edpf

November 29, 2024

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler,LabelEncoder
from sklearn.metrics import mean_squared_error,r2_score
```

[ ]:
```
a=pd.read_csv('energy_dataset.csv')
b=pd.read_csv('Electricity.csv')
```

```
<ipython-input-4-b5bcf0dafe30>:2: DtypeWarning: Columns (9,10,11,14,15,16,17)
have mixed types. Specify dtype option on import or set low_memory=False.
  b=pd.read_csv('Electricity.csv')
```

[ ]:
```
a.head()
```

[ ]:
```
                        time  generation biomass  \
0  2015-01-01 00:00:00+01:00               447.0
1  2015-01-01 01:00:00+01:00               449.0
2  2015-01-01 02:00:00+01:00               448.0
3  2015-01-01 03:00:00+01:00               438.0
4  2015-01-01 04:00:00+01:00               428.0

   generation fossil brown coal/lignite  generation fossil coal-derived gas  \
0                                 329.0                                 0.0
1                                 328.0                                 0.0
2                                 323.0                                 0.0
3                                 254.0                                 0.0
4                                 187.0                                 0.0

   generation fossil gas  generation fossil hard coal  generation fossil oil  \
0                 4844.0                       4821.0                  162.0
1                 5196.0                       4755.0                  158.0
2                 4857.0                       4581.0                  157.0
3                 4314.0                       4131.0                  160.0
4                 4130.0                       3840.0                  156.0
```

```
   generation fossil oil shale  generation fossil peat  generation geothermal  \
0                          0.0                     0.0                    0.0
1                          0.0                     0.0                    0.0
2                          0.0                     0.0                    0.0
3                          0.0                     0.0                    0.0
4                          0.0                     0.0                    0.0

   …  generation waste  generation wind offshore  generation wind onshore  \
0  …             196.0                       0.0                   6378.0
1  …             195.0                       0.0                   5890.0
2  …             196.0                       0.0                   5461.0
3  …             191.0                       0.0                   5238.0
4  …             189.0                       0.0                   4935.0

   forecast solar day ahead  forecast wind offshore eday ahead  \
0                      17.0                                NaN
1                      16.0                                NaN
2                       8.0                                NaN
3                       2.0                                NaN
4                       9.0                                NaN

   forecast wind onshore day ahead  total load forecast  total load actual  \
0                           6436.0              26118.0            25385.0
1                           5856.0              24934.0            24382.0
2                           5454.0              23515.0            22734.0
3                           5151.0              22642.0            21286.0
4                           4861.0              21785.0            20264.0

   price day ahead  price actual
0            50.10         65.41
1            48.10         64.92
2            47.33         64.48
3            42.27         59.32
4            38.41         56.04

[5 rows x 29 columns]
```

[ ]:
```
b.head()
```

[ ]:
```
           DateTime Holiday  HolidayFlag  DayOfWeek  WeekOfYear  Day  Month  \
0  01/11/2011 00:00     NaN            0          1          44    1     11
1  01/11/2011 00:30     NaN            0          1          44    1     11
2  01/11/2011 01:00     NaN            0          1          44    1     11
3  01/11/2011 01:30     NaN            0          1          44    1     11
4  01/11/2011 02:00     NaN            0          1          44    1     11

   Year  PeriodOfDay ForecastWindProduction SystemLoadEA  SMPEA  \
```

```
0  2011            0                 315.31      3388.77  49.26
1  2011            1                 321.80      3196.66  49.26
2  2011            2                 328.57      3060.71  49.10
3  2011            3                 335.60      2945.56  48.04
4  2011            4                 342.90      2849.34  33.75

  ORKTemperature ORKWindspeed CO2Intensity ActualWindProduction SystemLoadEP2  \
0           6.00         9.30       600.71               356.00       3159.60
1           6.00        11.10       605.42               317.00       2973.01
2           5.00        11.10       589.97               311.00       2834.00
3           6.00         9.30       585.94               313.00       2725.99
4           6.00        11.10       571.52               346.00       2655.64

  SMPEP2
0  54.32
1  54.23
2  54.23
3  53.47
4  39.87
```

[ ]:
```
a = a.drop(['generation fossil coal-derived gas','generation fossil oil shale',
                            'generation fossil peat', 'generation geothermal',
                            'generation hydro pumped storage aggregated',␣
 ↪'generation marine',
                            'generation wind offshore', 'forecast wind offshore␣
 ↪eday ahead',
                            'total load forecast', 'forecast solar day ahead',
                            'forecast wind onshore day ahead'],
                            axis=1)
```

[ ]:
```
a.columns
```

[ ]:
```
Index(['time', 'generation biomass', 'generation fossil brown coal/lignite',
       'generation fossil gas', 'generation fossil hard coal',
       'generation fossil oil', 'generation hydro pumped storage consumption',
       'generation hydro run-of-river and poundage',
       'generation hydro water reservoir', 'generation nuclear',
       'generation other', 'generation other renewable', 'generation solar',
       'generation waste', 'generation wind onshore', 'total load actual',
       'price day ahead', 'price actual'],
      dtype='object')
```

[ ]:
```
b.columns
```

[ ]:
```
Index(['DateTime', 'Holiday', 'HolidayFlag', 'DayOfWeek', 'WeekOfYear', 'Day',
       'Month', 'Year', 'PeriodOfDay', 'ForecastWindProduction',
       'SystemLoadEA', 'SMPEA', 'ORKTemperature', 'ORKWindspeed',
```

```
       'CO2Intensity', 'ActualWindProduction', 'SystemLoadEP2', 'SMPEP2'],
      dtype='object')
```

[ ]:
```
a.shape
```

[ ]:
```
(35064, 18)
```

[ ]:
```
b.shape
```

[ ]:
```
(38014, 18)
```

[ ]:
```
a.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 35064 entries, 0 to 35063
Data columns (total 18 columns):
 #   Column                                       Non-Null Count  Dtype
---  ------                                       --------------  -----
 0   time                                         35064 non-null  object
 1   generation biomass                           35045 non-null  float64
 2   generation fossil brown coal/lignite         35046 non-null  float64
 3   generation fossil gas                        35046 non-null  float64
 4   generation fossil hard coal                  35046 non-null  float64
 5   generation fossil oil                        35045 non-null  float64
 6   generation hydro pumped storage consumption  35045 non-null  float64
 7   generation hydro run-of-river and poundage   35045 non-null  float64
 8   generation hydro water reservoir             35046 non-null  float64
 9   generation nuclear                           35047 non-null  float64
 10  generation other                             35046 non-null  float64
 11  generation other renewable                   35046 non-null  float64
 12  generation solar                             35046 non-null  float64
 13  generation waste                             35045 non-null  float64
 14  generation wind onshore                      35046 non-null  float64
 15  total load actual                            35028 non-null  float64
 16  price day ahead                              35064 non-null  float64
 17  price actual                                 35064 non-null  float64
dtypes: float64(17), object(1)
memory usage: 4.8+ MB
```

[ ]:
```
b.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 38014 entries, 0 to 38013
Data columns (total 18 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   DateTime                38014 non-null  object
 1   Holiday                 1536 non-null   object
```

```
 2   HolidayFlag             38014 non-null  int64
 3   DayOfWeek               38014 non-null  int64
 4   WeekOfYear              38014 non-null  int64
 5   Day                     38014 non-null  int64
 6   Month                   38014 non-null  int64
 7   Year                    38014 non-null  int64
 8   PeriodOfDay             38014 non-null  int64
 9   ForecastWindProduction  38014 non-null  object
 10  SystemLoadEA            38014 non-null  object
 11  SMPEA                   38014 non-null  object
 12  ORKTemperature          38014 non-null  object
 13  ORKWindspeed            38014 non-null  object
 14  CO2Intensity            38014 non-null  object
 15  ActualWindProduction    38014 non-null  object
 16  SystemLoadEP2           38014 non-null  object
 17  SMPEP2                  38014 non-null  object
dtypes: int64(7), object(11)
memory usage: 5.2+ MB
```

[ ]:
```
a.isnull().sum()
```

[ ]:
```
time                                            0
generation biomass                             19
generation fossil brown coal/lignite           18
generation fossil gas                          18
generation fossil hard coal                    18
generation fossil oil                          19
generation hydro pumped storage consumption    19
generation hydro run-of-river and poundage     19
generation hydro water reservoir               18
generation nuclear                             17
generation other                               18
generation other renewable                     18
generation solar                               18
generation waste                               19
generation wind onshore                        18
total load actual                              36
price day ahead                                 0
price actual                                    0
dtype: int64
```

[ ]:
```
a=a.dropna()
a.isnull().sum()
```

[ ]:
```
time                                           0
generation biomass                             0
generation fossil brown coal/lignite           0
```

```
generation fossil gas                          0
generation fossil hard coal                    0
generation fossil oil                          0
generation hydro pumped storage consumption    0
generation hydro run-of-river and poundage     0
generation hydro water reservoir               0
generation nuclear                             0
generation other                               0
generation other renewable                     0
generation solar                               0
generation waste                               0
generation wind onshore                        0
total load actual                              0
price day ahead                                0
price actual                                   0
dtype: int64
```

[ ]:
```
b.isnull().sum()
```

[ ]:
```
DateTime                  0
Holiday                   0
HolidayFlag               0
DayOfWeek                 0
WeekOfYear                0
Day                       0
Month                     0
Year                      0
PeriodOfDay               0
ForecastWindProduction    0
SystemLoadEA              0
SMPEA                     0
ORKTemperature            0
ORKWindspeed              0
CO2Intensity              0
ActualWindProduction      0
SystemLoadEP2             0
SMPEP2                    0
dtype: int64
```

[ ]:
```
b=b.dropna()
b.isnull().sum()
```

[ ]:
```
DateTime                  0
Holiday                   0
HolidayFlag               0
DayOfWeek                 0
WeekOfYear                0
```

```
Day                        0
Month                      0
Year                       0
PeriodOfDay                0
ForecastWindProduction     0
SystemLoadEA               0
SMPEA                      0
ORKTemperature             0
ORKWindspeed               0
CO2Intensity               0
ActualWindProduction       0
SystemLoadEP2              0
SMPEP2                     0
dtype: int64
```

[ ]:
```
a.duplicated().sum()
```

[ ]: 0

[ ]:
```
b.duplicated().sum()
```

[ ]: 0

[ ]:
```
for i in a.select_dtypes(include='object').columns:
  print(a[i].value_counts())
  print(True)
```

```
time
2015-01-01 00:00:00+01:00    1
2017-09-01 14:00:00+02:00    1
2017-09-01 08:00:00+02:00    1
2017-09-01 09:00:00+02:00    1
2017-09-01 10:00:00+02:00    1
                            ..
2016-05-02 15:00:00+02:00    1
2016-05-02 14:00:00+02:00    1
2016-05-02 13:00:00+02:00    1
2016-05-02 12:00:00+02:00    1
2018-12-31 23:00:00+01:00    1
Name: count, Length: 35018, dtype: int64
True
```

[ ]:
```
for i in b.select_dtypes(include='object').columns:
  print(b[i].value_counts())
  print(True)
```

```
DateTime
24/12/2011 00:00    1
```

```
24/12/2011 00:30    1
30/03/2013 11:00    1
30/03/2013 10:30    1
30/03/2013 10:00    1
                   ..
07/05/2012 14:30    1
07/05/2012 14:00    1
07/05/2012 13:30    1
07/05/2012 13:00    1
31/12/2013 23:30    1
Name: count, Length: 1536, dtype: int64
True
Holiday
Christmas Eve           144
Christmas               144
St Stephen's Day        144
New Year's Eve          144
New Year's Day           96
St Patrick's Day         96
Good Friday              96
Holy Saturday            96
Easter                   96
Easter Monday            96
May Day                  96
June Bank Holiday        96
August Bank Holiday      96
October Bank Holiday     96
Name: count, dtype: int64
True
ForecastWindProduction
?          4
1190.60    2
553.60     2
1213.20    2
544.00     2
          ..
508.40     1
521.50     1
535.50     1
548.40     1
1064.0     1
Name: count, Length: 1505, dtype: int64
True
SystemLoadEA
?          2
4286.95    2
3759.39    2
3960.67    2
```

