

Note: Some of the runtimes may differ from what is reported in my documentation. I ran the whole notebook prior to submission and ran out of GPU runtime on google colab, so the run times will be longer in most cases but results should be similar

I organized everything in sections so it should all be very clear!

```
In [1]: import os
import datetime
import IPython
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import tensorflow as tf

# FROM TF TUTORIAL - MODIFIED
def read_csv(csv_path):
    df = pd.read_csv(csv_path)
    df.head()
```

```
Out[2]: /content/sample_data/Metro_Interstate_reduced.csv
```

## EXPLORATORY DATA ANALYSIS

RK: The first step is to examine the variables and variable types in the dataset:

```
In [3]: # RK
df.head()
```

	holiday	temp	rain	th	snow	th	clouds	all	weather_main	weather_description	date_time	traffic_volume
0	None	288.28	0.0	0.0	0.0	40			Clouds	scattered clouds	2012-10-02 09:00:00	5545
1	None	289.36	0.0	0.0	0.0	75			Clouds	broken clouds	2012-10-02 11:00:00	4516
2	None	289.58	0.0	0.0	0.0	90			Clouds	overcast clouds	2012-10-02 11:00:00	4767
3	None	290.13	0.0	0.0	0.0	90			Clouds	overcast clouds	2012-10-02 12:00:00	5036
4	None	291.14	0.0	0.0	0.0	75			Clouds	broken clouds	2012-10-02 13:00:00	4918

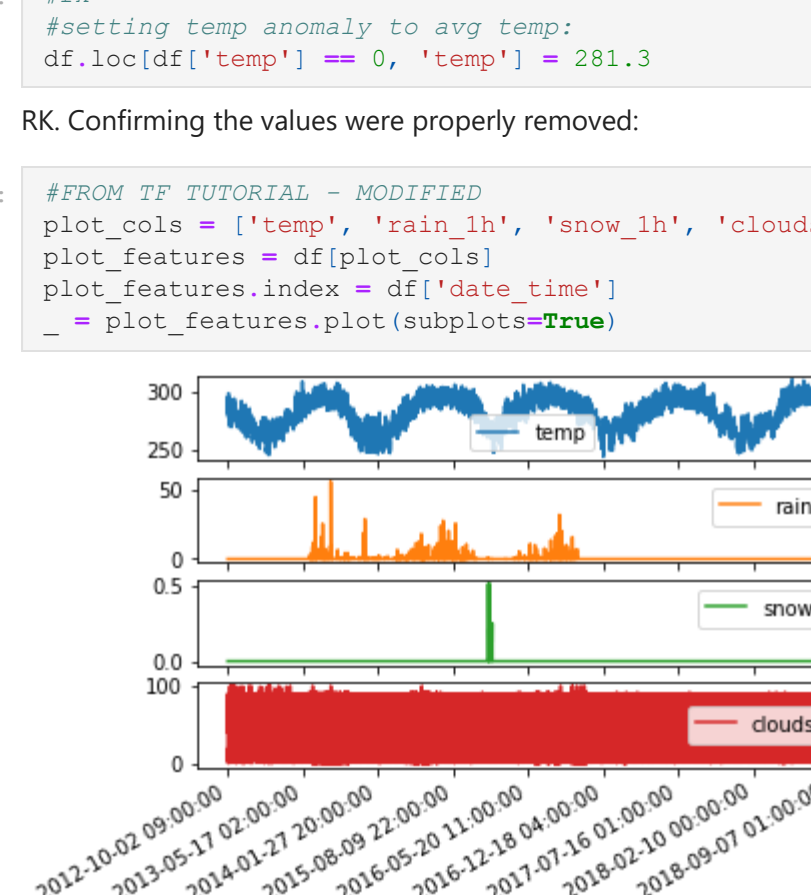
RK: The categorical variables: Holiday, Weather\_Main, Weather Description will have to be transformed. I will be converting these into dummy variables or a one hot vector.

The Date\_Time object will also have to be transformed

### Distribution of Numeric Variables

TF: Here is the evolution of a few features over time:

```
In [4]: # FROM TF TUTORIAL - MODIFIED
plot_cols = ['temp', 'rain_th', 'snow_th', 'clouds_all']
plot_features = df[plot_cols]
plot_features.index = df['date_time']
fig, axs = plt.subplots(4, 1, figsize=(10, 10))
plot_features.plot(subplots=True)
```



```
In [5]: df.describe().transpose()
```

	count	mean	std	min	25%	50%	75%	max
temp	40575.0	281.316763	13.816618	0.0	271.84	282.86	292.28	310.07
rain_th	40575.0	0.318632	48.812640	0.0	0.00	0.00	0.00	9831.30
snow_th	40575.0	0.000017	0.005676	0.0	0.00	0.00	0.00	0.51
clouds_all	40575.0	44.199162	38.683447	0.0	1.00	40.00	90.00	100.00
traffic_volume	40575.0	3290.650474	1984.772909	0.0	1248.50	3427.00	4952.00	7280.00

RK: We can see a very large max value for rain\_th. It is impossible for it to rain almost 10,000 mm in an hour. We also see a min of 0 for temp, temp is in Kelvin, this figure is also not possible.

Both of these will have to be fixed.

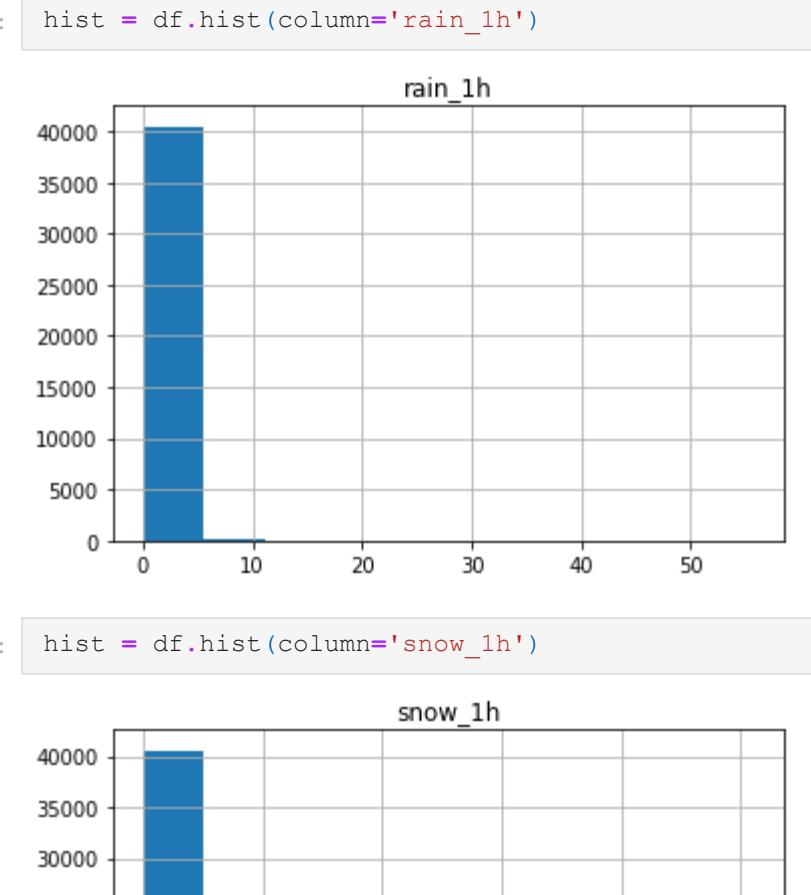
We also get a good idea of how the data is distributed. We can see the statistical summary for each variable which is particularly important for numeric variables. For instance, we can see that the vast majority of hours have no rain or snow as the 75% percentile is still 0.

```
In [6]: # RK
df['rain_th'] = df['rain_th'].clip(0, 400)
df['temp'] = df['temp'].clip(270, 310)
```

```
In [7]: # RK
df['temp'] = df['temp'].clip(270, 310)
```

RK: Confirming the values were properly removed:

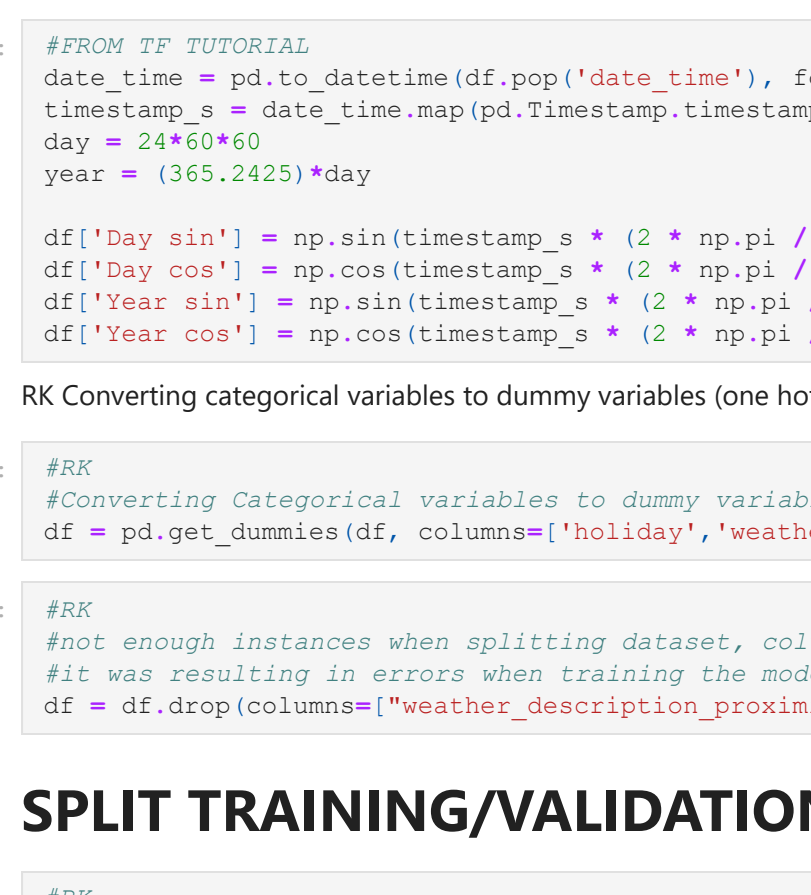
```
In [8]: # FROM TF TUTORIAL - MODIFIED
plot_cols = ['temp', 'rain_th', 'snow_th', 'clouds_all']
plot_features = df[plot_cols]
plot_features.index = df['date_time']
fig, axs = plt.subplots(4, 1, figsize=(10, 10))
plot_features.plot(subplots=True)
```



