```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import LabelEncoder, StandardScaler,
MinMaxScaler
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf


from sklearn.preprocessing import LabelEncoder

from plotly.subplots import make_subplots
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.stattools import acf, pacf
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler

df_weather_features = pd.read_csv( '/content/weatherdata_file.csv')


df_energy_features = pd.read_csv( '/content/energy_dataset.csv',)

df_weather_features.head()
```

{"type":"dataframe","variable_name":"df_weather_features"}

```
df_weather_features.shape

(178396, 19)

df_weather_features.columns

Index(['Unnamed: 0', 'dt_iso', 'city_name', 'temp', 'temp_min',
'temp_max',
       'pressure', 'humidity', 'wind_speed', 'wind_deg', 'rain_1h',
'rain_3h',
       'snow_3h', 'clouds_all', 'weather_id', 'weather_main',
       'weather_description', 'weather_icon', 'holiday'],
      dtype='object')

df_weather_features = df_weather_features.drop(['Unnamed: 0'], axis=1,
errors='ignore')
print(df_weather_features)

                           dt_iso city_name     temp  temp_min
temp_max  \
0       2014-12-31 23:00:00+00:00  Valencia  270.475   270.475
270.475
```

```
1       2015-01-01 00:00:00+00:00  Valencia  270.475   270.475
270.475
2       2015-01-01 01:00:00+00:00  Valencia  269.686   269.686
269.686
3       2015-01-01 02:00:00+00:00  Valencia  269.686   269.686
269.686
4       2015-01-01 03:00:00+00:00  Valencia  269.686   269.686
269.686
...                           ...       ...      ...       ...        .
..
178391  2018-12-31 18:00:00+00:00   Seville  287.760   287.150
288.150
178392  2018-12-31 19:00:00+00:00   Seville  285.760   285.150
286.150
178393  2018-12-31 20:00:00+00:00   Seville  285.150   285.150
285.150
178394  2018-12-31 21:00:00+00:00   Seville  284.150   284.150
284.150
178395  2018-12-31 22:00:00+00:00   Seville  283.970   282.150
285.150

        pressure  humidity  wind_speed  wind_deg  rain_1h  rain_3h
snow_3h  \
0           1001        77           1        62      0.0      0.0
0.0
1           1001        77           1        62      0.0      0.0
0.0
2           1002        78           0        23      0.0      0.0
0.0
3           1002        78           0        23      0.0      0.0
0.0
4           1002        78           0        23      0.0      0.0
0.0
...          ...       ...         ...       ...      ...      ...
...
178391      1028        54           3        30      0.0      0.0
0.0
178392      1029        62           3        30      0.0      0.0
0.0
178393      1028        58           4        50      0.0      0.0
0.0
178394      1029        57           4        60      0.0      0.0
0.0
178395      1029        70           3        50      0.0      0.0
0.0

        clouds_all  weather_id weather_main weather_description
weather_icon  \
0                0         800        clear        sky is clear
```

```
01n
1                 0          800        clear         sky is clear
01n
2                 0          800        clear         sky is clear
01n
3                 0          800        clear         sky is clear
01n
4                 0          800        clear         sky is clear
01n
...             ...          ...          ...                  ...
...
178391            0          800        clear         sky is clear
01n
178392            0          800        clear         sky is clear
01n
178393            0          800        clear         sky is clear
01n
178394            0          800        clear         sky is clear
01n
178395            0          800        clear         sky is clear
01n

        holiday
0             1
1             1
2             1
3             1
4             1
...         ...
178391        1
178392        1
178393        1
178394        1
178395        1

[178396 rows x 18 columns]
```

```
df_weather_features.duplicated().sum()
```

```
21
```

```
df_weather_features=df_weather_features.drop_duplicates()
```

```
df_weather_features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 178375 entries, 0 to 178395
Data columns (total 18 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   dt_iso               178375 non-null  object
```

```
 1   city_name             178375 non-null  object
 2   temp                  178375 non-null  float64
 3   temp_min              178375 non-null  float64
 4   temp_max              178375 non-null  float64
 5   pressure              178375 non-null  int64
 6   humidity              178375 non-null  int64
 7   wind_speed            178375 non-null  int64
 8   wind_deg              178375 non-null  int64
 9   rain_1h               178375 non-null  float64
 10  rain_3h               178375 non-null  float64
 11  snow_3h               178375 non-null  float64
 12  clouds_all            178375 non-null  int64
 13  weather_id            178375 non-null  int64
 14  weather_main          178375 non-null  object
 15  weather_description   178375 non-null  object
 16  weather_icon          178375 non-null  object
 17  holiday               178375 non-null  int64
dtypes: float64(6), int64(7), object(5)
memory usage: 25.9+ MB
```

```
df_weather_features.nunique()
```

```
dt_iso                 35064
city_name                  5
temp                   20743
temp_min               18553
temp_max               18591
pressure                 190
humidity                 100
wind_speed                36
wind_deg                 361
rain_1h                    7
rain_3h                   89
snow_3h                   66
clouds_all                97
weather_id                38
weather_main              12
weather_description       43
weather_icon              24
holiday                    2
dtype: int64
```

```
def df_convert_dtypes(df, convert_from, convert_to):
  values = df.select_dtypes(include=[convert_from]).columns
  for val in values:
         df[val] = df[val].astype(convert_to)

  return df
```

```
df_weather_features = df_convert_dtypes(df_weather_features, np.int64, np.float64)

df_weather_features = (df_weather_features.assign(time=pd.to_datetime(df_weather_features['dt_iso'], utc=True, infer_datetime_format=True)).drop(columns=['dt_iso']).set_index('time'))
```

```
<ipython-input-253-8c78dc69c458>:1: UserWarning:

The argument 'infer_datetime_format' is deprecated and will be removed in a future version. A strict version of it is now the default, see https://pandas.pydata.org/pdeps/0004-consistent-to-datetime-parsing.html. You can safely remove this argument.
```

```
missingvalues = df_weather_features.isnull().sum().sum()
print(f'There are {missingvalues} missing values or NaNs in df_weather_features.')
```

```
There are 0 missing values or NaNs in df_weather_features.
```

```
duplicaterows = df_weather_features.duplicated().sum()


print(f'There are {duplicaterows} duplicate rows in df_weather_features.')
```

```
There are 8442 duplicate rows in df_weather_features.
```

```
weather_description_unique = df_weather_features['weather_description'].unique()
weather_description_unique
```

