Time Series Analysis(TSA) is a method of analyzing data points collected over time to identify patterns,trends and seasonal variations. It is used to forecast future values based on historical data.

Time Series Analysis

Import Library

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.arima.model import ARIMA
```

Loading and Viewing Data

```
df=pd.read_csv(r"C:\My python Files\DailyDelhiClimateTrain.csv")
df.head()

         date   meantemp   humidity  wind_speed  meanpressure
0  2013-01-01  10.000000  84.500000    0.000000   1015.666667
1  2013-01-02   7.400000  92.000000    2.980000   1017.800000
2  2013-01-03   7.166667  87.000000    4.633333   1018.666667
3  2013-01-04   8.666667  71.333333    1.233333   1017.166667
4  2013-01-05   6.000000  86.833333    3.700000   1016.500000
```

Info

```
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1462 entries, 0 to 1461
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   date          1462 non-null   object 
 1   meantemp      1462 non-null   float64
 2   humidity      1462 non-null   float64
 3   wind_speed    1462 non-null   float64
 4   meanpressure  1462 non-null   float64
dtypes: float64(4), object(1)
memory usage: 57.2+ KB
```

Setting Date as index

```
#checking for null values
print(df[df['date'].isna()])
```

```
Empty DataFrame
Columns: [date, meantemp, humidity, wind_speed, meanpressure]
Index: []
```

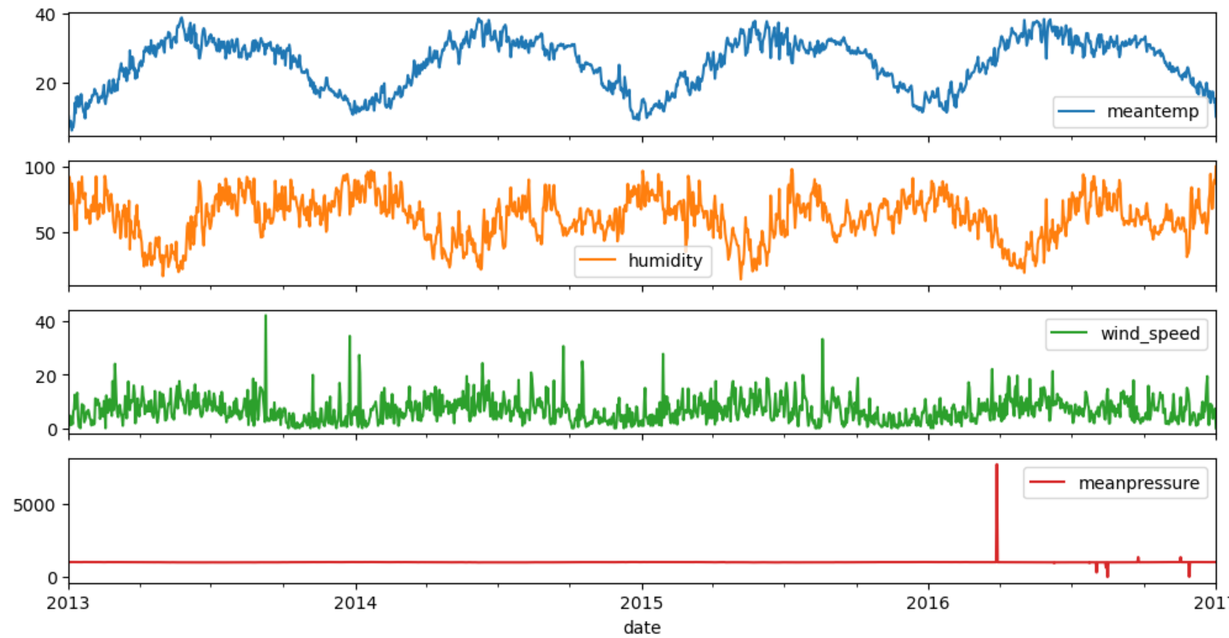
```
df['date']=pd.to_datetime(df['date'],errors='coerce')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1462 entries, 0 to 1461
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   date          1462 non-null   datetime64[ns]
 1   meantemp      1462 non-null   float64
 2   humidity      1462 non-null   float64
 3   wind_speed    1462 non-null   float64
 4   meanpressure  1462 non-null   float64
dtypes: datetime64[ns](1), float64(4)
memory usage: 57.2 KB
```

