Time series analysis (TSA)

import libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
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:\Users\DELL\Downloads\my_python\
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

set date as index

```
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
```

```
#checking the null values in single row
print(df[df['date'].isna()])
```

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

```
#convert object into data datype
df['date']=pd.to_datetime(df['date'],errors='coerce')
df.info()
```

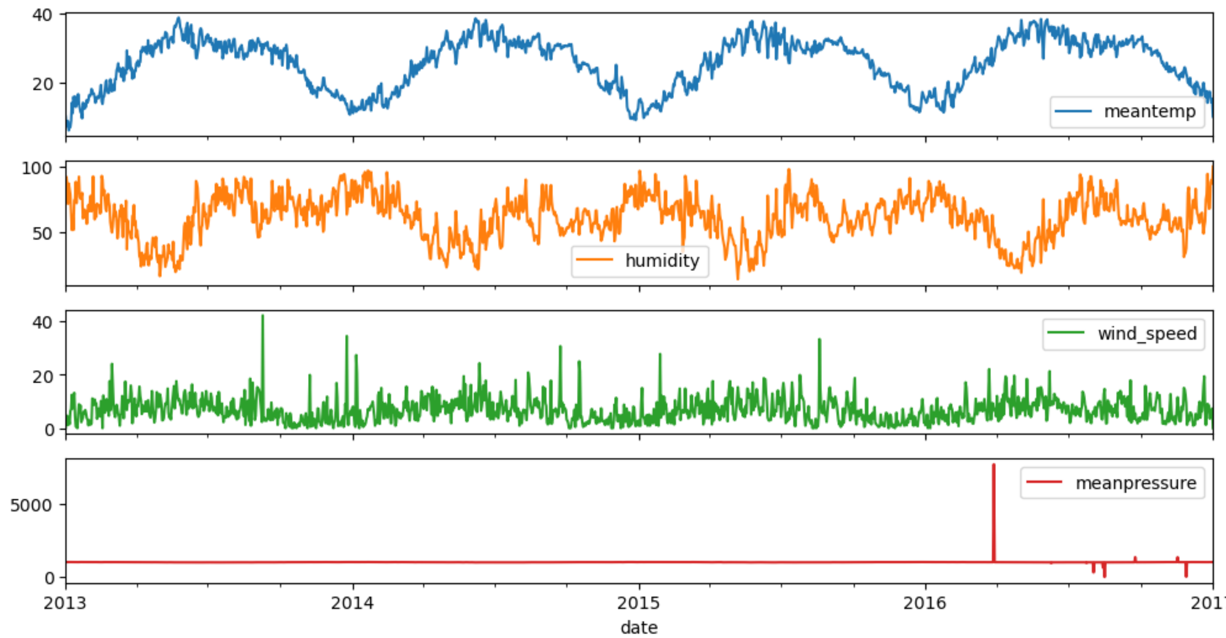
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1462 entries, 0 to 1461
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   date          1462 non-null   datetime64[ns]
 1   meantemp      1462 non-null   float64
 2   humidity  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

Visualize

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



CONCLUSION

1. meantemp :
   - every years starts with low temperature
   - the pattern of the temperature overthime is same
   - there is a high theparatur in mid of the year
2. humidity :
   - whenever the temperature is low in the year the humidity goes on high
   - whenever the temperature is high in the year the humidity goes on low
3. wind_speed :
   - there is a 3 spic in 2013-2014
   - there is a 2 spic in 2014-2015
   - there is a 1 spic in 2015-2016
4. meanpressure :
   - there is no observed value in the years 2013-2016
   - but there is a values that show pressure high in 2016-2017,may be it is error values

Stationarity :

A time series is stationary if its staticals properties (mean , variance , autocorrelation) reamin constant over thime .

