In [19]:
```
%%shell
jupyter nbconvert --to html /content/M2_A4_A01571214_Lautaro_Coteja.ipynb
```

```
[NbConvertApp] Converting notebook /content/M2_A4_A01571214_Lautaro_Coteja.ipynb to h
tml
[NbConvertApp] Writing 1890068 bytes to /content/M2_A4_A01571214_Lautaro_Coteja.html
```

Out[19]:

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

In [27]:
```
import pandas as pd
import matplotlib.pyplot as plt
import keras
```

1) Load your data

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

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

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

In [3]:
```
titles = [
    "Pressure",
    "Temperature",
```

```
    "Temperature in Kelvin",
    "Temperature (dew point)",
    "Relative Humidity",
    "Saturation vapor pressure",
    "Vapor pressure",
    "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:

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

Out[4]:

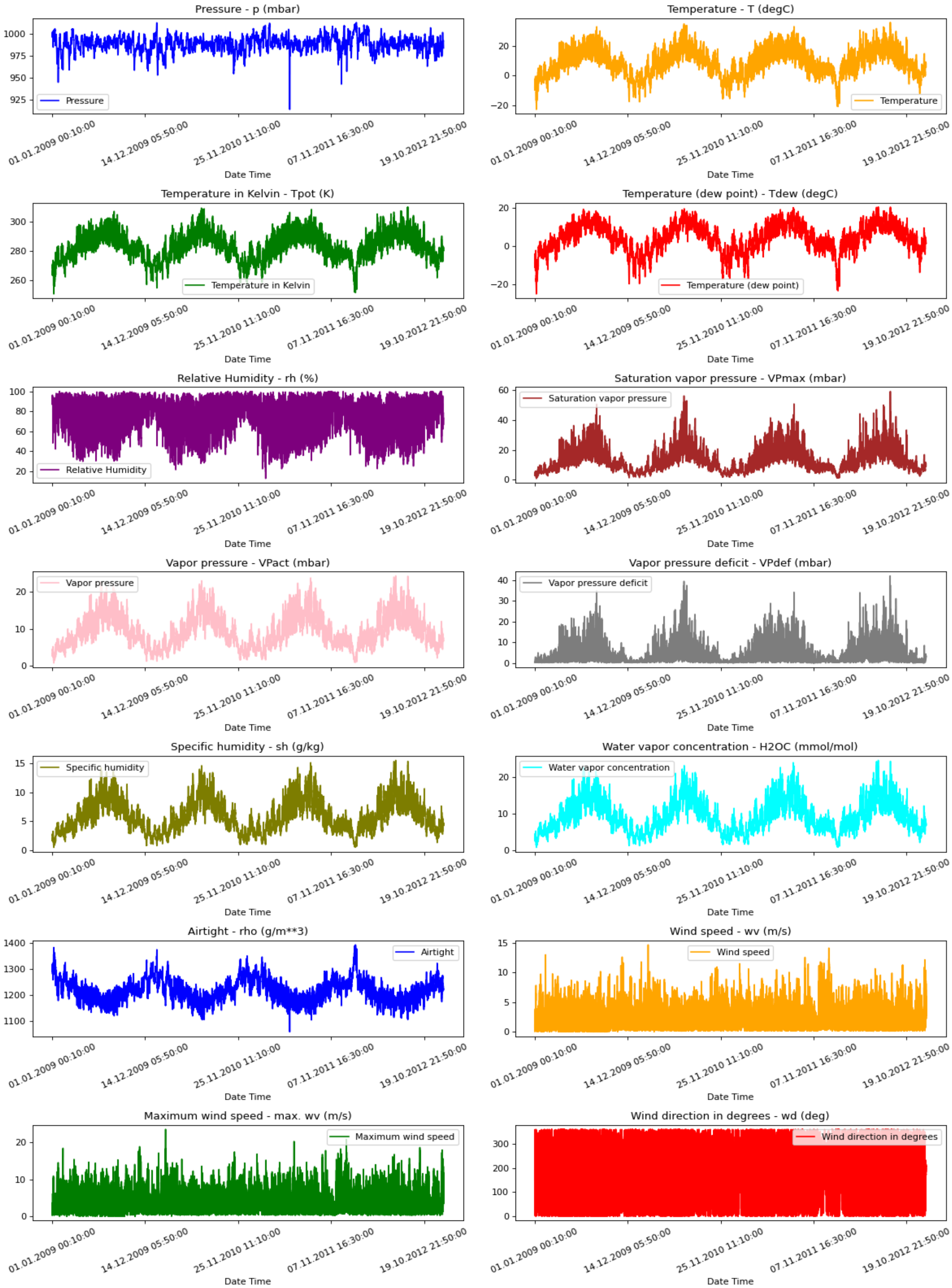
	Date Time	p (mbar)	T (degC)	Tpot (K)	Tdew (degC)	rh (%)	VPmax (mbar)	VPact (mbar)	VPdef (mbar)	sh (g/kg)	H2OC (mmol/mol)	(g/
0	01.01.2009 00:10:00	996.52	-8.02	265.40	-8.90	93.3	3.33	3.11	0.22	1.94	3.12	1
1	01.01.2009 00:20:00	996.57	-8.41	265.01	-9.28	93.4	3.23	3.02	0.21	1.89	3.03	1
2	01.01.2009 00:30:00	996.53	-8.51	264.91	-9.31	93.9	3.21	3.01	0.20	1.88	3.02	1
3	01.01.2009 00:40:00	996.51	-8.31	265.12	-9.07	94.2	3.26	3.07	0.19	1.92	3.08	1
4	01.01.2009 00:50:00	996.51	-8.27	265.15	-9.04	94.1	3.27	3.08	0.19	1.92	3.09	1

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

In [5]:
```
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:

In [6]:
```
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

In [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()
```

