```
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```
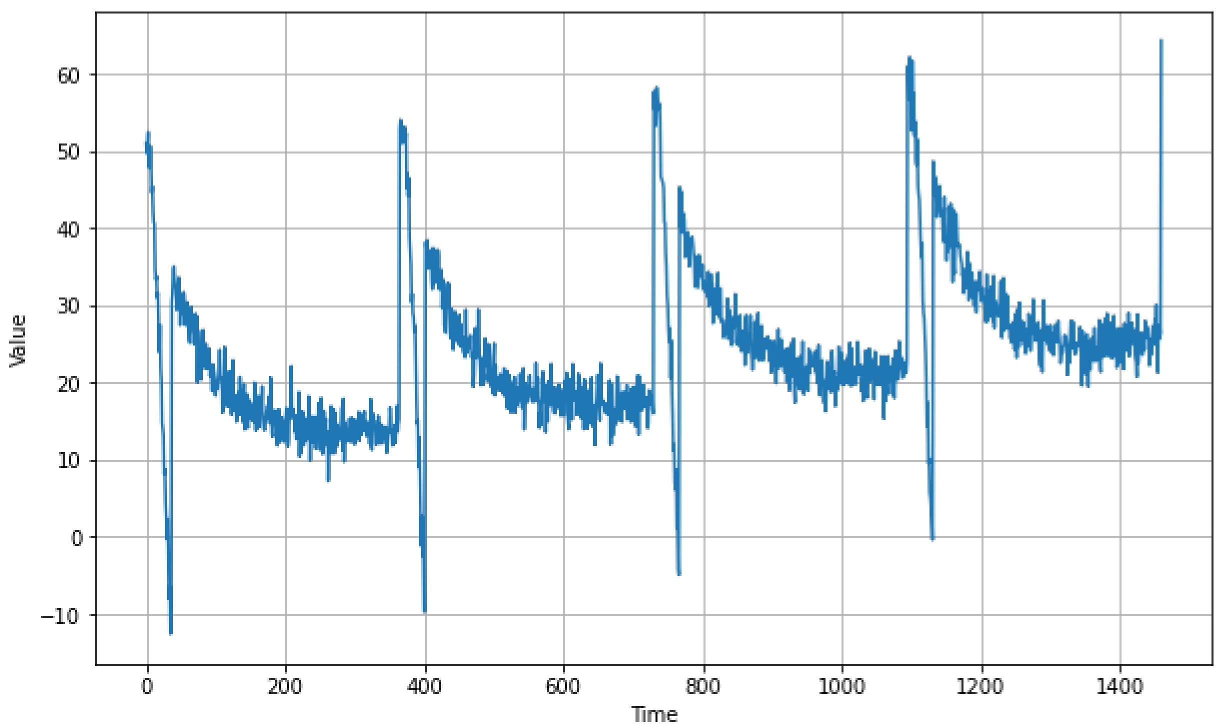

Licensed under the Apache License, Version 2.0 (the "License");

```
import tensorflow as tf
print(tf.__version__)

# EXPECTED OUTPUT
# 2.0.0-beta1 (or later)
```

```
2.3.0
```

```
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow import keras

#generate some random graph to work on
def plot_series(time, series, format="-", start=0, end=None):
    plt.plot(time[start:end], series[start:end], format)
    plt.xlabel("Time")
    plt.ylabel("Value")
    plt.grid(True)

def trend(time, slope=0):
    return slope * time

def seasonal_pattern(season_time):
    """Just an arbitrary pattern, you can change it if you wish"""
    return np.where(season_time < 0.1,
                    np.cos(season_time * 7 * np.pi),
                    1 / np.exp(5 * season_time))

def seasonality(time, period, amplitude=1, phase=0):
    """Repeats the same pattern at each period"""
    season_time = ((time + phase) % period) / period
    return amplitude * seasonal_pattern(season_time)

def noise(time, noise_level=1, seed=None):
    rnd = np.random.RandomState(seed)
```

```
    return rnd.randn(len(time)) * noise_level

time = np.arange(4 * 365 + 1, dtype="float32")
baseline = 10
series = trend(time, 0.1)
baseline = 10
amplitude = 40
slope = 0.01
noise_level = 2