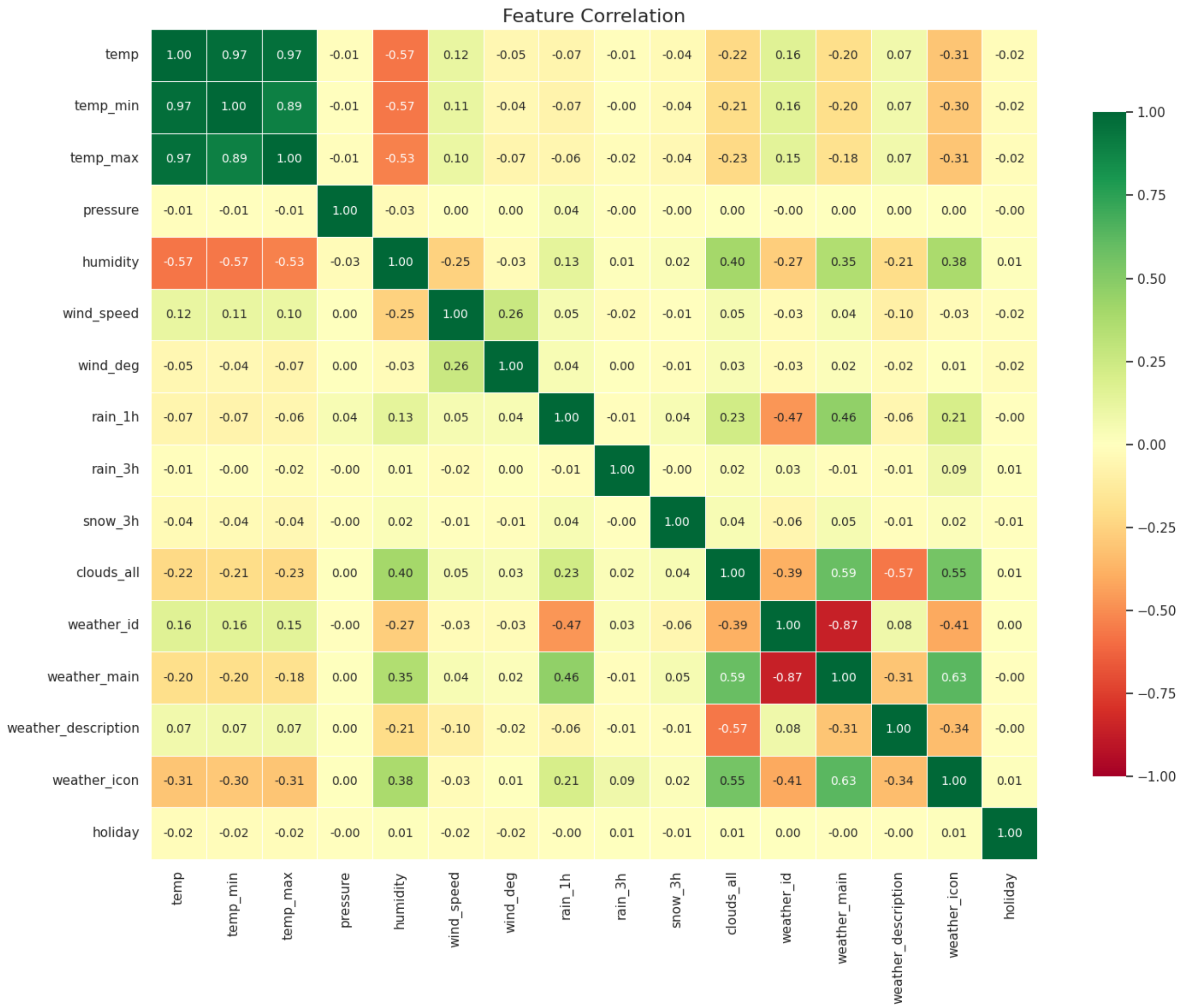
```
array(['sky is clear', 'few clouds', 'scattered clouds', 'broken clouds',
       'overcast clouds', 'light rain', 'moderate rain',
       'heavy intensity rain', 'mist', 'heavy intensity shower rain',
       'shower rain', 'very heavy rain', 'thunderstorm with heavy rain',
       'thunderstorm with light rain', 'thunderstorm with rain',
       'proximity thunderstorm', 'thunderstorm',
       'light intensity shower rain', 'light intensity drizzle', 'fog',
       'drizzle', 'smoke', 'heavy intensity drizzle', 'haze',
       'proximity shower rain', 'light intensity drizzle rain',
       'light snow', 'rain and snow', 'light rain and snow', 'snow',
       'light thunderstorm', 'heavy snow', 'sleet', 'rain and drizzle',
       'shower sleet', 'light shower sleet', 'light shower snow',
```

```
        'proximity moderate rain', 'ragged shower rain',
        'sand dust whirls', 'proximity drizzle', 'dust', 'squalls'],
      dtype=object)
```

```
weather_uniqueid = df_weather_features['weather_id'].unique()
weather_uniqueid
```

```
array([800., 801., 802., 803., 804., 500., 501., 502., 701., 522.,
521.,
       503., 202., 200., 201., 211., 520., 300., 741., 301., 711.,
302.,
       721., 310., 600., 616., 615., 601., 210., 602., 611., 311.,
612.,
       620., 531., 731., 761., 771.])
```

```
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np

def feat_corr(input_df):

    numeric_df = input_df.select_dtypes(include=np.number)


    corr = numeric_df.corr()


    plt.figure(figsize=(15, 12))
    sns.heatmap(corr, annot=True, fmt='.2f', cmap='RdYlGn', vmin=-1,
vmax=1,
                linewidths=0.5, cbar_kws={"shrink": 0.8},
annot_kws={"size": 10})

    plt.title('Feature Correlation', fontsize=16)
    plt.tight_layout()

    plt.show()

df_temp = df_weather_features.copy(deep = True)
labels = ['weather_id',
'weather_main','weather_description','weather_icon']
for col in labels:
    df_temp[col] =
LabelEncoder().fit_transform(df_weather_features[col])

feat_corr(df_temp)
```




```
col_drop_name = ['weather_id',
'weather_main','weather_description','weather_icon', 'temp_min',
'temp_max']
# col_drop_name = ['weather_id',
'weather_main','weather_description','weather_icon']
df_weather_features.drop(col_drop_name, axis = 1 , inplace = True)

missingvalues = df_weather_features.isnull().sum().sum()
print(f'There are {missingvalues} missing values or NaNs in
df_weather_features.')
```

```
There are 0 missing values or NaNs in df_weather_features.
```

```
duplicaterows = df_weather_features.duplicated().sum()


print(f'There are {duplicaterows} duplicate rows in
df_weather_features.')
```

```
There are 12907 duplicate rows in df_weather_features.

df_weather_features =
df_weather_features.reset_index().drop_duplicates()

df_weather_features
```

{"type":"dataframe","variable_name":"df_weather_features"}

```
df_energy_features.shape

(35064, 29)

df_energy_features.head()
```

{"type":"dataframe","variable_name":"df_energy_features"}

```
df_energy_features.columns

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

df_energy_features.duplicated().sum()

0

df_energy_features.isnull().sum()

time                                                  0
generation biomass                                   19
generation fossil brown coal/lignite                 18
generation fossil coal-derived gas                   18
generation fossil gas                                18
generation fossil hard coal                          18
```

```
generation fossil oil                                 19
generation fossil oil shale                           18
generation fossil peat                                18
generation geothermal                                 18
generation hydro pumped storage aggregated         35064
generation hydro pumped storage consumption           19
generation hydro run-of-river and poundage            19
generation hydro water reservoir                      18
generation marine                                     19
generation nuclear                                    17
generation other                                      18
generation other renewable                            18
generation solar                                      18
generation waste                                      19
generation wind offshore                              18
generation wind onshore                               18
forecast solar day ahead                               0
forecast wind offshore eday ahead                  35064
forecast wind onshore day ahead                        0
total load forecast                                    0
total load actual                                     36
price day ahead                                        0
price actual                                           0
dtype: int64
```

```
df_energy_features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 35064 entries, 0 to 35063
Data columns (total 29 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 coal-derived gas           35046 non-null
float64
 4   generation fossil gas                        35046 non-null
float64
 5   generation fossil hard coal                  35046 non-null
float64
 6   generation fossil oil                        35045 non-null
float64
 7   generation fossil oil shale                  35046 non-null
float64
```

```
 8   generation fossil peat                       35046 non-null
float64
 9   generation geothermal                        35046 non-null
float64
 10  generation hydro pumped storage aggregated   0 non-null
float64
 11  generation hydro pumped storage consumption  35045 non-null
float64
 12  generation hydro run-of-river and poundage   35045 non-null
float64
 13  generation hydro water reservoir             35046 non-null
float64
 14  generation marine                            35045 non-null
float64
 15  generation nuclear                           35047 non-null
float64
 16  generation other                             35046 non-null
float64
 17  generation other renewable                   35046 non-null
float64
 18  generation solar                             35046 non-null
float64
 19  generation waste                             35045 non-null
float64
 20  generation wind offshore                     35046 non-null
float64
 21  generation wind onshore                      35046 non-null
float64
 22  forecast solar day ahead                     35064 non-null
float64
 23  forecast wind offshore eday ahead            0 non-null
float64
 24  forecast wind onshore day ahead              35064 non-null
float64
 25  total load forecast                          35064 non-null
float64
 26  total load actual                            35028 non-null
float64
 27  price day ahead                              35064 non-null
float64
 28  price actual                                 35064 non-null
float64
dtypes: float64(28), object(1)
memory usage: 7.8+ MB


df_energy_features['time'] =
pd.to_datetime(df_energy_features['time'], utc=True,
infer_datetime_format=True)
df_energy_features= df_energy_features.set_index('time')
```

```
<ipython-input-272-5d91c7a4741e>:1: UserWarning:

The argument 'infer_datetime_format' is deprecated and will be removed
in a future version. A strict version of it is now the default, see
https://pandas.pydata.org/pdeps/0004-consistent-to-datetime-
parsing.html. You can safely remove this argument.
```

```
df_energy_features.describe()
```