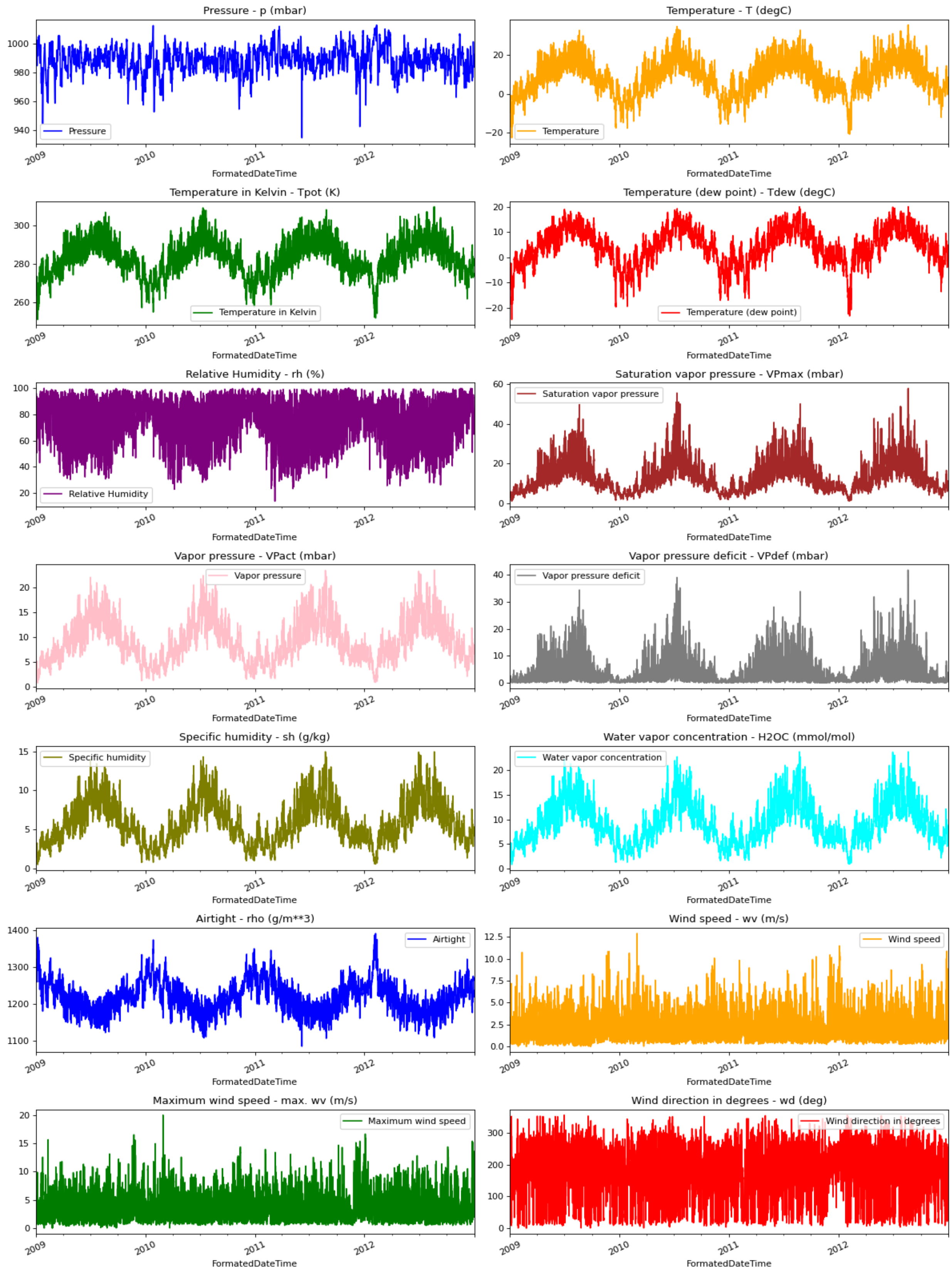
```
<ipython-input-7-e61db8939877>:3: FutureWarning: 'H' is deprecated and will be remove
d in a future version, please use 'h' instead.
  df_resampled = df[feature_keys].resample('H').mean()
```

Out[7]:

	FormatedDateTime	p (mbar)	T (degC)	Tpot (K)	Tdew (degC)	rh (%)	VPmax (mbar)	VPact (mbar)	
0	2009-01-01 00:00:00	996.528000	-8.304000	265.118000	-9.120000	93.780000	3.260000	3.058000	0
1	2009-01-01 01:00:00	996.525000	-8.065000	265.361667	-8.861667	93.933333	3.323333	3.121667	0
2	2009-01-01 02:00:00	996.745000	-8.763333	264.645000	-9.610000	93.533333	3.145000	2.940000	0
3	2009-01-01 03:00:00	996.986667	-8.896667	264.491667	-9.786667	93.200000	3.111667	2.898333	0
4	2009-01-01 04:00:00	997.158333	-9.348333	264.026667	-10.345000	92.383333	3.001667	2.775000	0

Let's look at our fields again

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



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.

In [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

In [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---------->

In [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)

In [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.

In [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)
```

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)

In [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	Pa
input_layer (InputLayer)	(None, 120, 7)	
lstm (LSTM)	(None, 32)	
dense (Dense)	(None, 1)	

Total params: 5,153 (20.13 KB)

Trainable params: 5,153 (20.13 KB)

Non-trainable params: 0 (0.00 B)

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

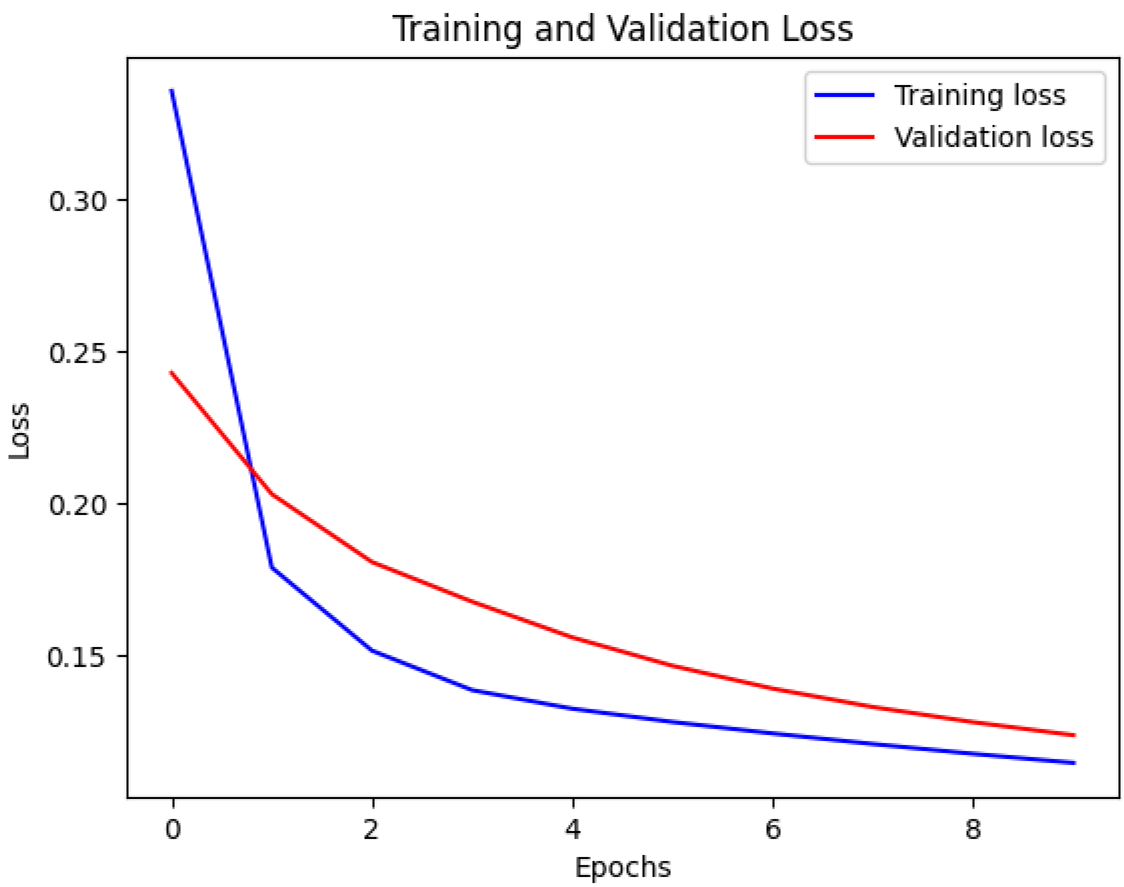
In [15]:
```
path_checkpoint = "model_checkpoint.weights.h5"
es_callback = keras.callbacks.EarlyStopping(monitor="val_loss", min_delta=0, patience=