# Create the series
series = baseline + trend(time, slope) + seasonality(time, period=365, amplitude=amplitude)
# Update with noise
series += noise(time, noise_level, seed=42)

plt.figure(figsize=(10, 6))
plot_series(time, series)
plt.show()

# EXPECTED OUTPUT
# Chart as in the screencast. First should have 5 distinctive 'peaks'
```



Now that we have the time series, let's split it so we can start forecasting

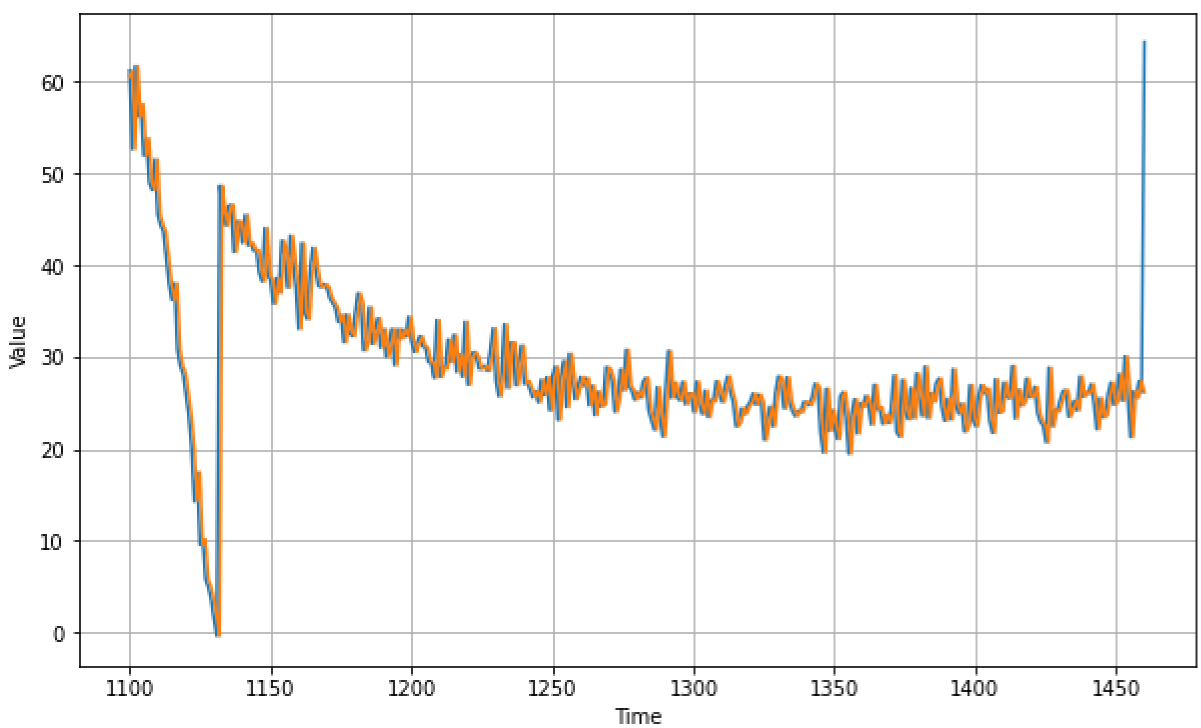
```
#split the graphs into train and test sets
#usually the entire graph is supplied as training data, cuz the most recent data
#is the most important for future forecasts
split_time = 1100
time_train = time[:split_time]
x_train = series[:split_time]
```

```
x_train = series[:split_time]
time_valid = time[split_time:]
x_valid = series[split_time:]
plt.figure(figsize=(10, 6))
plot_series(time_train, x_train)
plt.show()

plt.figure(figsize=(10, 6))
plot_series(time_valid, x_valid)
plt.show()