### Histograms of Numeric Variables

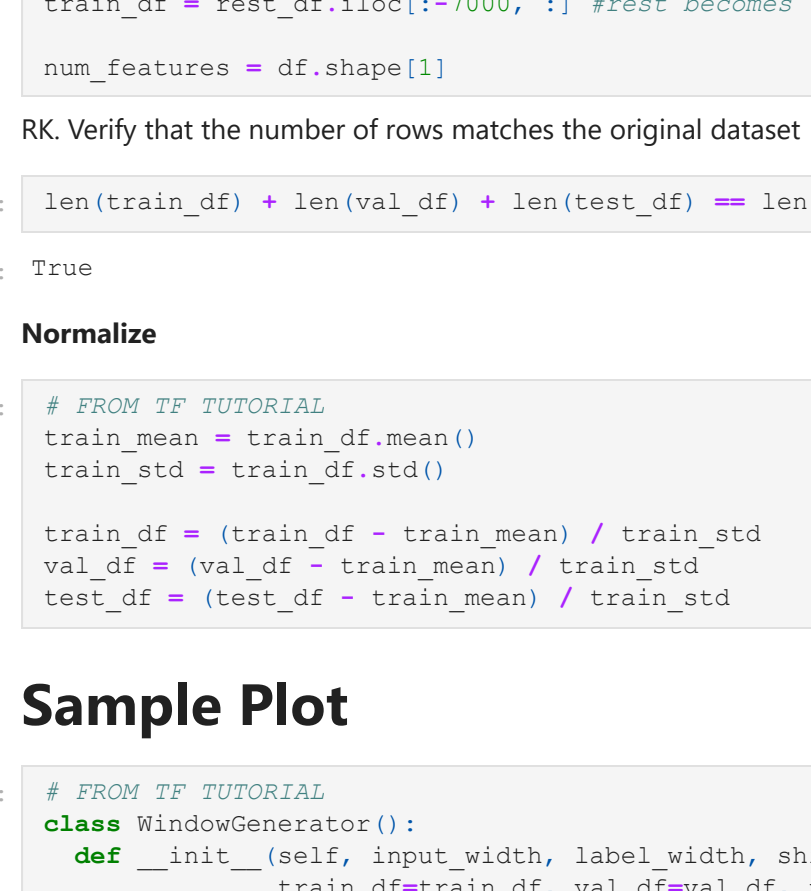
RK: The temperature distribution is almost symmetric, it is very close to a normal distribution but perhaps slightly left skewed. Most days the temperature is fairly similar with a few days that were more extreme.

```
In [9]: hist = df.hist(column='temp')
```



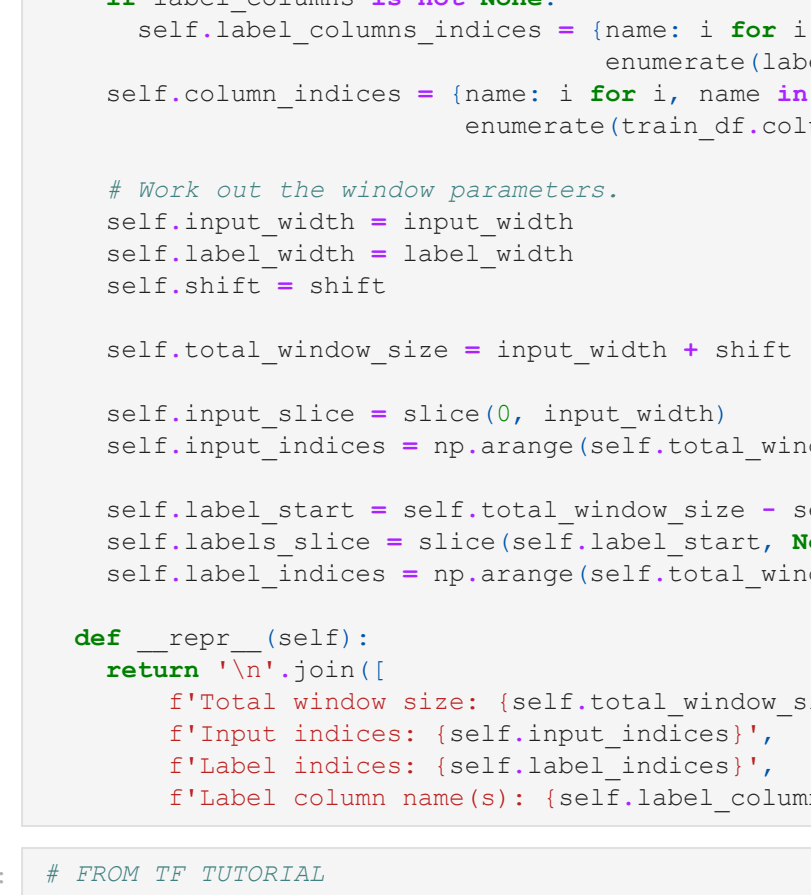
RK: The cloud distribution is interesting as it's typically either no clouds or 100% clouds with a few days falling in between.

```
In [10]: hist = df.hist(column='clouds_all')
```

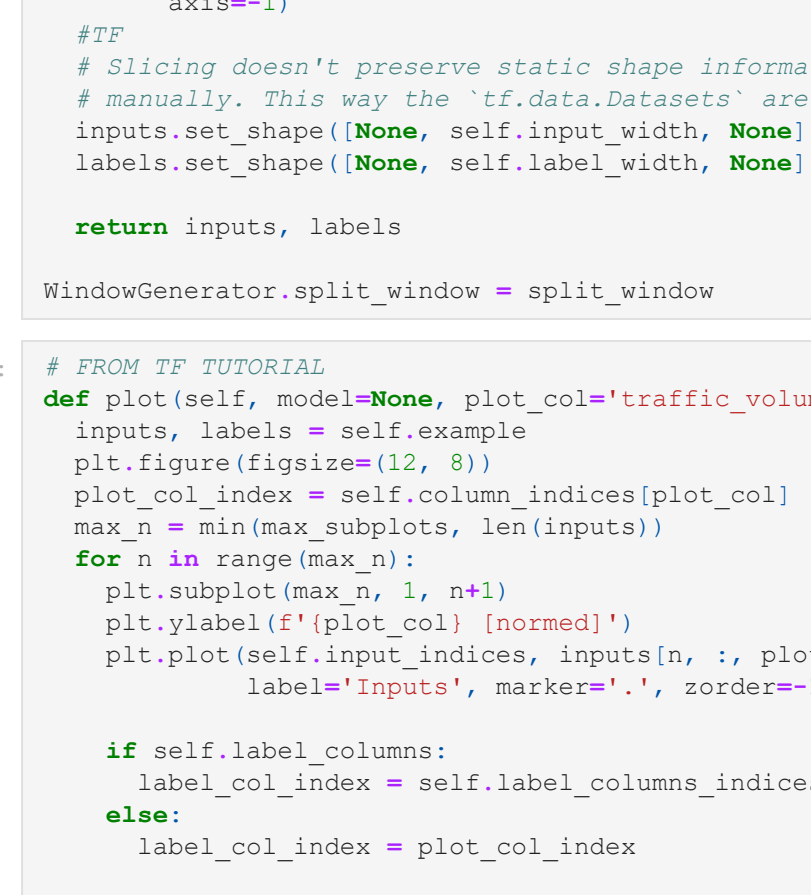


RK: As far as rain and snow goes, most hours of the day have no snow or rain. It's fairly rare in this dataset.

```
In [11]: hist = df.hist(column='rain_th')
```



```
In [12]: hist = df.hist(column='snow_th')
```



RK: Using the one steps in the TF Tutorial, the Date\_Time variable is converted into time of day and time of year variables. This is an example of feature engineering.

TF: You can get usable signals by using sine and cosine transforms to clear 'Time of day' and 'Time of year' signals

```
In [13]: # FROM TF TUTORIAL
time_index = df.index.to_datetime(df.pop('date_time'), format='%Y-%m-%d %H:%M:%S')
time_stamp = date_time.map(pd.Timestamp.timestamp)
day = 24*60*60
year = 365.2425*day

df['day_sin'] = np.sin(time_stamp * (2 * np.pi / day))
df['day_cos'] = np.cos(time_stamp * (2 * np.pi / day))
df['year_sin'] = np.sin(time_stamp * (2 * np.pi / year))
df['year_cos'] = np.cos(time_stamp * (2 * np.pi / year))
```

RK: Converting categorical variables to dummy variables (one hot encoding)

```
In [14]: # RK
df = df.get_dummies(df, columns=['holiday', 'weather_main', 'weather_description'])
```

```
In [15]: # RK
df = df.drop(columns=['weather_description', 'weather_description', 'weather_description'])
```

## SPLIT TRAINING/VALIDATION/TEST

```
In [16]: # FROM TF TUTORIAL
column_indices = (name, i for i, name in enumerate(df.columns))

# First 5000 records become test set
test_df = df.iloc[:5000]
train_df = df.iloc[5000:]

# Next 7000 records from the back become validation set
val_df = train_df.iloc[-7000:]
train_df = train_df[:-7000]

num_features = df.shape[1]
```

RK: Verify that the number of rows matches the original dataset

```
In [17]: len(train_df) + len(val_df) + len(test_df) == len(df)
```

Out[17]: True

### Normalise

```
In [18]: # FROM TF TUTORIAL
train_mean = train_df.mean()
train_std = train_df.std()

train_df = (train_df - train_mean) / train_std
test_df = (test_df - train_mean) / train_std
```

