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 [1]:
```
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("C:/Users/PC/OneDrive - Instituto Tecnologico y de Estudios Sup
df.head()
```

Out[2]:

	Date Time	p (mbar)	T (degC)	Tpot (K)	Tdew (degC)	rh (%)	VPmax (mbar)	VPact (mbar)	VPdef (mbar)	sh (g/kg)	(ı
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	
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	
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	01.01.2009 00:40:00	996.51	-8.31	265.12	-9.07	94.2	3.26	3.07	0.19	1.92	
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	

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]:

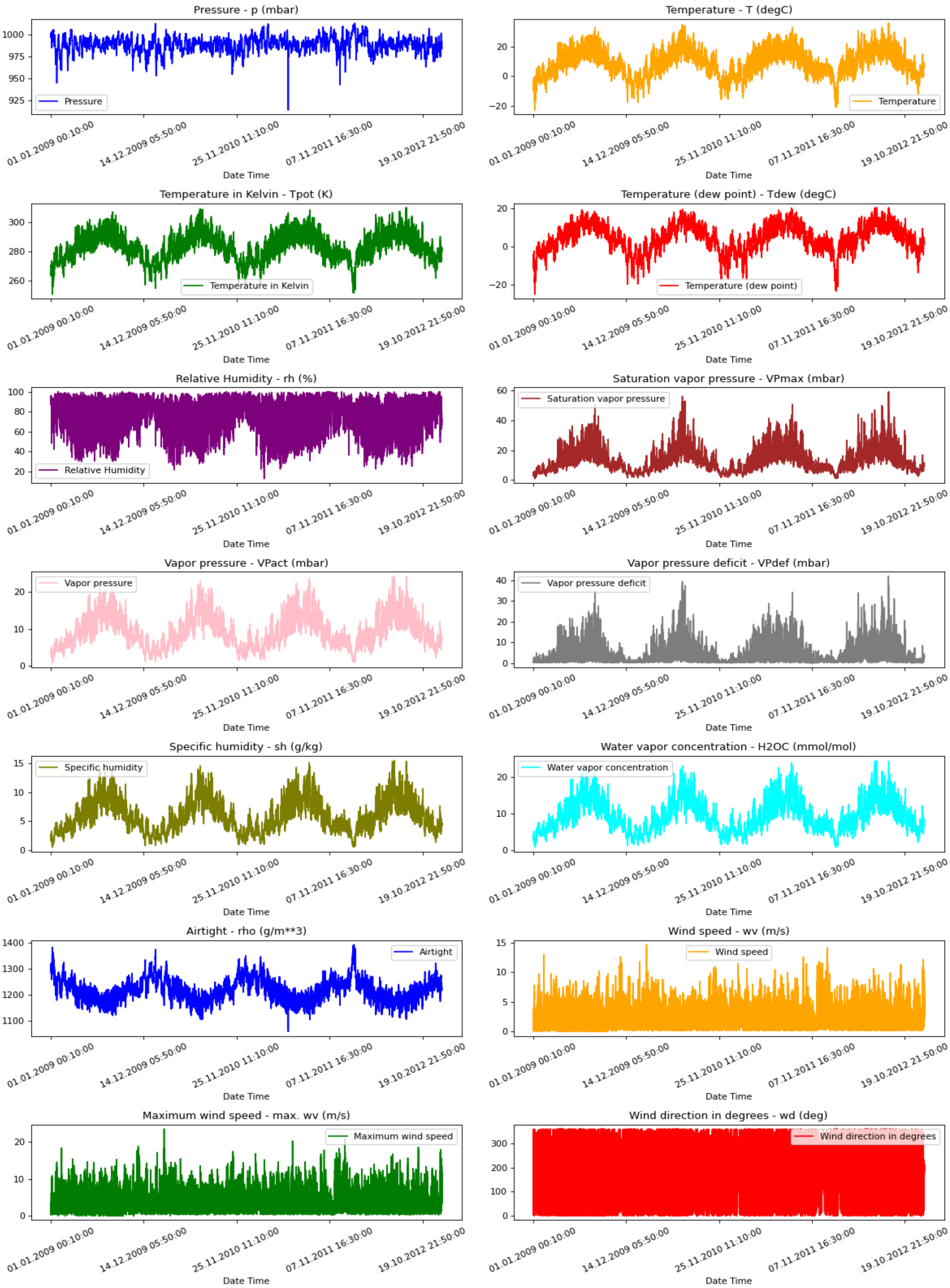
	Date Time	p (mbar)	T (degC)	Tpot (K)	Tdew (degC)	rh (%)	VPmax (mbar)	VPact (mbar)	VPdef (mbar)	sh (g/kg)	(ı
0	01.01.2009 00:10:00	996.52	-8.02	265.40	-8.90	93.3	3.33	3.11	0.22	1.94	
1	01.01.2009 00:20:00	996.57	-8.41	265.01	-9.28	93.4	3.23	3.02	0.21	1.89	
2	01.01.2009 00:30:00	996.53	-8.51	264.91	-9.31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

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:
df = df.set_index('FormatedDateTime')
df_resampled = df[feature_keys].resample('H').mean()
df_resampled = df_resampled.reset_index()