# EXPECTED OUTPUT
# Chart WITH 4 PEAKS between 50 and 65 and 3 troughs between -12 and 0
# Chart with 2 Peaks, first at slightly above 60, last at a little more than that, should als
```

Naive Forecast

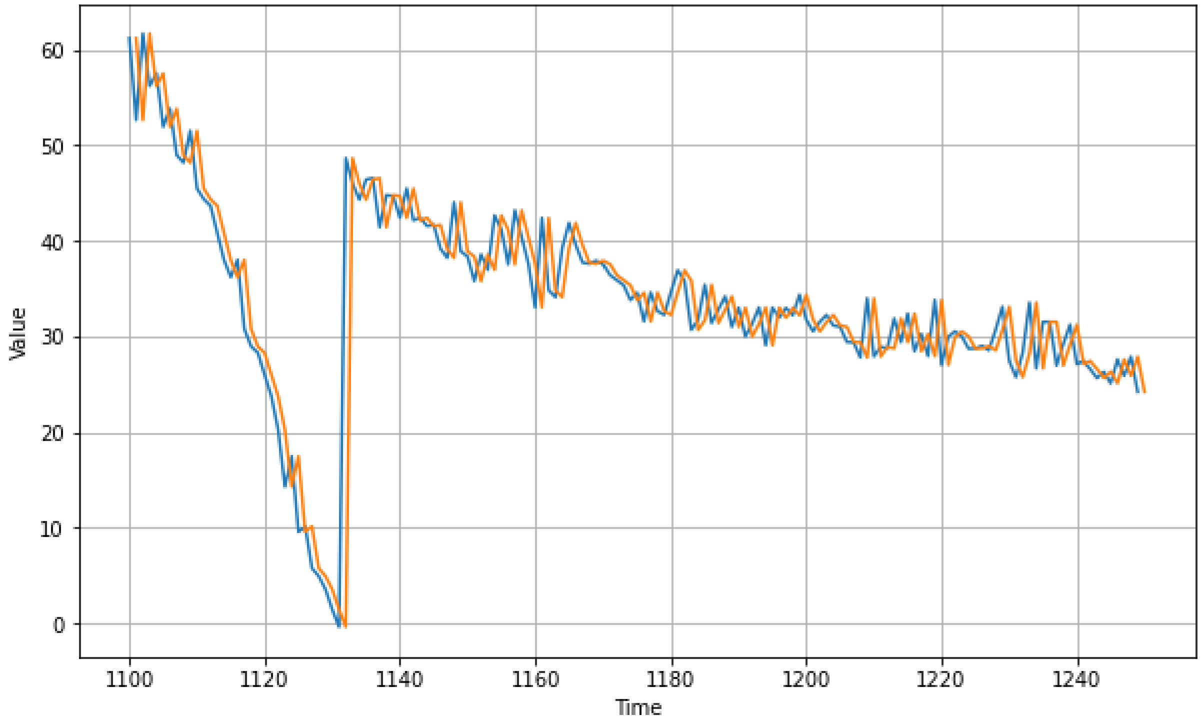
```
#naive forcasting - a method of forecasting
#where each point is 1 time step b4 the actual
naive_forecast = series[split_time -1 : -1]
```

```
plt.figure(figsize=(10, 6))
plot_series(time_valid, x_valid)
plot_series(time_valid, naive_forecast)

# Expected output: Chart similar to above, but with forecast overlay
```



Let's zoom in on the start of the validation period:

```
#zoom in to visualize the 1 time step difference
plt.figure(figsize=(10, 6))
#zoom into the first 150, for naive forecasts it'd be 1 time step ahead
plot_series(time_valid, x_valid, start=0, end=150)
plot_series(time_valid, naive_forecast, start=1, end=151)