```
4532.07    2
          ..
3773.39    1
3771.10    1
3806.61    1
3903.13    1
3624.25    1
Name: count, Length: 1528, dtype: int64
True
SMPEA
47.56     25
39.74     23
73.52     21
63.59     16
66.08     16
          ..
43.28      1
52.10      1
106.72     1
108.77     1
34.51      1
Name: count, Length: 644, dtype: int64
True
ORKTemperature
9.00     184
3.00     182
4.00     149
8.00     127
10.00    125
11.00    118
?        116
6.00      98
7.00      96
5.00      85
2.00      62
12.00     55
13.00     43
16.00     22
14.00     18
1.00      17
15.00     17
17.00     13
18.00      5
0.00       3
-0.00      1
Name: count, dtype: int64
True
ORKWindspeed
```

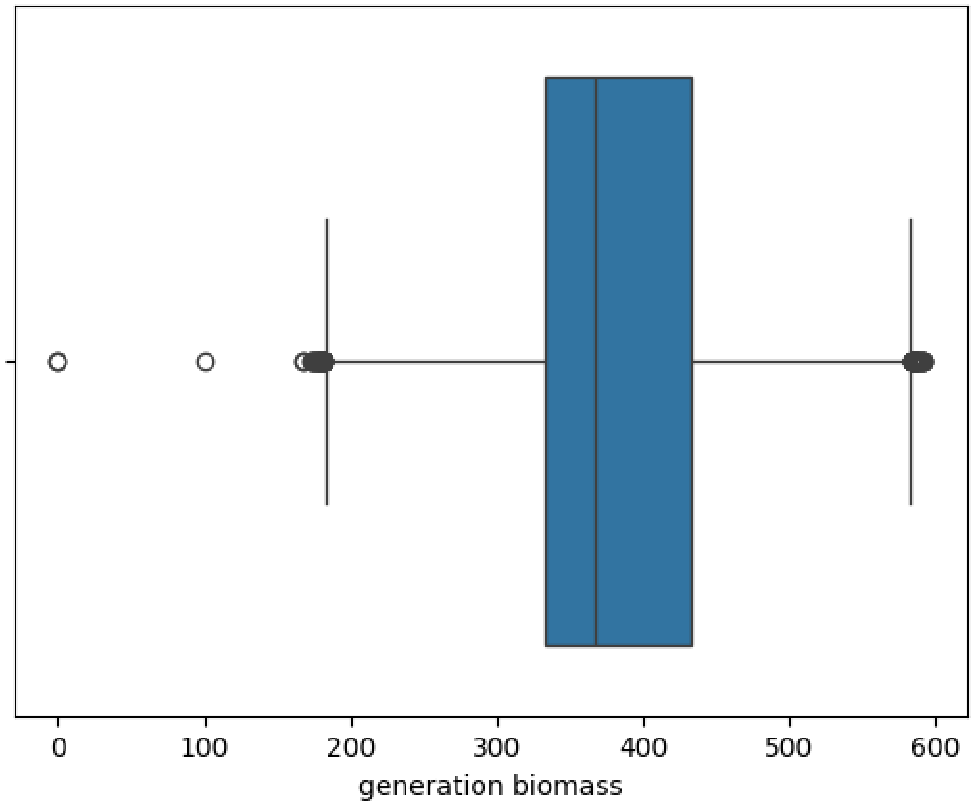
```
?        117
20.40    113
14.80    110
22.20    109
18.50    107
16.70    103
24.10     97
13.00     91
25.90     78
11.10     77
31.50     69
27.80     60
29.60     57
9.30      56
35.20     53
37.00     42
33.30     42
38.90     27
7.40      27
5.60      13
10.80     12
46.30      9
40.70      9
14.40      8
42.60      7
18.00      6
44.40      6
48.20      5
3.70       3
51.90      2
53.70      2
25.20      2
28.80      2
64.80      2
50.00      2
1.90       1
43.20      1
39.60      1
3.60       1
21.60      1
74.10      1
70.40      1
63.00      1
75.90      1
66.70      1
7.20       1
Name: count, dtype: int64
True
```

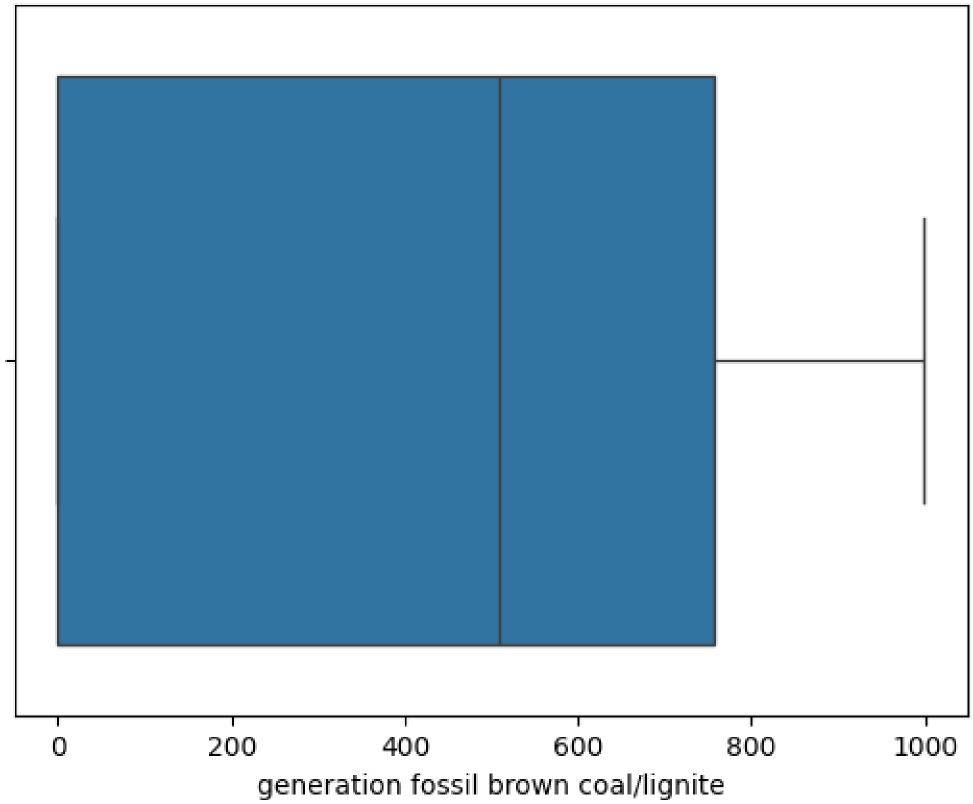
```
CO2Intensity
407.73    3
515.78    2
459.18    2
468.28    2
528.76    2
         ..
535.52    1
530.24    1
535.78    1
537.45    1
308.01    1
Name: count, Length: 1506, dtype: int64
True
ActualWindProduction
66.00     5
459.00    5
467.00    5
471.00    5
294.00    5
         ..
120.00    1
124.00    1
191.00    1
188.00    1
1020.0    1
Name: count, Length: 1076, dtype: int64
True
SystemLoadEP2
3799.50    3
3757.39    2
?          2
3136.15    1
4212.55    1
          ..
3823.41    1
3827.69    1
3850.06    1
3903.68    1
3517.08    1
Name: count, Length: 1532, dtype: int64
True
SMPEP2
47.76    24
66.08    24
39.74    23
34.70    19