df_resampled.head()
```

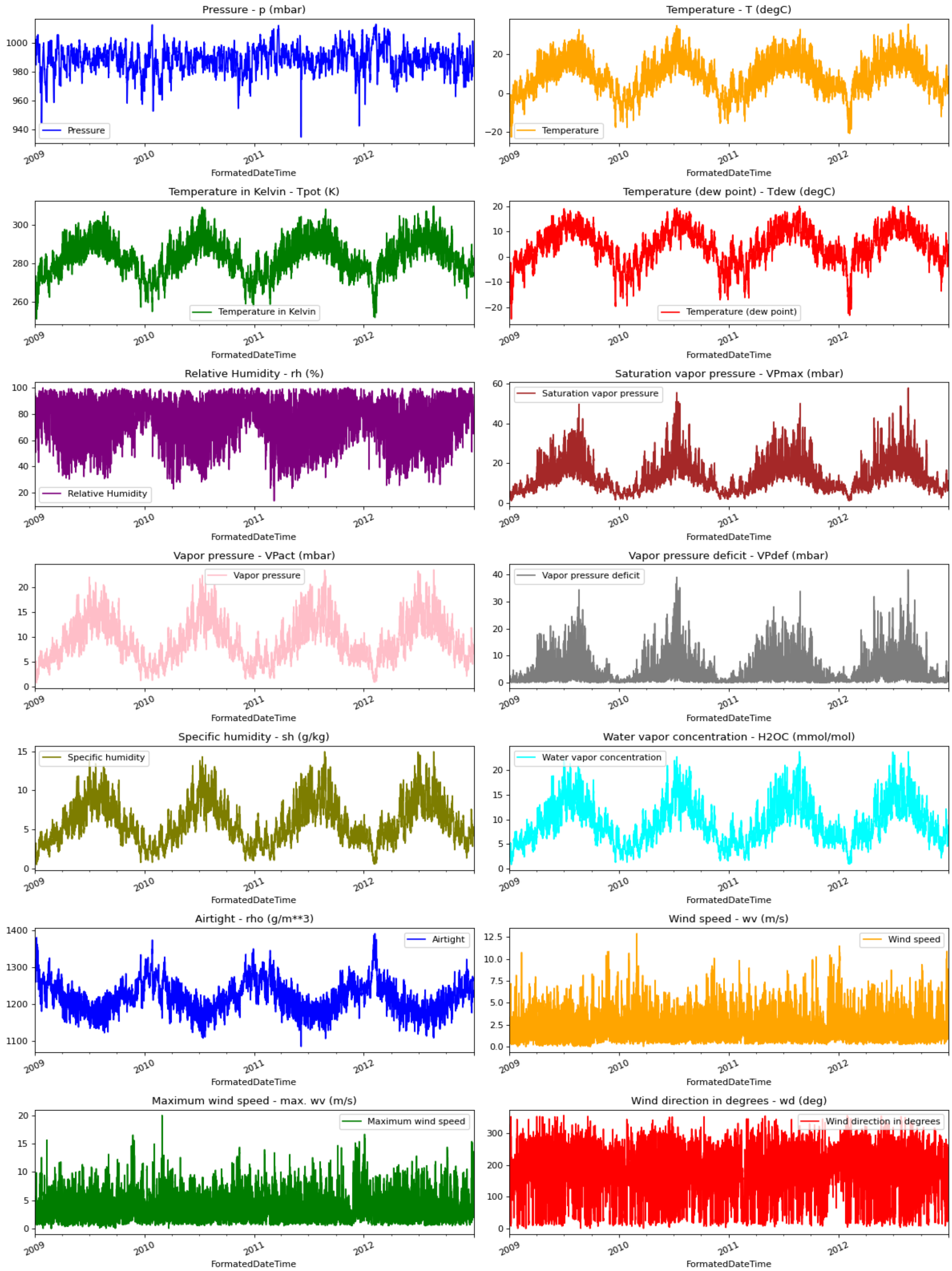
```
C:\Users\PC\AppData\Local\Temp\ipykernel_5660\3134505598.py:3: FutureWarning: 'H'
is deprecated and will be removed in a future version, please use 'h' instead.
  df_resampled = df[feature_keys].resample('H').mean()
```

Out[7]:

	FormatedDateTime	p (mbar)	T (degC)	Tpot (K)	Tdew (degC)	rh (%)	VPma (mba
0	2009-01-01 00:00:00	996.528000	-8.304000	265.118000	-9.120000	93.780000	3.2600(
1	2009-01-01 01:00:00	996.525000	-8.065000	265.361667	-8.861667	93.933333	3.3233:
2	2009-01-01 02:00:00	996.745000	-8.763333	264.645000	-9.610000	93.533333	3.1450(
3	2009-01-01 03:00:00	996.986667	-8.896667	264.491667	-9.786667	93.200000	3.1116(
4	2009-01-01 04:00:00	997.158333	-9.348333	264.026667	-10.345000	92.383333	3.0016(

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
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, Va
por 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
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)

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

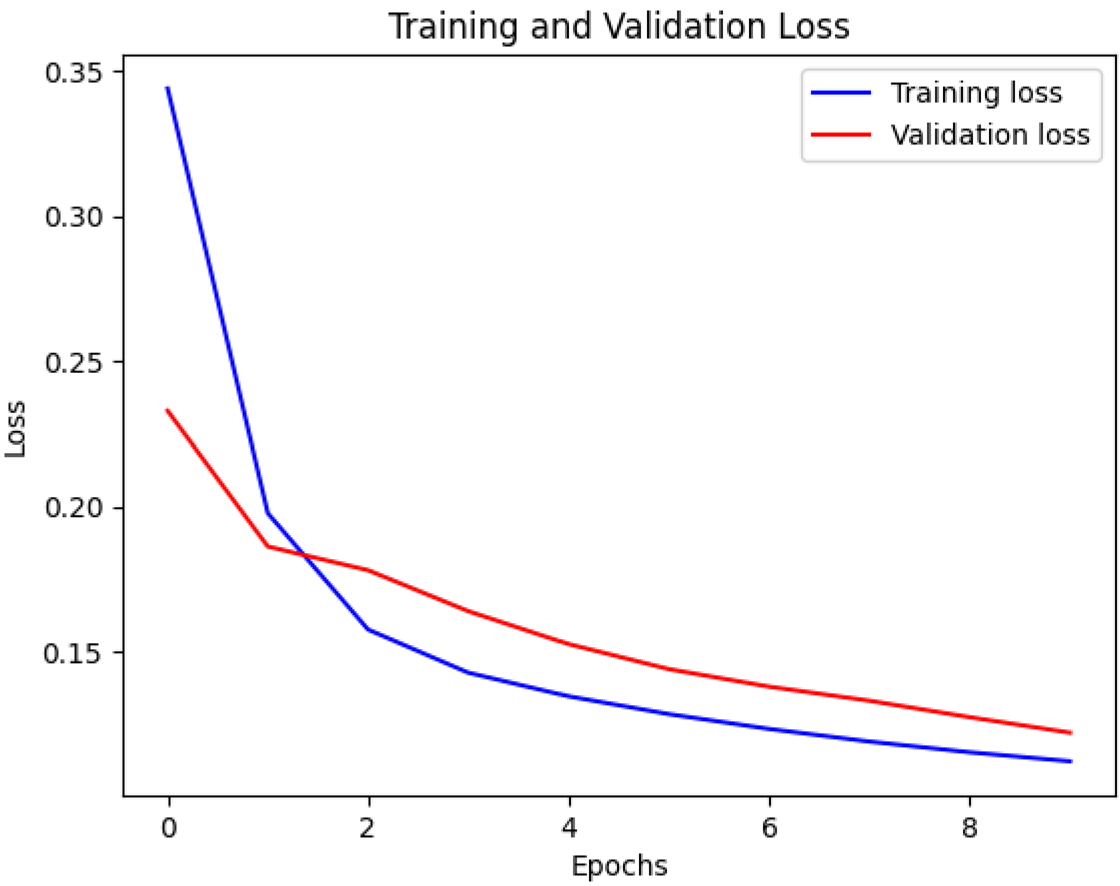
In [15]:
```
path_checkpoint = "model_checkpoint.weights.h5"
es_callback = keras.callbacks.EarlyStopping(monitor="val_loss", min_delta=0, pat

