss: 0.1250
Epoch 6: val_loss improved from 0.14703 to 0.13824, saving model to
model_checkpoint.weights.h5
96/96            21s 146ms/step -
loss: 0.1250 - val_loss: 0.1382
Epoch 7/10
95/96            0s 122ms/step -
loss: 0.1199
Epoch 7: val_loss improved from 0.13824 to 0.13152, saving model to
model_checkpoint.weights.h5
96/96            14s 147ms/step -
loss: 0.1198 - val_loss: 0.1315
Epoch 8/10
95/96            0s 118ms/step -
loss: 0.1155
Epoch 8: val_loss improved from 0.13152 to 0.12676, saving model to
model_checkpoint.weights.h5
96/96            14s 143ms/step -
loss: 0.1155 - val_loss: 0.1268
Epoch 9/10
95/96            0s 122ms/step -
loss: 0.1124
Epoch 9: val_loss improved from 0.12676 to 0.12350, saving model to
```

```
model_checkpoint.weights.h5
96/96              14s 144ms/step -
loss: 0.1124 - val_loss: 0.1235
Epoch 10/10
96/96              0s 122ms/step -
loss: 0.1103
Epoch 10: val_loss improved from 0.12350 to 0.12106, saving model to
model_checkpoint.weights.h5
96/96              14s 148ms/step -
loss: 0.1103 - val_loss: 0.1211
```

Plot the results of your training:

[16]:
```
def visualize_loss(history, title):
    loss = history.history["loss"]
    val_loss = history.history["val_loss"]
    epochs = range(len(loss))
    plt.figure()
    plt.plot(epochs, loss, "b", label="Training loss")
    plt.plot(epochs, val_loss, "r", label="Validation loss")
    plt.title(title)
    plt.xlabel("Epochs")
    plt.ylabel("Loss")
    plt.legend()
    plt.show()


visualize_loss(history, "Training and Validation Loss")
```

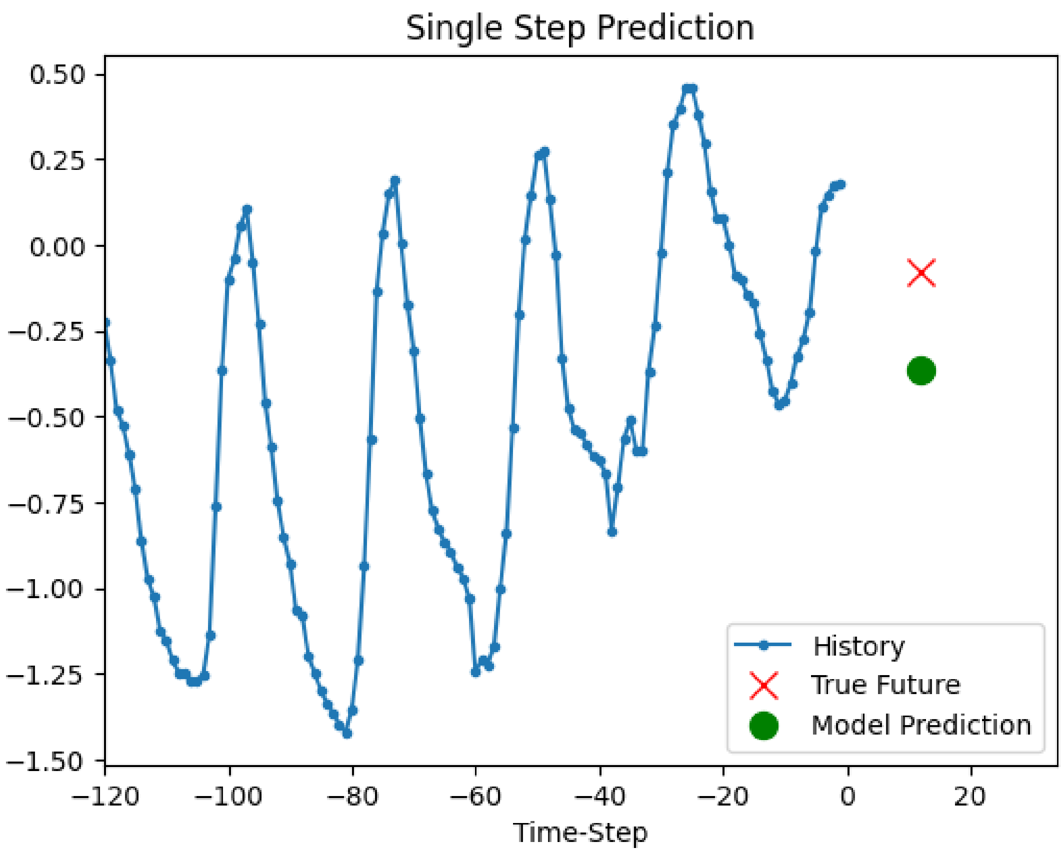


Make 5 predictions and display the predicted value

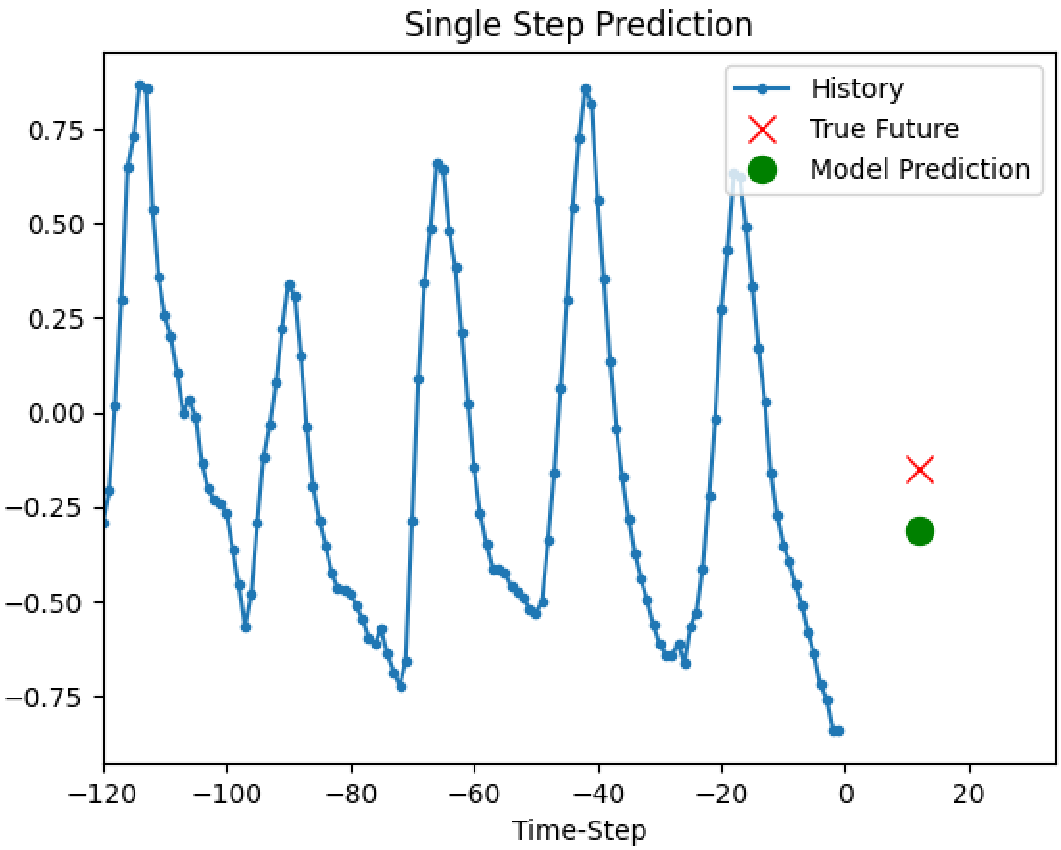
[17]:
```
def show_plot(plot_data, delta, title):
    labels = ["History", "True Future", "Model Prediction"]
    marker = [".-", "rx", "go"]
    time_steps = list(range(-(plot_data[0].shape[0]), 0))
    if delta:
        future = delta
    else:
        future = 0