44.52    16
```

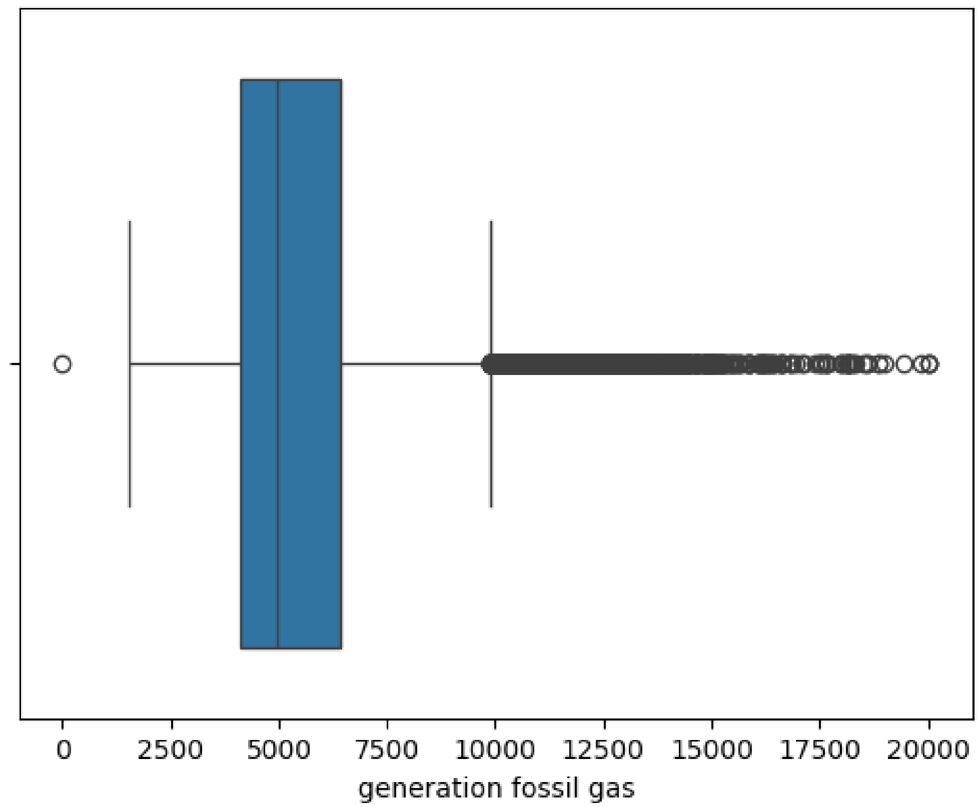
```
          ..
45.19      1
77.14      1
61.48      1
62.33      1
34.9       1
Name: count, Length: 656, dtype: int64
True
```

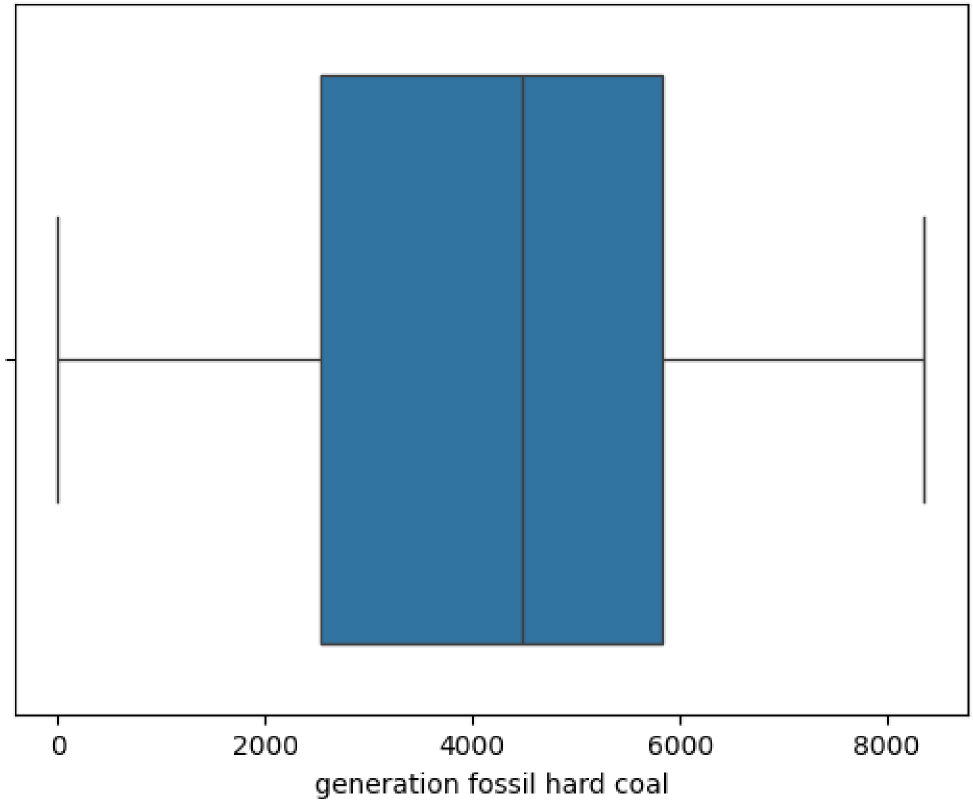
[ ]:
```
b["ForecastWindProduction"] = pd.to_numeric(b["ForecastWindProduction"],␣
↪errors= 'coerce')
b["SystemLoadEA"] = pd.to_numeric(b["SystemLoadEA"], errors= 'coerce')
b["SMPEA"] = pd.to_numeric(b["SMPEA"], errors= 'coerce')
b["ORKTemperature"] = pd.to_numeric(b["ORKTemperature"], errors= 'coerce')
b["ORKWindspeed"] = pd.to_numeric(b["ORKWindspeed"], errors= 'coerce')
b["CO2Intensity"] = pd.to_numeric(b["CO2Intensity"], errors= 'coerce')
b["ActualWindProduction"] = pd.to_numeric(b["ActualWindProduction"], errors=␣
↪'coerce')
b["SystemLoadEP2"] = pd.to_numeric(b["SystemLoadEP2"], errors= 'coerce')
b["SMPEP2"] = pd.to_numeric(b["SMPEP2"], errors= 'coerce')
```

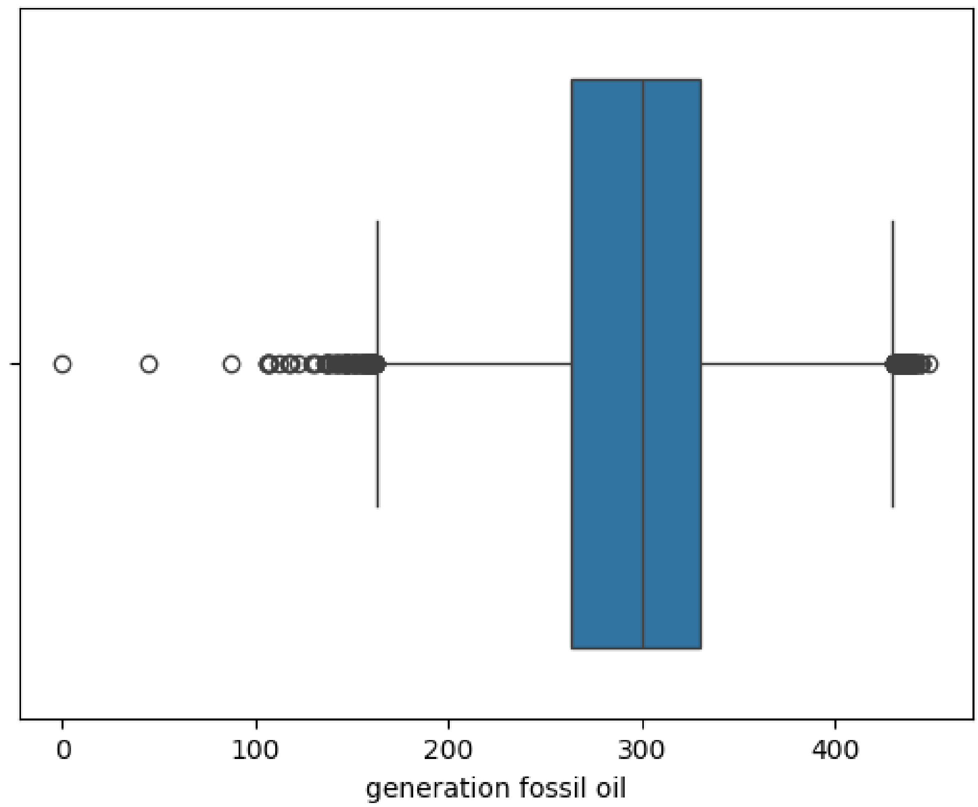
[ ]:
```
for i in a.select_dtypes(include="number").columns:
  sns.boxplot(a,x=i)
  plt.show()
```

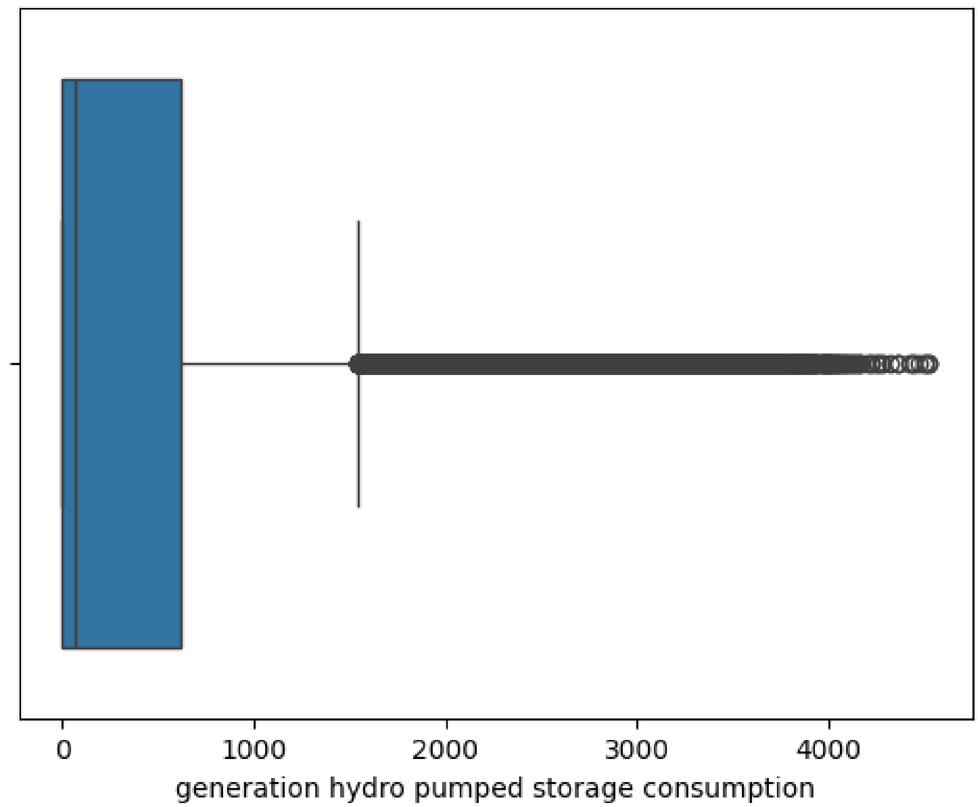

0
100
200
300
400
500
600
generation biomass

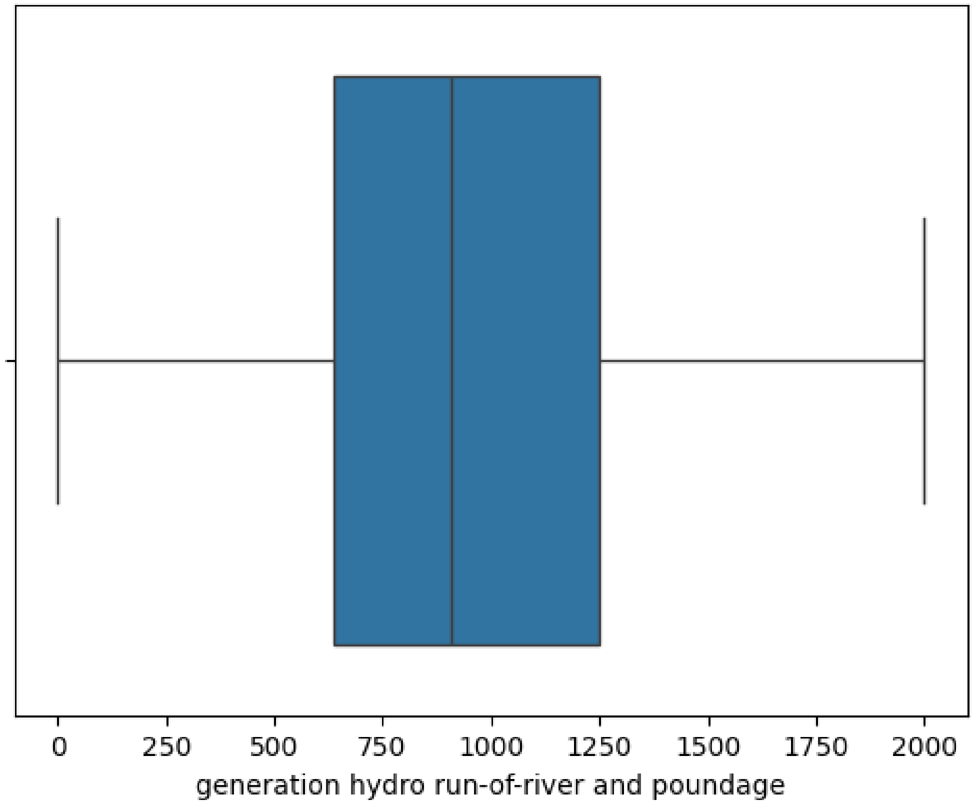

0
200
400
600
800
1000
generation fossil brown coal/lignite

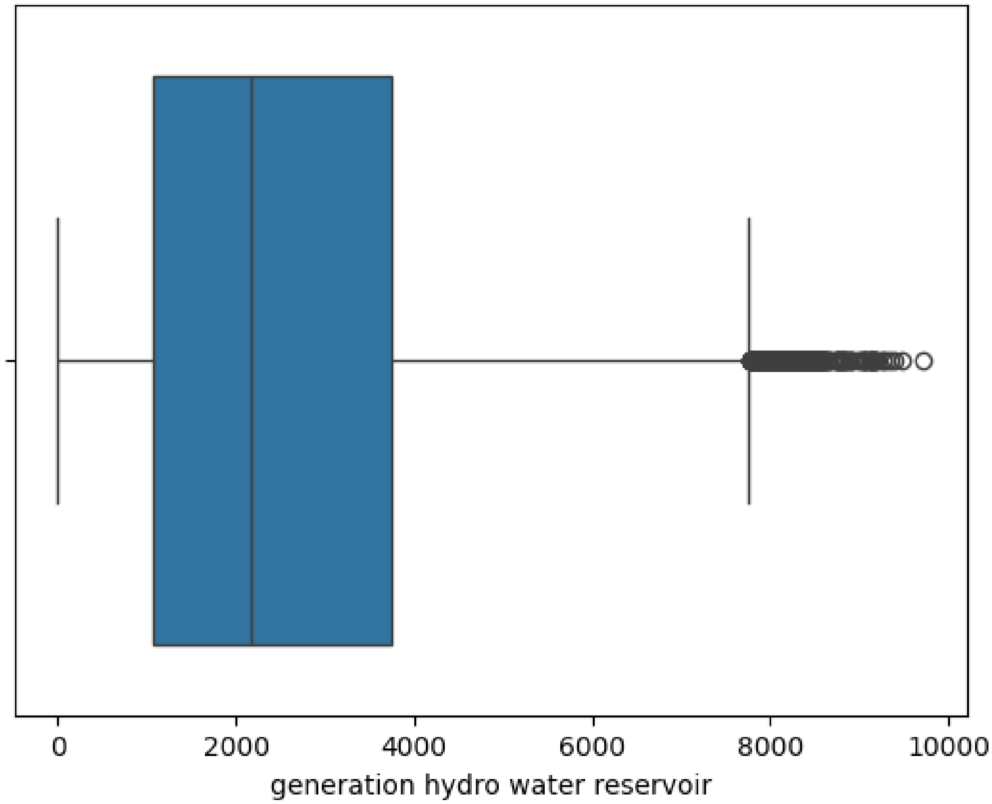

0
2500
5000
7500
10000
12500
15000
17500
20000
generation fossil gas

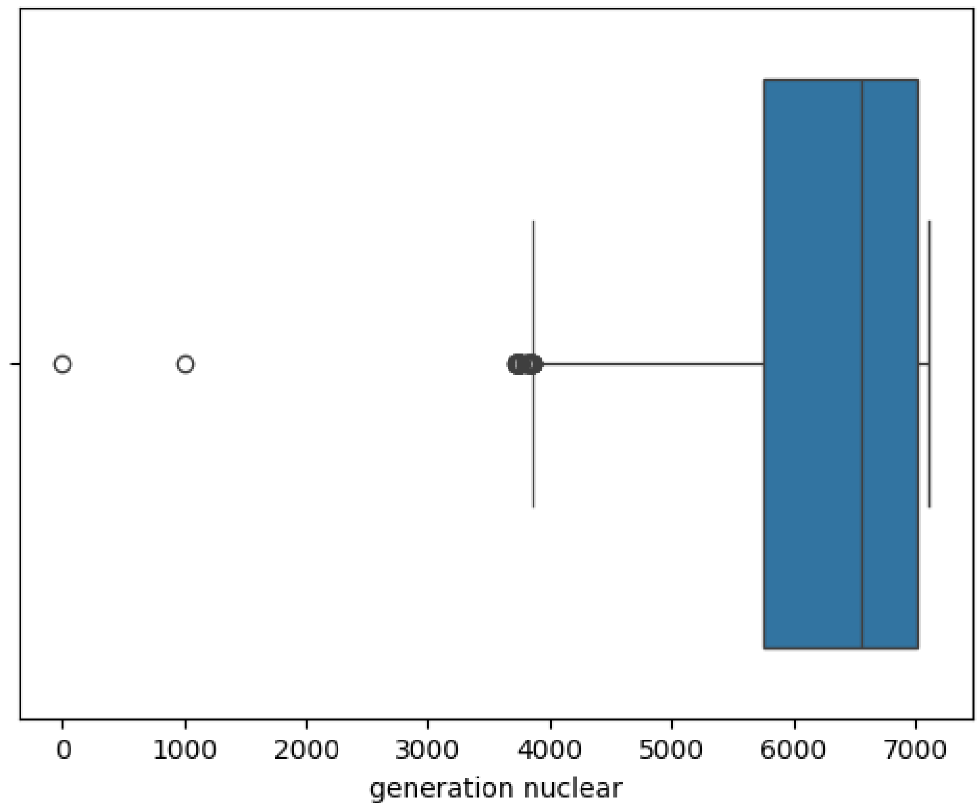

0
2000
4000
6000
8000
generation fossil hard coal

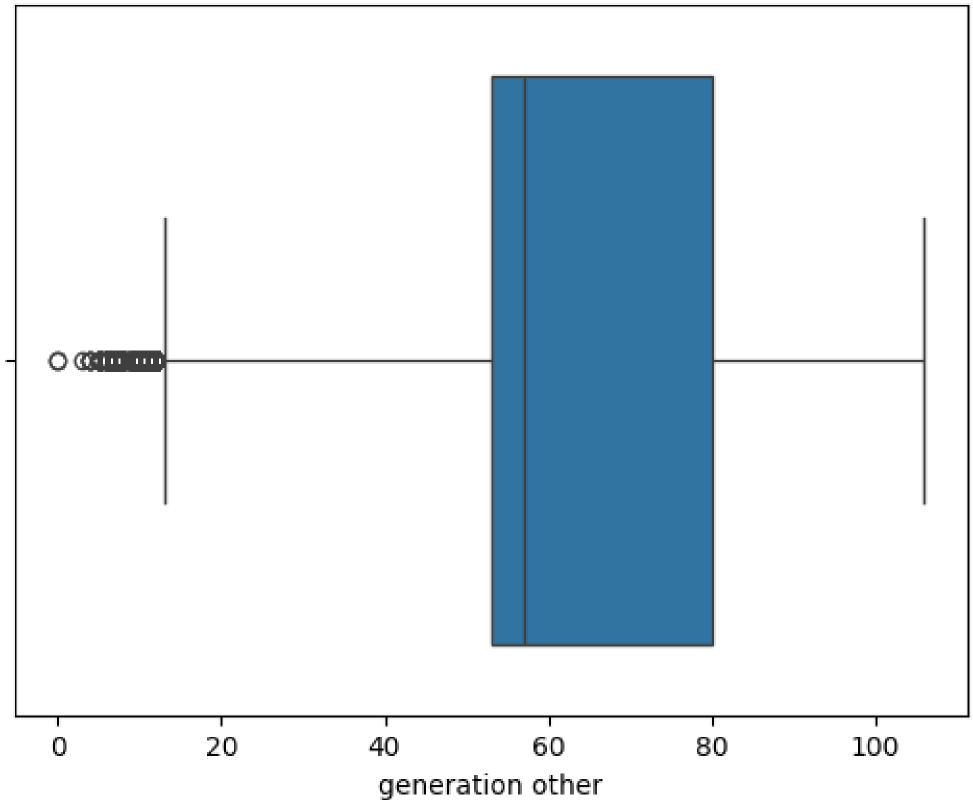

0
100
200
300
400
generation fossil oil

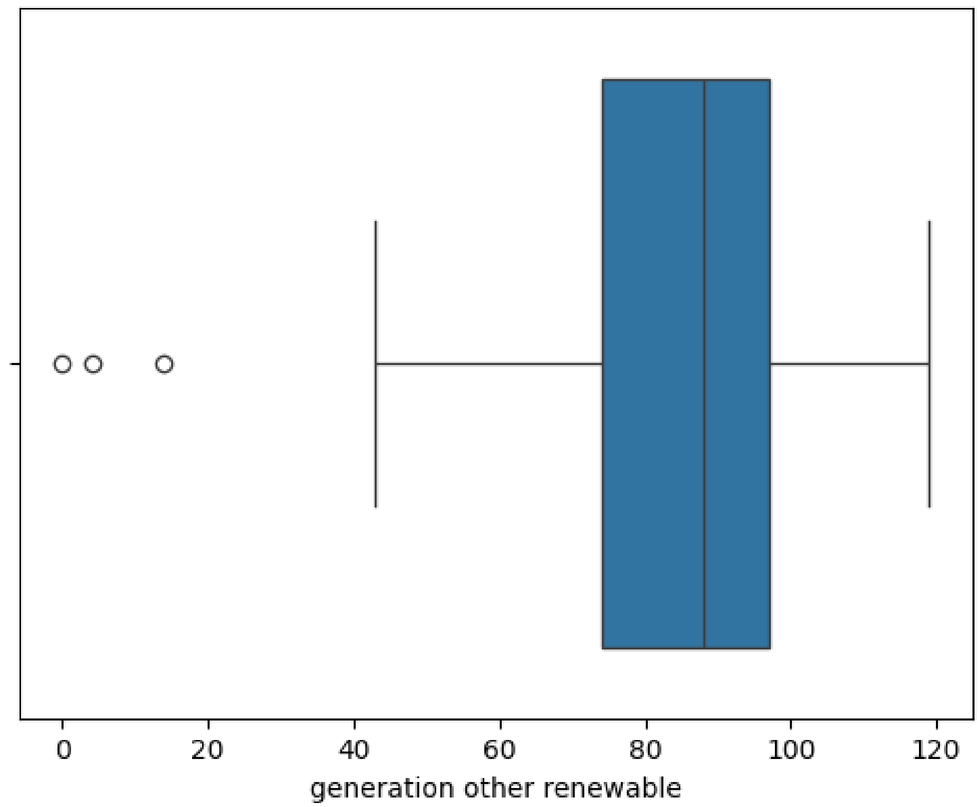

0
1000
2000
3000
4000
generation hydro pumped storage consumption

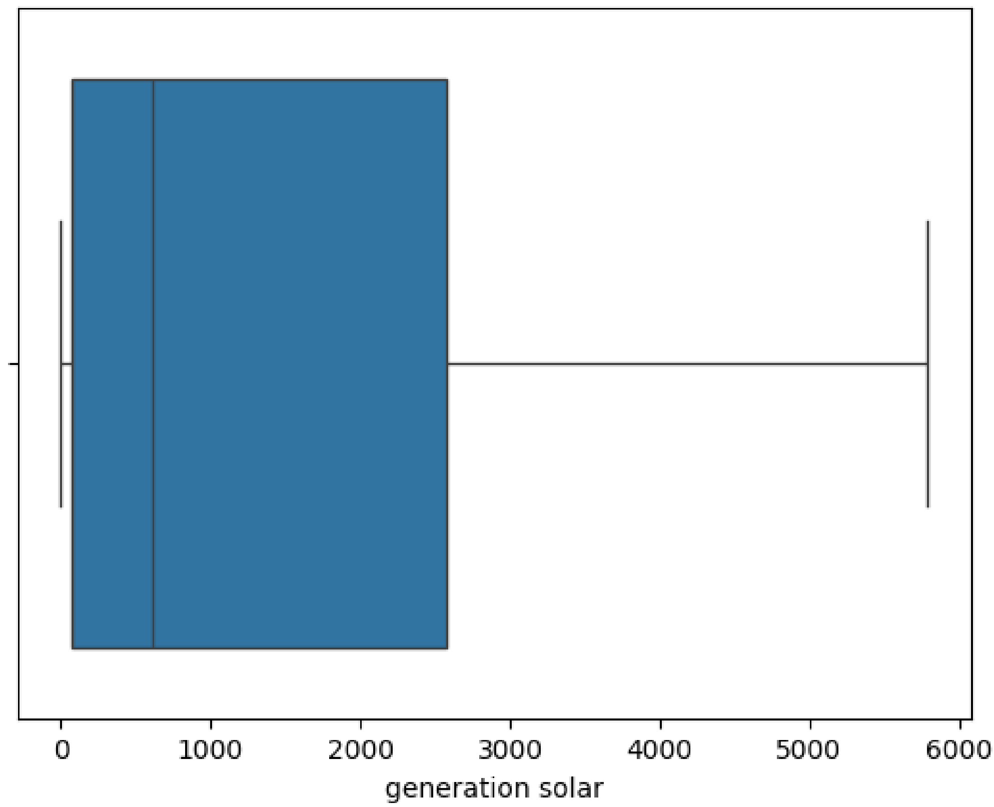

0
250
500
750
1000
1250
1500
1750
2000
generation hydro run-of-river and poundage

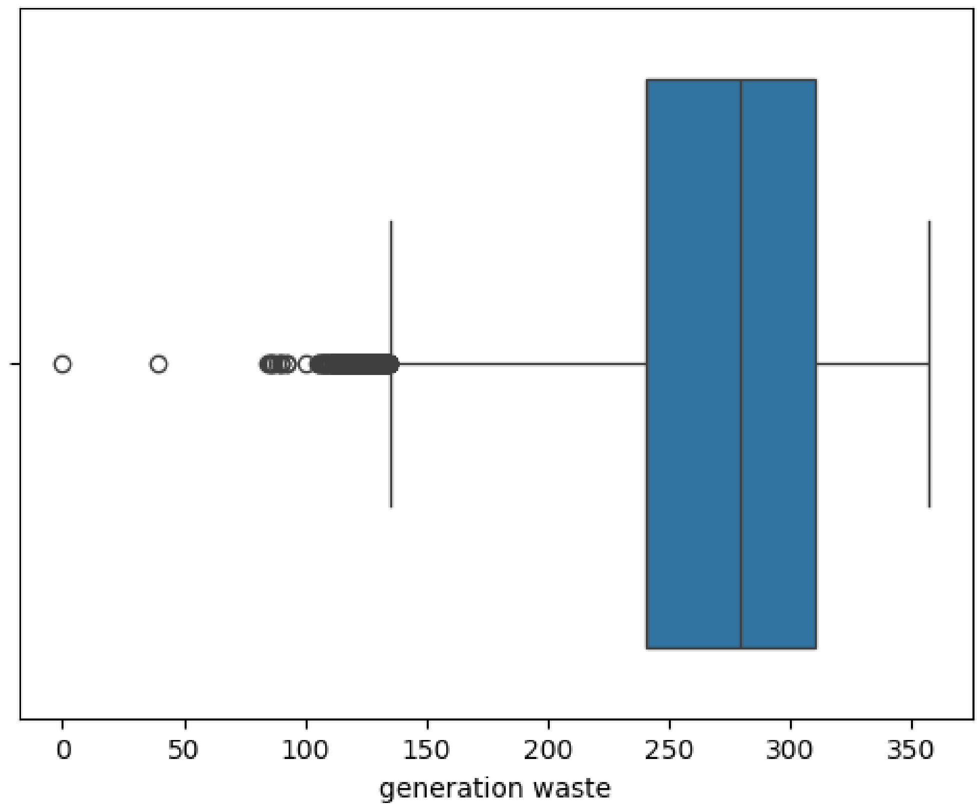

0
2000
4000
6000
8000
10000
generation hydro water reservoir

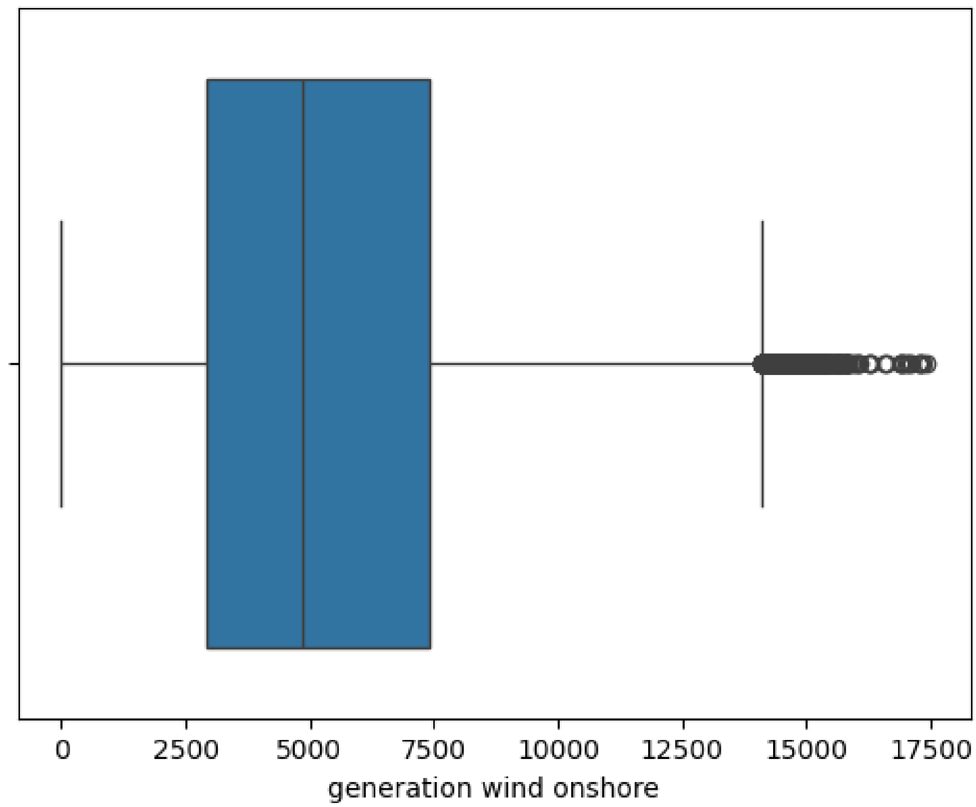

0
1000
2000
3000
4000
5000
6000
7000
generation nuclear

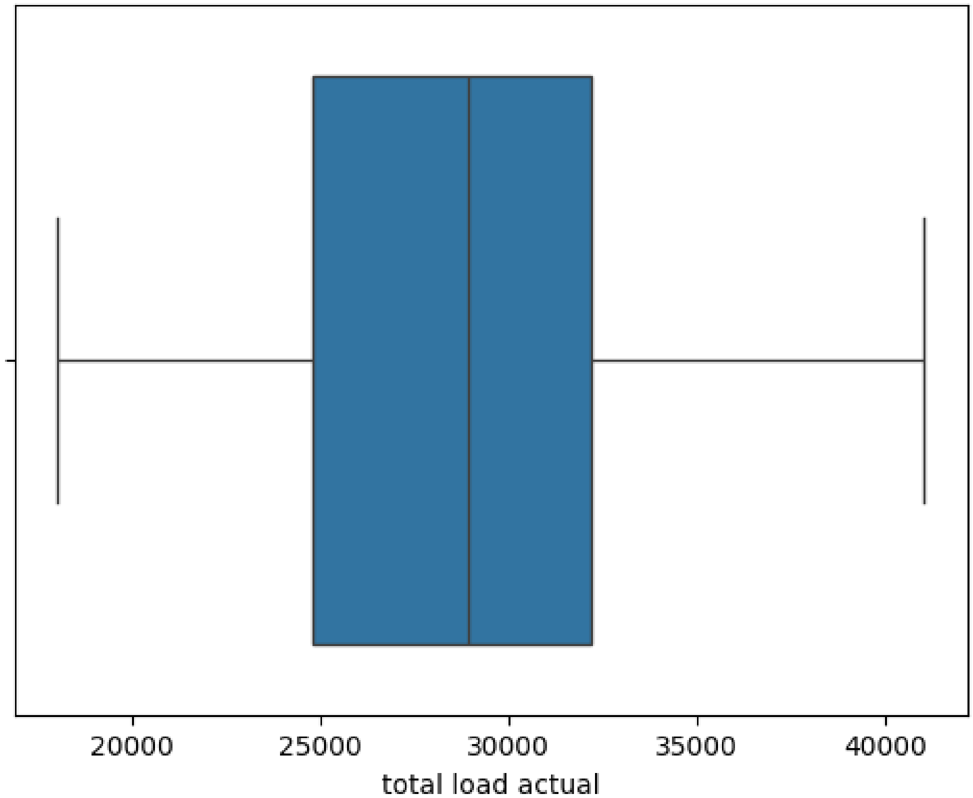

0
20
40
60
80
100
generation other