```
#setting Index
df.set_index("date",inplace=True)
df.head()
```

```
             meantemp   humidity  wind_speed  meanpressure
date
2013-01-01  10.000000  84.500000    0.000000   1015.666667
2013-01-02   7.400000  92.000000    2.980000   1017.800000
2013-01-03   7.166667  87.000000    4.633333   1018.666667
2013-01-04   8.666667  71.333333    1.233333   1017.166667
2013-01-05   6.000000  86.833333    3.700000   1016.500000
```

```
df.plot(figsize=(12,6),subplots=True)
plt.show()
```



1. Mean Temperature:
   - Temperature is following a trend.
   - That is there is increase in temperature at the start of the year,decrease in temperature at the end of the year
2. Humidity:
   - Humidity is High at the start of the year.
   - There is lot of fluctuation in the humidity
3. Wind Speed:
   - Here we can see spark in the end of 2013 year which may be cyclon or any environmental cause.
   - In 2014 starting 2 sparks,in 2015 also 2 sparks.
4. Mean pressure:
   - There is contant pressure upto 2016 year.
   - In 2016 year we can see a spark which may be a error value or not recorded properly.

Stationarity:

A time series is stationary if its statistical properties(mean,variance,autocorrelation) remain constant over time.

1. Hypothesis of the ADF Test:

- Null hypothesis(Ho) : The time series has a unit root(i,e.,it is non-stationary).
- Alternative Hypothesis(H1) : The time series does not have a unit root(i,e.,it is stationary).

1. Interpreting ADF test Result:

- If the p-value is less than 0.05,reject Ho->The series is stationary

- If the p-value is greater than 0.05,fail to reject Ho-> The series is non-stationary

```
adfuller_result=adfuller(df['meantemp'])

print(adfuller_result)

(-2.0210690559206728, 0.27741213723016056, 10, 1451, {'1%': -
3.4348647527922824, '5%': -2.863533960720434, '10%': -
2.567831568508802}, 5423.895746470953)

if adfuller_result[1] < 0.05:
    print("Stationary")
else:
    print("Non-Stationary")