Hypothese of the ADF test :

1. null hypothesis (h0) : the time series has a unit root .
2. alternative hypothesis (h1) : the time series does not have a unit root

interpreting ADf test results : p-values in index-1

1. if p-values is less than 0.05 , reject h0 the series is stationary
2. if p-values is greater than 0.05 , fail to reject h0 the series is non -stationary

- avg/mean, variance values are constant over the time
- null(n0)- non stationary , we can find it by using adfuller result ([0]- null, [1]-alternate), if p-values > 0.05 (NST) (not fit for arima)
- Alternate (n1) -statinary, if p-values < 0.05 (ST)

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

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

```
if adf_r[1]< 0.05 : # p-values always at the index of [1]
    print("Stationary")
else :
    print("Non Stationary ")#not fit for arima
```

```
Non Stationary
```

Differencing to remove trend :

```
if the series is non - stationary , apply differencing .
```

(Differencing is a technique used to make a sttionary time series stitioary by removing trend/seasonality)

(convert the non stationary to stationary)

.diff used to find the difference values that make an error/jump

---

temperature - [20,21,22,24,25,27,28,27] , by difference between the elements

difference =[1,1,2,1,2,1,-1]

the new series row function arround [0-2]

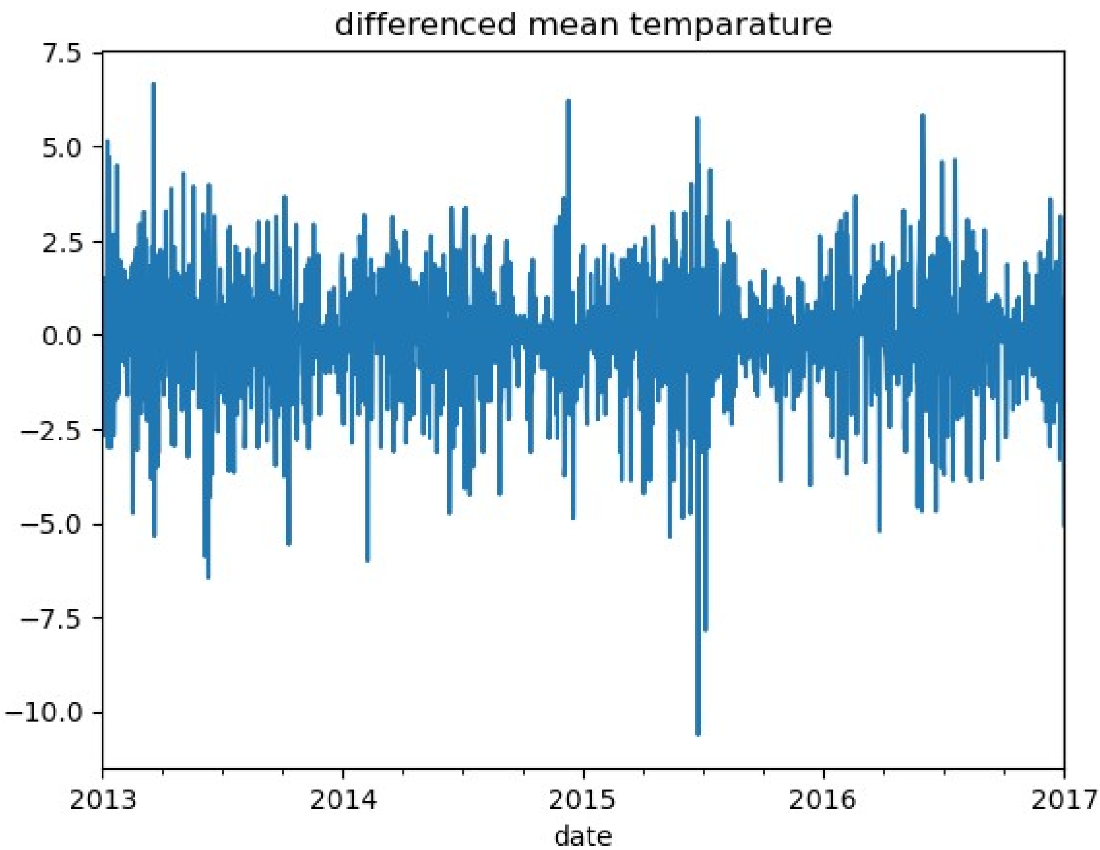
```
df['meandiff']=df['meantemp'].diff()
df.head()
```

date	meantemp	humidity	wind_speed	meanpressure	meandiff
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

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

```
stationary
```

```
df["meandiff"].plot(title="differenced mean temparature")
plt.show()
```