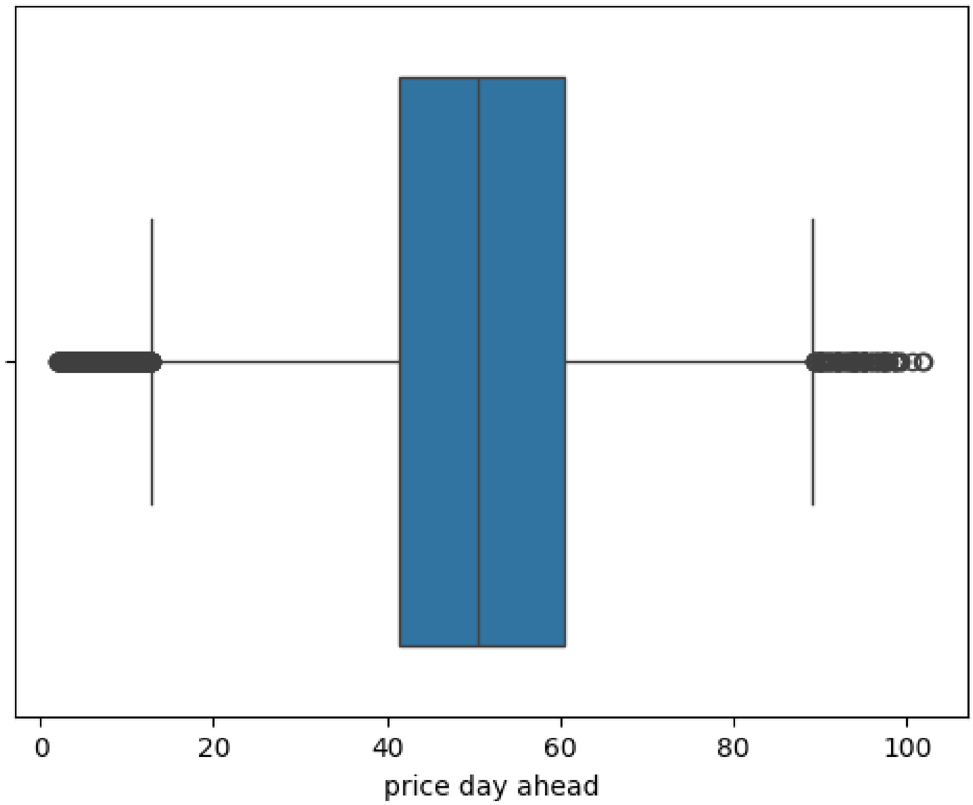

0
20
40
60
80
100
120
generation other renewable

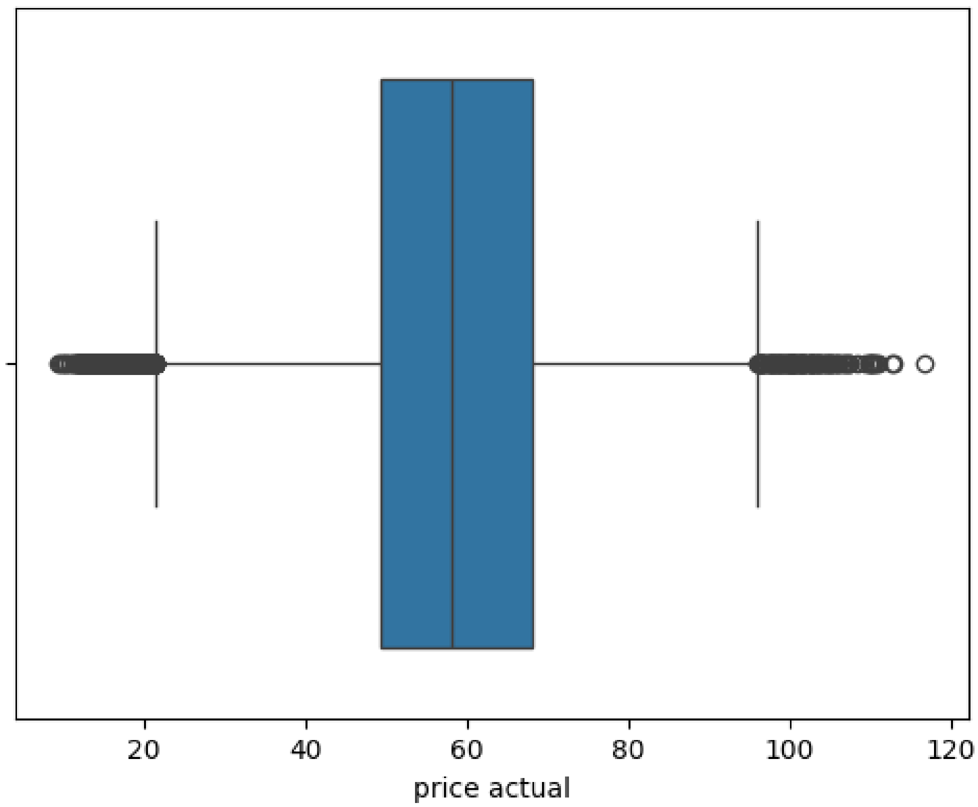

0
1000
2000
3000
4000
5000
6000
generation solar


0
50
100
150
200
250
300
350
generation waste

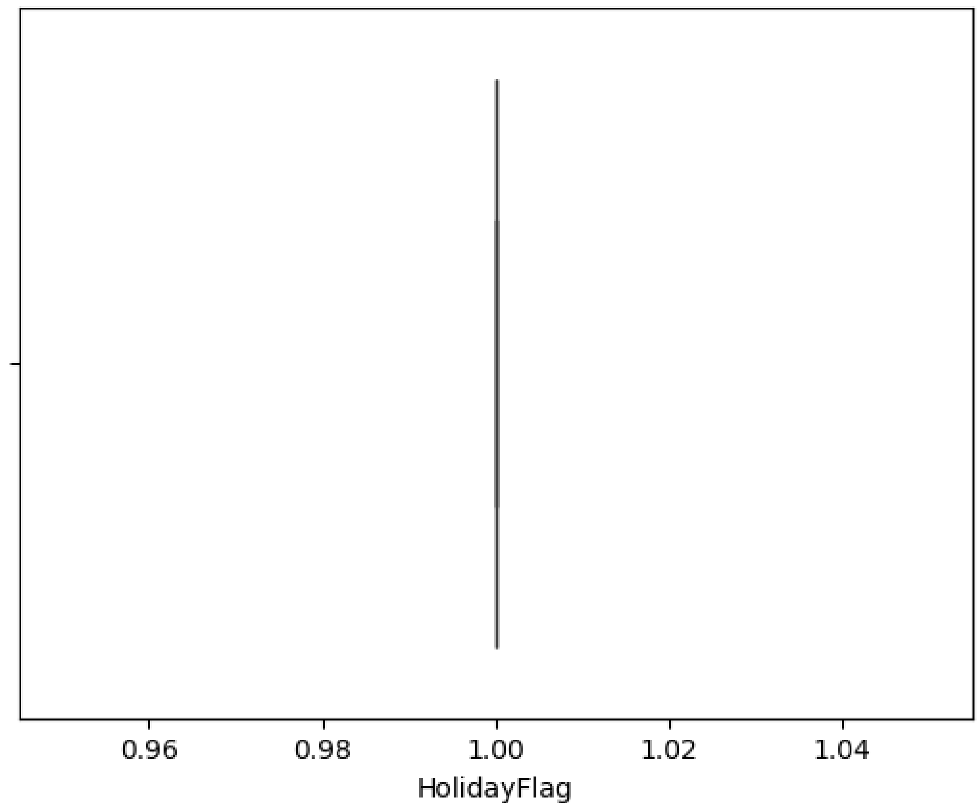

0
2500
5000
7500
10000
12500
15000
17500
generation wind onshore

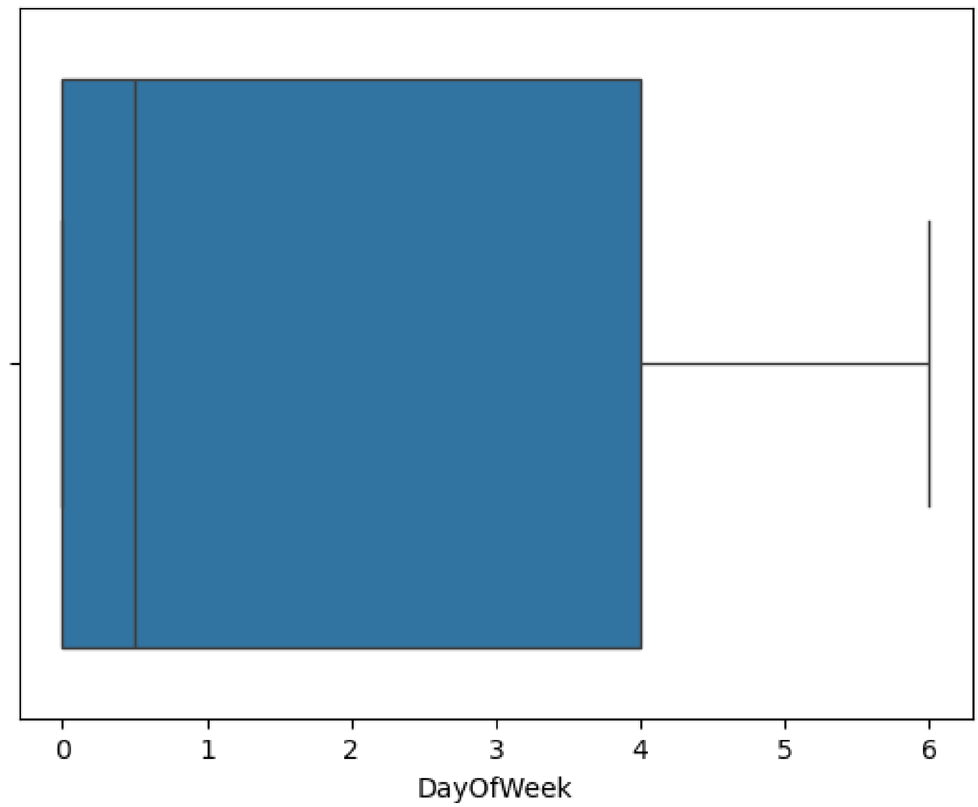

20000
25000
30000
35000
40000
total load actual

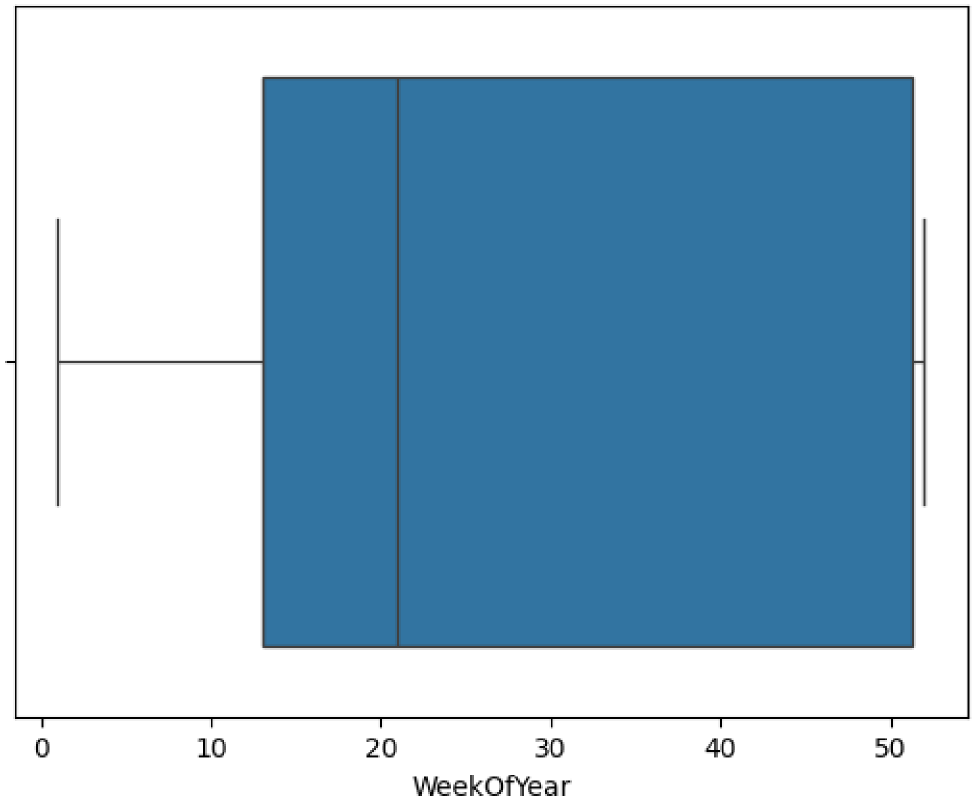

0
20
40
60
80
100
price day ahead

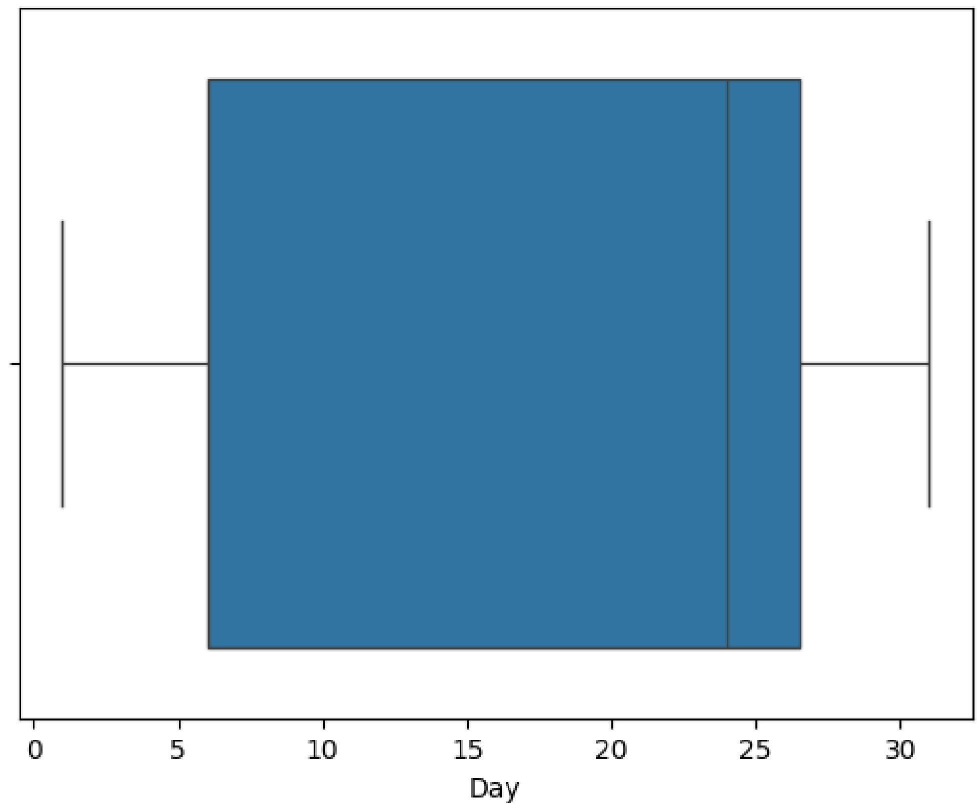


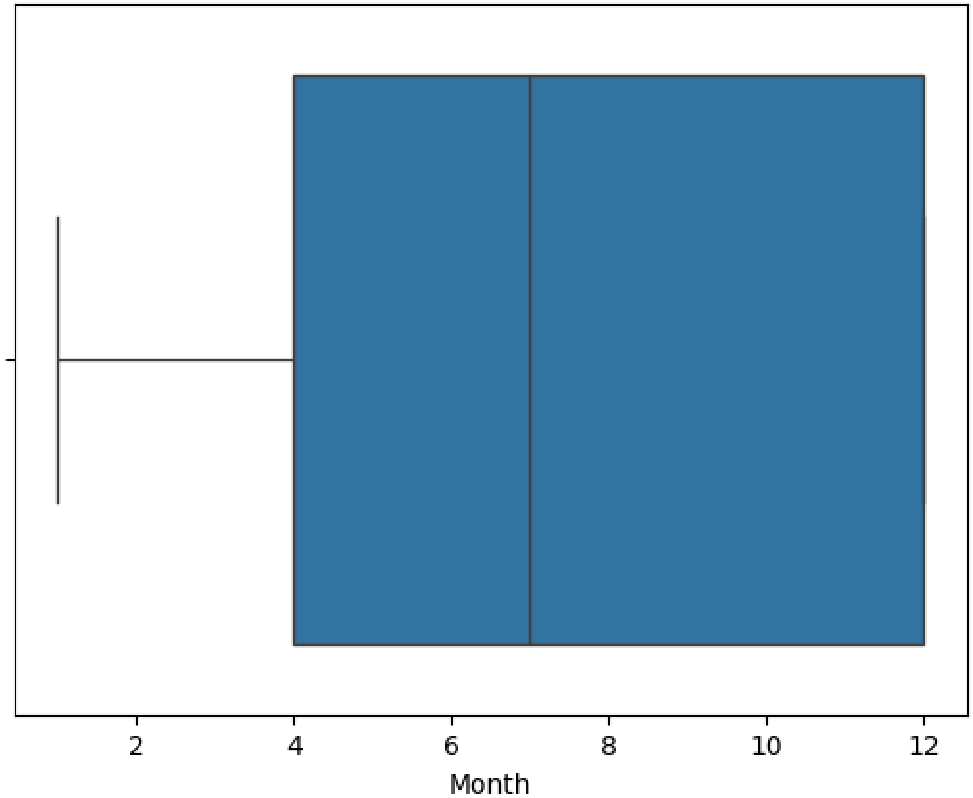
[ ]:
```
for i in b.select_dtypes(include="number").columns:
  sns.boxplot(b,x=i)
  plt.show()
```

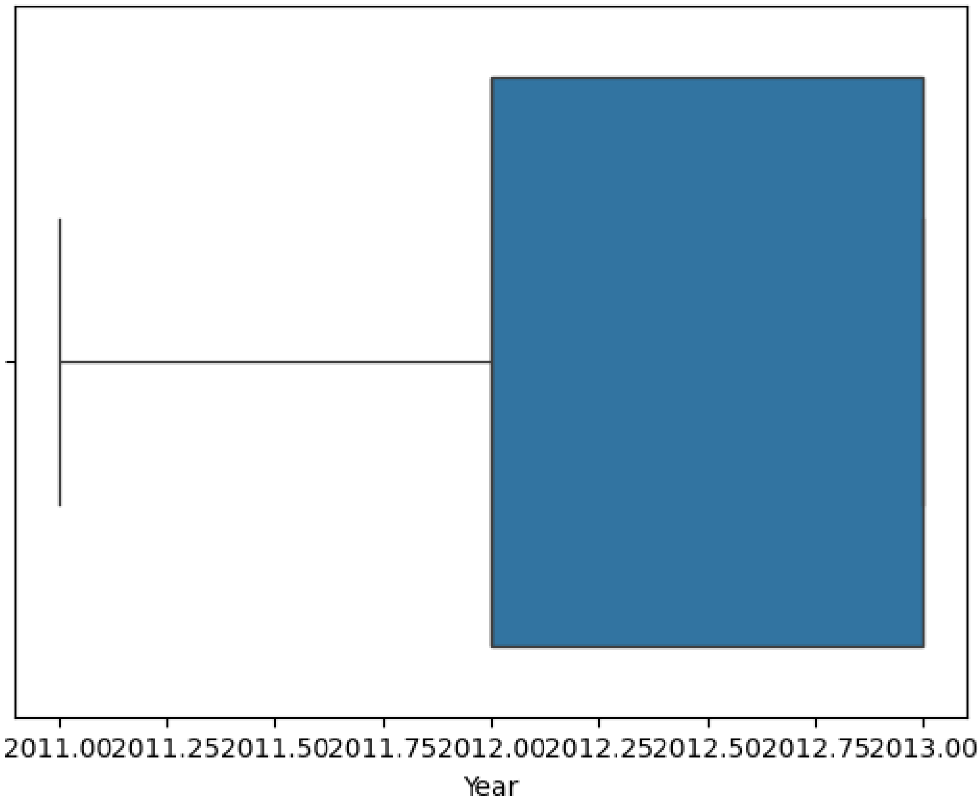

0.96
0.98
1.00
1.02
1.04
HolidayFlag

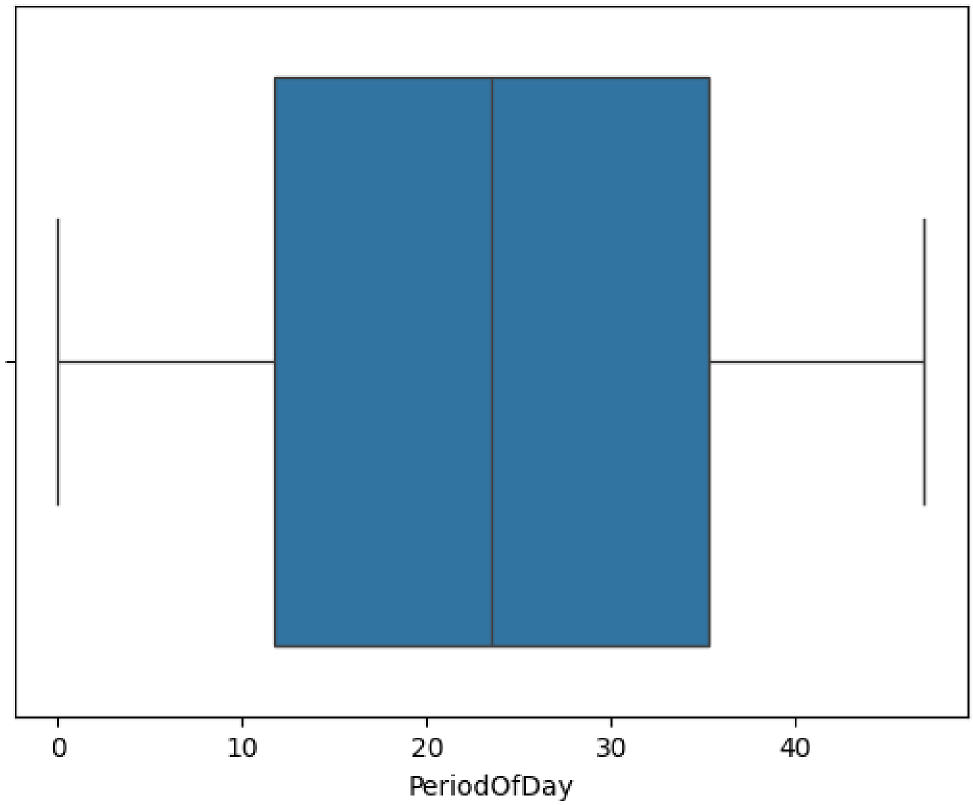

0
1
2
3
4
5
6
DayOfWeek

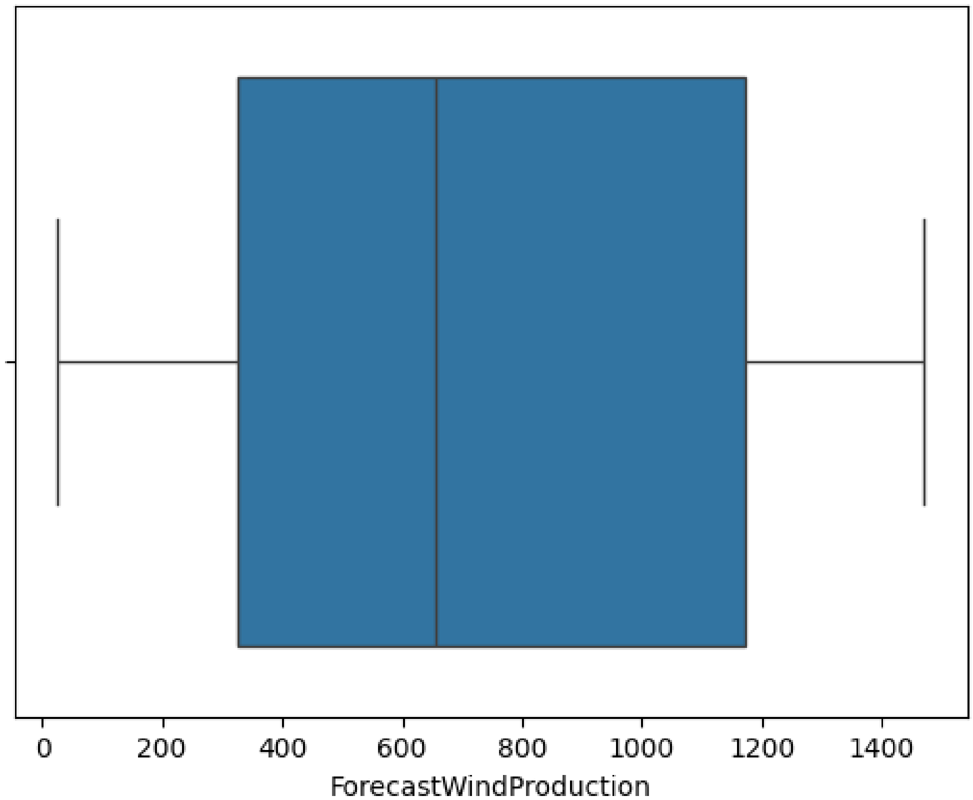

0
10
20
30
40
50
WeekOfYear

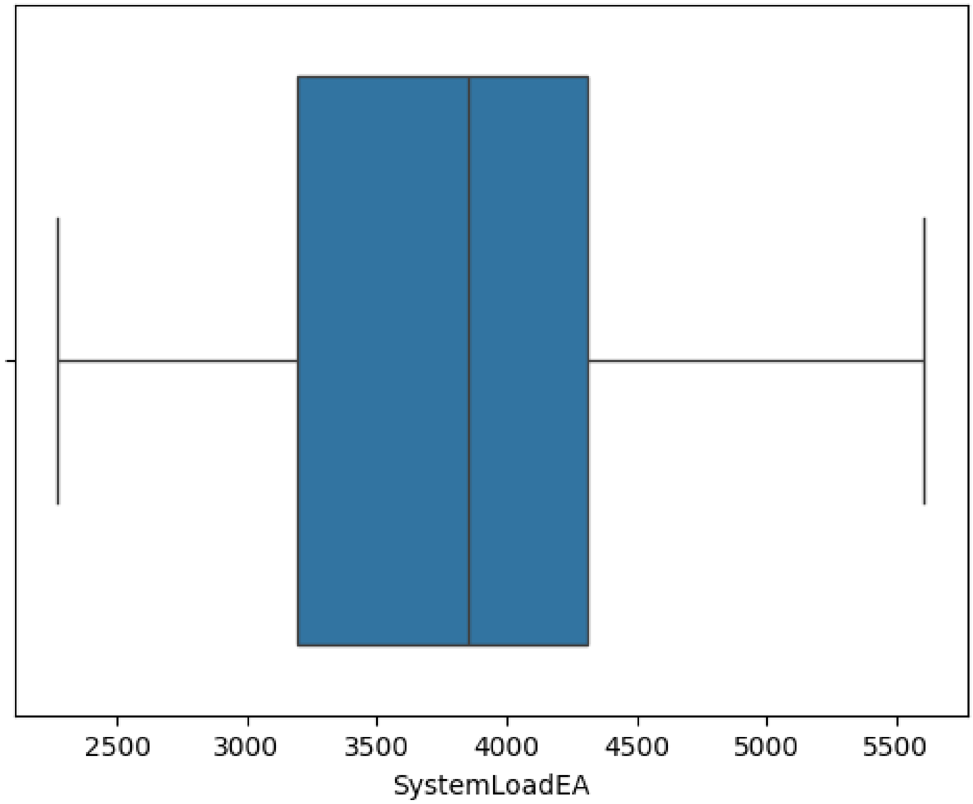

0
5
10
15
20
25
30
Day

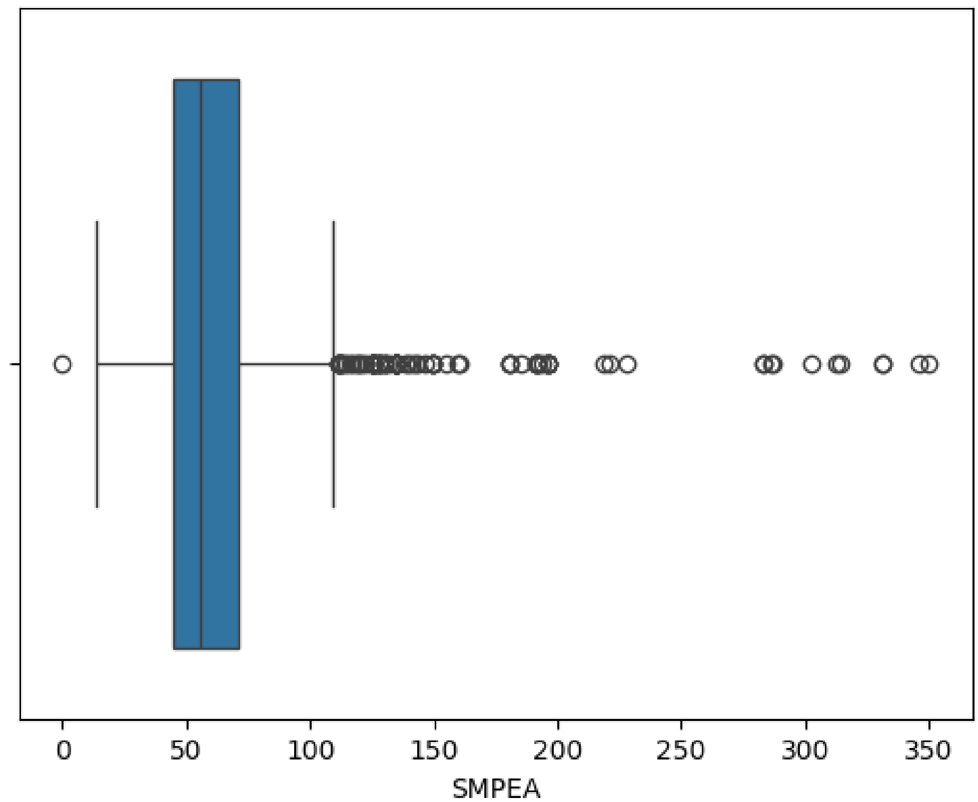

2
4
6
8
10
12
Month

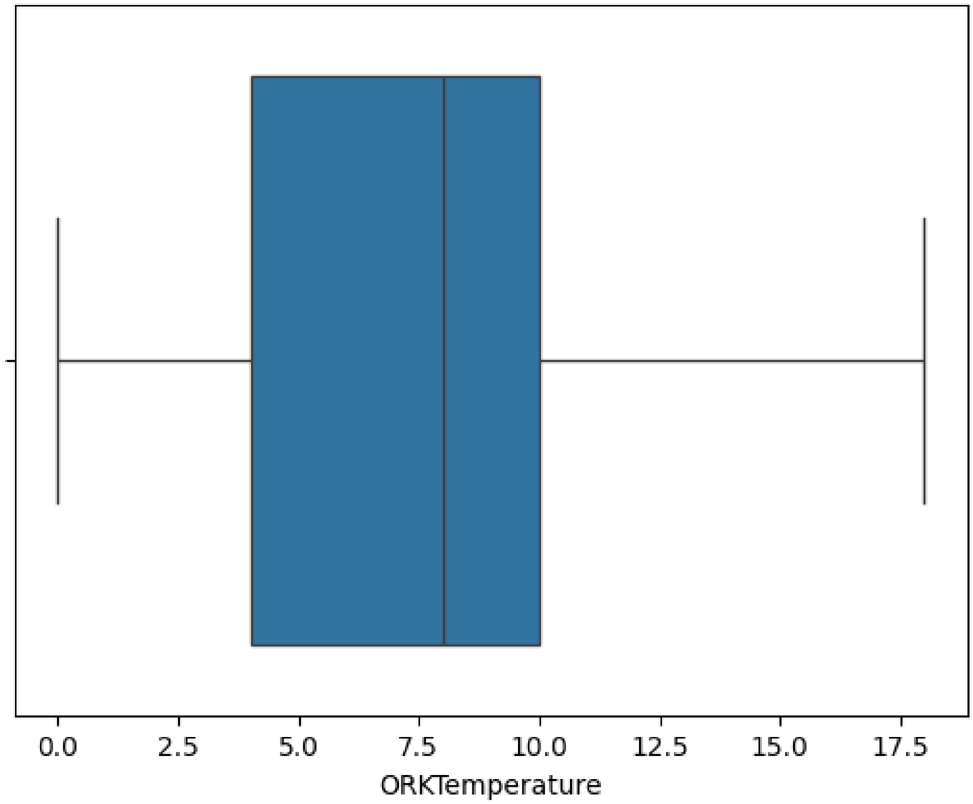

2011.00 2011.25 2011.50 2011.75 2012.00 2012.25 2012.50 2012.75 2013.00
Year

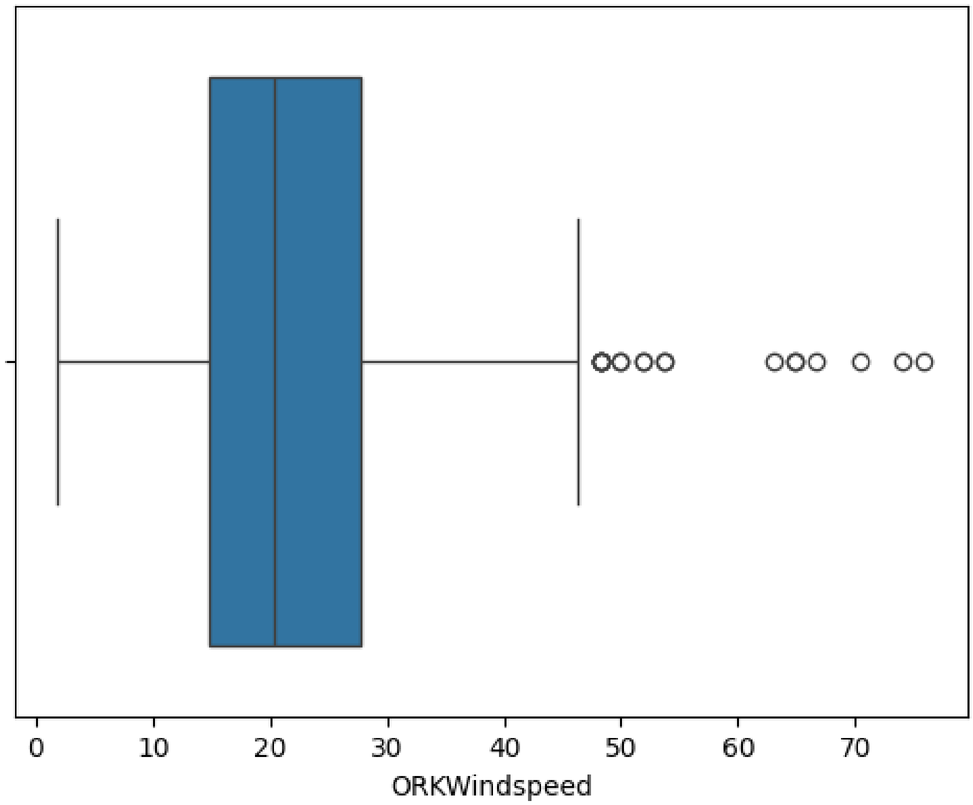

0
10
20
30
40
PeriodOfDay

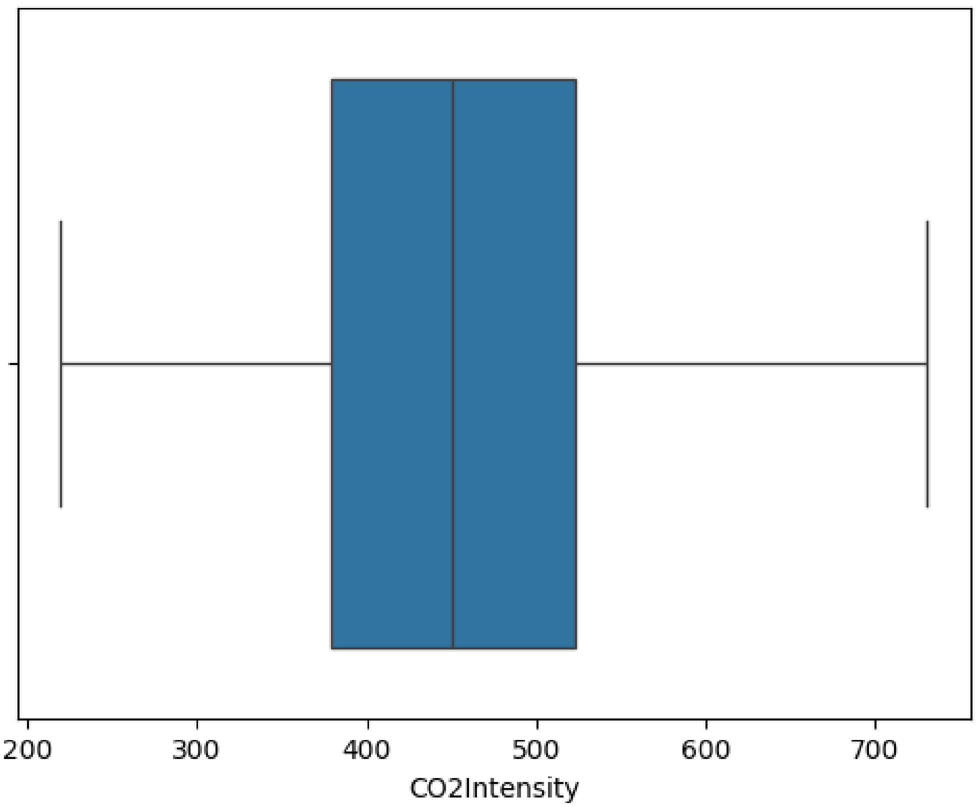

0
200
400
600
800
1000
1200
1400
ForecastWindProduction

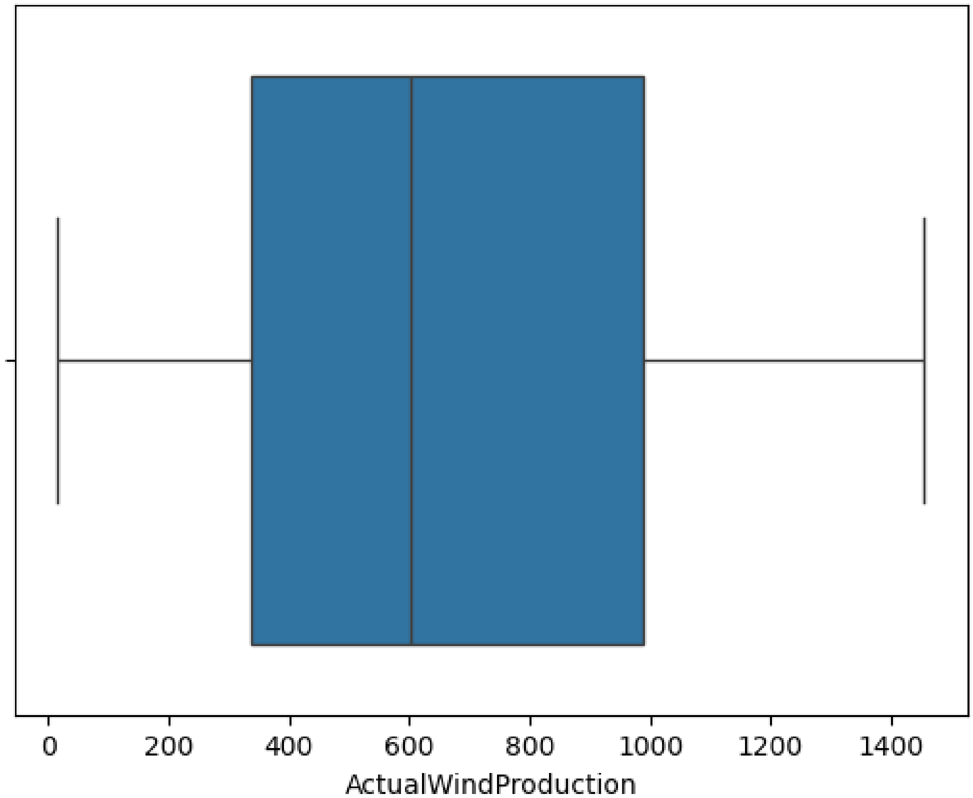

2500
3000
3500
4000
4500
5000
5500
SystemLoadEA

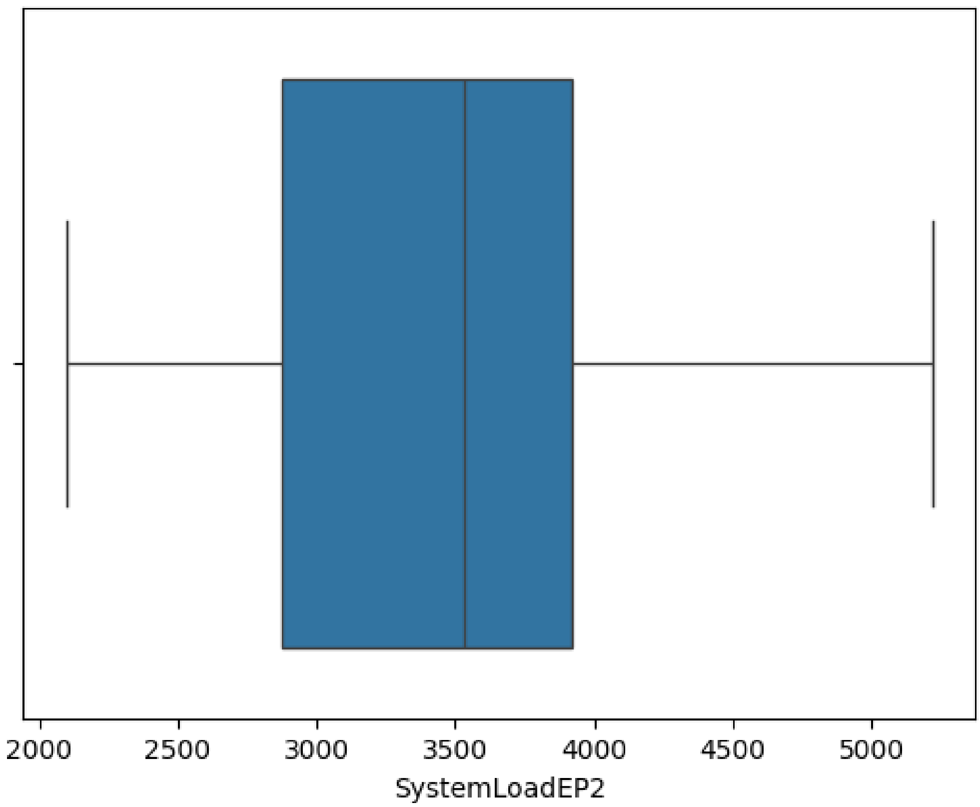

0
50
100
150
200
250
300
350
SMPEA

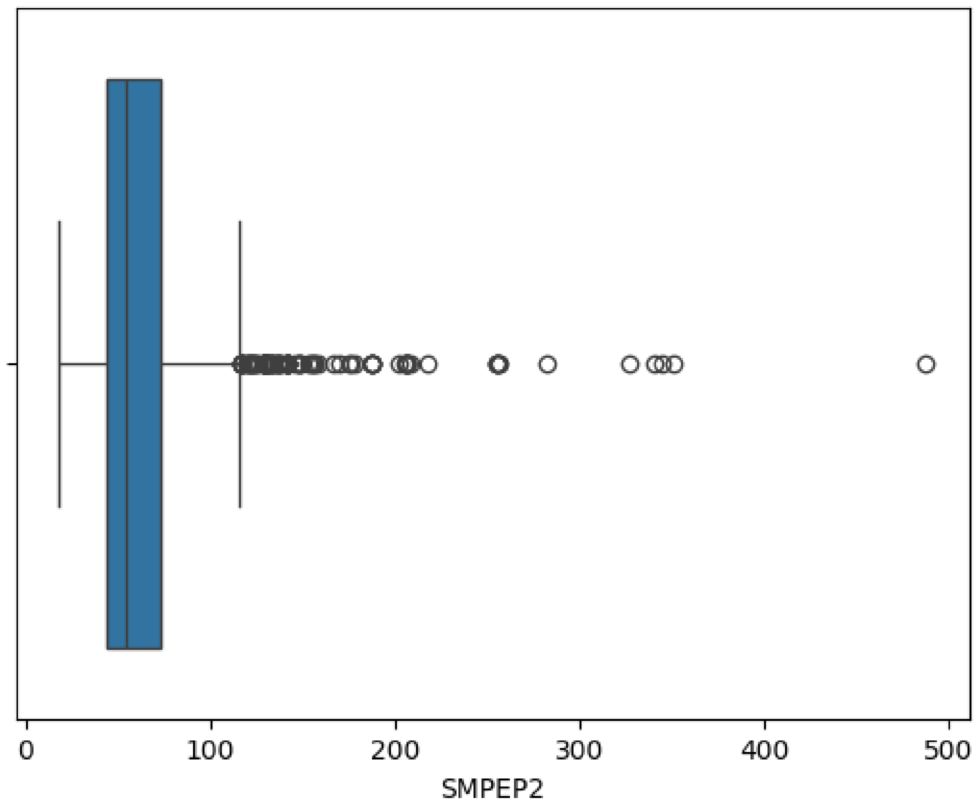

0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
ORKTemperature


0
10
20
30
40
50
60
70
ORKWindspeed

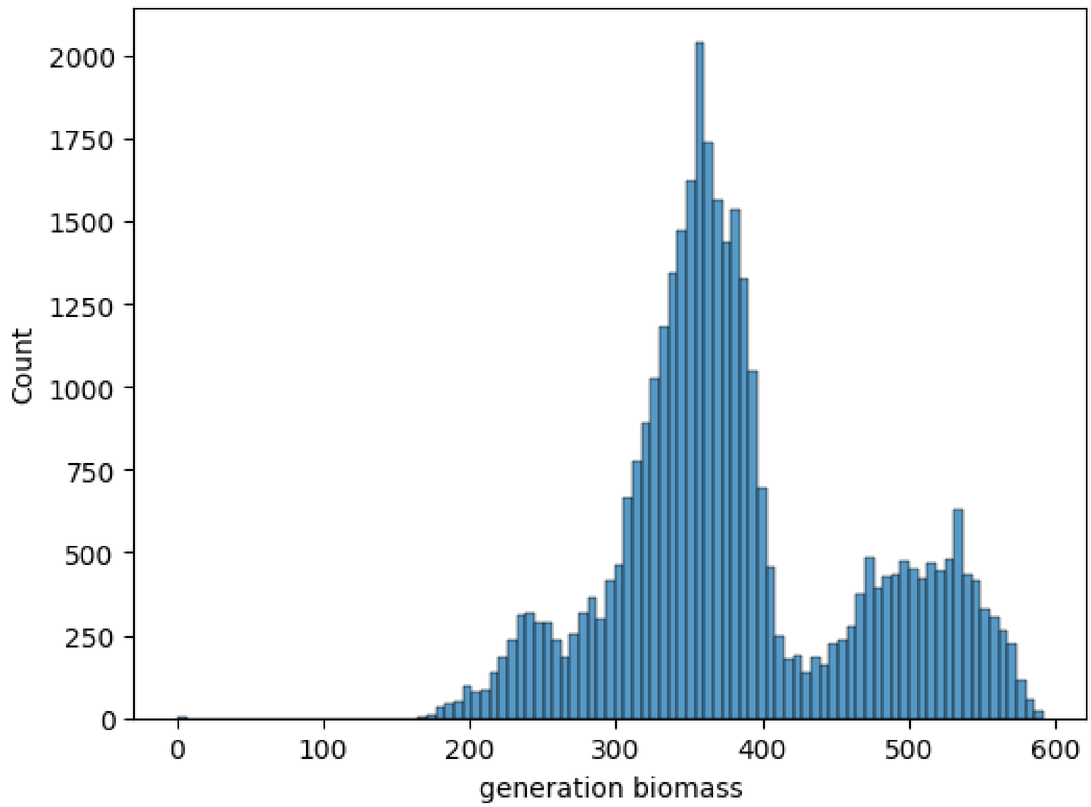

200
300
400
500
600
700
CO2Intensity

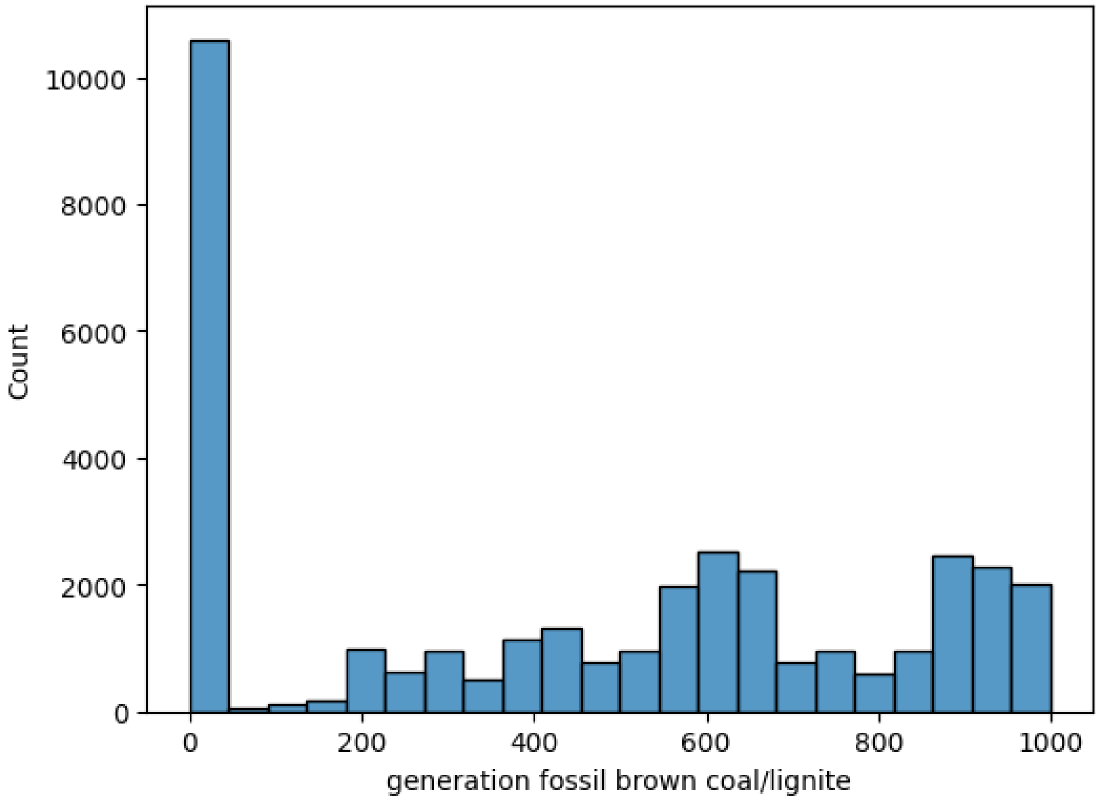

0
200
400
600
800
1000
1200
1400
ActualWindProduction

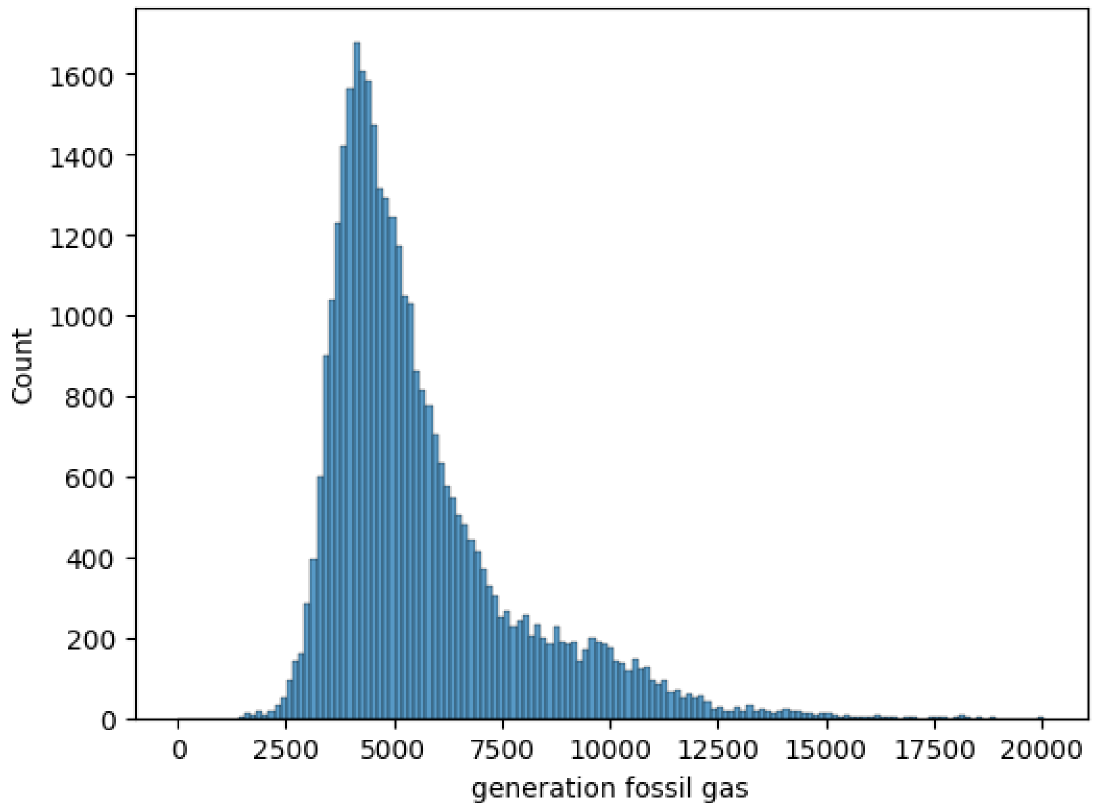

2000
2500
3000
3500
4000
4500
5000
SystemLoadEP2



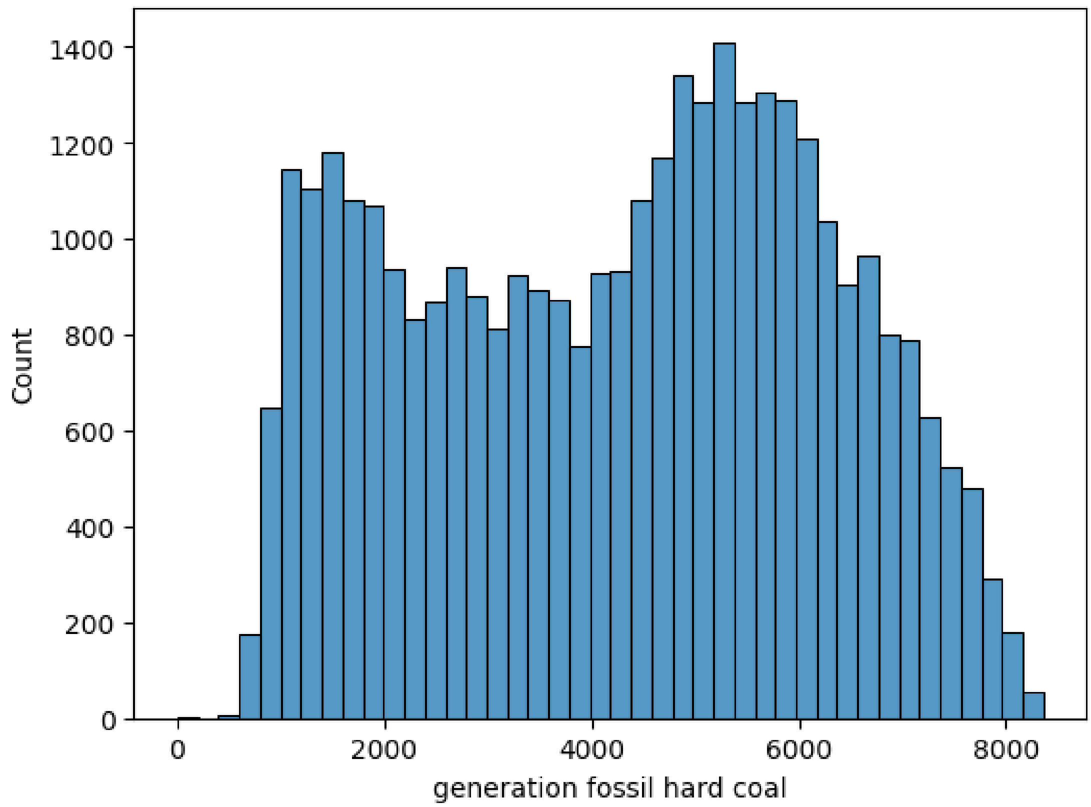
[ ]:
```
for i in a.select_dtypes(include="number").columns:
  sns.histplot(a,x=i)