    plt.title(title)
    for i, val in enumerate(plot_data):
        if i:
            plt.plot(future, plot_data[i], marker[i], markersize=10,␣
 ↪label=labels[i])
        else:
            plt.plot(time_steps, plot_data[i].flatten(), marker[i],␣
 ↪label=labels[i])
    plt.legend()
```

```
    plt.xlim([time_steps[0], (future + 5) * 2])
    plt.xlabel("Time-Step")
    plt.show()
    return


for x, y in dataset_val.take(5):
    show_plot(
        [x[0][:, 1].numpy(), y[0].numpy(), model.predict(x)[0]],
        12,
        "Single Step Prediction",
    )
```

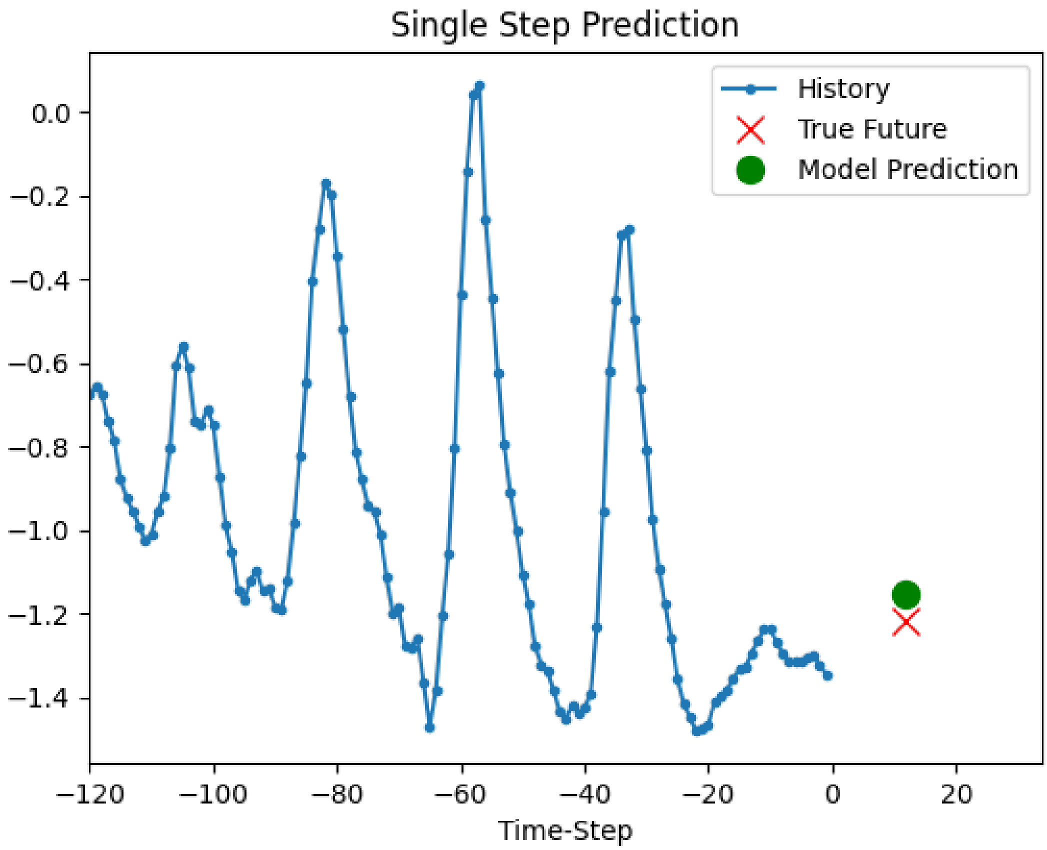
```
8/8                0s 12ms/step
```



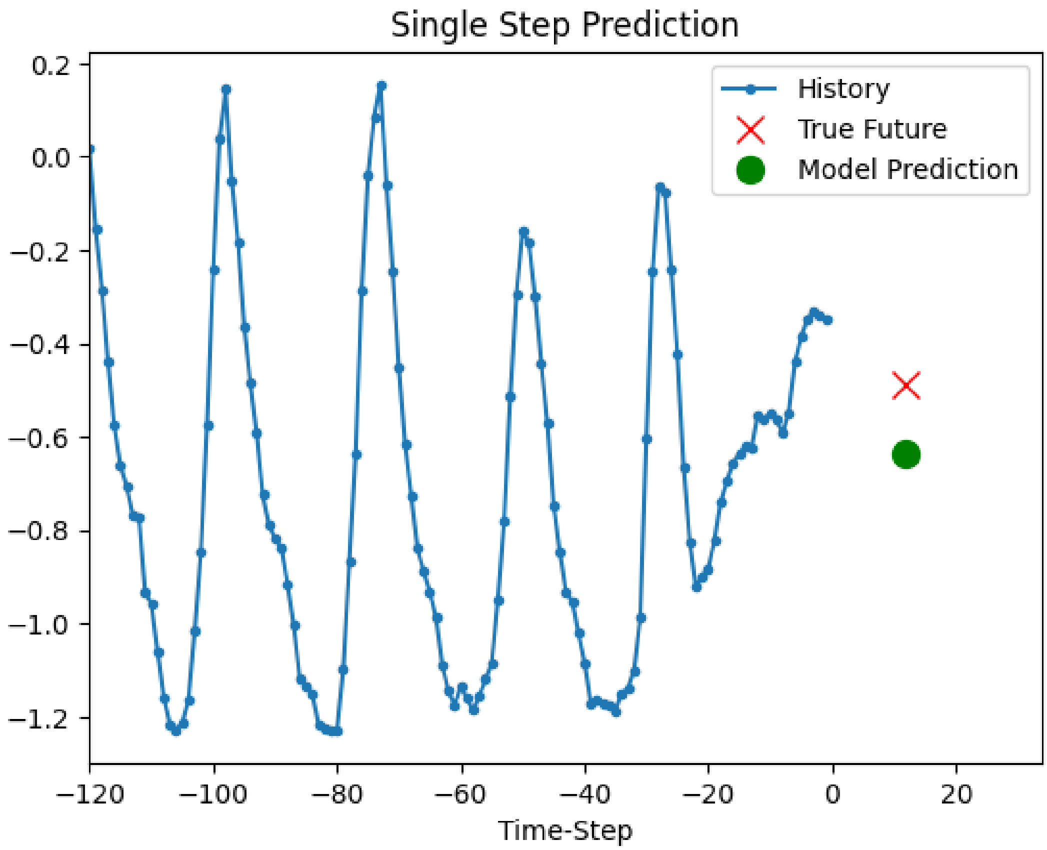