## Sample Plot

```
In [19]: # FROM TF TUTORIAL
class WindowGenerator():
    def __init__(self, input_width, label_width, shift,
                 train_df=train_df, val_df=val_df, test_df=test_df,
                 label_columns=None):
        # Store the raw data.
        self.train_df = train_df
        self.val_df = val_df
        self.test_df = test_df

        # Work out the label columns indices.
        self.label_columns = label_columns
        if label_columns is not None:
            self.label_columns_indices = (name, i for i, name in enumerate(label_columns))
            self.column_indices = (name, i for i, name in enumerate(train_df.columns))

        # Work out the window parameters.
        self.input_width = input_width
        self.label_width = label_width
        self.shift = shift

        self.total_window_size = input_width + shift
        self.input_slice = slice(0, input_width)
        self.label_slice = slice(input_width, self.total_window_size)
        self.label_indices = np.arange(self.total_window_size)
        self.label_slice = slice(self.label_slice)

        def repr(self):
            return '\n'.join([
                f'Input window size: {self.total_window_size}',
                f'Input indices: {self.input_slice}',
                f'Label indices: {self.label_indices}',
                f'Label column name(s): {self.label_columns}'])

        self.plot_window_size = self.total_window_size
        self.plot_input_slice = self.input_slice
        self.plot_label_slice = self.label_slice
        self.plot_label_indices = self.label_indices

        self.plot_inputs, self.plot_labels = self.plot_window_size, self.plot_label_indices

        self.plot_inputs, self.plot_labels = self.plot_window_size, self.plot_label_indices

        self.plot_inputs, self.plot_labels = self.plot_window_size, self.plot_label_indices
```

```
In [20]: # FROM TF TUTORIAL
def split_window(self, features):
    inputs = features[:, self.plot_input_slice, :]
    labels = features[:, self.plot_label_slice, :]
    if self.label_columns is not None:
        labels = tf.stack([
            labels[:, :, self.column_indices[name]] for name in self.label_columns,
            axis=-1])

    # Slicing doesn't preserve static shape information, so set the shapes
    # manually. This way the tf.data.Dataset API is easier to inspect.
    inputs = tf.data.Dataset.from_tensor_slices(inputs)
    labels = tf.data.Dataset.from_tensor_slices(labels)
    dataset = tf.data.Dataset.zip((inputs, labels))
    dataset = dataset.window(self.plot_window_size, shift=self.shift)
    return dataset
```

```
In [21]: # FROM TF TUTORIAL
def plot(self, self=None, plot_col='traffic_volume', max_subplots=3):
    inputs, labels = self.example
    plot_col_index = self.column_indices[plot_col]
    max_n = min(max_subplots, len(inputs))
    plt.figure(figsize=(10, 10))
    plt.subplot(max_n, 1, 1)
    plt.plot(self.train_df[plot_col], label='Inputs', marker='x', zorder=10)
    plt.plot(self.val_df[plot_col], label='Labels', marker='o', zorder=1)

    if self.label_columns:
        label_col_index = self.label_columns_indices[plot_col, None]
        self.plot_labels = self.plot_labels + self.plot_label_indices

    if self.plot_labels:
        plt.scatter(self.plot_labels, labels[:, :, label_col_index],
                    edgecolors='k', label='Labels', c='r', s=40)

    if model is not None:
        predictions = model(inputs)
        plt.scatter(self.plot_labels, predictions[:, :, label_col_index],
                    marker='x', edgecolors='k', label='Predictions',
                    c='b', s=40)

    if n == 0:
        plt.legend()

    plt.xlabel('Time [h]')
    WindowGenerator.plot = plot
```

### CREATE WINDOW - 7,1,3

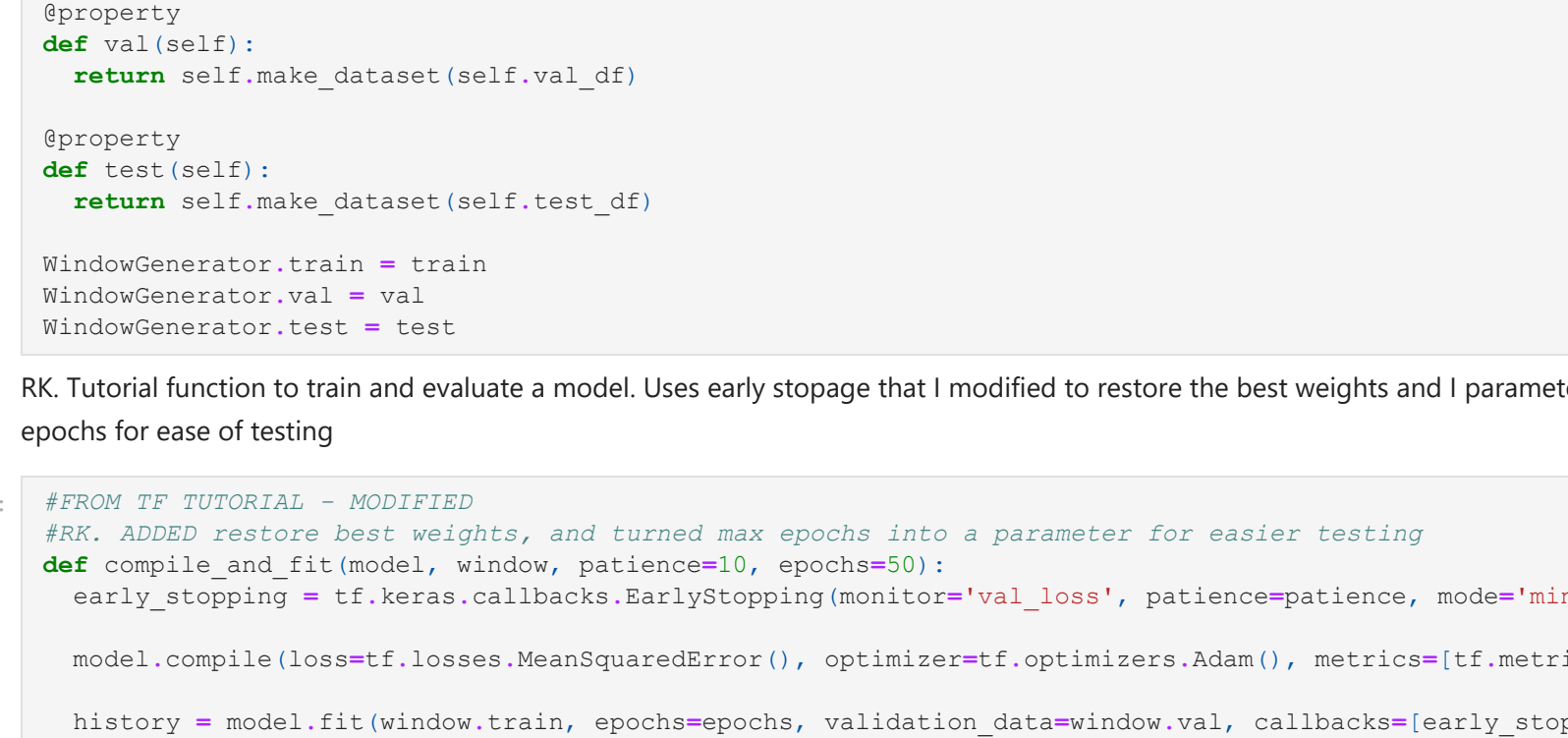
RK: The window has 7 inputs, and single output that is offset by 3 hours. The total window size should be 10.

```
In [22]: window_7_1_3 = WindowGenerator(input_width=7, label_width=1, shift=3, label_columns=['traffic_volume'])
window_7_1_3
```

```
Out[22]: Total window size: 10
Input indices: [0 1 2 3 4 5 6]
Label(s): [9]
Label column name(s): ['traffic_volume']
```

### Sample Test Plot using TF Tutorial Code

```
In [23]: # FROM TF TUTORIAL - MODIFIED
window_size = window_7_1_3.total_window_size # retrieve total window size - 10
split_window = tf.stack(np.array(train_df[window_size:]), # retrieve rows from training data
                        np.array(val_df[window_size:]), # retrieve rows from training data
                        np.array(test_df[window_size:])) # retrieve rows from training data
sample_inputs, sample_labels = window_7_1_3.split_window(sample_window) # retrieve inputs and labels from rows
window_7_1_3.example = sample_inputs, sample_labels
window_7_1_3.plot()
```



We can see that the window is working properly.

## MODEL FUNCTIONS

RK: Tutorial code to turn our split data into batches.

```
In [24]: # FROM TF TUTORIAL - MODIFIED
def make_data(self, validation_data, test_data):
    ds = tf.keras.preprocessing.timeseries_dataset_from_array(
        data=train_data,
        targets=None,
        sequence_length=self.total_window_size,
        sequence_stride=1,
        shuffle=True,
        batch_size=32,
        ds=ds.map(self.split_window))

    return ds

def make_train_dataset(self, validation_data, test_data):
    ds = ds.map(self.split_window)

    return ds

def make_val_dataset(self, validation_data, test_data):
    ds = ds.map(self.split_window)

    return ds
```

```
In [25]: # FROM TF TUTORIAL - slightly modified
def train(self):
    return self.make_train_dataset(self.train_df)

def val(self):
    return self.make_val_dataset(self.val_df)

def test(self):
    return self.make_test_dataset(self.test_df)

def plot(self):
    return self.plot(self.train_df, self.val_df, self.test_df)
```

RK: Tutorial function to train and evaluate a model. Uses early stopping that I modified to restore the best weights and I parameterized total epochs for ease of testing

```
In [26]: # FROM TF TUTORIAL - MODIFIED
def compile_and_fit(model, window, patience=10, epochs=50):
    early_stopping = tf.keras.callbacks.EarlyStopping(monitor='val_loss', patience=patience, mode='min', restore_best_weights=True)

    model.compile(loss=tf.keras.losses.MeanSquaredError(), optimizer=tf.keras.optimizers.Adam(), metrics=[tf.keras.metrics.MeanAbsoluteError()])

    history = model.fit(window.train, epochs=epochs, validation_data=(window.val, window.test), callbacks=[early_stopping])

    return history
```