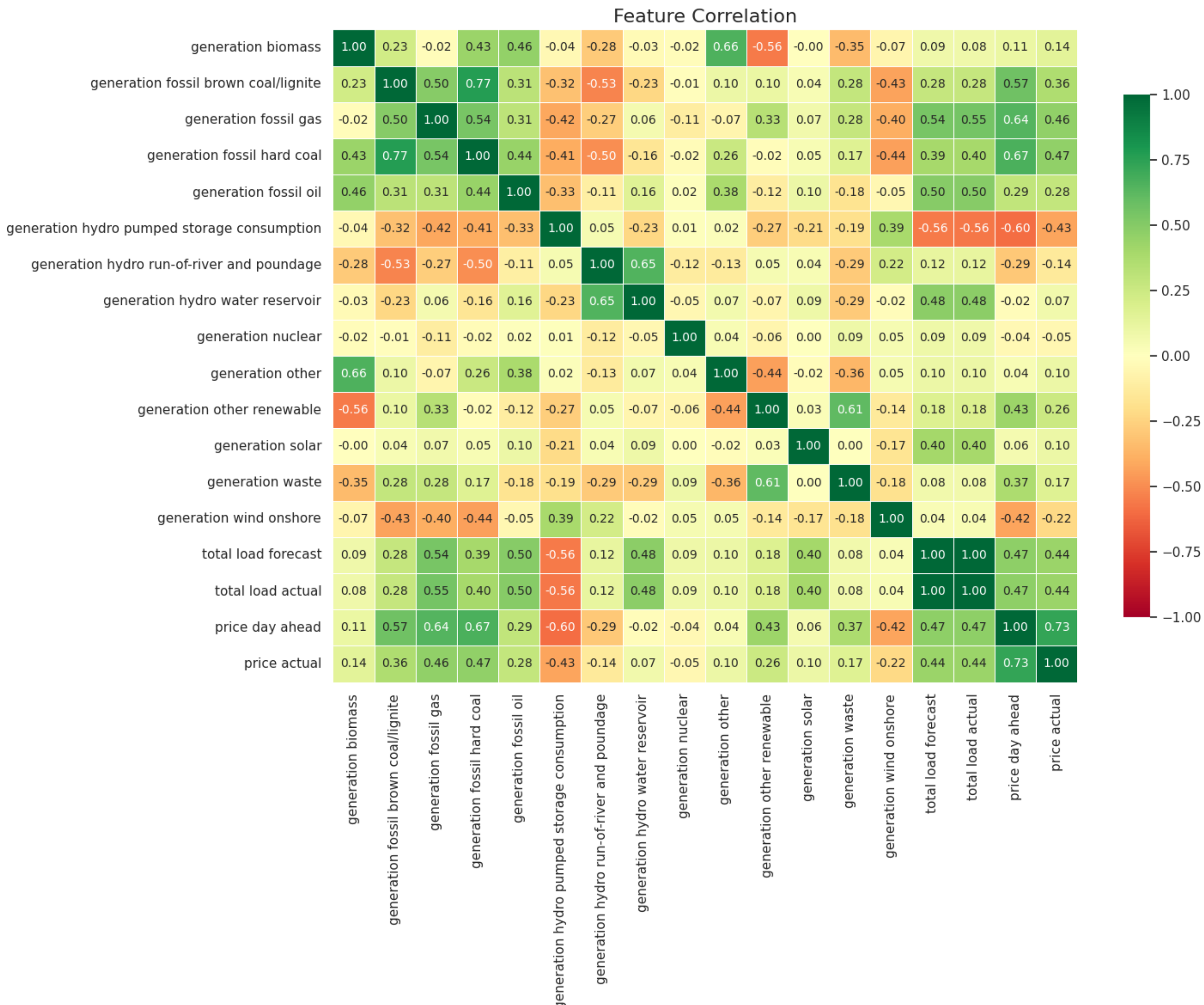
{"type":"dataframe"}

```
df_energy_features.nunique()
```

```
generation biomass                                423
generation fossil brown coal/lignite              956
generation fossil coal-derived gas                  1
generation fossil gas                            8297
generation fossil hard coal                      7266
generation fossil oil                             321
generation fossil oil shale                         1
generation fossil peat                              1
generation geothermal                               1
generation hydro pumped storage aggregated          0
generation hydro pumped storage consumption      3311
generation hydro run-of-river and poundage       1684
generation hydro water reservoir                 7029
generation marine                                   1
generation nuclear                               2388
generation other                                  103
generation other renewable                         78
generation solar                                 5331
generation waste                                  262
generation wind offshore                            1
generation wind onshore                         11465
forecast solar day ahead                         5356
forecast wind offshore eday ahead                   0
forecast wind onshore day ahead                 11332
total load forecast                             14790
total load actual                               15127
price day ahead                                  5747
price actual                                     6653
dtype: int64
```

```
# columns to be removed due to all 0 or Nan values
columns = ['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', 'forecast solar day ahead',
           'forecast wind onshore day ahead']

df_energy_features = df_energy_features.drop(columns, axis = 1)

feat_corr(df_energy_features)
```




```
df_energy_features.duplicated().sum()

0

df_energy_features.isnull().sum(axis=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 forecast                             0
total load actual                              36
price day ahead                                 0
price actual                                    0
dtype: int64
```

```
df_energy_features
```

{"summary":"{\n \"name\": \"df_energy_features\",\n \"rows\": 35064,\n \"fields\": [\n   {\n   \"column\": \"time\",\n   \"properties\": {\n   \"dtype\": \"date\",\n   \"min\": \"2014-12-31 23:00:00+00:00\",\n   \"max\": \"2018-12-31 22:00:00+00:00\",\n   \"num_unique_values\": 35064,\n   \"samples\": [\n   \"2015-09-10 21:00:00+00:00\",\n   \"2018-09-20 07:00:00+00:00\",\n   \"2016-01-04 13:00:00+00:00\"\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"generation biomass\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 85.3539430538196,\n   \"min\": 0.0,\n   \"max\": 592.0,\n   \"num_unique_values\": 423,\n   \"samples\": [\n   577.0,\n   227.0,\n   405.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"generation fossil brown coal/lignite\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 354.5685904349092,\n   \"min\": 0.0,\n   \"max\": 999.0,\n   \"num_unique_values\": 956,\n   \"samples\": [\n   883.0,\n   431.0,\n   601.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"generation fossil gas\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 2201.830477836224,\n   \"min\": 0.0,\n   \"max\": 20034.0,\n   \"num_unique_values\": 8297,\n   \"samples\": [\n   4880.0,\n   7674.0,\n   11327.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"generation fossil hard coal\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 1961.6010133302004,\n   \"min\": 0.0,\n   \"max\": 8359.0,\n   \"num_unique_values\": 7266,\n   \"samples\": [\n   5620.0,\n   4557.0,\n   1804.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"generation fossil oil\",\n

```
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
52.52067255592221,\n        \"min\": 0.0,\n        \"max\": 449.0,\n
\"num_unique_values\": 321,\n        \"samples\": [\n          290.0,\
n          210.0,\n          329.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"generation hydro pumped storage
consumption\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 792.4066137134466,\n        \"min\":
0.0,\n        \"max\": 4523.0,\n        \"num_unique_values\": 3311,\n
\"samples\": [\n          325.0,\n          2819.0,\n          689.0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"generation hydro run-of-river
and poundage\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 400.7775358935912,\n        \"min\":
0.0,\n        \"max\": 2000.0,\n        \"num_unique_values\": 1684,\n
\"samples\": [\n          435.0,\n          458.0,\n          879.0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"generation hydro water
reservoir\",\n      \"properties\": {\n        \"dtype\": \"number\",\
n        \"std\": 1835.1997450877438,\n        \"min\": 0.0,\n
\"max\": 9728.0,\n        \"num_unique_values\": 7029,\n
\"samples\": [\n          3051.0,\n          5160.0,\n
2557.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"generation nuclear\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 839.6679576780471,\n        \"min\":
0.0,\n        \"max\": 7117.0,\n        \"num_unique_values\": 2388,\n
\"samples\": [\n          6496.0,\n          6163.0,\n
6440.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"generation other\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 20.238380906782545,\n        \"min\":
0.0,\n        \"max\": 106.0,\n        \"num_unique_values\": 103,\n
\"samples\": [\n          95.0,\n          64.0,\n          99.0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"generation other renewable\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
14.077554099310847,\n        \"min\": 0.0,\n        \"max\": 119.0,\n
\"num_unique_values\": 78,\n        \"samples\": [\n          83.0,\n
73.0,\n          84.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"generation solar\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 1680.119887007093,\n        \"min\":
0.0,\n        \"max\": 5792.0,\n        \"num_unique_values\": 5331,\n
\"samples\": [\n          4158.0,\n          2093.0,\n
1187.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"generation waste\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 50.195535633578885,\n        \"min\":
```