- the data behaves as stationary
- average revolve around zero
- even after differencing there are some extreme weather changes
- there may be a outlier (positive values) in 2014-2015
- by observing there is an negative spic , means low temperature in 2015 -2016 in mid of year

decompositon -used to find the trends

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

- trends - the long term pattern (increase /decrease over the time)
- seasinality - the repeating patteren at fixed intervals (monthly sales spikes)
- residuals (noise) - the random variation that are not explained by trends or seasonality

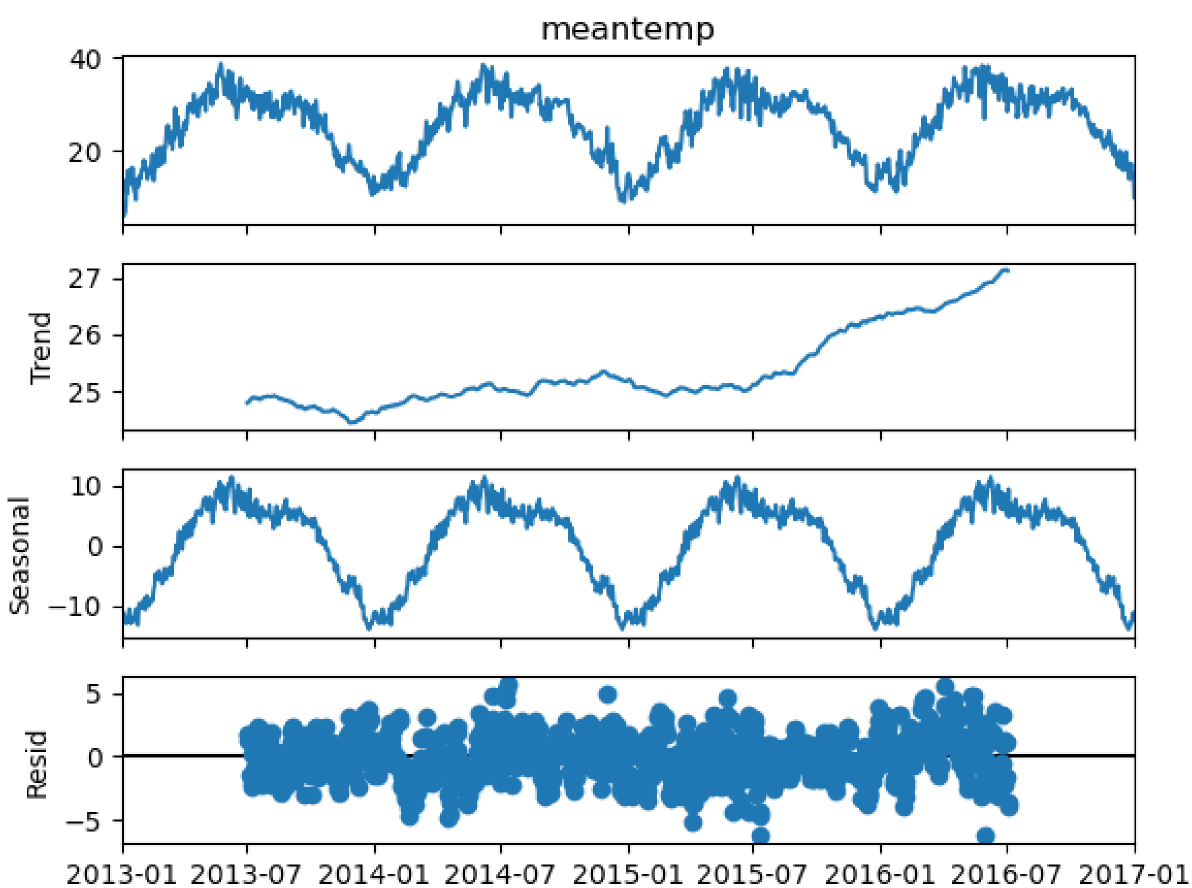
Interpreting tghe output :

- original seriea - the raw time series data
- trend components - the general directior of the data over time(increasing /decrease)
- seasonal component - the repeating patterns (higher sales in december)monthly analysis
- residual component - the remaining part of after removing trend & seasonal

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

```
<statsmodels.tsa.seasonal.DecomposeResult object at
0x0000021926C25D10>
```

```
decom.plot()
plt.show()
```