RK: Function I created to create prediction CSV. Takes in a model and window object. Creates prediction set, normalizes it and outputs it in the proper format for KAGGLE.

```
In [27]: # RK
def make_predictions(model, window):
    predictions = model.predict(window.test)

    # RK: normalize predictions
    predictions = (predictions * train_mean['traffic_volume']) + train_mean['traffic_volume']

    # RK: add ID and format rows for output
    output = []
    for i in range(len(predictions)):
        output.append([i, predictions[i]])

    # RK: write to csv for submission
    with open('FinalPredictions.csv', 'w') as f:
        writer = csv.writer(f)
        for row in output:
            writer.writerow(row)
```

RK: Function I created to plot MAE of training vs validation, as well as loss of training vs validation

```
In [28]: # RK
def plot_results(history):
    plt.plot(history.history['mean_absolute_error'], label='training MAE')
    plt.plot(history.history['val_mean_absolute_error'], label='valid MAE')
    plt.xlabel('Epoch')
    plt.ylabel('MAE')
    plt.ylim([0.0, 0.5])
    plt.legend(loc='upper right')
```

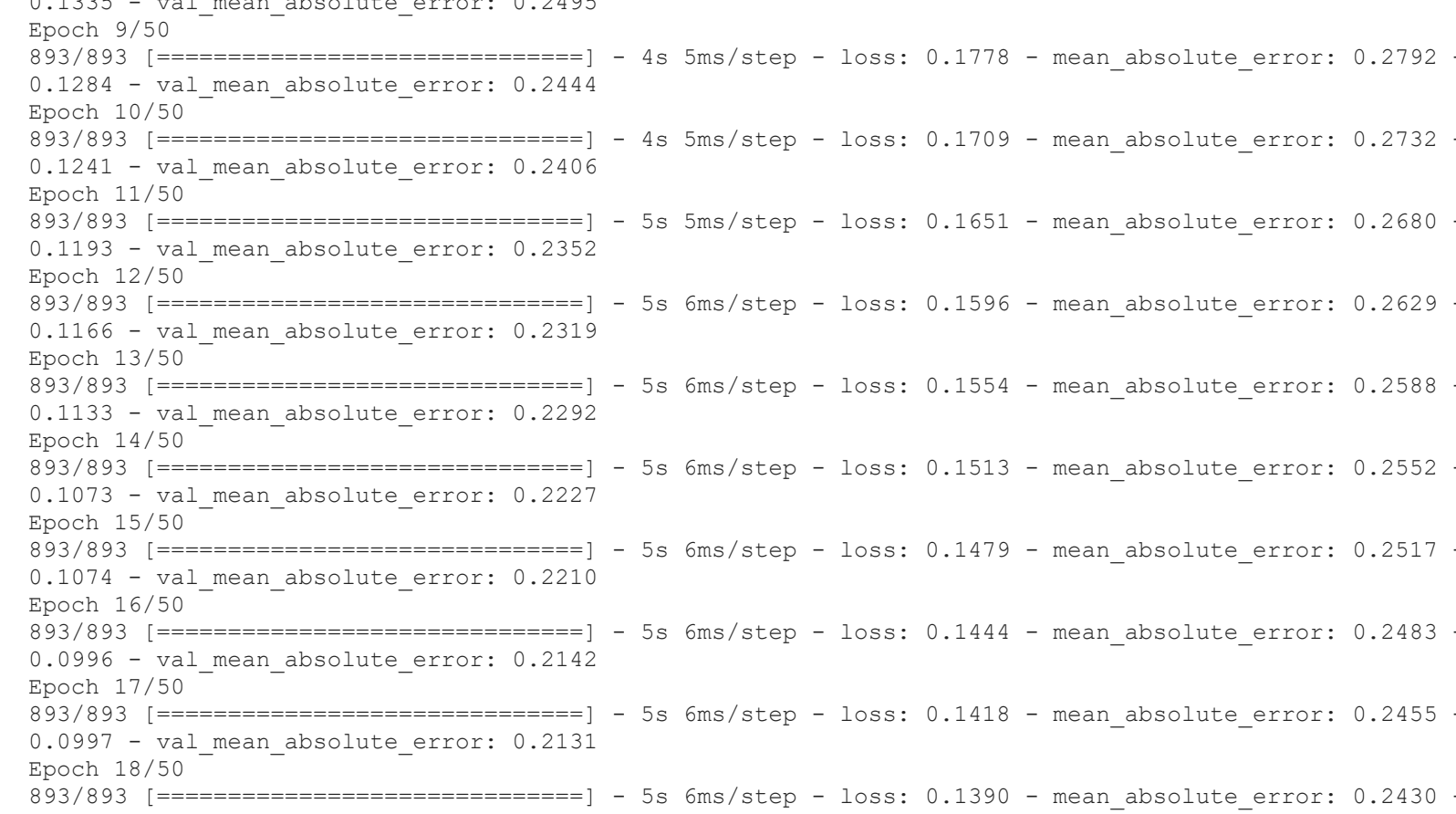
```
In [29]: # RK
plt.plot(history.history['loss'], label='training loss')
plt.plot(history.history['val_loss'], label='valid loss')
plt.xlabel('Epoch')
plt.ylabel('loss')
plt.ylim([0.0, 0.5])
plt.legend(loc='upper right')
```

### BUILDING MODELS - ALL CODE FROM THIS POINT IS COMPLETELY MINE

## BASELINE MODEL

```
In [29]: baseline_model = tf.keras.models.Sequential([
    tf.keras.layers.LSTM(77),
    tf.keras.layers.Dense(units=1)
])
```