0.0,\n   \"max\": 357.0,\n   \"num_unique_values\": 262,\n   \"samples\": [\n   344.0,\n   323.0,\n   308.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"generation wind onshore\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 3213.6915870178127,\n   \"min\": 0.0,\n   \"max\": 17436.0,\n   \"num_unique_values\": 11465,\n   \"samples\": [\n   5887.0,\n   8053.0,\n   6943.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"total load forecast\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 4594.100854174032,\n   \"min\": 18105.0,\n   \"max\": 41390.0,\n   \"num_unique_values\": 14790,\n   \"samples\": [\n   21970.0,\n   30045.0,\n   23844.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"total load actual\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 4574.987950049498,\n   \"min\": 18041.0,\n   \"max\": 41015.0,\n   \"num_unique_values\": 15127,\n   \"samples\": [\n   26099.0,\n   38645.0,\n   23443.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"price day ahead\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 14.618899685404326,\n   \"min\": 2.06,\n   \"max\": 101.99,\n   \"num_unique_values\": 5747,\n   \"samples\": [\n   33.63,\n   45.73,\n   32.64\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"price actual\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 14.204083293241405,\n   \"min\": 9.33,\n   \"max\": 116.8,\n   \"num_unique_values\": 6653,\n   \"samples\": [\n   83.51,\n   57.22,\n   54.1\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   }\n]\n}","type":"dataframe","variable_name":"df_energy_features"}

```
df_energy_features[df_energy_features.isna().any(axis=1)]
```

{"summary":"{\n \"name\": \"df_energy_features[df_energy_features\",\n \"rows\": 46,\n \"fields\": [\n   {\n   \"column\": \"time\",\n   \"properties\": {\n   \"dtype\": \"date\",\n   \"min\": \"2015-01-05 02:00:00+00:00\",\n   \"max\": \"2018-07-11 07:00:00+00:00\",\n   \"num_unique_values\": 46,\n   \"samples\": [\n   \"2016-09-28 07:00:00+00:00\",\n   \"2015-04-23 19:00:00+00:00\",\n   \"2015-05-02 08:00:00+00:00\"\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"generation biomass\",\n   \"properties\": {\n   \"dtype\":

```
\"number\",\n        \"std\": 136.92515683941565,\n        \"min\":
0.0,\n        \"max\": 569.0,\n        \"num_unique_values\": 26,\n
\"samples\": [\n          465.0,\n          220.0,\n          449.0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"generation fossil brown
coal/lignite\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 297.6701305367346,\n        \"min\":
0.0,\n        \"max\": 961.0,\n        \"num_unique_values\": 16,\n
\"samples\": [\n          312.0,\n          302.0,\n          326.0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"generation fossil gas\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
1927.7806440672164,\n        \"min\": 2969.0,\n        \"max\":
12336.0,\n        \"num_unique_values\": 28,\n        \"samples\": [\n
7386.0,\n          10064.0,\n          6127.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"generation fossil hard coal\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
2141.2732042374196,\n        \"min\": 0.0,\n        \"max\": 8250.0,\n
\"num_unique_values\": 27,\n        \"samples\": [\n          5912.0,\
n          5677.0,\n          6002.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"generation fossil oil\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
98.60468138421822,\n        \"min\": 0.0,\n        \"max\": 385.0,\n
\"num_unique_values\": 25,\n        \"samples\": [\n          340.0,\n
151.0,\n          222.0\n        ],\n        \"semantic_type\": \"\",\
n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"generation hydro pumped storage consumption\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
567.4673629180871,\n        \"min\": 0.0,\n        \"max\": 2270.0,\n
\"num_unique_values\": 11,\n        \"samples\": [\n          1340.0,\
n          480.0,\n          1413.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"generation hydro run-of-river and
poundage\",\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 439.1490151985514,\n        \"min\": 0.0,\n        \"max\":
1648.0,\n        \"num_unique_values\": 26,\n        \"samples\": [\n
1214.0,\n          1622.0,\n          980.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"generation hydro water
reservoir\",\n      \"properties\": {\n        \"dtype\": \"number\",\
n        \"std\": 2026.4761645532978,\n        \"min\": 0.0,\n
\"max\": 6895.0,\n        \"num_unique_values\": 27,\n
\"samples\": [\n          4684.0,\n          5289.0,\n
6187.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"generation nuclear\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 1906.493960566064,\n        \"min\":
```

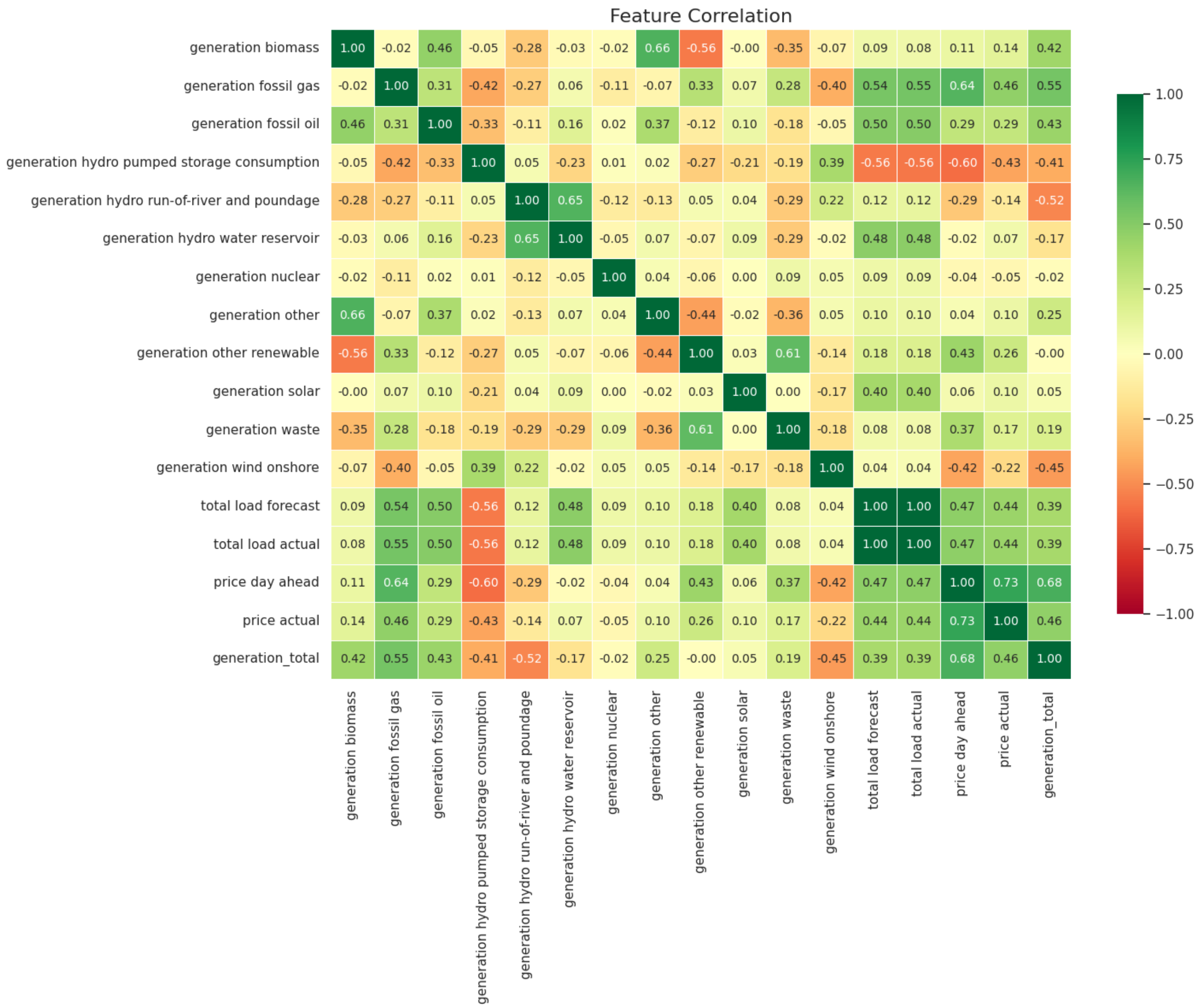
```
0.0,\n        \"max\": 7101.0,\n        \"num_unique_values\": 21,\n
\"samples\": [\n          7101.0,\n          6967.0,\n
5058.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"generation other\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 20.685347419939507,\n        \"min\":
0.0,\n        \"max\": 93.0,\n        \"num_unique_values\": 19,\n
\"samples\": [\n          44.0,\n          81.0,\n          51.0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"generation other renewable\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
21.98565549668801,\n        \"min\": 0.0,\n        \"max\": 96.0,\n
\"num_unique_values\": 18,\n        \"samples\": [\n          75.0,\n
71.0,\n          62.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"generation solar\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 1340.2586795250863,\n        \"min\":
0.0,\n        \"max\": 3836.0,\n        \"num_unique_values\": 26,\n
\"samples\": [\n          1281.0,\n          150.0,\n          48.0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"generation waste\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
72.87885588651646,\n        \"min\": 0.0,\n        \"max\": 309.0,\n
\"num_unique_values\": 21,\n        \"samples\": [\n          208.0,\n
299.0,\n          309.0\n        ],\n        \"semantic_type\": \"\",\
n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"generation wind onshore\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 2756.0547705276376,\n
\"min\": 0.0,\n        \"max\": 10903.0,\n
\"num_unique_values\": 27,\n        \"samples\": [\n          1857.0,\
n          10903.0,\n          1864.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"total load forecast\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
5778.164024515305,\n        \"min\": 20016.0,\n        \"max\":
39644.0,\n        \"num_unique_values\": 46,\n        \"samples\": [\n
31072.0,\n          31421.0,\n          39644.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"total load actual\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
7218.587889762251,\n        \"min\": 21182.0,\n        \"max\":
39304.0,\n        \"num_unique_values\": 10,\n        \"samples\": [\n
26583.0,\n          39304.0,\n          23614.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"price day ahead\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
14.878207673469248,\n        \"min\": 15.0,\n        \"max\": 75.71,\n
\"num_unique_values\": 44,\n        \"samples\": [\n          49.72,\n
58.49,\n          45.93\n        ],\n        \"semantic_type\": \"\",\
```