Non-Stationary
```

Differncing to Remove Trend:If the series is non-stationary,apply differencing.

Differencing is a technique uesd to make a non-stationary time series stationary by removing trends or seasonality.I t involves subtracting the previous observation from the current observation.

- temperature=[20,21,22,24,25,27,28,27]
- Difference=[Nan,1,1,2,1,2,1,-1]
- The new series fluctuates around -2 to 2.

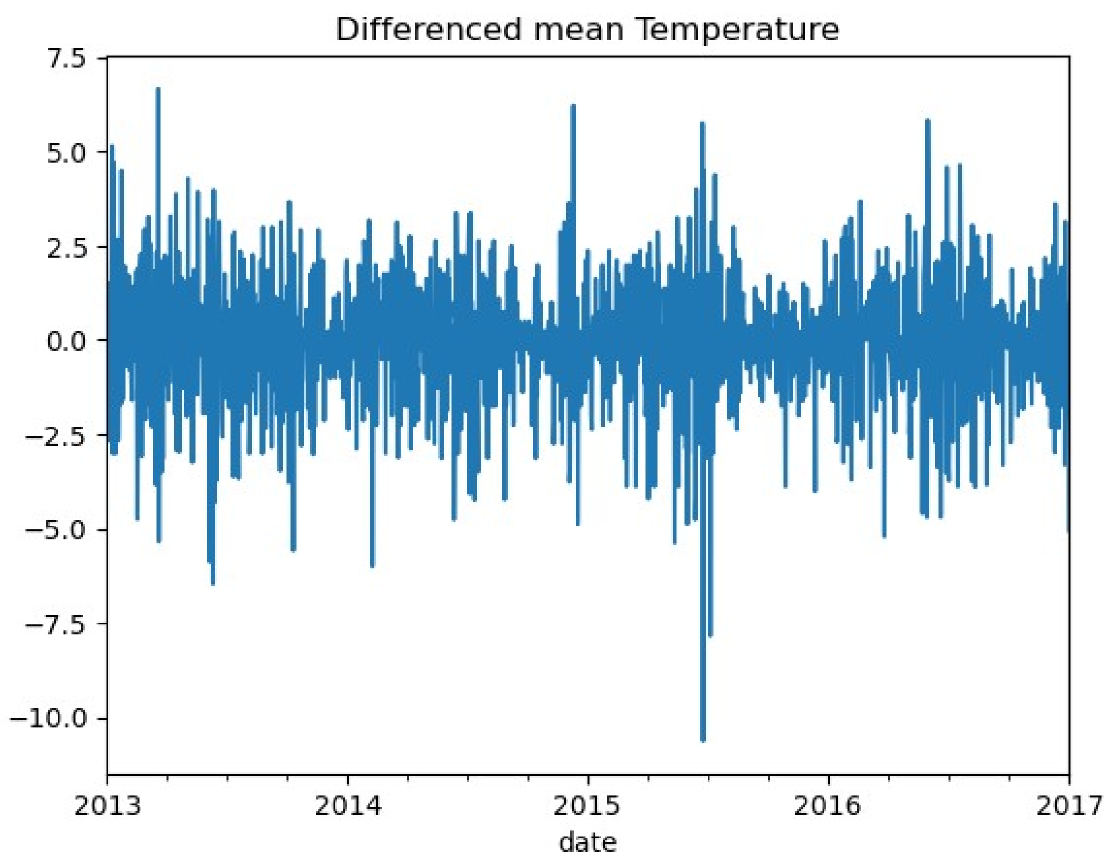
Differencing

```
df['meantemp_diff']=df['meantemp'].diff()
df.head()

             meantemp   humidity  wind_speed  meanpressure  
meantemp_diff
date

2013-01-01  10.000000  84.500000    0.000000   1015.666667  
NaN
2013-01-02   7.400000  92.000000    2.980000   1017.800000      -
2.600000
2013-01-03   7.166667  87.000000    4.633333   1018.666667      -
0.233333
2013-01-04   8.666667  71.333333    1.233333   1017.166667  
1.500000
2013-01-05   6.000000  86.833333    3.700000   1016.500000      -
2.666667
```

```python
adfuller_result_afterdiff=adfuller(df['meantemp_diff'].dropna())
if(adfuller_result_afterdiff[1] > 0.05):
    print("Non Stationary")
else:
    print("Stationary")
```