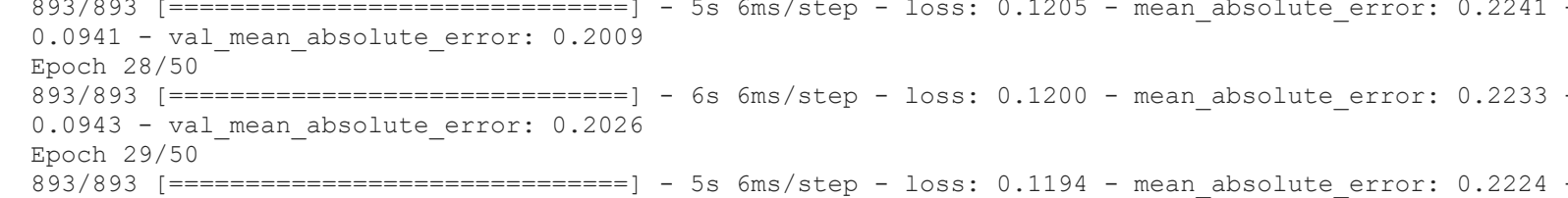
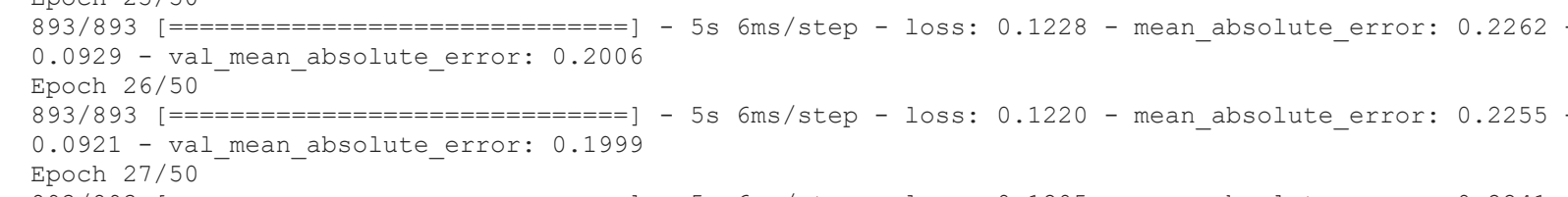
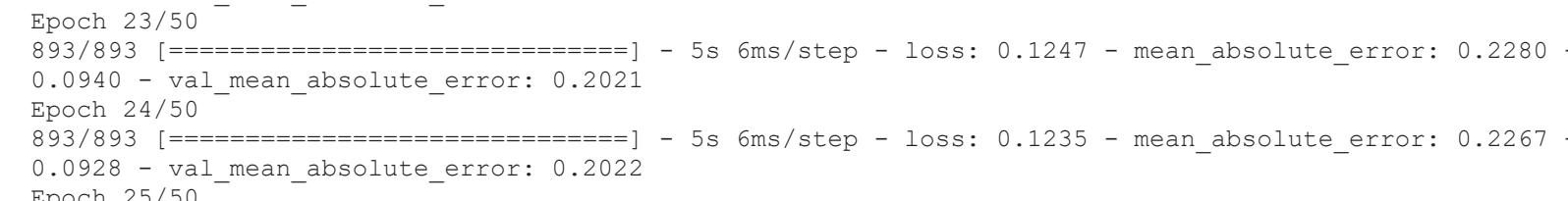
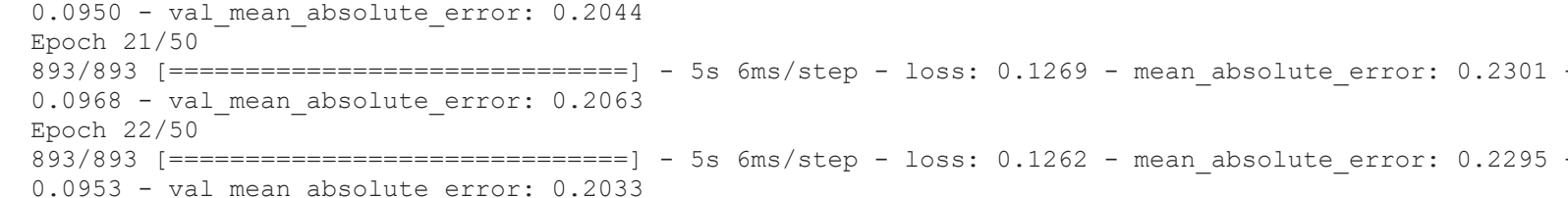
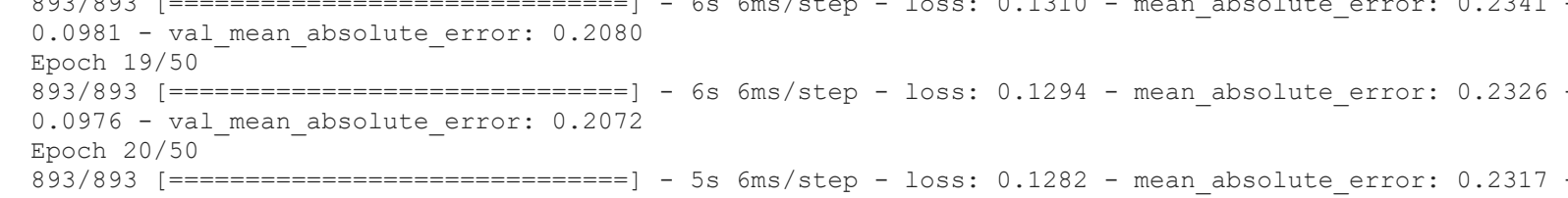
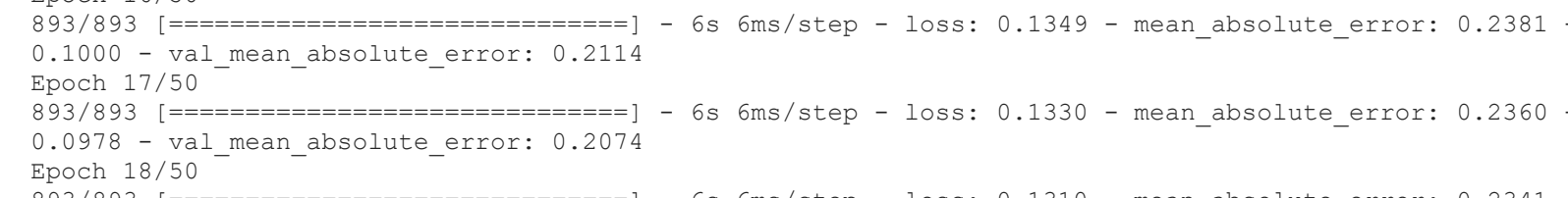
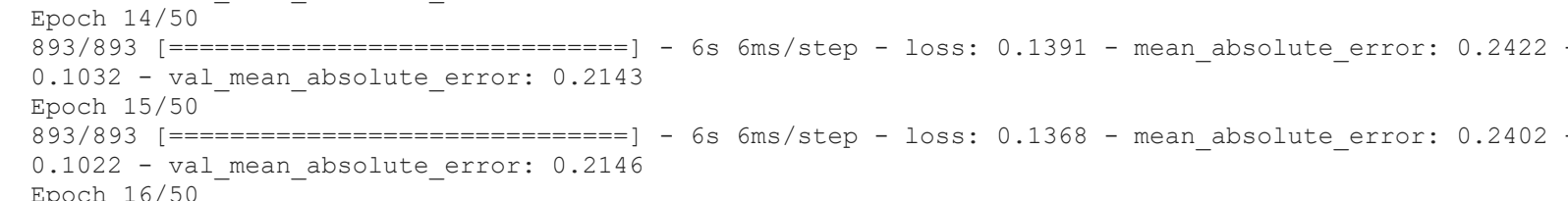
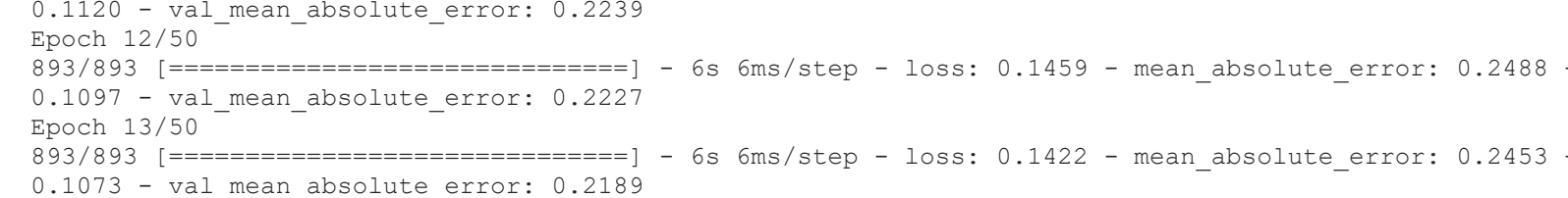
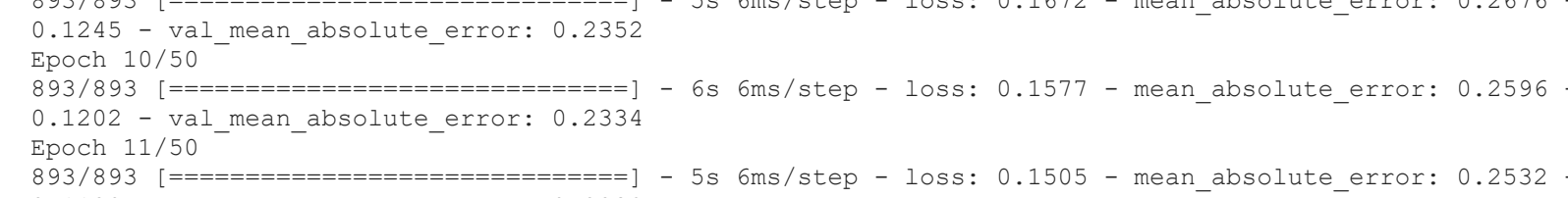
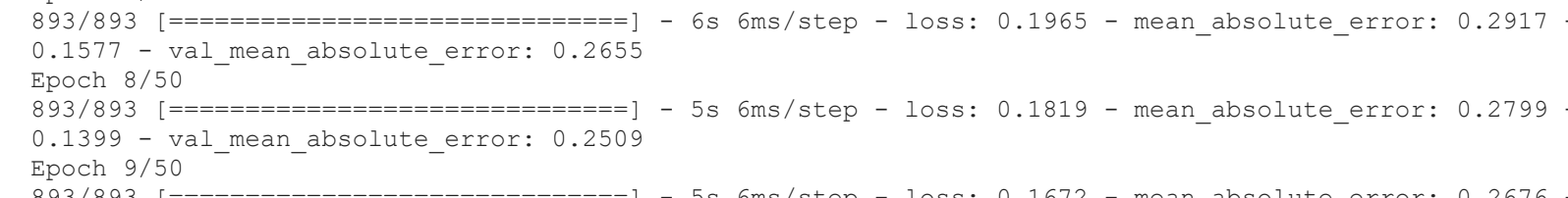
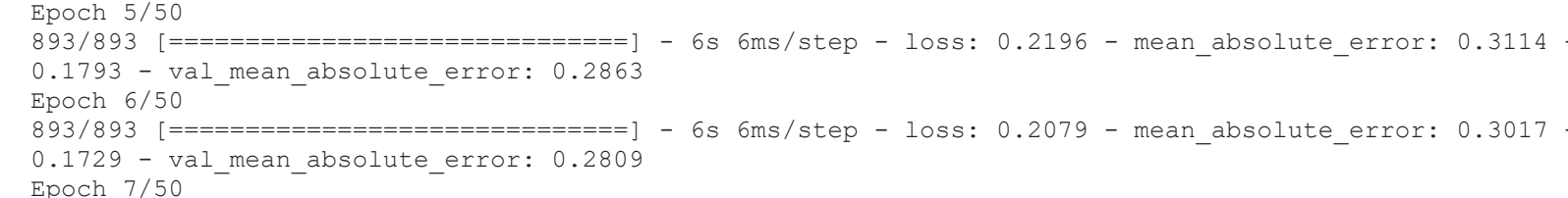
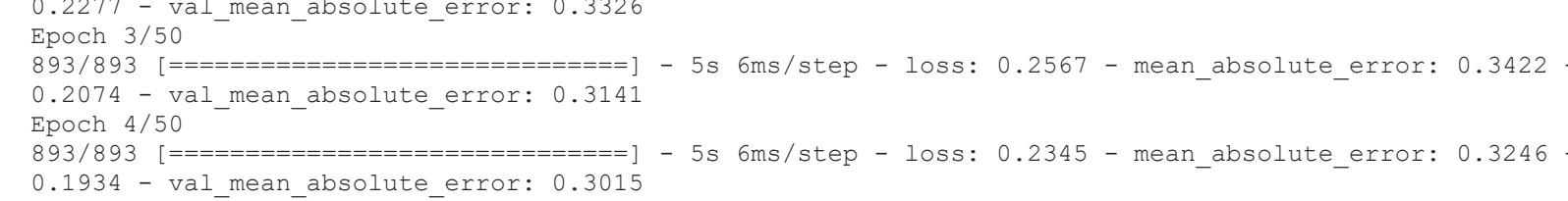
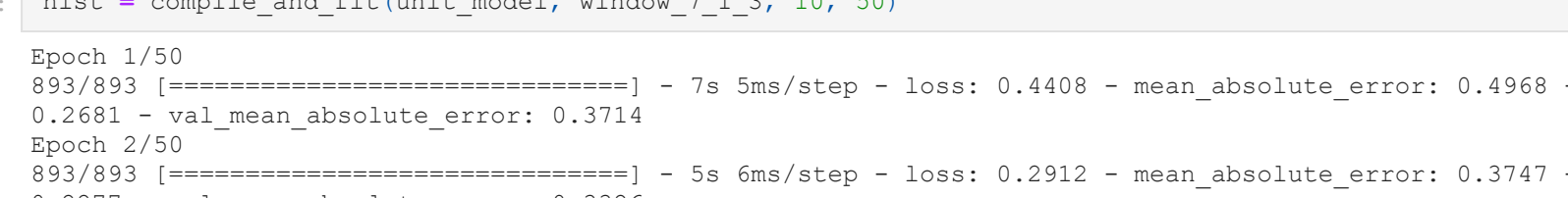
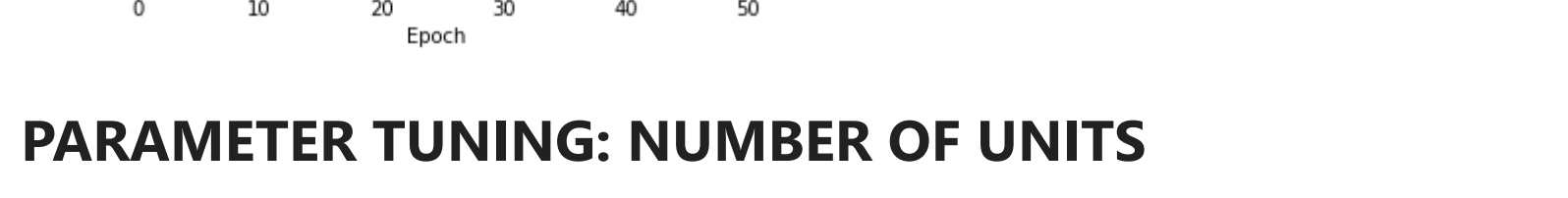
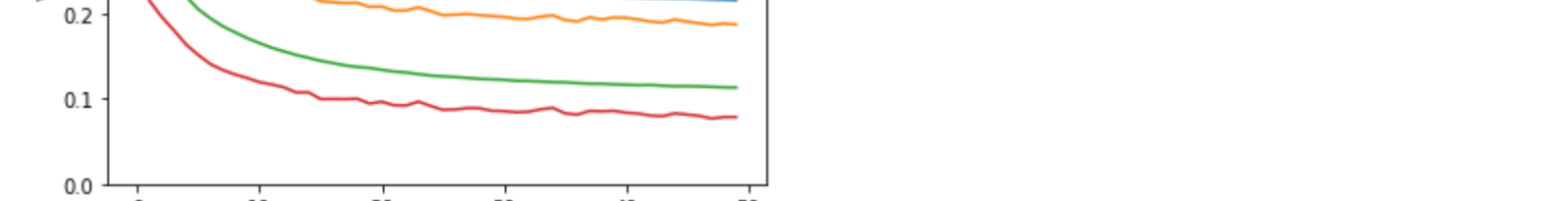