  plt.show()
```


2000
1750
1500
1250
1000
750
500
250
0
Count
0
100
200
300
400
500
600
generation biomass

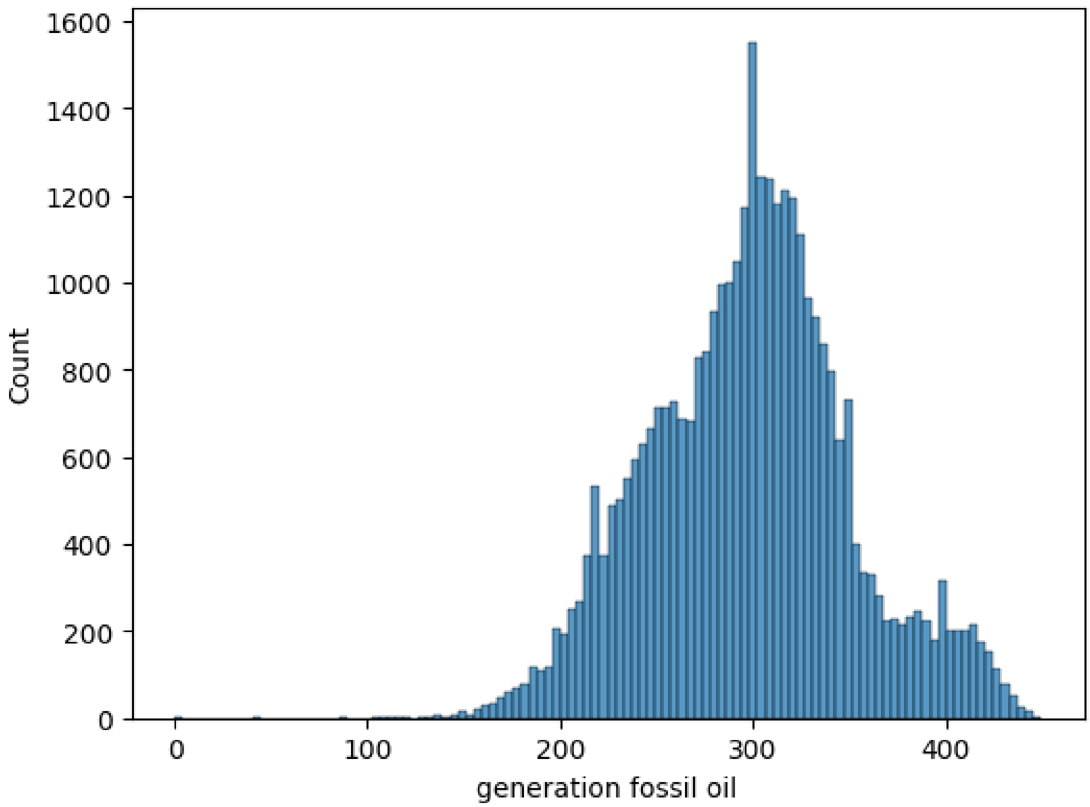

Count
10000
8000
6000
4000
2000
0
0
200
400
600
800
1000
generation fossil brown coal/lignite



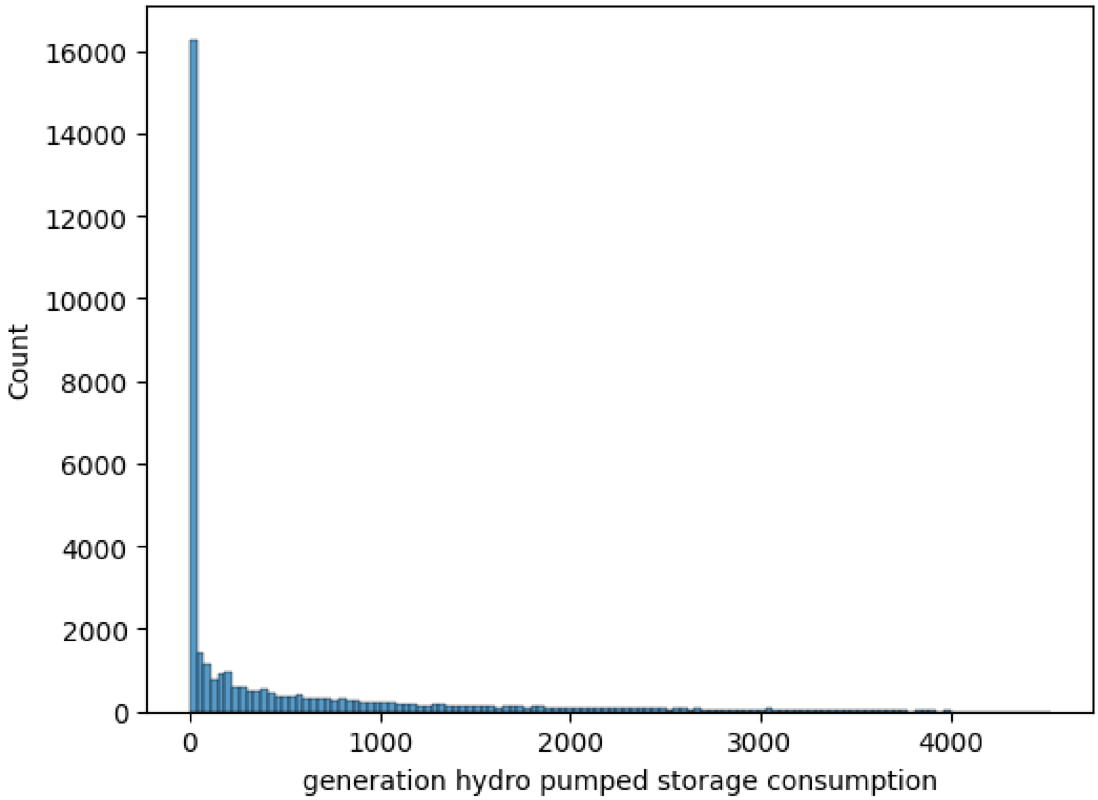
Count
1600
1400
1200
1000
800
600
400
200
0
0
2500
5000
7500
10000
12500
15000
17500
20000
generation fossil gas



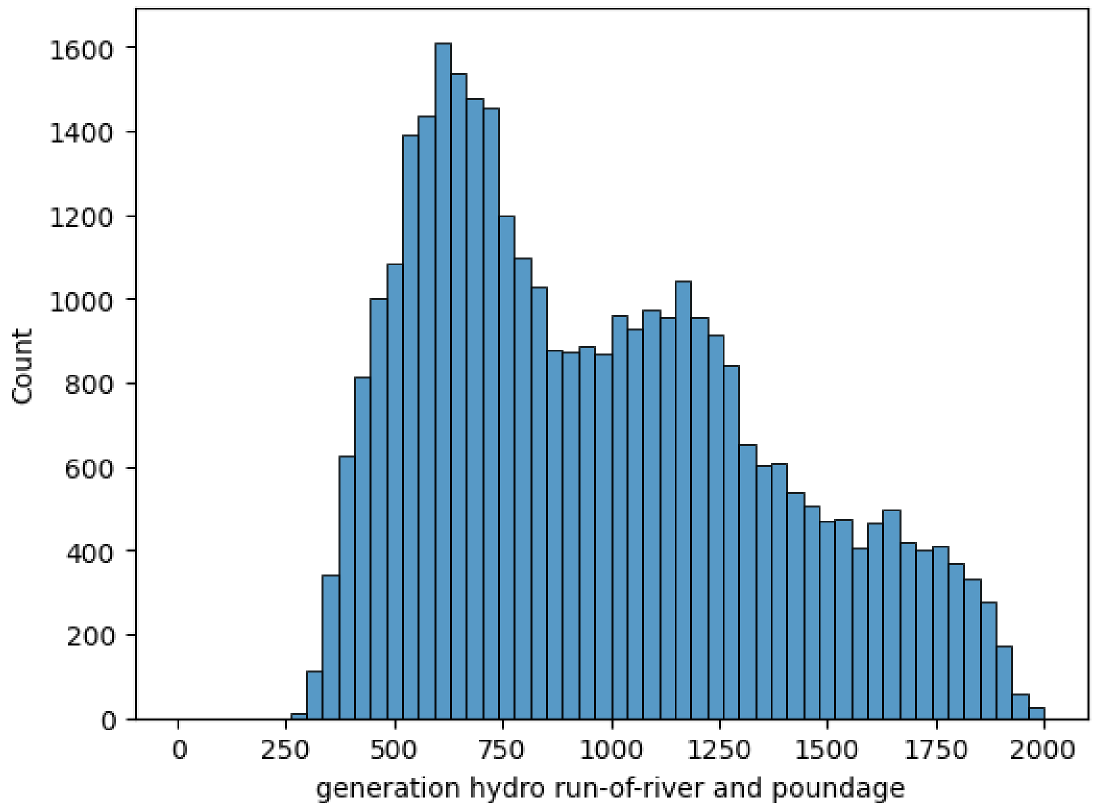
1400
1200
1000
800
600
400
200
0
Count
0
2000
4000
6000
8000
generation fossil hard coal



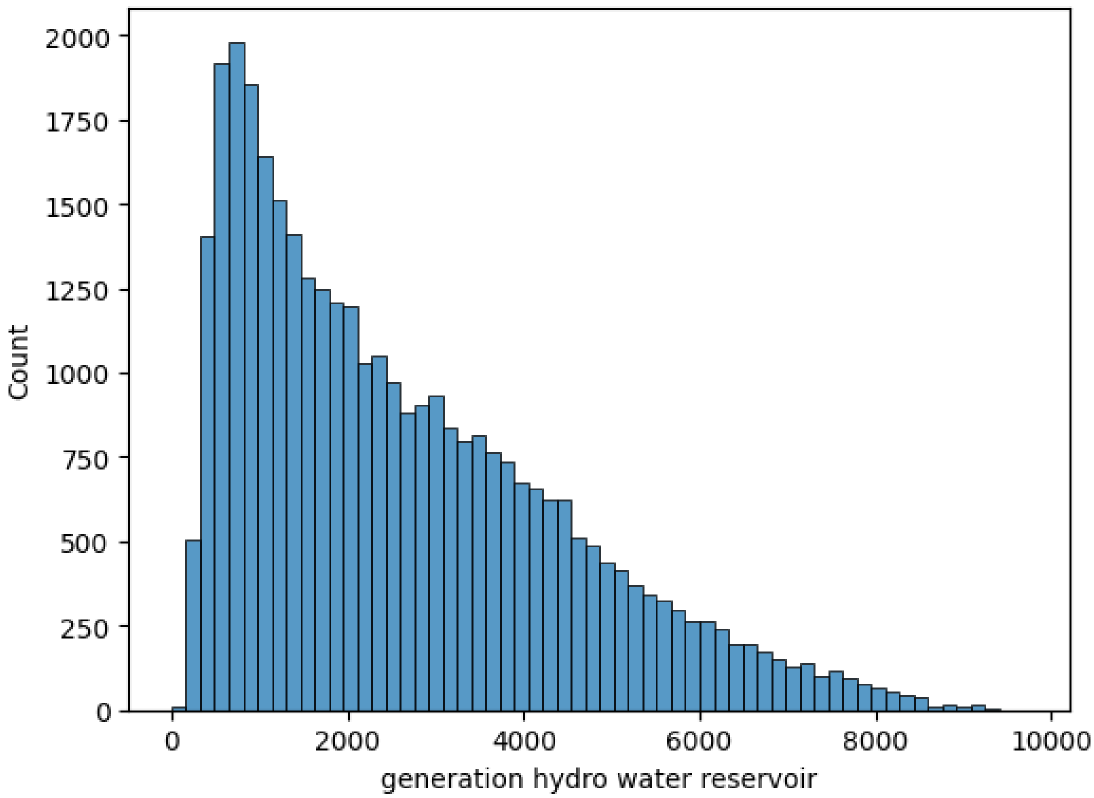
1600
1400
1200
1000
800
600
400
200
0
Count
0
100
200
300
400
generation fossil oil

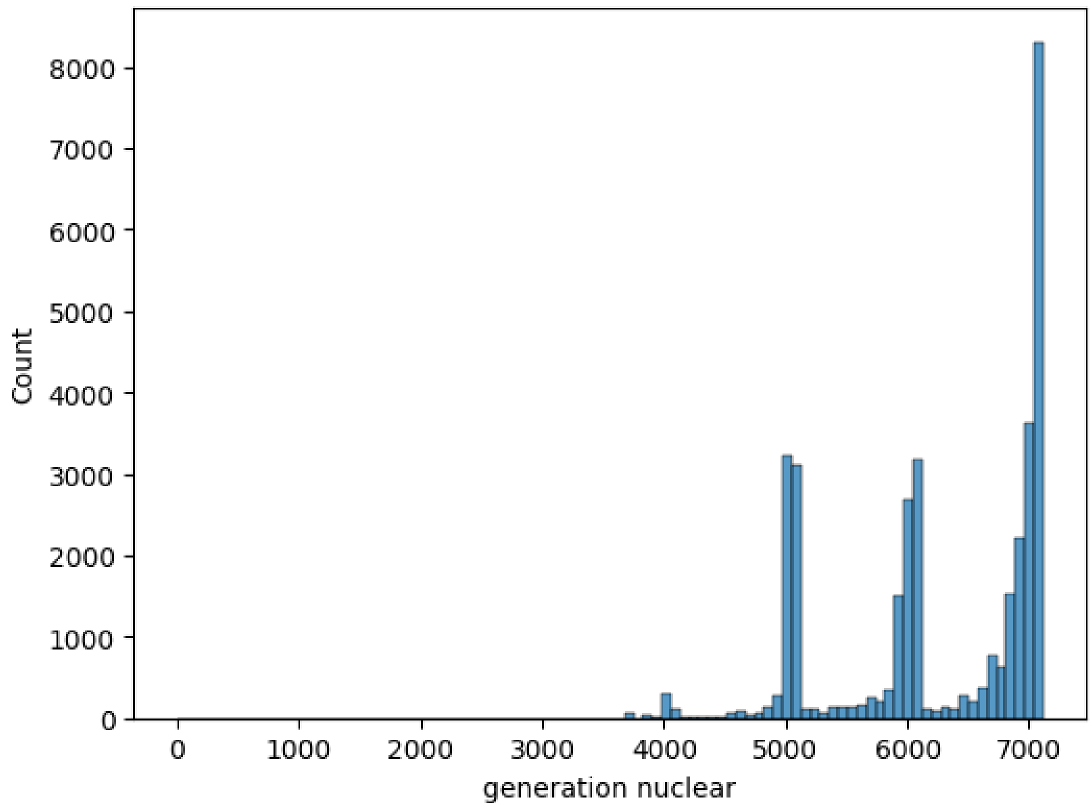


16000
14000
12000
10000
8000
6000
4000
2000
0
Count
0
1000
2000
3000
4000
generation hydro pumped storage consumption

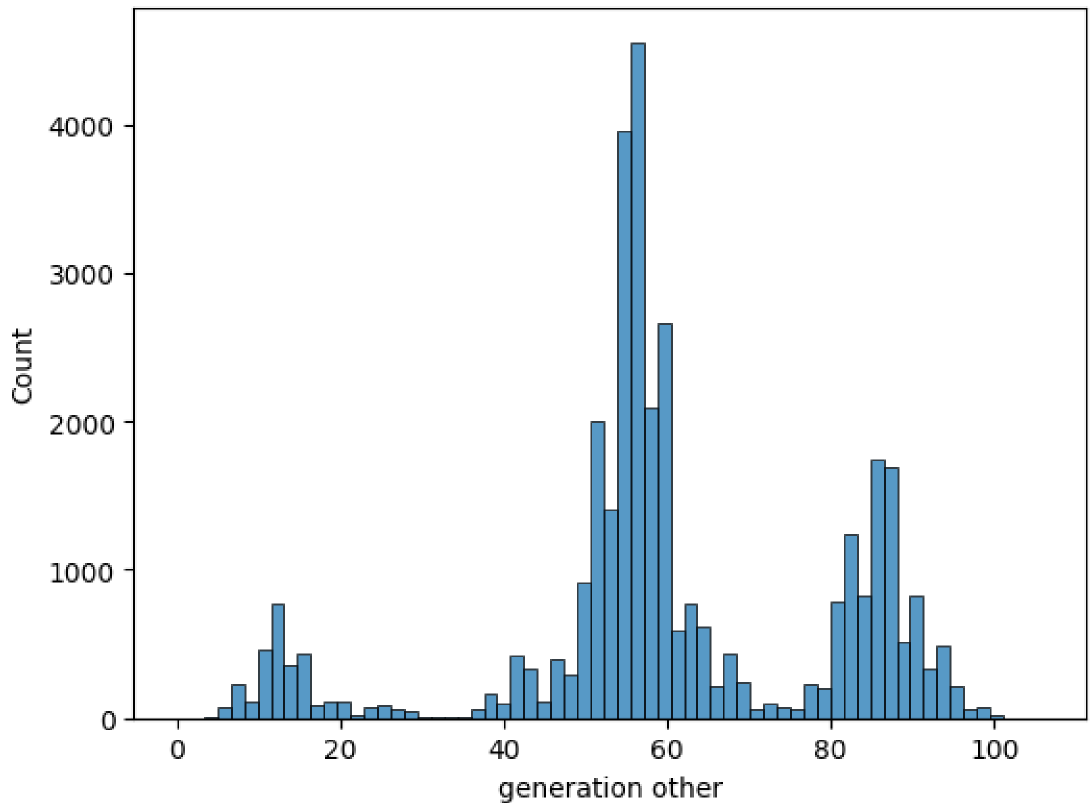


Count
0
200
400
600
800
1000
1200
1400
1600
0
250
500
750
1000
1250
1500
1750
2000
generation hydro run-of-river and poundage

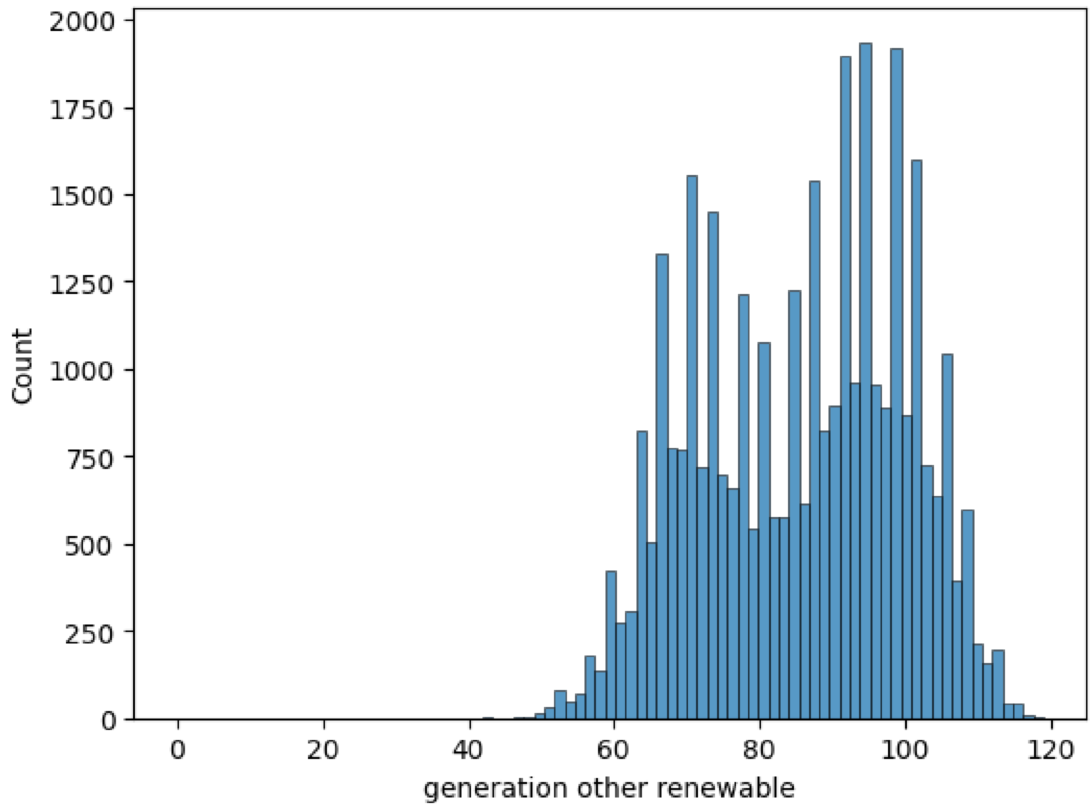

2000
1750
1500
1250
1000
750
500
250
0
Count
0
2000
4000
6000
8000
10000
generation hydro water reservoir

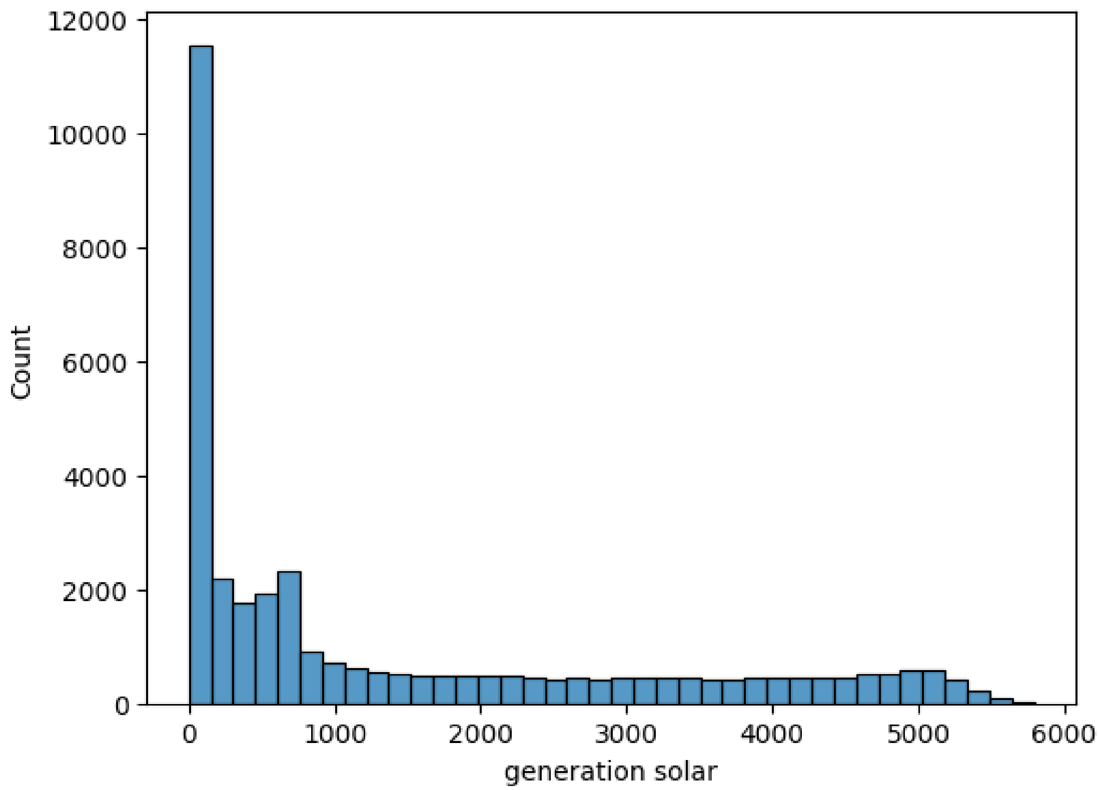


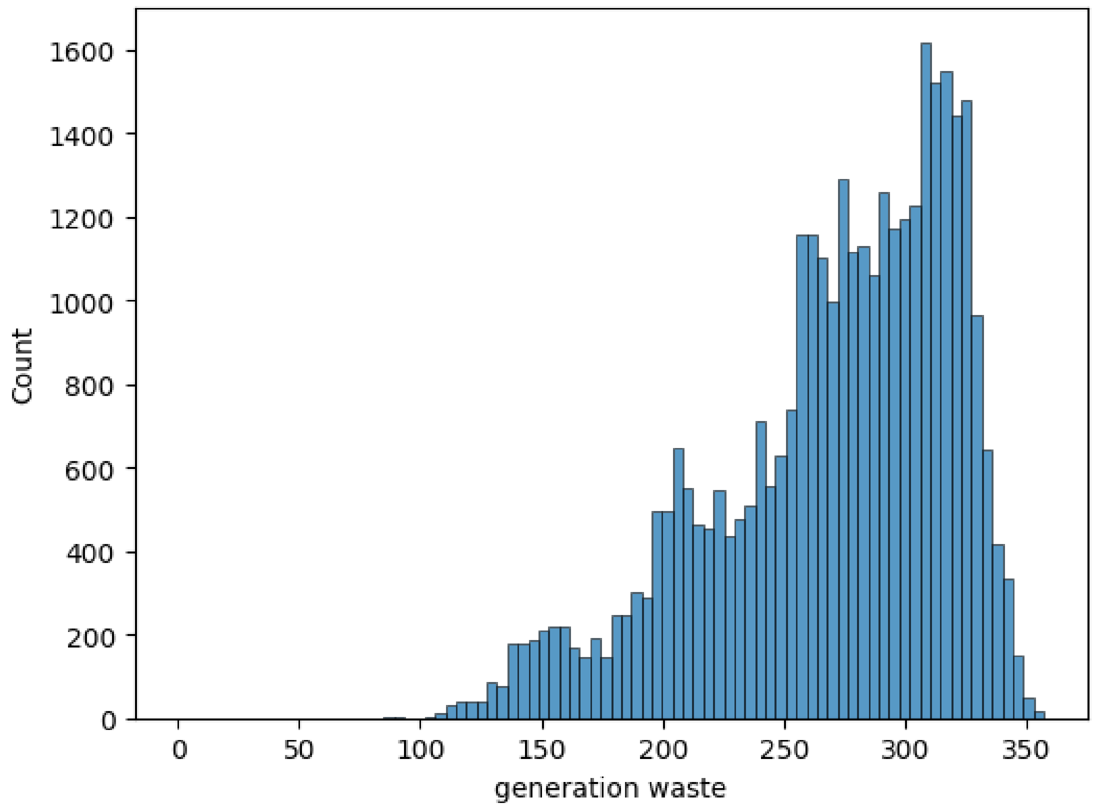
8000
7000
6000
5000
4000
3000
2000
1000
0
Count
0
1000
2000
3000
4000
5000
6000
7000
generation nuclear



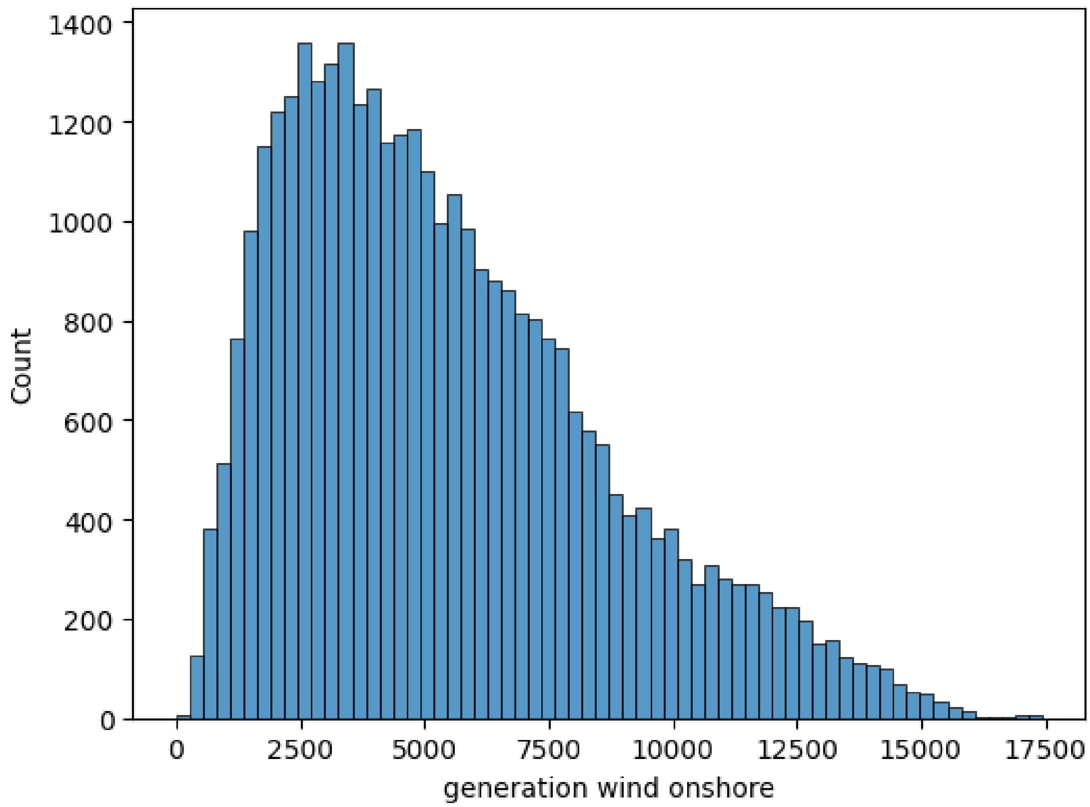
4000
3000
2000
1000
0
Count
0
20
40
60
80
100
generation other

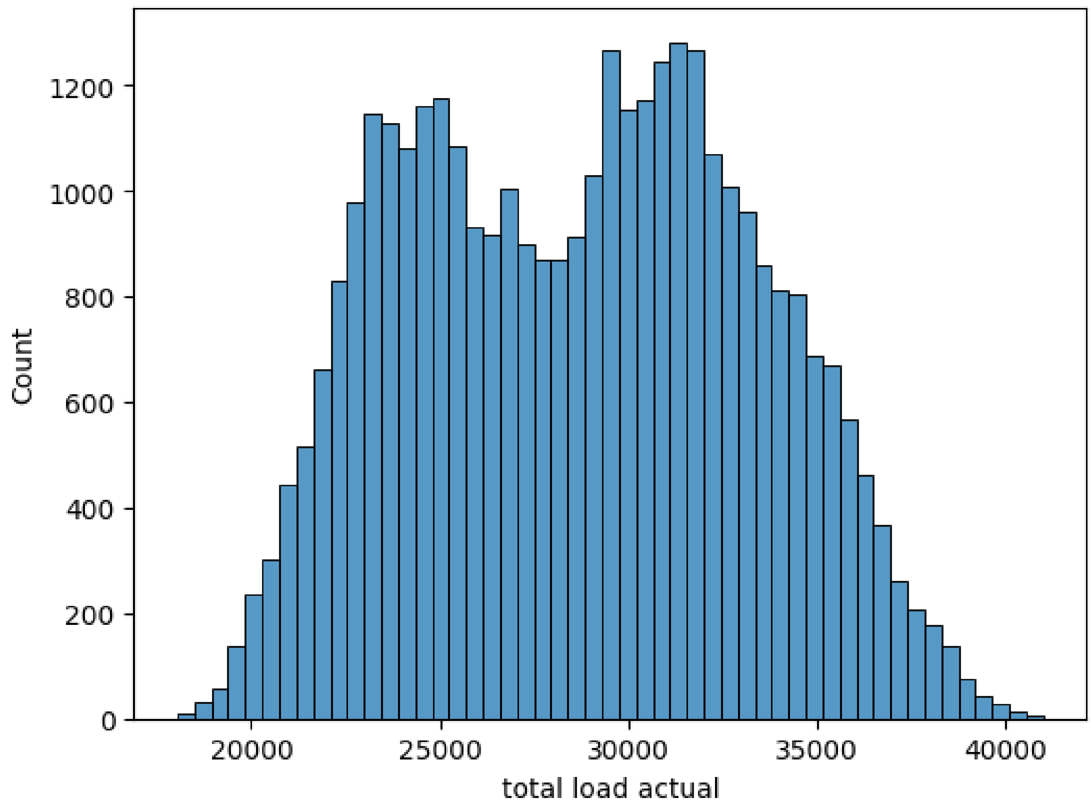

Count
generation other renewable
2000
1750
1500
1250
1000
750
500
250
0
0
20
40
60
80
100
120

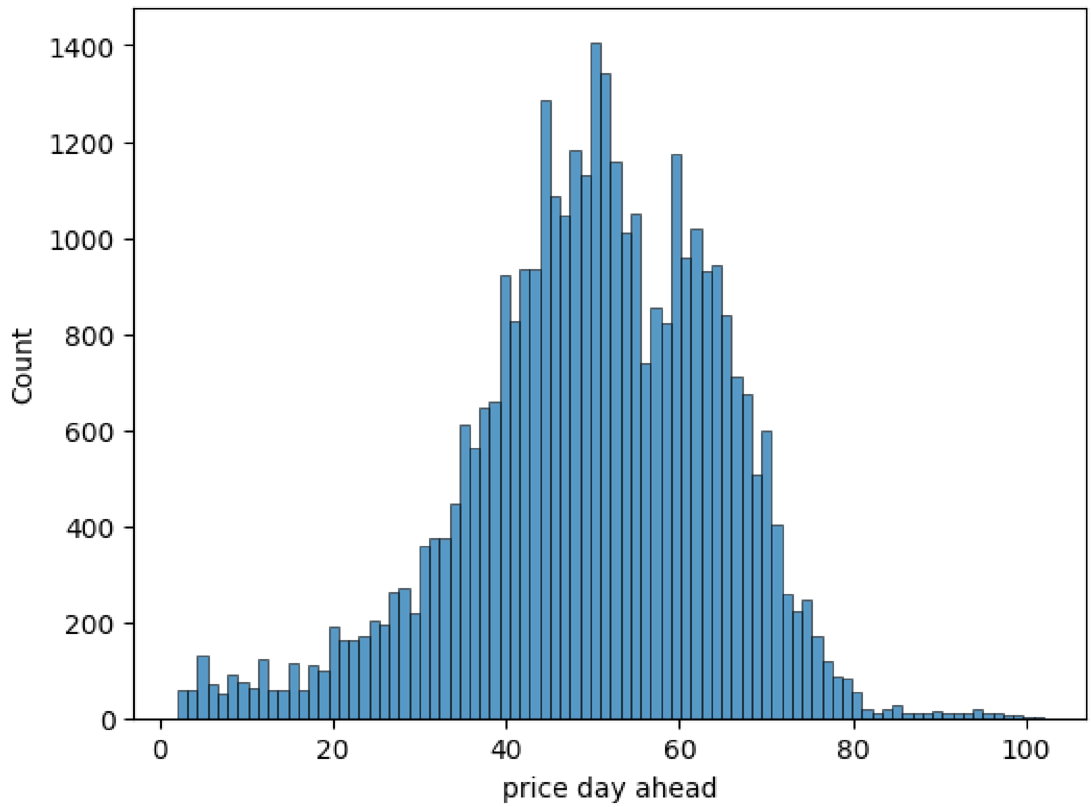

Count
12000
10000
8000
6000
4000
2000
0
0
1000
2000
3000
4000
5000
6000
generation solar



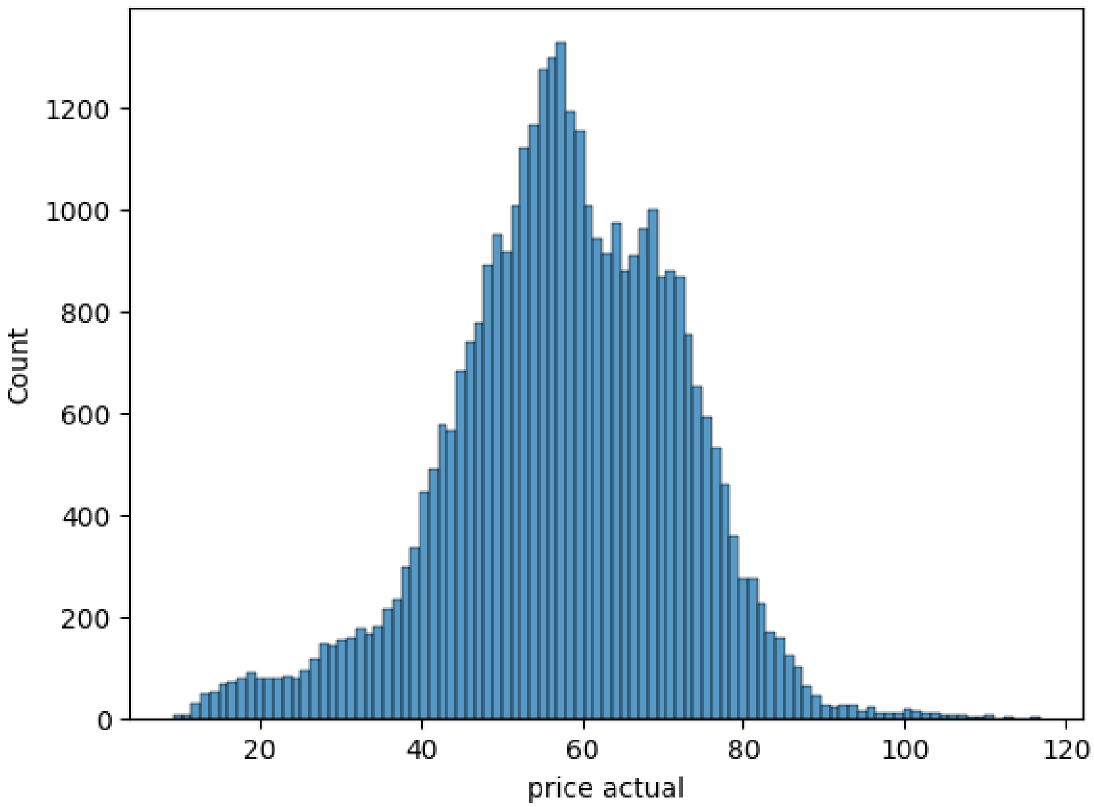
1600
1400
1200
1000
800
600
400
200
0
Count
0
50
100
150
200
250
300
350
generation waste


Count
generation wind onshore
0
200
400
600
800
1000
1200
1400
0
2500
5000
7500
10000
12500
15000
17500


Count
total load actual
0
200
400
600
800
1000
1200
20000
25000
30000
35000