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
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 125ms/step - loss: 0.5757
Epoch 1: val_loss improved from inf to 0.24283, saving model to model_checkpoint.weig
hts.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 18s 154ms/step - loss: 0.5708 - val_loss: 0.2428
Epoch 2/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 127ms/step - loss: 0.1929
Epoch 2: val_loss improved from 0.24283 to 0.20290, saving model to model_checkpoint.
weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 15s 152ms/step - loss: 0.1926 - val_loss: 0.2029
Epoch 3/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 151ms/step - loss: 0.1600
Epoch 3: val_loss improved from 0.20290 to 0.18052, saving model to model_checkpoint.
weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 17s 178ms/step - loss: 0.1599 - val_loss: 0.1805
Epoch 4/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step - loss: 0.1420
Epoch 4: val_loss improved from 0.18052 to 0.16745, saving model to model_checkpoint.
weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 15s 154ms/step - loss: 0.1420 - val_loss: 0.1675
Epoch 5/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 127ms/step - loss: 0.1349
Epoch 5: val_loss improved from 0.16745 to 0.15567, saving model to model_checkpoint.
weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 15s 156ms/step - loss: 0.1349 - val_loss: 0.1557
Epoch 6/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 127ms/step - loss: 0.1300
Epoch 6: val_loss improved from 0.15567 to 0.14634, saving model to model_checkpoint.
weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 15s 155ms/step - loss: 0.1300 - val_loss: 0.1463
Epoch 7/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 133ms/step - loss: 0.1262
Epoch 7: val_loss improved from 0.14634 to 0.13882, saving model to model_checkpoint.
weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 15s 159ms/step - loss: 0.1262 - val_loss: 0.1388
Epoch 8/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 128ms/step - loss: 0.1228
Epoch 8: val_loss improved from 0.13882 to 0.13275, saving model to model_checkpoint.
weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 15s 160ms/step - loss: 0.1228 - val_loss: 0.1328
Epoch 9/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 141ms/step - loss: 0.1195
Epoch 9: val_loss improved from 0.13275 to 0.12777, saving model to model_checkpoint.
weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 17s 179ms/step - loss: 0.1194 - val_loss: 0.1278
Epoch 10/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 128ms/step - loss: 0.1162
Epoch 10: val_loss improved from 0.12777 to 0.12348, saving model to model_checkpoin
t.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 18s 155ms/step - loss: 0.1161 - val_loss: 0.1235
```

Plot the results of your training:

In [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")
```