```
Stationary
```

```python
df['meantemp_diff'].plot(title="Differenced mean Temperature")
plt.show()
```



Conclusion:

1. The mean temperature is now stationary.
2. The average is around a zero.
3. After the differencing also there is some splike which means outlier is present.
4. In between 2015 and 2016 there is extreme low in temperature.
5. In 2015 starting there is extreme decrease in temperature.

Use Seasonal Decomposition to analyze trend,seasonality, and residuals

Seasonal decomposition is a techique uesd to break a time series into three main components:

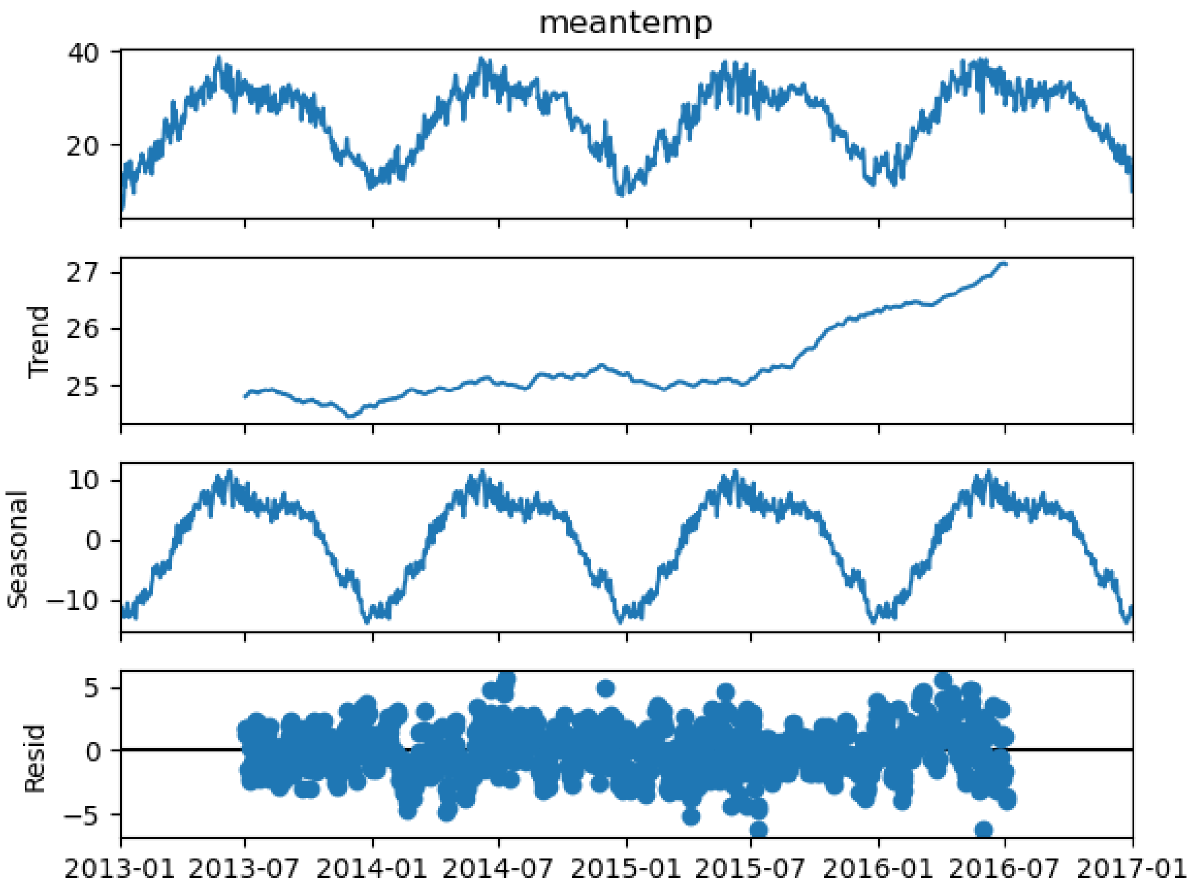
- Trend- The Long-term pattern (increase or decrease over time).
- Seasonality- The repeating pattern at fixed intervals(e.g.,higher sales in December).
- Residual component - The remaining part after removing trend and seasonality(random noise).

Interpreting th output:

- Original Series- The raw time series data.
- Trend Component- The general direction of the data over time.
- Seasonal Component- The repeating pattern(e.g.,higher sales in december)
- Residual Component- The remaining part after removing trend and seasonality(random noise)

Decomposing:

```
decomposing=seasonal_decompose(df['meantemp'],model='additive',period=
365)

decomposing.plot()
plt.show()
```



Conclusion:

1. Trend:
- Rapid increase in temperature from the year 2015
- There is a gradual increase but in 2016-01 , 2016-07 there is rapid increase.
- Over all increase is 2 degree.
1. Seasonal:
- Annual seasonal temperature is constant.
- There is a no difference in the seasonal temperature.
1. Residual:
- The average temparature is Zero.

ARIMA

```
#splitting data
len(df)

1462

print(len(df)*0.8)

1169.6000000000001
```

```
train=df.iloc[0:1169]
test=df.iloc[1169:]
```

```
mymodel=ARIMA(train['meantemp'],order=(1,1,1))
```

```
C:\Users\DELL\anaconda3\Lib\site-packages\statsmodels\tsa\base\
tsa_model.py:473: ValueWarning: No frequency information was provided,
so inferred frequency D will be used.
  self._init_dates(dates, freq)
C:\Users\DELL\anaconda3\Lib\site-packages\statsmodels\tsa\base\
tsa_model.py:473: ValueWarning: No frequency information was provided,
so inferred frequency D will be used.
  self._init_dates(dates, freq)
C:\Users\DELL\anaconda3\Lib\site-packages\statsmodels\tsa\base\
tsa_model.py:473: ValueWarning: No frequency information was provided,
so inferred frequency D will be used.
  self._init_dates(dates, freq)
```

