# TIME SERIES ANALYSIS - ENERGY DEMAND


Teesside University MSc Applied Artificial Intelligence

Machine Learning ICA

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## # Data Capture and Initial Analysis

```
# Data wrangling
import pandas as pd
import numpy as np
# Visuals.
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from datetime import datetime
# Machine Learning
from statsmodels.tsa.stattools import adfuller, acf,
grangercausalitytests
from statsmodels.tsa.seasonal import seasonal_decompose

#np.random.seed(3)
```

## Energy Demand Dataset

```
#import pandas to read the raw data csv file to a dataframe
preview_e = pd.read_csv("dataset.csv")

# To understand the number of rows and columns in the dataset
preview_e.shape

(45432, 17)

# Printing the first 5 rows of the dataset
preview_e.head()

                  Unnamed: 0  demand [MW]  solar_actual [MW]  \
0  2017-01-01 00:00:00+01:00     76345.25                0.0
1  2017-01-01 01:00:00+01:00     75437.00                0.0
2  2017-01-01 02:00:00+01:00     73368.25                0.0
3  2017-01-01 03:00:00+01:00     72116.00                0.0
4  2017-01-01 04:00:00+01:00     68593.75                0.0

   solar_forecast [MW]  solar_inferred_capacity [MW]  wind_actual [MW]
\
```

```
0                  NaN                        5756.44           597.50

1                  NaN                        5756.44           597.50

2                  NaN                        5756.44           635.25

3                  NaN                        5756.44           628.50

4                  NaN                        5756.44           608.50


   wind_inferred_capacity [MW]  albedo [%]  cloud_cover [%]  \
0                     10513.95         0.0             2.45   
1                     10513.95         0.0             2.48   
2                     10513.95         0.0             4.62   
3                     10513.95         0.0             6.13   
4                     10513.95         0.0             6.75   

   frozen_precipitation [%]  pressure [Pa]  radiation [W/m2]  \
0                     -3.80       102875.0               0.0   
1                     -3.46       102839.0               0.0   
2                     -5.48       102735.0               0.0   
3                     -6.91       102660.0               0.0   
4                     -7.50       102629.0               0.0   

   air_tmp [Kelvin]  ground_tmp [Kelvin]  apparent_tmp [Kelvin]  \
0            271.60               269.82                 269.84   
1            271.62               269.85                 269.79   
2            271.61               269.93                 269.58   
3            271.60               269.99                 269.44   
4            271.60               270.02                 269.38   

   wind_direction [angle]  wind_speed [m/s]  
0                   209.0              2.97  
1                   212.0              3.13  
2                   218.0              3.25  
3                   218.0              3.37  
4                   219.0              3.42  
```

```python
# Printing the last 5 rows of the dataset
preview_e.tail()
```

```
                      Unnamed: 0  demand [MW]  solar_actual [MW]  \
45427  2022-03-08 19:00:00+01:00     69881.25             170.00   
45428  2022-03-08 20:00:00+01:00     67759.00             166.25   
45429  2022-03-08 21:00:00+01:00     64427.50             169.25   
45430  2022-03-08 22:00:00+01:00     63364.25             165.50   
45431  2022-03-08 23:00:00+01:00     63996.50             168.25   

       solar_forecast [MW]  solar_inferred_capacity [MW]  wind_actual
```

```
[MW]  \
45427             250.16                        11244.01
4149.50
45428             130.32                        11244.01
5012.75
45429             130.32                        11244.01
5223.00
45430             134.79                        11244.01
5200.75
45431             133.64                        11244.01
5013.00

       wind_inferred_capacity [MW]  albedo [%]  cloud_cover [%]  \
45427                     16116.79       15.56            56.09
45428                     16116.79        0.44            55.01
45429                     16116.79        0.44            47.87
45430                     16116.79        0.44            43.63
45431                     16116.79        0.44            40.18

       frozen_precipitation [%]  pressure [Pa]  radiation [W/m2]  \
45427                    -42.02       101826.0            272.42
45428                    -43.17       101896.0              0.00
45429                    -44.17       101954.0              0.00
45430                    -45.54       102006.0              0.00
45431                    -45.92       102044.0              0.00

       air_tmp [Kelvin]  ground_tmp [Kelvin]  apparent_tmp [Kelvin]  \
45427            278.71               277.30                 276.89
45428            278.01               276.74                 276.17
45429            277.60               276.40                 275.72
45430            277.25               276.11                 275.32
45431            276.92               275.77                 274.99

       wind_direction [angle]  wind_speed [m/s]
45427                   175.0              5.08
45428                   172.0              4.90
45429                   173.0              4.80
45430                   179.0              4.68
45431                   182.0              4.57
```

```
# min, max count avg and percentile details of each column
preview_e.describe()
```

```
        demand [MW]  solar_actual [MW]  solar_forecast [MW]  \
count  45429.000000       45413.000000         45210.000000
mean   53521.014699        1286.331384          1278.808883
std    11809.492016        1782.730487          1761.346022
min    29415.000000           0.000000             0.000000
25%    44478.000000           0.000000             0.000000
50%    51757.000000         175.500000           154.450000
```

```
75%    61726.000000        2262.500000          2332.147500
max    94587.250000        8511.750000          7900.170000

       solar_inferred_capacity [MW]  wind_actual [MW]  \
count                  45432.000000      45413.000000
mean                    8255.743000       3614.698500
std                     1616.991295       2708.395258
min                     5756.440000        391.000000
25%                     6864.480000       1583.750000
50%                     7992.890000       2712.750000
75%                     9595.960000       4923.250000
max                    11244.010000      14475.750000

       wind_inferred_capacity [MW]    albedo [%]  cloud_cover [%]  \
count                 45432.000000  45415.000000     45416.000000
mean                  14319.562303     11.157362        55.270664
std                    1850.099922      8.476197        25.879619
min                   10494.090000      0.000000         0.000000
25%                   12256.000000      0.000000        34.760000
50%                   15009.340000     14.750000        57.830000
75%                   15985.940000     17.180000        76.960000
max                   16116.790000     31.550000        99.940000

       frozen_precipitation [%]  pressure [Pa]  radiation [W/m2]  \
count              45422.000000   45421.000000      45416.000000
mean                 -31.497639  101754.855772        160.796661
std                   20.049324     796.112329        220.426850
min                  -50.000000   97862.000000          0.000000
25%                  -47.380000  101346.000000          0.000000
50%                  -38.590000  101790.000000         26.525000
75%                  -21.360000  102219.000000        280.540000
max                   88.290000  104134.000000        916.430000

       air_tmp [Kelvin]  ground_tmp [Kelvin]  apparent_tmp [Kelvin]  \
count      45422.000000         45422.000000           45422.000000
mean         284.324071           284.243751             283.262665
std            6.849745             7.473270               7.857066
min          265.340000           265.250000             259.800000
25%          279.120000           278.600000             277.060000
50%          283.630000           283.385000             283.050000
75%          289.010000           288.970000             288.990000
max          308.000000           310.320000             308.370000

       wind_direction [angle]  wind_speed [m/s]
count            45421.000000      45421.000000
mean               190.253429          5.615327
std                 59.927779          2.156487
min                 50.000000          1.270000
25%                141.000000          4.070000
50%                193.000000          5.220000
```

```
75%                 240.000000         6.720000
max                 325.000000        16.930000
```

```python
# To understand the data types of the column data
preview_e.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45432 entries, 0 to 45431
Data columns (total 17 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   Unnamed: 0                    45432 non-null  object 
 1   demand [MW]                   45429 non-null  float64
 2   solar_actual [MW]             45413 non-null  float64
 3   solar_forecast [MW]           45210 non-null  float64
 4   solar_inferred_capacity [MW]  45432 non-null  float64
 5   wind_actual [MW]              45413 non-null  float64
 6   wind_inferred_capacity [MW]   45432 non-null  float64
 7   albedo [%]                    45415 non-null  float64
 8   cloud_cover [%]               45416 non-null  float64
 9   frozen_precipitation [%]      45422 non-null  float64
 10  pressure [Pa]                 45421 non-null  float64
 11  radiation [W/m2]              45416 non-null  float64
 12  air_tmp [Kelvin]              45422 non-null  float64
 13  ground_tmp [Kelvin]           45422 non-null  float64
 14  apparent_tmp [Kelvin]         45422 non-null  float64
 15  wind_direction [angle]        45421 non-null  float64
 16  wind_speed [m/s]              45421 non-null  float64
dtypes: float64(16), object(1)
memory usage: 5.9+ MB
```

```python
# To view the columns in the dataset
preview_e.columns
```

```
Index(['Unnamed: 0', 'demand [MW]', 'solar_actual [MW]',
'solar_forecast [MW]',
       'solar_inferred_capacity [MW]', 'wind_actual [MW]',
       'wind_inferred_capacity [MW]', 'albedo [%]', 'cloud_cover [%]',
       'frozen_precipitation [%]', 'pressure [Pa]', 'radiation
[W/m2]',
       'air_tmp [Kelvin]', 'ground_tmp [Kelvin]', 'apparent_tmp
[Kelvin]',
       'wind_direction [angle]', 'wind_speed [m/s]'],
      dtype='object')
```

### Column 1: apparent_tmp [Kelvin]']

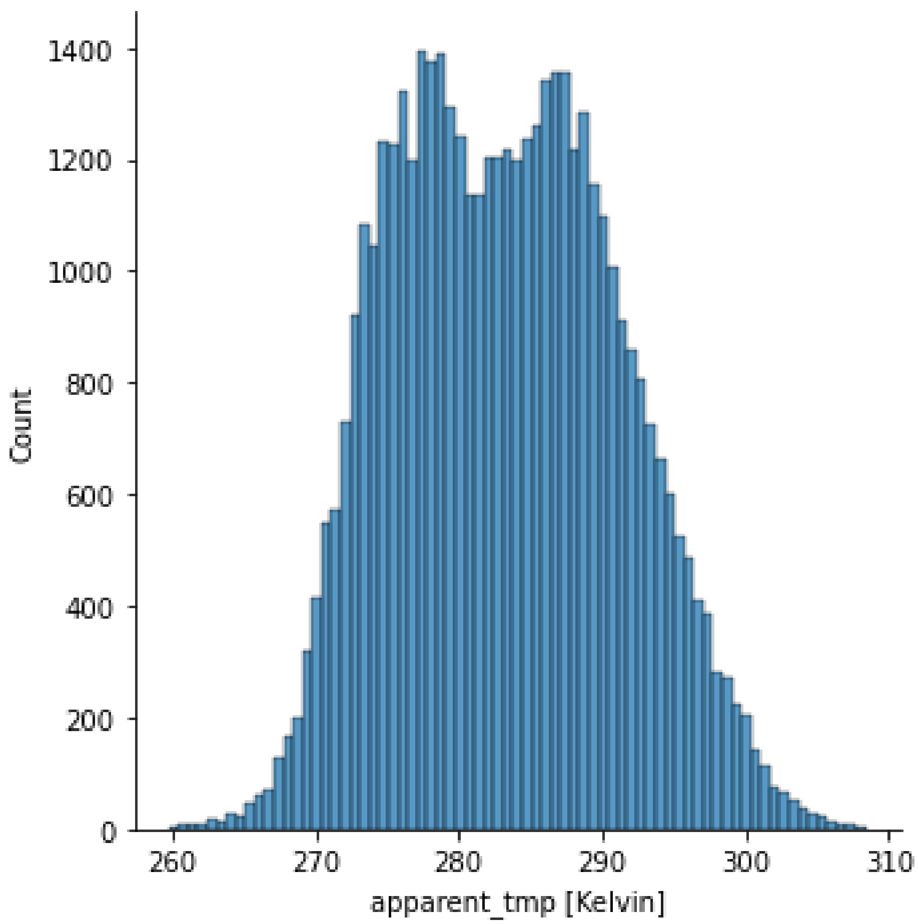
```python
# Analysing apparent_tmp [Kelvin] Column
preview_e['apparent_tmp [Kelvin]'].describe()
```

```
count    45422.000000
mean       283.262665
```

```
std           7.857066
min         259.800000
25%         277.060000
50%         283.050000
75%         288.990000
max         308.370000
Name: apparent_tmp [Kelvin], dtype: float64
```

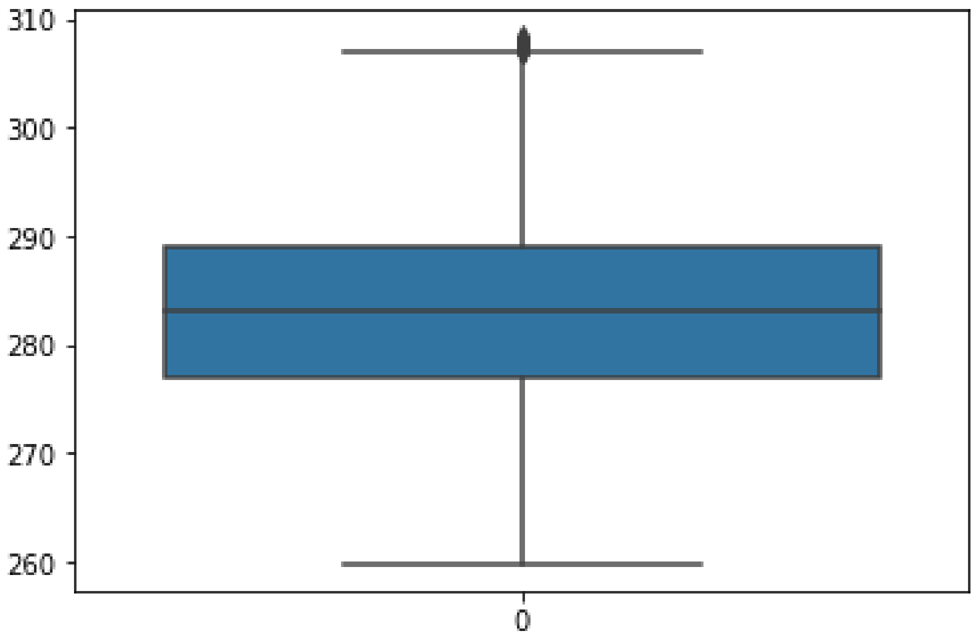
```
# visualising temp distribution
sns.displot(preview_e, x="apparent_tmp [Kelvin]")
```

```
<seaborn.axisgrid.FacetGrid at 0x2514e82d220>
```




```
# boxplot for analysisng outliers if any
sns.boxplot(data=preview_e["apparent_tmp [Kelvin]"])
```

```
<AxesSubplot:>
```



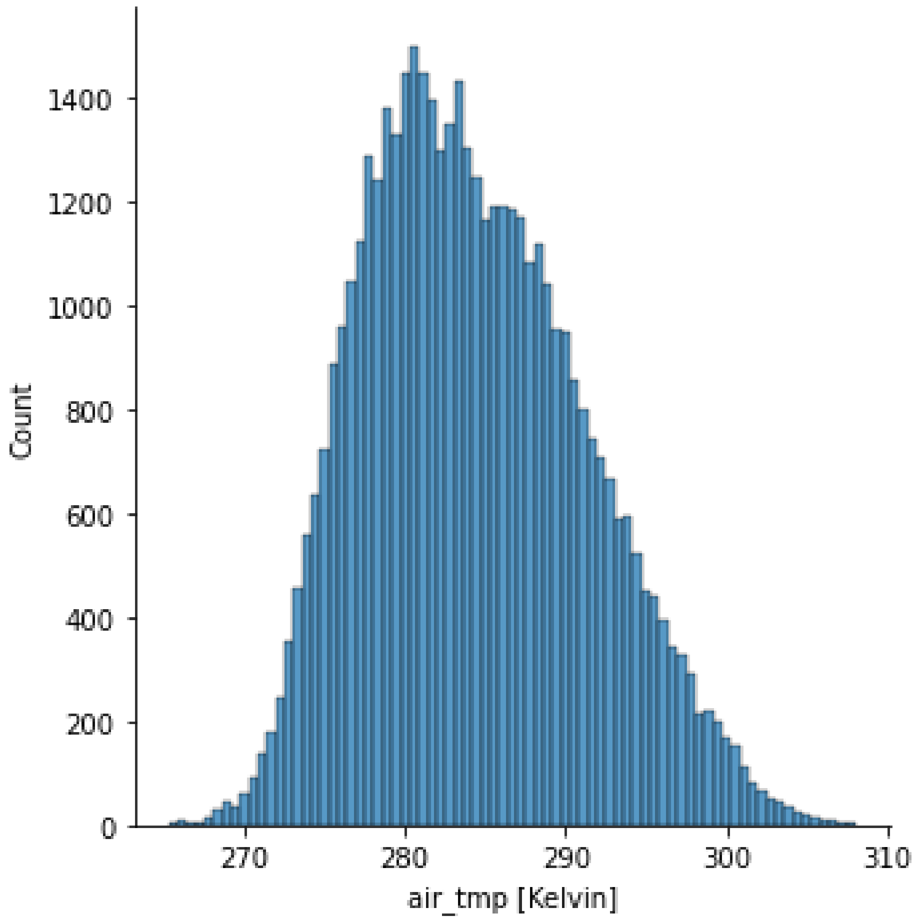

### Column 2: air_tmp [Kelvin]

```
# Analysing air_tmp [Kelvin] Column
preview_e['air_tmp [Kelvin]'].describe()
```

```
count    45422.000000
mean       284.324071
std          6.849745
min        265.340000
25%        279.120000
50%        283.630000
75%        289.010000
max        308.000000
Name: air_tmp [Kelvin], dtype: float64
```

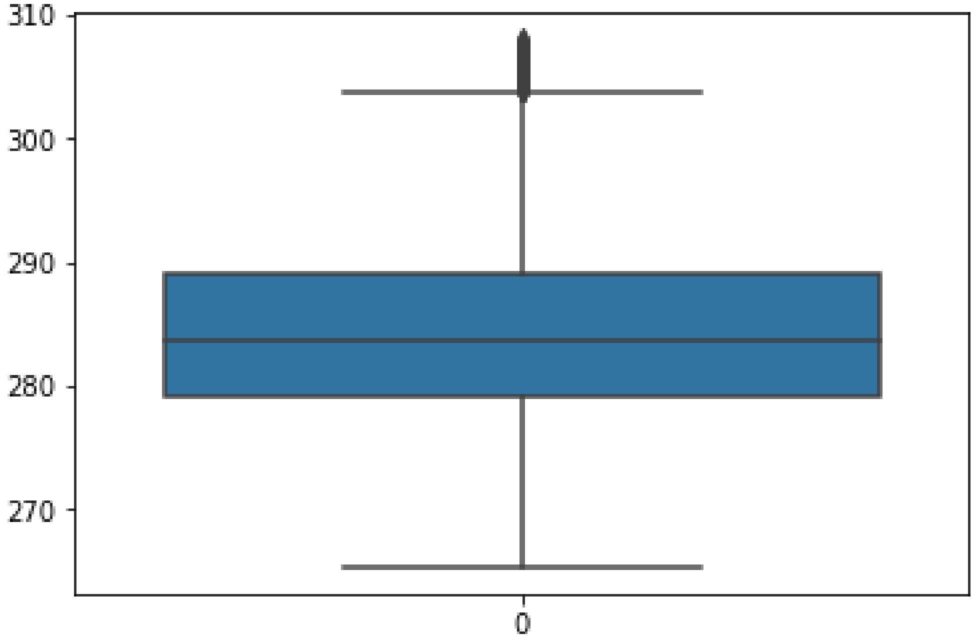
```
# visualising temp distribution
sns.displot(preview_e, x="air_tmp [Kelvin]")
```

```
<seaborn.axisgrid.FacetGrid at 0x2514f195430>
```




```python
# boxplot for analysisng outliers if any
sns.boxplot(data=preview_e["air_tmp [Kelvin]"])
```

```
<AxesSubplot:>
```



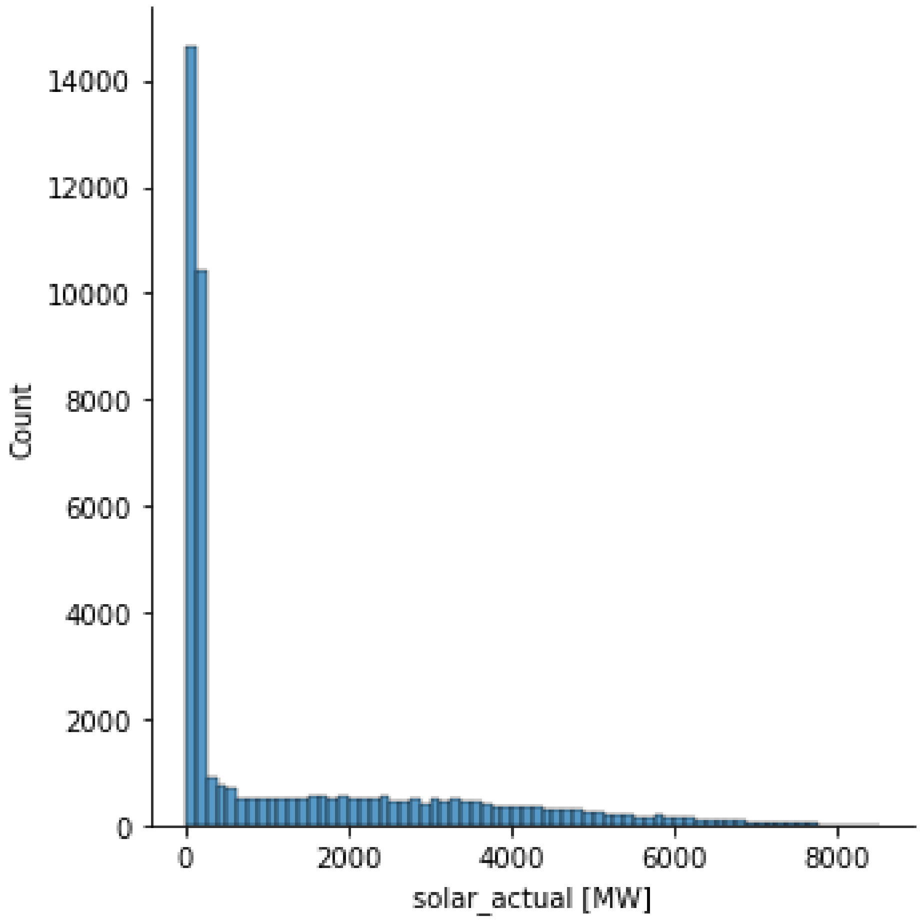

**Column 3 : solar_actual [MW]**

```
# Analysing solar_actual [MW] Column
preview_e['solar_actual [MW]'].describe()
```

```
count    45413.000000
mean      1286.331384
std       1782.730487
min          0.000000
25%          0.000000
50%        175.500000
75%       2262.500000
max       8511.750000
Name: solar_actual [MW], dtype: float64
```

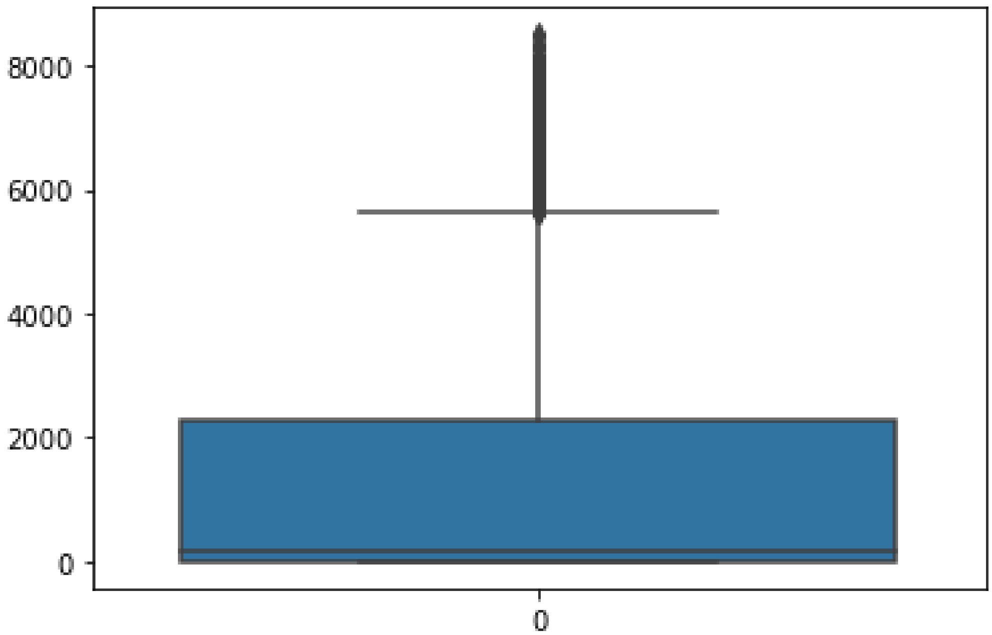
```
# visualising solar_actual [MW] distribution
sns.displot(preview_e, x="solar_actual [MW]")
```

```
<seaborn.axisgrid.FacetGrid at 0x2514f1e48e0>
```




```
# boxplot for analysisng outliers if any
sns.boxplot(data=preview_e["solar_actual [MW]"])
```

<AxesSubplot:>



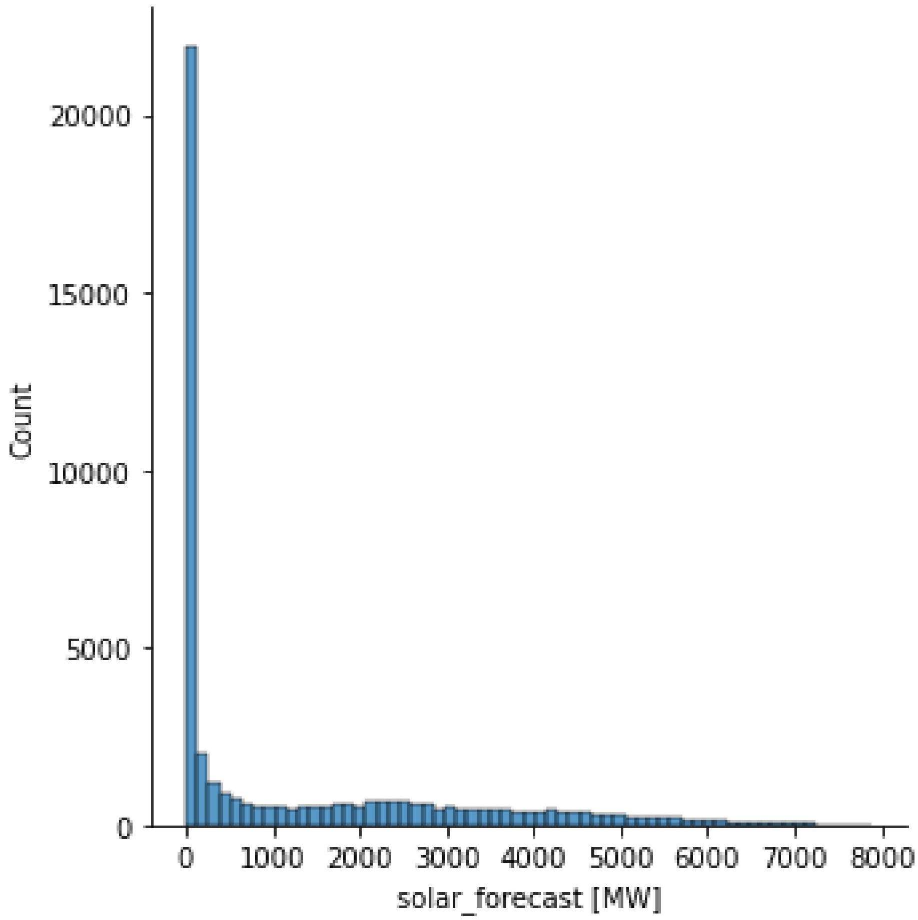

### Column 4 : solar_forecast [MW]

```
# Analysing  solar_forecast [MW] Column
preview_e['solar_forecast [MW]'].describe()
```

```
count    45210.000000
mean      1278.808883
std       1761.346022
min          0.000000
25%          0.000000
50%        154.450000
75%       2332.147500
max       7900.170000
Name: solar_forecast [MW], dtype: float64
```

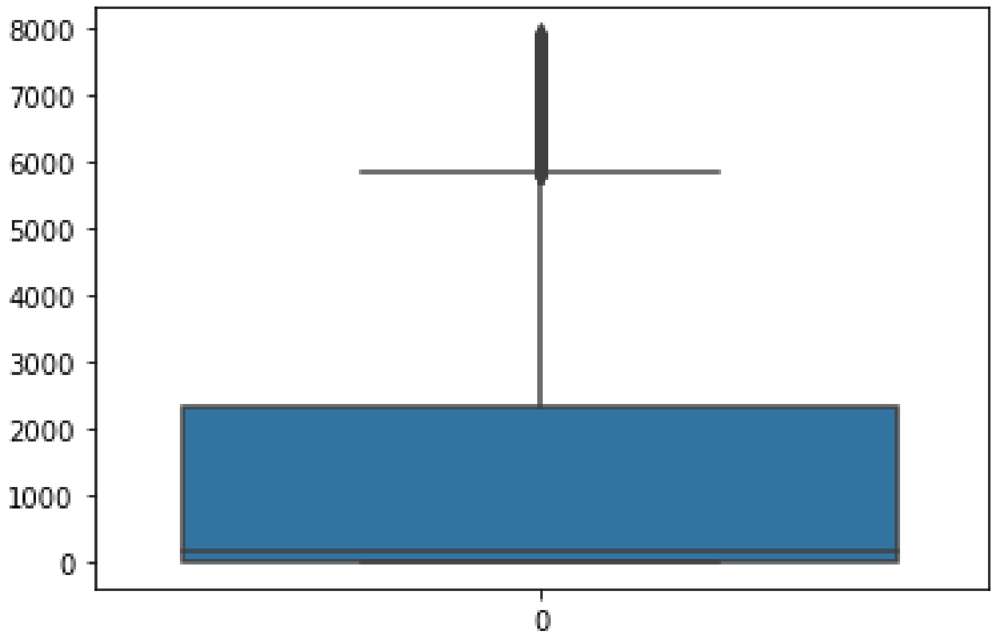
```
# visualising solar_actual [MW] distribution
sns.displot(preview_e, x="solar_forecast [MW]")
```

```
<seaborn.axisgrid.FacetGrid at 0x2514f1bf880>
```




```
#boxplot for analysisng outliers if any
sns.boxplot(data=preview_e["solar_forecast [MW]"])
```

```
<AxesSubplot:>
```