```
8/8                0s 11ms/step
```



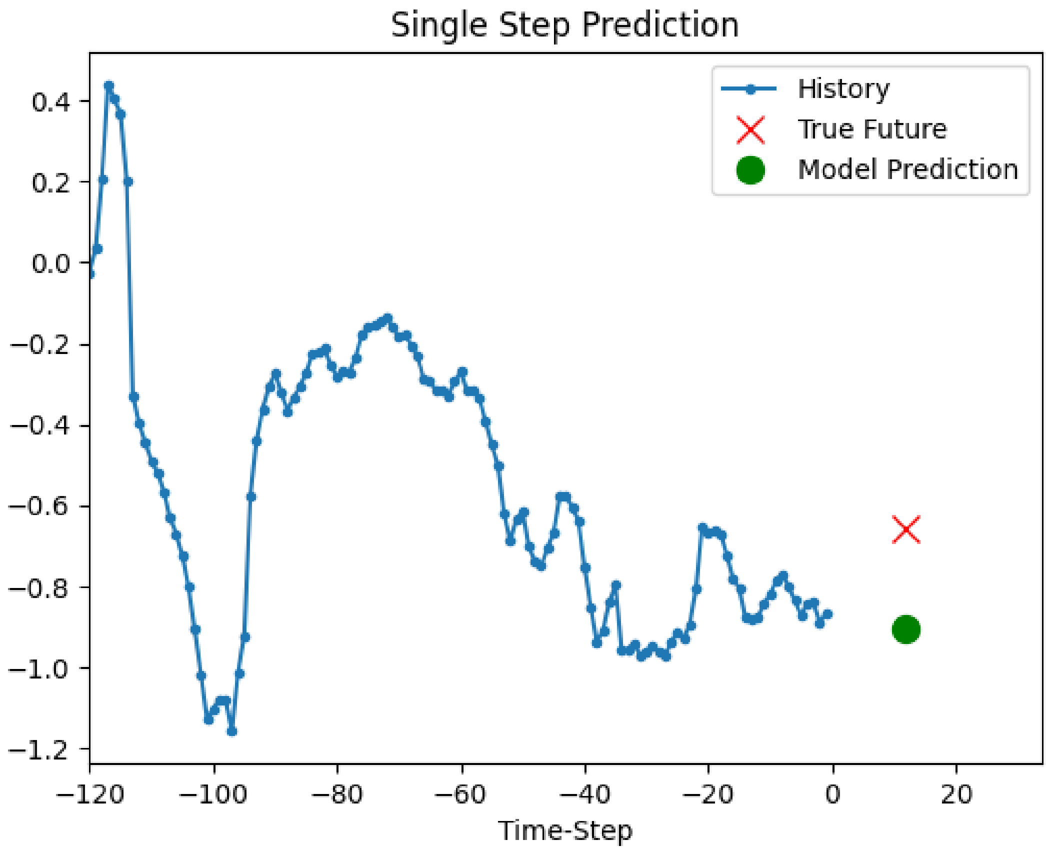