```
mymodel=mymodel.fit()
```

```
forecast=mymodel.forecast(steps=len(test))
print(forecast)
```

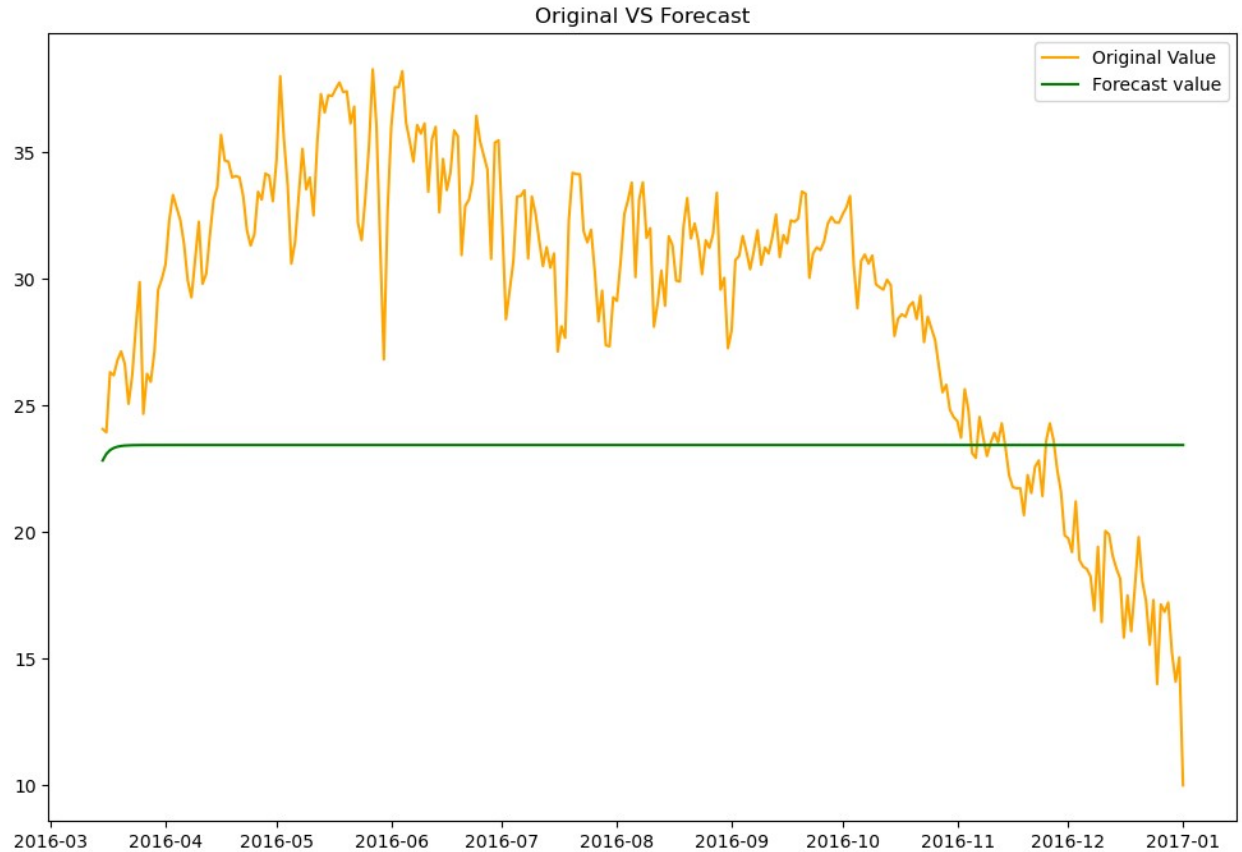
```
2016-03-15    22.826205
2016-03-16    23.085687
2016-03-17    23.234913
2016-03-18    23.320731
2016-03-19    23.370084
                ...
2016-12-28    23.436880
2016-12-29    23.436880
2016-12-30    23.436880
2016-12-31    23.436880
2017-01-01    23.436880
Freq: D, Name: predicted_mean, Length: 293, dtype: float64
```