n   \"description\": \"\"\n   }\n   },\n   {\n
\"column\": \"price actual\",\n   \"properties\": {\n
\"dtype\": \"number\",\n   \"std\": 22.569020505330933,\n
\"min\": 16.98,\n   \"max\": 88.95,\n
\"num_unique_values\": 46,\n   \"samples\": [\n   56.4,\n
82.57,\n   59.09\n   ],\n   \"semantic_type\": \"\",\
n   \"description\": \"\"\n   }\n   }\n]\
n}","type":"dataframe"}

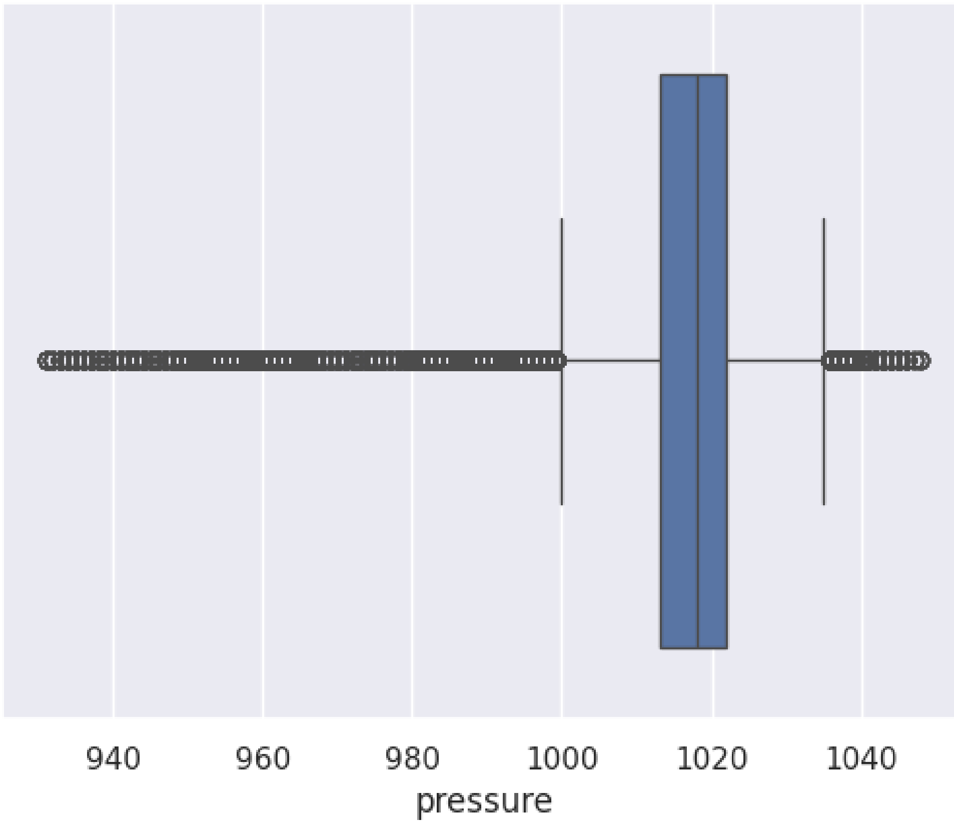
```
df_energy_features.interpolate(method='linear',
limit_direction='forward', inplace=True, axis=0)

df_energy_features.isnull().sum()
```

```
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 forecast                             0
total load actual                               0
price day ahead                                 0
price actual                                    0
dtype: int64
```

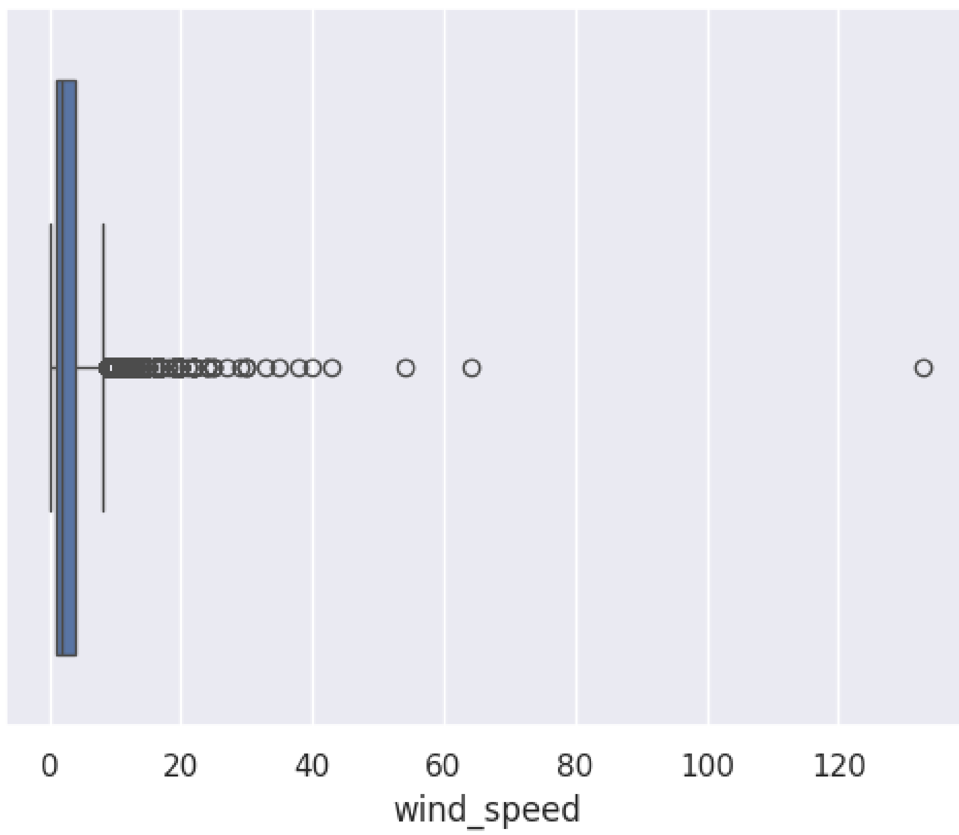
```
df_energy_features = (df_energy_features
              .assign(generation_total=df_energy_features['generation
fossil hard coal'] + df_energy_features['generation fossil brown
coal/lignite'])
              .drop(['generation fossil hard coal', 'generation fossil
brown coal/lignite'], axis=1))


feat_corr(df_energy_features)
```