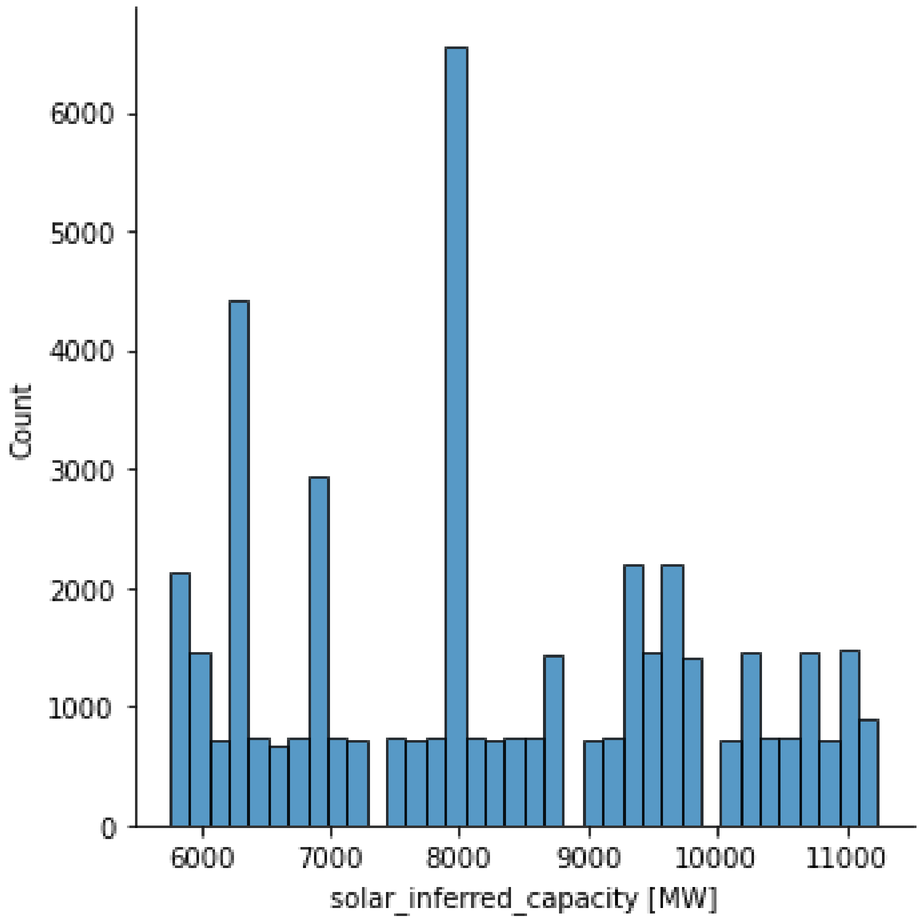

### Column 5 : solar_inferred_capacity [MW]

```
 # Analysing  solar_forecast [MW] [MW] Column
preview_e['solar_inferred_capacity [MW]'].describe()
```

```
count    45432.000000
mean      8255.743000
std       1616.991295
min       5756.440000
25%       6864.480000
50%       7992.890000
75%       9595.960000
max      11244.010000
Name: solar_inferred_capacity [MW], dtype: float64
```

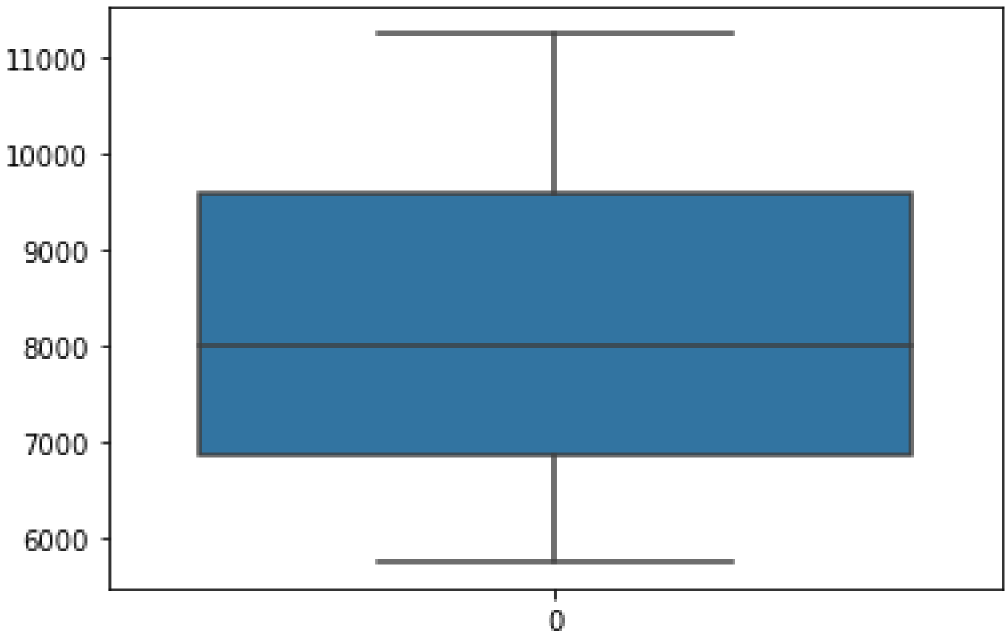
```
# visualising solar_inferred_capacity [MW]distribution
sns.displot(preview_e, x="solar_inferred_capacity [MW]")
```

```
<seaborn.axisgrid.FacetGrid at 0x2514f94d460>
```




```
#boxplot for analysisng outliers if any
sns.boxplot(data=preview_e["solar_inferred_capacity [MW]"])
```

<AxesSubplot:>



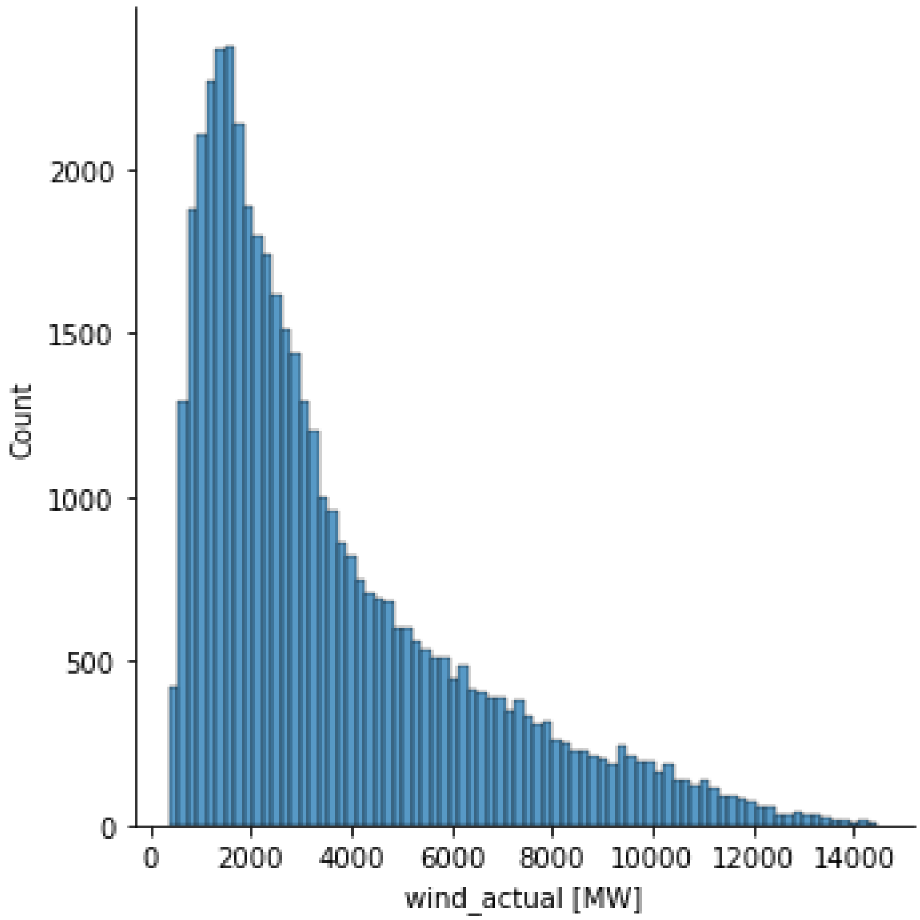

### Column 6 : wind_actual [MW]

```
 # Analysing  wind_actual [MW] Column
preview_e['wind_actual [MW]'].describe()
```

```
count    45413.000000
mean      3614.698500
std       2708.395258
min        391.000000
25%       1583.750000
50%       2712.750000
75%       4923.250000
max      14475.750000
Name: wind_actual [MW], dtype: float64
```

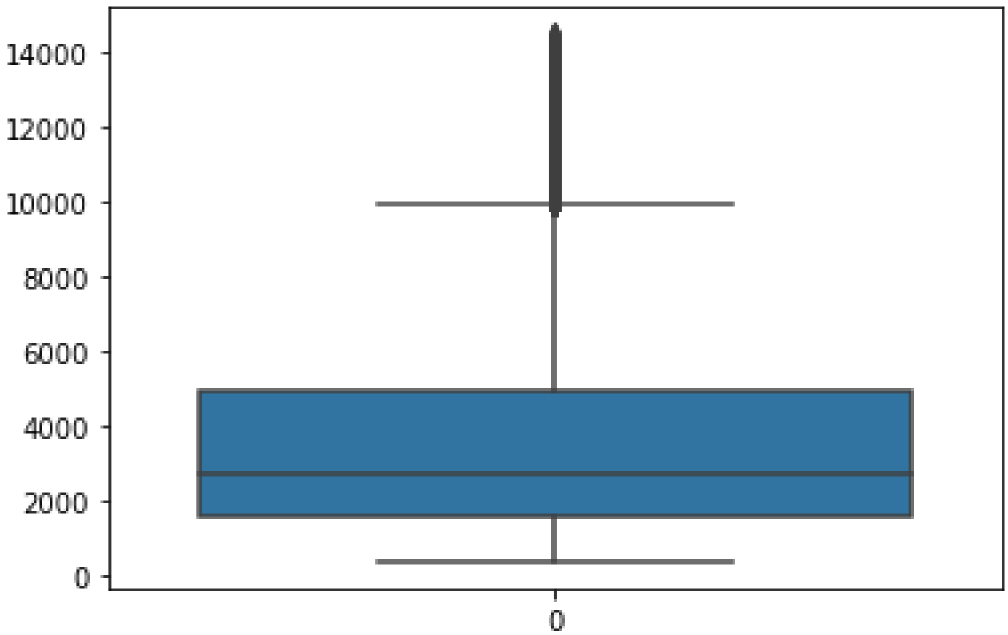
```
# visualising wind_actual [MW] distribution
sns.displot(preview_e, x="wind_actual [MW]")
```

```
<seaborn.axisgrid.FacetGrid at 0x2514ed55e20>
```




```
#boxplot for analysisng outliers if any
sns.boxplot(data=preview_e["wind_actual [MW]"])
```

```
<AxesSubplot:>
```



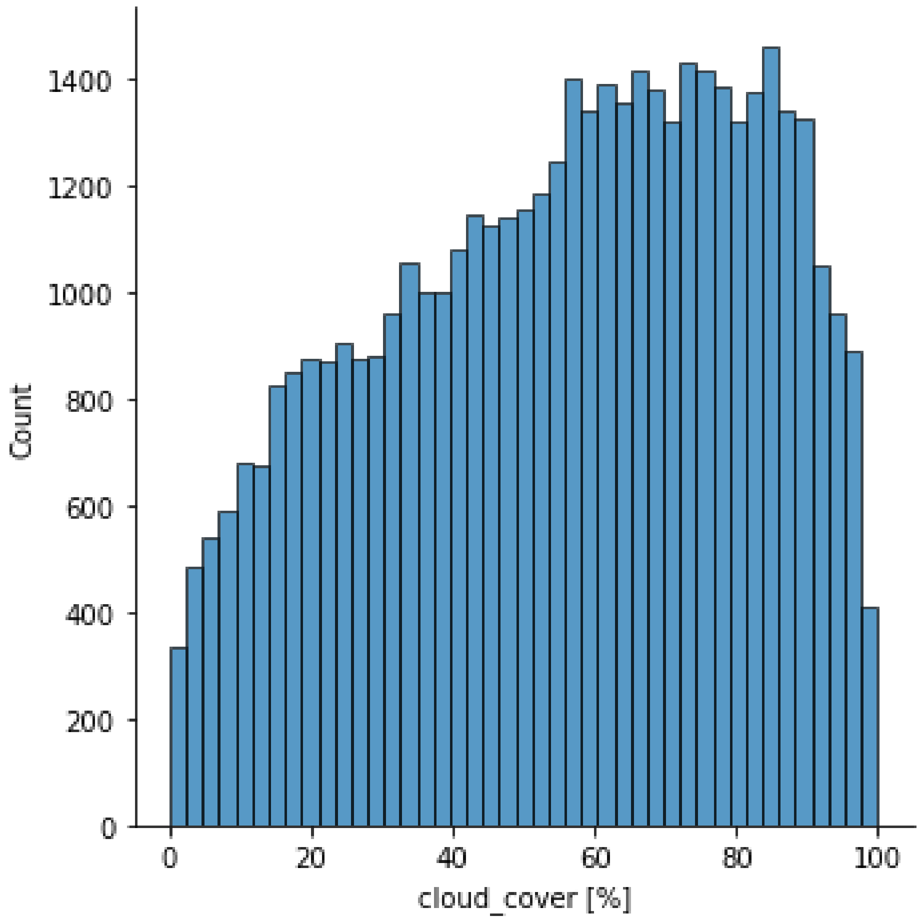

### Column 7 : cloud_cover [%]

```
# Analysing  wind_actual [MW] Column
preview_e['cloud_cover [%]'].describe()
```

```
count    45416.000000
mean        55.270664
std         25.879619
min          0.000000
25%         34.760000
50%         57.830000
75%         76.960000
max         99.940000
Name: cloud_cover [%], dtype: float64
```

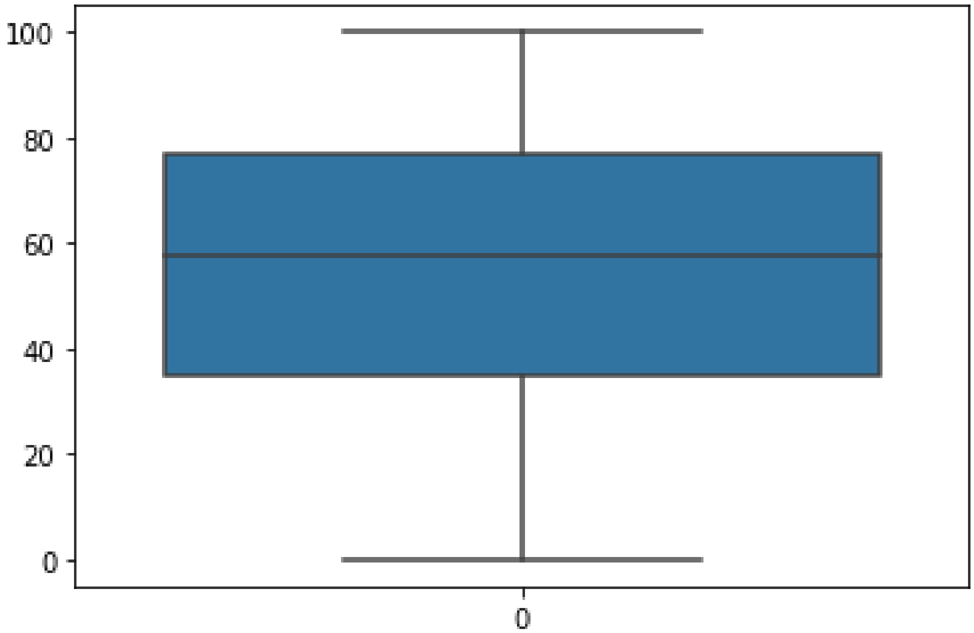
```
# visualising cloud_cover [%] distribution
sns.displot(preview_e, x="cloud_cover [%]")
```

```
<seaborn.axisgrid.FacetGrid at 0x25150e62a90>
```




```
#boxplot for analysisng outliers if any
sns.boxplot(data=preview_e["cloud_cover [%]"])
```

```
<AxesSubplot:>
```



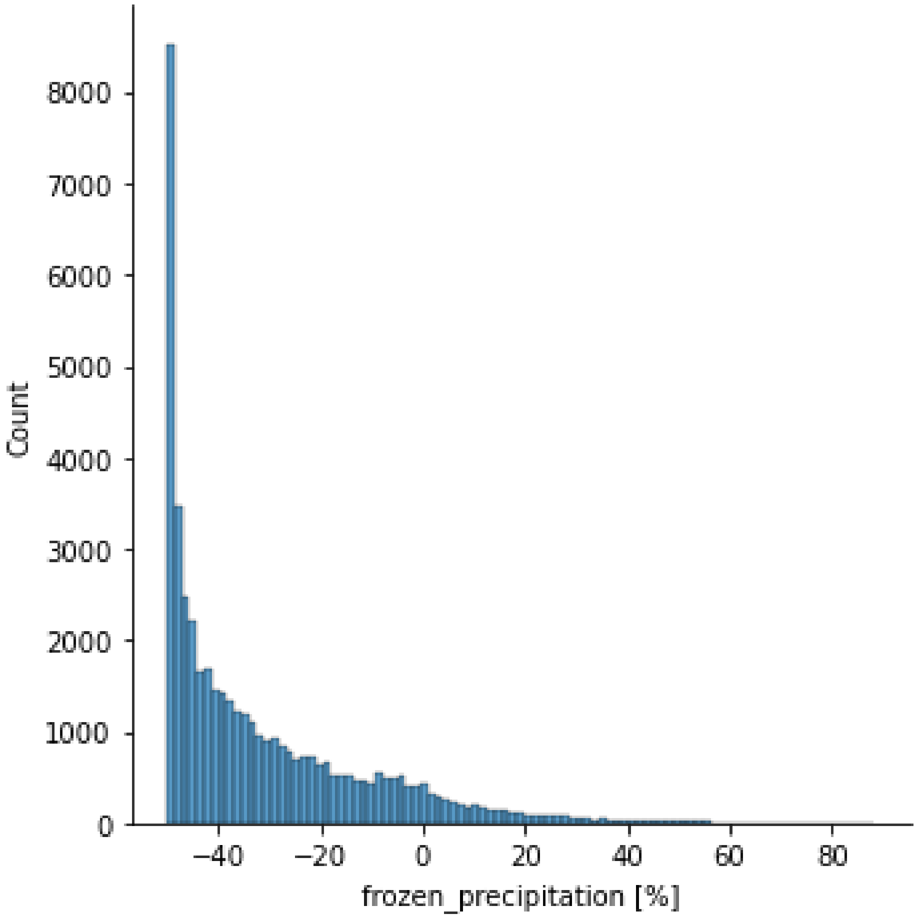

### Column 8 : frozen_precipitation [%]

```
# Analysing  frozen_precipitation [%] Column
preview_e['frozen_precipitation [%]'].describe()
```

```
count    45422.000000
mean       -31.497639
std         20.049324
min        -50.000000
25%        -47.380000
50%        -38.590000
75%        -21.360000
max         88.290000
Name: frozen_precipitation [%], dtype: float64
```

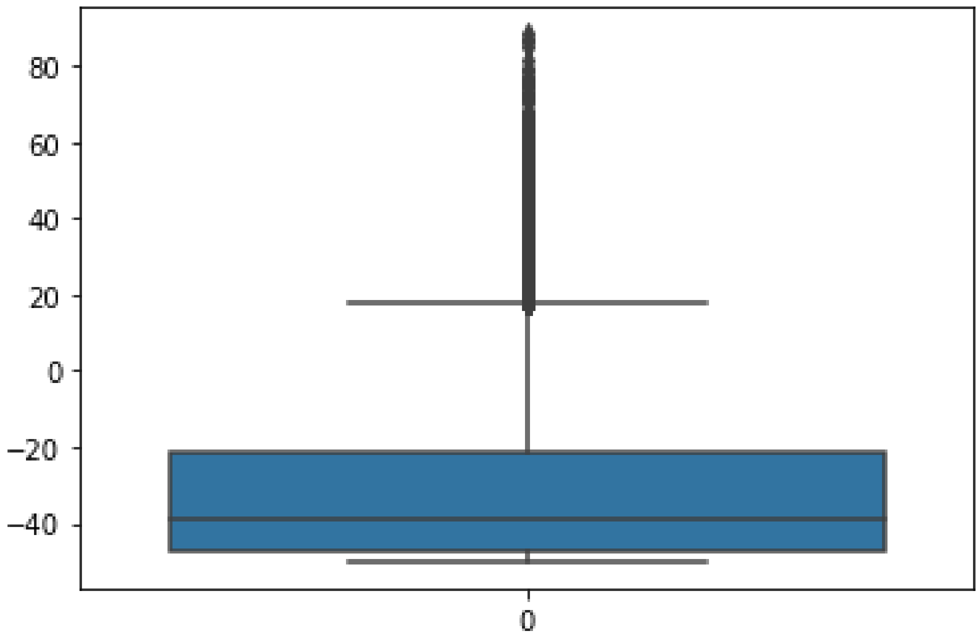
```
# visualising frozen_precipitation [%] distribution
sns.displot(preview_e, x="frozen_precipitation [%]")
```

```
<seaborn.axisgrid.FacetGrid at 0x2514fb81d60>
```




```
#boxplot for analysisng outliers if any
sns.boxplot(data=preview_e["frozen_precipitation [%]"])
```

```
<AxesSubplot:>
```



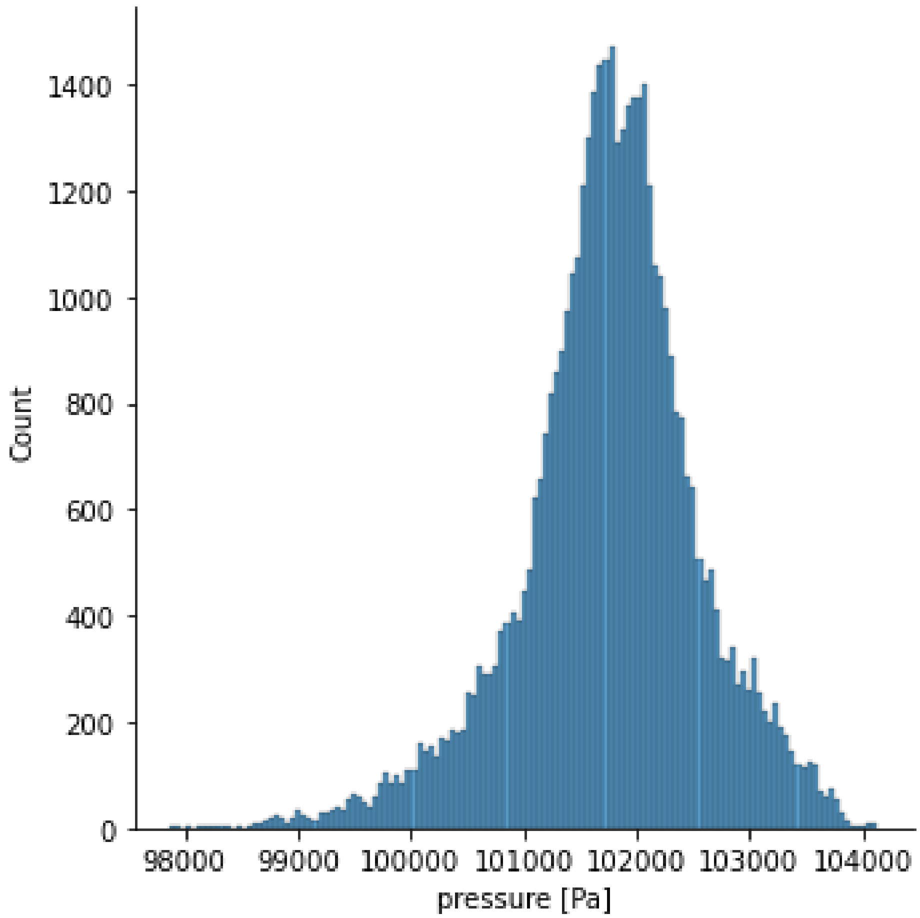

### Column 9 : pressure [Pa]

```
# Analysing  pressure [Pa] Column
preview_e['pressure [Pa]'].describe()
```

```
count     45421.000000
mean     101754.855772
std         796.112329
min       97862.000000
25%      101346.000000
50%      101790.000000
75%      102219.000000
max      104134.000000
Name: pressure [Pa], dtype: float64
```

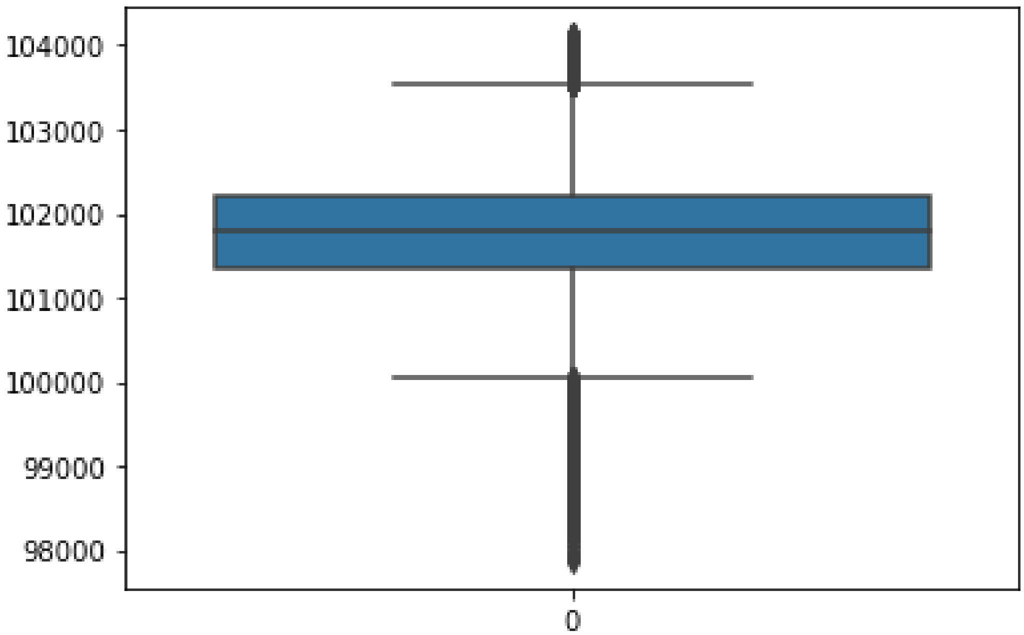
```
# visualising frozen_precipitation [%] distribution
sns.displot(preview_e, x="pressure [Pa]")
```

```
<seaborn.axisgrid.FacetGrid at 0x25151144610>
```




```
# boxplot for analysisng outliers if any
sns.boxplot(data=preview_e['pressure [Pa]'])
```

```
<AxesSubplot:>
```



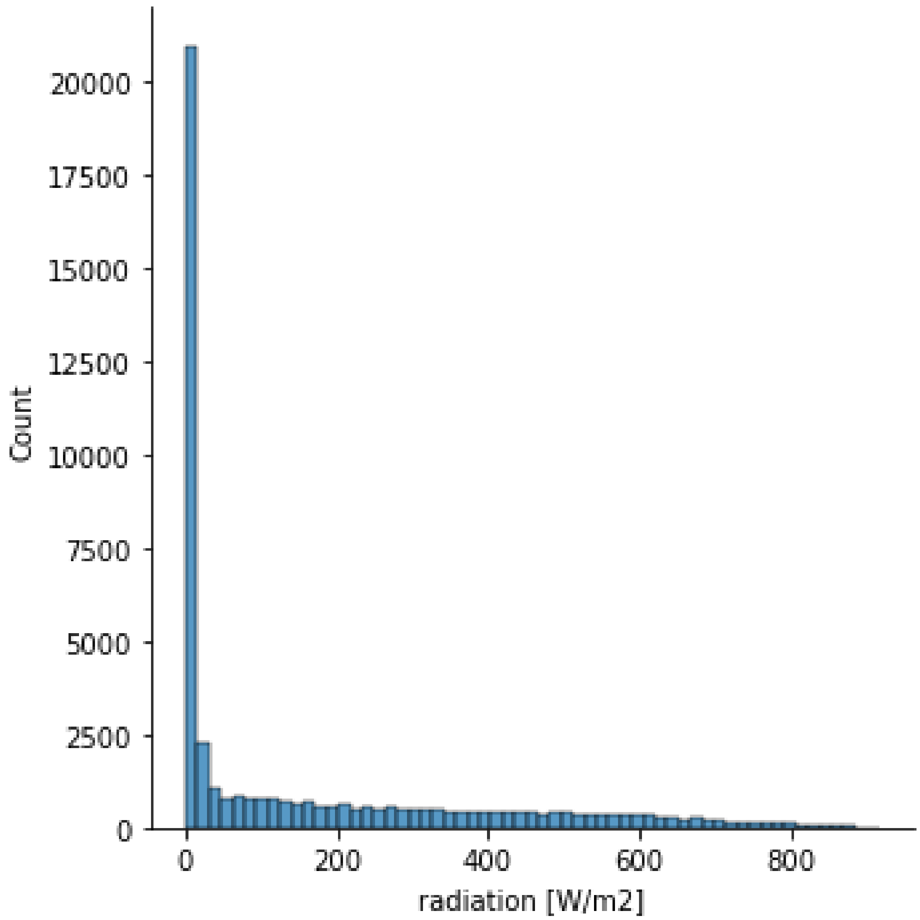

### Column 10 : radiation [W/m2]

```
# Analysing radiation [W/m2] Column
preview_e["radiation [W/m2]"].describe()
```

```
count    45416.000000
mean       160.796661
std        220.426850
min          0.000000
25%          0.000000
50%         26.525000
75%        280.540000
max        916.430000
Name: radiation [W/m2], dtype: float64
```

```
# visualising radiation [W/m2] distribution
sns.displot(preview_e, x="radiation [W/m2]")
```

```
<seaborn.axisgrid.FacetGrid at 0x25151379580>
```