# EXPECTED - Chart with X-Axis from 1100-1250 and Y Axes with series value and projections. P
```



Now let's compute the mean squared error and the mean absolute error between the forecasts and the predictions in the validation period:

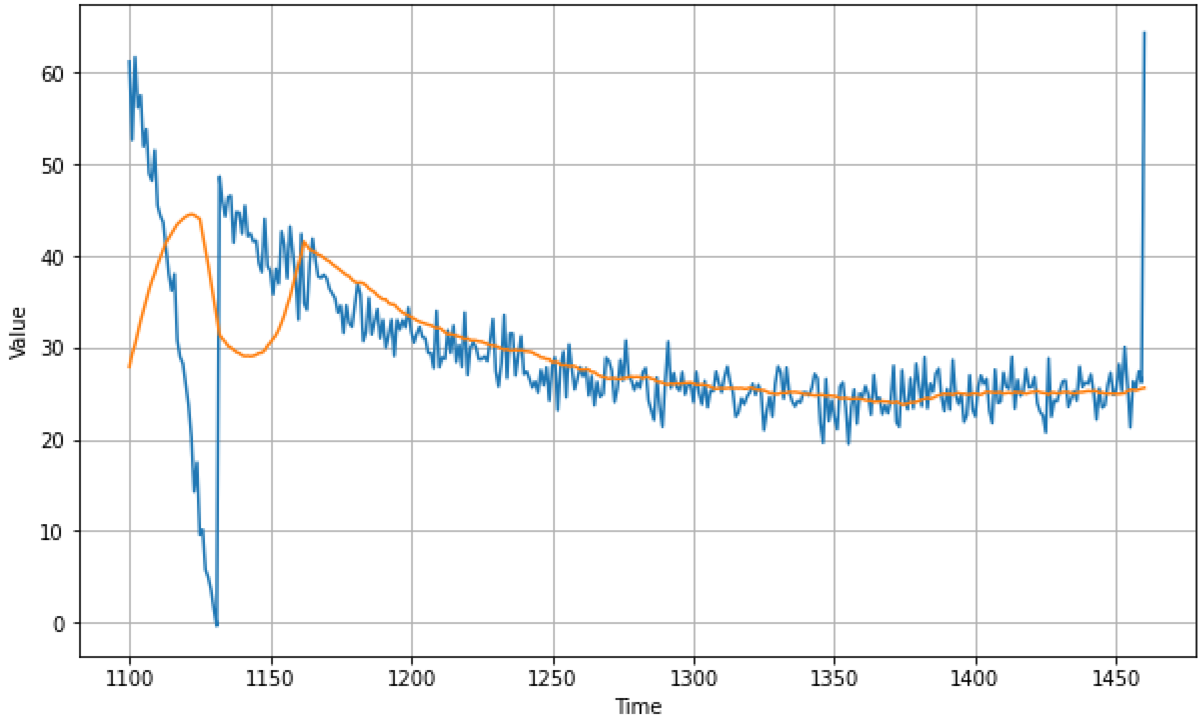
```
print(keras.metrics.mean_squared_error(x_valid, naive_forecast).numpy())
print(keras.metrics.mean_absolute_error(x_valid, naive_forecast).numpy())
# Expected Output
# 19.578304
# 2.6011968
```

```
19.578304
2.6011972
```

That's our baseline, now let's try a moving average:

```
def moving_average_forecast(series, window_size):
  """Forecasts the mean of the last few values.
     If window_size=1, then this is equivalent to naive forecast"""
  forecasts = []
  for time in range(len(series) - window_size):
    forecasts.append(series[time:time + window_size].mean())
  return np.array(forecasts)


moving_avg = moving_average_forecast(series, 30)[split_time - 30:]

plt.figure(figsize=(10, 6))
plot_series(time_valid, x_valid)
plot_series(time_valid, moving_avg)
```

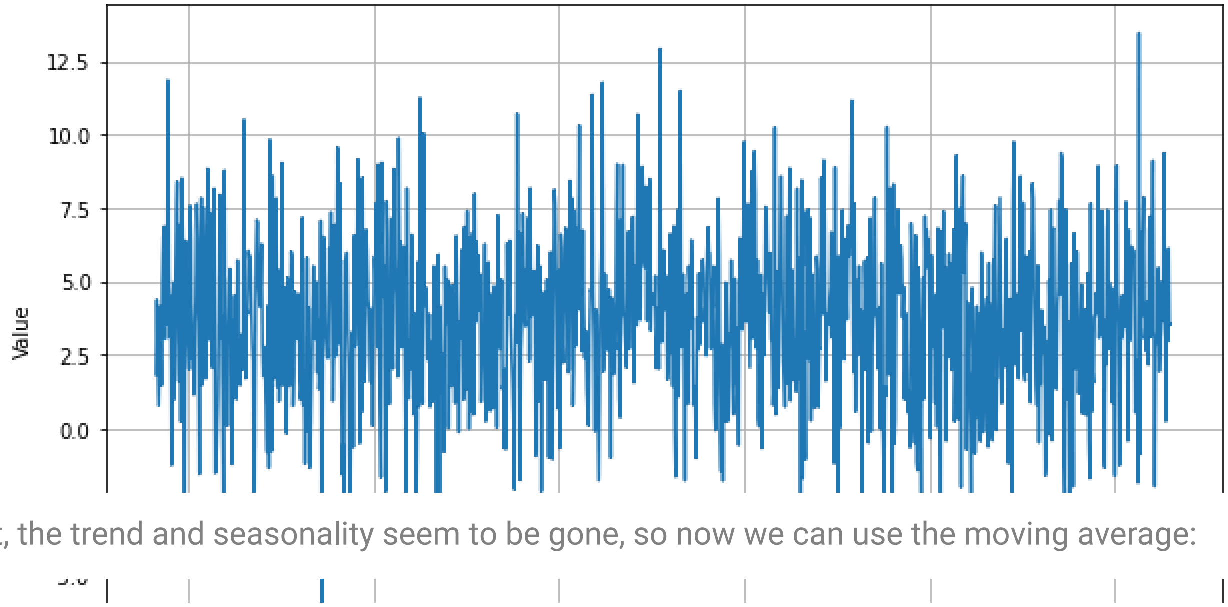
```
# EXPECTED OUTPUT
# CHart with time series from 1100->1450+ on X
# Time series plotted
# Moving average plotted over it
```