- Trend : by observing trend there is a rapid increases in the temperatue 26 - 27 from 2015-01 to 2016-07

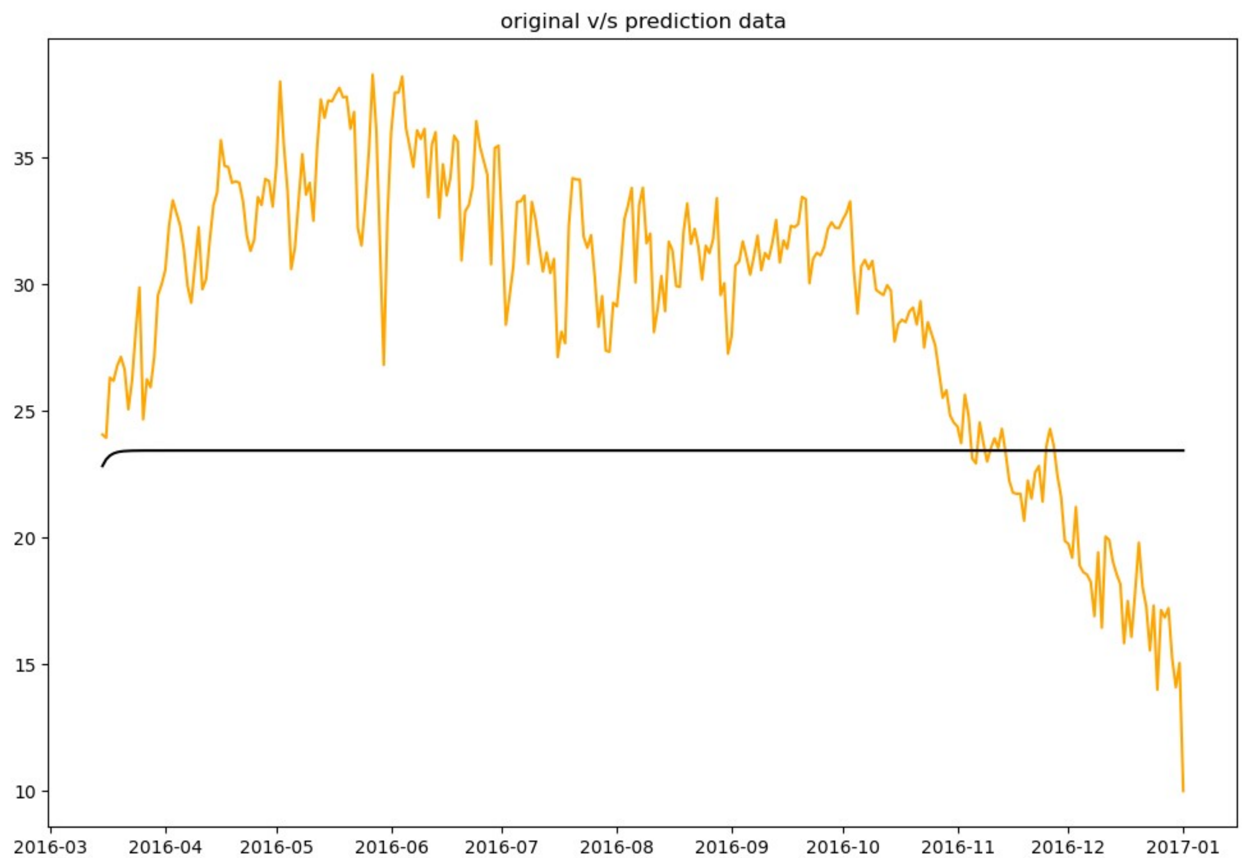
- In seasonal : which maintaince the consistance of the temperature
- In resid : There is an outlier between the 2016-01 to 2016-07

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:\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.head())

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
Freq: D, Name: predicted_mean, dtype: float64


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

C:\Users\DELL\AppData\Local\Temp\ipykernel_5372\3008320720.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
meandiff  \
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")
plt.plot(test.index,test['forecast'],color='k',label="original")
plt.title("original v/s prediction data")
plt.show()
```



ARIMA on difference values :

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

mymodel1=ARIMA(train1['meandiff'],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(test1))
print(forecast1.head())
```