```
test['forecast']=forecast
test.head()
```

```
C:\Users\DELL\AppData\Local\Temp\ipykernel_8368\2406814425.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  test['forecast']=forecast
```

```
             meantemp   humidity  wind_speed  meanpressure
meantemp_diff  \
```

```
date

2016-03-15  24.066667  58.933333    8.646667   1014.866667
1.691667
2016-03-16  23.937500  53.750000   10.881250   1012.812500      -
0.129167
2016-03-17  26.312500  50.312500    6.843750   1010.437500
2.375000
2016-03-18  26.187500  61.250000    6.712500   1009.812500      -
0.125000
2016-03-19  26.785714  61.857143    3.578571   1009.214286
0.598214

             forecast
date
2016-03-15  22.826205
2016-03-16  23.085687
2016-03-17  23.234913
2016-03-18  23.320731
2016-03-19  23.370084

plt.figure(figsize=[12,8])
plt.plot(test.index,test['meantemp'],color='orange',label='Original
Value')
plt.plot(test.index,test['forecast'],color='green',label='Forecast
value')
plt.title("Original VS Forecast")
plt.legend()
plt.show()
```




```
len(df)
```

```
1462
```

```
print(len(df)*0.08)
```

```
116.96000000000001
```

```
train1=df.iloc[0:1169]
test1=df.iloc[1169:]
```

```
adfuller_result_afterdiff=adfuller(df['meantemp_diff'].dropna())
```

```
len(df)
```

```
1462
```

```
train1=df.iloc[0:1169]
test1=df.iloc[1169:]
```

```
mymodel1=ARIMA(train1['meantemp_diff'],order=(1,1,1))
```

```
C:\Users\DELL\anaconda3\Lib\site-packages\statsmodels\tsa\base\
tsa_model.py:473: ValueWarning: No frequency information was provided,
so inferred frequency D will be used.
```

```
  self._init_dates(dates, freq)
C:\Users\DELL\anaconda3\Lib\site-packages\statsmodels\tsa\base\
tsa_model.py:473: ValueWarning: No frequency information was provided,
so inferred frequency D will be used.
  self._init_dates(dates, freq)
C:\Users\DELL\anaconda3\Lib\site-packages\statsmodels\tsa\base\
tsa_model.py:473: ValueWarning: No frequency information was provided,
so inferred frequency D will be used.
  self._init_dates(dates, freq)
```