```
print(keras.metrics.mean_squared_error(x_valid, moving_avg).numpy())
print(keras.metrics.mean_absolute_error(x_valid, moving_avg).numpy())
# EXPECTED OUTPUT
# 65.786224
# 4.3040023
```

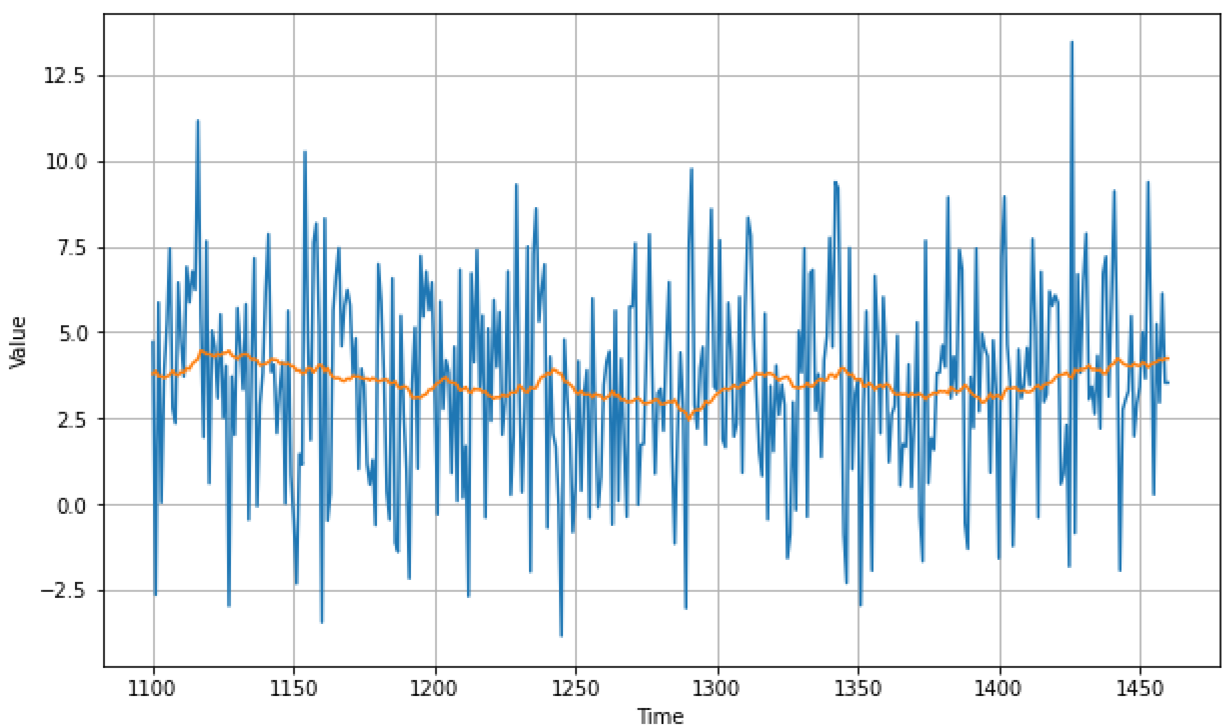
```
65.786224
4.3040023
```