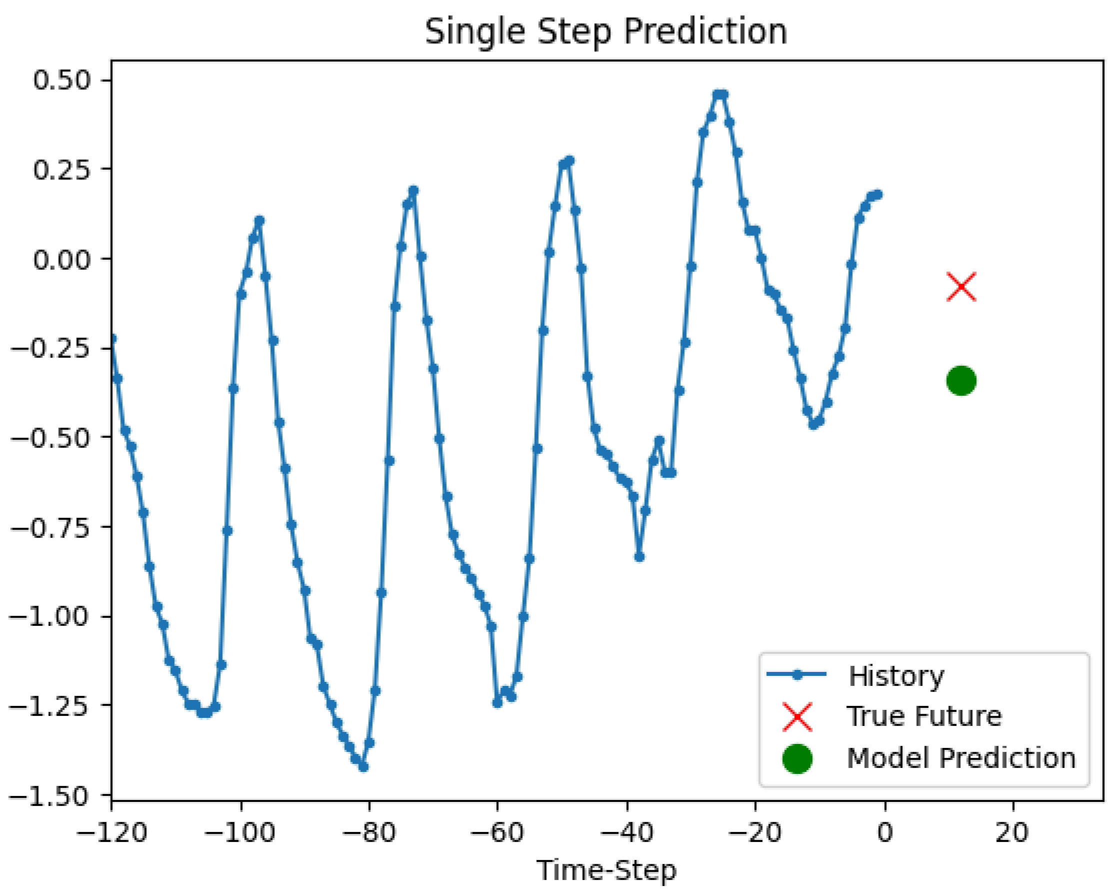


Make 5 predictions and display the predicted value

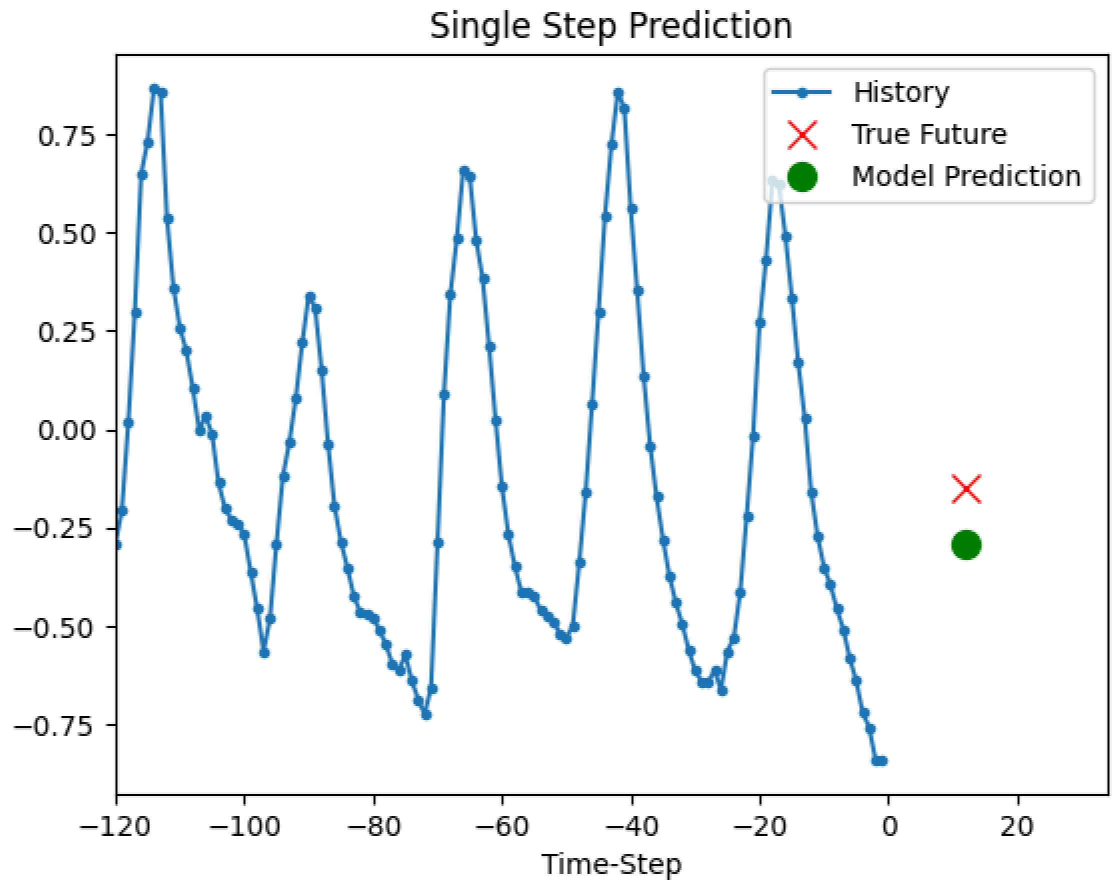
In [17]:
```
def show_plot(plot_data, delta, title):
    labels = ["History", "True Future", "Model Prediction"]
    marker = [".-", "rx", "go"]
    time_steps = list(range(-(plot_data[0].shape[0]), 0))
    if delta:
        future = delta
    else:
        future = 0
```

```
    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",
    )
```

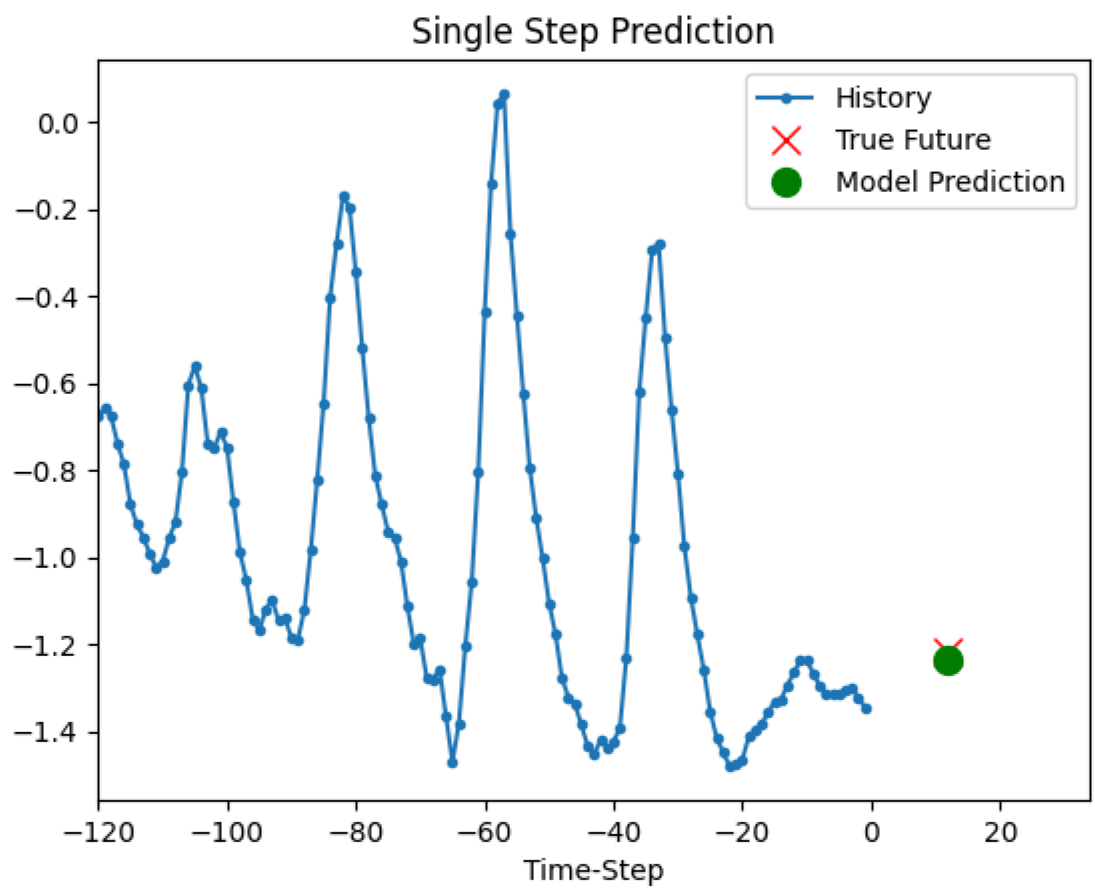
```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step
```



