TIME SERIES ANALYSIS

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

Import Libraries

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

Loading and viewing data

```
df = pd.read_csv(r"C:\Mypythonfiles\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
```

Seting date as Index

```
#checking for nulls in date columns
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()
```

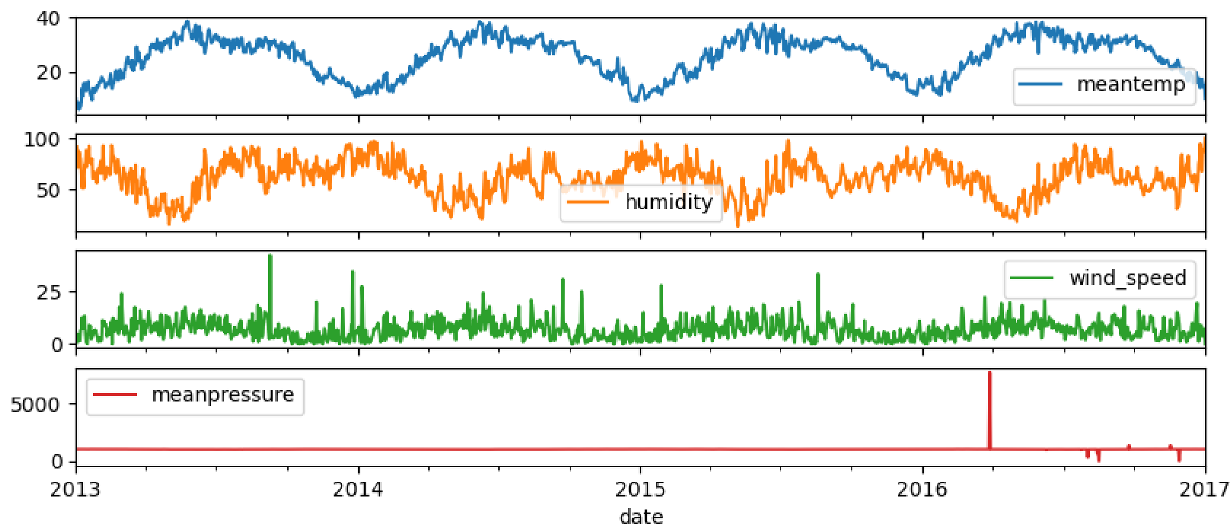
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1462 entries, 0 to 1461
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   date          1462 non-null   datetime64[ns]
 1   meantemp      1462 non-null   float64
 2   humidity  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

```
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
```

visualize

```
df.plot(figsize = (10,4), subplots = True)
plt.show()
```



Conclusion:

1. meantemp:
- eventually the temperature increses at the starting of the year and decreases ate the end of the year
- every year the temp has same fluctuations.
1. humidity:
- At the begining of the year the temp is raised eventually the temp decreases at the mid of the year
- it has more fluctuations compared to the meantemp.
1. wind_speed:
- here the wind speed is less but at the one point of the year the speed increases
- those fluctuations are called cyclone or the area may be damaged etc..
1. meanpreassure:
- it has constant pressure at the one point it has been fluctuated
- hence it can be recognised as any issue or wrong recored data

Stationarity

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

Hypoteses of the ADF Test:

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

Interpreting ADF Test Results:

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

stationary Results

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

(-2.021069055920672 8, 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
```

Differencing to Remove Trend: If The Series is non-stationary, apply differencing.

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

temperature = [20,21,22,24,25,27,28,27]

Difference = [1,1,2,1,2,1,-1]

- The new series fluctuates around zero -2 to 2

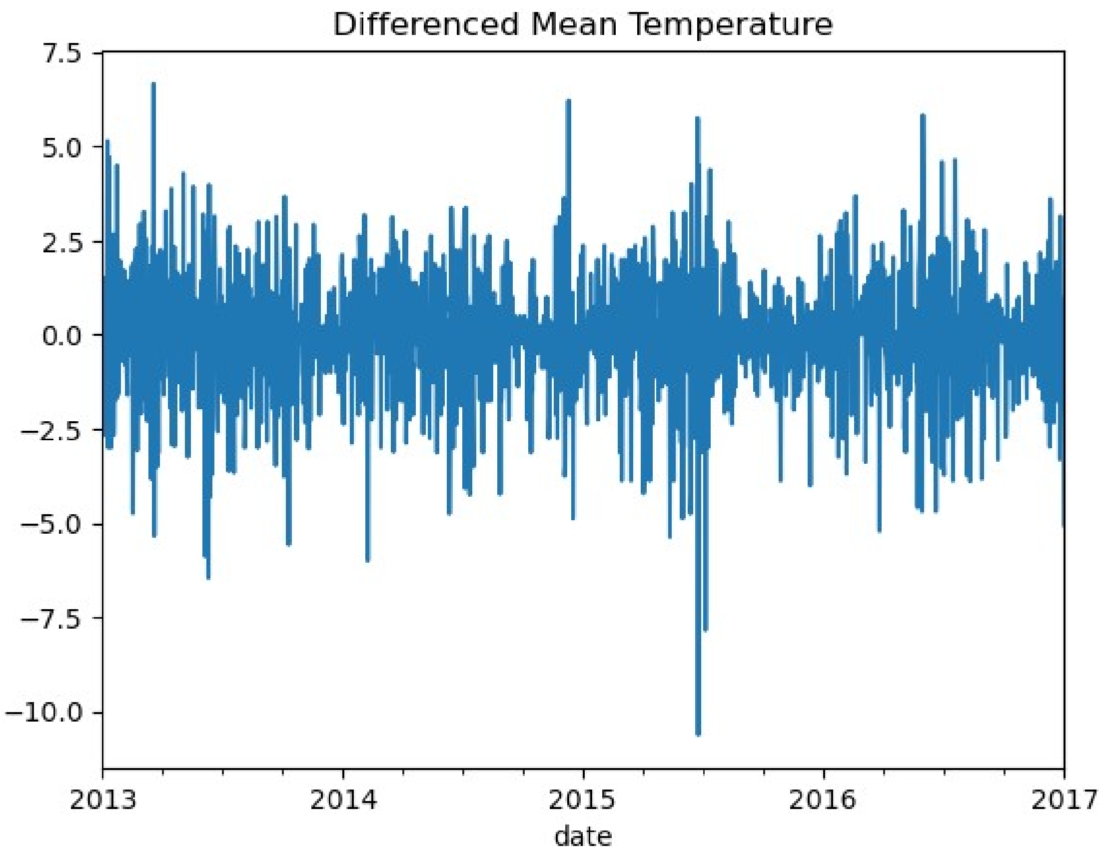
Differencing

```
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
```

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