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 40ms/step - loss: 0.4979
Epoch 1: val_loss improved from inf to 0.23283, saving model to model_checkpoint.
weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 6s 48ms/step - loss: 0.4947 - val_loss: 0.2328
Epoch 2/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 40ms/step - loss: 0.2018
Epoch 2: val_loss improved from 0.23283 to 0.18624, saving model to model_checkpo
int.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 5s 47ms/step - loss: 0.2017 - val_loss: 0.1862
Epoch 3/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 41ms/step - loss: 0.1583
Epoch 3: val_loss improved from 0.18624 to 0.17808, saving model to model_checkpo
int.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 5s 48ms/step - loss: 0.1583 - val_loss: 0.1781
Epoch 4/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 40ms/step - loss: 0.1427
Epoch 4: val_loss improved from 0.17808 to 0.16397, saving model to model_checkpo
int.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 4s 46ms/step - loss: 0.1427 - val_loss: 0.1640
Epoch 5/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 39ms/step - loss: 0.1360
Epoch 5: val_loss improved from 0.16397 to 0.15260, saving model to model_checkpo
int.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 4s 46ms/step - loss: 0.1359 - val_loss: 0.1526
Epoch 6/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 39ms/step - loss: 0.1309
Epoch 6: val_loss improved from 0.15260 to 0.14398, saving model to model_checkpo
int.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 4s 46ms/step - loss: 0.1309 - val_loss: 0.1440
Epoch 7/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 40ms/step - loss: 0.1269
Epoch 7: val_loss improved from 0.14398 to 0.13796, saving model to model_checkpo
int.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 4s 46ms/step - loss: 0.1268 - val_loss: 0.1380
Epoch 8/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 39ms/step - loss: 0.1233
Epoch 8: val_loss improved from 0.13796 to 0.13311, saving model to model_checkpo
int.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 4s 46ms/step - loss: 0.1232 - val_loss: 0.1331
Epoch 9/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 39ms/step - loss: 0.1202
Epoch 9: val_loss improved from 0.13311 to 0.12744, saving model to model_checkpo
int.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 4s 46ms/step - loss: 0.1201 - val_loss: 0.1274
Epoch 10/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 40ms/step - loss: 0.1169
Epoch 10: val_loss improved from 0.12744 to 0.12212, saving model to model_checkp
oint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 4s 46ms/step - loss: 0.1169 - val_loss: 0.1221
```

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")
```