```
8/8                0s 12ms/step
```




```
8/8                0s 12ms/step
```




```
8/8                0s 12ms/step
```



Now make a Time Series Forecasting where using the last 3 days you will predict the weather in the next 3 hours.

[18]:
```
split_fraction = 0.7

print(
    "Los parámetros seleccionados son:",
    ", ".join([titles[i] for i in [0, 1, 5, 7, 8, 10, 11]]),
)

selected_features = [feature_keys[i] for i in [0, 1, 5, 7, 8, 10, 11]]
features = df_resampled[selected_features]
features.index = df_resampled["FormatedDateTime"]
print(features.head())

features = normalize(features.values, train_split)
features = pd.DataFrame(features)
print(features.head())

train_data = features.loc[0 : train_split - 1]
```

```
val_data = features.loc[train_split:]

start = past + future
end = start + train_split

x_train = train_data[[i for i in range(7)]].values
y_train = features.iloc[start:end][[1]]

step = 1
sequence_length = past

dataset_train = keras.preprocessing.timeseries_dataset_from_array(
    x_train,
    y_train,
    sequence_length=sequence_length,
    sampling_rate=step,
    batch_size=batch_size,
)

x_end = len(val_data) - past - future
label_start = train_split + past + future

x_val = val_data.iloc[:x_end][[i for i in range(7)]].values
y_val = features.iloc[label_start:][[1]]

dataset_val = keras.preprocessing.timeseries_dataset_from_array(
    x_val,
    y_val,
    sequence_length=sequence_length,
    sampling_rate=step,
    batch_size=batch_size,
)

for batch in dataset_train.take(1):
    inputs, targets = batch

print("Forma de entrada:", inputs.numpy().shape)
print("Forma de salida:", targets.numpy().shape)

inputs = keras.layers.Input(shape=(inputs.shape[1], inputs.shape[2]))
lstm_out = keras.layers.LSTM(32)(inputs)
outputs = keras.layers.Dense(1)(lstm_out)

model = keras.Model(inputs=inputs, outputs=outputs)
model.compile(optimizer=keras.optimizers.Adam(learning_rate=learning_rate),␣
 ↪loss="mse")
model.summary()
```

```python
path_checkpoint = "model_checkpoint.weights.h5"
es_callback = keras.callbacks.EarlyStopping(monitor="val_loss", min_delta=0,␣
 ↪patience=5)

modelckpt_callback = keras.callbacks.ModelCheckpoint(
    monitor="val_loss",
    filepath=path_checkpoint,
    verbose=1,
    save_weights_only=True,
    save_best_only=True,
)

history = model.fit(
    dataset_train,
    epochs=epochs,
    validation_data=dataset_val,
    callbacks=[es_callback, modelckpt_callback],
)

number_of_samples = df_resampled.shape[0]
train_split = int(split_fraction * int(number_of_samples))

past = 72
future = 3

learning_rate = 0.001
batch_size = 256
epochs = 10

def normalize(data, train_split):
    data_mean = data[:train_split].mean(axis=0)
    data_std = data[:train_split].std(axis=0)
    return (data - data_mean) / data_std
```

```
Los parámetros seleccionados son: Pressure, Temperature, Saturation vapor
pressure, Vapor pressure deficit, Specific humidity, Airtight, Wind speed
                       p (mbar)  T (degC)  VPmax (mbar)  VPdef (mbar)  \
FormatedDateTime
2009-01-01 00:00:00  996.528000 -8.304000      3.260000      0.202000
2009-01-01 01:00:00  996.525000 -8.065000      3.323333      0.201667
2009-01-01 02:00:00  996.745000 -8.763333      3.145000      0.201667
2009-01-01 03:00:00  996.986667 -8.896667      3.111667      0.210000
2009-01-01 04:00:00  997.158333 -9.348333      3.001667      0.231667

                     sh (g/kg)  rho (g/m**3)  wv (m/s)
FormatedDateTime
```

```
2009-01-01 00:00:00   1.910000   1309.196000  0.520000
2009-01-01 01:00:00   1.951667   1307.981667  0.316667
2009-01-01 02:00:00   1.836667   1311.816667  0.248333
2009-01-01 03:00:00   1.811667   1312.813333  0.176667
2009-01-01 04:00:00   1.733333   1315.355000  0.290000
          0         1         2         3         4         5         6
0  0.988366 -1.936957 -1.314750 -0.797292 -1.472751  2.198783 -1.116409
1  0.988002 -1.909978 -1.306369 -0.797363 -1.457136  2.169559 -1.256715
2  1.014643 -1.988807 -1.329968 -0.797363 -1.500234  2.261854 -1.303867
3  1.043907 -2.003858 -1.334379 -0.795594 -1.509604  2.285840 -1.353320
4  1.064694 -2.054843 -1.348935 -0.790994 -1.538961  2.347009 -1.275116
Forma de entrada: (256, 120, 7)
Forma de salida: (256, 1)
```

Model: "functional_1"

```
 Layer (type)                       Output Shape
↪Param #

 input_layer_1 (InputLayer)         (None, 120, 7)
↪  0

 lstm_1 (LSTM)                      (None, 32)
↪5,120

 dense_1 (Dense)                    (None, 1)
↪ 33


 Total params: 5,153 (20.13 KB)

 Trainable params: 5,153 (20.13 KB)

 Non-trainable params: 0 (0.00 B)

Epoch 1/10
95/96             0s 131ms/step -
loss: 0.7063
Epoch 1: val_loss improved from inf to 0.25311, saving model to
model_checkpoint.weights.h5
96/96             18s 158ms/step -
loss: 0.7003 - val_loss: 0.2531
Epoch 2/10
95/96             0s 123ms/step -
```