40000

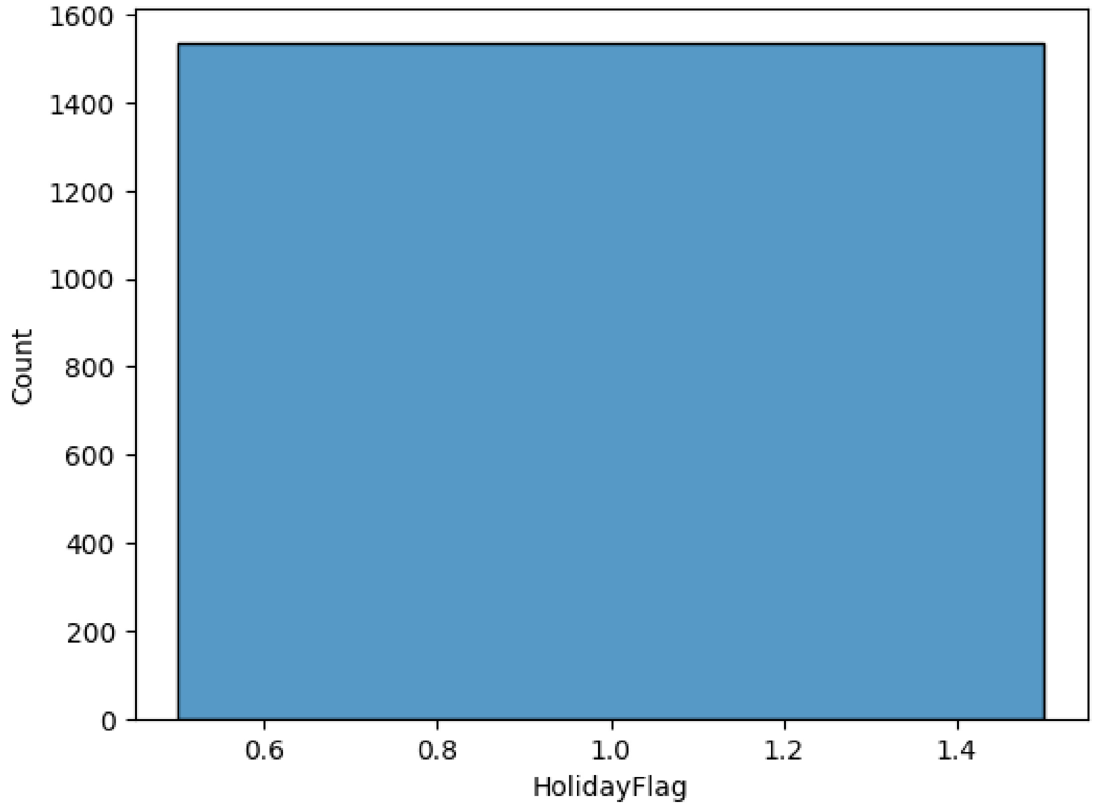


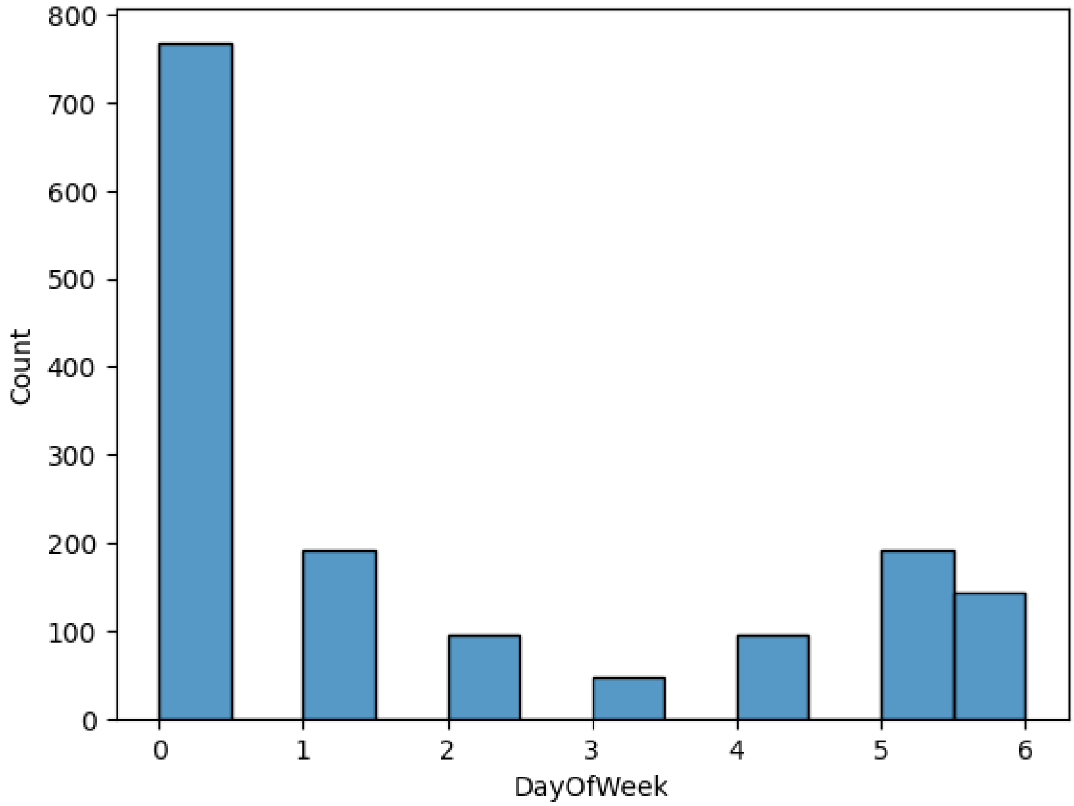
1400
1200
1000
800
600
400
200
0
Count
0
20
40
60
80
100
price day ahead

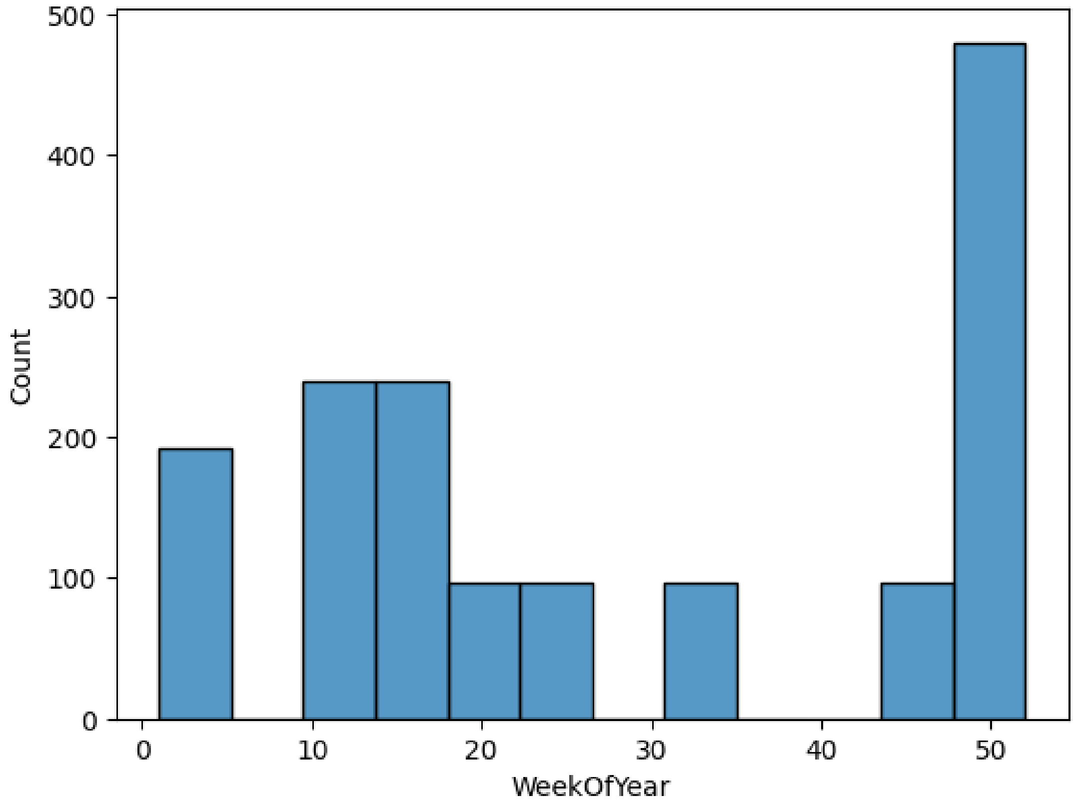


[ ]:

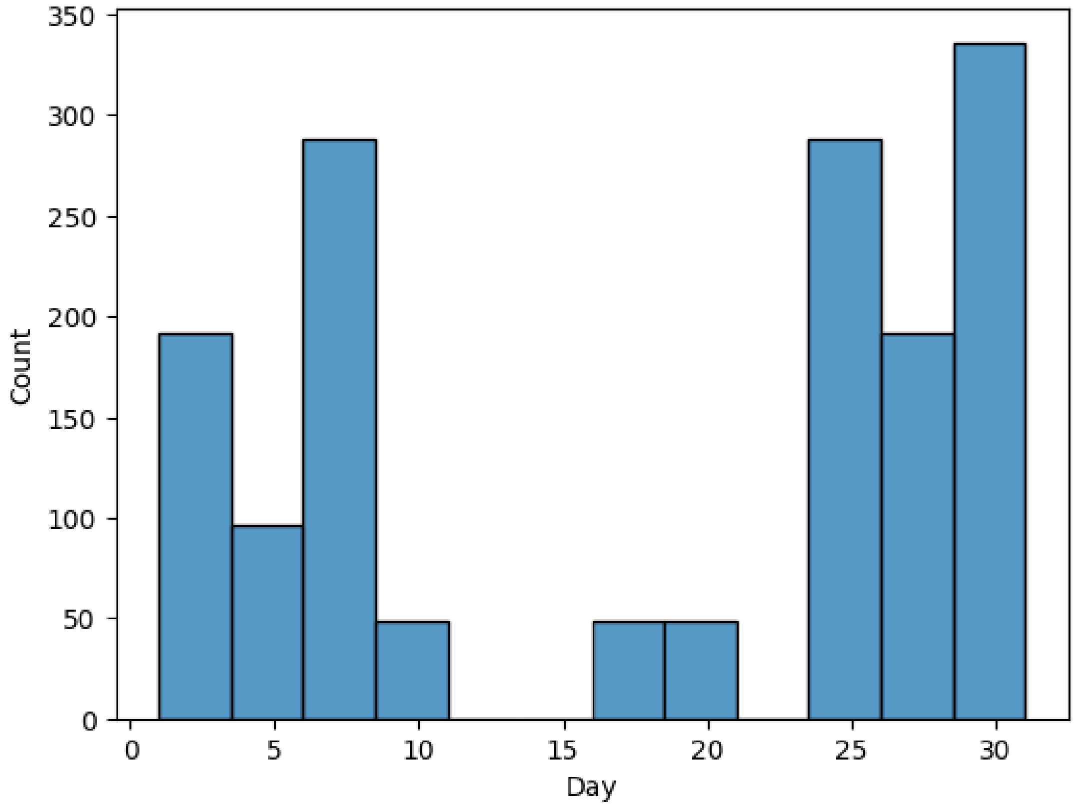
```
for i in b.select_dtypes(include="number").columns:
  sns.histplot(b,x=i)
  plt.show()
```


1600
1400
1200
1000
800
600
400
200
0
Count
0.6
0.8
1.0
1.2
1.4
HolidayFlag

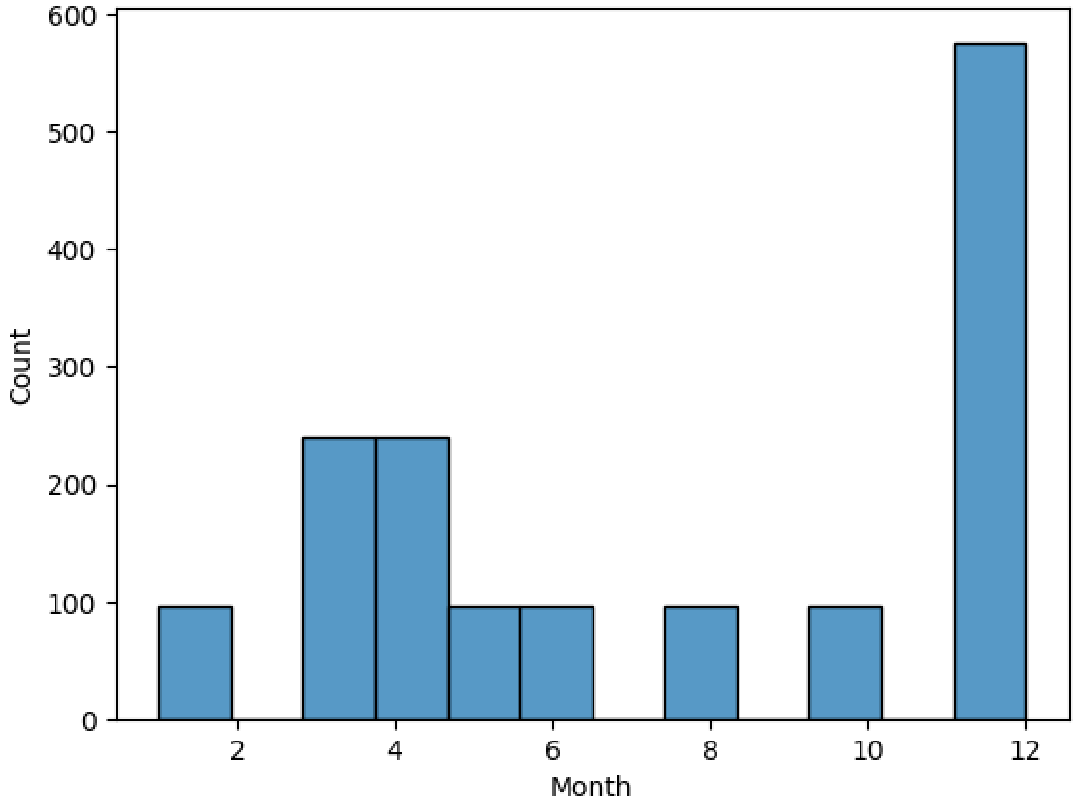

800
700
600
500
400
300
200
100
0
Count
0
1
2
3
4
5
6
DayOfWeek

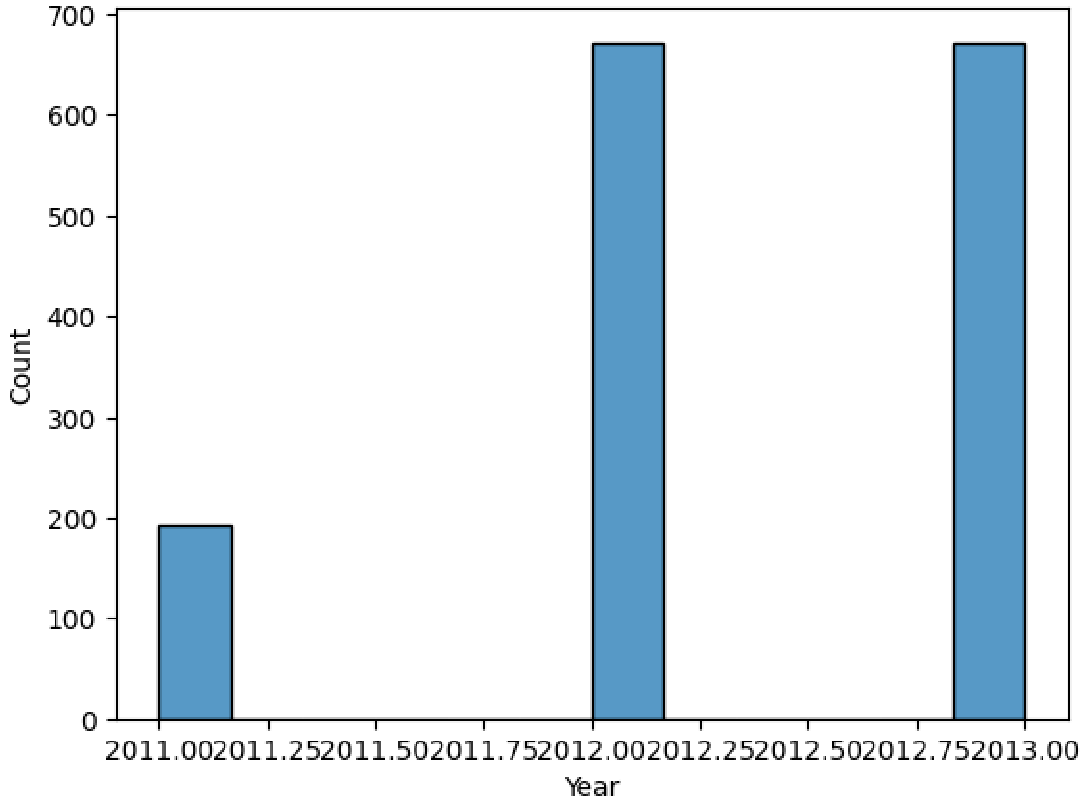


500
400
300
200
100
0
Count
0
10
20
30
40
50
WeekOfYear

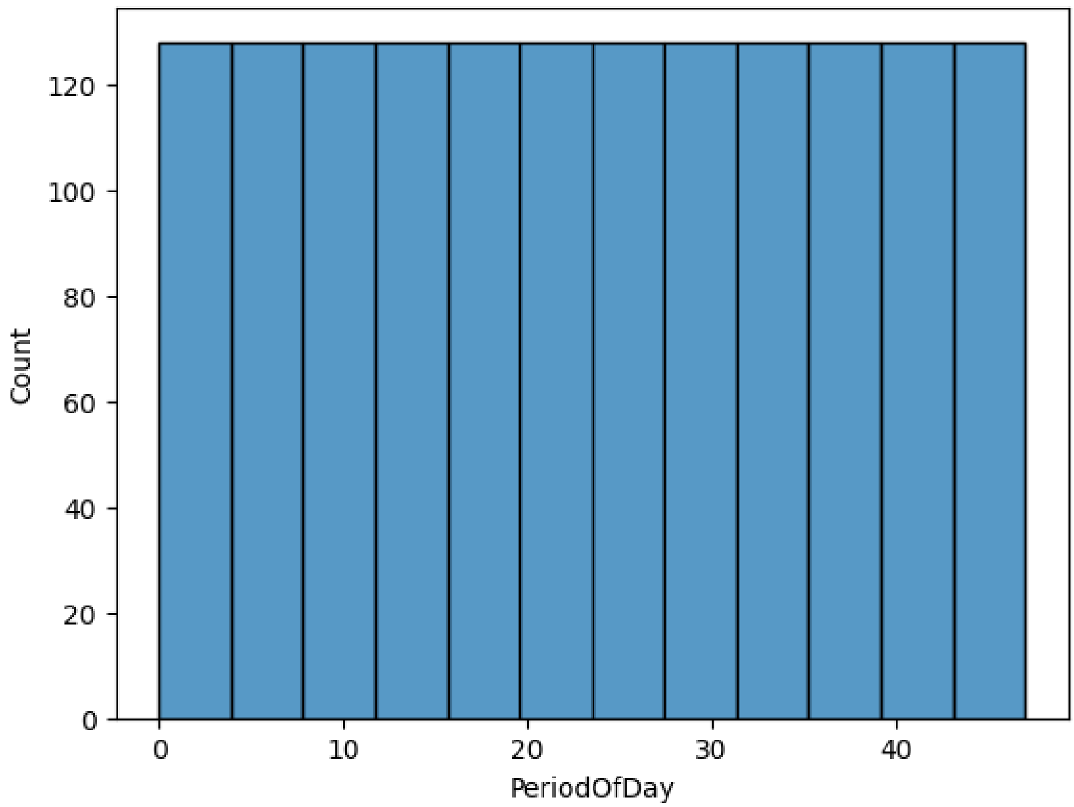


350
300
250
200
150
100
50
0
Count
0
5
10
15
20
25
30
Day

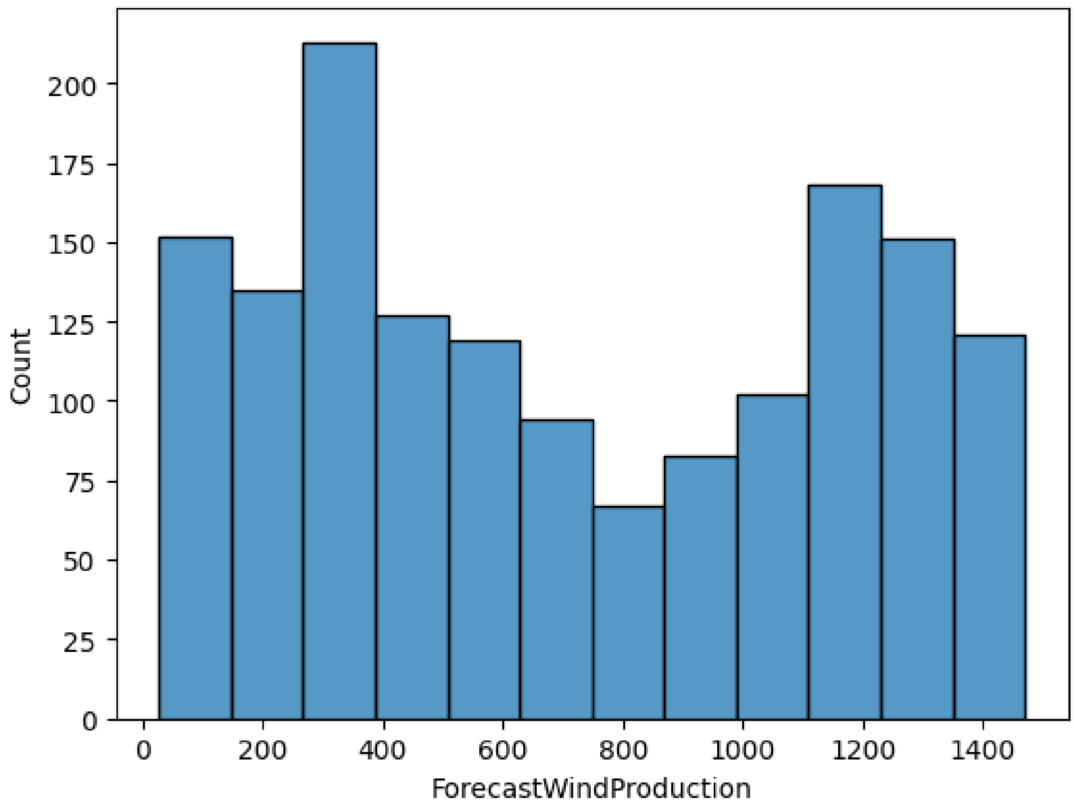

600
500
400
300
200
100
0
Count
2
4
6
8
10
12
Month

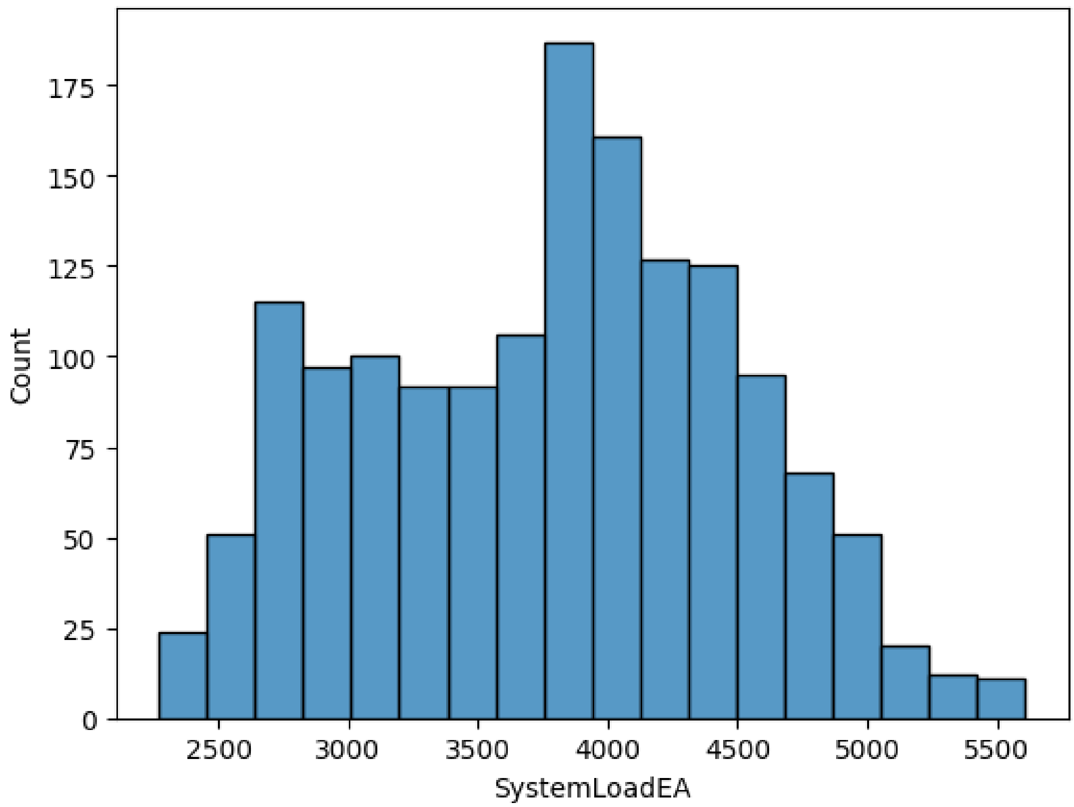


700
600
500
400
300
200
100
0
Count
2011.00
2011.25
2011.50
2011.75
2012.00
2012.25
2012.50
2012.75
2013.00
Year

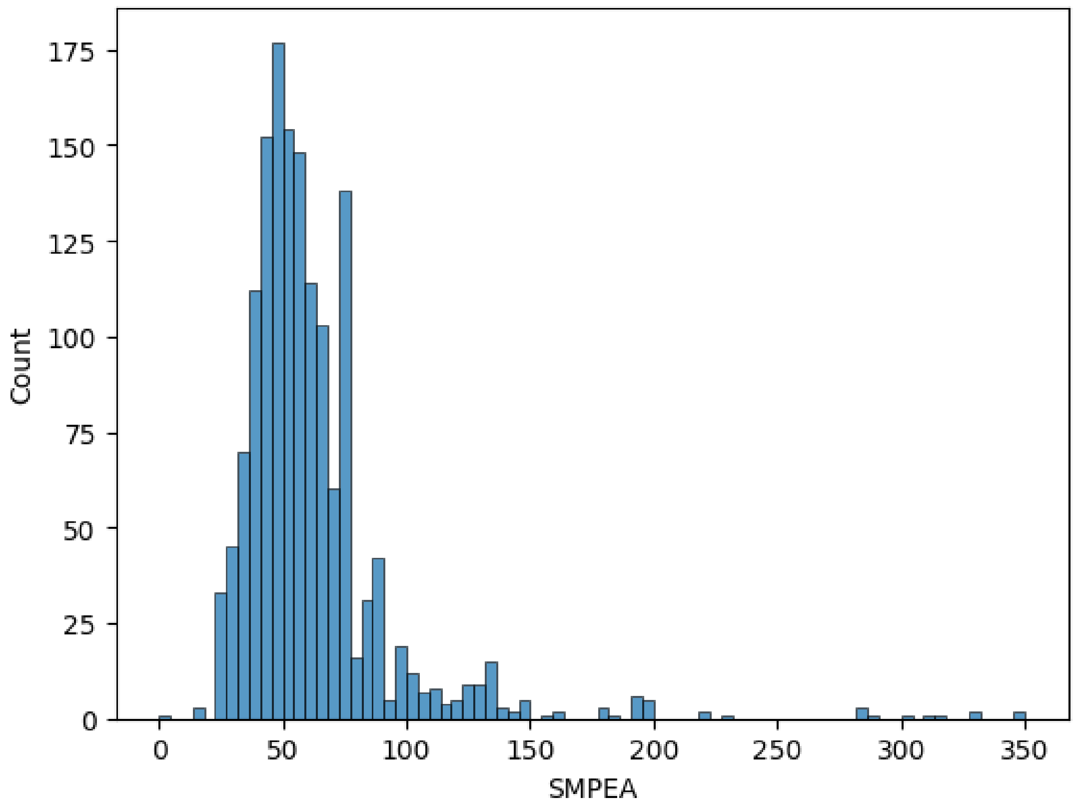


Count
0
20
40
60
80
100
120
0
10
20
30
40
PeriodOfDay

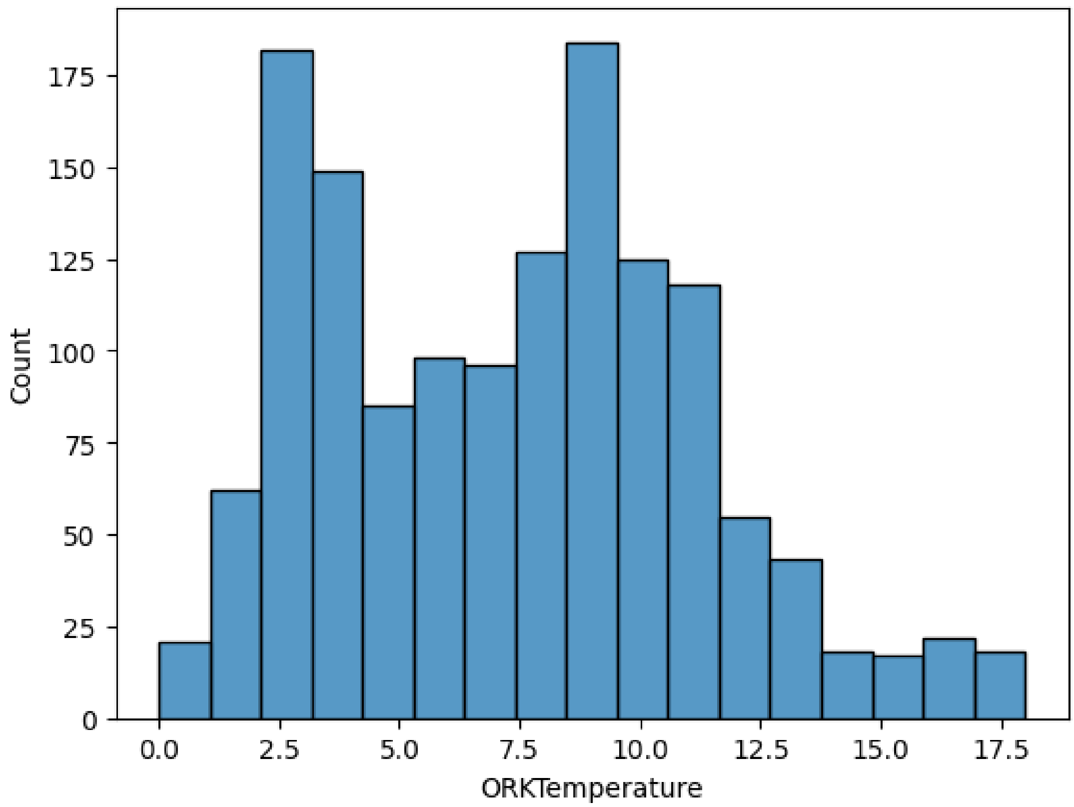

Count
ForecastWindProduction
0
25
50
75
100
125
150
175
200
0
200
400
600
800
1000
1200
1400



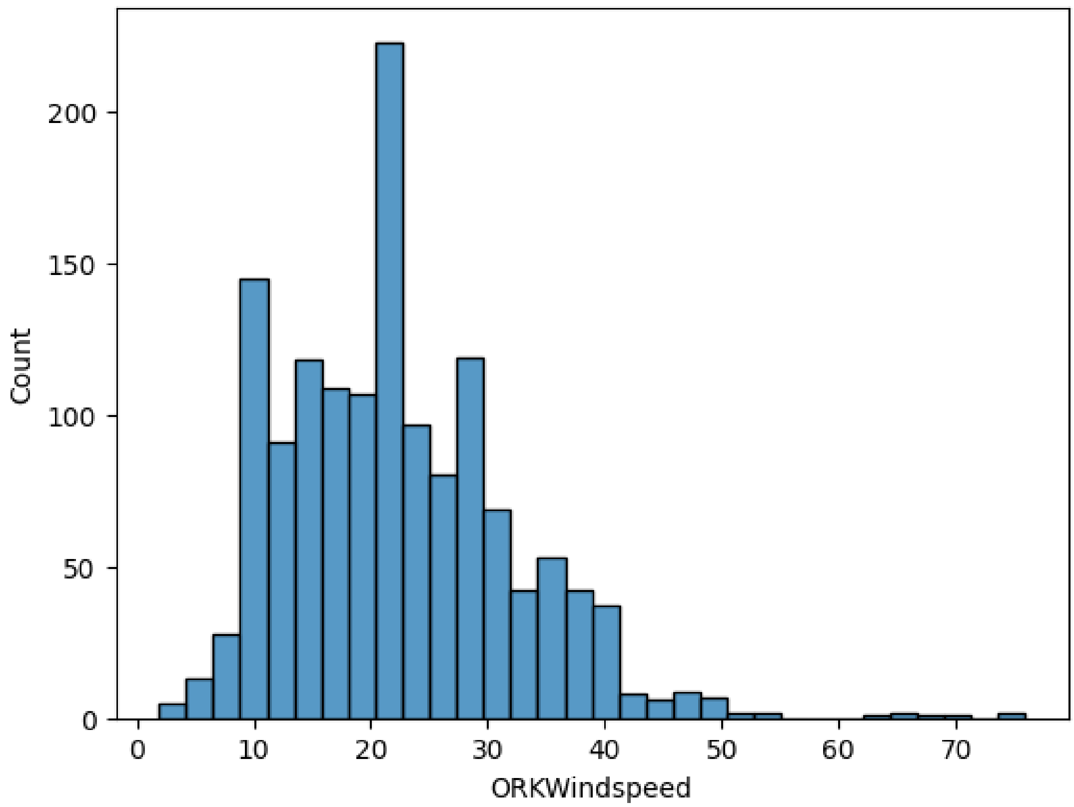
Count
SystemLoadEA
0
25
50
75
100
125
150
175
2500
3000
3500
4000
4500
5000
5500

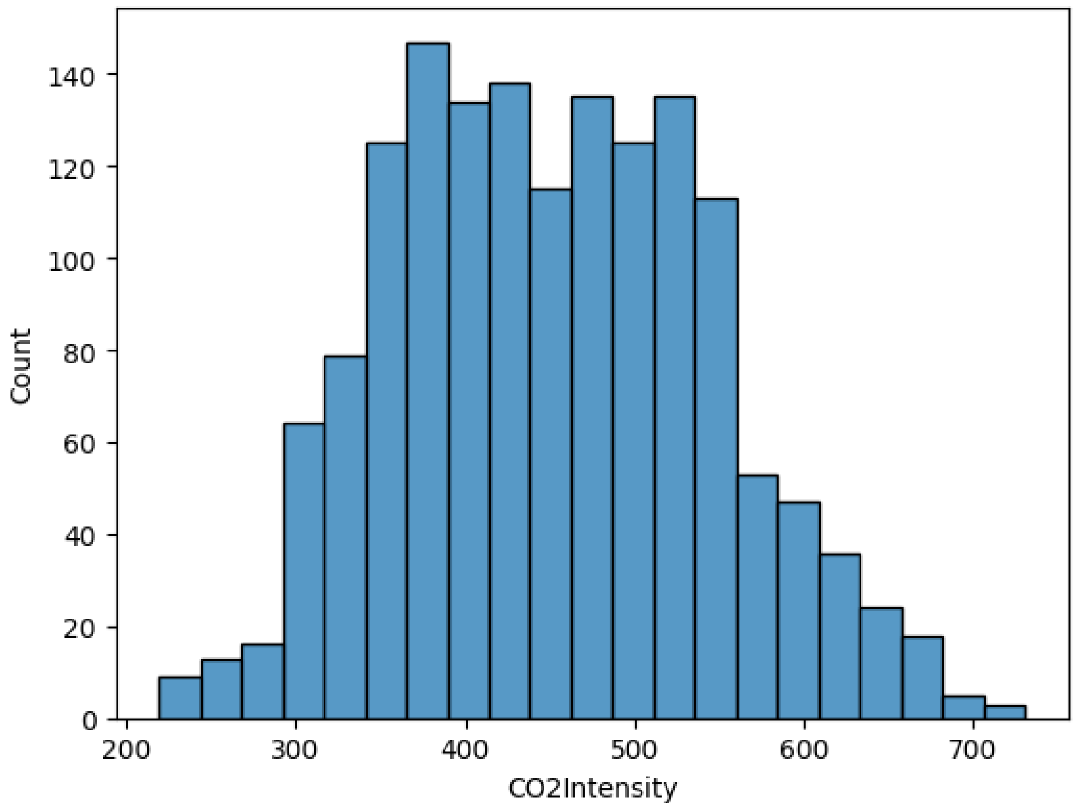


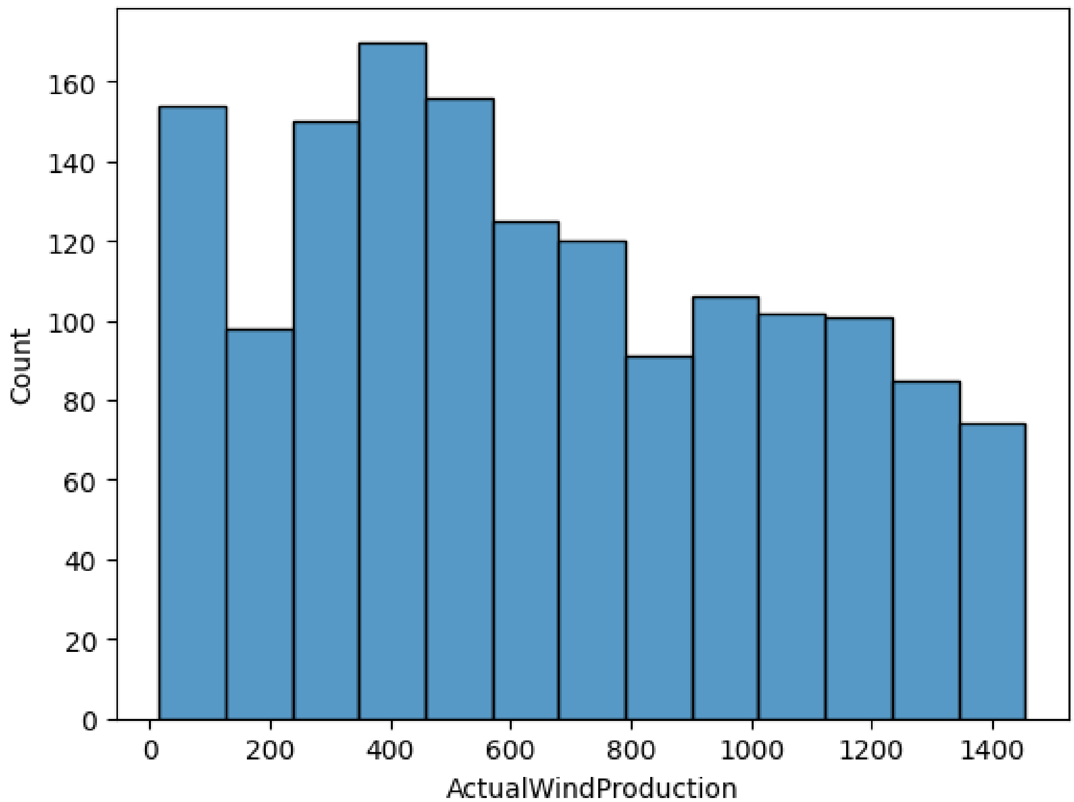
175
150
125
100
75
50
25
0
Count
0
50
100
150
200
250
300
350
SMPEA

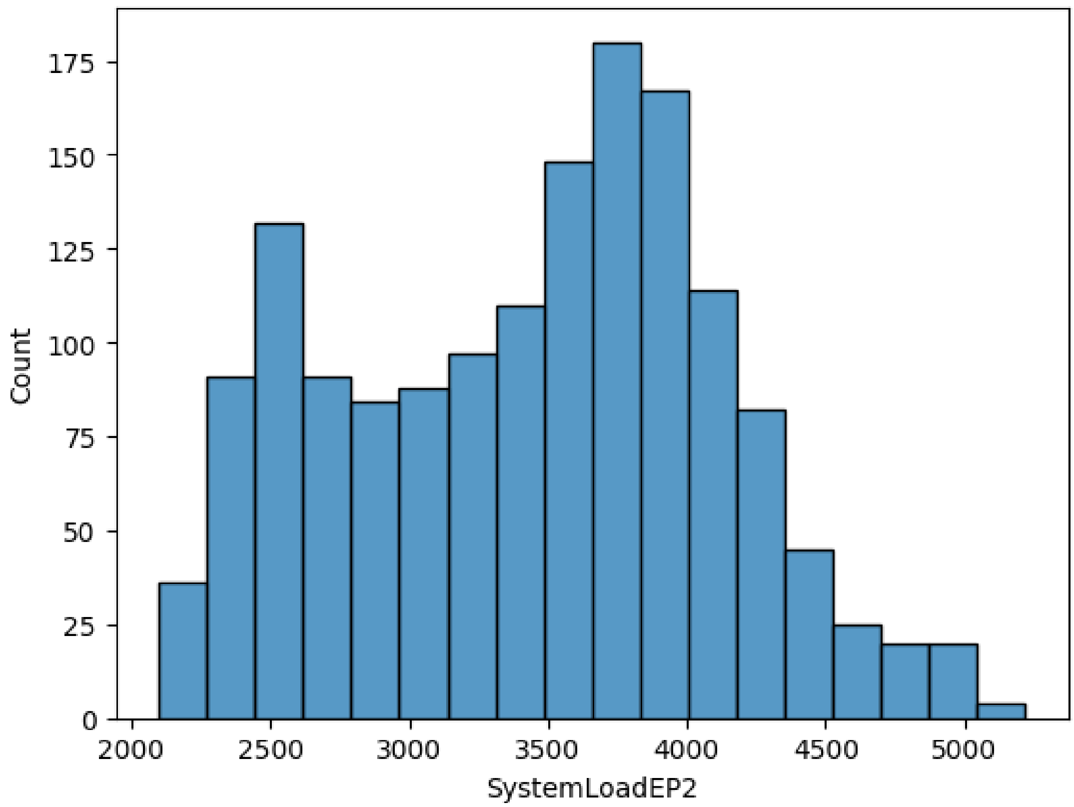


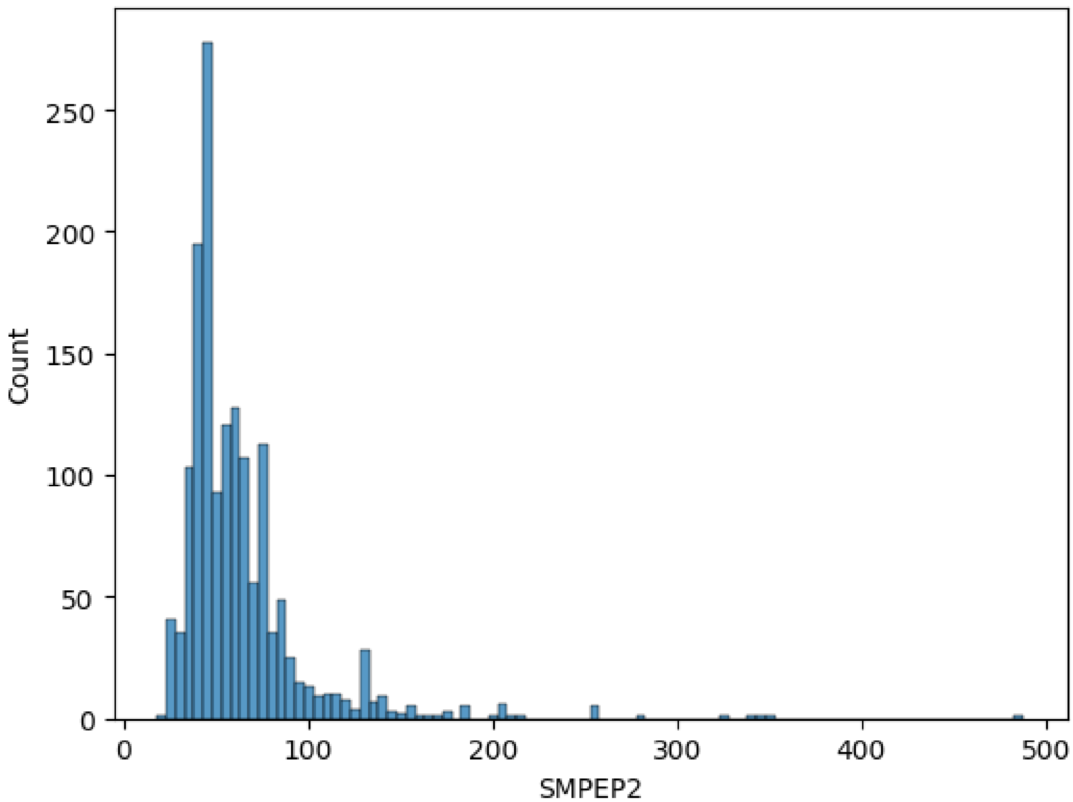
175
150
125
100
75
50
25
0
Count
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
ORKTemperature


Count
200
150
100
50
0
0
10
20
30
40
50
60
70
ORKWindspeed


140
120
100
80
60
40
20
0
Count
200
300
400
500
600
700
CO2Intensity


Count
0
20
40
60
80
100
120
140
160
0
200
400
600
800
1000
1200
1400
ActualWindProduction


175
150
125
100
75
50
25
0
Count
2000
2500
3000
3500
4000
4500
5000
SystemLoadEP2



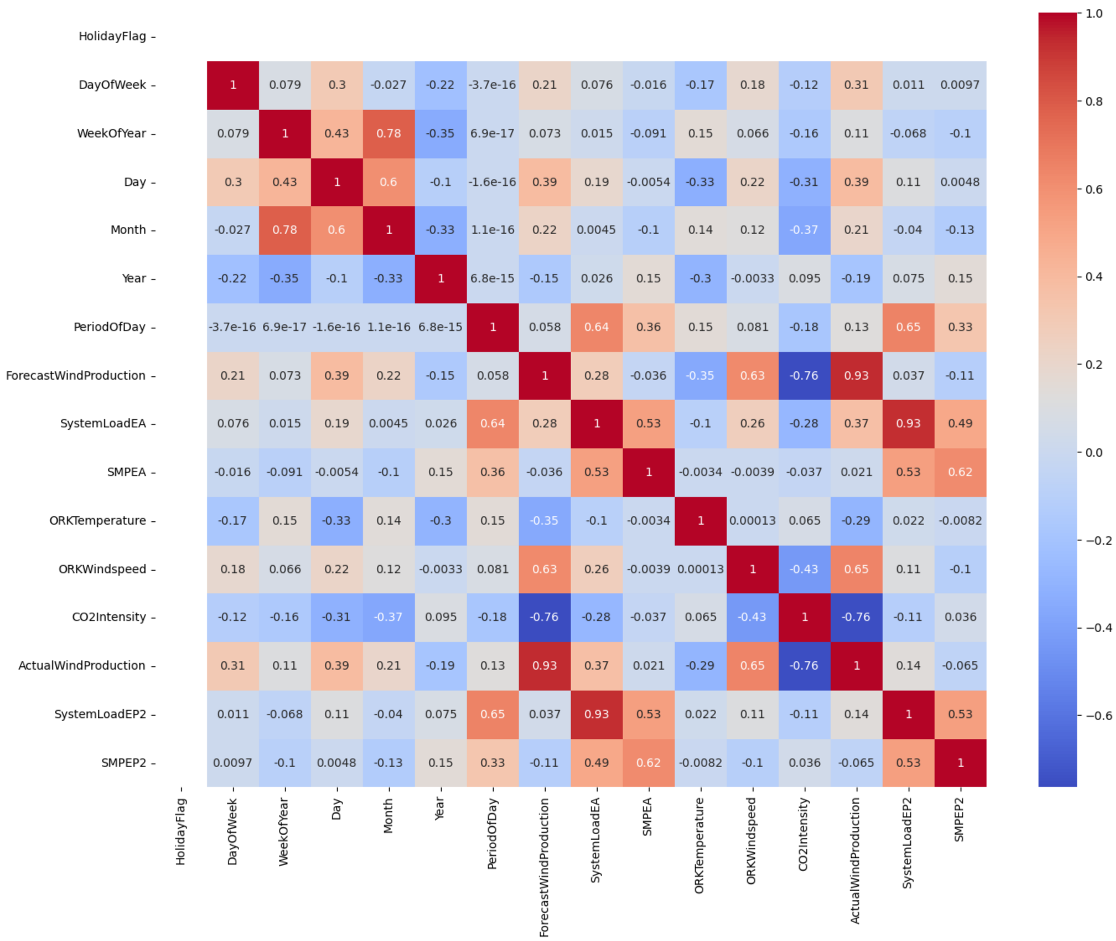