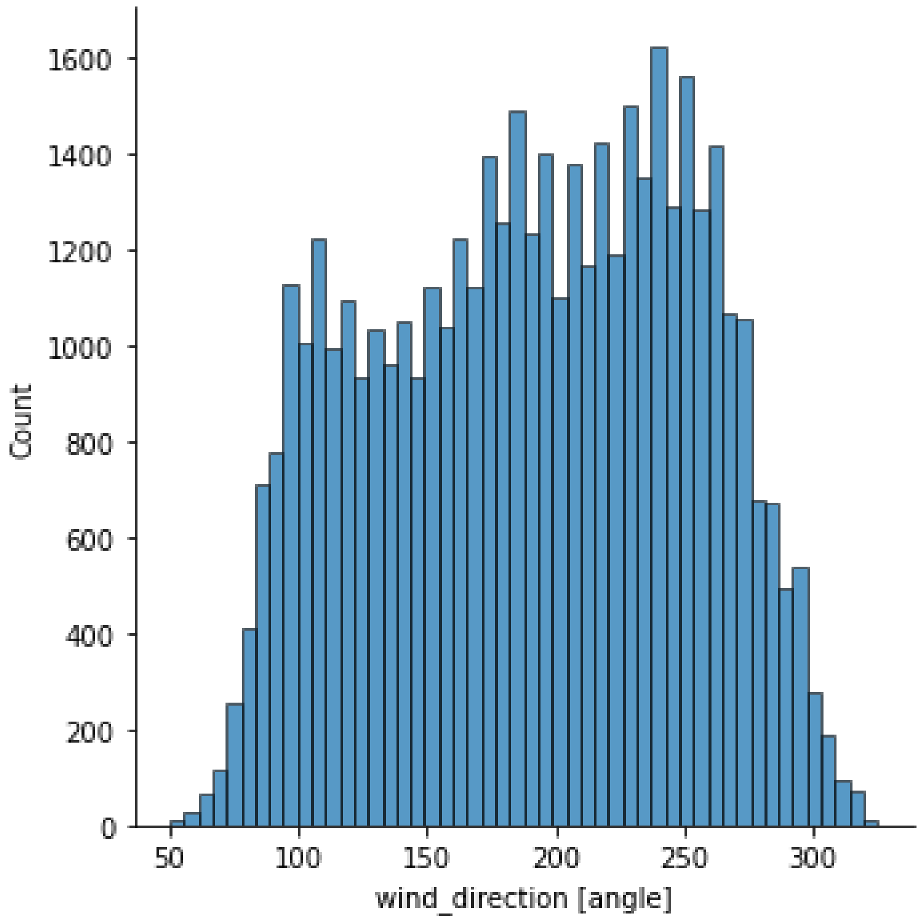

### Column 11 : wind_direction [angle]

```
# Analysing wind_direction [angle] Column
preview_e["wind_direction [angle]"].describe()
```

```
count    45421.000000
mean       190.253429
std         59.927779
min         50.000000
25%        141.000000
50%        193.000000
75%        240.000000
max        325.000000
Name: wind_direction [angle], dtype: float64
```

```
# visualising wind_direction [angle] distribution
sns.displot(preview_e, x="wind_direction [angle]")
```

```
<seaborn.axisgrid.FacetGrid at 0x25152440a30>
```



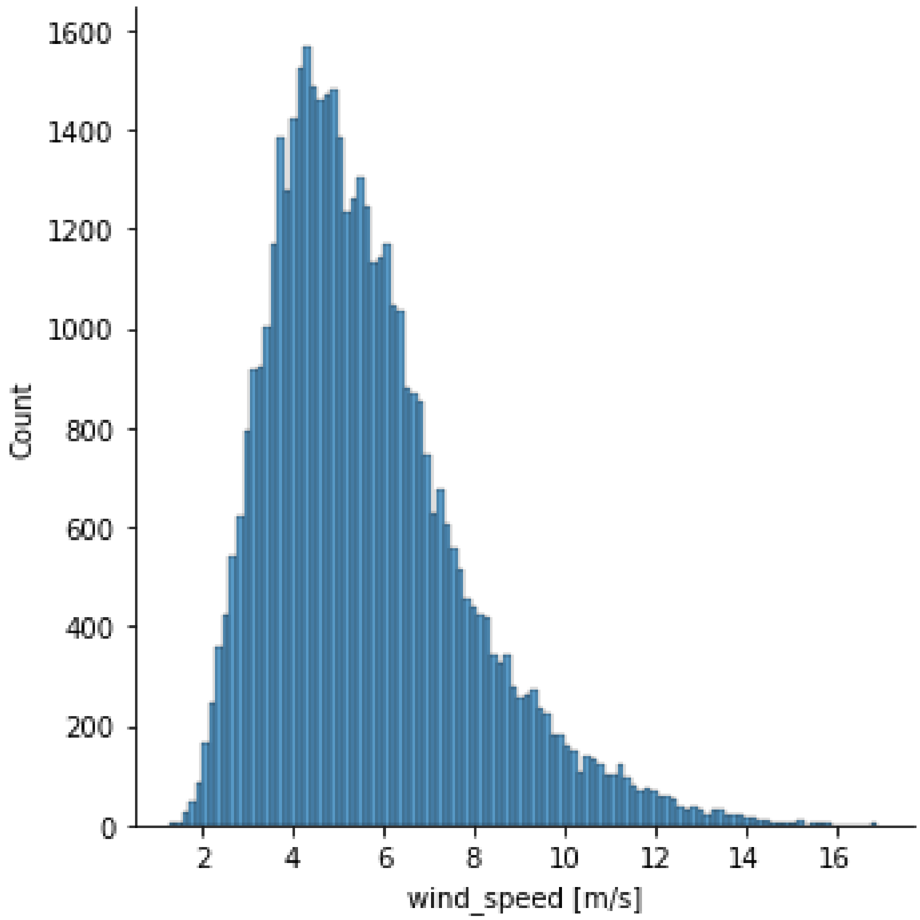

### Column 12 : wind_speed [m/s]

```
# Analysing wind_direction [angle] Column
preview_e["wind_speed [m/s]"].describe()
```

```
count    45421.000000
mean         5.615327
std          2.156487
min          1.270000
25%          4.070000
50%          5.220000
75%          6.720000
max         16.930000
Name: wind_speed [m/s], dtype: float64
```

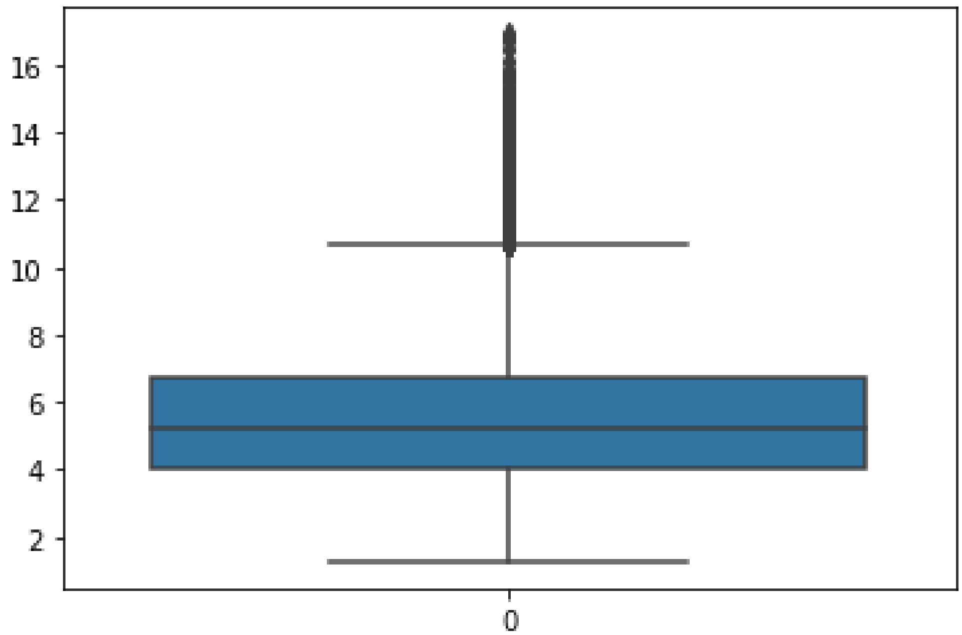
```
# visualising wind_direction [angle] distribution
sns.displot(preview_e, x="wind_speed [m/s]")
```

```
<seaborn.axisgrid.FacetGrid at 0x251524a6b80>
```




```
#boxplot for analysisng outliers if any
sns.boxplot(data=preview_e["wind_speed [m/s]"])
```

```
<AxesSubplot:>
```




### Column 13 : Date and Time

```
# Renaming Unamed column to Date
preview_e.rename(columns = {'Unnamed: 0':'date'}, inplace = True)

preview_e.head()

                        date  demand [MW]  solar_actual [MW]  \
0  2017-01-01 00:00:00+01:00     76345.25                0.0
1  2017-01-01 01:00:00+01:00     75437.00                0.0
2  2017-01-01 02:00:00+01:00     73368.25                0.0
3  2017-01-01 03:00:00+01:00     72116.00                0.0
4  2017-01-01 04:00:00+01:00     68593.75                0.0

   solar_forecast [MW]  solar_inferred_capacity [MW]  wind_actual [MW]
\
0                  NaN                       5756.44            597.50

1                  NaN                       5756.44            597.50

2                  NaN                       5756.44            635.25

3                  NaN                       5756.44            628.50

4                  NaN                       5756.44            608.50


   wind_inferred_capacity [MW]  albedo [%]  cloud_cover [%]  \
0                     10513.95         0.0             2.45
1                     10513.95         0.0             2.48
```

```
2                    10513.95        0.0             4.62
3                    10513.95        0.0             6.13
4                    10513.95        0.0             6.75

   frozen_precipitation [%]  pressure [Pa]  radiation [W/m2]  \
0                     -3.80       102875.0               0.0
1                     -3.46       102839.0               0.0
2                     -5.48       102735.0               0.0
3                     -6.91       102660.0               0.0
4                     -7.50       102629.0               0.0

   air_tmp [Kelvin]  ground_tmp [Kelvin]  apparent_tmp [Kelvin]  \
0            271.60               269.82                 269.84
1            271.62               269.85                 269.79
2            271.61               269.93                 269.58
3            271.60               269.99                 269.44
4            271.60               270.02                 269.38

   wind_direction [angle]  wind_speed [m/s]
0                   209.0              2.97
1                   212.0              3.13
2                   218.0              3.25
3                   218.0              3.37
4                   219.0              3.42
```

```
preview_e.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45432 entries, 0 to 45431
Data columns (total 17 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   date                          45432 non-null  object
 1   demand [MW]                   45429 non-null  float64
 2   solar_actual [MW]             45413 non-null  float64
 3   solar_forecast [MW]           45210 non-null  float64
 4   solar_inferred_capacity [MW]  45432 non-null  float64
 5   wind_actual [MW]              45413 non-null  float64
 6   wind_inferred_capacity [MW]   45432 non-null  float64
 7   albedo [%]                    45415 non-null  float64
 8   cloud_cover [%]               45416 non-null  float64
 9   frozen_precipitation [%]      45422 non-null  float64
 10  pressure [Pa]                 45421 non-null  float64
 11  radiation [W/m2]              45416 non-null  float64
 12  air_tmp [Kelvin]              45422 non-null  float64
 13  ground_tmp [Kelvin]           45422 non-null  float64
 14  apparent_tmp [Kelvin]         45422 non-null  float64
 15  wind_direction [angle]        45421 non-null  float64
 16  wind_speed [m/s]              45421 non-null  float64
```

```
dtypes: float64(16), object(1)
memory usage: 5.9+ MB
```

```python
# min date recorded in the dataset
preview_e.date.min()
```

```
'2017-01-01 00:00:00+01:00'
```

```python
#max date recorded in the dataset
preview_e.date.max()
```

```
'2022-03-08 23:00:00+01:00'
```

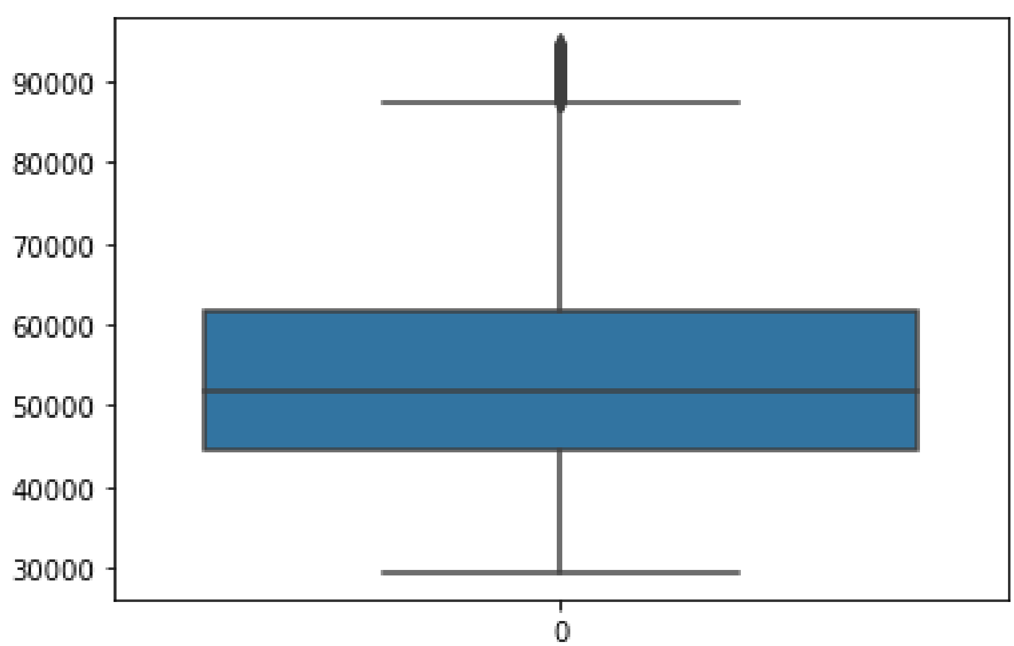
### Column 14 : demand [MW]

```python
# Analysing demand [MW] Column
preview_e["demand [MW]"].describe()
```

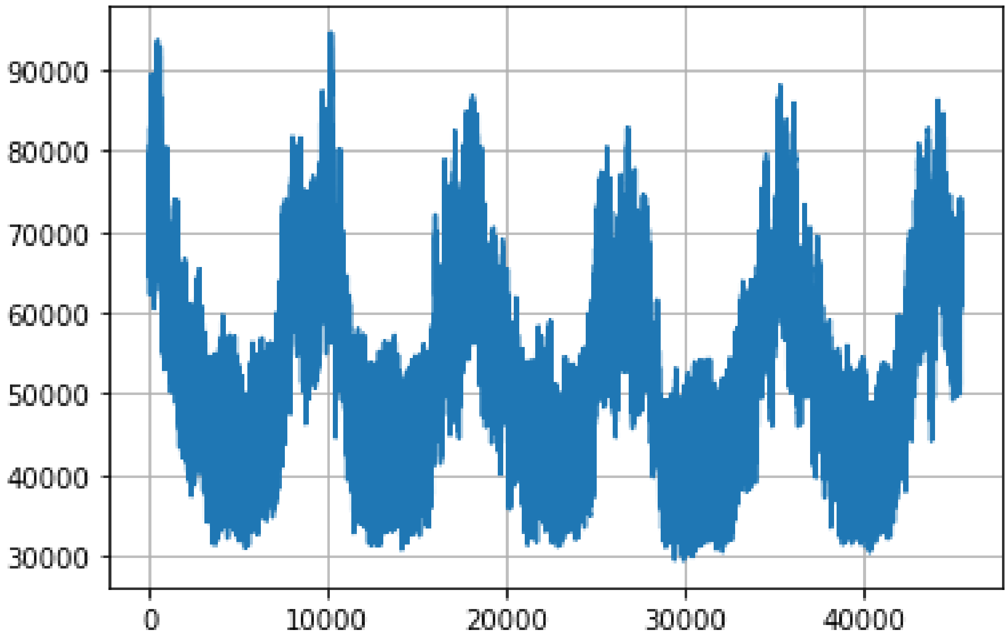
```
count    45429.000000
mean     53521.014699
std      11809.492016
min      29415.000000
25%      44478.000000
50%      51757.000000
75%      61726.000000
max      94587.250000
Name: demand [MW], dtype: float64
```

```python
#boxplot for analysisng outliers if any
sns.boxplot(data=preview_e["demand [MW]"])
```

```
<AxesSubplot:>
```



```
preview_e['demand [MW]'].plot(grid=True)
plt.show()
```



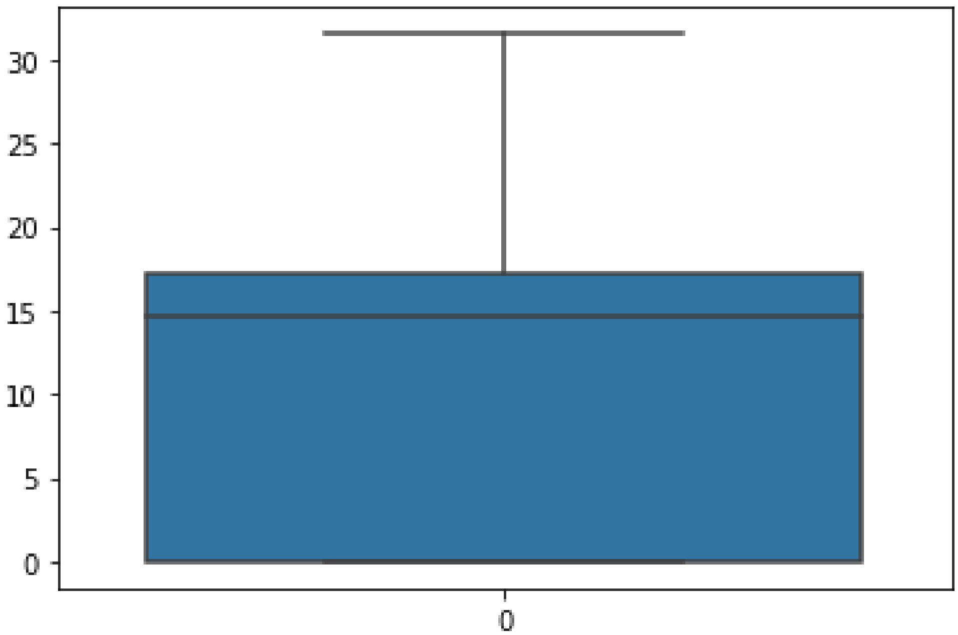

### Column 15 : albedo [%]

```
# Analysing albedo [%]] Column
preview_e["albedo [%]"].describe()
```

```
count    45415.000000
mean        11.157362
std          8.476197
min          0.000000
25%          0.000000
50%         14.750000
75%         17.180000
max         31.550000
Name: albedo [%], dtype: float64
```

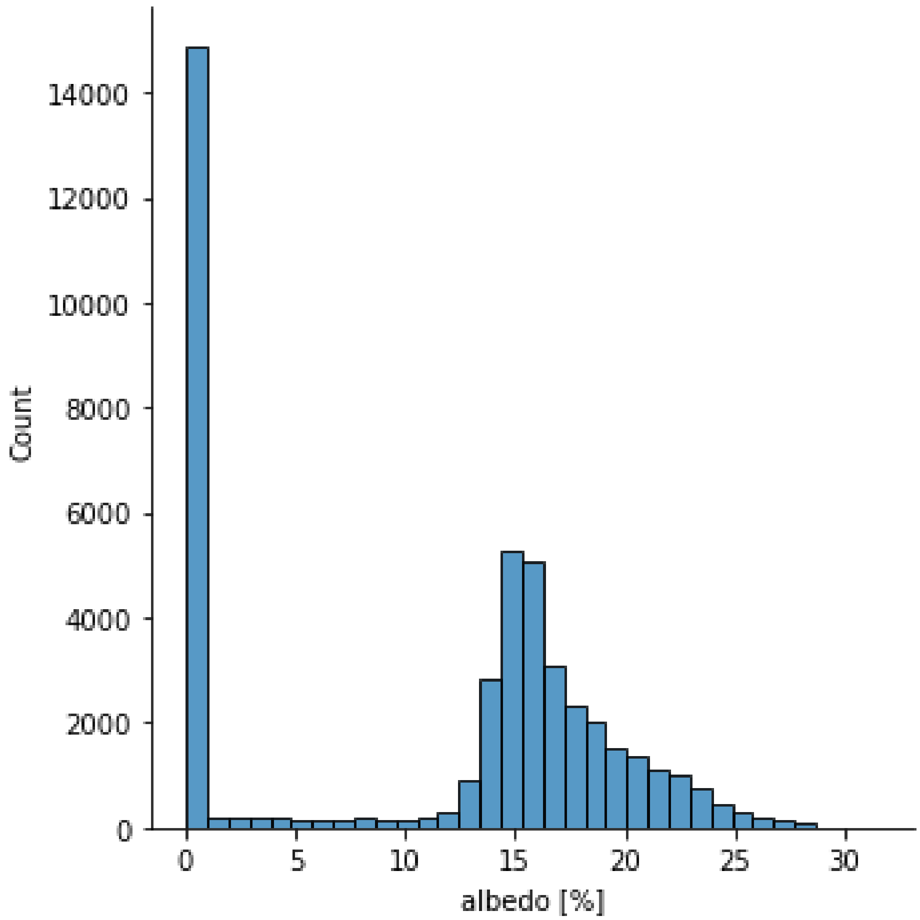
```
#boxplot for analysisng outliers if any
sns.boxplot(data=preview_e["albedo [%]"])
```

```
<AxesSubplot:>
```




```
# visualising wind_direction [angle] distribution
sns.displot(preview_e, x="albedo [%]")
```

```
<seaborn.axisgrid.FacetGrid at 0x25152bf7ac0>
```



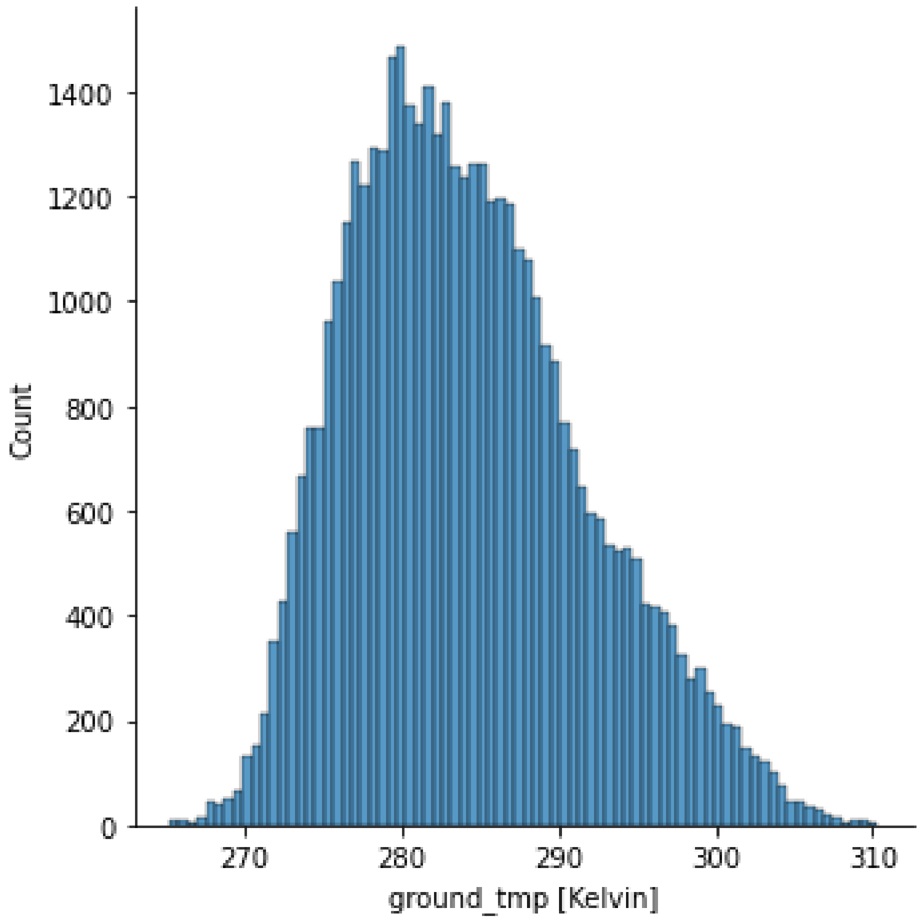

### Column 16 : ground_tmp [Kelvin]

```
# Analysing albedo [%]] Column
preview_e["ground_tmp [Kelvin]"].describe()
```

```
count    45422.000000
mean       284.243751
std          7.473270
min        265.250000
25%        278.600000
50%        283.385000
75%        288.970000
max        310.320000
Name: ground_tmp [Kelvin], dtype: float64
```

```
# visualising wind_direction [angle] distribution
sns.displot(preview_e, x="ground_tmp [Kelvin]")
```

```
<seaborn.axisgrid.FacetGrid at 0x25152c40eb0>
```



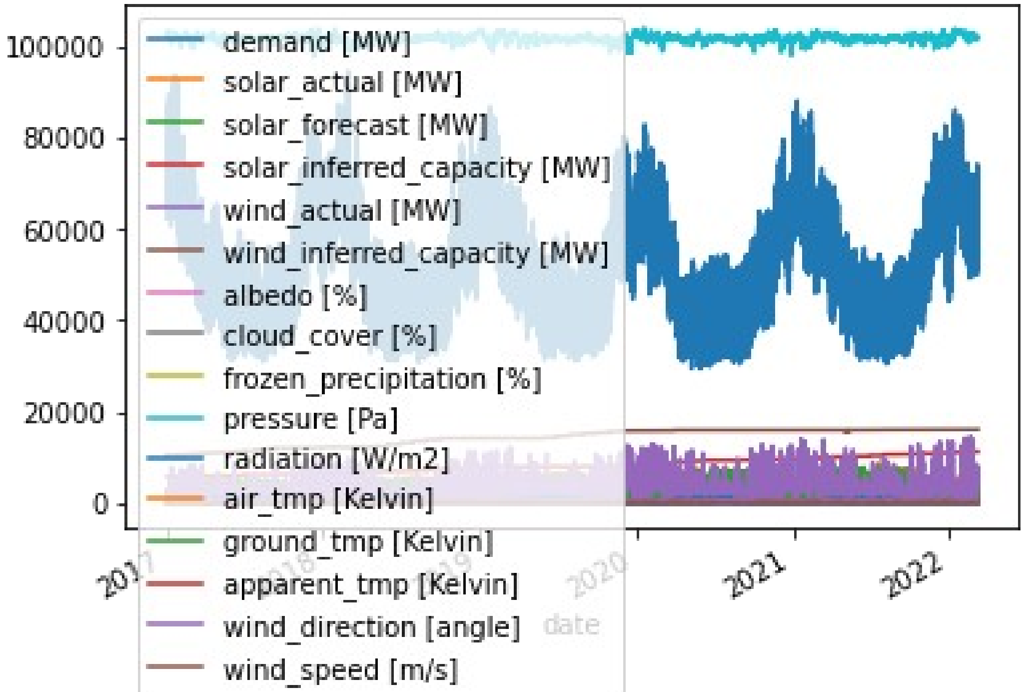

### CONCLUSIONS FROM UNIVARIATE ANALYSIS:

## Multivariate Analysis

## Analysing Columns against Date column

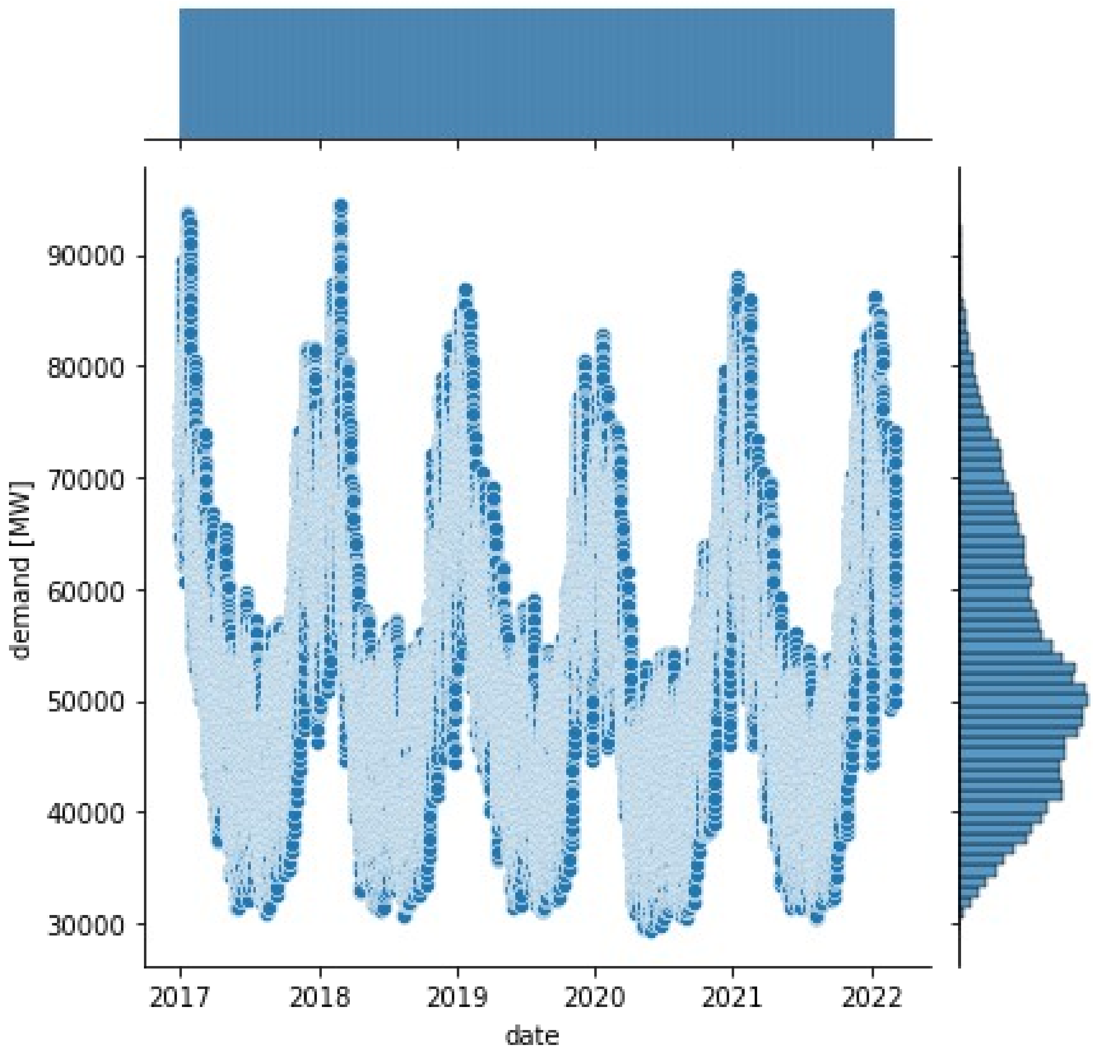
```
# plot showing date Vs other features in the traffic dataset
preview_e.set_index(pd.to_datetime(preview_e.date), drop=True).plot()
```

```
<AxesSubplot:xlabel='date'>
```