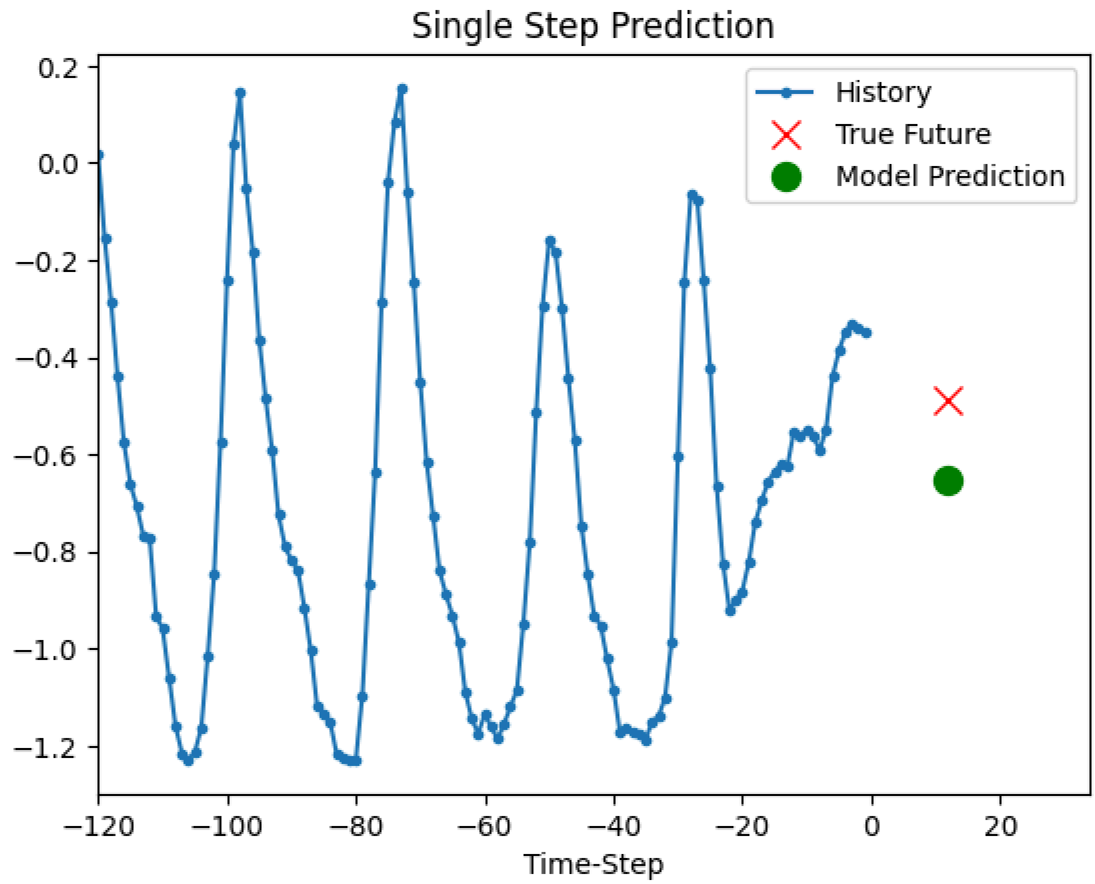

```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step
```



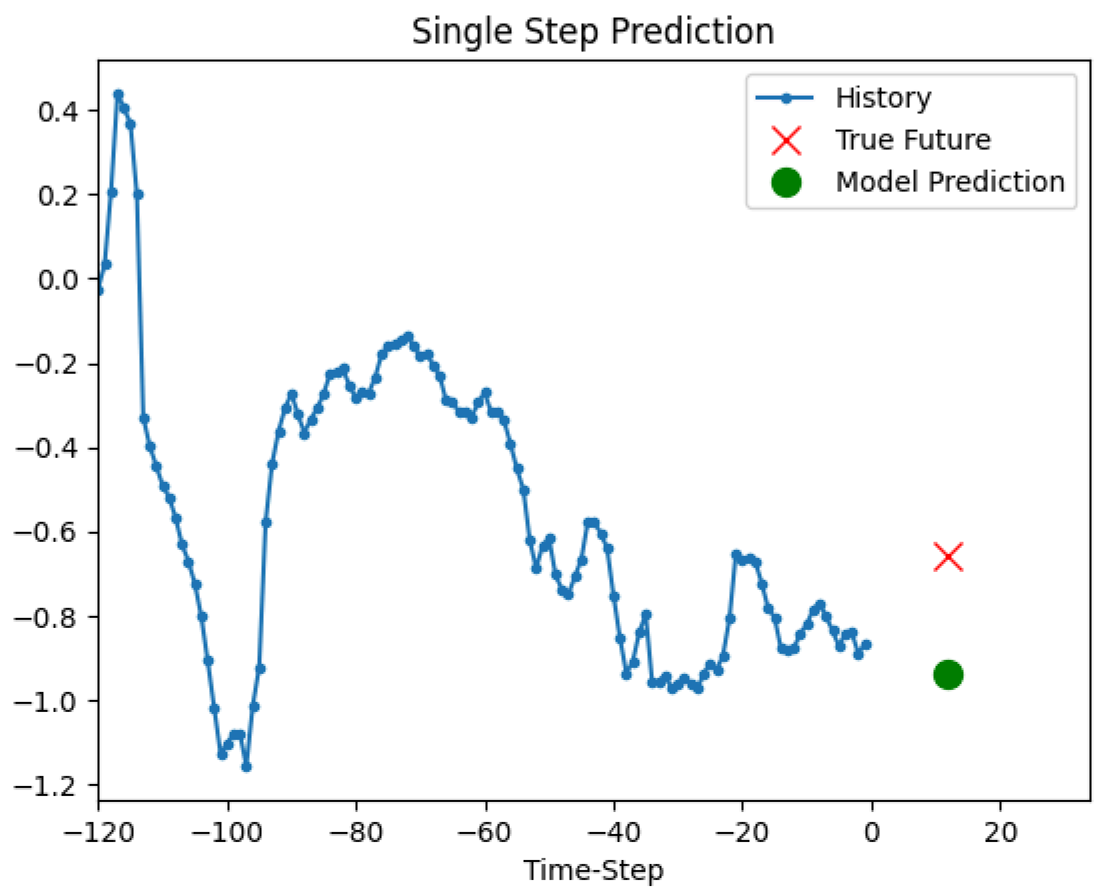

```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step
```




```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step
```




```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step
```