```
loss: 0.2131
Epoch 2: val_loss improved from 0.25311 to 0.18389, saving model to
model_checkpoint.weights.h5
96/96            14s 148ms/step -
loss: 0.2128 - val_loss: 0.1839
Epoch 3/10
95/96            0s 126ms/step -
loss: 0.1556
Epoch 3: val_loss improved from 0.18389 to 0.15997, saving model to
model_checkpoint.weights.h5
96/96            15s 151ms/step -
loss: 0.1555 - val_loss: 0.1600
Epoch 4/10
95/96            0s 120ms/step -
loss: 0.1399
Epoch 4: val_loss improved from 0.15997 to 0.14783, saving model to
model_checkpoint.weights.h5
96/96            14s 146ms/step -
loss: 0.1398 - val_loss: 0.1478
Epoch 5/10
95/96            0s 121ms/step -
loss: 0.1314
Epoch 5: val_loss improved from 0.14783 to 0.14032, saving model to
model_checkpoint.weights.h5
96/96            14s 145ms/step -
loss: 0.1313 - val_loss: 0.1403
Epoch 6/10
95/96            0s 117ms/step -
loss: 0.1262
Epoch 6: val_loss improved from 0.14032 to 0.13708, saving model to
model_checkpoint.weights.h5
96/96            13s 139ms/step -
loss: 0.1261 - val_loss: 0.1371
Epoch 7/10
95/96            0s 118ms/step -
loss: 0.1235
Epoch 7: val_loss improved from 0.13708 to 0.13408, saving model to
model_checkpoint.weights.h5
96/96            14s 142ms/step -
loss: 0.1234 - val_loss: 0.1341
Epoch 8/10
95/96            0s 119ms/step -
loss: 0.1205
Epoch 8: val_loss improved from 0.13408 to 0.13030, saving model to
model_checkpoint.weights.h5
96/96            14s 142ms/step -
loss: 0.1204 - val_loss: 0.1303
Epoch 9/10
```

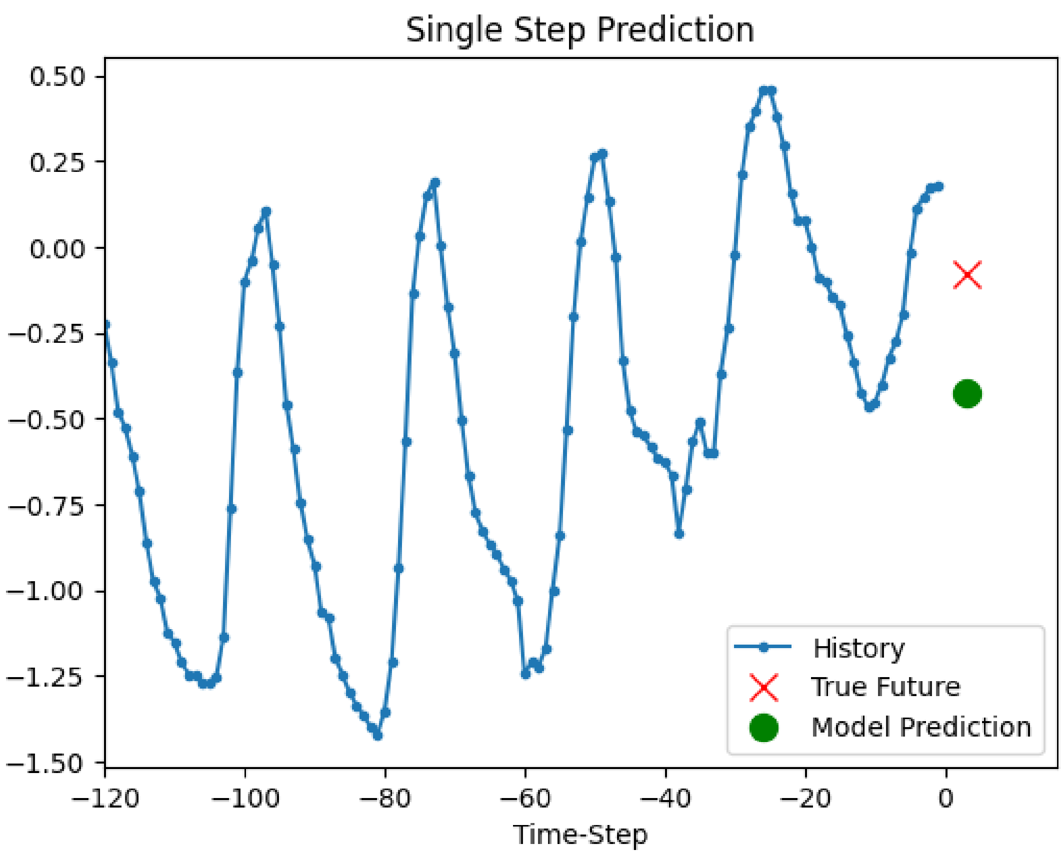
```
96/96              0s 131ms/step -
loss: 0.1173
Epoch 9: val_loss improved from 0.13030 to 0.12622, saving model to
model_checkpoint.weights.h5
96/96              15s 158ms/step -
loss: 0.1172 - val_loss: 0.1262
Epoch 10/10
95/96              0s 119ms/step -
loss: 0.1143
Epoch 10: val_loss improved from 0.12622 to 0.12243, saving model to
model_checkpoint.weights.h5
96/96              14s 143ms/step -
loss: 0.1142 - val_loss: 0.1224
```

[19]:

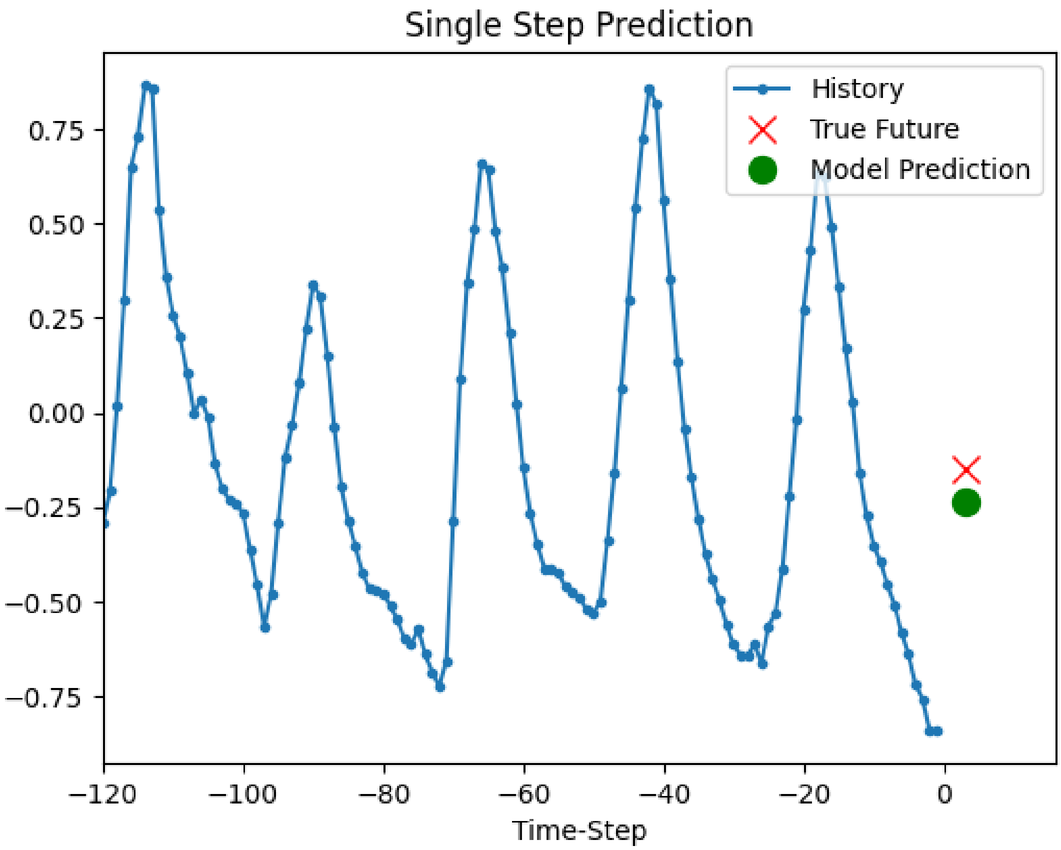
```python
def visualize_loss(history, title):
    loss = history.history["loss"]
    val_loss = history.history["val_loss"]
    epochs = range(len(loss))