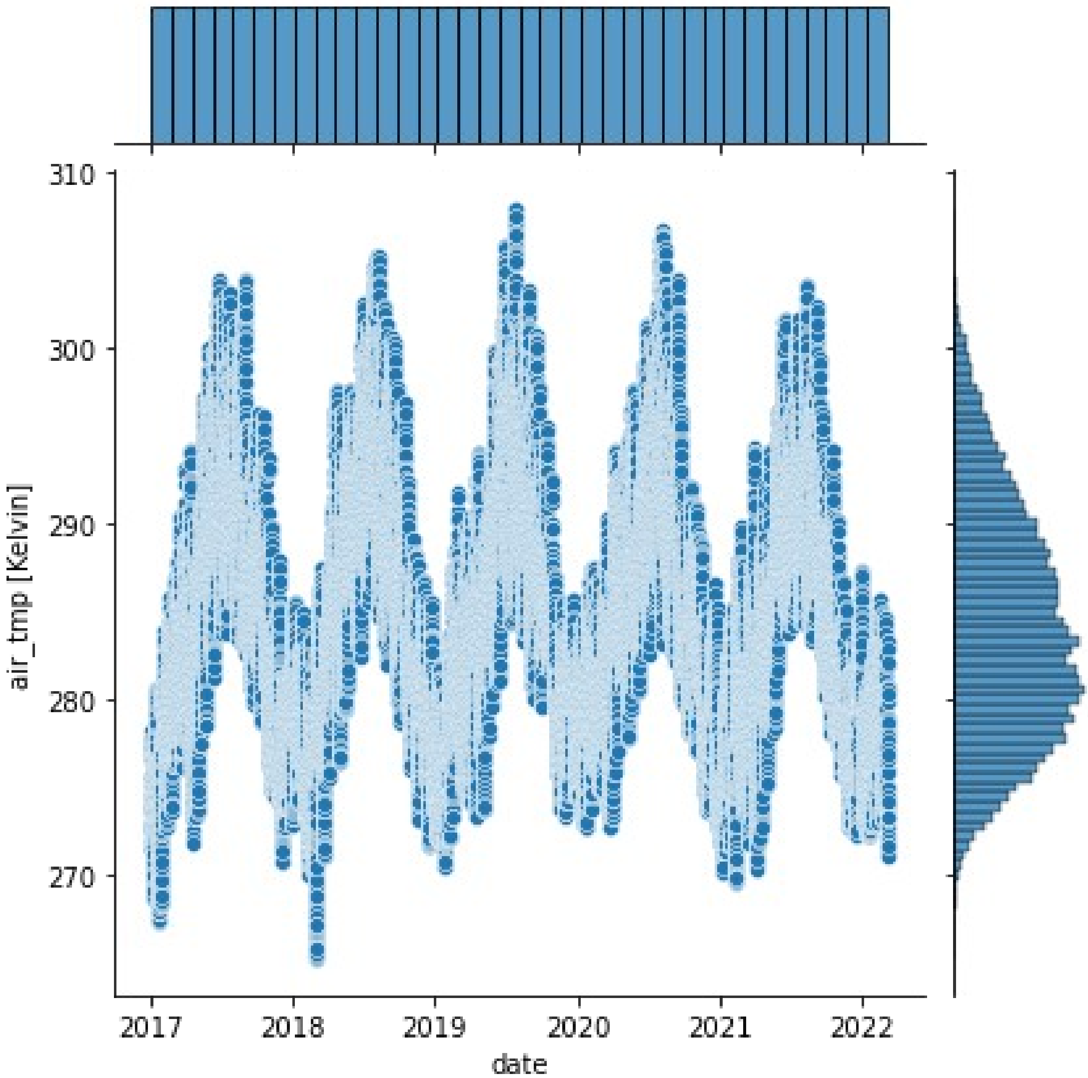

```
# Converting to Datetime
preview_e['date']= pd.to_datetime(preview_e['date'], utc=True)

preview_e['date_']=preview_e['date'].dt.date

# Plotting 2d join plot between date and demand [MW]
sns.jointplot(data=preview_e, x="date_", y="demand [MW]")
```

```
<seaborn.axisgrid.JointGrid at 0x251545d6f70>
```



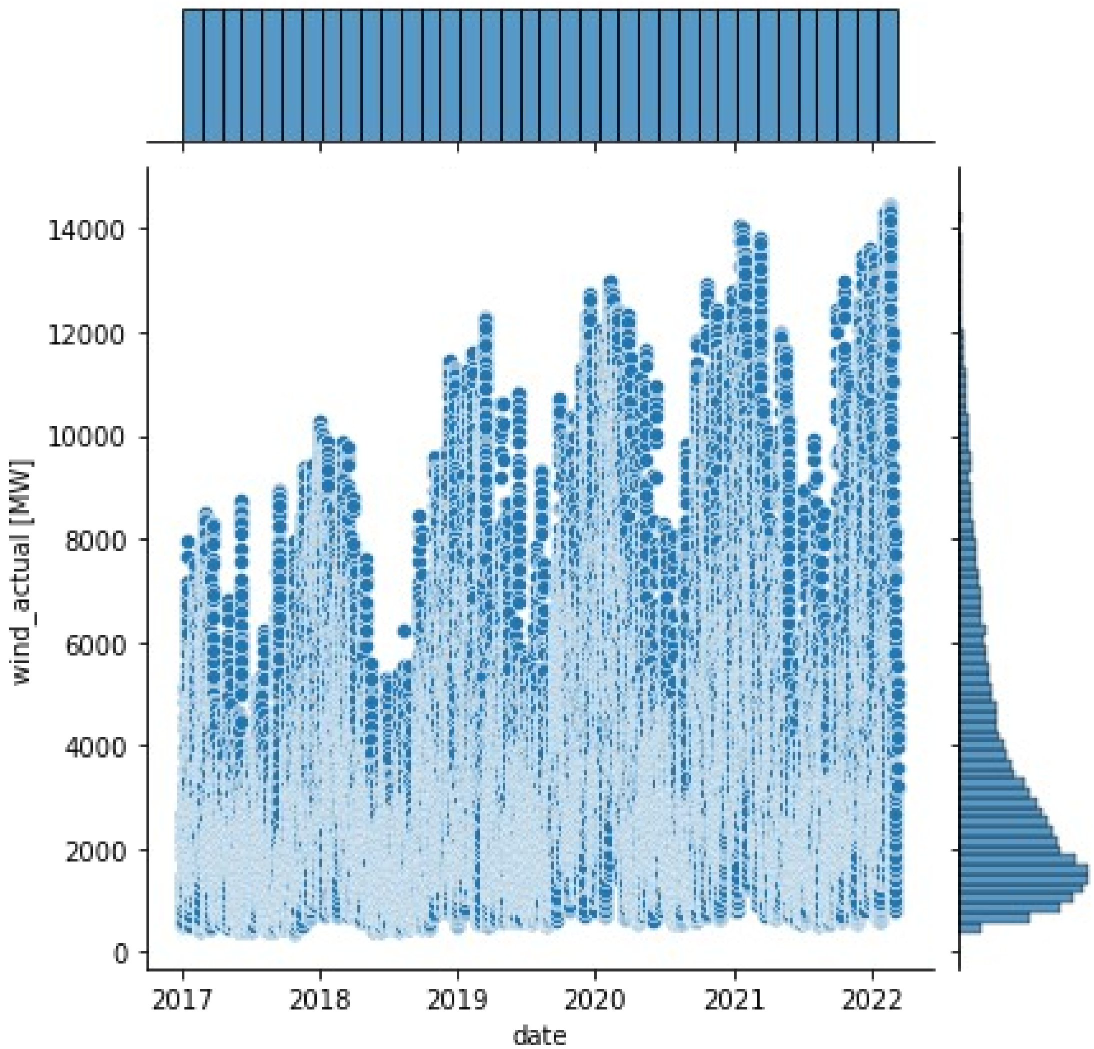

```python
# Plotting 2d join plot between date and air_tmp [Kelvin]
sns.jointplot(data=preview_e, x="date", y="air_tmp [Kelvin]")
```

```
<seaborn.axisgrid.JointGrid at 0x251598bb9d0>
```



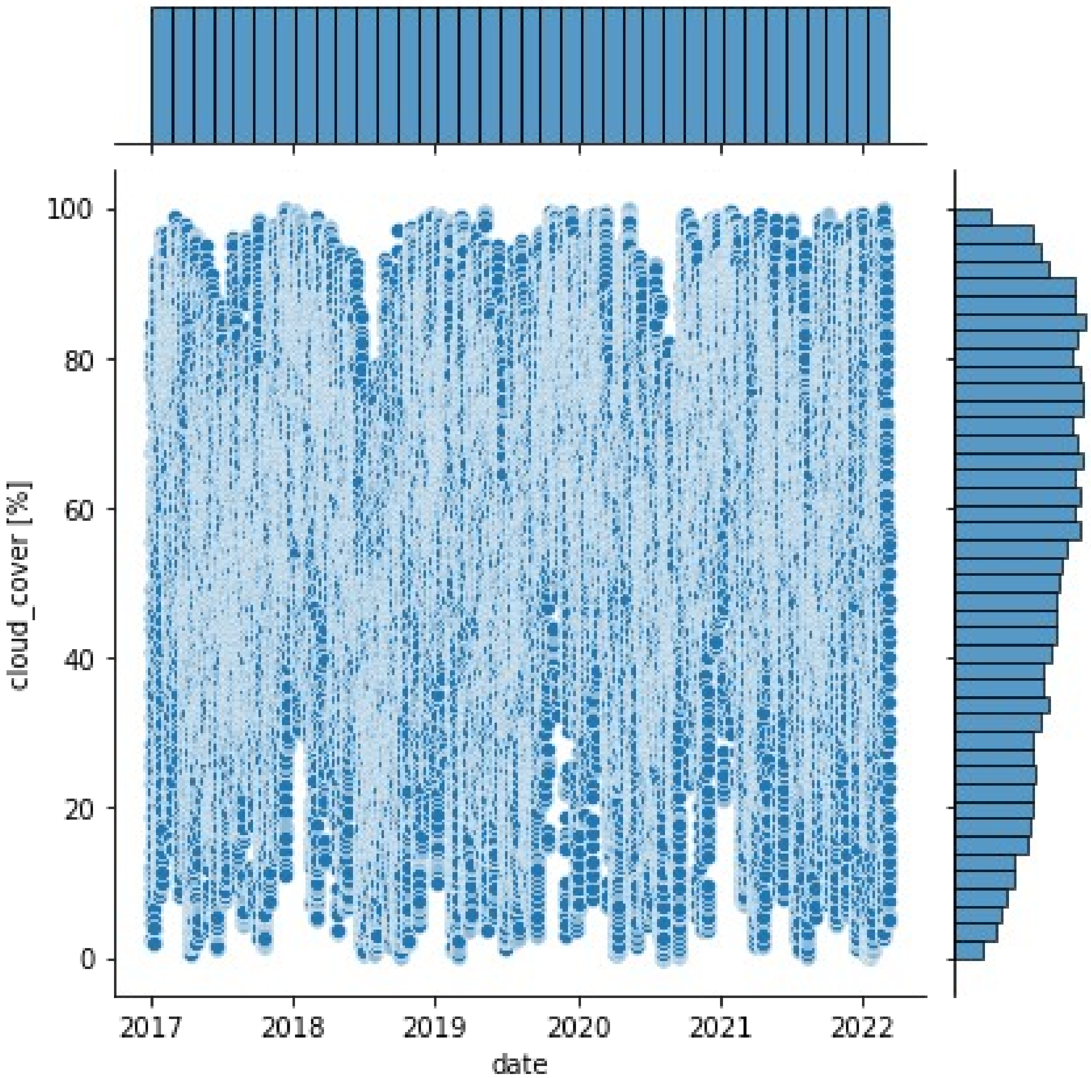

```
# Plotting 2d join plot between date and wind_actual [MW]
sns.jointplot(data=preview_e, x="date", y="wind_actual [MW]")
```

<seaborn.axisgrid.JointGrid at 0x25159c02040>



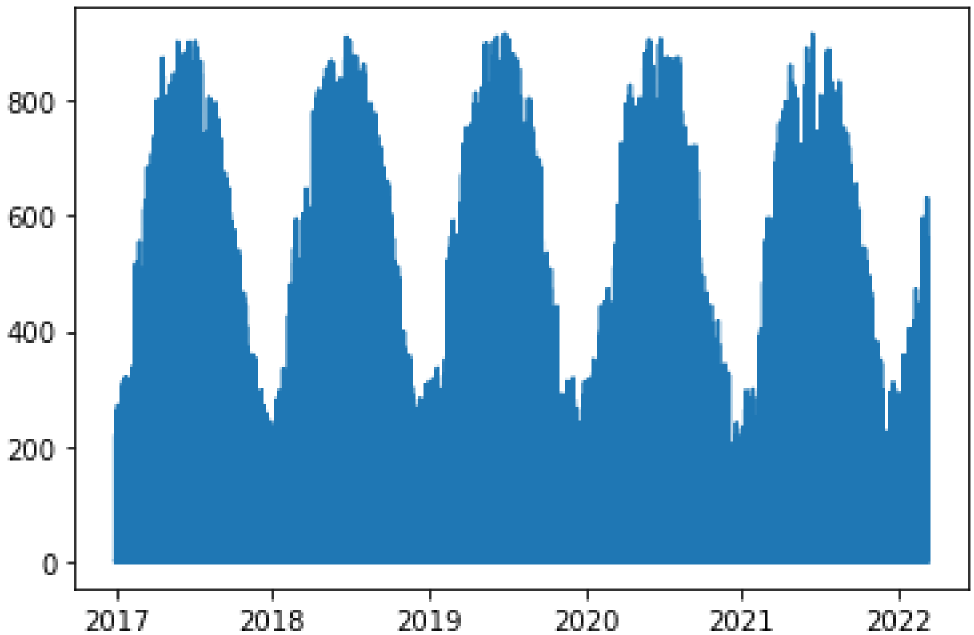

```
# Plotting 2d join plot between date and cloud_cover [%]
sns.jointplot(data=preview_e, x="date", y="cloud_cover [%]")
```

```
<seaborn.axisgrid.JointGrid at 0x2515a041ca0>
```



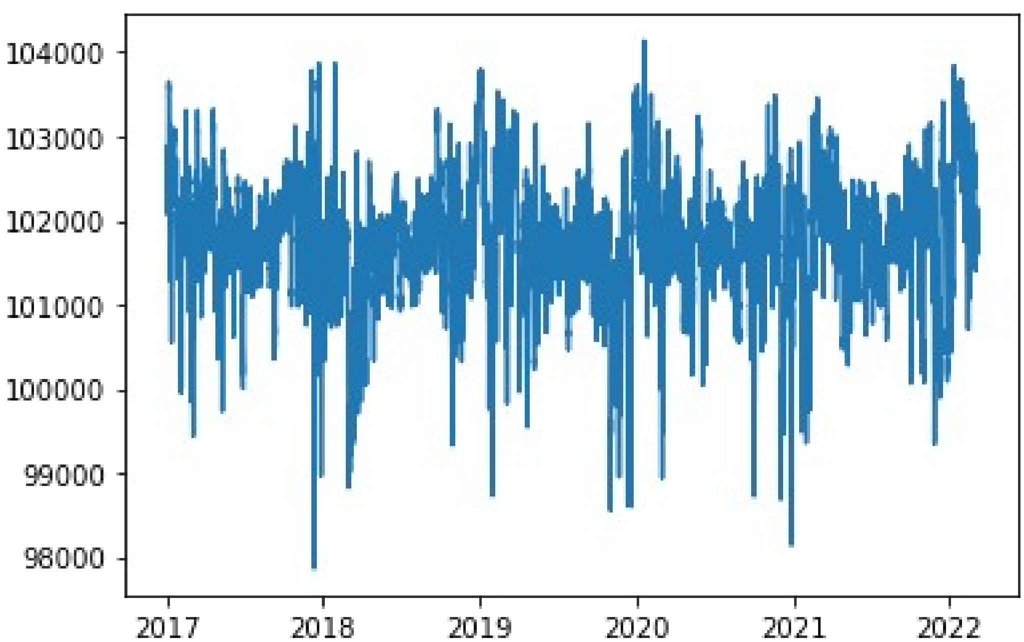

```
# Plotting relation between date and radiation [W/m2]
plt.plot(preview_e['date'],preview_e["radiation [W/m2]"])
```

```
[<matplotlib.lines.Line2D at 0x2515a1e7910>]
```



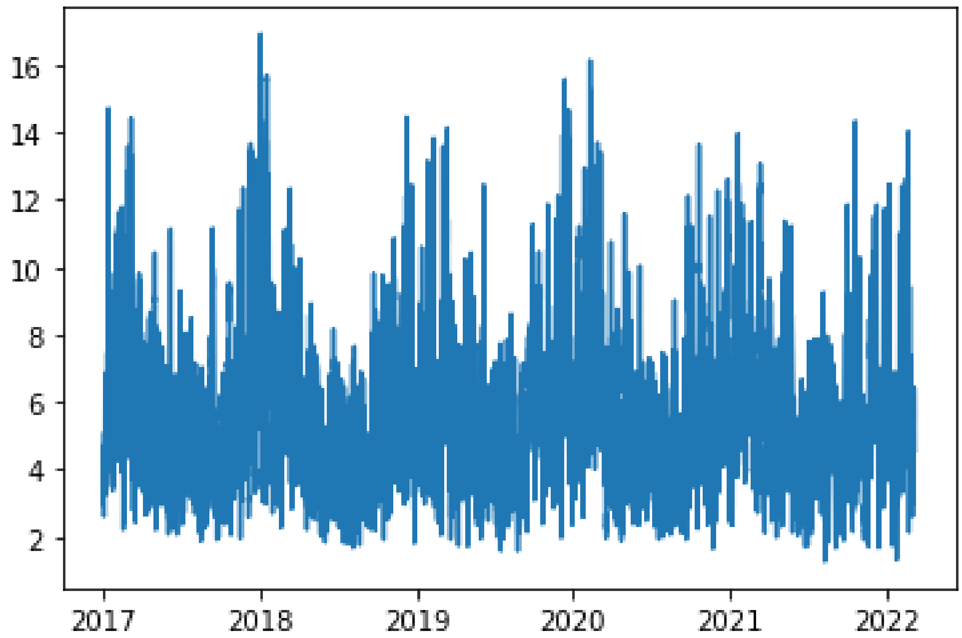

```
# Plotting relation between date and pressure [Pa]
plt.plot(preview_e['date'],preview_e["pressure [Pa]"])
```

```
[<matplotlib.lines.Line2D at 0x2515b514460>]
```

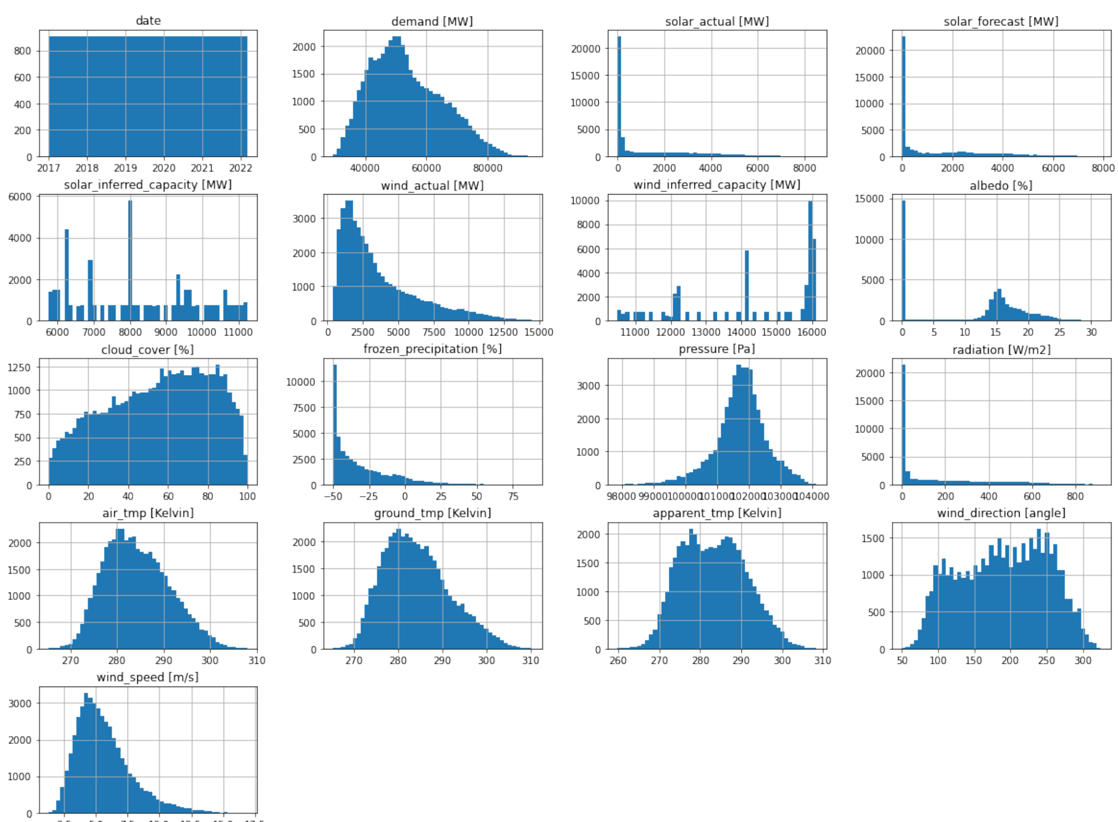



```
# Plotting relation between date and wind_speed [m/s]
plt.plot(preview_e['date'],preview_e["wind_speed [m/s]"])
```

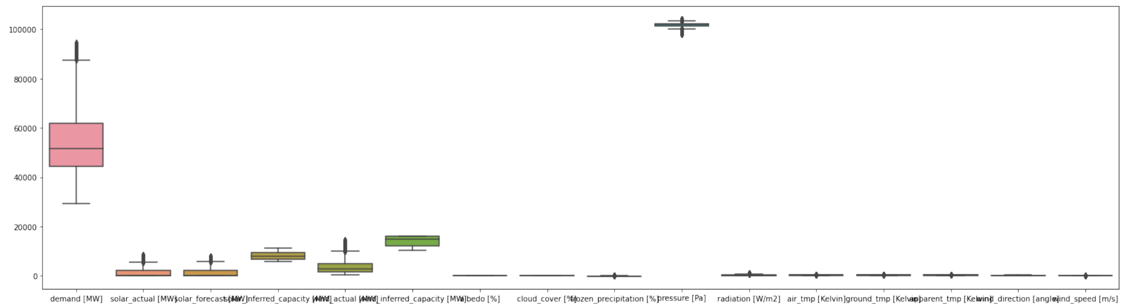
```
[<matplotlib.lines.Line2D at 0x2515b1c4580>]
```



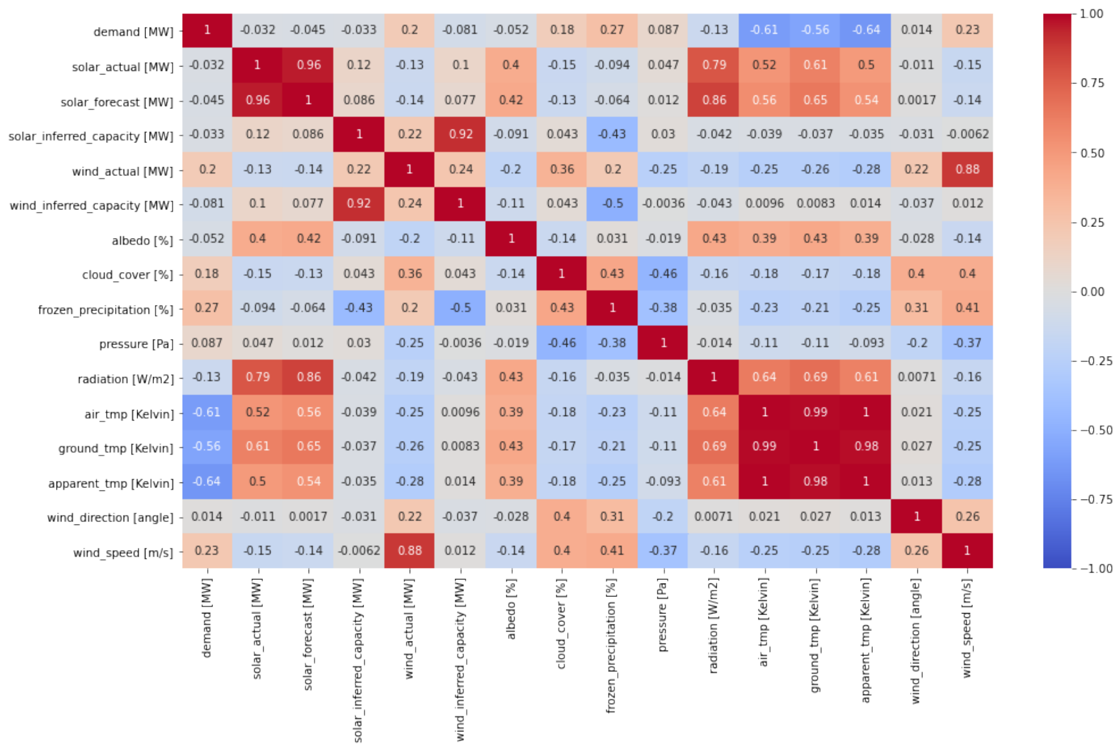

```
get_ipython().run_line_magic('matplotlib', 'inline')

preview_e.hist(bins=50, figsize=(20,15))
plt.show()
```



```python
#box plot for all the columns to check outliers
plt.figure(figsize=(26,7))
ax = sns.boxplot(data=preview_e)
```



```python
#pit plot to identify the relation between columns if any
#sns.pairplot(preview_e)

# plotting correlation

#Using Pearson Correlation
correlation_matrix = preview_e.corr()
plt.figure(figsize=(16,9))
sns.heatmap(correlation_matrix, annot=True, vmin=-1, vmax=1, center=
0, cmap= 'coolwarm')
plt.show()
```