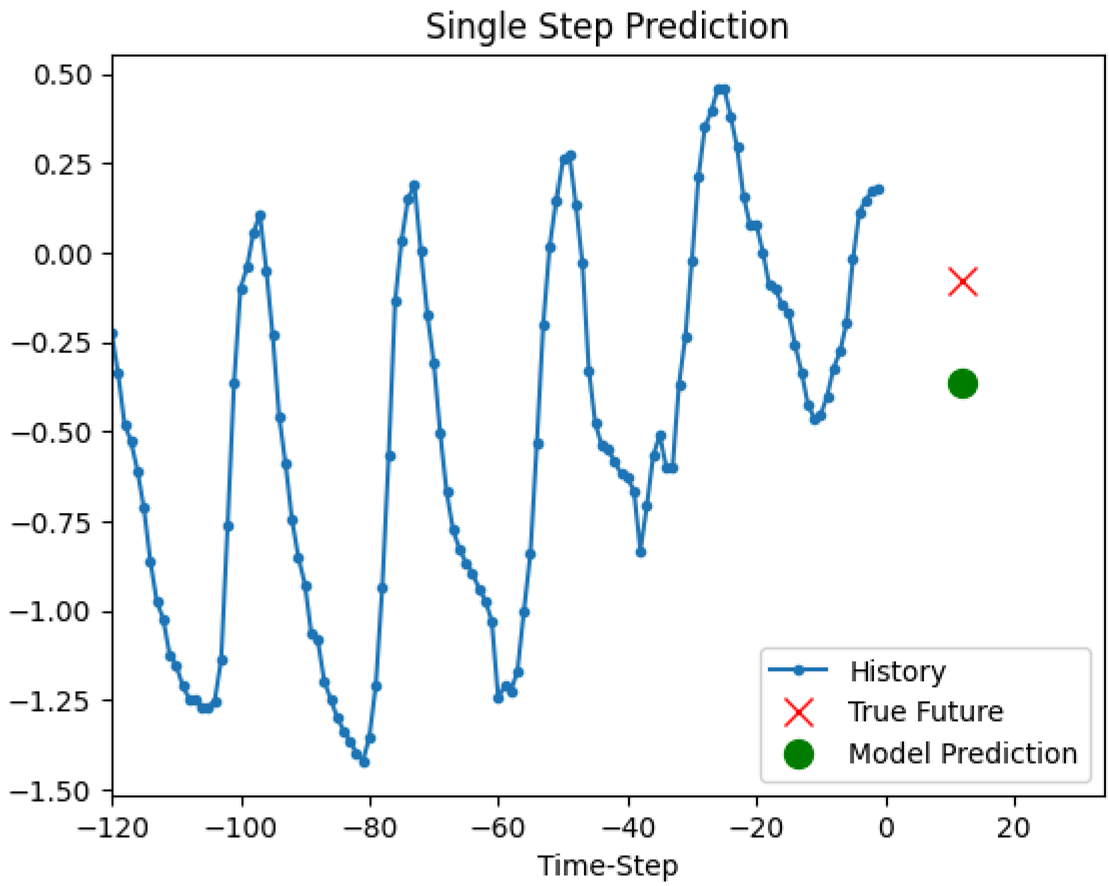


Make 5 predictions and display the predicted value

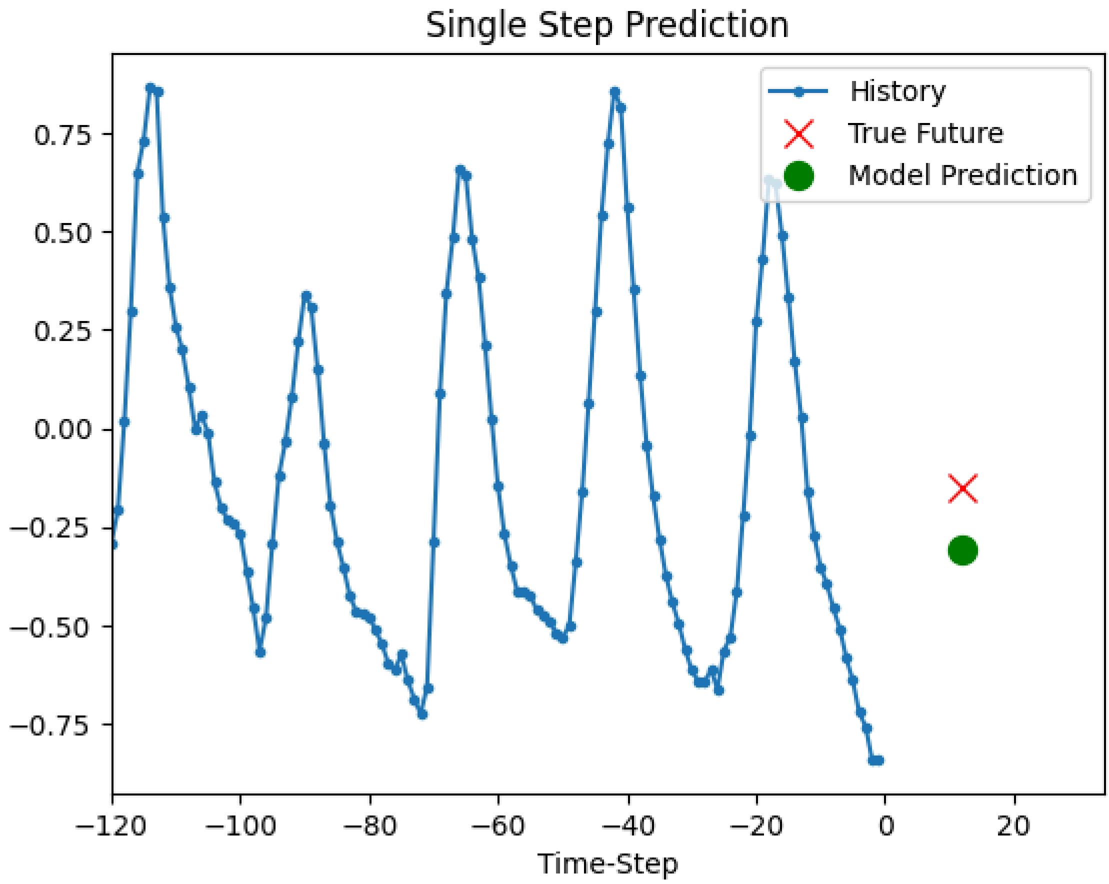
In [17]:
```
def show_plot(plot_data, delta, title):
    labels = ["History", "True Future", "Model Prediction"]
    marker = [".-", "rx", "go"]
    time_steps = list(range(-(plot_data[0].shape[0]), 0))
    if delta:
        future = delta
    else:
        future = 0

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

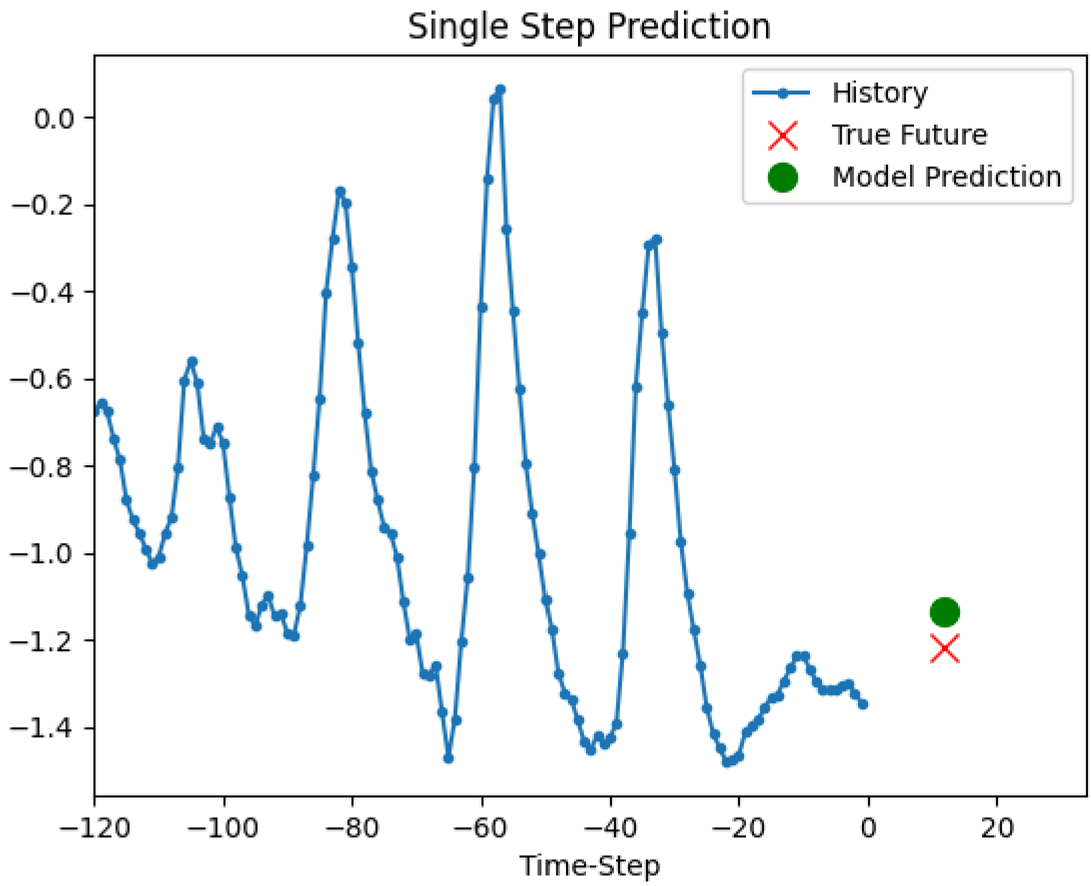
```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
```



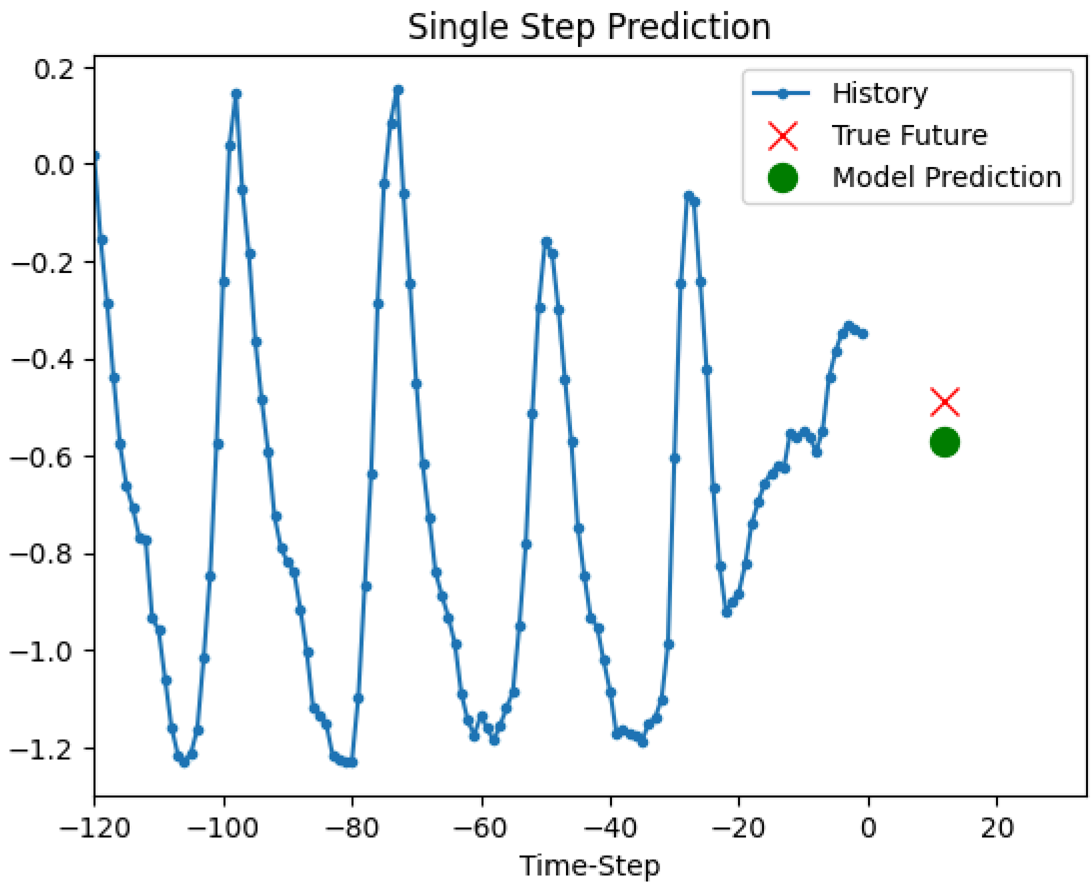