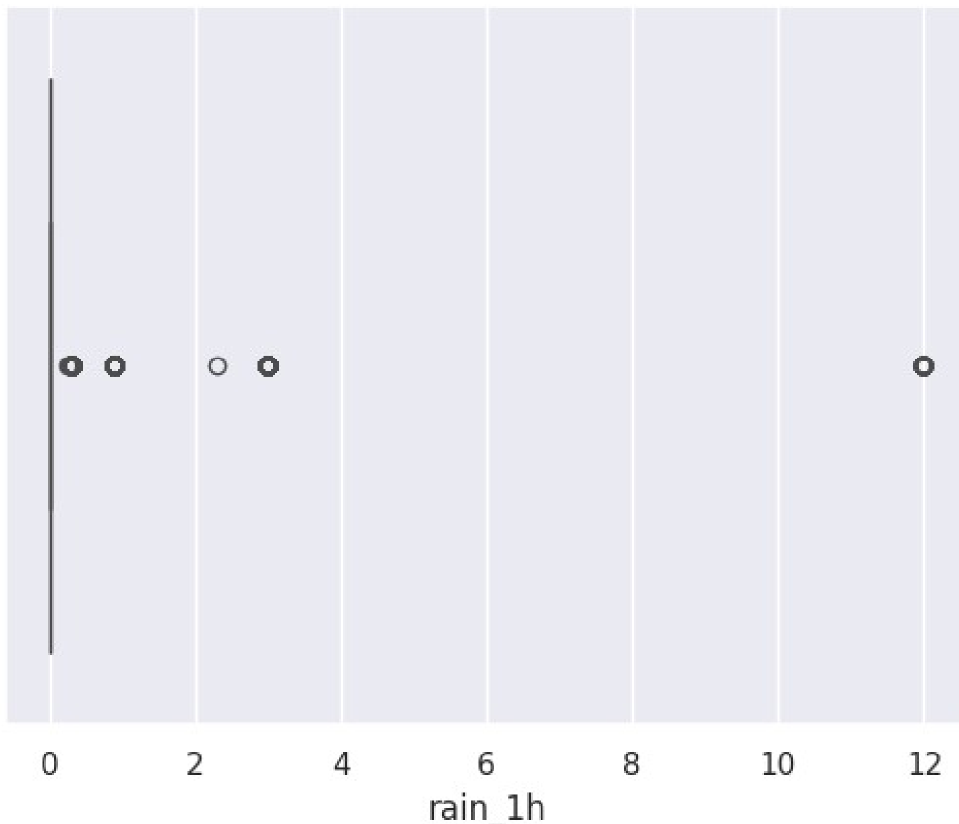

```
import statsmodels.api as sm

df_weather_features.loc[df_weather_features.pressure > 1050,
'pressure'] = np.nan
df_weather_features.loc[df_weather_features.pressure < 930,
'pressure'] = np.nan

df_weather_features['pressure'] =
df_weather_features['pressure'].where((df_weather_features['pressure']
<= 1051) & (df_weather_features['pressure'] >= 931), other=pd.NA)


if df_weather_features.index.duplicated().any():
    print("Duplicate index values found.")

sns.boxplot(x=df_weather_features['pressure'])
plt.show()
```



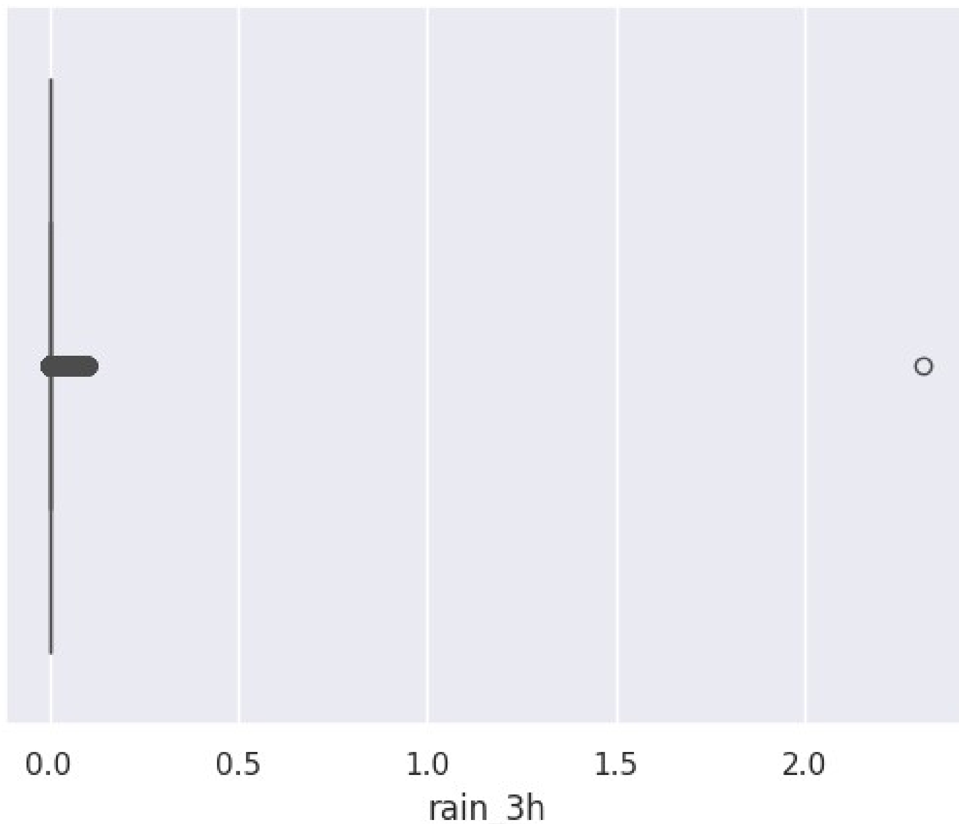

```
sns.boxplot(x=df_weather_features['wind_speed'])
plt.show()
```




```
sns.boxplot(x=df_weather_features['rain_1h'])
plt.show()
```




```
sns.boxplot(x=df_weather_features['rain_3h'])
plt.show()
```




```
df_weather_features.drop(['rain_3h'], axis = 1 , inplace = True)

print(f'Number of samples in df_energy is
{df_energy_features.shape[0]}')

city_list = df_weather_features['city_name'].unique()
grouped_weather = df_weather_features.groupby('city_name')

for city in city_list:
    print(f'Number of samples in df_weather in {city} is
{grouped_weather.get_group(city).shape[0]}')

Number of samples in df_energy is 35064
Number of samples in df_weather in Valencia is 35064
Number of samples in df_weather in Madrid is 35064
Number of samples in df_weather in Bilbao is 35064
Number of samples in df_weather in  Barcelona is 35064
Number of samples in df_weather in Seville is 35064

df_weather_cleaned =
df_weather_features.reset_index().drop_duplicates(subset=['time',
'city_name'], keep='first').set_index('time')

df_weather_cleaned
```

{"type":"dataframe","variable_name":"df_weather_cleaned"}

```
print(f'Number of samples in df_energy is
{df_energy_features.shape[0]}')

city_list = df_weather_features['city_name'].unique()
grouped_weather = df_weather_cleaned.groupby('city_name')

for city in city_list:
    print(f'Number of samples in df_weather in {city} is
{grouped_weather.get_group(city).shape[0]}')
```

```
Number of samples in df_energy is 35064
Number of samples in df_weather in Valencia is 35064
Number of samples in df_weather in Madrid is 35064
Number of samples in df_weather in Bilbao is 35064
Number of samples in df_weather in  Barcelona is 35064
Number of samples in df_weather in Seville is 35064
```

```
df_weather_all_cities = [grouped_weather.get_group(x) for x in
grouped_weather.groups]

df_weather_all_cities[0]
```