### CONCLUSIONS FROM Multi-VARIATE ANALYSIS:

## # Data Pre-Processing

```
#converting date to datetime64[ns] data type.
preview_e['date_']= pd.to_datetime(preview_e['date_'])
preview_e.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45432 entries, 0 to 45431
Data columns (total 18 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   date                           45432 non-null  datetime64[ns, UTC]
 1   demand [MW]                    45429 non-null  float64
 2   solar_actual [MW]              45413 non-null  float64
 3   solar_forecast [MW]            45210 non-null  float64
 4   solar_inferred_capacity [MW]  45432 non-null  float64
 5   wind_actual [MW]              45413 non-null  float64
 6   wind_inferred_capacity [MW]   45432 non-null  float64
 7   albedo [%]                     45415 non-null  float64
 8   cloud_cover [%]                45416 non-null  float64
 9   frozen_precipitation [%]       45422 non-null  float64
 10  pressure [Pa]                  45421 non-null  float64
 11  radiation [W/m2]               45416 non-null  float64
 12  air_tmp [Kelvin]               45422 non-null  float64
 13  ground_tmp [Kelvin]            45422 non-null  float64
 14  apparent_tmp [Kelvin]          45422 non-null  float64
 15  wind_direction [angle]         45421 non-null  float64
 16  wind_speed [m/s]               45421 non-null  float64
 17  date_                          45432 non-null  datetime64[ns]
dtypes: datetime64[ns, UTC](1), datetime64[ns](1), float64(16)
memory usage: 6.2 MB
```

```
preview_e.head()
```

```
                       date  demand [MW]  solar_actual [MW]  \
0 2016-12-31 23:00:00+00:00     76345.25                0.0
1 2017-01-01 00:00:00+00:00     75437.00                0.0
2 2017-01-01 01:00:00+00:00     73368.25                0.0
3 2017-01-01 02:00:00+00:00     72116.00                0.0
4 2017-01-01 03:00:00+00:00     68593.75                0.0

   solar_forecast [MW]  solar_inferred_capacity [MW]  wind_actual [MW]
\
0                  NaN                       5756.44            597.50

1                  NaN                       5756.44            597.50

2                  NaN                       5756.44            635.25
```

```
3                  NaN                       5756.44           628.50

4                  NaN                       5756.44           608.50


   wind_inferred_capacity [MW]  albedo [%]  cloud_cover [%]  \
0                   10513.95         0.0             2.45   
1                   10513.95         0.0             2.48   
2                   10513.95         0.0             4.62   
3                   10513.95         0.0             6.13   
4                   10513.95         0.0             6.75   

   frozen_precipitation [%]  pressure [Pa]  radiation [W/m2]  \
0                     -3.80       102875.0               0.0   
1                     -3.46       102839.0               0.0   
2                     -5.48       102735.0               0.0   
3                     -6.91       102660.0               0.0   
4                     -7.50       102629.0               0.0   

   air_tmp [Kelvin]  ground_tmp [Kelvin]  apparent_tmp [Kelvin]  \
0            271.60               269.82                 269.84   
1            271.62               269.85                 269.79   
2            271.61               269.93                 269.58   
3            271.60               269.99                 269.44   
4            271.60               270.02                 269.38   

   wind_direction [angle]  wind_speed [m/s]      date_
0                   209.0              2.97 2016-12-31
1                   212.0              3.13 2017-01-01
2                   218.0              3.25 2017-01-01
3                   218.0              3.37 2017-01-01
4                   219.0              3.42 2017-01-01
```

### Coverting temp values to celsuis

```
# converting Average temperature from Kelvin to Celsius

#preview_e['temp']= preview_e['temp']-273.15
#preview_e['temp'].describe()
```

## missing values

```
# To check the number of missing values in each column
preview_e.isna().sum()
```

```
date                             0
demand [MW]                      3
solar_actual [MW]               19
solar_forecast [MW]            222
solar_inferred_capacity [MW]     0
wind_actual [MW]                19
wind_inferred_capacity [MW]      0
```

```
albedo [%]                        17
cloud_cover [%]                   16
frozen_precipitation [%]          10
pressure [Pa]                     11
radiation [W/m2]                  16
air_tmp [Kelvin]                  10
ground_tmp [Kelvin]               10
apparent_tmp [Kelvin]             10
wind_direction [angle]            11
wind_speed [m/s]                  11
date_                              0
dtype: int64
```

```
# making new data frame with dropped NA values
new_data = preview_e.dropna(axis = 0, how ='any')

new_data
```

```
                           date  demand [MW]  solar_actual [MW]  \
192   2017-01-08 23:00:00+00:00     72921.75               0.00
193   2017-01-09 00:00:00+00:00     70956.00               0.00
194   2017-01-09 01:00:00+00:00     68422.50               0.00
195   2017-01-09 02:00:00+00:00     67520.50               0.00
196   2017-01-09 03:00:00+00:00     64729.25               0.00
...                         ...          ...                ...
45427 2022-03-08 18:00:00+00:00     69881.25             170.00
45428 2022-03-08 19:00:00+00:00     67759.00             166.25
45429 2022-03-08 20:00:00+00:00     64427.50             169.25
45430 2022-03-08 21:00:00+00:00     63364.25             165.50
45431 2022-03-08 22:00:00+00:00     63996.50             168.25

       solar_forecast [MW]  solar_inferred_capacity [MW]  wind_actual
[MW]  \
192                   0.55                       5756.44
1151.00
193                   0.55                       5756.44
1103.75
194                   0.55                       5756.44
1111.00
195                   0.06                       5756.44
1165.00
196                   0.06                       5756.44
1210.75
...                    ...                           ...
...
45427               250.16                      11244.01
4149.50
45428               130.32                      11244.01
5012.75
45429               130.32                      11244.01
```

```
5223.00
45430              134.79                      11244.01
5200.75
45431              133.64                      11244.01
5013.00

       wind_inferred_capacity [MW]  albedo [%]  cloud_cover [%]  \
192                       10513.95        0.00            64.91
193                       10513.95        0.00            63.71
194                       10513.95        0.00            59.69
195                       10513.95        0.00            56.84
196                       10513.95        0.00            55.66
...                            ...         ...              ...
45427                     16116.79       15.56            56.09
45428                     16116.79        0.44            55.01
45429                     16116.79        0.44            47.87
45430                     16116.79        0.44            43.63
45431                     16116.79        0.44            40.18

       frozen_precipitation [%]  pressure [Pa]  radiation [W/m2]  \
192                       -1.06       103114.0              0.00
193                       -0.96       103109.0              0.00
194                       -0.48       103070.0              0.00
195                       -0.14       103042.0              0.00
196                        0.00       103031.0              0.00
...                         ...            ...               ...
45427                    -42.02       101826.0            272.42
45428                    -43.17       101896.0              0.00
45429                    -44.17       101954.0              0.00
45430                    -45.54       102006.0              0.00
45431                    -45.92       102044.0              0.00

       air_tmp [Kelvin]  ground_tmp [Kelvin]  apparent_tmp [Kelvin]  \
192              274.13               273.44                 271.90
193              274.01               273.32                 271.78
194              273.82               273.14                 271.51
195              273.68               273.01                 271.32
196              273.63               272.96                 271.24
...                 ...                  ...                    ...
45427            278.71               277.30                 276.89
45428            278.01               276.74                 276.17
45429            277.60               276.40                 275.72
45430            277.25               276.11                 275.32
45431            276.92               275.77                 274.99

       wind_direction [angle]  wind_speed [m/s]      date_
192                     178.0              4.14 2017-01-08
193                     180.0              4.13 2017-01-09
194                     180.0              4.04 2017-01-09
195                     190.0              4.07 2017-01-09
```

```
196                    190.0              4.10 2017-01-09
...                      ...               ...        ...
45427                  175.0              5.08 2022-03-08
45428                  172.0              4.90 2022-03-08
45429                  173.0              4.80 2022-03-08
45430                  179.0              4.68 2022-03-08
45431                  182.0              4.57 2022-03-08

[45202 rows x 18 columns]
```

**Now we compare sizes of data frames so that we can come to know how many rows had at least 1 Null value**

```
# Now we compare sizes of data frames so that we can come to know how many rows had at least 1 Null value
print("Old data frame length:", len(preview_e))
print("New data frame length:", len(new_data))
print("Number of rows with at least 1 NA value: ",
      (len(preview_e)-len(new_data)))
```

```
Old data frame length: 45432
New data frame length: 45202
Number of rows with at least 1 NA value:  230
```

## # Research Questions

## What is being Analysed?

## Why is it being Analysed?

## How is it being analysed?

### Suitable Algorithms - Regrerssion Analysis

### Suitable Algorithms - TimeSeries Analysis

## Identifying targets and variables for regression analysis:

## ## Preparing Data for Regression Analysis

### Remove unused columns before encoding

```
#print all the column names
new_data.columns
```

```
Index(['date', 'demand [MW]', 'solar_actual [MW]', 'solar_forecast [MW]',
       'solar_inferred_capacity [MW]', 'wind_actual [MW]',
       'wind_inferred_capacity [MW]', 'albedo [%]', 'cloud_cover [%]',
       'frozen_precipitation [%]', 'pressure [Pa]', 'radiation [W/m2]',
       'air_tmp [Kelvin]', 'ground_tmp [Kelvin]', 'apparent_tmp
```

```
[Kelvin]',
       'wind_direction [angle]', 'wind_speed [m/s]', 'date_'],
      dtype='object')
```

```python
# check the data type of the columns
new_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 45202 entries, 192 to 45431
Data columns (total 18 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   date                          45202 non-null  datetime64[ns, UTC]
 1   demand [MW]                   45202 non-null  float64
 2   solar_actual [MW]             45202 non-null  float64
 3   solar_forecast [MW]           45202 non-null  float64
 4   solar_inferred_capacity [MW]  45202 non-null  float64
 5   wind_actual [MW]              45202 non-null  float64
 6   wind_inferred_capacity [MW]   45202 non-null  float64
 7   albedo [%]                    45202 non-null  float64
 8   cloud_cover [%]               45202 non-null  float64
 9   frozen_precipitation [%]      45202 non-null  float64
 10  pressure [Pa]                 45202 non-null  float64
 11  radiation [W/m2]              45202 non-null  float64
 12  air_tmp [Kelvin]              45202 non-null  float64
 13  ground_tmp [Kelvin]           45202 non-null  float64
 14  apparent_tmp [Kelvin]         45202 non-null  float64
 15  wind_direction [angle]        45202 non-null  float64
 16  wind_speed [m/s]              45202 non-null  float64
 17  date_                         45202 non-null  datetime64[ns]
dtypes: datetime64[ns, UTC](1), datetime64[ns](1), float64(16)
memory usage: 6.6 MB
```

```python
# visualising top 5 rows od the dataframe
new_data.head()
```

```
                         date  demand [MW]  solar_actual [MW]  \
192 2017-01-08 23:00:00+00:00     72921.75                0.0
193 2017-01-09 00:00:00+00:00     70956.00                0.0
194 2017-01-09 01:00:00+00:00     68422.50                0.0
195 2017-01-09 02:00:00+00:00     67520.50                0.0
196 2017-01-09 03:00:00+00:00     64729.25                0.0

     solar_forecast [MW]  solar_inferred_capacity [MW]  wind_actual
[MW]  \
192                 0.55                       5756.44
1151.00
193                 0.55                       5756.44
1103.75
194                 0.55                       5756.44
1111.00
```

```
195                0.06                       5756.44
1165.00
196                0.06                       5756.44
1210.75

     wind_inferred_capacity [MW]  albedo [%]  cloud_cover [%]  \
192                     10513.95         0.0            64.91
193                     10513.95         0.0            63.71
194                     10513.95         0.0            59.69
195                     10513.95         0.0            56.84
196                     10513.95         0.0            55.66

     frozen_precipitation [%]  pressure [Pa]  radiation [W/m2]  \
192                     -1.06       103114.0               0.0
193                     -0.96       103109.0               0.0
194                     -0.48       103070.0               0.0
195                     -0.14       103042.0               0.0
196                      0.00       103031.0               0.0

     air_tmp [Kelvin]  ground_tmp [Kelvin]  apparent_tmp [Kelvin]  \
192            274.13               273.44                 271.90
193            274.01               273.32                 271.78
194            273.82               273.14                 271.51
195            273.68               273.01                 271.32
196            273.63               272.96                 271.24

     wind_direction [angle]  wind_speed [m/s]      date_
192                   178.0              4.14 2017-01-08
193                   180.0              4.13 2017-01-09
194                   180.0              4.04 2017-01-09
195                   190.0              4.07 2017-01-09
196                   190.0              4.10 2017-01-09
```

```
# saving a copy of Energy Demand data to perform timeseries analysis
new_data_ts = new_data

# Split date and time fields for deeper analysis

new_data['year'] = new_data['date_'].dt.year
new_data['month'] = new_data['date_'].dt.month
new_data['day'] = new_data['date_'].dt.day
new_data['weekday'] = new_data['date_'].dt.day_name()
new_data['date_time'] = new_data['date_'].dt.hour
new_data= new_data.rename(columns={"date_": "time"})

new_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 45202 entries, 192 to 45431
Data columns (total 23 columns):
```

```
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   date                           45202 non-null  datetime64[ns, UTC]
 1   demand [MW]                    45202 non-null  float64
 2   solar_actual [MW]              45202 non-null  float64
 3   solar_forecast [MW]            45202 non-null  float64
 4   solar_inferred_capacity [MW]   45202 non-null  float64
 5   wind_actual [MW]               45202 non-null  float64
 6   wind_inferred_capacity [MW]    45202 non-null  float64
 7   albedo [%]                     45202 non-null  float64
 8   cloud_cover [%]                45202 non-null  float64
 9   frozen_precipitation [%]       45202 non-null  float64
 10  pressure [Pa]                  45202 non-null  float64
 11  radiation [W/m2]               45202 non-null  float64
 12  air_tmp [Kelvin]               45202 non-null  float64
 13  ground_tmp [Kelvin]            45202 non-null  float64
 14  apparent_tmp [Kelvin]          45202 non-null  float64
 15  wind_direction [angle]         45202 non-null  float64
 16  wind_speed [m/s]               45202 non-null  float64
 17  time                           45202 non-null  datetime64[ns]
 18  year                           45202 non-null  int64
 19  month                          45202 non-null  int64
 20  day                            45202 non-null  int64
 21  weekday                        45202 non-null  object
 22  date_time                      45202 non-null  int64
dtypes: datetime64[ns, UTC](1), datetime64[ns](1), float64(16),
int64(4), object(1)
memory usage: 8.3+ MB

<ipython-input-79-3815aa2f9600>:3: 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
  new_data['year'] = new_data['date_'].dt.year
<ipython-input-79-3815aa2f9600>:4: 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
  new_data['month'] = new_data['date_'].dt.month
<ipython-input-79-3815aa2f9600>:5: 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
  new_data['day'] = new_data['date_'].dt.day
<ipython-input-79-3815aa2f9600>:6: 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
  new_data['weekday'] = new_data['date_'].dt.day_name()
<ipython-input-79-3815aa2f9600>:7: 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
  new_data['date_time'] = new_data['date_'].dt.hour
```

```
# visualising top 6 rows od the dataframe
new_data.head()
```

```
                         date  demand [MW]  solar_actual [MW]  \
192 2017-01-08 23:00:00+00:00     72921.75                0.0
193 2017-01-09 00:00:00+00:00     70956.00                0.0
194 2017-01-09 01:00:00+00:00     68422.50                0.0
195 2017-01-09 02:00:00+00:00     67520.50                0.0
196 2017-01-09 03:00:00+00:00     64729.25                0.0

     solar_forecast [MW]  solar_inferred_capacity [MW]  wind_actual
[MW]  \
192                 0.55                       5756.44
1151.00
193                 0.55                       5756.44
1103.75
194                 0.55                       5756.44
1111.00
195                 0.06                       5756.44
1165.00
196                 0.06                       5756.44
1210.75

     wind_inferred_capacity [MW]  albedo [%]  cloud_cover [%]  \
192                     10513.95         0.0            64.91
193                     10513.95         0.0            63.71
194                     10513.95         0.0            59.69
195                     10513.95         0.0            56.84
196                     10513.95         0.0            55.66
```

```
     frozen_precipitation [%]  ...  ground_tmp [Kelvin]  \
192                     -1.06  ...               273.44
193                     -0.96  ...               273.32
194                     -0.48  ...               273.14
195                     -0.14  ...               273.01
196                      0.00  ...               272.96

     apparent_tmp [Kelvin]  wind_direction [angle]  wind_speed
[m/s]  \
192                 271.90                   178.0              4.14

193                 271.78                   180.0              4.13

194                 271.51                   180.0              4.04

195                 271.32                   190.0              4.07

196                 271.24                   190.0              4.10


          time  year  month day  weekday  date_time
192 2017-01-08  2017      1   8   Sunday          0
193 2017-01-09  2017      1   9   Monday          0
194 2017-01-09  2017      1   9   Monday          0
195 2017-01-09  2017      1   9   Monday          0
196 2017-01-09  2017      1   9   Monday          0

[5 rows x 23 columns]
```

```python
# removing unused cols from taffic data frame,

cols = ['date','time','date']
new_data.drop(cols, axis=1, inplace=True)
new_data.head()
```

```
     demand [MW]  solar_actual [MW]  solar_forecast [MW]  \
192     72921.75                0.0                 0.55
193     70956.00                0.0                 0.55
194     68422.50                0.0                 0.55
195     67520.50                0.0                 0.06
196     64729.25                0.0                 0.06

     solar_inferred_capacity [MW]  wind_actual [MW]  \
192                       5756.44           1151.00
193                       5756.44           1103.75
194                       5756.44           1111.00
195                       5756.44           1165.00
196                       5756.44           1210.75
```

```
     wind_inferred_capacity [MW]  albedo [%]  cloud_cover [%]  \
192                     10513.95         0.0            64.91
193                     10513.95         0.0            63.71
194                     10513.95         0.0            59.69
195                     10513.95         0.0            56.84
196                     10513.95         0.0            55.66

     frozen_precipitation [%]  pressure [Pa]  ...  air_tmp [Kelvin]  \
192                     -1.06       103114.0  ...            274.13
193                     -0.96       103109.0  ...            274.01
194                     -0.48       103070.0  ...            273.82
195                     -0.14       103042.0  ...            273.68
196                      0.00       103031.0  ...            273.63

     ground_tmp [Kelvin]  apparent_tmp [Kelvin]  wind_direction
[angle]  \
192               273.44                 271.90
178.0
193               273.32                 271.78
180.0
194               273.14                 271.51
180.0
195               273.01                 271.32
190.0
196               272.96                 271.24
190.0

     wind_speed [m/s]  year  month  day  weekday date_time
192              4.14  2017      1    8   Sunday         0
193              4.13  2017      1    9   Monday         0
194              4.04  2017      1    9   Monday         0
195              4.07  2017      1    9   Monday         0
196              4.10  2017      1    9   Monday         0

[5 rows x 21 columns]
```

```python
def weekday_info(weekday):
    '''
    This approach encodes the weekdays with whole integers
    and converts category days to numeric values.
    '''
    if weekday == 'Monday':
        return "1"
    elif weekday == 'Tuesday':
        return "2"
    elif weekday == 'Wednesday':
        return "3"
    elif weekday == 'Thursday':
        return "4"
    elif weekday == 'Friday':
```

```
        return "5"
    elif weekday == 'Saturday':
        return "6"
    else:
        return '0'

new_data['weekday'] = new_data['weekday'].apply(weekday_info)
new_data.head(10)
```

```
     demand [MW]  solar_actual [MW]  solar_forecast [MW]  \
192     72921.75               0.00                 0.55   
193     70956.00               0.00                 0.55   
194     68422.50               0.00                 0.55   
195     67520.50               0.00                 0.06   
196     64729.25               0.00                 0.06   
197     63864.50               0.00                 0.06   
198     66086.75               0.00                 0.55   
199     71651.00               0.00                 0.55   
200     78221.25              27.75                17.27   
201     81002.00             108.25               105.75   

     solar_inferred_capacity [MW]  wind_actual [MW]  \
192                       5756.44           1151.00   
193                       5756.44           1103.75   
194                       5756.44           1111.00   
195                       5756.44           1165.00   
196                       5756.44           1210.75   
197                       5756.44           1185.25   
198                       5756.44           1168.00   
199                       5756.44           1241.00   
200                       5756.44           1320.00   
201                       5756.44           1389.50   

     wind_inferred_capacity [MW]  albedo [%]  cloud_cover [%]  \
192                     10513.95        0.00            64.91   
193                     10513.95        0.00            63.71   
194                     10513.95        0.00            59.69   
195                     10513.95        0.00            56.84   
196                     10513.95        0.00            55.66   
197                     10513.95        0.00            55.56   
198                     10513.95        0.00            55.36   
199                     10513.95        3.34            56.22   
200                     10513.95       11.41            58.53   
201                     10513.95       19.49            60.84   

     frozen_precipitation [%]  pressure [Pa]  ...  air_tmp [Kelvin]  \
192                     -1.06       103114.0  ...            274.13   
193                     -0.96       103109.0  ...            274.01   
194                     -0.48       103070.0  ...            273.82   
195                     -0.14       103042.0  ...            273.68   
```

```
196                       0.00       103031.0  ...            273.63
197                      -0.29       103010.0  ...            273.57
198                      -0.87       102967.0  ...            273.45
199                      -0.89       102942.0  ...            273.66
200                      -0.25       102931.0  ...            274.34
201                       0.39       102920.0  ...            275.00

     ground_tmp [Kelvin]  apparent_tmp [Kelvin]  wind_direction
[angle]  \
192               273.44                 271.90
178.0
193               273.32                 271.78
180.0
194               273.14                 271.51
180.0
195               273.01                 271.32
190.0
196               272.96                 271.24
190.0
197               272.90                 271.19
198.0
198               272.77                 271.09
209.0
199               273.08                 271.35
206.0
200               273.98                 272.12
213.0
201               274.88                 272.89
220.0

     wind_speed [m/s]  year  month  day  weekday date_time
192              4.14  2017      1    8        0         0
193              4.13  2017      1    9        1         0
194              4.04  2017      1    9        1         0
195              4.07  2017      1    9        1         0
196              4.10  2017      1    9        1         0
197              4.08  2017      1    9        1         0
198              4.12  2017      1    9        1         0
199              4.15  2017      1    9        1         0
200              4.10  2017      1    9        1         0
201              4.14  2017      1    9        1         0

[10 rows x 21 columns]
```

### Encoding data

```
#https://scikit-learn.org/stable/modules/preprocessing.html
#encoding-features

from sklearn.preprocessing import LabelEncoder
```

```python
#Assigning the new_data dataset to a new variable process_data
process_data = new_data
process_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 45202 entries, 192 to 45431
Data columns (total 21 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   demand [MW]                   45202 non-null  float64
 1   solar_actual [MW]             45202 non-null  float64
 2   solar_forecast [MW]           45202 non-null  float64
 3   solar_inferred_capacity [MW]  45202 non-null  float64
 4   wind_actual [MW]              45202 non-null  float64
 5   wind_inferred_capacity [MW]   45202 non-null  float64
 6   albedo [%]                    45202 non-null  float64
 7   cloud_cover [%]               45202 non-null  float64
 8   frozen_precipitation [%]      45202 non-null  float64
 9   pressure [Pa]                 45202 non-null  float64
 10  radiation [W/m2]              45202 non-null  float64
 11  air_tmp [Kelvin]              45202 non-null  float64
 12  ground_tmp [Kelvin]           45202 non-null  float64
 13  apparent_tmp [Kelvin]         45202 non-null  float64
 14  wind_direction [angle]        45202 non-null  float64
 15  wind_speed [m/s]              45202 non-null  float64
 16  year                          45202 non-null  int64
 17  month                         45202 non-null  int64
 18  day                           45202 non-null  int64
 19  weekday                       45202 non-null  object
 20  date_time                     45202 non-null  int64
dtypes: float64(16), int64(4), object(1)
memory usage: 7.6+ MB
```

```python
#scaling the data in dataset to normalise
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
process_data = pd.DataFrame(scaler.fit_transform(process_data),
columns=process_data.columns)
process_data.head()
```

```
   demand [MW]  solar_actual [MW]  solar_forecast [MW]  \
0     1.661492          -0.722664            -0.725794
1     1.493961          -0.722664            -0.725794
2     1.278043          -0.722664            -0.725794
3     1.201170          -0.722664            -0.726072
4     0.963285          -0.722664            -0.726072

   solar_inferred_capacity [MW]  wind_actual [MW]  \
0                     -1.557135         -0.912398
1                     -1.557135         -0.929831
```

```
2                    -1.557135        -0.927156
3                    -1.557135        -0.907233
4                    -1.557135        -0.890354

   wind_inferred_capacity [MW]  albedo [%]  cloud_cover [%]  \
0                    -2.080709   -1.318214         0.369773
1                    -2.080709   -1.318214         0.323381
2                    -2.080709   -1.318214         0.167967
3                    -2.080709   -1.318214         0.057785
4                    -2.080709   -1.318214         0.012166

   frozen_precipitation [%]  pressure [Pa]  ...  air_tmp [Kelvin]  \
0                  1.531549       1.718827  ...         -1.500526
1                  1.536558       1.712526  ...         -1.518108
2                  1.560602       1.663380  ...         -1.545947
3                  1.577633       1.628095  ...         -1.566460
4                  1.584646       1.614234  ...         -1.573786

   ground_tmp [Kelvin]  apparent_tmp [Kelvin]  wind_direction [angle]
\
0            -1.456613              -1.458455               -0.204843

1            -1.472720              -1.473784               -0.171491

2            -1.496879              -1.508276               -0.171491

3            -1.514328              -1.532548               -0.004730

4            -1.521039              -1.542768               -0.004730


   wind_speed [m/s]      year     month       day   weekday  date_time

0         -0.684923 -1.418166 -1.536461 -0.877211 -1.499552        0.0

1         -0.689554 -1.418166 -1.536461 -0.763467 -0.999480        0.0

2         -0.731232 -1.418166 -1.536461 -0.763467 -0.999480        0.0

3         -0.717339 -1.418166 -1.536461 -0.763467 -0.999480        0.0

4         -0.703446 -1.418166 -1.536461 -0.763467 -0.999480        0.0


[5 rows x 21 columns]
```

```
#Scaling the data because of huge diff between the scales of traffic
volume and other features
```

```python
target = pd.DataFrame(process_data['demand [MW]'])
labels = pd.DataFrame(process_data.drop('demand [MW]', axis=1 ))

display(labels.head(),target.head())
```

```
   solar_actual [MW]  solar_forecast [MW]  solar_inferred_capacity
[MW]  \
0          -0.722664            -0.725794                      -
1.557135
1          -0.722664            -0.725794                      -
1.557135
2          -0.722664            -0.725794                      -
1.557135
3          -0.722664            -0.726072                      -
1.557135
4          -0.722664            -0.726072                      -
1.557135

   wind_actual [MW]  wind_inferred_capacity [MW]  albedo [%]
cloud_cover [%]  \
0         -0.912398                    -2.080709   -1.318214
0.369773
1         -0.929831                    -2.080709   -1.318214
0.323381
2         -0.927156                    -2.080709   -1.318214
0.167967
3         -0.907233                    -2.080709   -1.318214
0.057785
4         -0.890354                    -2.080709   -1.318214
0.012166

   frozen_precipitation [%]  pressure [Pa]  radiation [W/m2]  \
0                  1.531549       1.718827          -0.73046
1                  1.536558       1.712526          -0.73046
2                  1.560602       1.663380          -0.73046
3                  1.577633       1.628095          -0.73046
4                  1.584646       1.614234          -0.73046

   air_tmp [Kelvin]  ground_tmp [Kelvin]  apparent_tmp [Kelvin]  \
0         -1.500526            -1.456613              -1.458455
1         -1.518108            -1.472720              -1.473784
2         -1.545947            -1.496879              -1.508276
3         -1.566460            -1.514328              -1.532548
4         -1.573786            -1.521039              -1.542768

   wind_direction [angle]  wind_speed [m/s]      year     month
day  \
0               -0.204843         -0.684923 -1.418166 -1.536461 -
0.877211
1               -0.171491         -0.689554 -1.418166 -1.536461 -
```

```
0.763467
2             -0.171491        -0.731232 -1.418166 -1.536461 -
0.763467
3             -0.004730        -0.717339 -1.418166 -1.536461 -
0.763467
4             -0.004730        -0.703446 -1.418166 -1.536461 -
0.763467

    weekday  date_time
0 -1.499552        0.0
1 -0.999480        0.0
2 -0.999480        0.0
3 -0.999480        0.0
4 -0.999480        0.0

   demand [MW]
0     1.661492
1     1.493961
2     1.278043
3     1.201170
4     0.963285
```

```
# creating a dummy variable
dummy_var = pd.get_dummies(labels)
dummy_var
```

```
       solar_actual [MW]  solar_forecast [MW]  solar_inferred_capacity
[MW]  \
0              -0.722664            -0.725794                     -
1.557135
1              -0.722664            -0.725794                     -
1.557135
2              -0.722664            -0.725794                     -
1.557135
3              -0.722664            -0.726072                     -
1.557135
4              -0.722664            -0.726072                     -
1.557135
...                  ...                  ...
...
45197          -0.627421            -0.584080
1.846476
45198          -0.629522            -0.652118
1.846476
45199          -0.627842            -0.652118
1.846476
45200          -0.629943            -0.649581
1.846476
45201          -0.628402            -0.650234
1.846476
```

```
       wind_actual [MW]  wind_inferred_capacity [MW]  albedo [%]  \
0             -0.912398                    -2.080709   -1.318214
1             -0.929831                    -2.080709   -1.318214
2             -0.927156                    -2.080709   -1.318214
3             -0.907233                    -2.080709   -1.318214
4             -0.890354                    -2.080709   -1.318214
...                 ...                          ...         ...
45197          0.193862                     0.969265    0.520270
45198          0.512348                     0.969265   -1.266226
45199          0.589917                     0.969265   -1.266226
45200          0.581708                     0.969265   -1.266226
45201          0.512440                     0.969265   -1.266226

       cloud_cover [%]  frozen_precipitation [%]  pressure [Pa]  \
0             0.369773                  1.531549       1.718827
1             0.323381                  1.536558       1.712526
2             0.167967                  1.560602       1.663380
3             0.057785                  1.577633       1.628095
4             0.012166                  1.584646       1.614234
...                ...                       ...            ...
45197         0.028790                 -0.520205       0.095747
45198        -0.012963                 -0.577811       0.183958
45199        -0.288997                 -0.627903       0.257047
45200        -0.452916                 -0.696528       0.322575
45201        -0.586294                 -0.715563       0.370461

       radiation [W/m2]  air_tmp [Kelvin]  ground_tmp [Kelvin]  \
0             -0.730460         -1.500526            -1.456613
1             -0.730460         -1.518108            -1.472720
2             -0.730460         -1.545947            -1.496879
3             -0.730460         -1.566460            -1.514328
4             -0.730460         -1.573786            -1.521039
...                 ...               ...                  ...
45197          0.503796         -0.829459            -0.938524
45198         -0.730460         -0.932024            -1.013687
45199         -0.730460         -0.992098            -1.059322
45200         -0.730460         -1.043380            -1.098245
45201         -0.730460         -1.091732            -1.143880

       apparent_tmp [Kelvin]  wind_direction [angle]  wind_speed [m/s]
\
0                  -1.458455               -0.204843         -0.684923

1                  -1.473784               -0.171491         -0.689554

2                  -1.508276               -0.171491         -0.731232

3                  -1.532548               -0.004730         -0.717339
```

```
4                  -1.542768                -0.004730         -0.703446

...                      ...                      ...               ...

45197              -0.820996                -0.254871         -0.249618

45198              -0.912974                -0.304900         -0.332974

45199              -0.970460                -0.288224         -0.379283

45200              -1.021559                -0.188167         -0.434854

45201              -1.063715                -0.138139         -0.485794


           year     month       day   weekday  date_time
0     -1.418166 -1.536461 -0.877211 -1.499552        0.0
1     -1.418166 -1.536461 -0.763467 -0.999480        0.0
2     -1.418166 -1.536461 -0.763467 -0.999480        0.0
3     -1.418166 -1.536461 -0.763467 -0.999480        0.0
4     -1.418166 -1.536461 -0.763467 -0.999480        0.0
...         ...       ...       ...       ...        ...
45197  1.932587 -0.964524 -0.877211 -0.499408        0.0
45198  1.932587 -0.964524 -0.877211 -0.499408        0.0
45199  1.932587 -0.964524 -0.877211 -0.499408        0.0
45200  1.932587 -0.964524 -0.877211 -0.499408        0.0
45201  1.932587 -0.964524 -0.877211 -0.499408        0.0

[45202 rows x 20 columns]
```

```
# printing the dummy varible and target to check columns and values
display(dummy_var,target)
```

```
       solar_actual [MW]  solar_forecast [MW]  solar_inferred_capacity
[MW]  \
0              -0.722664            -0.725794                     -
1.557135
1              -0.722664            -0.725794                     -
1.557135
2              -0.722664            -0.725794                     -
1.557135
3              -0.722664            -0.726072                     -
1.557135
4              -0.722664            -0.726072                     -
1.557135
...                  ...                  ...
...
45197          -0.627421            -0.584080
1.846476
45198          -0.629522            -0.652118
```

```
1.846476
45199         -0.627842           -0.652118
1.846476
45200         -0.629943           -0.649581
1.846476
45201         -0.628402           -0.650234
1.846476

       wind_actual [MW]  wind_inferred_capacity [MW]  albedo [%]  \
0             -0.912398                    -2.080709   -1.318214
1             -0.929831                    -2.080709   -1.318214
2             -0.927156                    -2.080709   -1.318214
3             -0.907233                    -2.080709   -1.318214
4             -0.890354                    -2.080709   -1.318214
...                 ...                          ...         ...
45197          0.193862                     0.969265    0.520270
45198          0.512348                     0.969265   -1.266226
45199          0.589917                     0.969265   -1.266226
45200          0.581708                     0.969265   -1.266226
45201          0.512440                     0.969265   -1.266226

       cloud_cover [%]  frozen_precipitation [%]  pressure [Pa]  \
0             0.369773                  1.531549       1.718827
1             0.323381                  1.536558       1.712526
2             0.167967                  1.560602       1.663380
3             0.057785                  1.577633       1.628095
4             0.012166                  1.584646       1.614234
...                ...                       ...            ...
45197         0.028790                 -0.520205       0.095747
45198        -0.012963                 -0.577811       0.183958
45199        -0.288997                 -0.627903       0.257047
45200        -0.452916                 -0.696528       0.322575
45201        -0.586294                 -0.715563       0.370461

       radiation [W/m2]  air_tmp [Kelvin]  ground_tmp [Kelvin]  \
0             -0.730460         -1.500526            -1.456613
1             -0.730460         -1.518108            -1.472720
2             -0.730460         -1.545947            -1.496879
3             -0.730460         -1.566460            -1.514328
4             -0.730460         -1.573786            -1.521039
...                 ...               ...                  ...
45197          0.503796         -0.829459            -0.938524
45198         -0.730460         -0.932024            -1.013687
45199         -0.730460         -0.992098            -1.059322
45200         -0.730460         -1.043380            -1.098245
45201         -0.730460         -1.091732            -1.143880

       apparent_tmp [Kelvin]  wind_direction [angle]  wind_speed [m/s]
\
0                  -1.458455               -0.204843         -0.684923
```

```
1                    -1.473784                -0.171491          -0.689554

2                    -1.508276                -0.171491          -0.731232

3                    -1.532548                -0.004730          -0.717339

4                    -1.542768                -0.004730          -0.703446

...                        ...                      ...                ...

45197                -0.820996                -0.254871          -0.249618

45198                -0.912974                -0.304900          -0.332974

45199                -0.970460                -0.288224          -0.379283

45200                -1.021559                -0.188167          -0.434854

45201                -1.063715                -0.138139          -0.485794
```

```
           year     month       day   weekday  date_time
0     -1.418166 -1.536461 -0.877211 -1.499552        0.0
1     -1.418166 -1.536461 -0.763467 -0.999480        0.0
2     -1.418166 -1.536461 -0.763467 -0.999480        0.0
3     -1.418166 -1.536461 -0.763467 -0.999480        0.0
4     -1.418166 -1.536461 -0.763467 -0.999480        0.0
...         ...       ...       ...       ...        ...
45197  1.932587 -0.964524 -0.877211 -0.499408        0.0
45198  1.932587 -0.964524 -0.877211 -0.499408        0.0
45199  1.932587 -0.964524 -0.877211 -0.499408        0.0
45200  1.932587 -0.964524 -0.877211 -0.499408        0.0
45201  1.932587 -0.964524 -0.877211 -0.499408        0.0

[45202 rows x 20 columns]
```

```
       demand [MW]
0         1.661492
1         1.493961
2         1.278043
3         1.201170
4         0.963285
...            ...
45197     1.402365
45198     1.221496
45199     0.937568
45200     0.846953
45201     0.900836
```

```
[45202 rows x 1 columns]
```