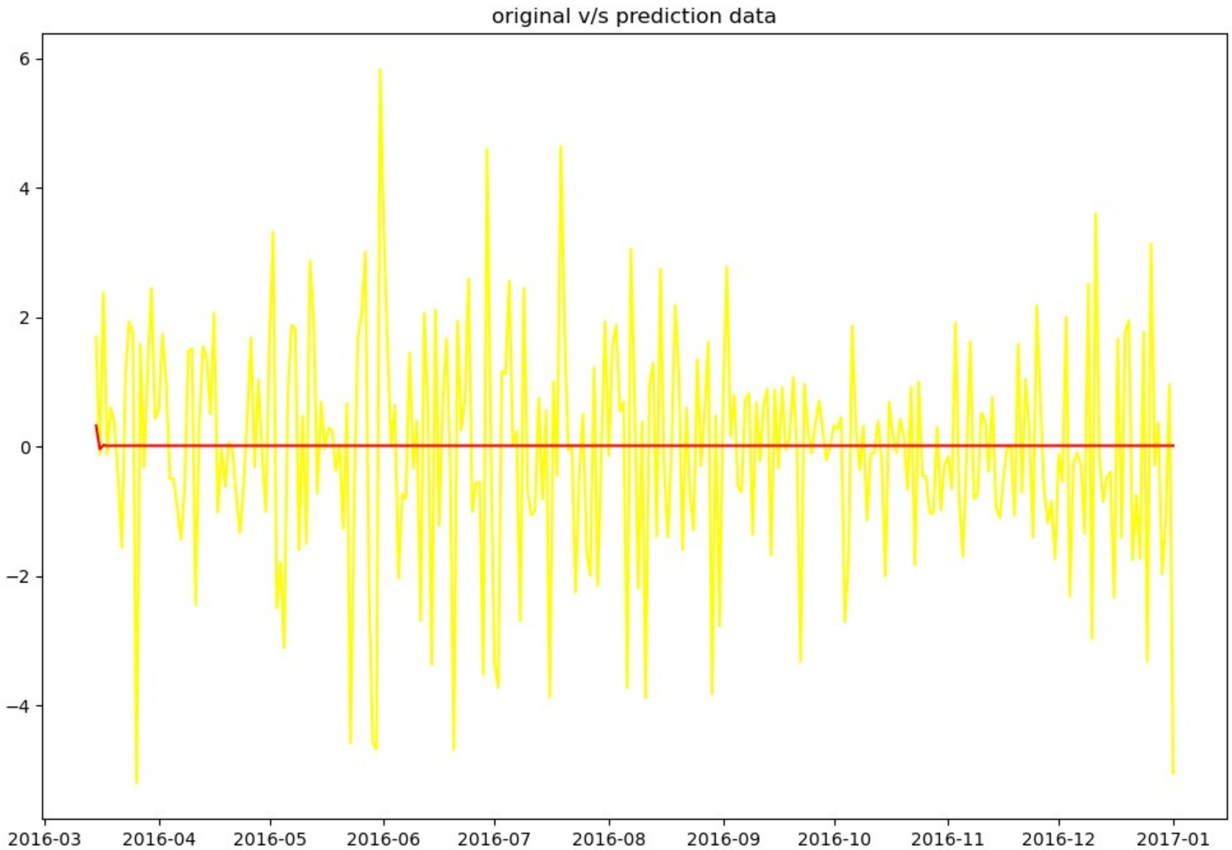
```
2016-03-15    0.322914
2016-03-16   -0.040400
2016-03-17    0.019656
2016-03-18    0.009729
2016-03-19    0.011370
Freq: D, Name: predicted_mean, dtype: float64
```

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

```
C:\Users\DELL\AppData\Local\Temp\ipykernel_5372\4011570898.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_dif']=forecast1
```

```
             meantemp   humidity  wind_speed  meanpressure
meandiff  \
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_dif
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['meandiff'],color='yellow',label="original"
)
plt.plot(test1.index,test1['forecast_dif'],color='red',label="original
")
plt.title("original v/s prediction data")
plt.show()
```



- 15th march , original values =24.066667 , model says there is -0.040438 changes on next day
- 24.066667 - 0.040438 = 24.02 (predicted) ~ 23.9375000(oroginal)