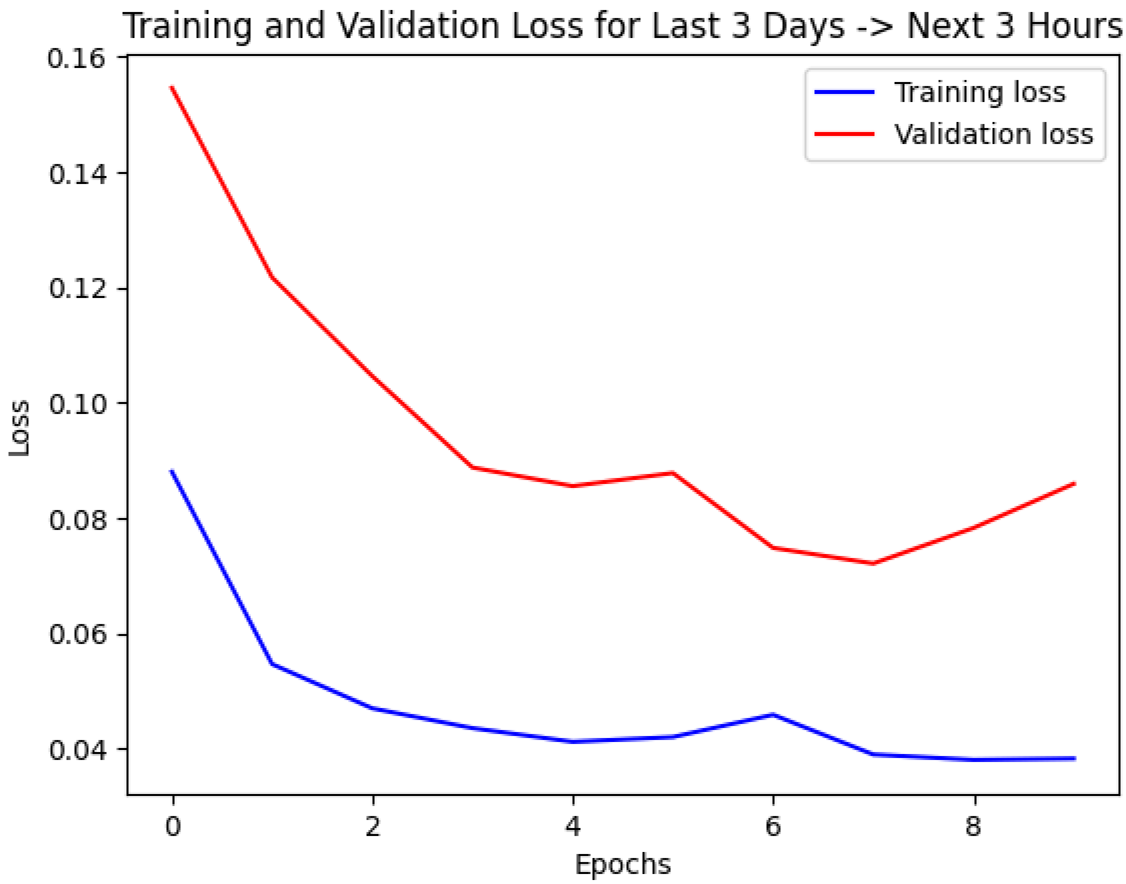


Now make a Time Series Forecasting where using the last 3 days you will predict the weather in the next 3 hours.

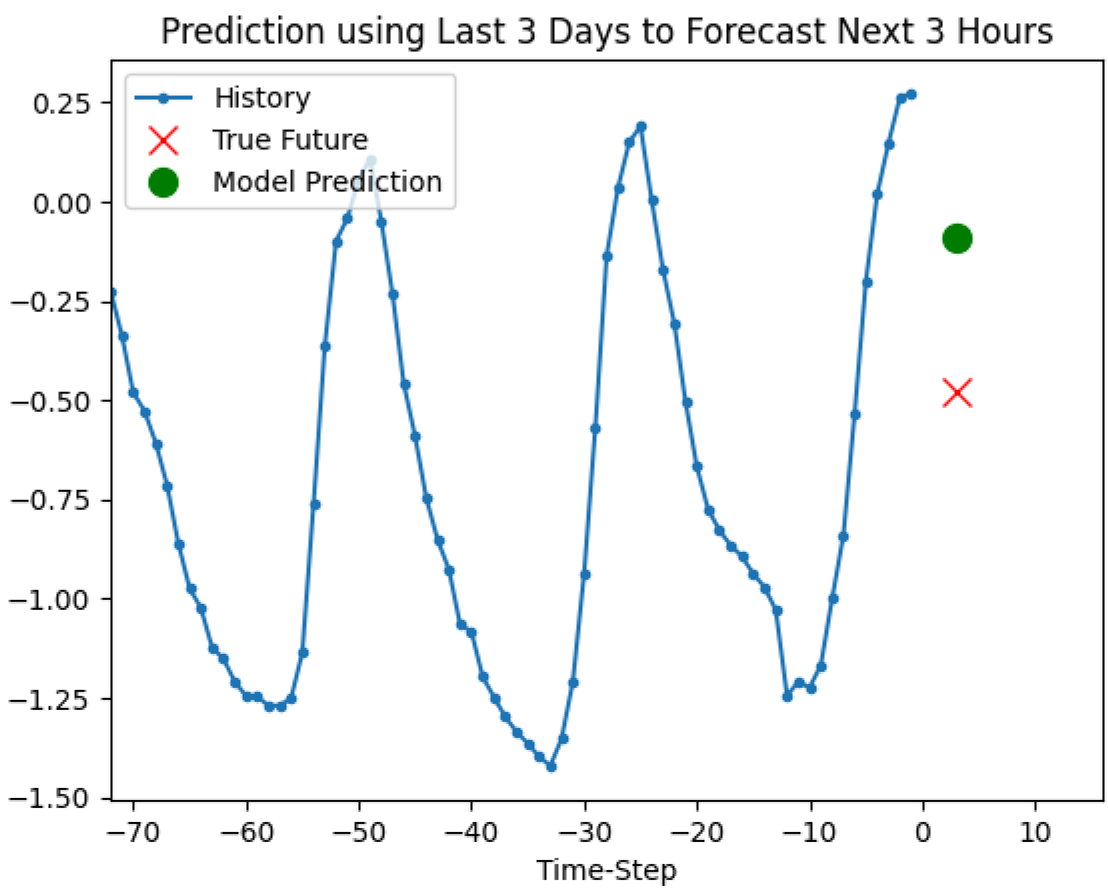
In [33]:
```
# Definir los parámetros para el nuevo pronóstico
past_days = 3 * 24  # 3 días (cada día tiene 24 horas)
future_hours = 3  # 3 horas en el futuro

# Crear el dataset de entrenamiento utilizando los últimos 3 días para predecir las pr
start = past_days + future_hours
end = start + train_split

x_train = train_data[selected_features].values
y_train = features.iloc[start:end]['T (degC)']

sequence_length = past_days

# Dataset de entrenamiento para la nueva tarea
dataset_train = keras.preprocessing.timeseries_dataset_from_array(
    x_train,
    y_train,
    sequence_length=sequence_length,
    sampling_rate=step,
    batch_size=batch_size,
)

# Crear el dataset de validación
x_end = len(val_data) - past_days - future_hours
label_start = train_split + past_days + future_hours

# Usamos los nombres de las columnas seleccionadas
x_val = val_data.iloc[:x_end][selected_features].values  # Usar los nombres de columna
y_val = features.iloc[label_start:]['T (degC)']  # Ajustar la columna objetivo por su


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

# Definir el modelo
inputs = keras.layers.Input(shape=(sequence_length, 7))
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"

# Definir los callbacks y entrenar el modelo
path_checkpoint = "model_checkpoint_last3days_next3hours.weights.h5"
es_callback = keras.callbacks.EarlyStopping(monitor="val_loss", 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],
)

# Visualizar la pérdida durante el entrenamiento
visualize_loss(history, "Training and Validation Loss for Last 3 Days -> Next 3 Hours"

# Hacer y mostrar predicciones
for x, y in dataset_val.take(5):
    show_plot(
        [x[0][:, 1].numpy(), y[0].numpy(), model.predict(x)[0]],
        future_hours,
        "Prediction using Last 3 Days to Forecast Next 3 Hours",
    )
```