## PCA - Principal Component Analysis

```
# performing PCA on the dataset - simplifying the data dimentionality
but retians the trend and patterns

from sklearn.decomposition import PCA

pca = PCA(n_components=0.95)
pca.fit(labels)

data = pca.transform(labels)
data
```

```
array([[-2.78471225,  2.90469216, -2.10942872, ...,  0.22299709,
        -1.03870001,  0.64435663],
       [-2.78910591,  2.90562839, -2.14325658, ...,  0.21829444,
        -1.01771968,  0.60906081],
       [-2.79665642,  2.90472032, -2.20308567, ...,  0.23598449,
        -0.98910709,  0.45822987],
       ...,
       [-2.20293239, -2.9963833 , -0.45897433, ..., -0.14323728,
        -0.91133233, -0.45771111],
       [-2.21443235, -3.03441813, -0.57577993, ..., -0.20329663,
        -0.85894256, -0.5810874 ],
       [-2.22266904, -3.05007221, -0.69886001, ..., -0.21841557,
        -0.81541014, -0.68695632]])
```

```
# view shape of the features and labels
display(data.shape,labels.shape)
```

```
(45202, 11)

(45202, 20)
```

```
from sklearn import model_selection

#split data as training and testing set 80% and 20% respectively
from sklearn.model_selection import train_test_split

ft_train, ft_test, lb_train, lb_test = train_test_split(data , target,
test_size=0.20, random_state = 2)
display(ft_train.shape,ft_test.shape)
```

```
(36161, 11)

(9041, 11)
```

# Applying Machine Learning Algorithms

## Multiple Linear Regression

### MLR with SKlearn

```
from sklearn import linear_model


X = ft_train
Y = lb_train
x = ft_test
y = lb_test


# with sklearn getting multiple linear regression model
regr = linear_model.LinearRegression()
regr.fit(X, Y)

print('Intercept:', regr.intercept_)
print('\nCoefficients:', regr.coef_)

# prediction with sklearn
lb_pred = regr.predict(x)
print ('\n Predicted : ', lb_pred)
```

```
Intercept: [0.00094522]

Coefficients: [[-0.18155873  0.01764568  0.04553938  0.39974097 -
0.05768068  0.04373949
  -0.05093017 -0.11469166  0.2545215   0.27969645  0.09930878]]

 Predicted :  [[ 1.07324433]
 [-0.09303835]
 [-0.87059143]
 ...
 [ 0.08873127]
 [ 0.08924766]
 [-0.98638567]]
```

```
from sklearn.metrics import r2_score, mean_absolute_error
from sklearn.metrics import mean_squared_error
from math import sqrt


#predicted output values for test inputs
pred = lb_pred
# output values from the test set
test = lb_test
```

```
print('Multiple Linear Regression')
print('-----------------------------')

MAE = mean_absolute_error(test, pred)
print('MAE : {}'.format(round(MAE, 2)))

MSE = mean_squared_error(test, pred)
print('MSE : {}'.format(round(MSE, 2)))

RMSE = sqrt(MSE)
print('RMSE  : %f' % RMSE)

R2_SCORE=r2_score(test, pred)
print('R2_SCORE  : %f' % R2_SCORE)
```

```
Multiple Linear Regression
------------------------------
MAE : 0.54
MSE : 0.45
RMSE  : 0.667367
R2_SCORE  : 0.557940
```

### MLR with stats Model

```
# with statsmodels
import statsmodels.api as sm
X = sm.add_constant(X) # adding a constant

model = sm.OLS(Y, X).fit()
predictions = model.predict(X)

print_model = model.summary()
print(print_model)
```

```
                            OLS Regression Results

======================================================================
========
Dep. Variable:            demand [MW]   R-squared:
0.542
Model:                            OLS   Adj. R-squared:
0.542
Method:                 Least Squares   F-statistic:
3895.
Date:                Thu, 26 May 2022   Prob (F-statistic):
0.00
Time:                        22:18:38   Log-Likelihood:
-37141.
No. Observations:               36161   AIC:
7.431e+04
Df Residuals:                   36149   BIC:
```

```
7.441e+04
Df Model:                          11

Covariance Type:            nonrobust

======================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
--------
const          0.0009      0.004      0.266      0.790      -0.006
0.008
x1            -0.1816      0.002   -116.846      0.000      -0.185
-0.179
x2             0.0176      0.002      8.949      0.000       0.014
0.022
x3             0.0455      0.002     20.770      0.000       0.041
0.050
x4             0.3997      0.003    138.955      0.000       0.394
0.405
x5            -0.0577      0.003    -16.758      0.000      -0.064
-0.051
x6             0.0437      0.004     12.302      0.000       0.037
0.051
x7            -0.0509      0.004    -13.598      0.000      -0.058
-0.044
x8            -0.1147      0.004    -29.309      0.000      -0.122
-0.107
x9             0.2545      0.004     61.575      0.000       0.246
0.263
x10            0.2797      0.004     63.527      0.000       0.271
0.288
x11            0.0993      0.005     18.325      0.000       0.089
0.110
======================================================================
========
Omnibus:                      356.263   Durbin-Watson:
1.974
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
230.437
Skew:                           0.032   Prob(JB):
9.15e-51
Kurtosis:                       2.614   Cond. No.
3.49
======================================================================
========

Notes:
```

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

## Support Vector Regressor

```
import numpy as np
np.random.seed(seed=5)

import warnings
warnings.simplefilter("ignore", UserWarning)

from sklearn.svm import SVR
from sklearn.pipeline import make_pipeline


# Train the model using the training sets for c=10 and e=0.4
regr = SVR(C=10, epsilon=0.4)
regr.fit(ft_train, lb_train)

# Make predictions using the testing set
lb_pred = regr.predict(ft_test)

#predicted output values for test inputs
pred = lb_pred
# output values from the test set
test = lb_test

print('Support Vector Regressor')
print('------------------------------')

print('Accuracy : {}'.format(regr.score(ft_test, lb_test)))

MAE = mean_absolute_error(test, pred)
print('MAE : {}'.format(round(MAE, 2)))

MSE = mean_squared_error(test, pred)
print('MSE : {}'.format(round(MSE, 2)))

RMSE = sqrt(MSE)
print('RMSE  : %f' % RMSE)

R2_SCORE=r2_score(test, pred)
print('R2_SCORE  : %f' % R2_SCORE)
```

```
Support Vector Regressor
------------------------------
Accuracy : 0.9021214271293617
MAE : 0.25
MSE : 0.1
```

```
RMSE  : 0.314027
R2_SCORE  : 0.902121
```

### KNN Regressor

```
from sklearn.neighbors import KNeighborsRegressor

# checking the accuracy while looping through the neighbors count from
1 to 9
for n in range(1,10):
    knn = KNeighborsRegressor(n_neighbors = n)
    knn.fit(ft_train, lb_train)
    lb_pred = knn.predict(ft_test)
    print('KNeighborsRegressor: n = {} , Accuracy is:
{}'.format(n,knn.score(ft_test, lb_test)))
```

```
KNeighborsRegressor: n = 1 , Accuracy is: 0.9330912296321977
KNeighborsRegressor: n = 2 , Accuracy is: 0.9368616346234755
KNeighborsRegressor: n = 3 , Accuracy is: 0.9282242321250205
KNeighborsRegressor: n = 4 , Accuracy is: 0.9191727791237678
KNeighborsRegressor: n = 5 , Accuracy is: 0.9106532757284097
KNeighborsRegressor: n = 6 , Accuracy is: 0.9023029954702092
KNeighborsRegressor: n = 7 , Accuracy is: 0.8950332665738461
KNeighborsRegressor: n = 8 , Accuracy is: 0.8884318350134284
KNeighborsRegressor: n = 9 , Accuracy is: 0.8833946271672667
```

```
#predicted output values for test inputs
pred = lb_pred
# output values from the test set
test = lb_test

print('KNeighborsRegressor')
print('------------------------------')
# initialising the regressor for n=2
knn = KNeighborsRegressor(n_neighbors = 2)

# applying the model for the test values
knn.fit(ft_train, lb_train)

# predicting the out put values for test inputs
lb_pred = knn.predict(ft_test)

print('Accuracy : {}'.format(knn.score(ft_test, lb_test)))

MAE = mean_absolute_error(test, pred)
print('MAE : {}'.format(round(MAE, 2)))

MSE = mean_squared_error(test, pred)
print('MSE : {}'.format(round(MSE, 2)))

RMSE = sqrt(MSE)
```

```python
print('RMSE  : %f' % RMSE)

R2_SCORE=r2_score(test, pred)
print('R2_SCORE  : %f' % R2_SCORE)#predicted output values for test
inputs
pred = lb_pred
# output values from the test set
test = lb_test

print('KNeighborsRegressor')
print('------------------------------')
# initialising the regressor for n=2
knn = KNeighborsRegressor(n_neighbors = 2)

# applying the model for the test values
knn.fit(ft_train, lb_train)

# predicting the out put values for test inputs
lb_pred = knn.predict(ft_test)

print('Accuracy : {}'.format(knn.score(ft_test, lb_test)))

MAE = mean_absolute_error(test, pred)
print('MAE : {}'.format(round(MAE, 2)))

MSE = mean_squared_error(test, pred)
print('MSE : {}'.format(round(MSE, 2)))

RMSE = sqrt(MSE)
print('RMSE  : %f' % RMSE)

R2_SCORE=r2_score(test, pred)
print('R2_SCORE  : %f' % R2_SCORE)
```

```
KNeighborsRegressor
------------------------------
Accuracy : 0.9368616346234755
MAE : 0.27
MSE : 0.12
RMSE  : 0.342754
R2_SCORE  : 0.883395
KNeighborsRegressor
------------------------------
Accuracy : 0.9368616346234755
MAE : 0.18
MSE : 0.06
RMSE  : 0.252215
R2_SCORE  : 0.936862
```

## MLP Regressor ( Multi Layer Perceptron Model)

```
import numpy as np
s=3;
np.random.seed(seed=s)

from sklearn.neural_network import MLPRegressor
from sklearn import metrics

# creating mlp regressor model from sklearn
model = MLPRegressor()

#Training the model with test data
model.fit(ft_train, lb_train)

#predicting the output for test inputs
lb_pred = model.predict(ft_test)

#predicted output values for test inputs
pred = lb_pred
# output values from the test set
test = lb_test

print('Multi Layer Perceptron Model')
print('------------------------------')

print('Accuracy : {}'.format(metrics.r2_score(test, pred)))

MAE = mean_absolute_error(test, pred)
print('MAE : {}'.format(round(MAE, 2)))

MSE = mean_squared_error(test, pred)
print('MSE : {}'.format(round(MSE, 2)))

RMSE = sqrt(MSE)
print('RMSE  : %f' % RMSE)

R2_SCORE=r2_score(test, pred)
print('R2_SCORE  : %f' % R2_SCORE)
```

```
Multi Layer Perceptron Model
------------------------------
Accuracy : 0.897587747928458
MAE : 0.25
MSE : 0.1
RMSE  : 0.321218
R2_SCORE  : 0.897588
```

NumPy random seed is a function that sets the NumPy pseudo-random number generator's random seed.

It is required as an input for NumPy to generate pseudo-random integers for random processes.

# Time-Series Analysis

## Data preparation

```
# fetching the originally pre processed data before performing
regression analysis.
new_data_ts.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 45202 entries, 192 to 45431
Data columns (total 23 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   date                          45202 non-null  datetime64[ns, UTC]
 1   demand [MW]                   45202 non-null  float64
 2   solar_actual [MW]             45202 non-null  float64
 3   solar_forecast [MW]           45202 non-null  float64
 4   solar_inferred_capacity [MW]  45202 non-null  float64
 5   wind_actual [MW]              45202 non-null  float64
 6   wind_inferred_capacity [MW]   45202 non-null  float64
 7   albedo [%]                    45202 non-null  float64
 8   cloud_cover [%]               45202 non-null  float64
 9   frozen_precipitation [%]      45202 non-null  float64
 10  pressure [Pa]                 45202 non-null  float64
 11  radiation [W/m2]              45202 non-null  float64
 12  air_tmp [Kelvin]              45202 non-null  float64
 13  ground_tmp [Kelvin]           45202 non-null  float64
 14  apparent_tmp [Kelvin]         45202 non-null  float64
 15  wind_direction [angle]        45202 non-null  float64
 16  wind_speed [m/s]              45202 non-null  float64
 17  date_                         45202 non-null  datetime64[ns]
 18  year                          45202 non-null  int64
 19  month                         45202 non-null  int64
 20  day                           45202 non-null  int64
 21  weekday                       45202 non-null  object
 22  date_time                     45202 non-null  int64
dtypes: datetime64[ns, UTC](1), datetime64[ns](1), float64(16),
int64(4), object(1)
memory usage: 8.3+ MB

new_data_ts.head()

                         date  demand [MW]  solar_actual [MW]  \
192 2017-01-08 23:00:00+00:00     72921.75                0.0
193 2017-01-09 00:00:00+00:00     70956.00                0.0
194 2017-01-09 01:00:00+00:00     68422.50                0.0
195 2017-01-09 02:00:00+00:00     67520.50                0.0
```

```
196 2017-01-09 03:00:00+00:00     64729.25               0.0

     solar_forecast [MW]  solar_inferred_capacity [MW]  wind_actual
[MW]  \
192                0.55                       5756.44
1151.00
193                0.55                       5756.44
1103.75
194                0.55                       5756.44
1111.00
195                0.06                       5756.44
1165.00
196                0.06                       5756.44
1210.75

     wind_inferred_capacity [MW]  albedo [%]  cloud_cover [%]  \
192                     10513.95         0.0            64.91
193                     10513.95         0.0            63.71
194                     10513.95         0.0            59.69
195                     10513.95         0.0            56.84
196                     10513.95         0.0            55.66

     frozen_precipitation [%]  ...  ground_tmp [Kelvin]  \
192                     -1.06  ...               273.44
193                     -0.96  ...               273.32
194                     -0.48  ...               273.14
195                     -0.14  ...               273.01
196                      0.00  ...               272.96

     apparent_tmp [Kelvin]  wind_direction [angle]  wind_speed
[m/s]  \
192                 271.90                   178.0              4.14

193                 271.78                   180.0              4.13

194                 271.51                   180.0              4.04

195                 271.32                   190.0              4.07

196                 271.24                   190.0              4.10


         date_  year  month day  weekday  date_time
192 2017-01-08  2017      1   8   Sunday          0
193 2017-01-09  2017      1   9   Monday          0
194 2017-01-09  2017      1   9   Monday          0
195 2017-01-09  2017      1   9   Monday          0
196 2017-01-09  2017      1   9   Monday          0
```

```
[5 rows x 23 columns]
```

```python
# getting list of columns from new_data_ts
new_data_ts.columns
```

```
Index(['date', 'demand [MW]', 'solar_actual [MW]', 'solar_forecast
[MW]',
       'solar_inferred_capacity [MW]', 'wind_actual [MW]',
       'wind_inferred_capacity [MW]', 'albedo [%]', 'cloud_cover [%]',
       'frozen_precipitation [%]', 'pressure [Pa]', 'radiation
[W/m2]',
       'air_tmp [Kelvin]', 'ground_tmp [Kelvin]', 'apparent_tmp
[Kelvin]',
       'wind_direction [angle]', 'wind_speed [m/s]', 'date_', 'year',
'month',
       'day', 'weekday', 'date_time'],
      dtype='object')
```

```python
# performing univariate time series analysis so keep date_time ,
traffic_volume column and remove other data
cols = ["date", 'solar_actual [MW]', 'solar_forecast [MW]',
'solar_inferred_capacity [MW]', 'wind_actual [MW]',
'wind_inferred_capacity [MW]',
       'albedo [%]','cloud_cover [%]','frozen_precipitation
[%]','pressure [Pa]','radiation [W/m2]','air_tmp [Kelvin]',"ground_tmp
[Kelvin]","apparent_tmp [Kelvin]",'wind_direction [angle]','wind_speed
[m/s]','year','month','day','weekday','date_time']
new_data_ts.drop(cols, axis=1, inplace=True)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\pandas\core\frame.py:4308:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  return super().drop(
```

```python
new_data_ts.head()
```

```
     demand [MW]      date_
192     72921.75 2017-01-08
193     70956.00 2017-01-09
194     68422.50 2017-01-09
195     67520.50 2017-01-09
196     64729.25 2017-01-09
```

```python
# data is recorded per hour, so we group data by data
new_data_ts = new_data_ts.groupby('date_')['demand
```

```
[MW]'].mean().reset_index()
new_data_ts.head()
```

```
       date_   demand [MW]
0 2017-01-08  72921.750000
1 2017-01-09  75206.875000
2 2017-01-10  74969.802083
3 2017-01-11  73123.010417
4 2017-01-12  71852.322917
```

```
new_data_ts['demand [MW]'] = new_data_ts['demand [MW]'].astype(int)
```

```
# setting date as index to create univariate dataset
timeSeries= new_data_ts.set_index(['date_'])
timeSeries.index
```

```
DatetimeIndex(['2017-01-08', '2017-01-09', '2017-01-10', '2017-01-11',
               '2017-01-12', '2017-01-13', '2017-01-14', '2017-01-15',
               '2017-01-16', '2017-01-17',
               ...
               '2022-02-27', '2022-02-28', '2022-03-01', '2022-03-02',
               '2022-03-03', '2022-03-04', '2022-03-05', '2022-03-06',
               '2022-03-07', '2022-03-08'],
              dtype='datetime64[ns]', name='date_', length=1886,
freq=None)
```

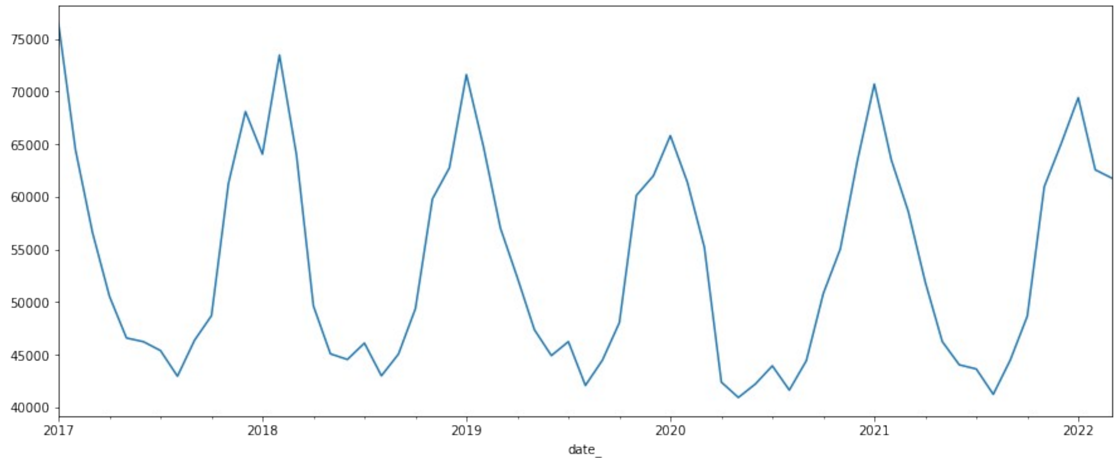
```
timeSeries.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1886 entries, 2017-01-08 to 2022-03-08
Data columns (total 1 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   demand [MW]  1886 non-null   int32
dtypes: int32(1)
memory usage: 22.1 KB
```

```
# creating a timeseries object by resampling by monthly average.

# getting values of monthly by calculating average
timeSeries = timeSeries['demand [MW]'].resample('MS').mean()

timeSeries.head()
```

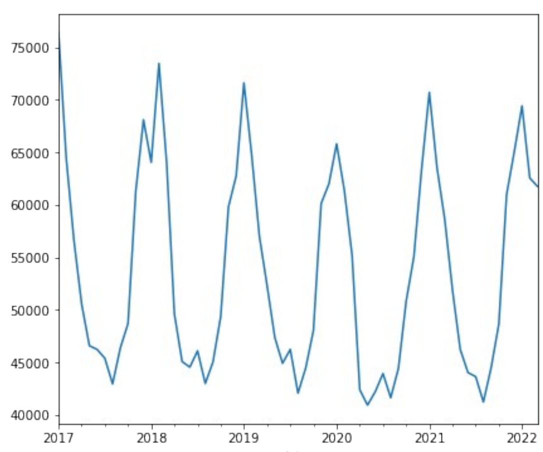
```
date_
2017-01-01    76451.875000
2017-02-01    64459.821429
2017-03-01    56607.774194
2017-04-01    50537.400000
2017-05-01    46589.225806
Freq: MS, Name: demand [MW], dtype: float64
```

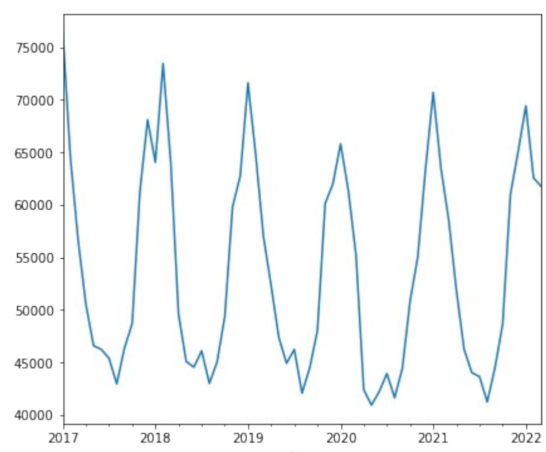
```python
#plotting the timeseries object
timeSeries.plot(figsize=(15, 6))
plt.show()
```



```python
# analysing the time series by filling missing values (if any) by mean
using ffill and interpolate methods

#timeSeries_filled= timeSeries.ffill()
#timeSeries_filled= timeSeries.interpolate(limit=2,
limit_direction="forward");


timeSeries_filled = timeSeries.interpolate();

fig, axs = plt.subplots(1,2, figsize=(15, 6))

timeSeries.plot(ax=axs[0])
timeSeries_filled.plot(ax=axs[1])
```

```
<AxesSubplot:xlabel='date_'>
```





## Moving Average Analysis

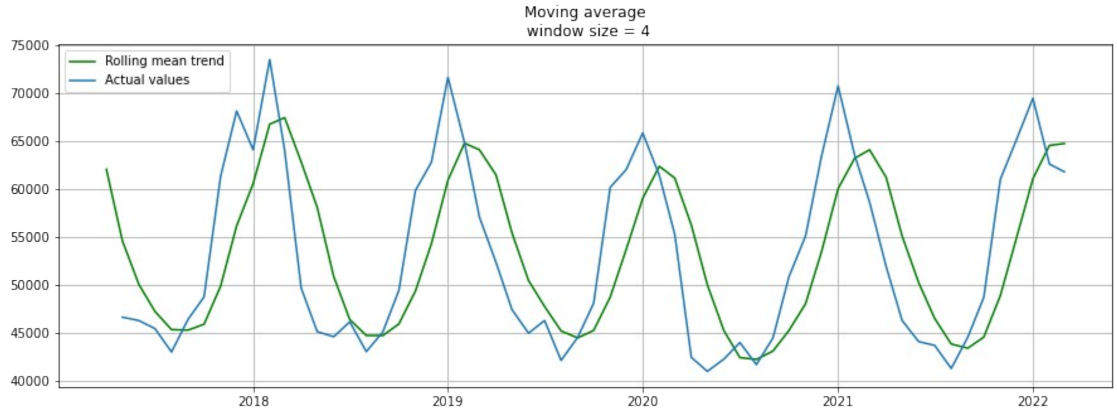
A moving average is a collection of averages derived from historical data.