```
diff_series = (series[365:] - series[:-365])
diff_time = time[365:]

plt.figure(figsize=(10, 6))
plot_series(diff_time, diff_series)
plt.show()

# EXPECETED OUTPUT: CHart with diffs
```



Great, the trend and seasonality seem to be gone, so now we can use the moving average:

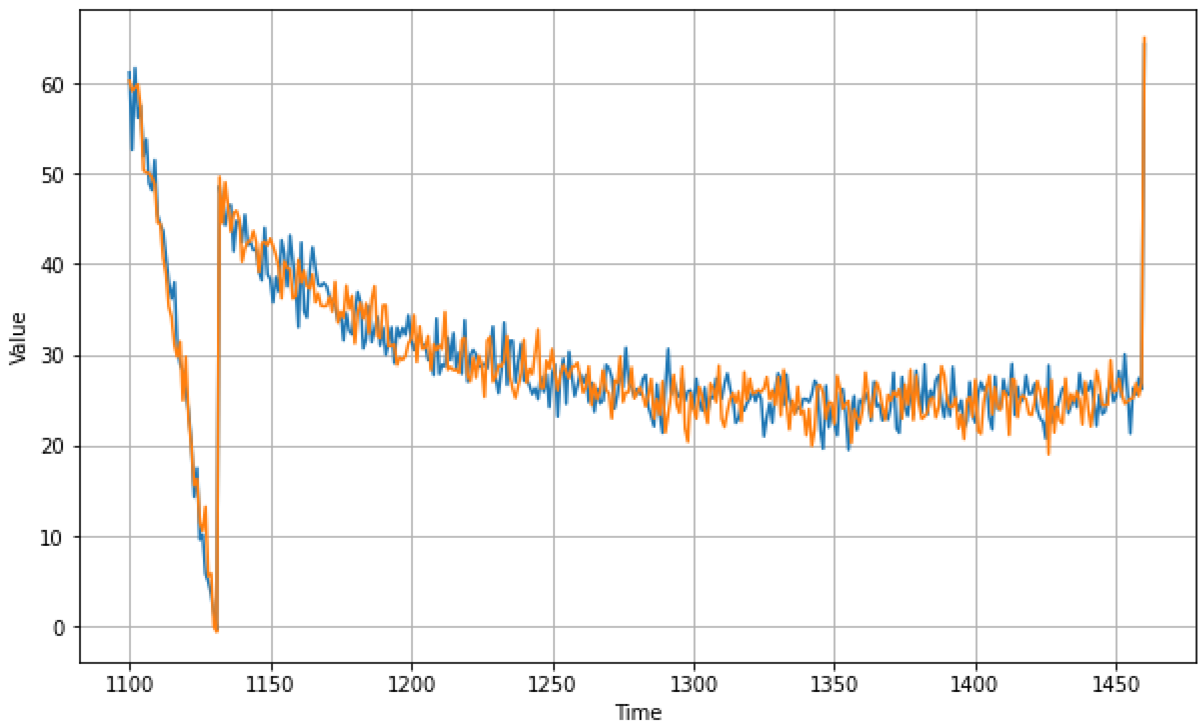
```
diff_moving_avg = moving_average_forecast(diff_series, 50)[split_time - 365 - 50:]

plt.figure(figsize=(10, 6))
plot_series(time_valid, diff_series[split_time - 365:])
plot_series(time_valid, diff_moving_avg)
plt.show()

# Expected output. Diff chart from 1100->1450 +
# Overlaid with moving average
```



Now let's bring back the trend and seasonality by adding the past values from t − 365:

```
diff_moving_avg_plus_past = series[split_time - 365:-365] + diff_moving_avg
```