```
[ ]: from scipy import stats
     import numpy as np

     # Select only numerical features for z-score calculation
     numerical_cols = a.select_dtypes(include=np.number).columns
     d_numerical = a[numerical_cols]

     # Calculate z-scores for numerical features
     z_scores = stats.zscore(d_numerical)

     # Filter outliers based on z-scores
     d_outliers = d_numerical[(np.abs(z_scores) < 3).all(axis=1)]
```

```
[ ]: from scipy import stats
     # Select only numerical features for z-score calculation
     numerical_cols = b.select_dtypes(include=np.number).columns
     d_numerical = b[numerical_cols]

     # Calculate z-scores for numerical features
     z_scores = stats.zscore(d_numerical)
```

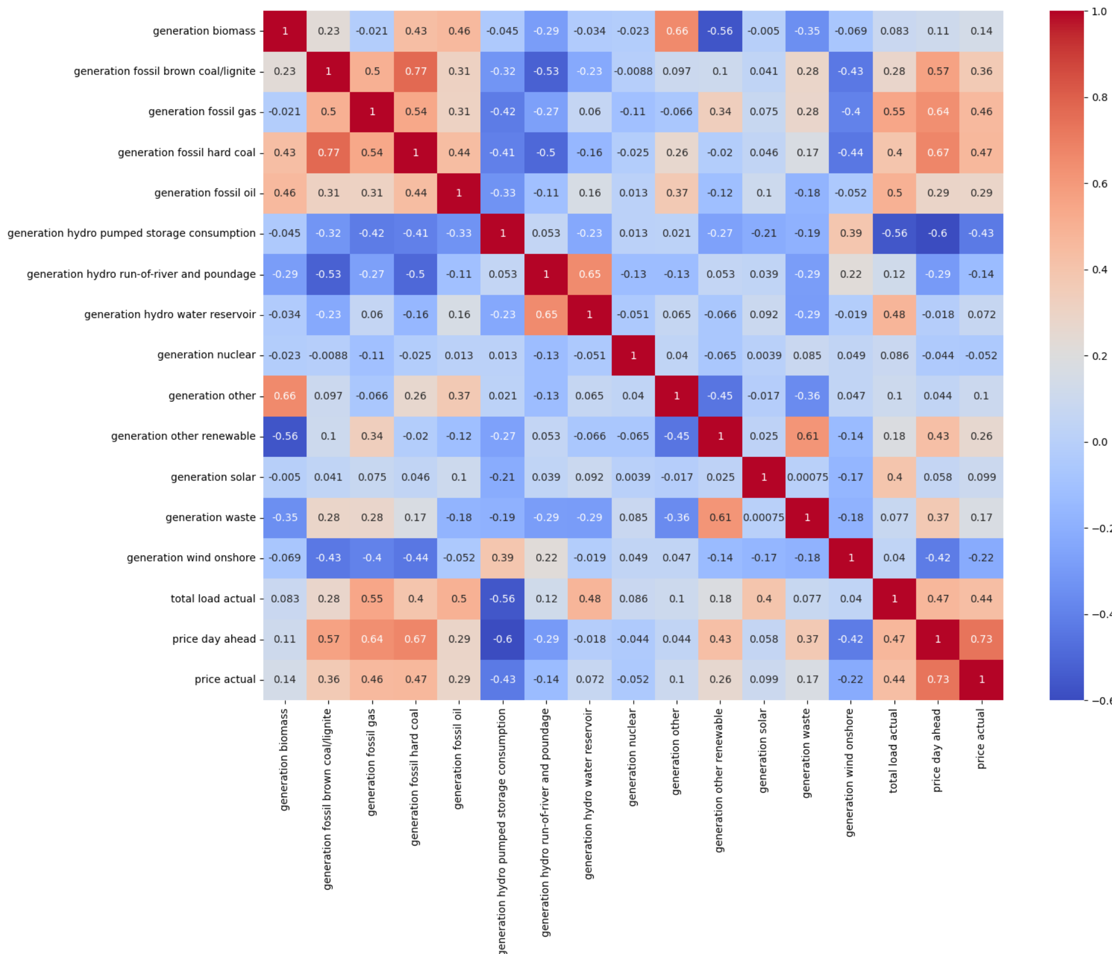
```
# Filter outliers based on z-scores
d_outliers = d_numerical[(np.abs(z_scores) < 3).all(axis=1)]
```

```
[ ]: b['DateTime'] = pd.to_datetime(b['DateTime'], errors='coerce')

# Extract relevant features for correlation
# Excluding the 'DateTime' column
numerical_features = b.select_dtypes(include=np.number).columns
correlations = b[numerical_features].corr(method='pearson')
plt.figure(figsize=(16, 12))
sns.heatmap(correlations, cmap="coolwarm", annot=True)
plt.show()
```

```
<ipython-input-29-c85d5e1ed666>:1: UserWarning: Parsing dates in %d/%m/%Y %H:%M
format when dayfirst=False (the default) was specified. Pass `dayfirst=True` or
specify a format to silence this warning.
  b['DateTime'] = pd.to_datetime(b['DateTime'], errors='coerce')
```

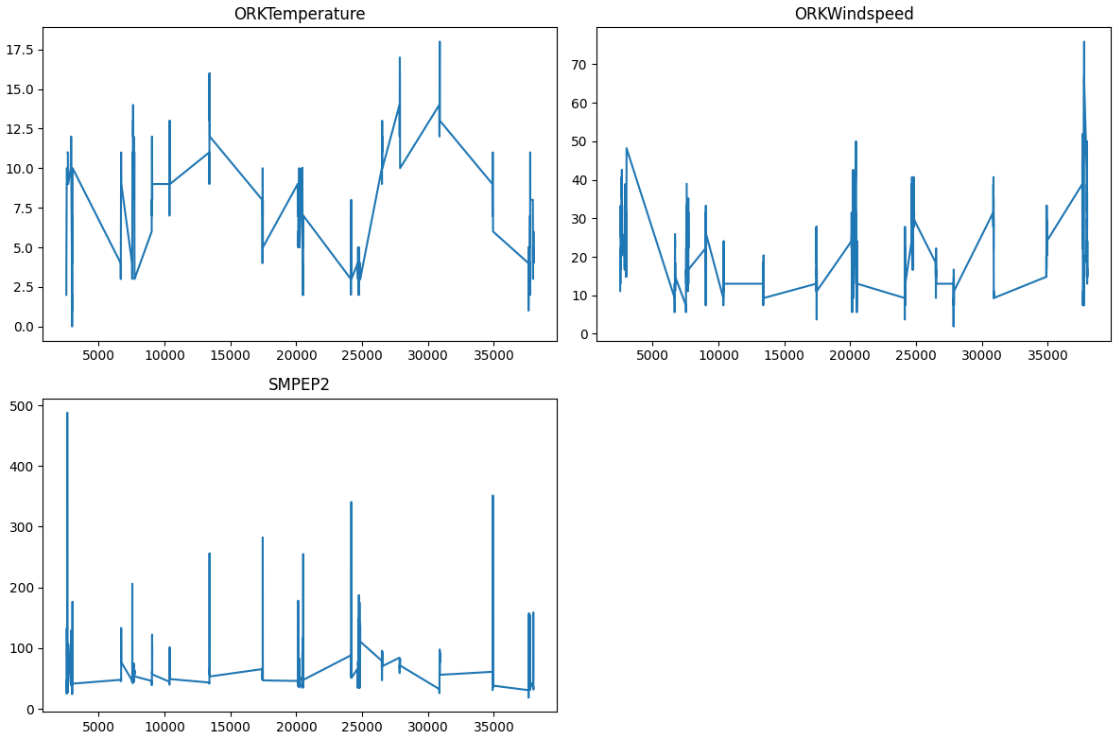


```
[ ]: numerical_features = a.select_dtypes(include=np.number).columns
     correlations = a[numerical_features].corr(method='pearson')
     plt.figure(figsize=(16, 12))
     sns.heatmap(correlations, cmap="coolwarm", annot=True)
     plt.show()
```




```
[ ]: fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(12,8))

     # select the columns to plot
     columns_to_plot = ['ORKTemperature', 'ORKWindspeed', 'SMPEP2']

     # loop through the subplots and plot each column
     for i, ax in enumerate(axes.flat):
         if i < len(columns_to_plot):
             ax.plot(b.index, b[columns_to_plot[i]])
             ax.set_title(columns_to_plot[i])
         else:
```

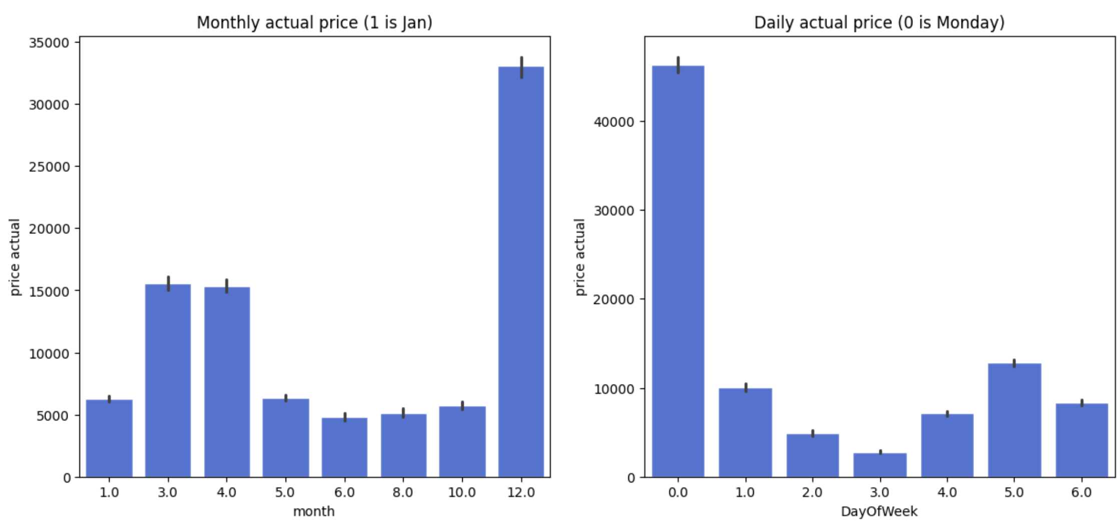
```
        ax.set_visible(False)

plt.tight_layout()  # adjust the spacing between subplots
plt.show()
```




```
[ ]: # Convert 'month' and 'weekday' columns to numeric in DataFrame 'b'
# First check if the 'month' column exists
if 'month' not in b.columns:
    # If not, extract month from the 'DateTime' column
    b['month'] = b['DateTime'].dt.month
else:
    # If it exists, try converting to numeric
    b['month'] = pd.to_numeric(b['month'], errors='coerce')

# Similarly, check for 'DayOfWeek' and extract if needed
if 'DayOfWeek' not in b.columns:
    b['DayOfWeek'] = b['DateTime'].dt.dayofweek
else:
    b['DayOfWeek'] = pd.to_numeric(b['DayOfWeek'], errors='coerce')


# Reset index of DataFrames 'a' and 'b' to ensure numeric index
a = a.reset_index(drop=True)
```

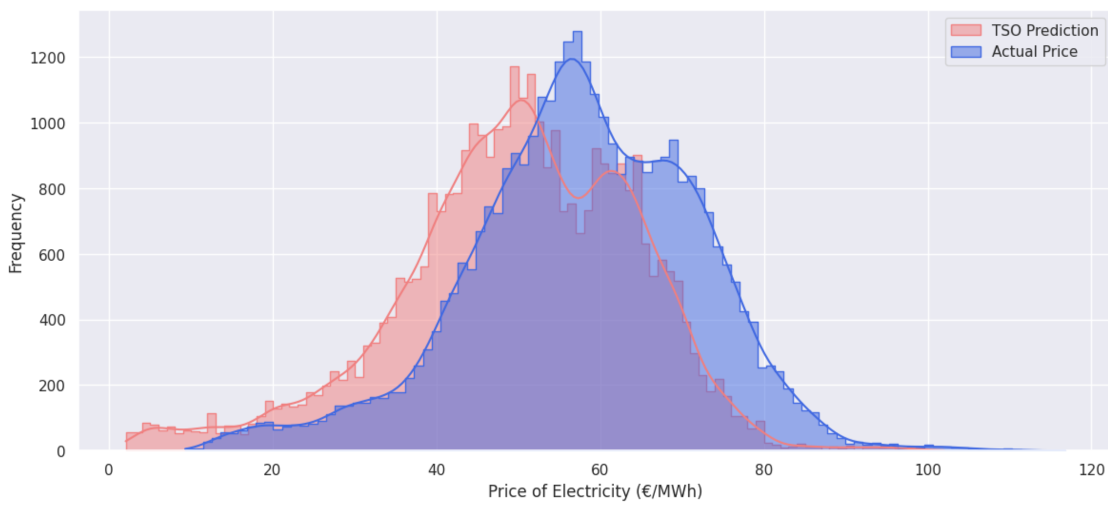
```
b = b.reset_index(drop=True)


fig, axes = plt.subplots(ncols=2, figsize=(14, 6))
sns.set(style="darkgrid")

sns.barplot(
    x=b["month"],
    y=a["price actual"],
    estimator=sum,
    color='royalblue',
    ax=axes[0]);
axes[0].set_title('Monthly actual price (1 is Jan)')

sns.barplot(
    x=b["DayOfWeek"],
    y=a["price actual"],
    estimator=sum,
    color='royalblue',
    ax=axes[1]);
axes[1].set_title('Daily actual price (0 is Monday)')
```

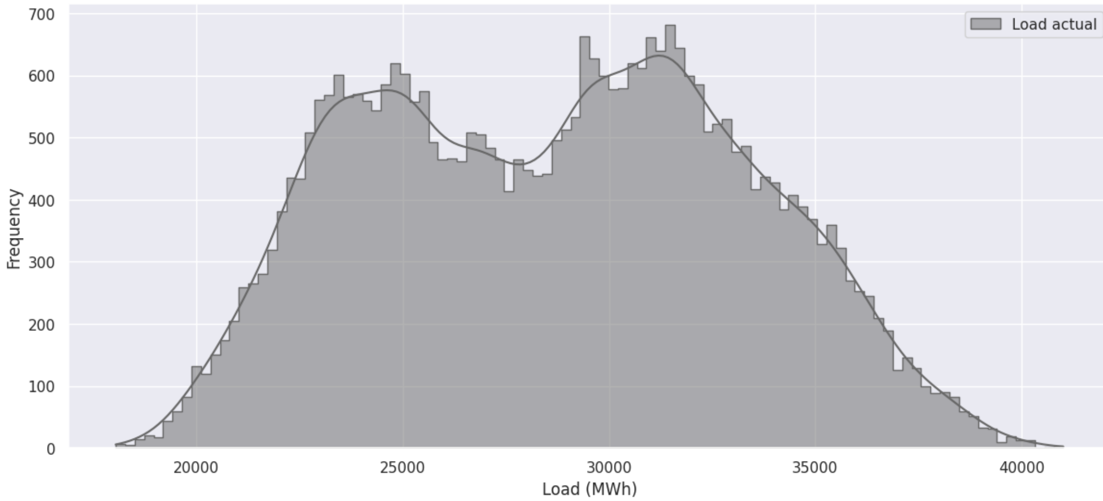
[ ]: Text(0.5, 1.0, 'Daily actual price (0 is Monday)')



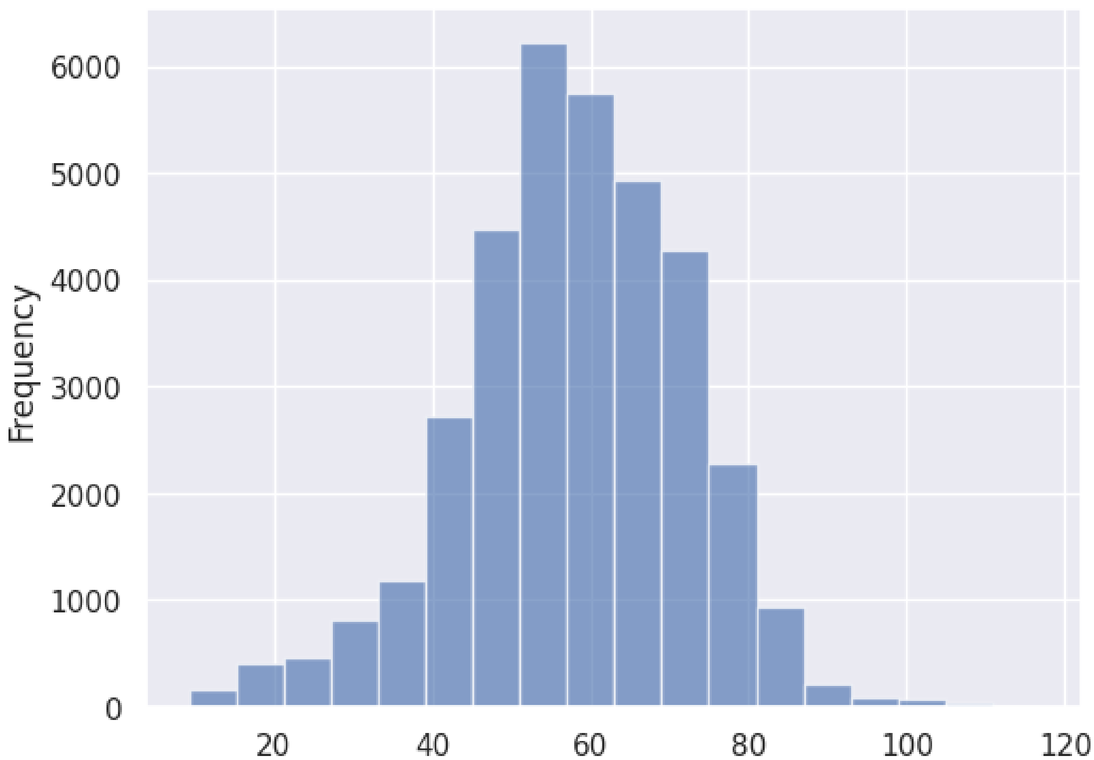
[ ]:
```
plt.figure(figsize=(14,6))

gr = sns.histplot(a['price day ahead'], bins=100, label='TSO Prediction',␣
↪element="step", color='lightcoral', kde = True)
```

```
gr = sns.histplot(a['price actual'], bins=100, label='Actual Price',␣
 ↪element="step", color='royalblue', kde = True)


gr.set(xlabel="Price of Electricity (€/MWh)", ylabel="Frequency")
plt.legend()
plt.show()

plt.figure(figsize=(14,6))
gr = sns.histplot(a['total load actual'], bins=100, label='Load actual',␣
 ↪element="step", color='dimgrey', kde = True)


gr.set(xlabel="Load (MWh)", ylabel="Frequency")
plt.legend()
plt.show()
```






```
[ ]: ax = a['price actual'].plot.hist(bins=18, alpha=0.65)
```




```
[ ]: x = b[["Day", "Month", "ForecastWindProduction", "SystemLoadEA",
                "SMPEA", "ORKTemperature", "ORKWindspeed", "CO2Intensity",
                "ActualWindProduction", "SystemLoadEP2"]]
```

```
y = b["SMPEP2"]
from sklearn.model_selection import train_test_split
xtrain, xtest, ytrain, ytest = train_test_split(x, y,
                                                test_size=0.2,
                                                random_state=42)
```

[ ]:
```
from sklearn.ensemble import RandomForestRegressor
x = x[y.notna()]  # Select rows in 'x' where 'y' is not NaN
y = y[y.notna()]  # Select rows in 'y' where 'y' is not NaN

# Now proceed with train-test split and model fitting:
xtrain, xtest, ytrain, ytest = train_test_split(x, y,
                                                test_size=0.2,
                                                random_state=42)

model = RandomForestRegressor()
model.fit(xtrain, ytrain)
```

[ ]: RandomForestRegressor()

[ ]:
```
#features = [["Day", "Month", "ForecastWindProduction", "SystemLoadEA",␣
 ↪"SMPEA", "ORKTemperature", "ORKWindspeed", "CO2Intensity",␣
 ↪"ActualWindProduction", "SystemLoadEP2"]]
features = np.array([[10, 12, 54.10, 4241.05, 49.56, 9.0, 14.8, 491.32, 54.0,␣
 ↪4426.84]])
model.predict(features)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:493: UserWarning: X does
not have valid feature names, but RandomForestRegressor was fitted with feature
names
  warnings.warn(
```

[ ]: array([96.874])

[ ]:
```
x = b[["Day", "Month", "ForecastWindProduction", "SystemLoadEA",
          "SMPEA", "ORKTemperature", "ORKWindspeed", "CO2Intensity",
          "ActualWindProduction", "SystemLoadEP2"]]
# x=data.drop("SMPEP2",axis=1)
y = b["SMPEP2"]
x = x[y.notna()]
y = y[y.notna()]
from sklearn.model_selection import train_test_split
xtrain, xtest, ytrain, ytest = train_test_split(x, y,
                                                test_size=0.3,
                                                random_state=42)
```

[ ]:
```
from sklearn.ensemble import RandomForestRegressor
#Randomforest use for complex data and objective data
model = RandomForestRegressor(n_estimators=100,random_state=42)
model.fit(xtrain, ytrain)
```

[ ]:
```
RandomForestRegressor(random_state=42)
```

[ ]:
```
y_pred=model.predict(xtest)
print(xtest.shape)
print(ytest.shape)
print(y_pred.shape)
```

```
(461, 10)
(461,)
(461,)
```

[ ]:
```
from sklearn.metrics import r2_score,mean_squared_error,mean_absolute_error
mean_y=ytest.mean()
#r2_score based on coefficients detemination
print("R2_Score:",r2_score(ytest,y_pred))
forest_mae=mean_absolute_error(ytest,y_pred)
forest_mse=mean_squared_error(ytest,y_pred)
print("Mean_Absolute_error:",forest_mae)
print("Mean_squared_error:",forest_mse)
print('prediction accuracy: ' +str(1-forest_mae/mean_y))
print("Score:",model.score(xtrain,ytrain))
```

```
R2_Score: 0.6508303318614891
Mean_Absolute_error: 9.335721908893717
Mean_squared_error: 440.4399490283731
prediction accuracy: 0.8564028850430396
Score: 0.9402453787052225
```

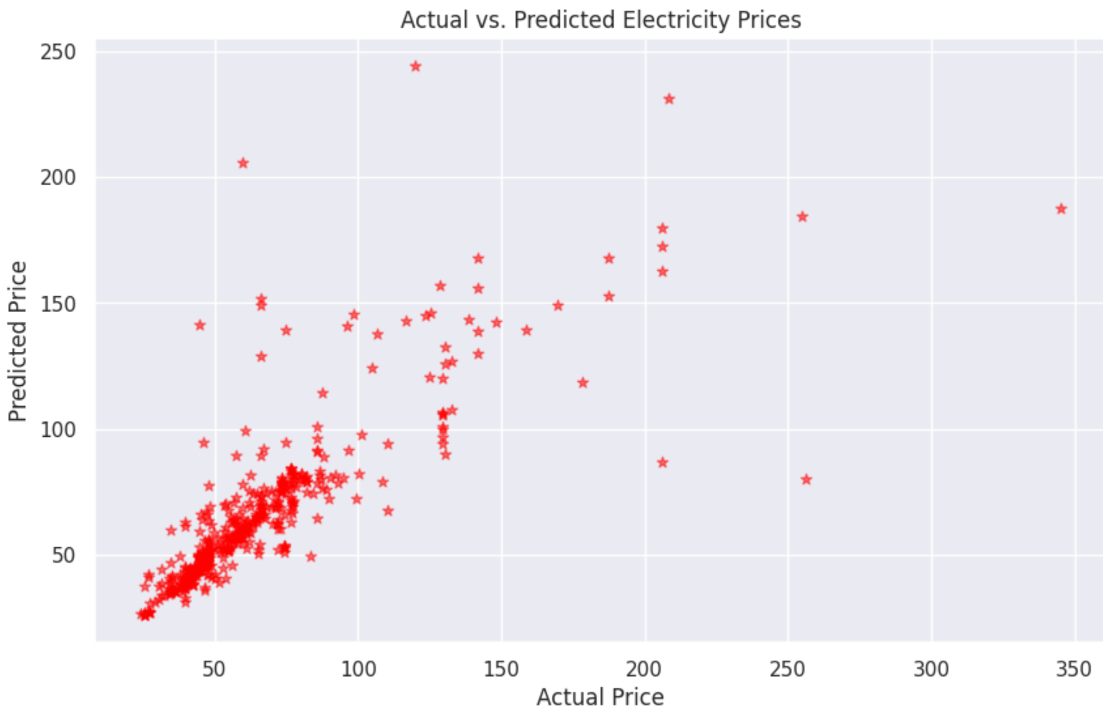
[ ]:
```
df=pd.DataFrame({"actual":ytest,"predicted":y_pred})
df.tail()
```

[ ]:

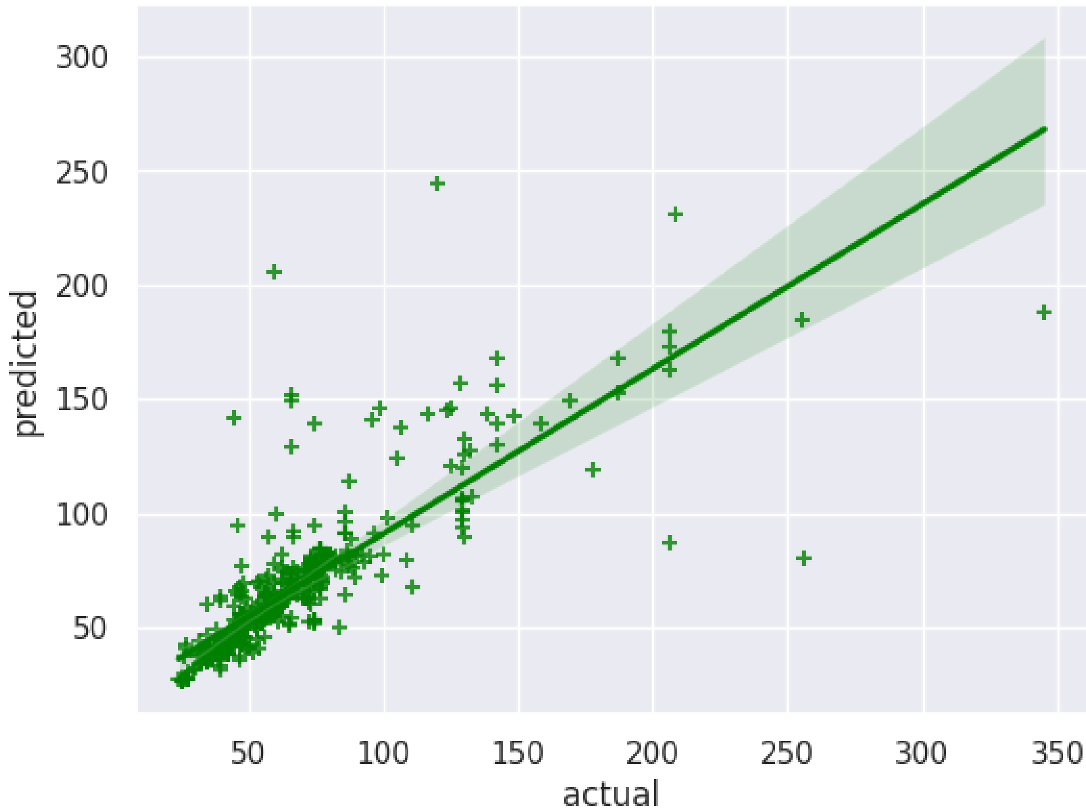
	actual	predicted
296	43.79	43.8099
548	85.53	78.6173
1329	53.70	70.5455
864	47.76	51.7430
986	77.68	80.3780

[ ]:
```
plt.figure(figsize=(10, 6))
plt.scatter(ytest, y_pred, alpha=0.5,c="red",marker="*")
plt.xlabel('Actual Price')
plt.ylabel('Predicted Price')
```

```
plt.title('Actual vs. Predicted Electricity Prices')
plt.show()
```



[ ]:
```
import seaborn as sns
sns.regplot(x="actual",y="predicted",data=df,color='green',marker="+")
plt.show()
```




```
[ ]: x1 = a[['generation other', 'generation other renewable', 'generation␣
     ↪solar','generation wind onshore','total load actual']]
     y1 = a["price actual"]
     from sklearn.model_selection import train_test_split
     xtrain1, xtest1, ytrain1, ytest1 = train_test_split(x1, y1,
                                                         test_size=0.2,
                                                         random_state=42)
```

```
[ ]: from sklearn.ensemble import RandomForestRegressor
     x1 = x1[y1.notna()]  # Select rows in 'x' where 'y' is not NaN
     y1 = y1[y1.notna()]  # Select rows in 'y' where 'y' is not NaN

     # Now proceed with train-test split and model fitting:
     xtrain1, xtest1, ytrain1, ytest1 = train_test_split(x1, y1,
                                                         test_size=0.2,
                                                         random_state=42)


     model = RandomForestRegressor()
     model.fit(xtrain1, ytrain1)
```

[ ]: RandomForestRegressor()

[ ]:
```
from sklearn.ensemble import RandomForestRegressor
#Randomforest use for complex data and objective data
model = RandomForestRegressor(n_estimators=100,random_state=42)
model.fit(xtrain1, ytrain1)
```

[ ]: RandomForestRegressor(random_state=42)

[ ]:
```
y_pred1=model.predict(xtest1)
print(xtest1.shape)
print(ytest1.shape)
print(y_pred1.shape)
```

```
(7004, 5)
(7004,)
(7004,)
```

[ ]:
```
from sklearn.metrics import r2_score,mean_squared_error,mean_absolute_error
mean_y=ytest1.mean()
#r2_score based on coefficients detemination
print("R2_Score:",r2_score(ytest1,y_pred1))
forest_mae=mean_absolute_error(ytest1,y_pred1)
forest_mse=mean_squared_error(ytest1,y_pred1)
print("Mean_Absolute_error:",forest_mae)
print("Mean_squared_error:",forest_mse)
print('prediction accuracy: ' +str(1-forest_mae/mean_y))
print("Score:",model.score(xtrain1,ytrain1))
```

```
R2_Score: 0.5619784818948926
Mean_Absolute_error: 6.912253055396916
Mean_squared_error: 85.33370120319533
prediction accuracy: 0.8804081851343178
Score: 0.9398671857857921
```

[ ]:
```
df=pd.DataFrame({"actual":ytest1,"predicted":y_pred1})
df.tail()
```

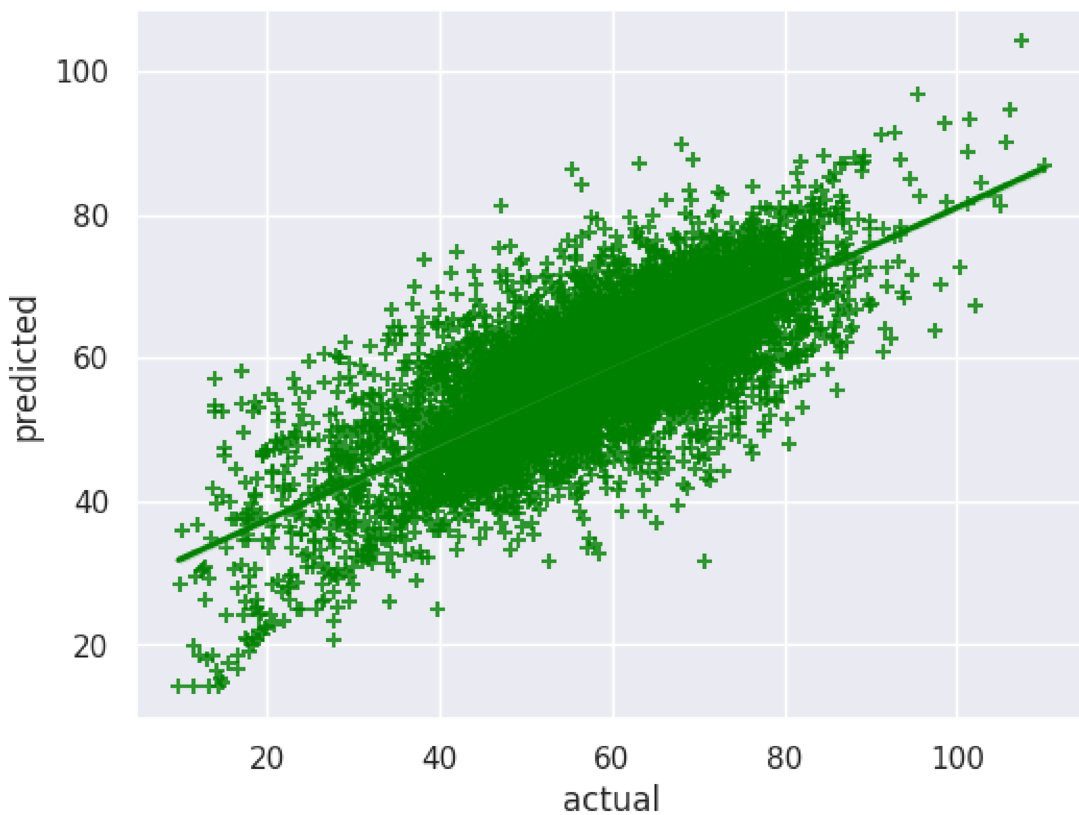
[ ]:

	actual	predicted
14286	50.39	51.7310
15770	72.02	66.4437
18512	49.56	50.6510
31931	66.87	63.8230
33034	82.15	75.6050

[ ]:
```
plt.figure(figsize=(10, 6))
plt.scatter(ytest1, y_pred1, alpha=0.5,c="red",marker="*")
```

```
plt.xlabel('Actual Price')
plt.ylabel('Predicted Price')
plt.title('Actual vs. Predicted Electricity Prices')
plt.show()
```

[ ]:
```
import seaborn as sns
sns.regplot(x="actual",y="predicted",data=df,color='green',marker="+")
plt.show()
```




```
[ ]: X_demand = a[['generation solar', 'generation other renewable', 'generation␣
     ↪wind onshore', 'total load actual']]
     y_demand = a['price actual']

     X_price = b[['ORKTemperature', 'ORKWindspeed', 'SystemLoadEP2', 'DayOfWeek']]
     y_price = b['SMPEP2']

     # Split datasets into training and testing sets
     X_demand_train, X_demand_test, y_demand_train, y_demand_test =␣
     ↪train_test_split(X_demand, y_demand, test_size=0.2, random_state=42)
     X_price_train, X_price_test, y_price_train, y_price_test =␣
     ↪train_test_split(X_price, y_price, test_size=0.2, random_state=42)
```