{"summary":"{\n \"name\": \"df_weather_all_cities[0]\",\n \"rows\":
35064,\n \"fields\": [\n   {\n   \"column\": \"time\",\n
\"properties\": {\n   \"dtype\": \"date\",\n   \"min\":
\"2014-12-31 23:00:00+00:00\",\n   \"max\": \"2018-12-31
22:00:00+00:00\",\n   \"num_unique_values\": 35064,\n
\"samples\": [\n   \"2015-09-10 21:00:00+00:00\",\n
\"2018-09-20 07:00:00+00:00\",\n   \"2016-01-04
13:00:00+00:00\"\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"index\",\n   \"properties\": {\n   \"dtype\": \"number\",\n
\"std\": 10236,\n   \"min\": 107350,\n   \"max\": 142821,\n
\"num_unique_values\": 35064,\n   \"samples\": [\n
113461,\n   140294,\n   116253\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   },\n   {\n   \"column\": \"city_name\",\n
\"properties\": {\n   \"dtype\": \"category\",\n
\"num_unique_values\": 1,\n   \"samples\": [\n   \"
Barcelona\"\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"temp\",\n   \"properties\": {\n   \"dtype\": \"number\",\n
\"std\": 6.723623493439147,\n   \"min\": 262.24,\n
\"max\": 309.15,\n   \"num_unique_values\": 5296,\n
\"samples\": [\n   280.96\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   },\n   {\n   \"column\": \"pressure\",\n   \"properties\":
{\n   \"dtype\": \"number\",\n   \"std\":

```
7.526447844007588,\n        \"min\": 932.0,\n        \"max\": 1039.0,\
n        \"num_unique_values\": 62,\n        \"samples\": [\n
984.0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"humidity\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 17.72080890337698,\n        \"min\":
0.0,\n        \"max\": 100.0,\n        \"num_unique_values\": 99,\n
\"samples\": [\n          31.0\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"wind_speed\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 1.9960811671624321,\n
\"min\": 0.0,\n        \"max\": 15.0,\n        \"num_unique_values\":
16,\n        \"samples\": [\n          7.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"wind_deg\",\n      \"properties\":
{\n        \"dtype\": \"number\",\n        \"std\":
108.56450488979964,\n        \"min\": 0.0,\n        \"max\": 360.0,\n
\"num_unique_values\": 361,\n        \"samples\": [\n          192.0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"rain_1h\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
0.6677707337523273,\n        \"min\": 0.0,\n        \"max\": 12.0,\n
\"num_unique_values\": 5,\n        \"samples\": [\n          0.3\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"snow_3h\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
0.0,\n        \"min\": 0.0,\n        \"max\": 0.0,\n
\"num_unique_values\": 1,\n        \"samples\": [\n          0.0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"clouds_all\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
27.32844286577024,\n        \"min\": 0.0,\n        \"max\": 100.0,\n
\"num_unique_values\": 86,\n        \"samples\": [\n          49.0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"holiday\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
0.2525137547258822,\n        \"min\": 0.0,\n        \"max\": 1.0,\n
\"num_unique_values\": 2,\n        \"samples\": [\n          0.0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    }\n  ]\n}","type":"dataframe"}

# Loop through each DataFrame in the list and drop the 'index' column
for i in range(len(df_weather_all_cities)):
    df_weather_all_cities[i] =
df_weather_all_cities[i].drop(['index'], axis=1, errors='ignore')

# Print the first DataFrame in the list (or any specific one)
print(df_weather_all_cities[0])
```

```
                          city_name     temp  pressure  humidity  \
time
2014-12-31 23:00:00+00:00   Barcelona  281.625    1035.0     100.0
2015-01-01 00:00:00+00:00   Barcelona  281.625    1035.0     100.0
2015-01-01 01:00:00+00:00   Barcelona  281.286    1036.0     100.0
2015-01-01 02:00:00+00:00   Barcelona  281.286    1036.0     100.0
2015-01-01 03:00:00+00:00   Barcelona  281.286    1036.0     100.0
...                               ...      ...       ...       ...
2018-12-31 18:00:00+00:00   Barcelona  284.130    1027.0      71.0
2018-12-31 19:00:00+00:00   Barcelona  282.640    1027.0      62.0
2018-12-31 20:00:00+00:00   Barcelona  282.140    1028.0      53.0
2018-12-31 21:00:00+00:00   Barcelona  281.130    1028.0      50.0
2018-12-31 22:00:00+00:00   Barcelona  280.130    1028.0     100.0

                           wind_speed  wind_deg  rain_1h  snow_3h
clouds_all  \
time

2014-12-31 23:00:00+00:00         7.0      58.0      0.0      0.0
0.0
2015-01-01 00:00:00+00:00         7.0      58.0      0.0      0.0
0.0
2015-01-01 01:00:00+00:00         7.0      48.0      0.0      0.0
0.0
2015-01-01 02:00:00+00:00         7.0      48.0      0.0      0.0
0.0
2015-01-01 03:00:00+00:00         7.0      48.0      0.0      0.0
0.0
...                               ...       ...      ...      ...
...
2018-12-31 18:00:00+00:00         1.0     250.0      0.0      0.0
0.0
2018-12-31 19:00:00+00:00         3.0     270.0      0.0      0.0
0.0
2018-12-31 20:00:00+00:00         4.0     300.0      0.0      0.0
0.0
2018-12-31 21:00:00+00:00         5.0     320.0      0.0      0.0
0.0
2018-12-31 22:00:00+00:00         5.0     310.0      0.0      0.0
0.0

                           holiday
time
2014-12-31 23:00:00+00:00      1.0
2015-01-01 00:00:00+00:00      1.0
2015-01-01 01:00:00+00:00      1.0
2015-01-01 02:00:00+00:00      1.0
2015-01-01 03:00:00+00:00      1.0
...                            ...
2018-12-31 18:00:00+00:00      1.0
```

```
2018-12-31 19:00:00+00:00      1.0
2018-12-31 20:00:00+00:00      1.0
2018-12-31 21:00:00+00:00      1.0
2018-12-31 22:00:00+00:00      1.0

[35064 rows x 10 columns]

df_weather_energy = df_energy_features

for df_city in df_weather_all_cities:
    city_name = df_city.iloc[0]['city_name'].replace(' ', '')
    df_temp_city = df_city.add_suffix(f'_{city_name}')
    df_weather_energy = pd.concat([df_weather_energy, df_temp_city],
axis=1)
    df_weather_energy =
df_weather_energy.drop(f'city_name_{city_name}' , axis=1)

df_weather_energy.isnull().sum()

generation biomass                                0
generation fossil gas                             0
generation fossil oil                             0
generation hydro pumped storage consumption       0
generation hydro run-of-river and poundage        0
                                                 ..
wind_deg_Valencia                                 0
rain_1h_Valencia                                  0
snow_3h_Valencia                                  0
clouds_all_Valencia                               0
holiday_Valencia                                  0
Length: 62, dtype: int64

df_weather_energy.duplicated().sum()

0

df_weather_energy
```

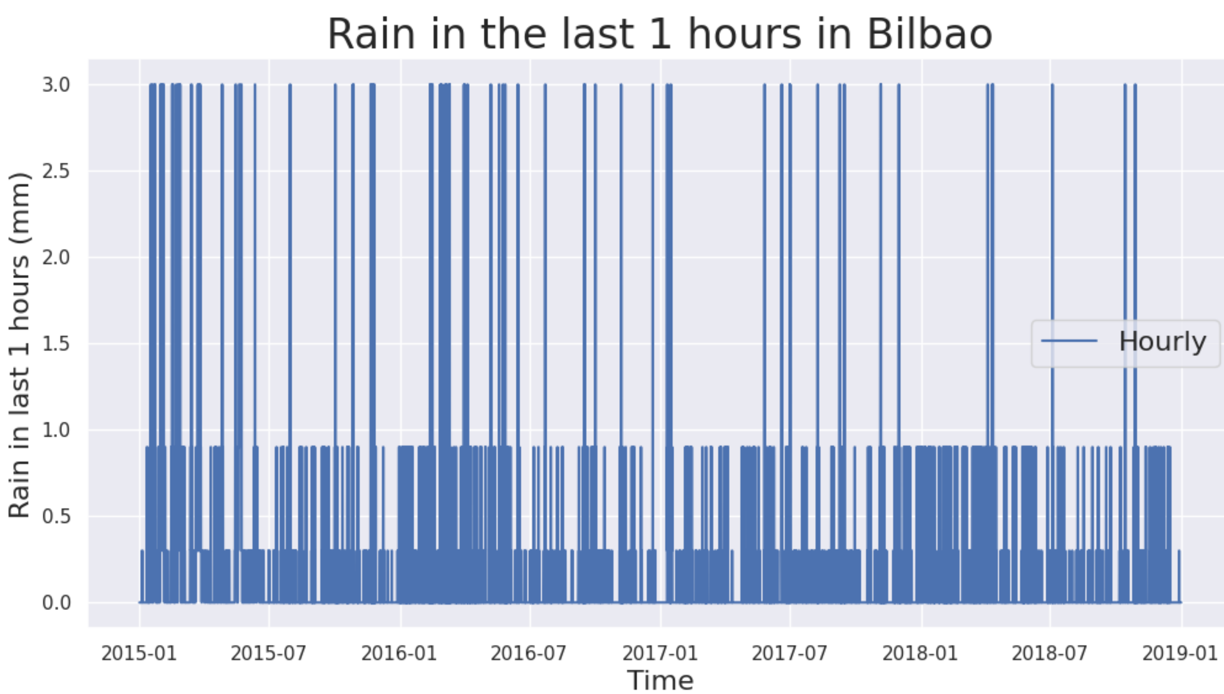
{"type":"dataframe","variable_name":"df_weather_energy"}

```
df_weather_energy.columns

Index(['generation biomass', 'generation fossil gas', '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
forecast',
```