```
diff_moving_avg_plus_past = series[split_time - 365:-365] + diff_moving_avg

plt.figure(figsize=(10, 6))
plot_series(time_valid, x_valid)
plot_series(time_valid, diff_moving_avg_plus_past)
plt.show()
# Expected output: Chart from 1100->1450+ on X. Same chart as earlier for time series, but pr
```



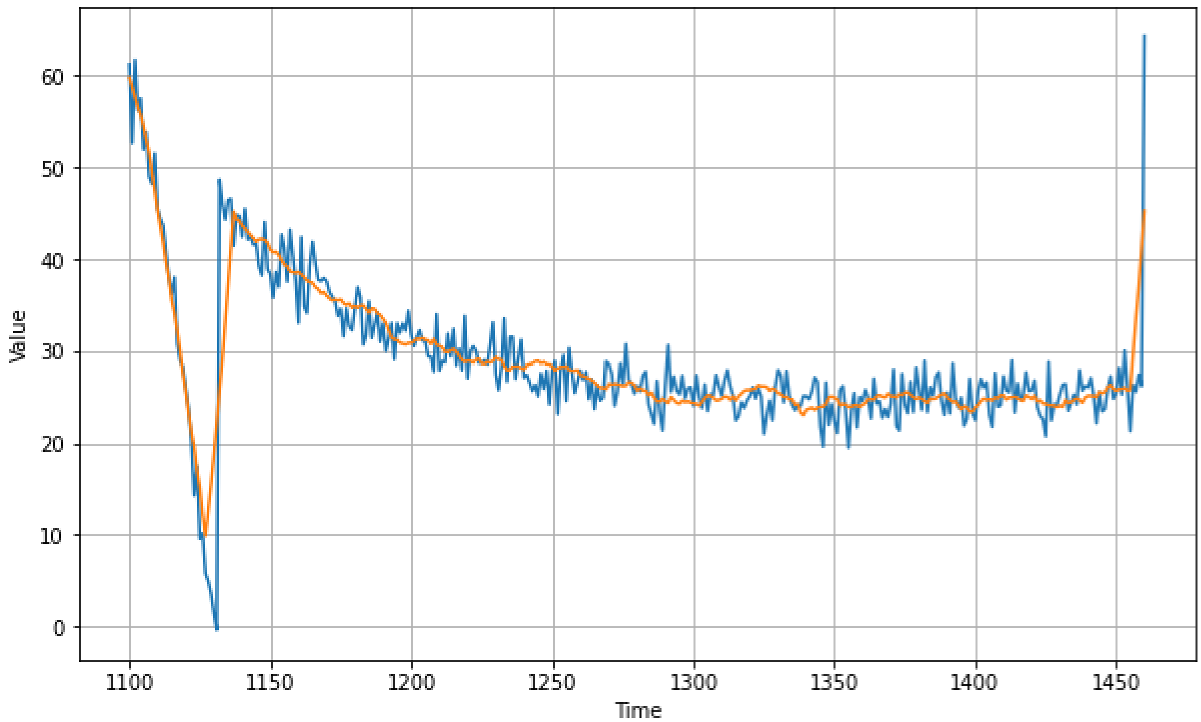

```
print(keras.metrics.mean_squared_error(x_valid, diff_moving_avg_plus_past).numpy())
print(keras.metrics.mean_absolute_error(x_valid, diff_moving_avg_plus_past).numpy())
# EXPECTED OUTPUT
# 8.498155
# 2.327179
```

```
8.498155
2.327179
```

Better than naive forecast, good. However the forecasts look a bit too random, because we're just adding past values, which were noisy. Let's use a moving averaging on past values to remove some of the noise:

```
diff_moving_avg_plus_smooth_past = moving_average_forecast(series[split_time - 370:-360], 10)

plt.figure(figsize=(10, 6))
plot_series(time_valid, x_valid)
plot_series(time_valid, diff_moving_avg_plus_smooth_past)
plt.show()

# EXPECTED OUTPUT:
```

```
# Similar chart to above, but the overlaid projections are much smoother
```




```
print(keras.metrics.mean_squared_error(x_valid, diff_moving_avg_plus_smooth_past).numpy())
print(keras.metrics.mean_absolute_error(x_valid, diff_moving_avg_plus_smooth_past).numpy())
# EXPECTED OUTPUT
# 12.527958
# 2.2034433
```

```
12.527956
2.2034435
```