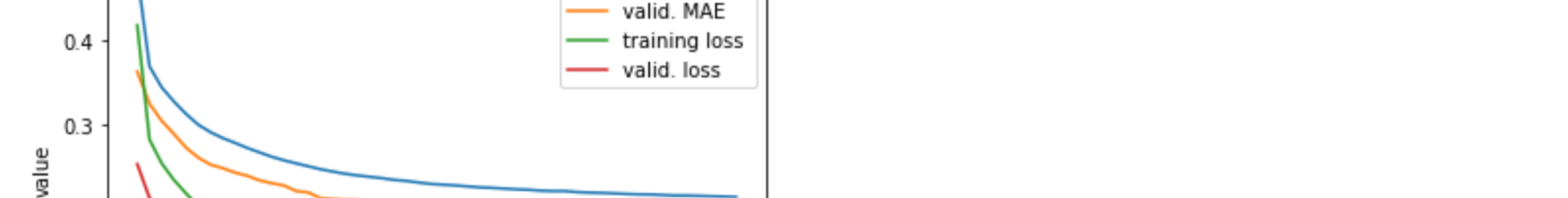
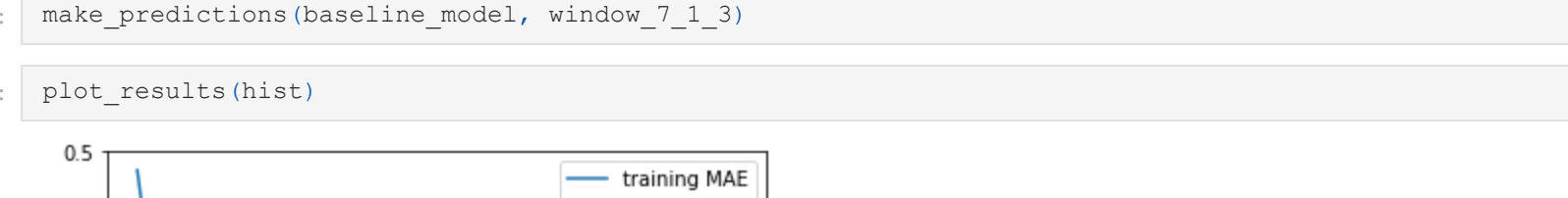
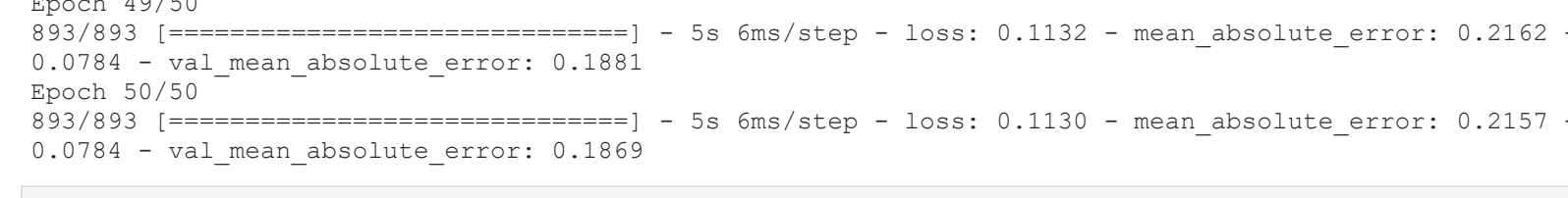
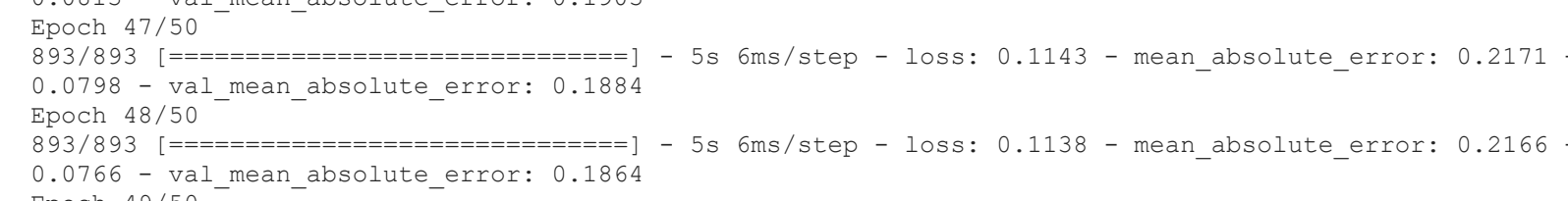
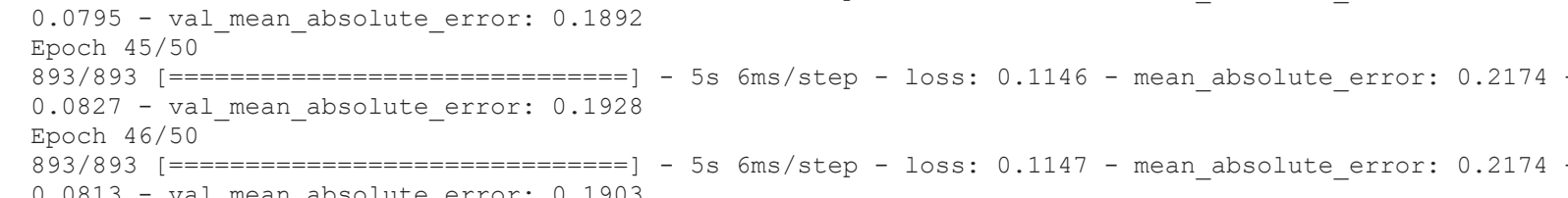
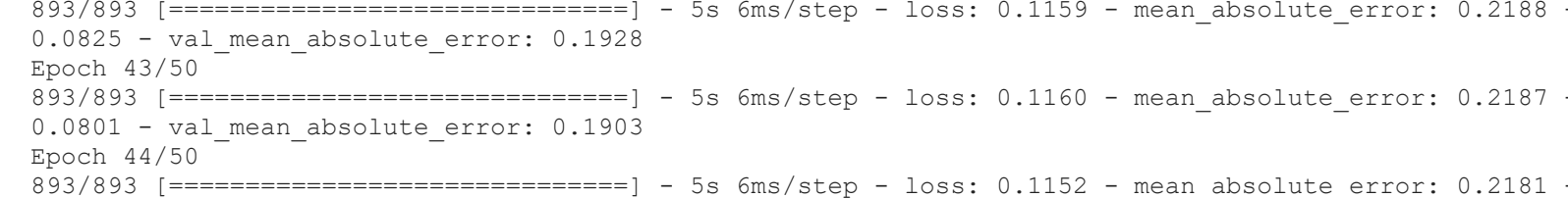
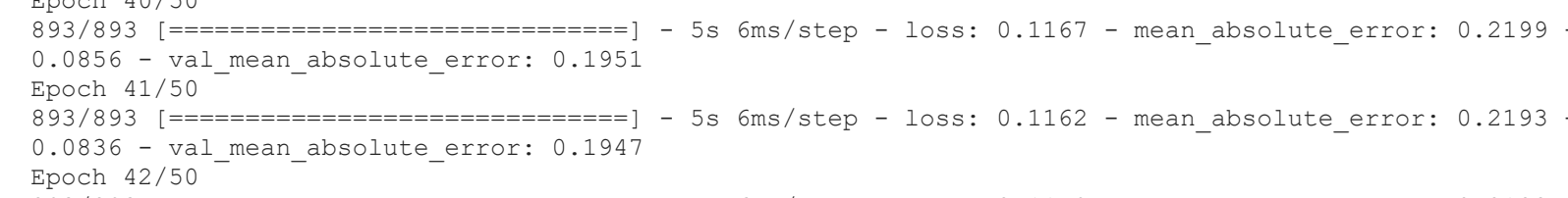
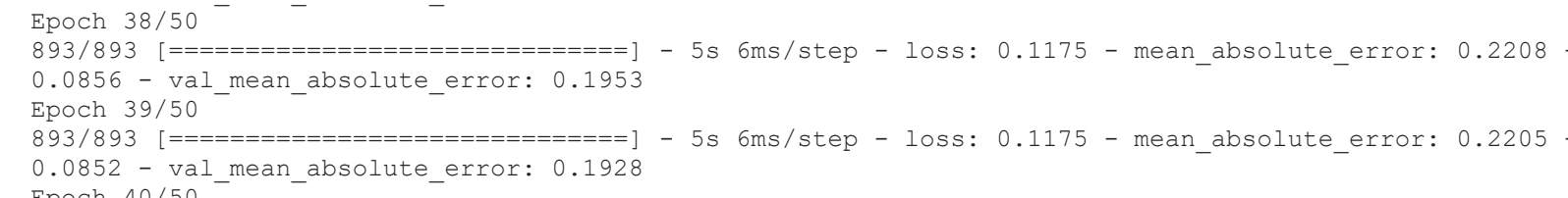
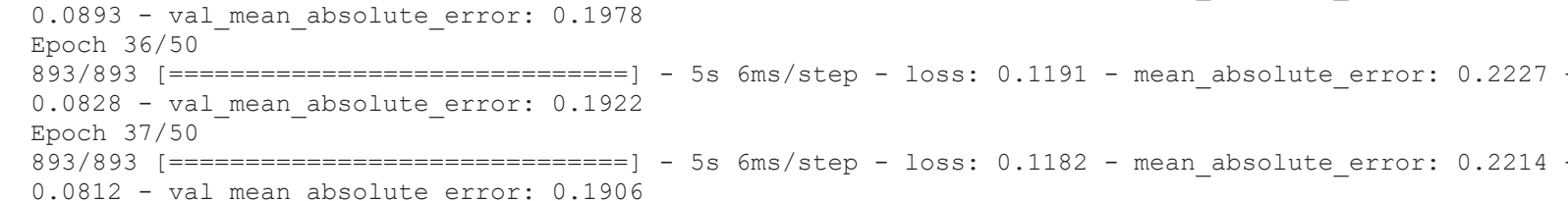
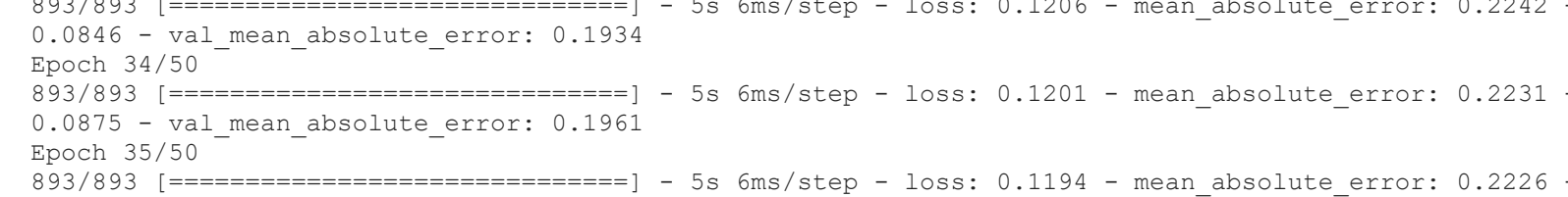
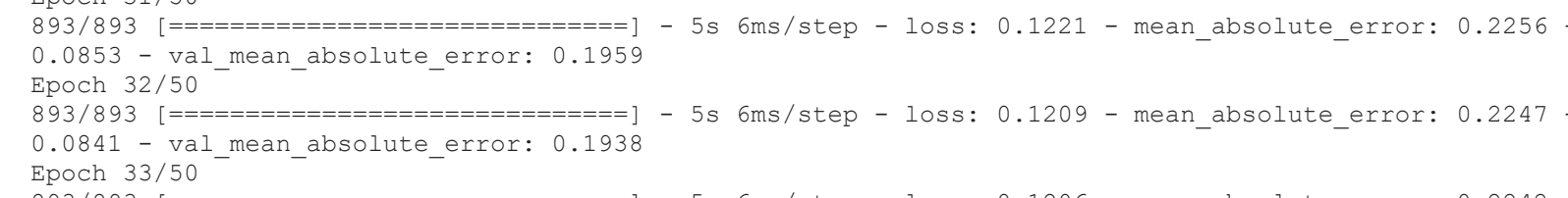
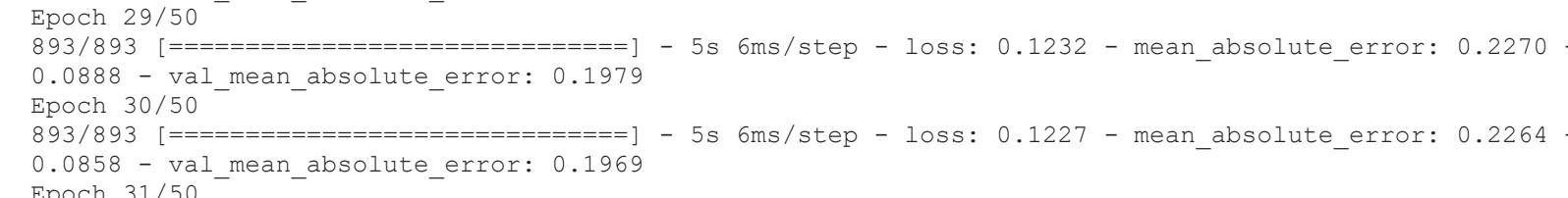
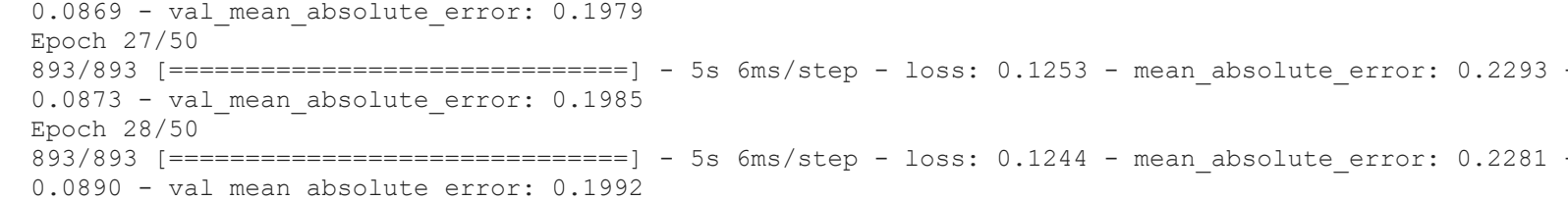
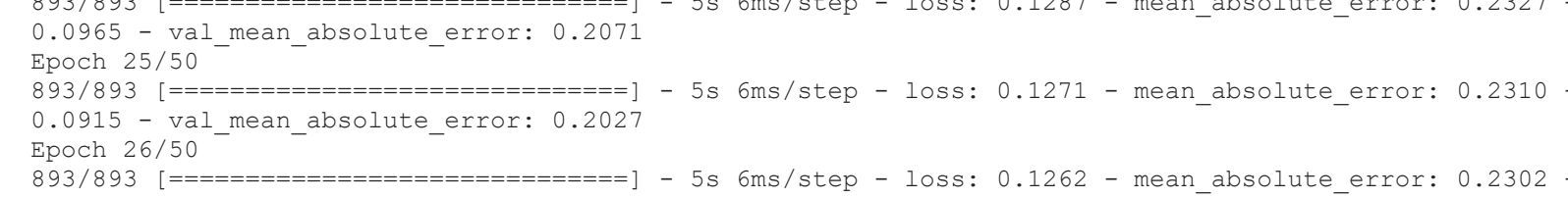
```
In [30]: hist = compile_and_fit(baseline_model, window_7_1_3, 10, 50)
```