```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
```



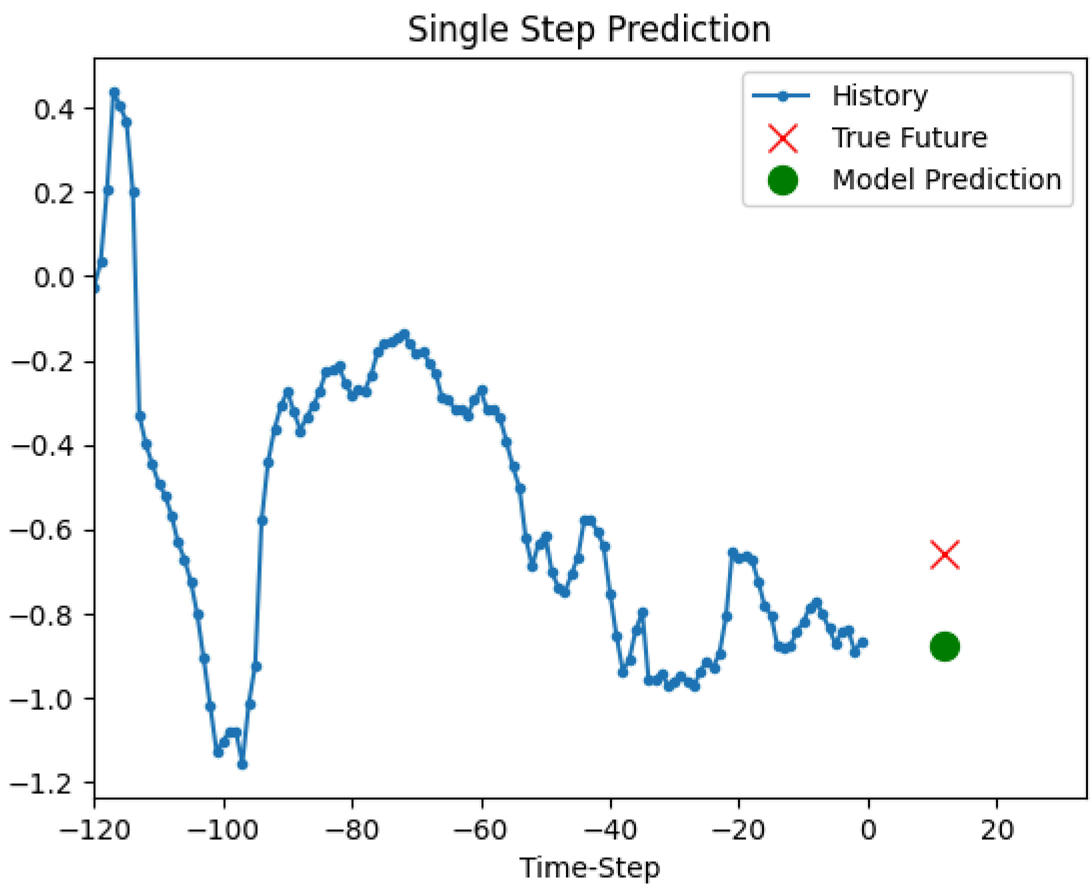
8/8 0s 5ms/step



8/8 0s 5ms/step




```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
```



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

In [24]:
```
# Ajustes para 3 días (72 horas) de datos y predicción de las próximas 3 horas

# Número de muestras en el pasado utilizadas para predecir el futuro
past = 72  # 72 horas (3 días)
# Número de muestras en el futuro para predecir (el valor en la 72ª hora es nues
future = 3  # Predicción de las próximas 3 horas
```

In [25]:
```
# Reajustar el dataset de entrenamiento y validación
start = past + future
end = start + train_split

# Ajustar el dataset de entrenamiento con secuencias de 72 horas
x_train = train_data[[i for i in range(7)]].values
y_train = features.iloc[start:end][[1]]

step = 1
sequence_length = past
```

In [26]:
```
# Crear dataset de entrenamiento con secuencias de 72 horas y predicción de 3 ho
dataset_train = keras.preprocessing.timeseries_dataset_from_array(
    x_train,
    y_train,
    sequence_length=sequence_length,
    sampling_rate=step,
    batch_size=batch_size,
)
```

In [27]:
```
# Ajustar el conjunto de validación
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, 72, 7)
Target shape: (256, 1)
```

In [28]:
```
# Definir el modelo nuevamente
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
model.summary()
```

Model: "functional_2"

Layer (type)	Output Shape	Param #
input_layer_2 (InputLayer)	(None, 72, 7)	0
lstm_2 (LSTM)	(None, 32)	5,120
dense_2 (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)

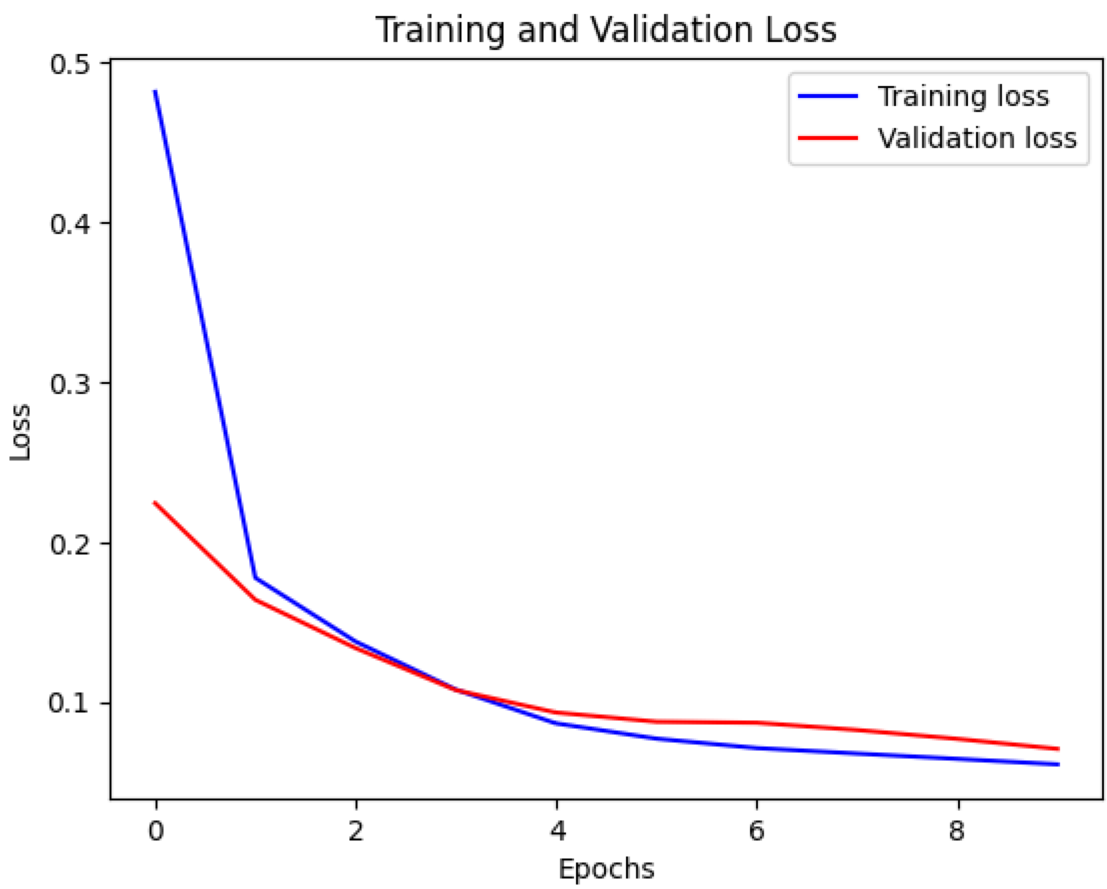
In [29]:

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