```
stationary
```

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



Conclusion:

1. the average is around zero
2. even after describing there is a outliers
3. mean temperature is stationary
4. there is a extreme low temperature in month between 2015 to 2016

5. negative temperature is known as lower temperative(spik)

use seasonal decomposition to analyze trend,seasonality and residuals.

seasonal decomposition is a technique used to break a time series into three main components:

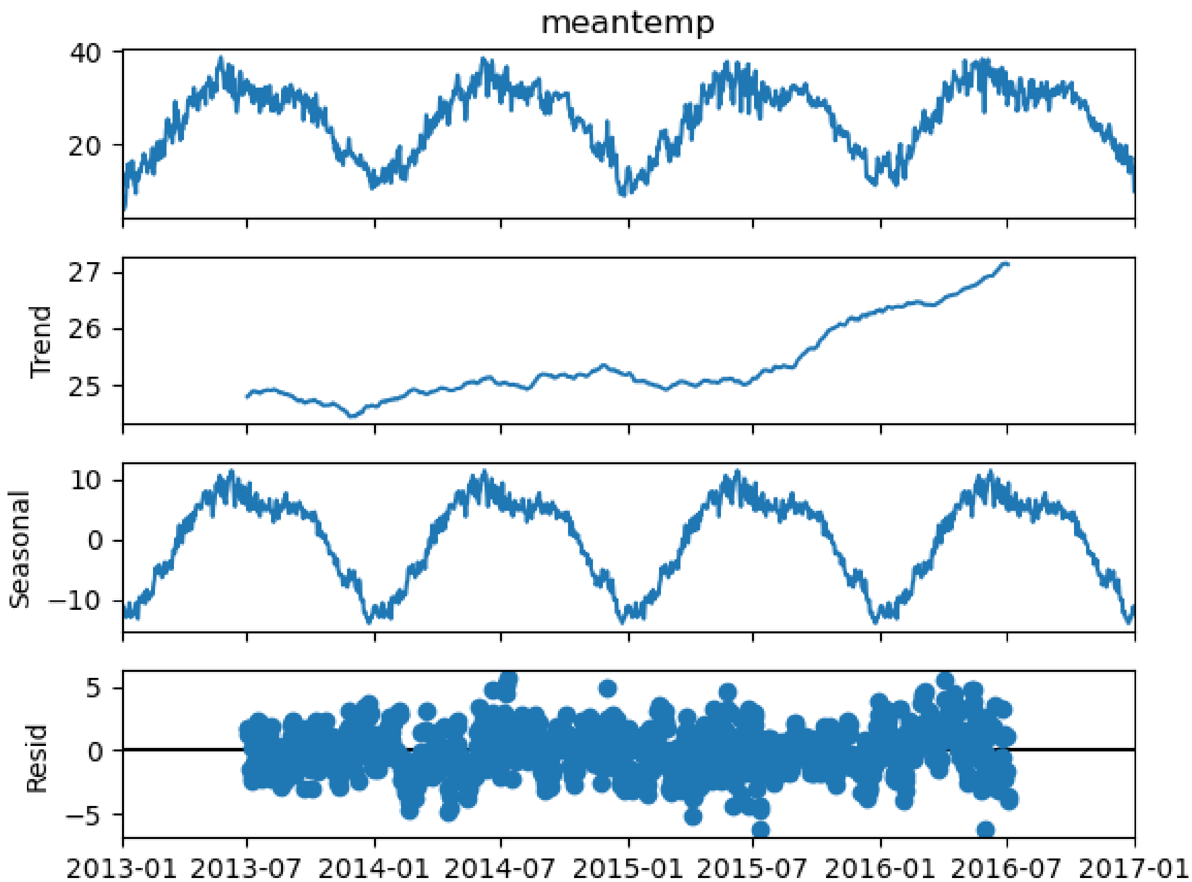
- Trend - The long term pattern (increase or decrease over time)
- seasonality - the repeating patterns at fixed intervals(eg.,monthly sales spikes)
- Residual(Noise) - The random variations that are not explained by trend or seasonality.

Interpreting the Output

- Original series - The raw time series data.
- Trend component - The general direction of the data over time.
- seasonal component - The repeating patterns(e.g.,higher scales 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 temp from the year 2015
- temp level started from the year 2013 is 25
- overall increase is 2 degres
1. sesonal - anual seasonal temp is consistent.
- temp increase at the starting of the year and gradually decrease in the end of the year
1. resid - avg residual is zero.

ARIMA

```
#splitting data
len(df)

1462

len(df)*0.8

1169.6000000000001

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

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

```
C:\ProgramData\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:\ProgramData\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:\ProgramData\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)
```

```
----------------------------------------------------------------------
-----
AttributeError                            Traceback (most recent call
last)
Cell In[87], line 1
----> 1 forecast = mymodel.forecast(steps = len(test))
      2 print(forecast)

AttributeError: 'ARIMA' object has no attribute 'forecast'
```