Any number of time periods can be used to calculate moving averages.

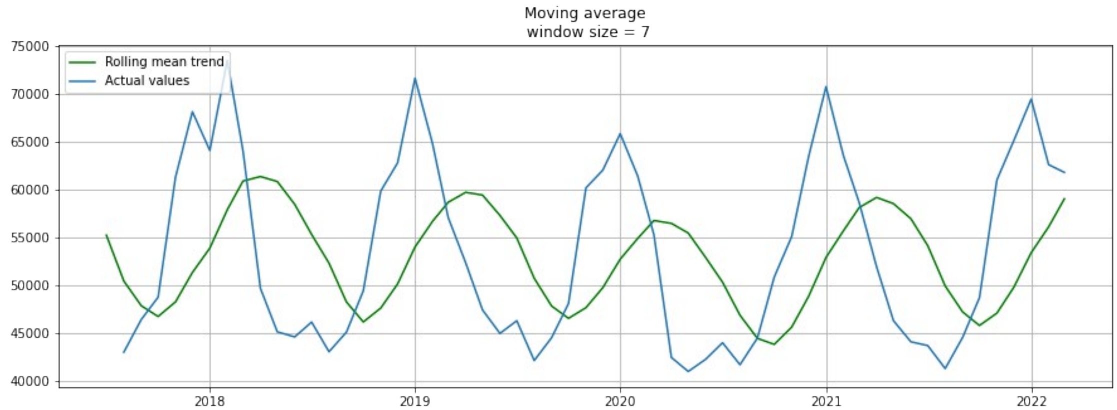
```
from sklearn.metrics import r2_score, median_absolute_error,
mean_absolute_error
from sklearn.metrics import median_absolute_error, mean_squared_error,
mean_squared_log_error

def mean_absolute_percentage_error(y_true, y_pred):
    return np.mean(np.abs((y_true - y_pred) / y_true)) * 100

#Calculate average of last n observations
def moving_average(series, n):
    return np.average(series[-n:])

def plotMovingAverage(series, window, plot_intervals=False,
scale=1.96, plot_anomalies=False):

    """
        series - dataframe with timeseries
        window - rolling window size
        plot_intervals - show confidence intervals
        plot_anomalies - show anomalies

    """
    rolling_mean = series.rolling(window=window).mean()

    plt.figure(figsize=(15,5))
    plt.title("Moving average\n window size = {}".format(window))
    plt.plot(rolling_mean, "g", label="Rolling mean trend")

    # Plot confidence intervals for smoothed values
    if plot_intervals:
        mae = mean_absolute_error(series[window:],
rolling_mean[window:])
        deviation = np.std(series[window:] - rolling_mean[window:])
        lower_bond = rolling_mean - (mae + scale * deviation)
        upper_bond = rolling_mean + (mae + scale * deviation)
        plt.plot(upper_bond, "r--", label="Upper Bond / Lower Bond")
        plt.plot(lower_bond, "r--")

        # Having the intervals, find abnormal values
        if plot_anomalies:
            anomalies = pd.DataFrame(series[series.name])
            anomalies[series<lower_bond] = series[series<lower_bond]
            anomalies[series>upper_bond] = series[series>upper_bond]
            plt.plot(anomalies, "ro", markersize=10)
```

```
    plt.plot(series[window:], label="Actual values")
    plt.legend(loc="upper left")
    plt.grid(True)
```

```
# Plotting the timeseries plot
plotMovingAverage(timeSeries, 4)
```




```
# Plotting the timeseries plot for missing and filled data
#plotMovingAverage(timeSeries_filled, 4)

plotMovingAverage(timeSeries, 7) # weekly smoothing
```



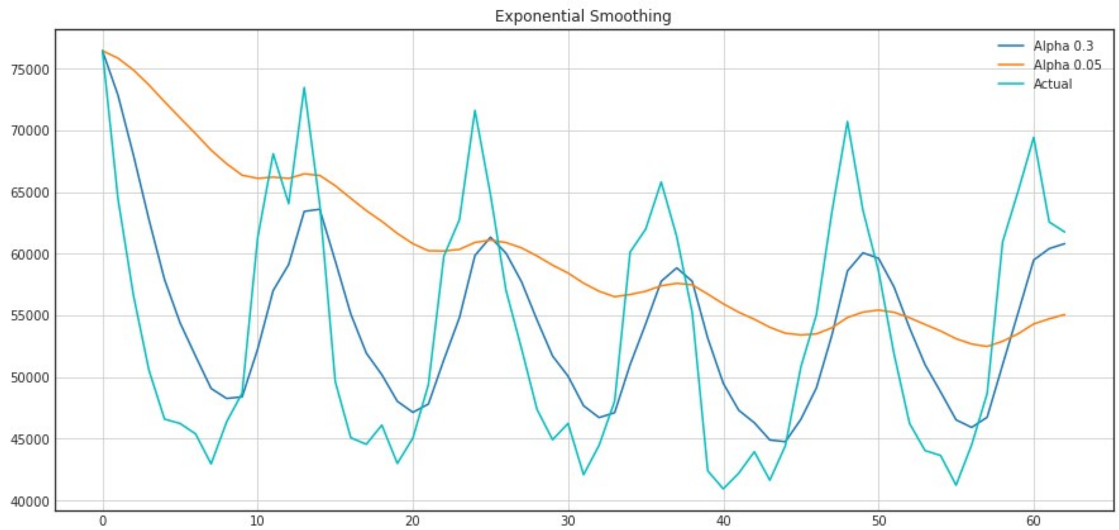

```
#plotMovingAverage(timeSeries_filled, 7) # weekly smoothing
```

### Weighted Average Analysis

A weighted average is a calculation that considers the relative value of the values in a data collection.

Each number in the data set is multiplied by a predefined weight before the final computation is completed when calculating a weighted average.

```python
def weighted_average(series, weights):
    """
        Calculate weighted average on the series.
        Assuming weights are sorted in descending order
        (larger weights are assigned to more recent observations).
    """
    result = 0.0
    for n in range(len(weights)):
        result += series.iloc[-n-1] * weights[n]
    return float(result)

def exponential_smoothing(series, alpha):
    """
        series - dataset with timestamps
        alpha - float [0.0, 1.0], smoothing parameter
    """
    result = [series[0]] # first value is same as series
    for n in range(1, len(series)):
        result.append(alpha * series[n] + (1 - alpha) * result[n-1])
    return result

def plotExponentialSmoothing(series, alphas):
    """
        Plots exponential smoothing with different alphas

        series - dataset with timestamps
        alphas - list of floats, smoothing parameters

    """
    with plt.style.context('seaborn-white'):
        plt.figure(figsize=(15, 7))
        for alpha in alphas:
            plt.plot(exponential_smoothing(series, alpha),
label="Alpha {}".format(alpha))
        plt.plot(series.values, "c", label = "Actual")
        plt.legend(loc="best")
        plt.axis('tight')
        plt.title("Exponential Smoothing")
        plt.grid(True);

plotExponentialSmoothing(timeSeries.astype(int), [0.3, 0.05])
```



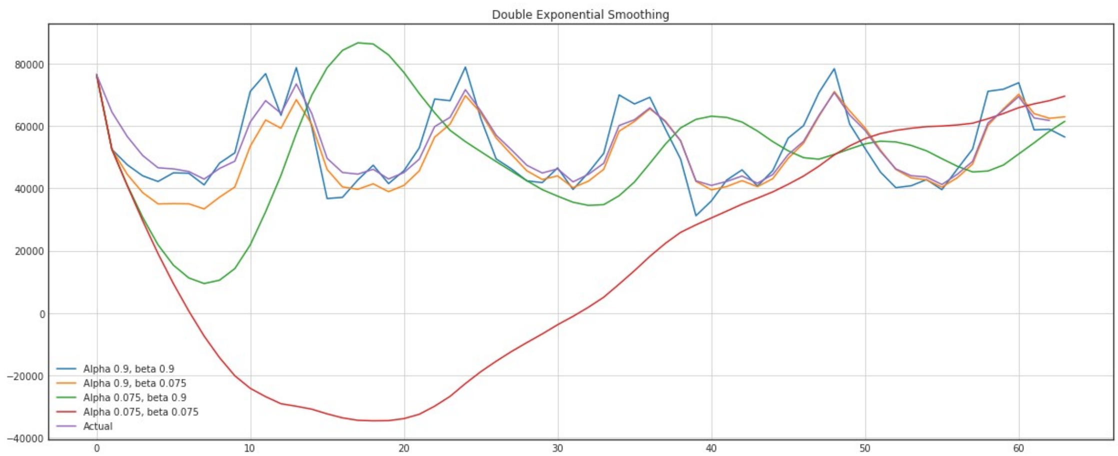

### Eponential Smooting

Exponentially smoothed forecasts are weighted averages of previous observations, with the weights decaying exponentially as the observations get older.

In other words, the larger the related weight, the more recent the observation.

```
def double_exponential_smoothing(series, alpha, beta):
    """
        series - dataset with timeseries
        alpha - float [0.0, 1.0], smoothing parameter for level
        beta - float [0.0, 1.0], smoothing parameter for trend
    """
    # first value is same as series
    result = [series[0]]
    for n in range(1, len(series)+1):
        if n == 1:
            level, trend = series[0], series[1] - series[0]
        if n >= len(series): # forecasting
            value = result[-1]
        else:
            value = series[n]
        last_level, level = level, alpha*value + (1-
alpha)*(level+trend)
        trend = beta*(level-last_level) + (1-beta)*trend
        result.append(level+trend)
    return result

def plotDoubleExponentialSmoothing(series, alphas, betas):
    """
        Plots double exponential smoothing with different alphas and
betas

        series - dataset with timestamps
```

```
        alphas - list of floats, smoothing parameters for level
        betas - list of floats, smoothing parameters for trend
    """

    with plt.style.context('seaborn-white'):
        plt.figure(figsize=(20, 8))
        for alpha in alphas:
            for beta in betas:
                plt.plot(double_exponential_smoothing(series, alpha,
beta), label="Alpha {}, beta {}".format(alpha, beta))
        plt.plot(series.values, label = "Actual")
        plt.legend(loc="best")
        plt.axis('tight')
        plt.title("Double Exponential Smoothing")
        plt.grid(True)

plotDoubleExponentialSmoothing(timeSeries.astype(int), alphas=[0.9,
0.075], betas=[0.9, 0.075])
```




### Time Series - Decomposition

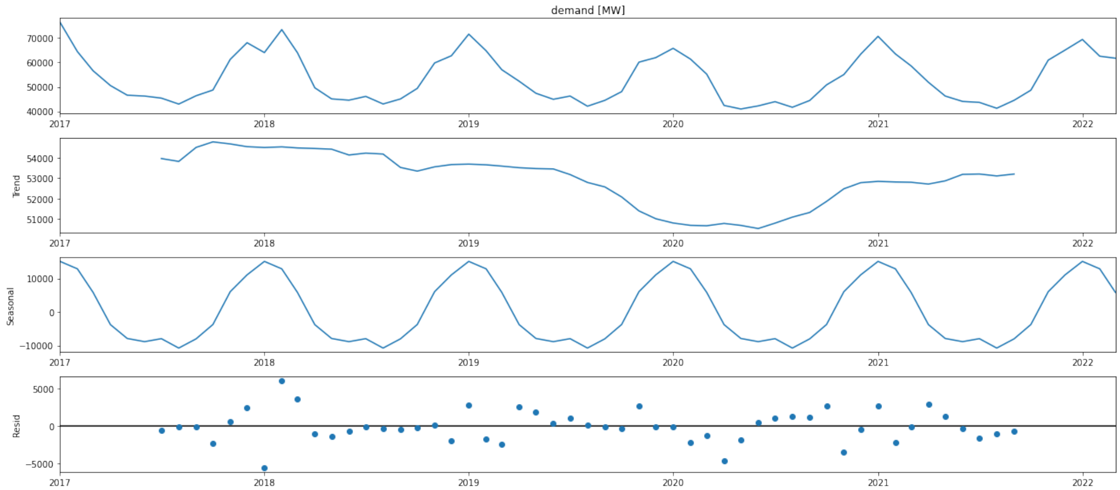
Because time series data can display a wide range of patterns, it's often useful to break it down into numerous components, each reflecting a different pattern category.

We commonly combine the trend and cycle into a single trend-cycle component when decomposing a time series into components (sometimes called the trend for simplicity).

As a result, we consider a time series to have three parts: a trend-cycle component, a seasonal component, and a remainder component (containing anything else in the time series).

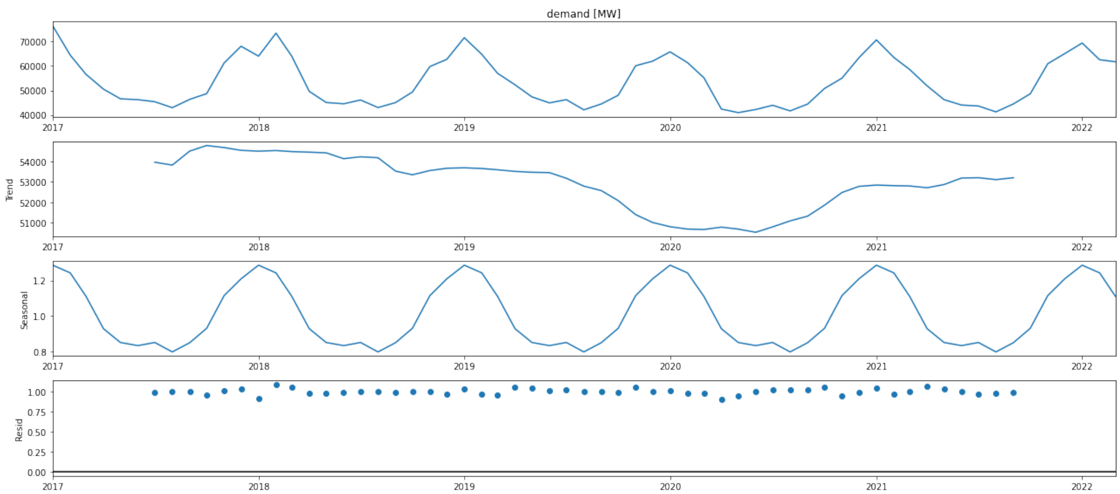
```
import statsmodels.api as sm
from pylab import rcParams

rcParams['figure.figsize'] = 18, 8
decomposition = sm.tsa.seasonal_decompose(timeSeries,
model='additive')
```

```
fig = decomposition.plot()
plt.show()
```




```
rcParams['figure.figsize'] = 18, 8
decomposition = sm.tsa.seasonal_decompose(timeSeries,
model='multiplicative')
```

```
fig = decomposition.plot()
plt.show()
```



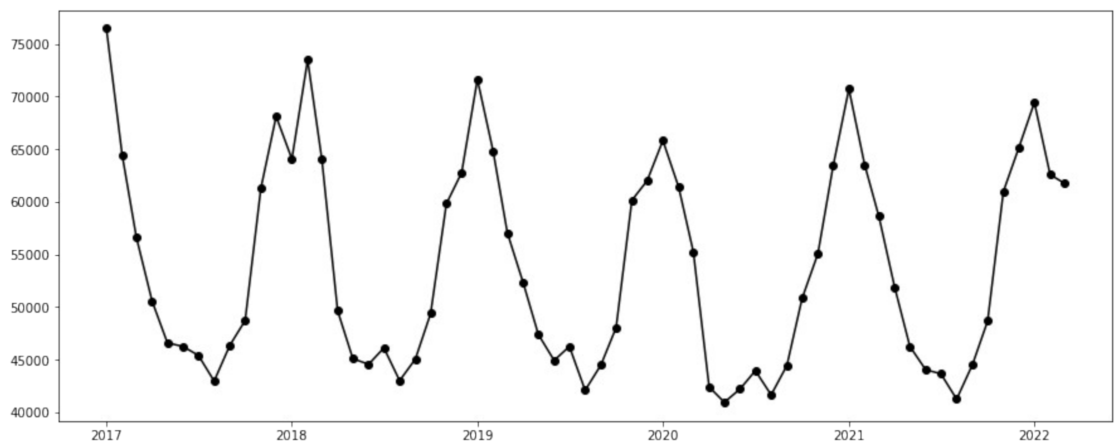

### Stats Model

Stats model is a Python module that includes classes and functions for estimating a variety of statistical models,

executing statistical tests, and exploring statistical data.

```
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.tsa.api import ExponentialSmoothing,
SimpleExpSmoothing, Holt
%matplotlib inline

fit1 = SimpleExpSmoothing(timeSeries,
initialization_method="heuristic").fit(smoothing_level=0.2,optimized=F
alse)
fcast1 = fit1.forecast(3).rename(r'$\alpha=0.2$')
fit2 = SimpleExpSmoothing(timeSeries,
initialization_method="heuristic").fit(smoothing_level=0.2,optimized=F
alse)
fcast2 = fit2.forecast(3).rename(r'$\alpha=0.6$')

plt.figure(figsize=(15, 6))

#plt.plot(timeSeries, marker='o', color='orange')
plt.plot(timeSeries, marker='o', color='black')
```

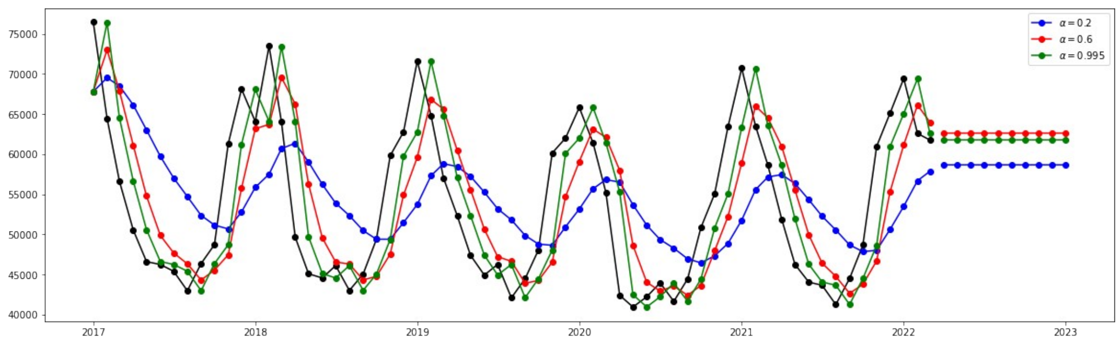
```
[<matplotlib.lines.Line2D at 0x2515bb089d0>]
```




```
fit1 = SimpleExpSmoothing(timeSeries,
initialization_method="heuristic").fit(smoothing_level=0.2,optimized=F
alse)
fcast1 = fit1.forecast(10).rename(r'$\alpha=0.2$')
fit2 = SimpleExpSmoothing(timeSeries,
initialization_method="heuristic").fit(smoothing_level=0.6,optimized=F
alse)
fcast2 = fit2.forecast(10).rename(r'$\alpha=0.6$')
fit3 = SimpleExpSmoothing(timeSeries,
initialization_method="estimated").fit()
fcast3 = fit3.forecast(10).rename(r'$\alpha=
%s$'%fit3.model.params['smoothing_level'])
```

```
plt.figure(figsize=(20, 6))
plt.plot(timeSeries, marker='o', color='black')
plt.plot(fit1.fittedvalues, marker='o', color='blue')
line1, = plt.plot(fcast1, marker='o', color='blue')
plt.plot(fit2.fittedvalues, marker='o', color='red')
line2, = plt.plot(fcast2, marker='o', color='red')
plt.plot(fit3.fittedvalues, marker='o', color='green')
line3, = plt.plot(fcast3, marker='o', color='green')
plt.legend([line1, line2, line3], [fcast1.name, fcast2.name,
fcast3.name])
```

```
<matplotlib.legend.Legend at 0x2515ba854f0>
```



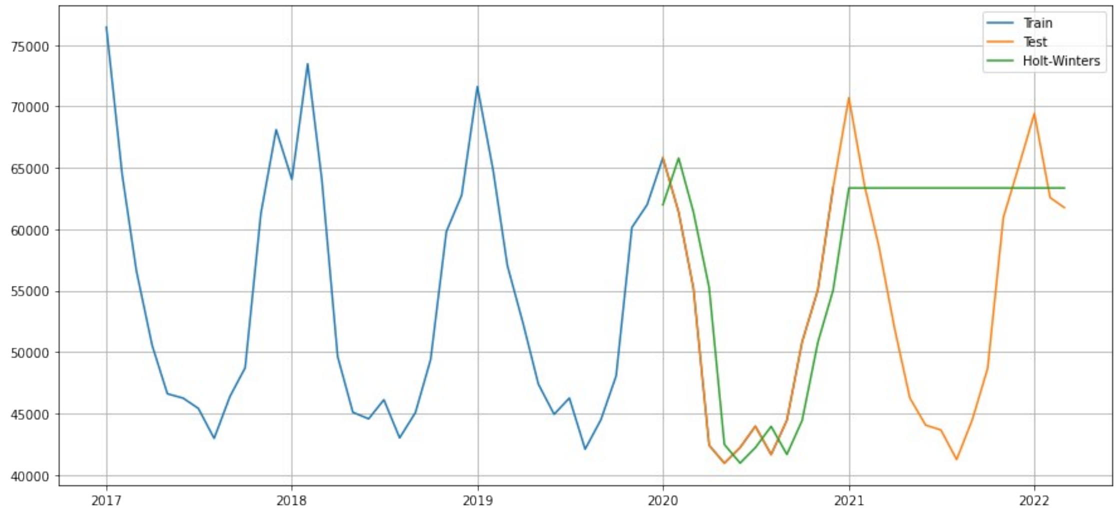

## Unsupervised

### Holt-Winters Forecast

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.holtwinters import ExponentialSmoothing


train, test = timeSeries[:'2020'], timeSeries['2020':]
model = ExponentialSmoothing(train, seasonal_periods=12).fit()
pred = model.predict(start=test.index[0], end=test.index[-1])

plt.figure(figsize=(15, 7))
plt.plot(train.index, train, label='Train')
plt.plot(test.index, test, label='Test')
plt.plot(pred.index, pred, label='Holt-Winters')
plt.legend(loc="upper right")
plt.grid(True)

from sklearn.metrics import mean_absolute_error
from sklearn.metrics import r2_score
from math import sqrt

print("Unsupervised - without missing values ")
```

```
print('Holt-Winters')
print("----------------")

MAE = mean_absolute_error(test, pred)
print('MAE : {}'.format(round(MAE, 2)))

MSE = mean_squared_error(test, pred)
print('MSE : {}'.format(round(MSE, 2)))


RMSE = sqrt(MSE)
print('RMSE  : %f' % RMSE)


R2_SCORE=r2_score(test, pred)
print('R2_SCORE  : %f' % R2_SCORE)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\
holtwinters\model.py:427: FutureWarning: After 0.13 initialization
must be handled at model creation
  warnings.warn(

Unsupervised - without missing values
Holt-Winters
----------------
MAE : 7556.53
MSE : 102168691.71
RMSE  : 10107.852972
R2_SCORE  : -0.077558
```




### ARIMA using sklearn (timeseries values)

```
import itertools

p = d = q = range(0, 2)
```

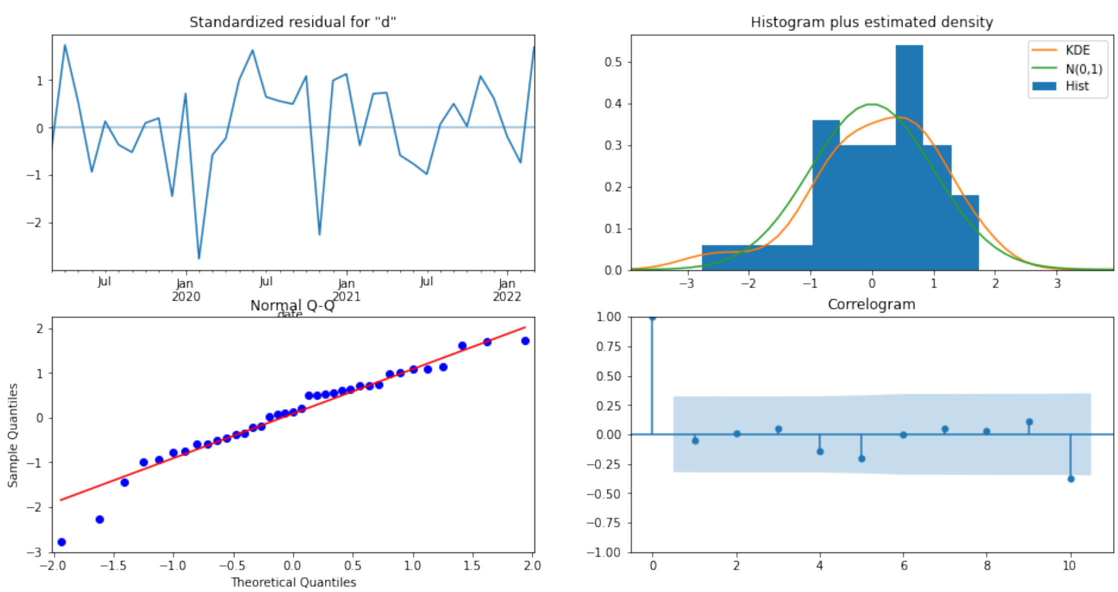
```
pdq = list(itertools.product(p, d, q))
seasonal_pdq = [(x[0], x[1], x[2], 12) for x in
list(itertools.product(p, d, q))]
print('Examples of parameter combinations for Seasonal ARIMA...')
print('SARIMAX: {} x {}'.format(pdq[1], seasonal_pdq[1]))
print('SARIMAX: {} x {}'.format(pdq[1], seasonal_pdq[2]))
print('SARIMAX: {} x {}'.format(pdq[2], seasonal_pdq[3]))
print('SARIMAX: {} x {}'.format(pdq[2], seasonal_pdq[4]))

import warnings
warnings.filterwarnings("ignore")


for param in pdq:
    for param_seasonal in seasonal_pdq:
        try:
            mod = sm.tsa.statespace.SARIMAX(timeSeries,
                                            order=param,

seasonal_order=param_seasonal,

enforce_stationarity=False,

enforce_invertibility=False)
            results = mod.fit()
            print('ARIMA{}x{}12 - AIC:{}'.format(param,
param_seasonal, results.aic))
        except:
            continue
```