```
Epoch 1/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step - loss: 0.9407
Epoch 1: val_loss did not improve from 0.12212
96/96 ━━━━━━━━━━━━━━━━━━━━ 4s 29ms/step - loss: 0.9312 - val_loss: 0.2244
Epoch 2/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - loss: 0.1968
Epoch 2: val_loss did not improve from 0.12212
96/96 ━━━━━━━━━━━━━━━━━━━━ 3s 28ms/step - loss: 0.1964 - val_loss: 0.1640
Epoch 3/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - loss: 0.1406
Epoch 3: val_loss did not improve from 0.12212
96/96 ━━━━━━━━━━━━━━━━━━━━ 3s 29ms/step - loss: 0.1405 - val_loss: 0.1338
Epoch 4/10
94/96 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - loss: 0.1110
Epoch 4: val_loss improved from 0.12212 to 0.10749, saving model to model_checkpo
int.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 3s 26ms/step - loss: 0.1109 - val_loss: 0.1075
Epoch 5/10
95/96 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step - loss: 0.0902
Epoch 5: val_loss improved from 0.10749 to 0.09342, saving model to model_checkpo
int.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 3s 27ms/step - loss: 0.0901 - val_loss: 0.0934
Epoch 6/10
94/96 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - loss: 0.0811
Epoch 6: val_loss improved from 0.09342 to 0.08768, saving model to model_checkpo
int.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 3s 29ms/step - loss: 0.0810 - val_loss: 0.0877
Epoch 7/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - loss: 0.0764
Epoch 7: val_loss improved from 0.08768 to 0.08707, saving model to model_checkpo
int.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 3s 27ms/step - loss: 0.0763 - val_loss: 0.0871
Epoch 8/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step - loss: 0.0744
Epoch 8: val_loss improved from 0.08707 to 0.08251, saving model to model_checkpo
int.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 3s 27ms/step - loss: 0.0743 - val_loss: 0.0825
Epoch 9/10
94/96 ━━━━━━━━━━━━━━━━━━━━ 0s 23ms/step - loss: 0.0701
Epoch 9: val_loss improved from 0.08251 to 0.07697, saving model to model_checkpo
int.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 3s 28ms/step - loss: 0.0699 - val_loss: 0.0770
Epoch 10/10
96/96 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - loss: 0.0647
Epoch 10: val_loss improved from 0.07697 to 0.07071, saving model to model_checkp
oint.weights.h5
96/96 ━━━━━━━━━━━━━━━━━━━━ 3s 26ms/step - loss: 0.0647 - val_loss: 0.0707
```

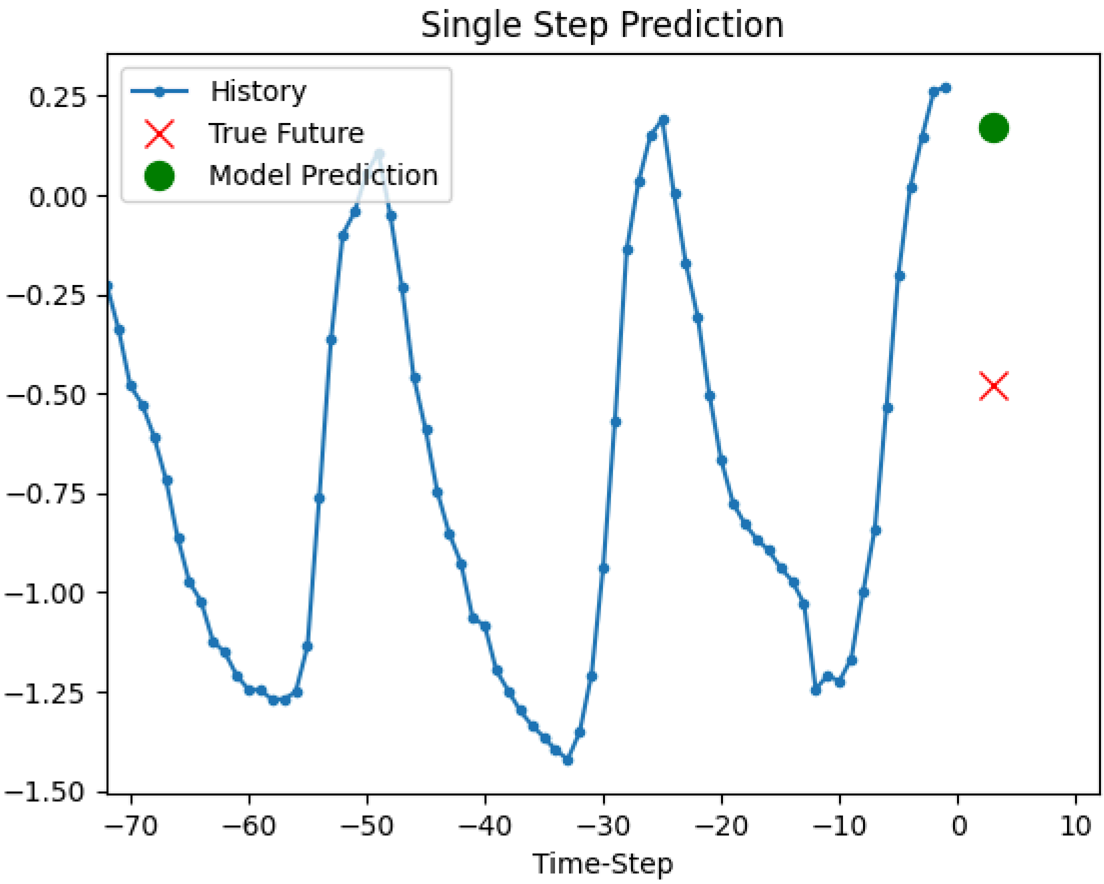
In [30]:

```
# Visualizar la perdida durante el entrenamiento y validación
visualize_loss(history, "Training and Validation Loss")
```

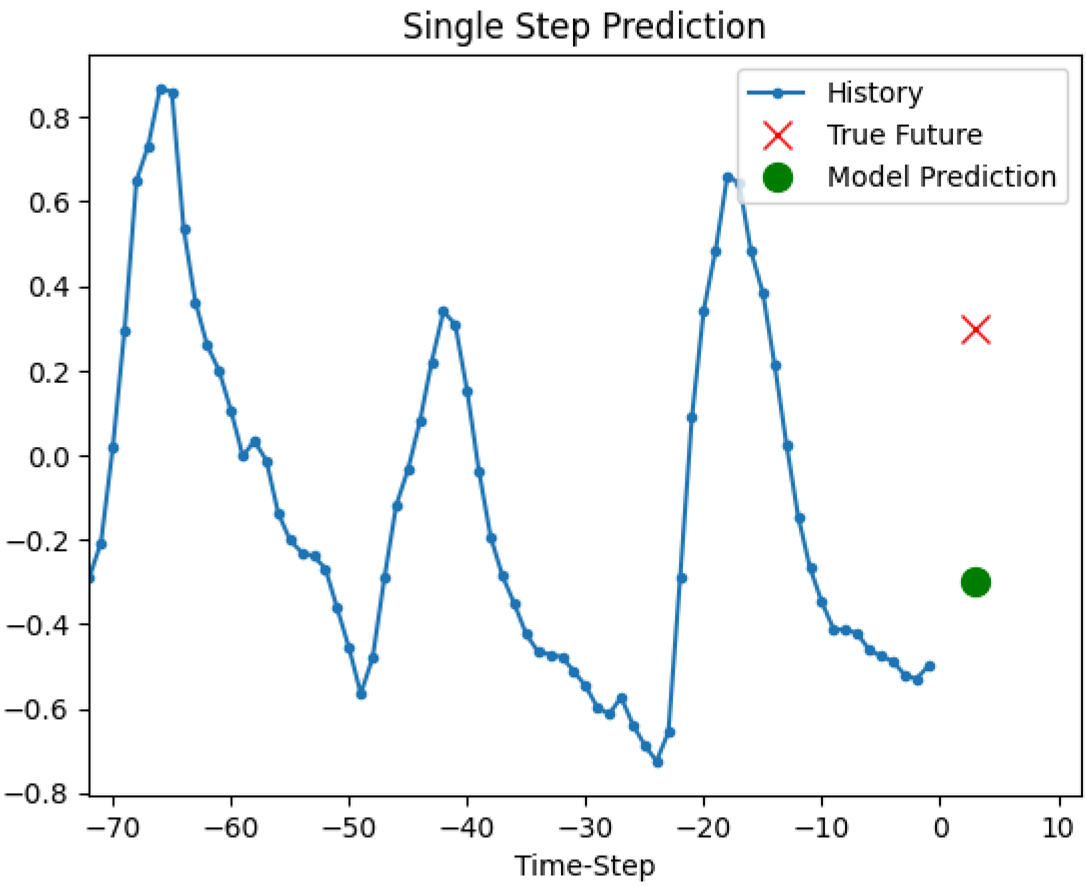


In [31]:
```
# Hacer predicciones y visualizar
def show_plot(plot_data, delta, title):
    labels = ["History", "True Future", "Model Prediction"]
    marker = [".-", "rx", "go"]
    time_steps = list(range(-(plot_data[0].shape[0]), 0))
    if delta:
        future = delta
    else:
        future = 0