    plt.figure()
    plt.plot(epochs, loss, "b", label="Training loss")
    plt.plot(epochs, val_loss, "r", label="Validation loss")
    plt.title(title)
    plt.xlabel("Epochs")
    plt.ylabel("Loss")
    plt.legend()
    plt.show()

def show_plot(plot_data, delta, title):
    labels = ["History", "True Future", "Model Prediction"]
    marker = [".-", "rx", "go"]
    time_steps = list(range(-(plot_data[0].shape[0]), 0))

    future = delta if delta else 0

    plt.title(title)
    for i, val in enumerate(plot_data):
        if i:
            plt.plot(future, plot_data[i], marker[i], markersize=10,␣
 ↪label=labels[i])
        else:
            plt.plot(time_steps, plot_data[i].flatten(), marker[i],␣
 ↪label=labels[i])

    plt.legend()
    plt.xlim([time_steps[0], (future + 5) * 2])
    plt.xlabel("Time-Step")
```

```
    plt.show()
    return

for x, y in dataset_val.take(5):
    show_plot(
        [x[0][:, 1].numpy(), y[0].numpy(), model.predict(x)[0]],
        3,
        "Single Step Prediction",
    )

visualize_loss(history, "Training and Validation Loss")
```

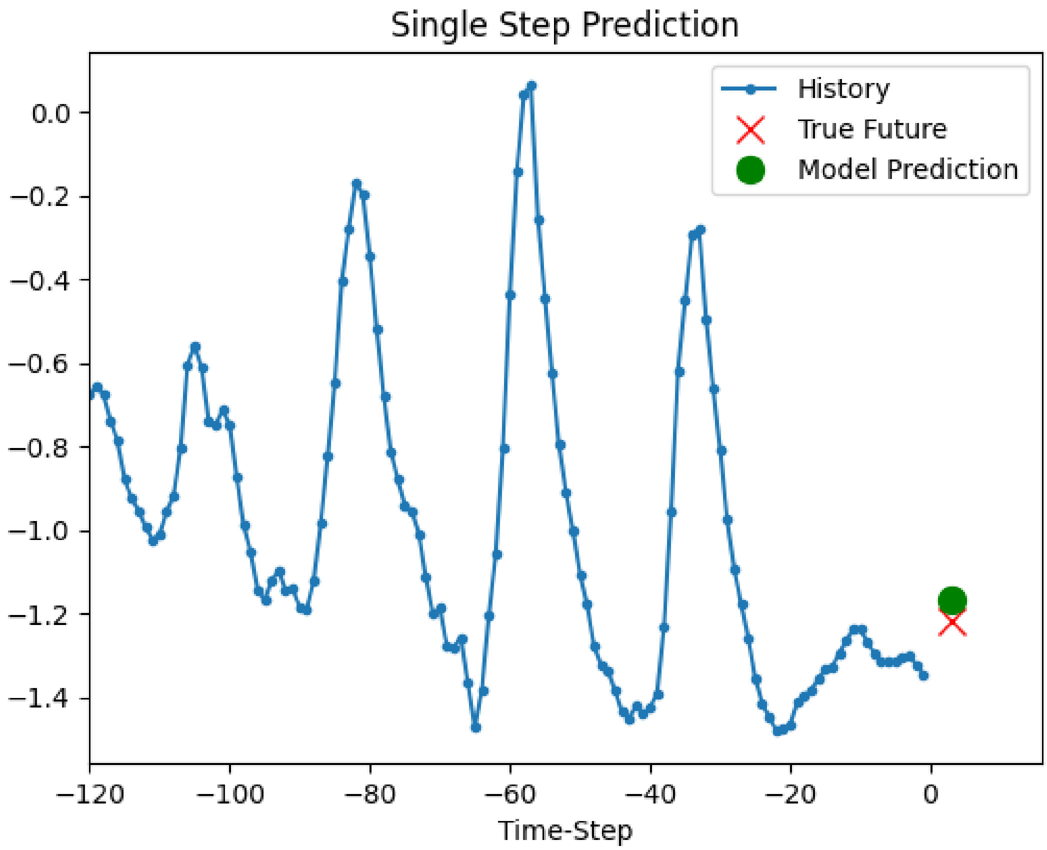
```
8/8              0s 12ms/step
```



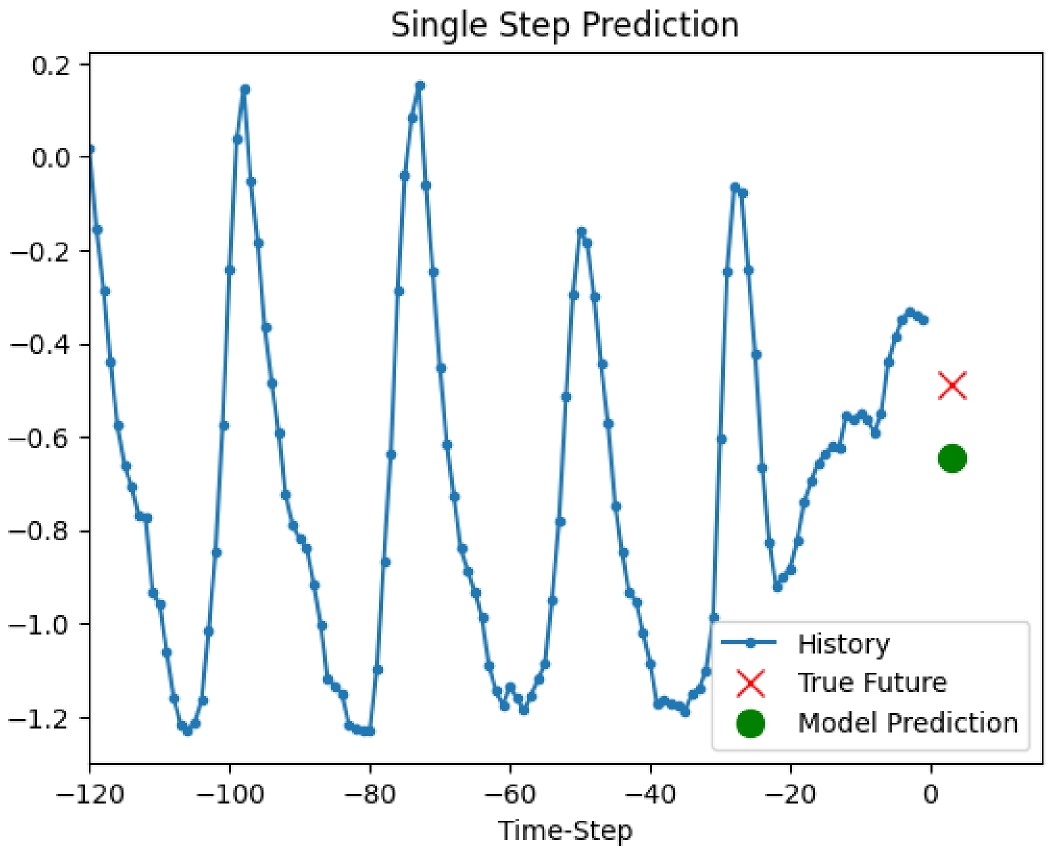

```
8/8              0s 12ms/step
```



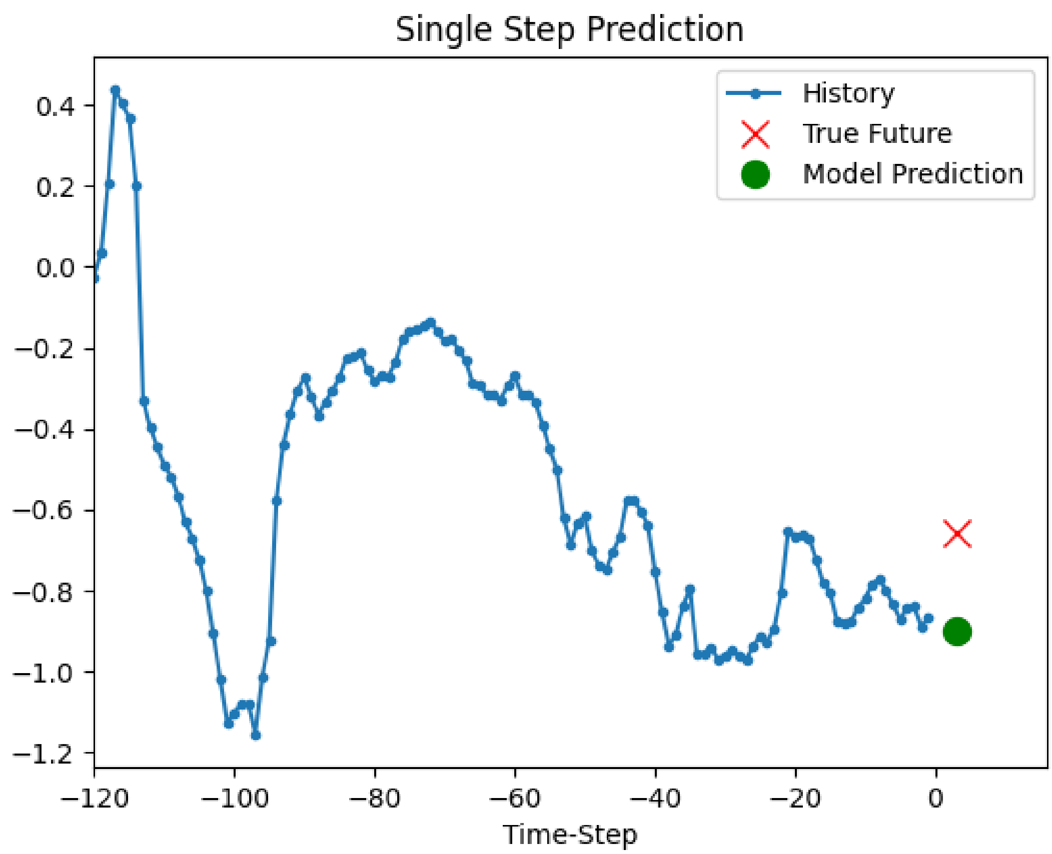