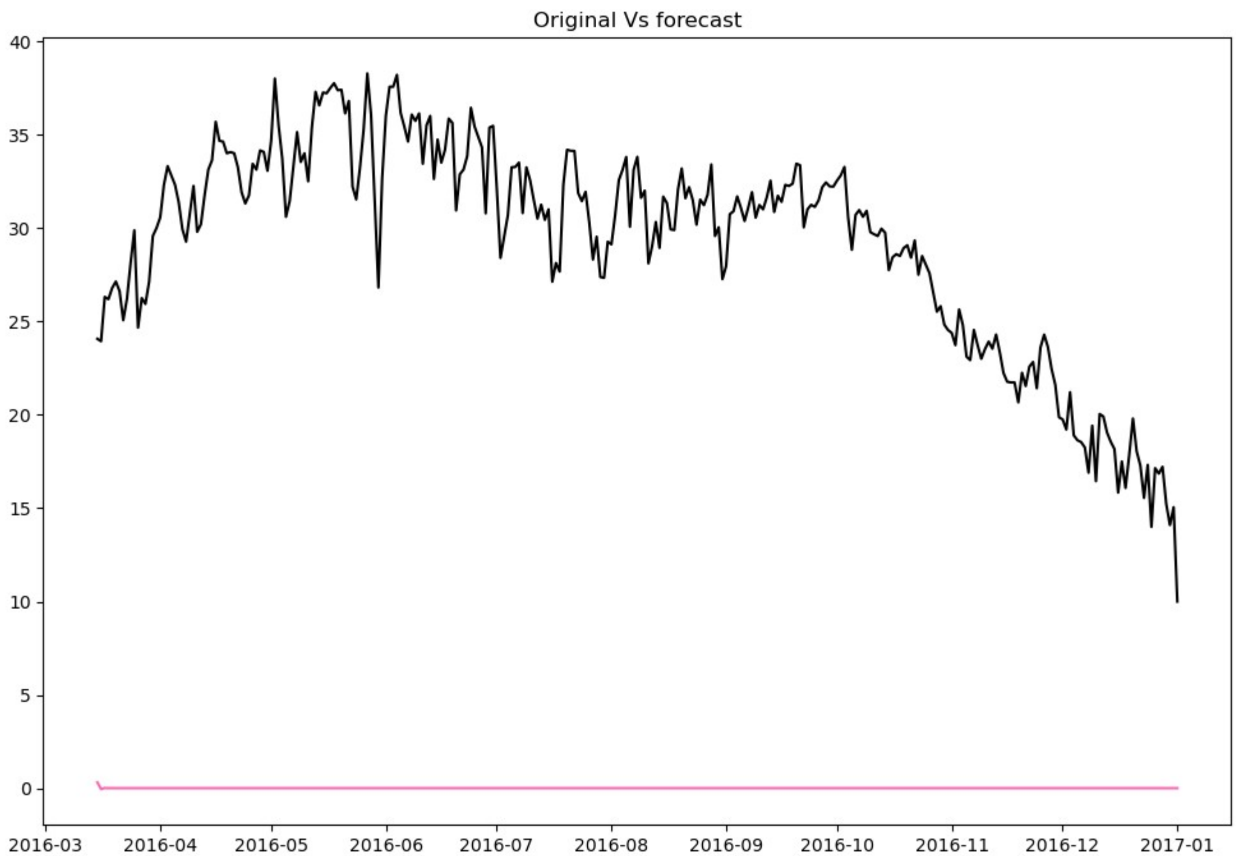
```
test['forecast'] = forecast
test.head()
```

```
C:\Users\DELL\AppData\Local\Temp\ipykernel_6708\2382496083.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  0.322914
2016-03-16 -0.040400
2016-03-17  0.019656
2016-03-18  0.009729
2016-03-19  0.011370
```