    plt.title(title)
    for i, val in enumerate(plot_data):
        if i:
            plt.plot(future, plot_data[i], marker[i], markersize=10, label=label
        else:
            plt.plot(time_steps, plot_data[i].flatten(), marker[i], label=labels
    plt.legend()
    plt.xlim([time_steps[0], (future + 3) * 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",
    )
```

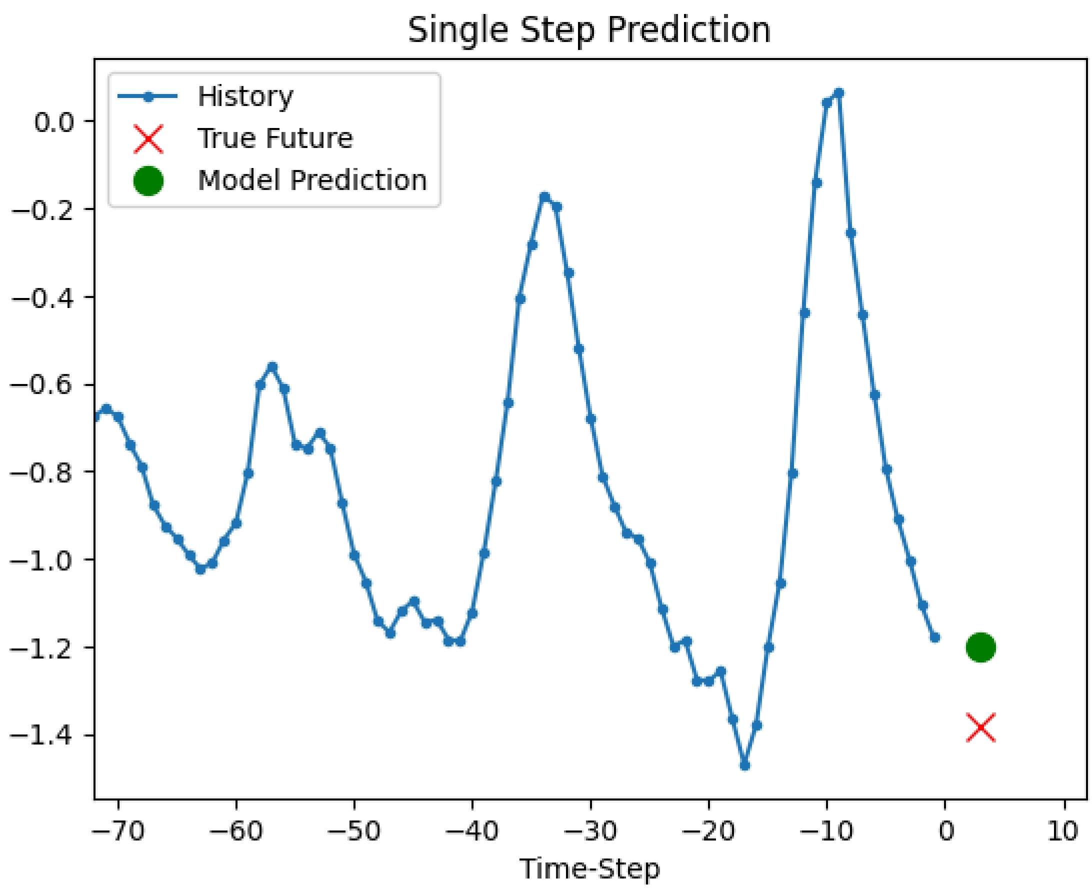
```
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
```



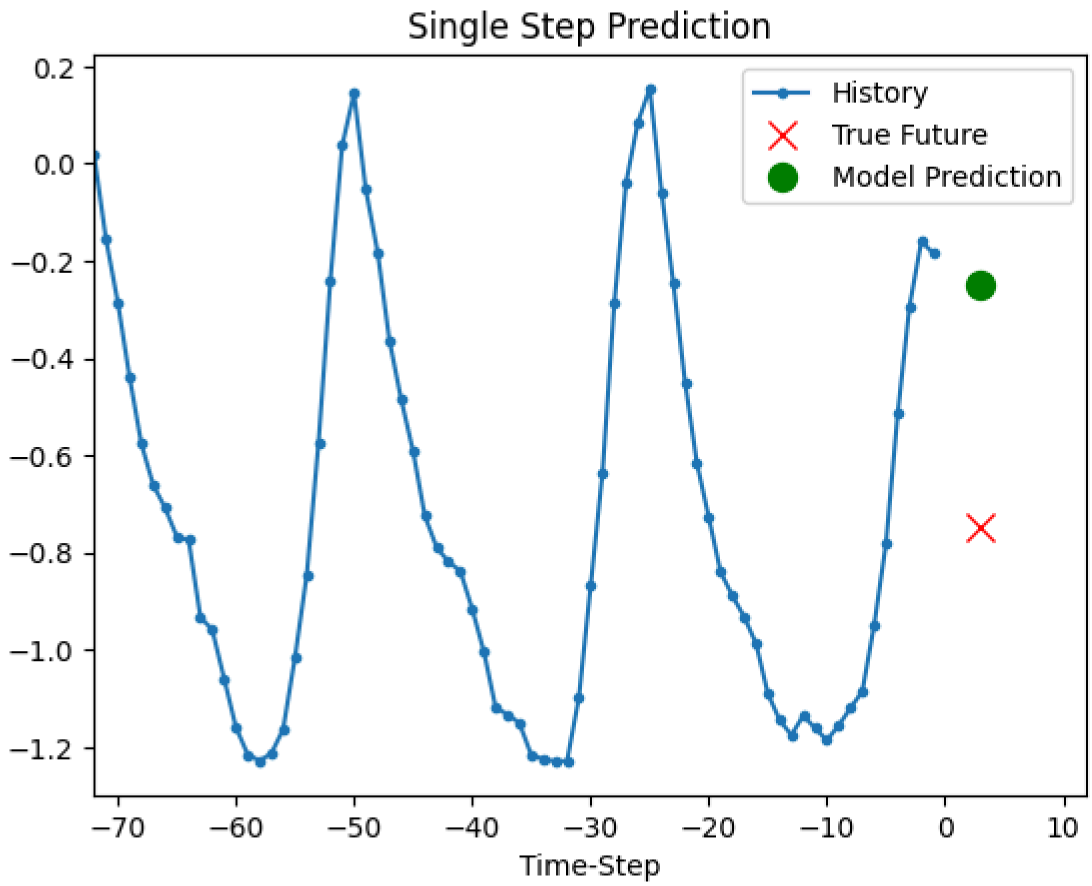
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step



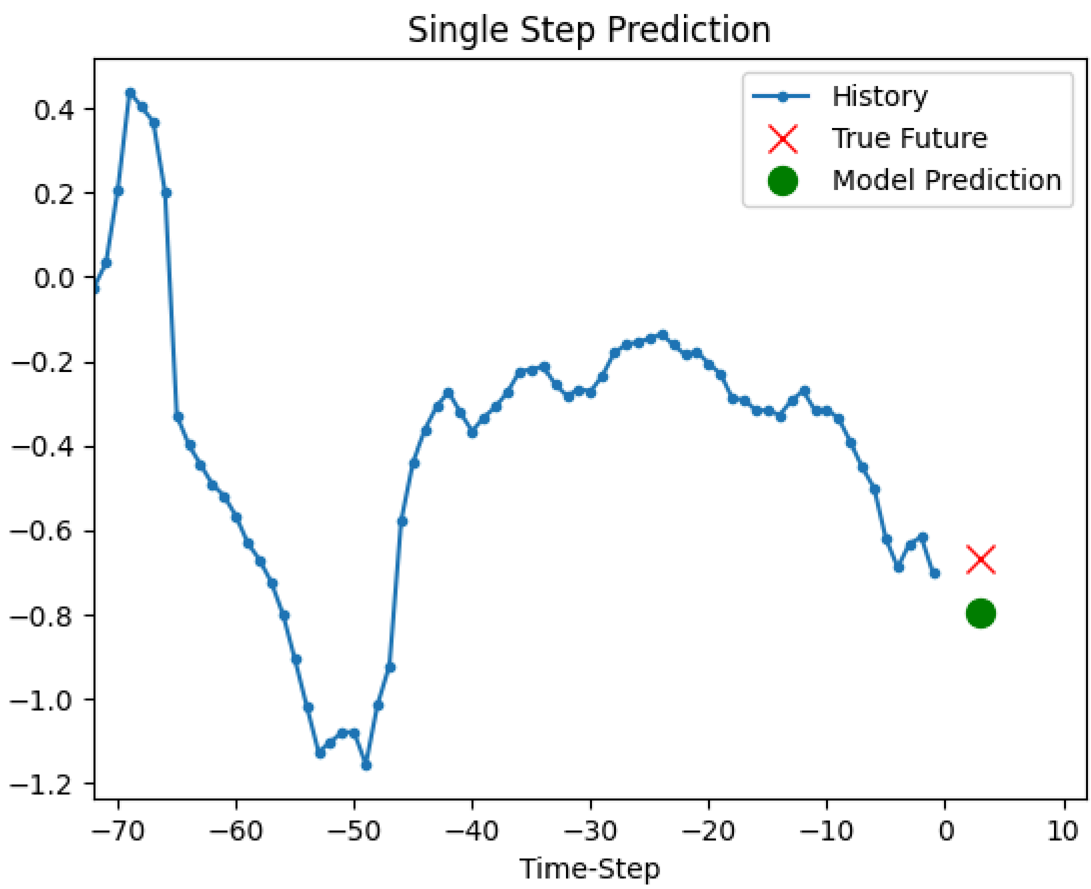
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step



8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step



8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step



Comparación de resultados y conclusión

Primer Modelo (Predicción a 12 horas)

Entrada: El modelo utiliza datos de las últimas 120 horas (5 días) para predecir la temperatura 12 horas en el futuro.

Configuración: La red tiene una capa LSTM con 32 unidades y una capa de salida densa con una activación lineal.

Rendimiento:

- El modelo mejora constantemente durante las primeras 10 épocas.
- El error cuadrático medio (loss) en el conjunto de validación empieza en 0.2328 y mejora hasta 0.1221, mostrando que el modelo aprende a hacer predicciones con una precisión adecuada para una predicción de 12 horas.

Segundo Modelo (Predicción a 3 horas)

- **Entrada**: En esta variante, el modelo utiliza datos de las últimas 72 horas (3 días) para predecir la temperatura a 3 horas en el futuro.

- **Configuración**: Similar al primer modelo, usa una capa LSTM con 32 unidades y una capa densa de salida con activación lineal.

- **Rendimiento**:
    - Durante las primeras 10 épocas, el modelo muestra una mejora notable en las métricas de validación. El error cuadrático medio (val_loss) comienza en 0.2244 y mejora hasta 0.0707.
    - El modelo se comporta bien para predicciones a corto plazo, ajustándose rápidamente a los datos.

Conclusión:

- El primer modelo, que predice a 12 horas, muestra un rendimiento sólido con una disminución significativa del error de validación, pero el segundo modelo, que predice a 3 horas, logra un error de validación menor.
- **Elección del modelo** depende del horizonte de predicción requerido. Para predicciones a corto plazo, el segundo modelo es más preciso. Sin embargo, para predicciones a mediano plazo (12 horas), el primer modelo sigue siendo una opción válida y eficiente.