```
Examples of parameter combinations for Seasonal ARIMA...
SARIMAX: (0, 0, 1) x (0, 0, 1, 12)
SARIMAX: (0, 0, 1) x (0, 1, 0, 12)
SARIMAX: (0, 1, 0) x (0, 1, 1, 12)
SARIMAX: (0, 1, 0) x (1, 0, 0, 12)
ARIMA(0, 0, 0)x(0, 0, 0, 12)12 - AIC:1529.4529986768473
ARIMA(0, 0, 0)x(0, 0, 1, 12)12 - AIC:36979.12674710643
ARIMA(0, 0, 0)x(0, 1, 0, 12)12 - AIC:974.9172940291796
ARIMA(0, 0, 0)x(0, 1, 1, 12)12 - AIC:728.6171044130301
ARIMA(0, 0, 0)x(1, 0, 0, 12)12 - AIC:1003.464506609924
ARIMA(0, 0, 0)x(1, 0, 1, 12)12 - AIC:983.965315406852
ARIMA(0, 0, 0)x(1, 1, 0, 12)12 - AIC:740.2776908932278
ARIMA(0, 0, 0)x(1, 1, 1, 12)12 - AIC:721.8502997668725
ARIMA(0, 0, 1)x(0, 0, 0, 12)12 - AIC:1463.4127020989029
ARIMA(0, 0, 1)x(0, 0, 1, 12)12 - AIC:1168.1496956151823
ARIMA(0, 0, 1)x(0, 1, 0, 12)12 - AIC:946.5001550405634
ARIMA(0, 0, 1)x(0, 1, 1, 12)12 - AIC:704.241653940591
ARIMA(0, 0, 1)x(1, 0, 0, 12)12 - AIC:1283.0525892810222
ARIMA(0, 0, 1)x(1, 0, 1, 12)12 - AIC:1165.095142007383
ARIMA(0, 0, 1)x(1, 1, 0, 12)12 - AIC:740.2208336422344
```

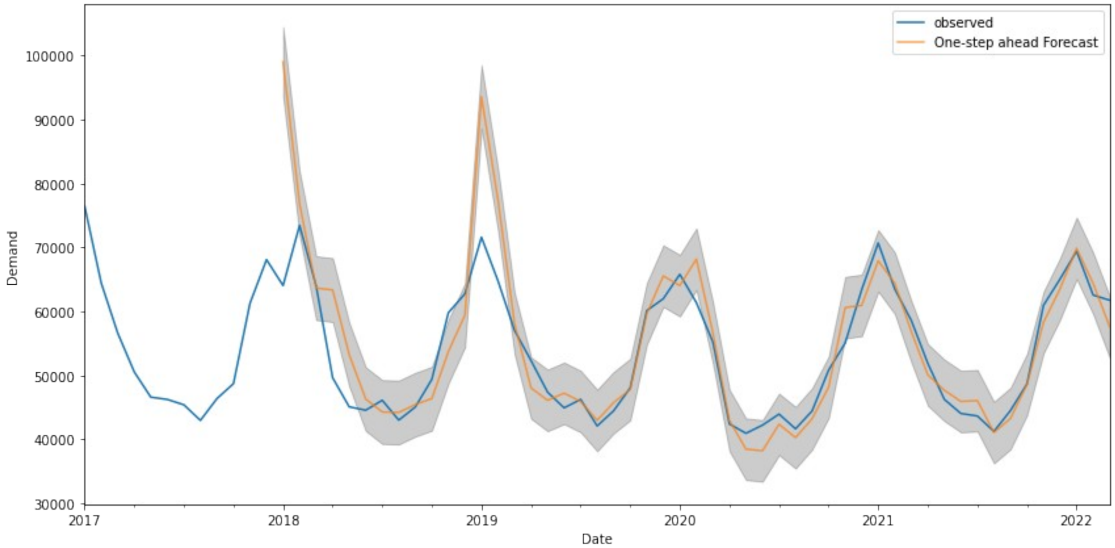
```
ARIMA(0, 0, 1)x(1, 1, 1, 12)12 - AIC:703.1558707596579
ARIMA(0, 1, 0)x(0, 0, 0, 12)12 - AIC:1236.8124689226552
ARIMA(0, 1, 0)x(0, 0, 1, 12)12 - AIC:981.9591370666511
ARIMA(0, 1, 0)x(0, 1, 0, 12)12 - AIC:969.9131572350192
ARIMA(0, 1, 0)x(0, 1, 1, 12)12 - AIC:720.5845887585635
ARIMA(0, 1, 0)x(1, 0, 0, 12)12 - AIC:994.973520327766
ARIMA(0, 1, 0)x(1, 0, 1, 12)12 - AIC:944.16555660298
ARIMA(0, 1, 0)x(1, 1, 0, 12)12 - AIC:714.062328251859
ARIMA(0, 1, 0)x(1, 1, 1, 12)12 - AIC:715.4813719669074
ARIMA(0, 1, 1)x(0, 0, 0, 12)12 - AIC:1209.926209397649
ARIMA(0, 1, 1)x(0, 0, 1, 12)12 - AIC:959.4664120557484
ARIMA(0, 1, 1)x(0, 1, 0, 12)12 - AIC:941.1205535176771
ARIMA(0, 1, 1)x(0, 1, 1, 12)12 - AIC:695.0949881738712
ARIMA(0, 1, 1)x(1, 0, 0, 12)12 - AIC:986.0867561973172
ARIMA(0, 1, 1)x(1, 0, 1, 12)12 - AIC:942.1482055102979
ARIMA(0, 1, 1)x(1, 1, 0, 12)12 - AIC:714.9936863704281
ARIMA(0, 1, 1)x(1, 1, 1, 12)12 - AIC:685.0710622368141
ARIMA(1, 0, 0)x(0, 0, 0, 12)12 - AIC:1261.2370147117474
ARIMA(1, 0, 0)x(0, 0, 1, 12)12 - AIC:1670.6536273148165
ARIMA(1, 0, 0)x(0, 1, 0, 12)12 - AIC:975.929415645413
ARIMA(1, 0, 0)x(0, 1, 1, 12)12 - AIC:727.5945725356273
ARIMA(1, 0, 0)x(1, 0, 0, 12)12 - AIC:991.4816515172772
ARIMA(1, 0, 0)x(1, 0, 1, 12)12 - AIC:995.8409631400853
ARIMA(1, 0, 0)x(1, 1, 0, 12)12 - AIC:708.6174658122454
ARIMA(1, 0, 0)x(1, 1, 1, 12)12 - AIC:707.5120943419913
ARIMA(1, 0, 1)x(0, 0, 0, 12)12 - AIC:1231.3544998483242
ARIMA(1, 0, 1)x(0, 0, 1, 12)12 - AIC:1469.5631854552096
ARIMA(1, 0, 1)x(0, 1, 0, 12)12 - AIC:947.9912501808698
ARIMA(1, 0, 1)x(0, 1, 1, 12)12 - AIC:706.130197053063
ARIMA(1, 0, 1)x(1, 0, 0, 12)12 - AIC:984.0506076450021
ARIMA(1, 0, 1)x(1, 0, 1, 12)12 - AIC:962.8782028145083
ARIMA(1, 0, 1)x(1, 1, 0, 12)12 - AIC:710.4825618666116
ARIMA(1, 0, 1)x(1, 1, 1, 12)12 - AIC:690.4539774469157
ARIMA(1, 1, 0)x(0, 0, 0, 12)12 - AIC:1226.6431771336781
ARIMA(1, 1, 0)x(0, 0, 1, 12)12 - AIC:982.2503041700056
ARIMA(1, 1, 0)x(0, 1, 0, 12)12 - AIC:966.4518174220825
ARIMA(1, 1, 0)x(0, 1, 1, 12)12 - AIC:721.0718781438582
ARIMA(1, 1, 0)x(1, 0, 0, 12)12 - AIC:967.6702238150813
ARIMA(1, 1, 0)x(1, 0, 1, 12)12 - AIC:944.5143795042173
ARIMA(1, 1, 0)x(1, 1, 0, 12)12 - AIC:688.8386257104978
ARIMA(1, 1, 0)x(1, 1, 1, 12)12 - AIC:690.1983011866371
ARIMA(1, 1, 1)x(0, 0, 0, 12)12 - AIC:1209.2528148836234
ARIMA(1, 1, 1)x(0, 0, 1, 12)12 - AIC:961.1412577456258
ARIMA(1, 1, 1)x(0, 1, 0, 12)12 - AIC:942.6766187288772
ARIMA(1, 1, 1)x(0, 1, 1, 12)12 - AIC:706.7747360864905
ARIMA(1, 1, 1)x(1, 0, 0, 12)12 - AIC:958.196634073435
ARIMA(1, 1, 1)x(1, 0, 1, 12)12 - AIC:941.0012691845412
ARIMA(1, 1, 1)x(1, 1, 0, 12)12 - AIC:690.7623294481328
ARIMA(1, 1, 1)x(1, 1, 1, 12)12 - AIC:673.0220430999167
```

```python
import statsmodels.api as sm

mod = sm.tsa.statespace.SARIMAX(timeSeries,
                                order=(1, 1, 1),
                                seasonal_order=(1, 1, 0, 12),
                                enforce_stationarity=False,
                                enforce_invertibility=False)
results = mod.fit()
#print(results.summary())
print(results.summary().tables[1])

results.plot_diagnostics(figsize=(16, 8))
plt.show()
```

```
======================================================================
========
                 coef    std err          z      P>|z|      [0.025
0.975]
----------------------------------------------------------------------
--------
ar.L1         -0.4309      0.332     -1.299      0.194      -1.081
0.219
ma.L1         -0.0720      0.330     -0.218      0.827      -0.719
0.575
ar.S.L12      -0.6702      0.095     -7.045      0.000      -0.857
-0.484
sigma2      6.044e+06   1.62e+06      3.731      0.000    2.87e+06
9.22e+06
======================================================================
========
```



```
pred = results.get_prediction(start=pd.to_datetime('2018-01-01'),
dynamic=False)
pred_ci = pred.conf_int()
ax = timeSeries['2017':].plot(label='observed')
pred.predicted_mean.plot(ax=ax, label='One-step ahead Forecast',
alpha=.7, figsize=(14, 7))
ax.fill_between(pred_ci.index,
                pred_ci.iloc[:, 0],
                pred_ci.iloc[:, 1], color='k', alpha=.2)
ax.set_xlabel('Date')
ax.set_ylabel('Demand')
plt.legend()
plt.show()

from math import sqrt

predicted = pred.predicted_mean
expected = timeSeries['2018-01-01':]
print("Unsupervised")
print('ARIMA(1, 1, 1)x(0, 1, 1, 12)12')
print("---------------------------------")

MAE = mean_absolute_error(expected, predicted)
print('MAE : {}'.format(round(MAE, 2)))

MSE = mean_squared_error(expected, predicted)
print('MSE : {}'.format(round(MSE, 2)))

RMSE = sqrt(MSE)
print('RMSE  : %f' % RMSE)

R2_SCORE=r2_score(expected, predicted)
print('R2_SCORE  : %f' % R2_SCORE)
```




```
Unsupervised
ARIMA(1, 1, 1)x(0, 1, 1, 12)12
---------------------------------
MAE : 3638.73
MSE : 47522931.62
RMSE  : 6893.687810
R2_SCORE  : 0.486274
```

## Supervised Learning

### 7.3.2 Augmented Dickey Fuller Test - to check Stationarity

p-value <= 0.05: Reject the null hypothesis (H0), the data does not have a unit root and is stationary.

```
demand_series_st = timeSeries

from pandas import read_csv
from statsmodels.tsa.stattools import adfuller
series = demand_series_st
X = series.values
result = adfuller(X)

print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
print('Critical Values:')
for key, value in result[4].items():
        print('\t%s: %.3f' % (key, value))
```

```
ADF Statistic: -1.526439
p-value: 0.520394
Critical Values:
     1%: -3.563
```

```
    5%: -2.919
    10%: -2.597
```

### KPSS (Kwiatkowski-Phillips-Schmidt-Shin) Test

The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test figures out if a time series is stationary around a mean or linear trend,

or is non-stationary due to a unit root.

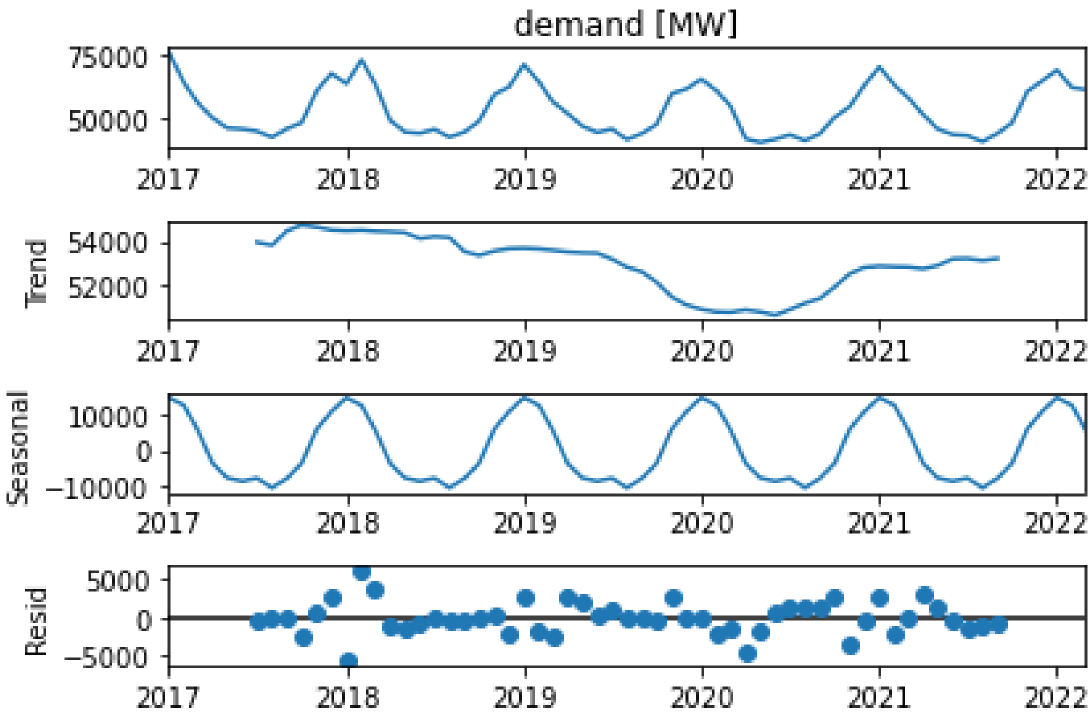
```
#define function for kpss test
from statsmodels.tsa.stattools import kpss

#define KPSS
def kpss_test(timeseries):
    print ('Results of KPSS Test:')
    kpsstest = kpss(timeseries, regression='c')
    kpss_output = pd.Series(kpsstest[0:3], index=['Test Statistic','p-value','Lags Used'])

    for key,value in kpsstest[3].items():
        kpss_output['Critical Value (%s)'%key] = value

    print (kpss_output)


kpss_test(demand_series_st)
```

```
Results of KPSS Test:
Test Statistic            0.260318
p-value                   0.100000
Lags Used                11.000000
Critical Value (10%)      0.347000
Critical Value (5%)       0.463000
Critical Value (2.5%)     0.574000
Critical Value (1%)       0.739000
dtype: float64
```

```
# Case 4: KPSS = not stationary and ADF = stationary -> difference stationary, use differencing to make series stationary
demand_series_st.head()
```

```
date_
2017-01-01    76451.875000
2017-02-01    64459.821429
2017-03-01    56607.774194
2017-04-01    50537.400000
2017-05-01    46589.225806
Freq: MS, Name: demand [MW], dtype: float64
```

```
# to eliminate seasonality differenciating twice
demand_series_st = timeSeries - timeSeries.shift(2)
demand_series_st=demand_series_st.dropna()

decomposition = sm.tsa.seasonal_decompose(timeSeries,
model='additive')
fig = decomposition.plot()
plt.show()
```




```
timeSeries = demand_series_st
```

### ARIMA using sklearn ( without missing values)

```
import itertools

p = d = q = range(0, 2)
pdq = list(itertools.product(p, d, q))
seasonal_pdq = [(x[0], x[1], x[2], 12) for x in
list(itertools.product(p, d, q))]
print('Examples of parameter combinations for Seasonal ARIMA...')
print('SARIMAX: {} x {}'.format(pdq[1], seasonal_pdq[1]))
print('SARIMAX: {} x {}'.format(pdq[1], seasonal_pdq[2]))
print('SARIMAX: {} x {}'.format(pdq[2], seasonal_pdq[3]))
print('SARIMAX: {} x {}'.format(pdq[2], seasonal_pdq[4]))

import warnings
warnings.filterwarnings("ignore")
```

```
for param in pdq:
    for param_seasonal in seasonal_pdq:
        try:
            mod = sm.tsa.statespace.SARIMAX(timeSeries_filled,
                                            order=param,

seasonal_order=param_seasonal,

enforce_stationarity=False,

enforce_invertibility=False)
            results = mod.fit()
            print('ARIMA{}x{}12 - AIC:{}'.format(param,
param_seasonal, results.aic))
        except:
            continue
```

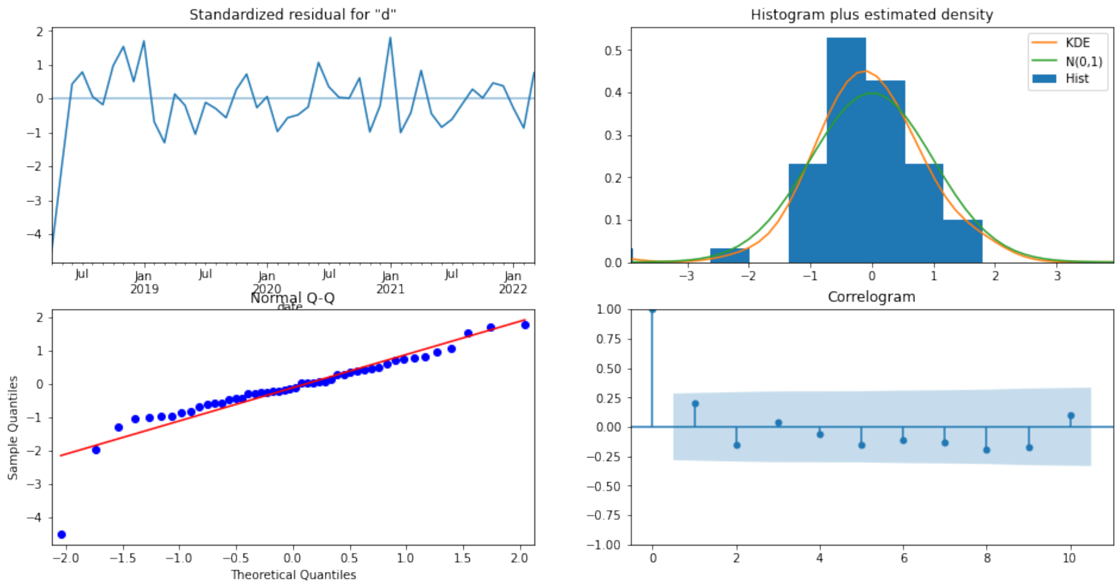
```
Examples of parameter combinations for Seasonal ARIMA...
SARIMAX: (0, 0, 1) x (0, 0, 1, 12)
SARIMAX: (0, 0, 1) x (0, 1, 0, 12)
SARIMAX: (0, 1, 0) x (0, 1, 1, 12)
SARIMAX: (0, 1, 0) x (1, 0, 0, 12)
ARIMA(0, 0, 0)x(0, 0, 0, 12)12 - AIC:1529.4529986768473
ARIMA(0, 0, 0)x(0, 0, 1, 12)12 - AIC:36979.12674710643
ARIMA(0, 0, 0)x(0, 1, 0, 12)12 - AIC:974.9172940291796
ARIMA(0, 0, 0)x(0, 1, 1, 12)12 - AIC:728.6171044130301
ARIMA(0, 0, 0)x(1, 0, 0, 12)12 - AIC:1003.464506609924
ARIMA(0, 0, 0)x(1, 0, 1, 12)12 - AIC:983.965315406852
ARIMA(0, 0, 0)x(1, 1, 0, 12)12 - AIC:740.2776908932278
ARIMA(0, 0, 0)x(1, 1, 1, 12)12 - AIC:721.8502997668725
ARIMA(0, 0, 1)x(0, 0, 0, 12)12 - AIC:1463.4127020989029
ARIMA(0, 0, 1)x(0, 0, 1, 12)12 - AIC:1168.1496956151823
ARIMA(0, 0, 1)x(0, 1, 0, 12)12 - AIC:946.5001550405634
ARIMA(0, 0, 1)x(0, 1, 1, 12)12 - AIC:704.241653940591
ARIMA(0, 0, 1)x(1, 0, 0, 12)12 - AIC:1283.0525892810222
ARIMA(0, 0, 1)x(1, 0, 1, 12)12 - AIC:1165.095142007383
ARIMA(0, 0, 1)x(1, 1, 0, 12)12 - AIC:740.2208336422344
ARIMA(0, 0, 1)x(1, 1, 1, 12)12 - AIC:703.1558707596579
ARIMA(0, 1, 0)x(0, 0, 0, 12)12 - AIC:1236.8124689226552
ARIMA(0, 1, 0)x(0, 0, 1, 12)12 - AIC:981.9591370666511
ARIMA(0, 1, 0)x(0, 1, 0, 12)12 - AIC:969.9131572350192
ARIMA(0, 1, 0)x(0, 1, 1, 12)12 - AIC:720.5845887585635
ARIMA(0, 1, 0)x(1, 0, 0, 12)12 - AIC:994.973520327766
ARIMA(0, 1, 0)x(1, 0, 1, 12)12 - AIC:944.16555660298
ARIMA(0, 1, 0)x(1, 1, 0, 12)12 - AIC:714.062328251859
ARIMA(0, 1, 0)x(1, 1, 1, 12)12 - AIC:715.4813719669074
ARIMA(0, 1, 1)x(0, 0, 0, 12)12 - AIC:1209.926209397649
ARIMA(0, 1, 1)x(0, 0, 1, 12)12 - AIC:959.4664120557484
ARIMA(0, 1, 1)x(0, 1, 0, 12)12 - AIC:941.1205535176771
ARIMA(0, 1, 1)x(0, 1, 1, 12)12 - AIC:695.0949881738712
```

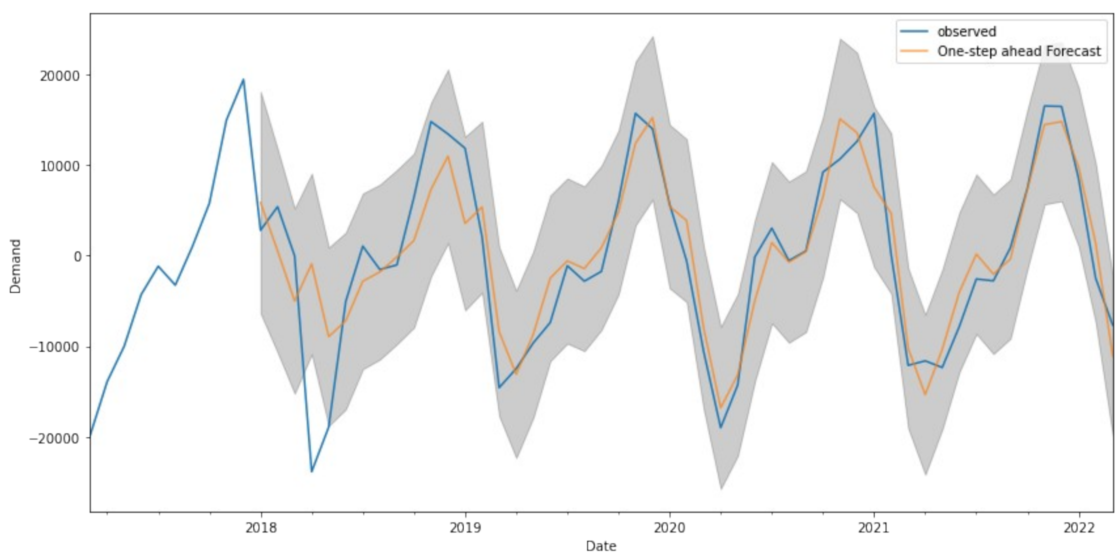
```
ARIMA(0, 1, 1)x(1, 0, 0, 12)12 - AIC:986.0867561973172
ARIMA(0, 1, 1)x(1, 0, 1, 12)12 - AIC:942.1482055102979
ARIMA(0, 1, 1)x(1, 1, 0, 12)12 - AIC:714.9936863704281
ARIMA(0, 1, 1)x(1, 1, 1, 12)12 - AIC:685.0710622368141
ARIMA(1, 0, 0)x(0, 0, 0, 12)12 - AIC:1261.2370147117474
ARIMA(1, 0, 0)x(0, 0, 1, 12)12 - AIC:1670.6536273148165
ARIMA(1, 0, 0)x(0, 1, 0, 12)12 - AIC:975.929415645413
ARIMA(1, 0, 0)x(0, 1, 1, 12)12 - AIC:727.5945725356273
ARIMA(1, 0, 0)x(1, 0, 0, 12)12 - AIC:991.4816515172772
ARIMA(1, 0, 0)x(1, 0, 1, 12)12 - AIC:995.8409631400853
ARIMA(1, 0, 0)x(1, 1, 0, 12)12 - AIC:708.6174658122454
ARIMA(1, 0, 0)x(1, 1, 1, 12)12 - AIC:707.5120943419913
ARIMA(1, 0, 1)x(0, 0, 0, 12)12 - AIC:1231.3544998483242
ARIMA(1, 0, 1)x(0, 0, 1, 12)12 - AIC:1469.5631854552096
ARIMA(1, 0, 1)x(0, 1, 0, 12)12 - AIC:947.9912501808698
ARIMA(1, 0, 1)x(0, 1, 1, 12)12 - AIC:706.130197053063
ARIMA(1, 0, 1)x(1, 0, 0, 12)12 - AIC:984.0506076450021
ARIMA(1, 0, 1)x(1, 0, 1, 12)12 - AIC:962.8782028145083
ARIMA(1, 0, 1)x(1, 1, 0, 12)12 - AIC:710.4825618666116
ARIMA(1, 0, 1)x(1, 1, 1, 12)12 - AIC:690.4539774469157
ARIMA(1, 1, 0)x(0, 0, 0, 12)12 - AIC:1226.6431771336781
ARIMA(1, 1, 0)x(0, 0, 1, 12)12 - AIC:982.2503041700056
ARIMA(1, 1, 0)x(0, 1, 0, 12)12 - AIC:966.4518174220825
ARIMA(1, 1, 0)x(0, 1, 1, 12)12 - AIC:721.0718781438582
ARIMA(1, 1, 0)x(1, 0, 0, 12)12 - AIC:967.6702238150813
ARIMA(1, 1, 0)x(1, 0, 1, 12)12 - AIC:944.5143795042173
ARIMA(1, 1, 0)x(1, 1, 0, 12)12 - AIC:688.8386257104978
ARIMA(1, 1, 0)x(1, 1, 1, 12)12 - AIC:690.1983011866371
ARIMA(1, 1, 1)x(0, 0, 0, 12)12 - AIC:1209.2528148836234
ARIMA(1, 1, 1)x(0, 0, 1, 12)12 - AIC:961.1412577456258
ARIMA(1, 1, 1)x(0, 1, 0, 12)12 - AIC:942.6766187288772
ARIMA(1, 1, 1)x(0, 1, 1, 12)12 - AIC:706.7747360864905
ARIMA(1, 1, 1)x(1, 0, 0, 12)12 - AIC:958.196634073435
ARIMA(1, 1, 1)x(1, 0, 1, 12)12 - AIC:941.0012691845412
ARIMA(1, 1, 1)x(1, 1, 0, 12)12 - AIC:690.7623294481328
ARIMA(1, 1, 1)x(1, 1, 1, 12)12 - AIC:673.0220430999167
```

```python
# '2017-03-01 00:00:00'
# '2022-03-08 22:00:00'
import statsmodels.api as sm

mod = sm.tsa.statespace.SARIMAX(timeSeries,
                                order=(1, 1, 1),
                                seasonal_order=(1,1,1, 12))
results = mod.fit()
print(results.summary().tables[1])

results.plot_diagnostics(figsize=(16, 8))
plt.show()
```

```
pred = results.get_prediction(start=pd.to_datetime('2018-01-01'),
dynamic=False)
pred_ci = pred.conf_int()
ax = timeSeries['2017':].plot(label='observed')
pred.predicted_mean.plot(ax=ax, label='One-step ahead Forecast',
alpha=.7, figsize=(14, 7))
ax.fill_between(pred_ci.index,
                pred_ci.iloc[:, 0],
                pred_ci.iloc[:, 1], color='k', alpha=.2)
ax.set_xlabel('Date')
ax.set_ylabel('Demand')
plt.legend()
plt.show()

from math import sqrt

predicted = pred.predicted_mean
expected = timeSeries['2018-01-01':]

print("Supervised Learning")
print('ARIMA(2, 0, 2)x(0, 0, 3, 12)12 ')
print("---------------------------------")

MAE = mean_absolute_error(expected, predicted)
print('MAE : {}'.format(round(MAE, 2)))

MSE = mean_squared_error(expected, predicted)
print('MSE : {}'.format(round(MSE, 2)))

RMSE = sqrt(MSE)
print('RMSE  : %f' % RMSE)

R2_SCORE=r2_score(expected, predicted)
print('R2_SCORE  : %f' % R2_SCORE)

======================================================================
========
                 coef    std err          z      P>|z|      [0.025
0.975]
----------------------------------------------------------------------
--------
ar.L1          0.2178      0.110      1.985      0.047       0.003
0.433
ma.L1         -0.9998      0.152     -6.584      0.000      -1.297
-0.702
ar.S.L12      -0.3314      0.203     -1.636      0.102      -0.728
0.066
ma.S.L12      -0.4688      0.298     -1.572      0.116      -1.053
0.116
sigma2      1.932e+07   7.86e-09   2.46e+15      0.000    1.93e+07
```

```
1.93e+07
======================================================================
========
```




```
Supervised Learning
ARIMA(2, 0, 2)x(0, 0, 3, 12)12
---------------------------------
MAE : 3306.25
MSE : 23661942.28
RMSE  : 4864.354251
R2_SCORE  : 0.765355
```

## Accuracy of different Algorithms:

### 8.2 Regression Analysis

### ### Multiple Linear Regression

MAE : 0.54

MSE : 0.45

RMSE : 0.667367

R2_SCORE : 0.557940

### ### Support Vector Regressor

Accuracy : 0.9021214271293617

MAE : 0.25

MSE : 0.1

RMSE : 0.314027

R2_SCORE : 0.902121

### ### K Neighbors Regressor

Accuracy : 0.9368616346234755

MAE : 0.27

MSE : 0.12

RMSE : 0.342754

R2_SCORE : 0.883395

KNeighborsRegressor

### ### Multi Layer Perceptron Model

Accuracy : 0.897587747928458

MAE : 0.25

MSE : 0.1

RMSE : 0.321218

R2_SCORE : 0.897588

## 8.1 Time-Series Analysis (SK Learn)

### ### Unsupervised - Holt-Winters

MAE : 7556.53

MSE : 102168691.71

RMSE : 10107.852972

R2_SCORE : -0.077558

### ### Unsupervised - ARIMA(1, 1, 1)x(0, 1, 1, 12)12

MAE : 3638.73

MSE : 47522931.62

RMSE : 6893.687810

R2_SCORE : 0.486274

### ### Supervised Learning- ARIMA(2, 0, 2)x(0, 0, 3, 12)12

MAE : 3306.25

MSE : 23661942.28

RMSE : 4864.354251

R2_SCORE : 0.765355