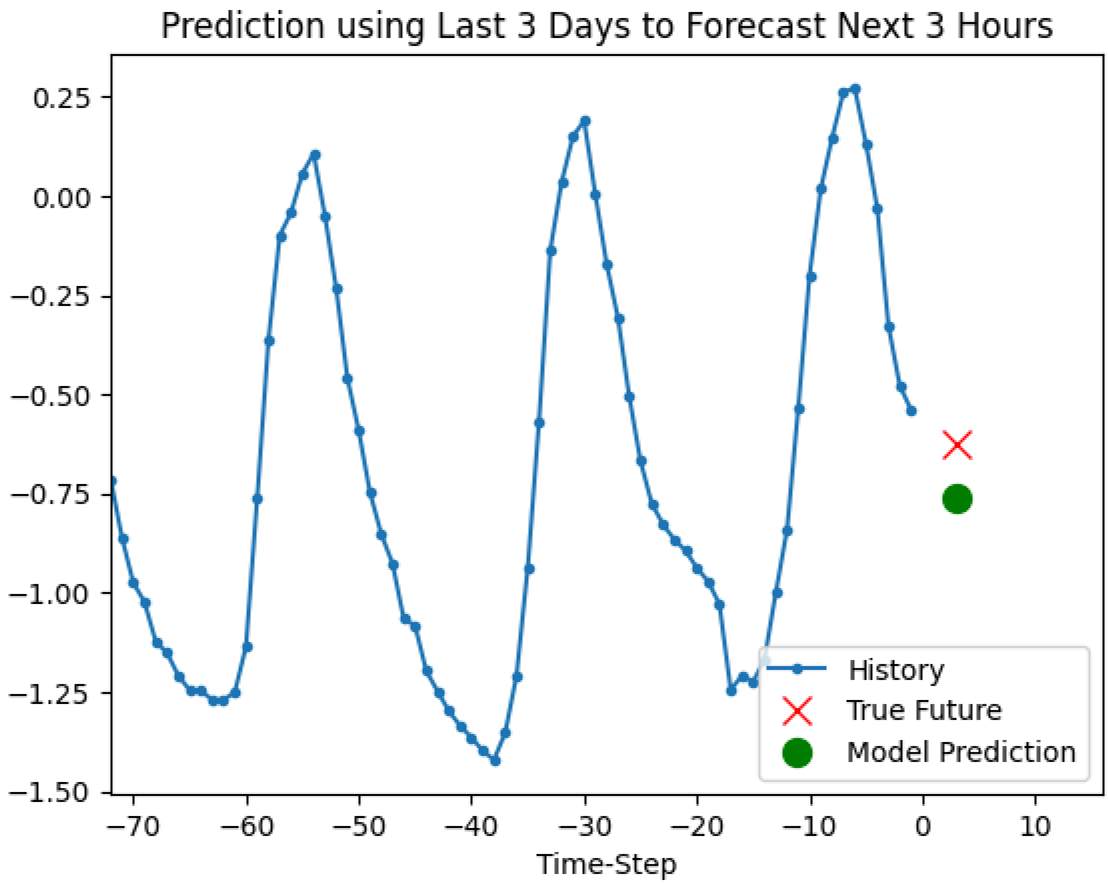
```
Epoch 1/10
4894/4895 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.1482
Epoch 1: val_loss improved from inf to 0.15459, saving model to model_checkpoint_last
3days_next3hours.weights.h5
4895/4895 ━━━━━━━━━━━━━━━━━━━━ 143s 28ms/step - loss: 0.1482 - val_loss: 0.1546
Epoch 2/10
4895/4895 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - loss: 0.0679
Epoch 2: val_loss improved from 0.15459 to 0.12170, saving model to model_checkpoint_
last3days_next3hours.weights.h5
4895/4895 ━━━━━━━━━━━━━━━━━━━━ 137s 27ms/step - loss: 0.0679 - val_loss: 0.1217
Epoch 3/10
4894/4895 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.0546
Epoch 3: val_loss improved from 0.12170 to 0.10458, saving model to model_checkpoint_
last3days_next3hours.weights.h5
4895/4895 ━━━━━━━━━━━━━━━━━━━━ 148s 28ms/step - loss: 0.0546 - val_loss: 0.1046
Epoch 4/10
4895/4895 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.0495
Epoch 4: val_loss improved from 0.10458 to 0.08872, saving model to model_checkpoint_
last3days_next3hours.weights.h5
4895/4895 ━━━━━━━━━━━━━━━━━━━━ 137s 28ms/step - loss: 0.0495 - val_loss: 0.0887
Epoch 5/10
4894/4895 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.0462
Epoch 5: val_loss improved from 0.08872 to 0.08549, saving model to model_checkpoint_
last3days_next3hours.weights.h5
4895/4895 ━━━━━━━━━━━━━━━━━━━━ 135s 28ms/step - loss: 0.0462 - val_loss: 0.0855
Epoch 6/10
4893/4895 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - loss: 0.0455
Epoch 6: val_loss did not improve from 0.08549
4895/4895 ━━━━━━━━━━━━━━━━━━━━ 134s 27ms/step - loss: 0.0455 - val_loss: 0.0878
Epoch 7/10
4893/4895 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.0506
Epoch 7: val_loss improved from 0.08549 to 0.07477, saving model to model_checkpoint_
last3days_next3hours.weights.h5
4895/4895 ━━━━━━━━━━━━━━━━━━━━ 135s 27ms/step - loss: 0.0506 - val_loss: 0.0748
Epoch 8/10
4895/4895 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.0431
Epoch 8: val_loss improved from 0.07477 to 0.07206, saving model to model_checkpoint_
last3days_next3hours.weights.h5
4895/4895 ━━━━━━━━━━━━━━━━━━━━ 135s 28ms/step - loss: 0.0431 - val_loss: 0.0721
Epoch 9/10
4895/4895 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step - loss: 0.0409
Epoch 9: val_loss did not improve from 0.07206
4895/4895 ━━━━━━━━━━━━━━━━━━━━ 140s 29ms/step - loss: 0.0409 - val_loss: 0.0782
Epoch 10/10
4895/4895 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - loss: 0.0426
Epoch 10: val_loss did not improve from 0.07206
4895/4895 ━━━━━━━━━━━━━━━━━━━━ 133s 27ms/step - loss: 0.0426 - val_loss: 0.0859
```