```
[ ]: from sklearn.preprocessing import StandardScaler
     scaler = StandardScaler()
     X_demand_train = scaler.fit_transform(X_demand_train)
     X_demand_test = scaler.transform(X_demand_test)
     X_price_train = scaler.fit_transform(X_price_train)
     X_price_test = scaler.transform(X_price_test)
```

[ ]:
```
demand_model = RandomForestRegressor(n_estimators=100, random_state=42)
price_model = RandomForestRegressor(n_estimators=100, random_state=42)
demand_model
price_model
```

[ ]:
```
RandomForestRegressor(random_state=42)
```

[ ]:
```
y_price_train = y_price_train.fillna(y_price_train.mean())
demand_model.fit(X_demand_train, y_demand_train)
price_model.fit(X_price_train, y_price_train)
```

[ ]:
```
RandomForestRegressor(random_state=42)
```

[ ]:
```
y_demand_pred = demand_model.predict(X_demand_test)
y_price_pred = price_model.predict(X_price_test)
y_demand_pred
y_price_pred
```

[ ]:
```
array([ 76.8931    ,  53.83420553,  46.6126    ,  67.7888    ,
        30.9693    ,  72.325     ,  50.0044    ,  45.5821    ,
        44.4215    ,  64.3995    , 128.7634    ,  40.832     ,
        57.7946    ,  43.0079    ,  56.0574    ,  50.6928    ,
       177.2786    ,  54.2986    ,  43.3691    ,  51.5463    ,
       130.8587    ,  46.3073    ,  59.7007    ,  56.0754    ,
        53.1855    ,  47.91851011,  52.0967    , 111.5042    ,
        63.0768    ,  71.5591    ,  64.7616    ,  56.6301    ,
        51.9563    ,  41.6201    ,  39.2667    ,  66.3468    ,
        66.9334    ,  51.5545    ,  39.181     ,  49.0381    ,
        61.0205    , 137.8287    ,  62.839     ,  41.4411    ,
        52.3993    ,  58.5041    ,  25.7961    ,  78.7184    ,
       111.5505    ,  67.5582    ,  55.8549    ,  88.6534    ,
        68.1429    , 136.5884    ,  55.849     ,  58.089     ,
        42.3458    ,  40.765     ,  44.1973    ,  46.7587    ,
        61.0623    ,  48.2365    ,  70.3026    ,  59.0384    ,
        45.3507    ,  57.5633    , 135.2015    ,  55.0919    ,
        58.5331    ,  48.7652    ,  58.1623    ,  59.4652    ,
        57.573     ,  49.6817    ,  52.8568    ,  47.1625    ,
        66.3888    ,  47.2975    ,  62.5945    ,  52.9234    ,
        56.9624    ,  40.6615    ,  63.7398    ,  46.07637004,
        35.3277    ,  45.9041    ,  68.816     ,  76.8452    ,
        82.3516    ,  72.1035    ,  46.6583    ,  47.1555    ,
        45.2769    , 137.8717    ,  40.1673    ,  60.2132    ,
        74.8665    ,  59.877     ,  45.1273    , 162.5328    ,
        61.7872    ,  41.2775    ,  44.451     ,  44.0564    ,
        61.96243502, 104.4222    ,  35.5654    ,  34.8579    ,
        43.0909    ,  58.7176    ,  46.3921    ,  72.5926    ,
        41.3812    ,  68.569     ,  40.9944    ,  40.8154    ,
```

127.5202 ,	54.6453 ,	72.5442 ,	109.3147 ,
75.188 ,	83.4889 ,	69.6593 ,	35.0712 ,
57.8501 ,	45.5998 ,	68.122 ,	65.4632 ,
76.8483 ,	64.3886 ,	45.1225 ,	94.9731 ,
140.2894 ,	86.1183 ,	50.3834 ,	46.8981 ,
77.7132 ,	57.633 ,	49.4745 ,	43.084 ,
37.3671 ,	41.2386 ,	78.1156 ,	39.564 ,
48.5268 ,	54.7166 ,	68.4496 ,	41.9577 ,
46.17937004,	95.3627 ,	97.4507 ,	65.7636 ,
133.6594 ,	80.2073 ,	141.6817 ,	40.3192 ,
41.9758 ,	49.9324 ,	54.6652 ,	76.5903 ,
38.7199 ,	68.3099 ,	75.2104 ,	54.9983 ,
53.5617 ,	69.1965 ,	36.943 ,	41.204 ,
132.9636 ,	81.4291 ,	69.4469 ,	49.7773 ,
63.7539 ,	67.3022 ,	63.7535 ,	62.9529 ,
41.9507 ,	25.8106 ,	135.6484 ,	65.4927 ,
70.9677 ,	52.845 ,	144.3586 ,	47.061 ,
59.576 ,	74.7309 ,	27.4603 ,	57.0643 ,
40.5499 ,	26.9876 ,	37.3461 ,	75.2065 ,
52.8974 ,	49.3151 ,	69.0996 ,	40.1189 ,
130.6139 ,	46.8973 ,	55.7335 ,	46.8171 ,
43.6961 ,	106.9197 ,	147.8928 ,	55.5374 ,
45.4033 ,	49.1746 ,	86.5385 ,	184.0874 ,
72.1592 ,	72.109 ,	160.2468 ,	80.7618 ,
64.2645 ,	59.3818 ,	69.3467 ,	49.5515 ,
73.388 ,	45.6755 ,	40.1637 ,	48.3758 ,
40.6009 ,	56.5182 ,	63.9288 ,	50.5937 ,
50.4175 ,	57.719 ,	72.4413 ,	52.3126 ,
49.3947 ,	83.3144 ,	66.1876 ,	76.7301 ,
72.1997 ,	127.0913 ,	78.032 ,	58.1625 ,
46.4009 ,	126.5081 ,	47.7602 ,	159.2599 ,
43.9263 ,	66.3255 ,	100.3273 ,	71.0483 ,
85.9562 ,	68.7941 ,	51.3557 ,	55.4261 ,
39.8626 ,	63.277 ,	41.9277 ,	73.9727 ,
77.5202 ,	56.8709 ,	46.6919 ,	61.7029 ,
50.2706 ,	75.051 ,	40.4801 ,	51.1581 ,
68.8525 ,	90.8992 ,	62.113 ,	68.9075 ,
64.0512 ,	50.7702 ,	79.9193 ,	96.2554 ,
70.8949 ,	67.9203 ,	58.0926 ,	42.4744 ,
74.519 ,	73.6755 ,	72.8835 ,	39.2413 ,
89.5915 ,	123.8596 ,	73.017 ,	54.7477 ,
57.4481 ,	69.8499 ,	132.2607 ,	38.5735 ,
58.9972 ,	54.996 ,	37.392 ,	58.7448 ,
157.2456 ,	49.3114 ,	25.7961 ,	50.6647 ,
57.706 ,	53.0993 ,	85.5844 ,	75.4799 ,
62.1218 ,	68.0291 ,	131.362 ,	42.9055 ,
90.6359 ,	75.3235 ,	66.5958 ,	62.6574 ,

```
63.7359     , 119.113      ,  68.1649     ,  40.3658    ])
```

[ ]:
```
demand_mse = mean_squared_error(y_demand_test, y_demand_pred)
price_mse = mean_squared_error(y_price_test, y_price_pred)
demand_mse
price_mse
```

[ ]:
```
636.8217246720737
```

[ ]:
```
print(f'Demand MSE: {demand_mse:.2f}')
print(f'Price MSE: {price_mse:.2f}')
```

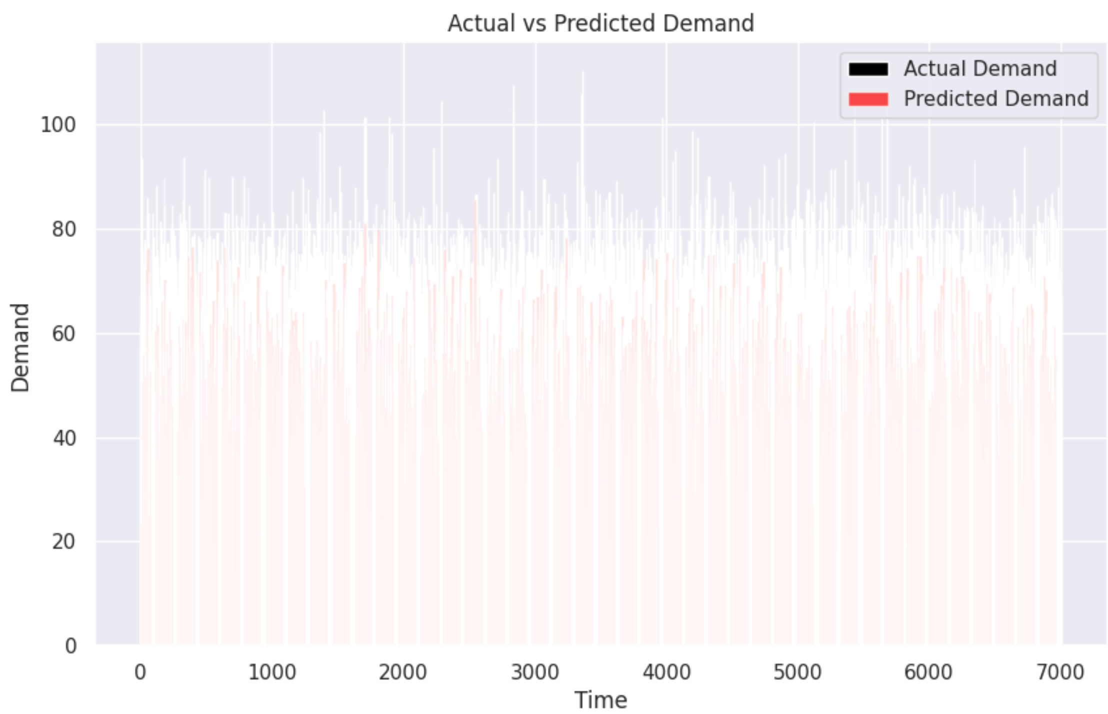
```
Demand MSE: 110.36
Price MSE: 636.82
```

[ ]:
```
#features = [['generation other renewable', 'generation solar', 'generation␣
↪wind onshore', 'total load actual',price day ahead]]
features = np.array([[ 45.0 , 50.0 , 4568.0 ,        35478.0        , 60.
↪10        ]])
model.predict(features)
```

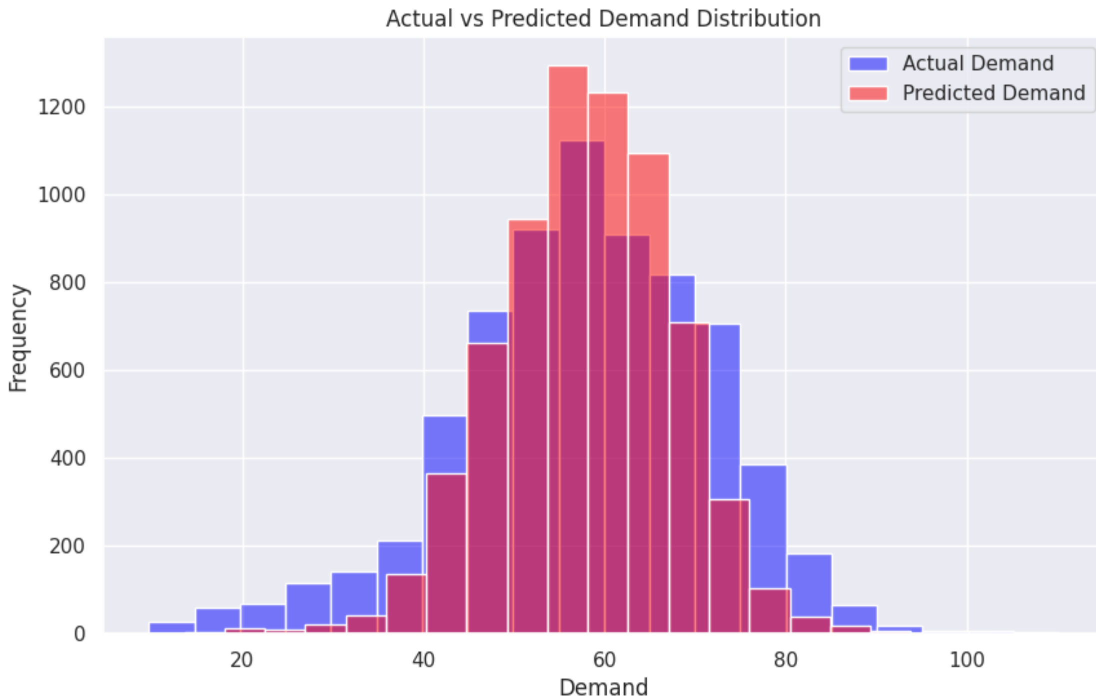
```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:493: UserWarning: X does
not have valid feature names, but RandomForestRegressor was fitted with feature
names
  warnings.warn(
```

[ ]:
```
array([33.6549])
```

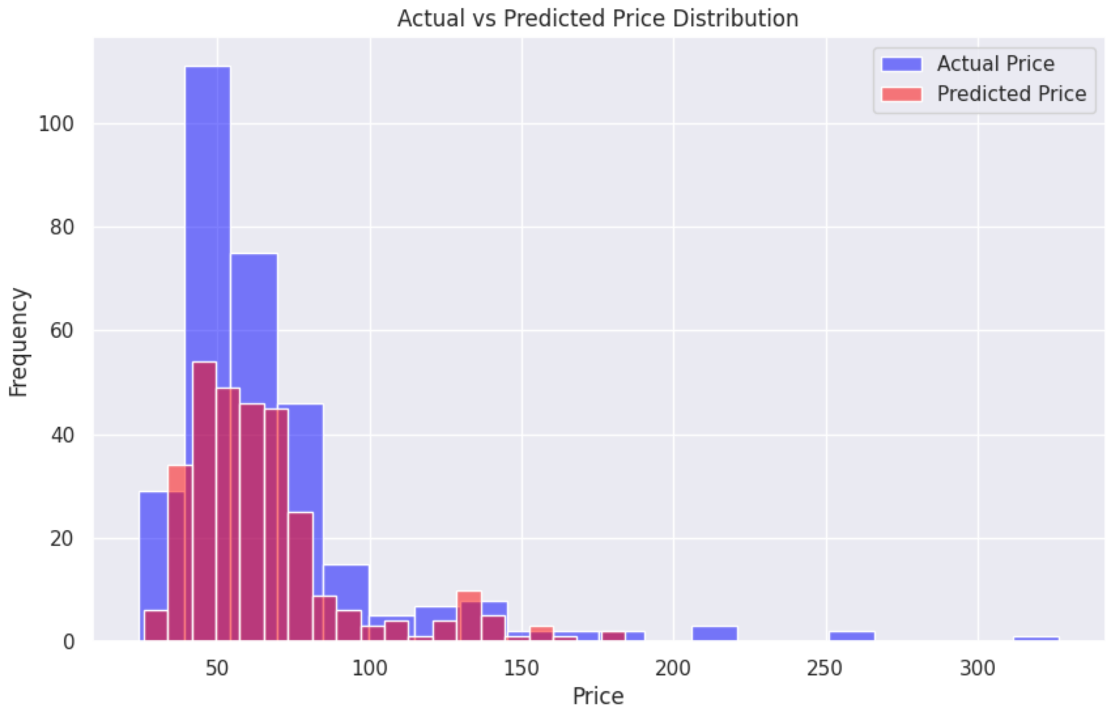
[ ]:
```
plt.figure(figsize=(10, 6))
plt.bar(range(len(y_demand_test)), y_demand_test, label='Actual Demand',␣
↪color='black')
plt.bar(range(len(y_demand_pred)), y_demand_pred, label='Predicted Demand',␣
↪color='red', alpha=0.7)
plt.title('Actual vs Predicted Demand')
plt.xlabel('Time')
plt.ylabel('Demand')
plt.legend(loc='upper right')
plt.grid(True)
plt.show()
```



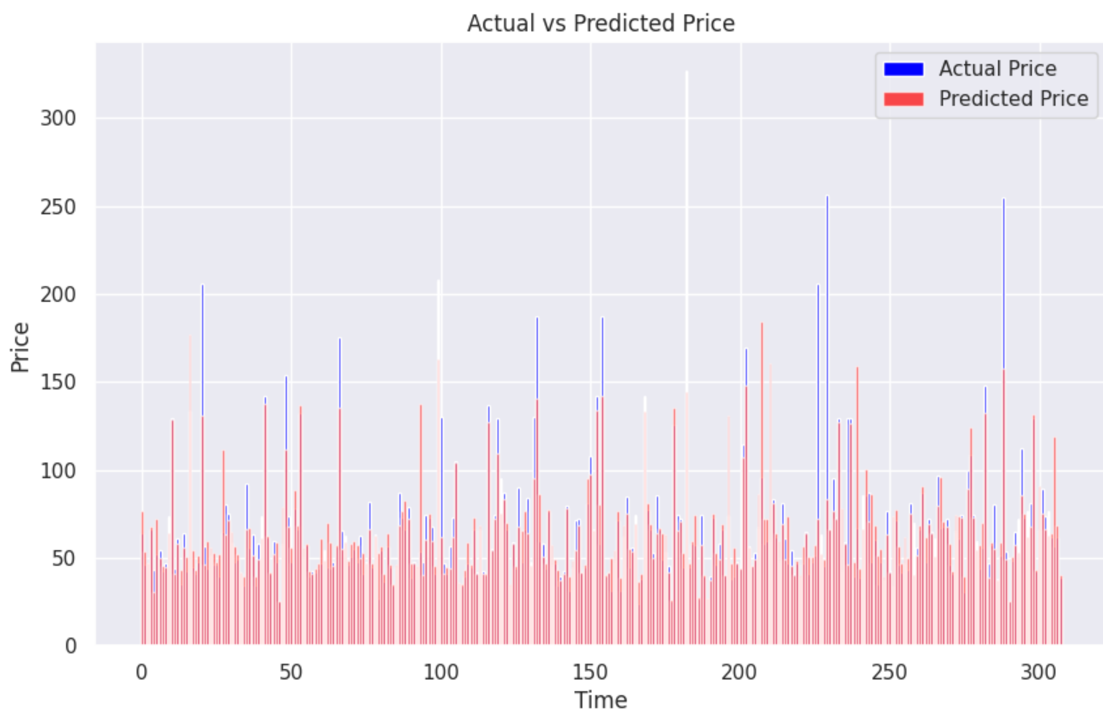
[ ]:
```
plt.figure(figsize=(10, 6))
sns.histplot(y_demand_test, label='Actual Demand', alpha=0.5, bins=20,␣
↪color='blue')
sns.histplot(y_demand_pred, label='Predicted Demand', alpha=0.5, bins=20,␣
↪color='red')
plt.title('Actual vs Predicted Demand Distribution')
plt.xlabel('Demand')
plt.ylabel('Frequency')
plt.legend(loc='upper right')
plt.show()
```



[ ]:
```
plt.figure(figsize=(10, 6))
sns.histplot(y_price_test, label='Actual Price', alpha=0.5, bins=20,␣
  ↪color='blue')
sns.histplot(y_price_pred, label='Predicted Price', alpha=0.5, bins=20,␣
  ↪color='red')
plt.title('Actual vs Predicted Price Distribution')
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.legend(loc='upper right')
plt.show()
```



[ ]:
```
plt.figure(figsize=(10, 6))
plt.bar(range(len(y_price_test)), y_price_test, label='Actual Price',␣
  ↪color='blue')
plt.bar(range(len(y_price_pred)), y_price_pred, label='Predicted Price',␣
  ↪color='red', alpha=0.7)
plt.title('Actual vs Predicted Price')
plt.xlabel('Time')
plt.ylabel('Price')
plt.legend(loc='upper right')
plt.grid(True)
plt.show()
```




```
[ ]: from sklearn.model_selection import GridSearchCV

param_grid_demand = {
    'n_estimators': [10, 50, 100, 200],
    'max_depth': [5, 10, 15],
    'min_samples_split': [2, 5, 10]
}

param_grid_price = {
    'n_estimators': [10, 50, 100, 200],
    'max_depth': [5, 10, 15],
    'min_samples_split': [2, 5, 10]
}
```

```
[ ]: grid_search_demand = GridSearchCV(RandomForestRegressor(random_state=42),␣
      ↪param_grid_demand, cv=5)
grid_search_demand.fit(X_demand_train, y_demand_train)
```

```
[ ]: GridSearchCV(cv=5, estimator=RandomForestRegressor(random_state=42),
                  param_grid={'max_depth': [5, 10, 15],
                              'min_samples_split': [2, 5, 10],
                              'n_estimators': [10, 50, 100, 200]})
```

[ ]:
```
grid_search_price = GridSearchCV(RandomForestRegressor(random_state=42),␣
    ↪param_grid_price, cv=5)
grid_search_price.fit(X_price_train, y_price_train)
```

[ ]:
```
GridSearchCV(cv=5, estimator=RandomForestRegressor(random_state=42),
             param_grid={'max_depth': [5, 10, 15],
                         'min_samples_split': [2, 5, 10],
                         'n_estimators': [10, 50, 100, 200]})
```

[ ]:
```
print(f"Best parameters demand: {grid_search_demand.best_params_}")
print(f"Best score demand: {grid_search_demand.best_score_}")
```

```
Best parameters demand: {'max_depth': 15, 'min_samples_split': 2,
'n_estimators': 200}
Best score demand: 0.4389011614617485
```

[ ]:
```
print(f"Best parameters price: {grid_search_price.best_params_}")
print(f"Best score price: {grid_search_price.best_score_}")
```

```
Best parameters price: {'max_depth': 15, 'min_samples_split': 10,
'n_estimators': 100}
Best score price: 0.48257326033087045
```

[ ]:
```
demand_model = grid_search_demand.best_estimator_
price_model = grid_search_price.best_estimator_
demand_model
price_model
```

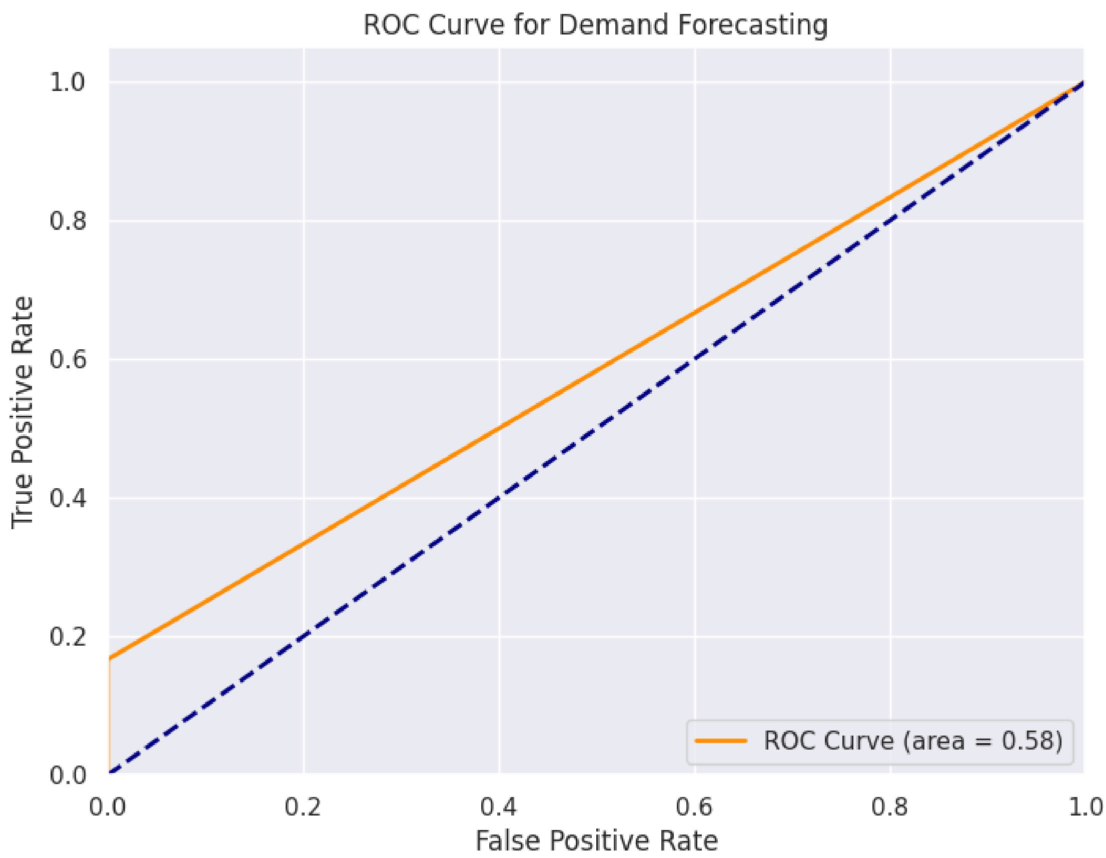
[ ]:
```
RandomForestRegressor(max_depth=15, min_samples_split=10, random_state=42)
```

[ ]:
```
from sklearn.metrics import roc_curve, auc
y_pred_demand_binary = (y_demand_pred > 100).astype(int)  # Example threshold
fpr, tpr, thresholds = roc_curve(y_demand_test > 100, y_pred_demand_binary)
roc_auc = auc(fpr, tpr)
print(f'Demand Forecasting ROC-AUC: {roc_auc}')
```

```
Demand Forecasting ROC-AUC: 0.5833333333333334
```

[ ]:
```
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC Curve (area = %0.2f)' %␣
    ↪roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Demand Forecasting')
```

```
plt.legend(loc="lower right")
plt.show()
```



[ ]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪roc_auc_score, roc_curve
y_pred_demand_binary = (y_demand_pred > 100).astype(int)
accuracy = accuracy_score(y_demand_test > 100, y_pred_demand_binary)
precision = precision_score(y_demand_test > 100, y_pred_demand_binary)
recall = recall_score(y_demand_test > 100, y_pred_demand_binary)
print(f'Demand Forecasting Accuracy: {accuracy}')
print(f'Demand Forecasting Precision: {precision}')
print(f'Demand Forecasting Recall: {recall}')
```

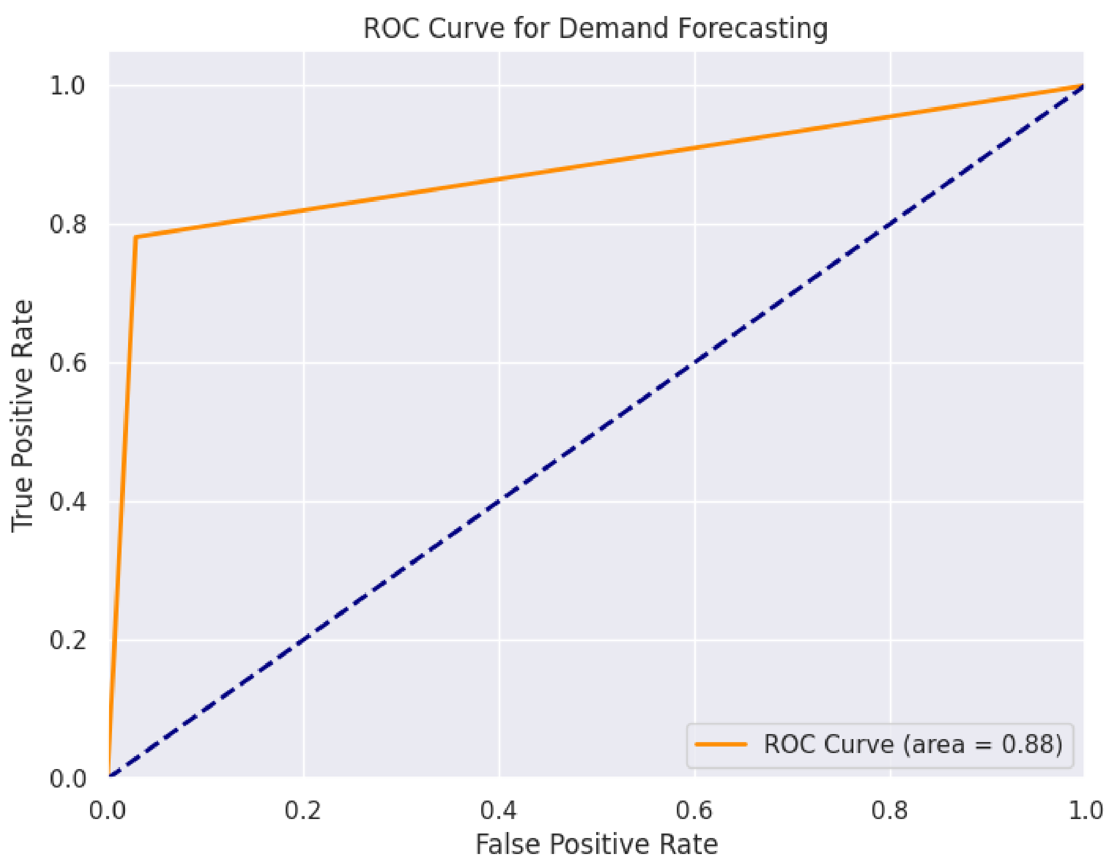
```
Demand Forecasting Accuracy: 0.9985722444317533
Demand Forecasting Precision: 1.0
Demand Forecasting Recall: 0.16666666666666666
```

[ ]:
```
from sklearn.metrics import roc_curve, auc
y_pred_price_binary = (y_price_pred > 100).astype(int)  # Example threshold
fpr, tpr, thresholds = roc_curve(y_price_test > 100, y_pred_price_binary)
```

```
roc_auc = auc(fpr, tpr)
print(f'Price Forecasting ROC-AUC: {roc_auc}')
```

```
Price Forecasting ROC-AUC: 0.8761322463768116
```

[ ]:
```
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC Curve (area = %0.2f)' %
 ↪roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Demand Forecasting')
plt.legend(loc="lower right")
plt.show()
```



[ ]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score,
 ↪roc_auc_score, roc_curve
y_pred_price_binary = (y_price_pred > 100).astype(int)
```

```
accuracy = accuracy_score(y_price_test > 100, y_pred_price_binary)
precision = precision_score(y_price_test > 100, y_pred_price_binary)
recall = recall_score(y_price_test > 100, y_pred_price_binary)
print(f'Price Forecasting Accuracy: {accuracy}')
print(f'Price Forecasting Precision: {precision}')
print(f'Price Forecasting Recall: {recall}')
```

```
Price Forecasting Accuracy: 0.9512987012987013
Price Forecasting Precision: 0.7575757575757576
Price Forecasting Recall: 0.78125
```

[ ]:
```
future_dates = pd.date_range(start='2024-12-01', end='2025-01-01', freq='D')

# Create input features
future_X_demand = pd.DataFrame({
    'generation solar': np.repeat(500, 31),  # assumed solar generation
    'generation other renewable': np.repeat(200, 31),  # assumed other␣
 ↪renewable generation
    'generation wind onshore': np.repeat(300, 31),  # assumed wind onshore␣
 ↪generation
    'total load actual': np.repeat(10000, 31)  # assumed total load
})

# Predict future demand
future_demand_pred = demand_model.predict(future_X_demand)

# Print predictions
print("Next Month Demand Prediction:")
print(future_demand_pred)
```

```
Next Month Demand Prediction:
[88.0899 88.0899 88.0899 88.0899 88.0899 88.0899 88.0899 88.0899 88.0899
 88.0899 88.0899 88.0899 88.0899 88.0899 88.0899 88.0899 88.0899 88.0899
 88.0899 88.0899 88.0899 88.0899 88.0899 88.0899 88.0899 88.0899 88.0899
 88.0899 88.0899 88.0899 88.0899]
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:486: UserWarning: X has
feature names, but RandomForestRegressor was fitted without feature names
  warnings.warn(
```

[ ]:
```
future_dates = pd.date_range(start='2024-12-01', end='2025-01-01', freq='D')

# Create input features
future_X_price = pd.DataFrame({
    'ORKTemperature': np.repeat(10, 31),  # assumed temperature
    'ORKWindspeed': np.repeat(5, 31),  # assumed wind speed
    'SystemLoadEP2': np.repeat(5000, 31),  # assumed system load
    'DayOfWeek': np.repeat(1, 31)  # assumed day of week
```

```
})

# Predict future prices
future_price_pred = price_model.predict(future_X_price)

# Print predictions
print("Next Month Price Prediction:")
print(future_price_pred)
```

```
Next Month Price Prediction:
[152.4536 152.4536 152.4536 152.4536 152.4536 152.4536 152.4536 152.4536
 152.4536 152.4536 152.4536 152.4536 152.4536 152.4536 152.4536 152.4536
 152.4536 152.4536 152.4536 152.4536 152.4536 152.4536 152.4536 152.4536
 152.4536 152.4536 152.4536 152.4536 152.4536 152.4536 152.4536]
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:486: UserWarning: X has
feature names, but RandomForestRegressor was fitted without feature names
  warnings.warn(
```

[ ]:
```
month_d=future_demand_pred.mean()
print("Next Month Demand Prediction:",month_d)
month_p=future_price_pred.mean()
print("Next Month Price Prediction:",month_p)
```

```
Next Month Demand Prediction: 88.0899
Next Month Price Prediction: 152.45359999999997
```