### PARAMETER TUNING: NUMBER OF UNITS

```
In [33]: unit_model = tf.keras.models.Sequential([
    tf.keras.layers.LSTM(77),
    tf.keras.layers.Dense(units=1)
])
```

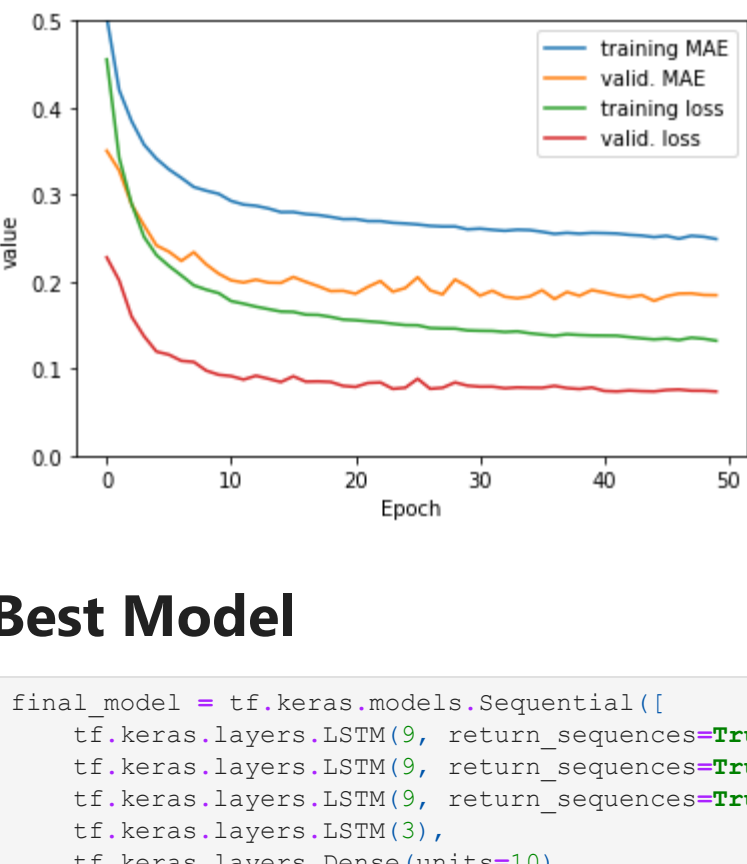
```
In [34]: hist = compile_and_fit(unit_model, window_7_1_3, 10, 50)
```