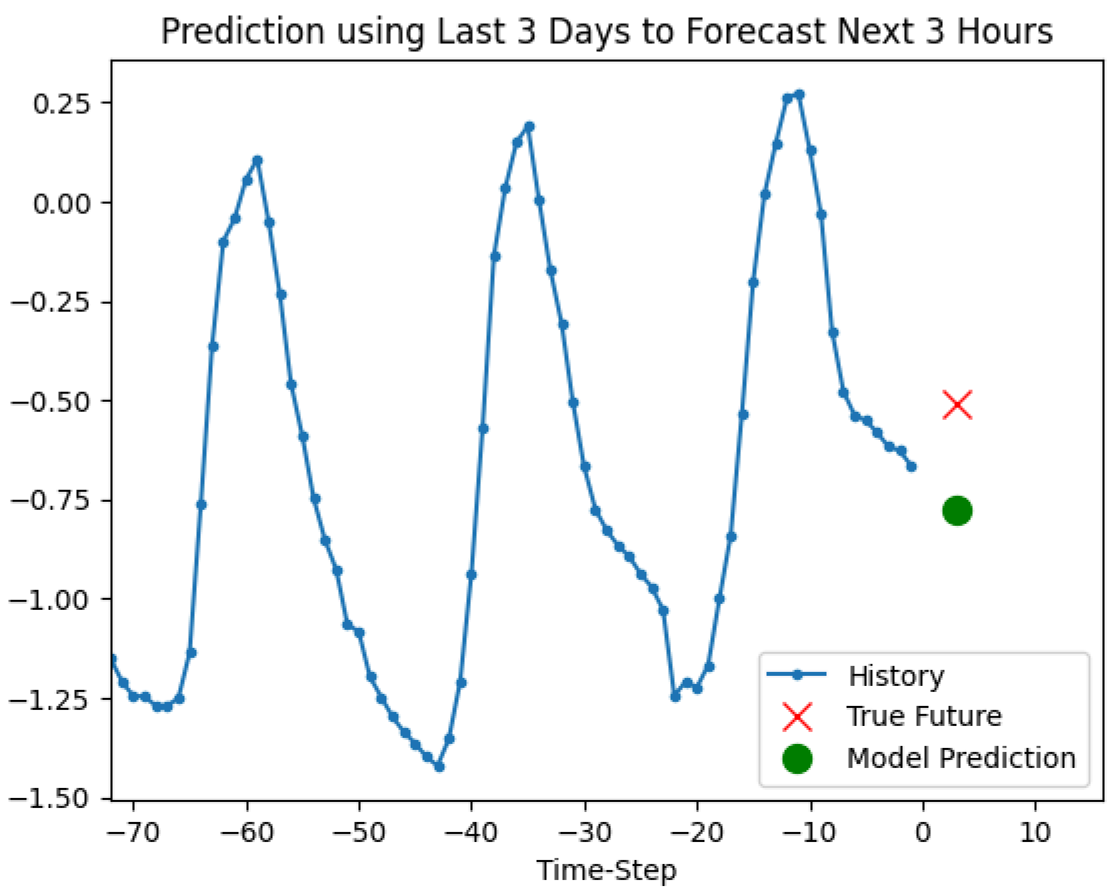

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 190ms/step
```



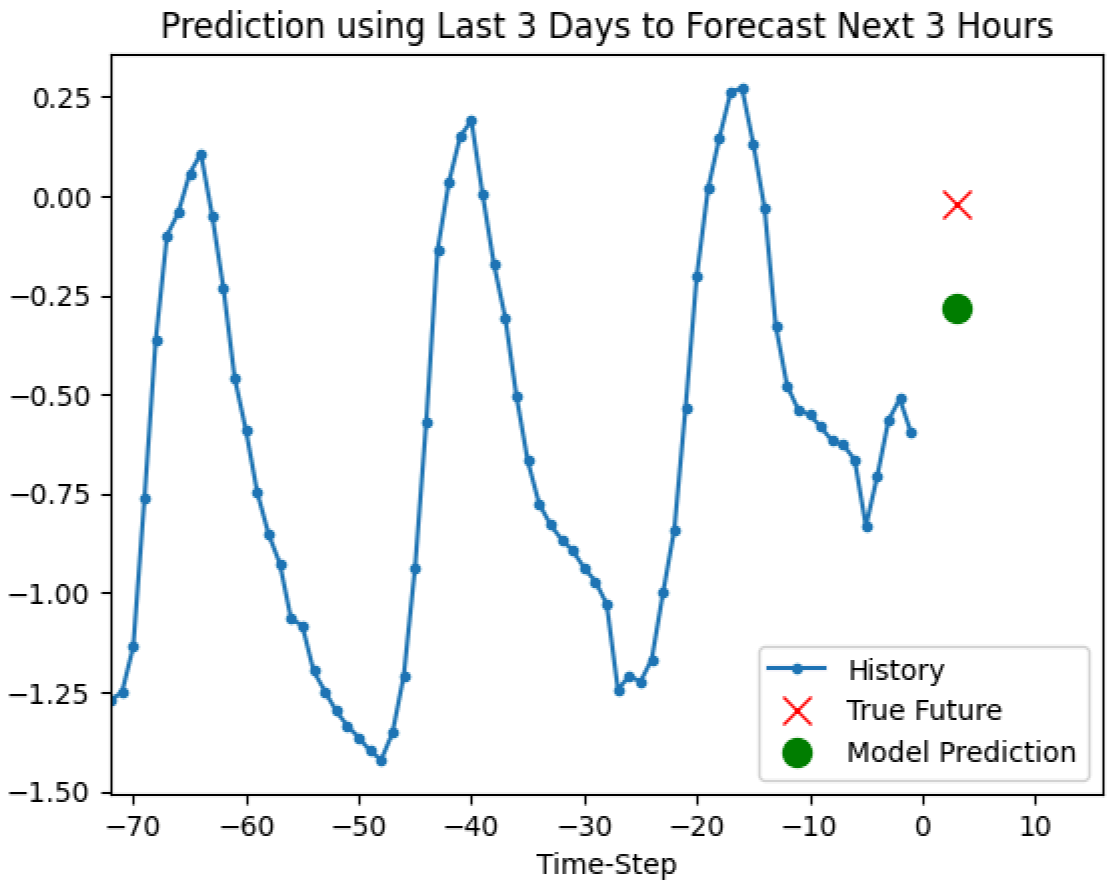

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step
```




```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
```




```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
```




```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 37ms/step
```