```
8/8                0s 14ms/step
```

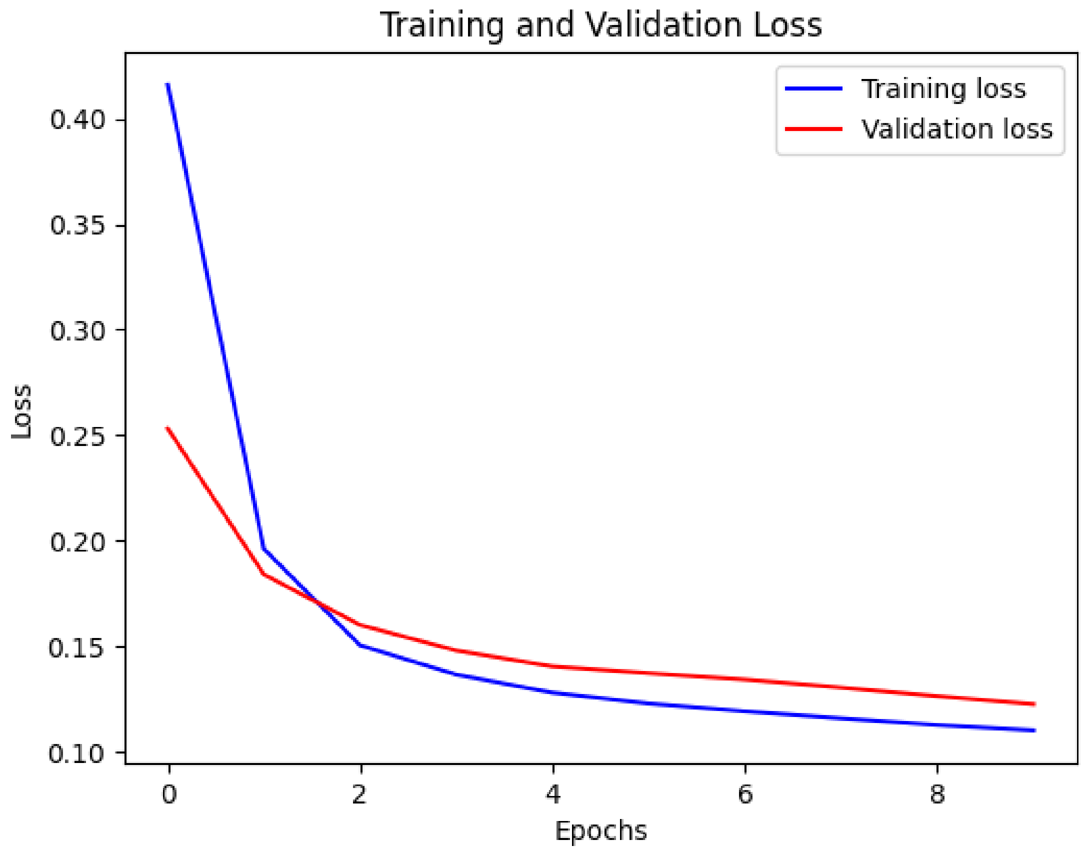



```
8/8                    0s 16ms/step
```




```
8/8                0s 19ms/step
```


Single Step Prediction
History
True Future
Model Prediction
0.4
0.2
0.0
−0.2
−0.4
−0.6
−0.8
−1.0
−1.2
−120
−100
−80
−60
−40
−20
0
Time-Step



Como podemos analisar con los resultados del nuevo modelo creado este fucniona razonablemente bien en la predicción que queremos hacer de las próximas 3 horas usando los datos de los últimos 3 días. Podemos ver en las graficas que el modelo captura las tendencias generales El entrenamiento fue fectivo, ya que vemos como las pérdidas de entrenamiento y validación están disminuyendo de manera adecuada.

Los cambios principales en el nuevo modelo para predecir las siguientes 3 horas con los ultimos 3 días fueron:

Se ajustó la duración de los datos historicos, se cambió past de 120 o sea 5 días, a 72 o sea 3 días. Tambien se cambió a futuro, es decir se cambió future de 12 horas a 3 horas. En cuanto a las características seleccionadas se mantienen las características previamente seleccionadas para la predicción.

El val_loss del modelo original es: 0.1211 y el nuevo val_loss es de: 0.1224 . Como vemos la diferencia entre ambos valores de pérdida de validación es muy pequeña , o sea que la diferencia es minima, lo cual nos da a entender que tienen un rendimiento muy similar, es normal que haya una pequeña diferencia ya que se ajustó el modelo, sin embargo no se ve afectado de manera significativa.