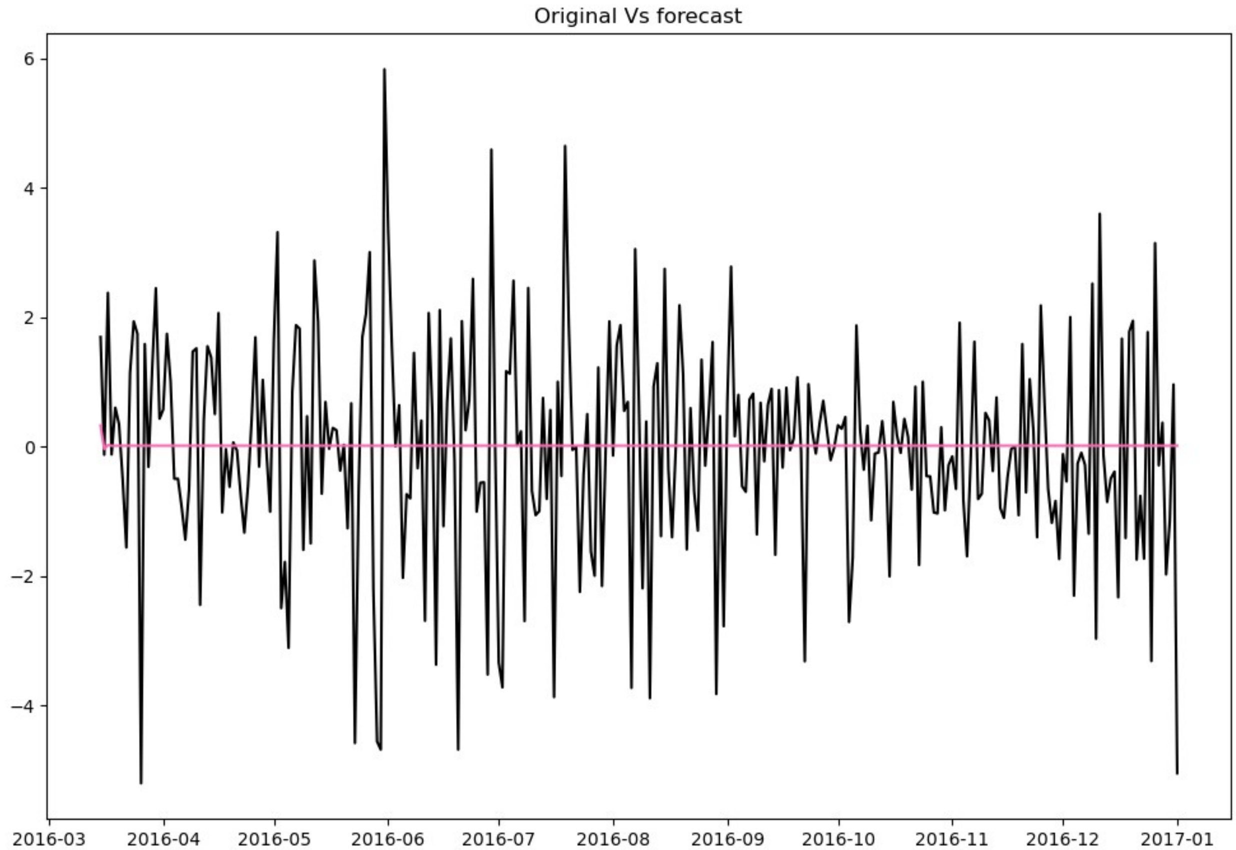
```
plt.figure(figsize=(12,8))
plt.plot(test.index,test['meantemp'], color = 'k', label= 'original')
plt.plot(test.index,test['forecast'], color = 'hotpink', label =
'Forecast')
plt.title("Original Vs forecast")
plt.show()
```



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

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

C:\ProgramData\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:\ProgramData\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:\ProgramData\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()

forecast1 = mymodel1.forecast(steps = len(test))
print(forecast1)

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['forecast1'] = forecast1
test1.head()

C:\Users\DELL\AppData\Local\Temp\ipykernel_6708\2863689936.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['forecast1'] = forecast1

             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

            forecast1
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 = 'k', label=
'original')
plt.plot(test1.index,test1['forecast1'], color = 'hotpink', label =
'Forecast')
plt.title("Original Vs forecast")
plt.show()
```



conclusion:

1. 15 mar , original value = 24.066667, model says there is -0.040438 change on next day

- 24.066667-0.040438 = 24.02(predicted) ~ 23.937500(oroginal)