## Best Model

```
In [57]: final_model = tf.keras.models.Sequential([
tf.keras.layers.LSTM(9, return_sequences=True),
tf.keras.layers.LSTM(9, return_sequences=True),
tf.keras.layers.LSTM(9, return_sequences=True),
tf.keras.layers.LSTM(3),
tf.keras.layers.Dense(units=10),
tf.keras.layers.Dense(units=1)
])
```

```
In [59]: hist = compile_and_fit(final_model, window_7_1_3, 20, 50)

Epoch 1/50
893/893 [=====] - 24s 21ms/step - loss: 0.1599 - mean_absolute_error: 0.2624 - val_loss: 0.1055 - val_mean_absolute_error: 0.2254
Epoch 2/50
893/893 [=====] - 17s 19ms/step - loss: 0.1519 - mean_absolute_error: 0.2544 - val_loss: 0.1036 - val_mean_absolute_error: 0.2228
Epoch 3/50
893/893 [=====] - 16s 18ms/step - loss: 0.1470 - mean_absolute_error: 0.2487 - val_loss: 0.1036 - val_mean_absolute_error: 0.2229
Epoch 4/50
893/893 [=====] - 17s 19ms/step - loss: 0.1414 - mean_absolute_error: 0.2434 - val_loss: 0.1084 - val_mean_absolute_error: 0.2136
Epoch 5/50
893/893 [=====] - 17s 19ms/step - loss: 0.1383 - mean_absolute_error: 0.2404 - val_loss: 0.1084 - val_mean_absolute_error: 0.2219
Epoch 6/50
893/893 [=====] - 17s 19ms/step - loss: 0.1342 - mean_absolute_error: 0.2366 - val_loss: 0.10917 - val_mean_absolute_error: 0.2098
Epoch 7/50
893/893 [=====] - 17s 19ms/step - loss: 0.1316 - mean_absolute_error: 0.2330 - val_loss: 0.10913 - val_mean_absolute_error: 0.2102
Epoch 8/50
893/893 [=====] - 17s 19ms/step - loss: 0.1286 - mean_absolute_error: 0.2305 - val_loss: 0.10919 - val_mean_absolute_error: 0.2127
Epoch 9/50
893/893 [=====] - 17s 19ms/step - loss: 0.1271 - mean_absolute_error: 0.2289 - val_loss: 0.10919 - val_mean_absolute_error: 0.2060
Epoch 10/50
893/893 [=====] - 17s 19ms/step - loss: 0.1244 - mean_absolute_error: 0.2268 - val_loss: 0.10938 - val_mean_absolute_error: 0.2095
Epoch 11/50
893/893 [=====] - 17s 19ms/step - loss: 0.1227 - mean_absolute_error: 0.2254 - val_loss: 0.10884 - val_mean_absolute_error: 0.2068
Epoch 12/50
893/893 [=====] - 17s 19ms/step - loss: 0.1188 - mean_absolute_error: 0.2219 - val_loss: 0.10971 - val_mean_absolute_error: 0.2132
Epoch 13/50
893/893 [=====] - 17s 19ms/step - loss: 0.1179 - mean_absolute_error: 0.2210 - val_loss: 0.10913 - val_mean_absolute_error: 0.2067
Epoch 14/50
893/893 [=====] - 17s 19ms/step - loss: 0.1158 - mean_absolute_error: 0.2188 - val_loss: 0.10864 - val_mean_absolute_error: 0.2021
Epoch 15/50
893/893 [=====] - 17s 19ms/step - loss: 0.1149 - mean_absolute_error: 0.2180 - val_loss: 0.10909 - val_mean_absolute_error: 0.2037
Epoch 16/50
893/893 [=====] - 17s 19ms/step - loss: 0.1142 - mean_absolute_error: 0.2168 - val_loss: 0.10884 - val_mean_absolute_error: 0.1980
Epoch 17/50
893/893 [=====] - 17s 19ms/step - loss: 0.1125 - mean_absolute_error: 0.2154 - val_loss: 0.10887 - val_mean_absolute_error: 0.1923
Epoch 18/50
893/893 [=====] - 17s 19ms/step - loss: 0.1107 - mean_absolute_error: 0.2138 - val_loss: 0.10845 - val_mean_absolute_error: 0.1943
Epoch 19/50
893/893 [=====] - 17s 19ms/step - loss: 0.1100 - mean_absolute_error: 0.2128 - val_loss: 0.10758 - val_mean_absolute_error: 0.1949
Epoch 20/50
893/893 [=====] - 17s 19ms/step - loss: 0.1087 - mean_absolute_error: 0.2115 - val_loss: 0.10744 - val_mean_absolute_error: 0.1888
Epoch 21/50
893/893 [=====] - 17s 19ms/step - loss: 0.1086 - mean_absolute_error: 0.2114 - val_loss: 0.10884 - val_mean_absolute_error: 0.1888
Epoch 22/50
893/893 [=====] - 17s 19ms/step - loss: 0.1073 - mean_absolute_error: 0.2099 - val_loss: 0.10853 - val_mean_absolute_error: 0.1960
Epoch 23/50
893/893 [=====] - 17s 19ms/step - loss: 0.1067 - mean_absolute_error: 0.2097 - val_loss: 0.10884 - val_mean_absolute_error: 0.1995
Epoch 24/50
893/893 [=====] - 17s 19ms/step - loss: 0.1063 - mean_absolute_error: 0.2097 - val_loss: 0.10884 - val_mean_absolute_error: 0.1995
Epoch 25/50
893/893 [=====] - 17s 18ms/step - loss: 0.1065 - mean_absolute_error: 0.2092 - val_loss: 0.10884 - val_mean_absolute_error: 0.1888
Epoch 26/50
893/893 [=====] - 17s 19ms/step - loss: 0.1046 - mean_absolute_error: 0.2075 - val_loss: 0.10821 - val_mean_absolute_error: 0.1901
Epoch 27/50
893/893 [=====] - 17s 19ms/step - loss: 0.1052 - mean_absolute_error: 0.2075 - val_loss: 0.10884 - val_mean_absolute_error: 0.1966
Epoch 28/50
893/893 [=====] - 17s 19ms/step - loss: 0.1041 - mean_absolute_error: 0.2064 - val_loss: 0.10884 - val_mean_absolute_error: 0.1837
Epoch 29/50
893/893 [=====] - 17s 19ms/step - loss: 0.1023 - mean_absolute_error: 0.2051 - val_loss: 0.10884 - val_mean_absolute_error: 0.1837
Epoch 30/50
893/893 [=====] - 17s 18ms/step - loss: 0.1022 - mean_absolute_error: 0.2048 - val_loss: 0.10884 - val_mean_absolute_error: 0.1837
Epoch 31/50
893/893 [=====] - 17s 19ms/step - loss: 0.1018 - mean_absolute_error: 0.2036 - val_loss: 0.10884 - val_mean_absolute_error: 0.1837
Epoch 32/50
893/893 [=====] - 17s 19ms/step - loss: 0.1018 - mean_absolute_error: 0.2040 - val_loss: 0.10884 - val_mean_absolute_error: 0.1837
Epoch 33/50
893/893 [=====] - 17s 19ms/step - loss: 0.1010 - mean_absolute_error: 0.2034 - val_loss: 0.10884 - val_mean_absolute_error: 0.1837
Epoch 34/50
893/893 [=====] - 17s 19ms/step - loss: 0.0993 - mean_absolute_error: 0.2023 - val_loss: 0.10884 - val_mean_absolute_error: 0.1837
Epoch 35/50
893/893 [=====] - 17s 19ms/step - loss: 0.0997 - mean_absolute_error: 0.2019 - val_loss: 0.10884 - val_mean_absolute_error: 0.1837
Epoch 36/50
893/893 [=====] - 17s 19ms/step - loss: 0.0971 - mean_absolute_error: 0.1997 - val_loss: 0.10884 - val_mean_absolute_error: 0.1837
Epoch 37/50
893/893 [=====] - 17s 19ms/step - loss: 0.0971 - mean_absolute_error: 0.1997 - val_loss: 0.10884 - val_mean_absolute_error: 0.1837
Epoch 38/50
893/893 [=====] - 17s 19ms/step - loss: 0.0985 - mean_absolute_error: 0.2009 - val_loss: 0.10884 - val_mean_absolute_error: 0.1837
Epoch 39/50
893/893 [=====] - 17s 19ms/step - loss: 0.0985 - mean_absolute_error: 0.1994 - val_loss: 0.10884 - val_mean_absolute_error: 0.1837
Epoch 40/50
893/893 [=====] - 17s 19ms/step - loss: 0.0974 - mean_absolute_error: 0.1997 - val_loss: 0.10884 - val_mean_absolute_error: 0.1837
Epoch 41/50
893/893 [=====] - 17s 19ms/step - loss: 0.0974 - mean_absolute_error: 0.1997 - val_loss: 0.10884 - val_mean_absolute_error: 0.1837
Epoch 42/50
893/893 [=====] - 17s 19ms/step - loss: 0.0974 - mean_absolute_error: 0.1997 - val_loss: 0.10884 - val_mean_absolute_error: 0.1837
Epoch 43/50
893/893 [=====] - 17s 19ms/step - loss: 0.0974 - mean_absolute_error: 0.1997 - val_loss: 0.10884 - val_mean_absolute_error: 0.1837
Epoch 44/50
893/893 [=====] - 17s 19ms/step - loss: 0.0974 - mean_absolute_error: 0.1997 - val_loss: 0.10884 - val_mean_absolute_error: 0.1837
Epoch 45/50
893/893 [=====] - 17s 19ms/step - loss: 0.0949 - mean_absolute_error: 0.1969 - val_loss: 0.10884 - val_mean_absolute_error: 0.1837
Epoch 46/50
893/893 [=====] - 17s 19ms/step - loss: 0.0947 - mean_absolute_error: 0.1971 - val_loss: 0.10884 - val_mean_absolute_error: 0.1837
Epoch 47/50
893/893 [=====] - 17s 19ms/step - loss: 0.0936 - mean_absolute_error: 0.1956 - val_loss: 0.10884 - val_mean_absolute_error: 0.1837
Epoch 48/50
893/893 [=====] - 17s 19ms/step - loss: 0.0933 - mean_absolute_error: 0.1951 - val_loss: 0.10884 - val_mean_absolute_error: 0.1837
Epoch 49/50
893/893 [=====] - 17s 19ms/step - loss: 0.0942 - mean_absolute_error: 0.1958 - val_loss: 0.10884 - val_mean_absolute_error: 0.1837
Epoch 50/50
893/893 [=====] - 17s 19ms/step - loss: 0.0921 - mean_absolute_error: 0.1944 - val_loss: 0.10884 - val_mean_absolute_error: 0.1901
```



```
In [61]: make_predictions(final_model, window_7_1_3)
```