```
mymodel1=mymodel1.fit()
```

```
forecast_diff=mymodel.forecast(steps=len(test))
print(forecast_diff)
```

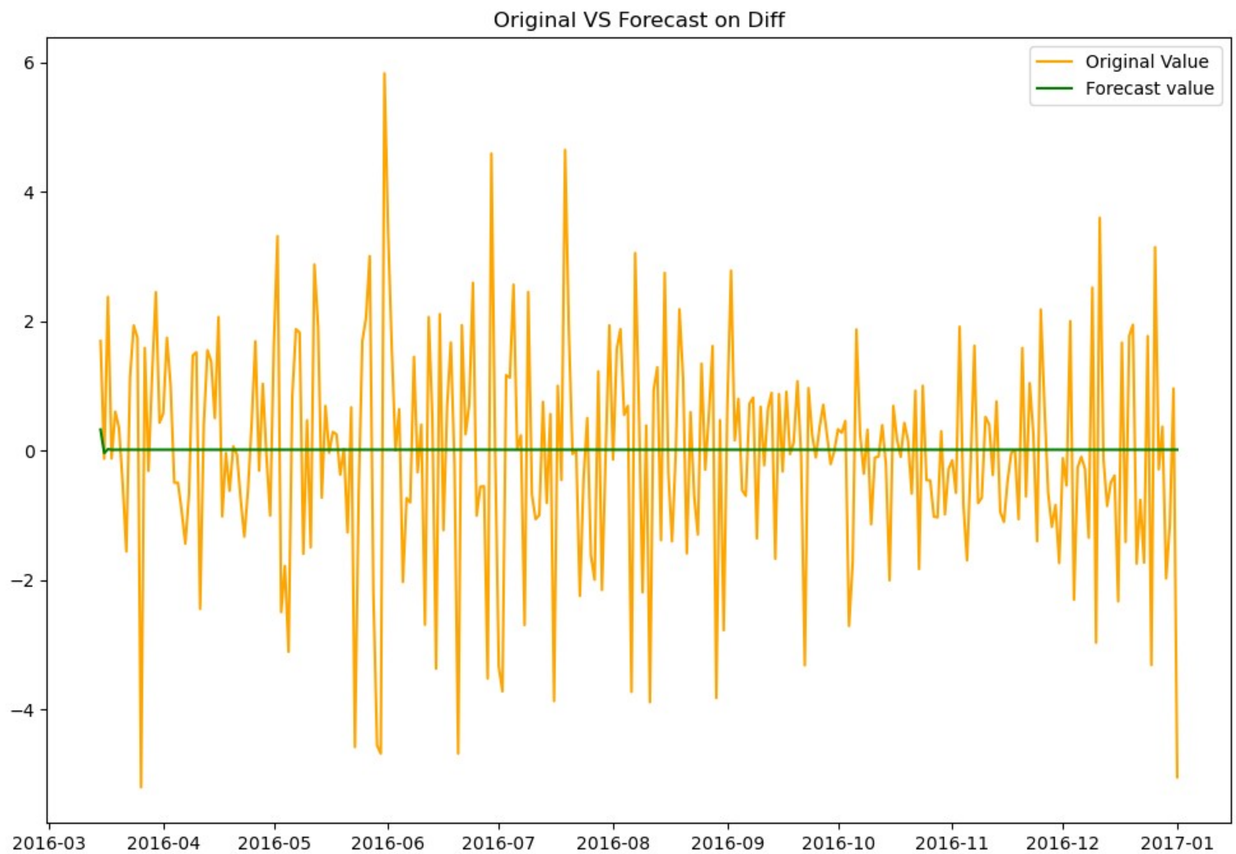
```
2016-03-15    0.322914
2016-03-16   -0.040400
2016-03-17    0.019656
2016-03-18    0.009729
2016-03-19    0.011370
                ...
2016-12-28    0.011137
2016-12-29    0.011137
2016-12-30    0.011137
2016-12-31    0.011137
2017-01-01    0.011137
Freq: D, Name: predicted_mean, Length: 293, dtype: float64
```

```
test1['forecast_diff']=forecast_diff
test1.head()
```

```
C:\Users\DELL\AppData\Local\Temp\ipykernel_8368\594841171.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  test1['forecast_diff']=forecast_diff
```

```
             meantemp   humidity  wind_speed  meanpressure
meantemp_diff  \
date

2016-03-15  24.066667  58.933333    8.646667   1014.866667
1.691667
2016-03-16  23.937500  53.750000   10.881250   1012.812500      -
0.129167
2016-03-17  26.312500  50.312500    6.843750   1010.437500
2.375000
```

```
2016-03-18  26.187500  61.250000   6.712500   1009.812500      -
0.125000
2016-03-19  26.785714  61.857143   3.578571   1009.214286
0.598214

            forecast_diff
date
2016-03-15       0.322914
2016-03-16      -0.040400
2016-03-17       0.019656
2016-03-18       0.009729
2016-03-19       0.011370

plt.figure(figsize=[12,8])
plt.plot(test1.index,test1['meantemp_diff'],color='orange',label='Orig
inal Value')
plt.plot(test1.index,test1['forecast_diff'],color='green',label='Forec
ast value')
plt.title("Original VS Forecast on Diff")
plt.legend()
plt.show()
```



15th March, Original value is 24.06666, model says there is -0.40438 change on next day.
24.066667 - 0.40438 = 24.02 (predicted) ~ 23.93700 (Original)