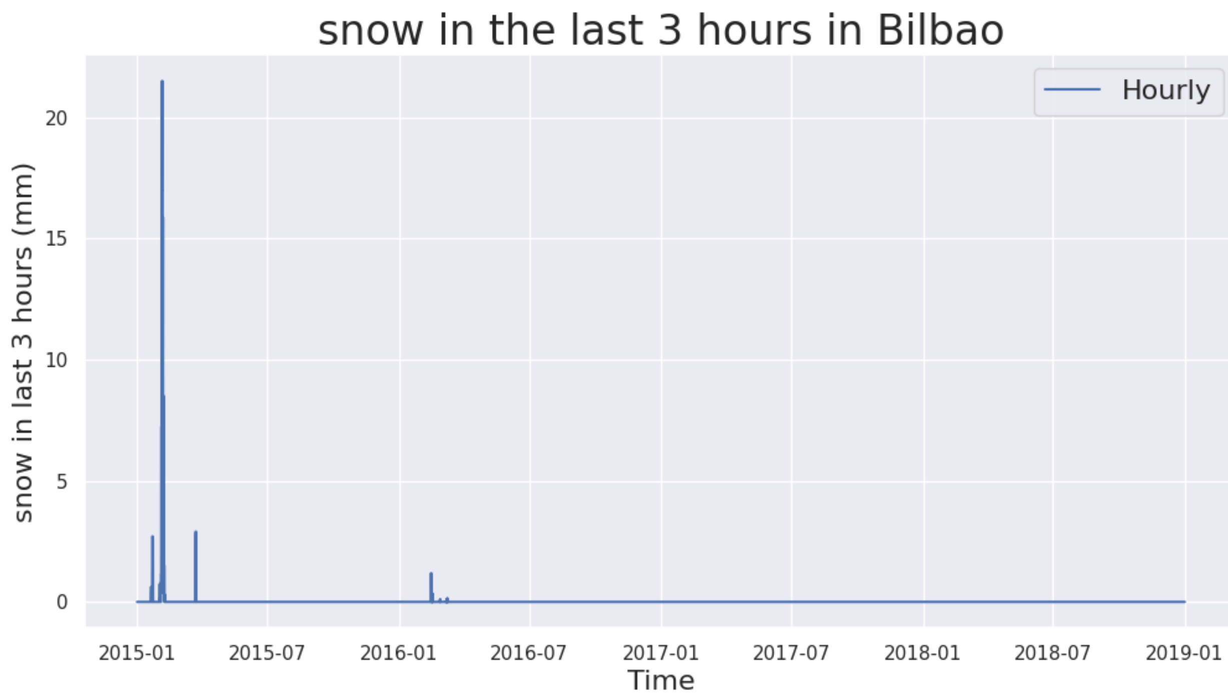
```
       'total load actual', 'price day ahead', 'price actual',
       'generation_total', 'temp_Barcelona', 'pressure_Barcelona',
       'humidity_Barcelona', 'wind_speed_Barcelona',
'wind_deg_Barcelona',
       'rain_1h_Barcelona', 'snow_3h_Barcelona',
'clouds_all_Barcelona',
       'holiday_Barcelona', 'temp_Bilbao', 'pressure_Bilbao',
       'humidity_Bilbao', 'wind_speed_Bilbao', 'wind_deg_Bilbao',
       'rain_1h_Bilbao', 'snow_3h_Bilbao', 'clouds_all_Bilbao',
       'holiday_Bilbao', 'temp_Madrid', 'pressure_Madrid',
'humidity_Madrid',
       'wind_speed_Madrid', 'wind_deg_Madrid', 'rain_1h_Madrid',
       'snow_3h_Madrid', 'clouds_all_Madrid', 'holiday_Madrid',
'temp_Seville',
       'pressure_Seville', 'humidity_Seville', 'wind_speed_Seville',
       'wind_deg_Seville', 'rain_1h_Seville', 'snow_3h_Seville',
       'clouds_all_Seville', 'holiday_Seville', 'temp_Valencia',
       'pressure_Valencia', 'humidity_Valencia',
'wind_speed_Valencia',
       'wind_deg_Valencia', 'rain_1h_Valencia', 'snow_3h_Valencia',
       'clouds_all_Valencia', 'holiday_Valencia'],
      dtype='object')
```

```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

def plot_series(df=None, column=None, series=None,
                label=None, ylabel=None, title=None, start=0,
end=None):

    sns.set()

    # Create the figure and axis
    fig, px = plt.subplots(figsize=(12, 6))  # More reasonable default
size

    # Set the x-axis label
    px.set_xlabel('Time', fontsize=16)

    # Plot from DataFrame if 'column' is provided
    if df is not None and column is not None:
        # Slice the DataFrame for start:end
        px.plot(df[column].iloc[start:end], label=label)

    # Plot from Series if 'series' is provided
    elif series is not None and not series.empty:
        px.plot(series.iloc[start:end], label=label)

    # Set the y-axis label if provided
```

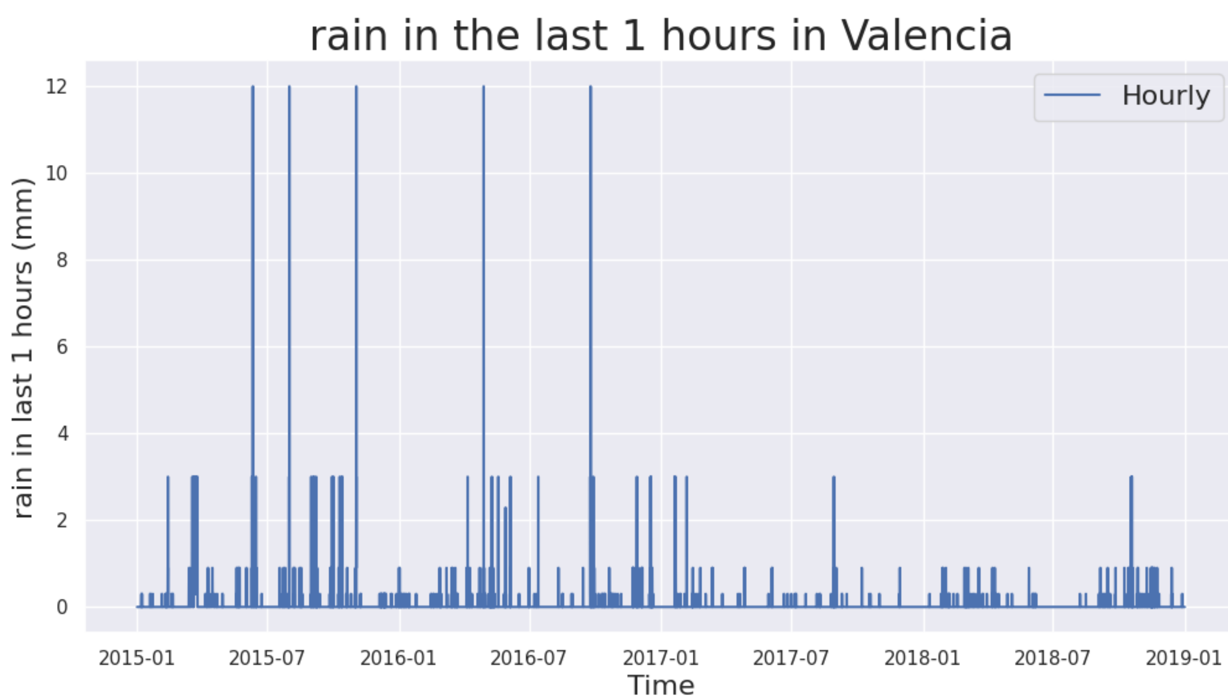
```
    if ylabel:
        px.set_ylabel(ylabel, fontsize=16)

    # Set the title if provided
    if title:
        px.set_title(title, fontsize=24)

    # Add legend if label is provided
    if label:
        px.legend(fontsize=16)

    # Enable grid
    px.grid(True)

    # Return the axis object
    return px

px = plot_series(df_weather_energy, 'rain_1h_Bilbao',
                 label='Hourly', ylabel='Rain in last 1 hours (mm)',
                 title='Rain in the last 1 hours in Bilbao')
plt.show()
```



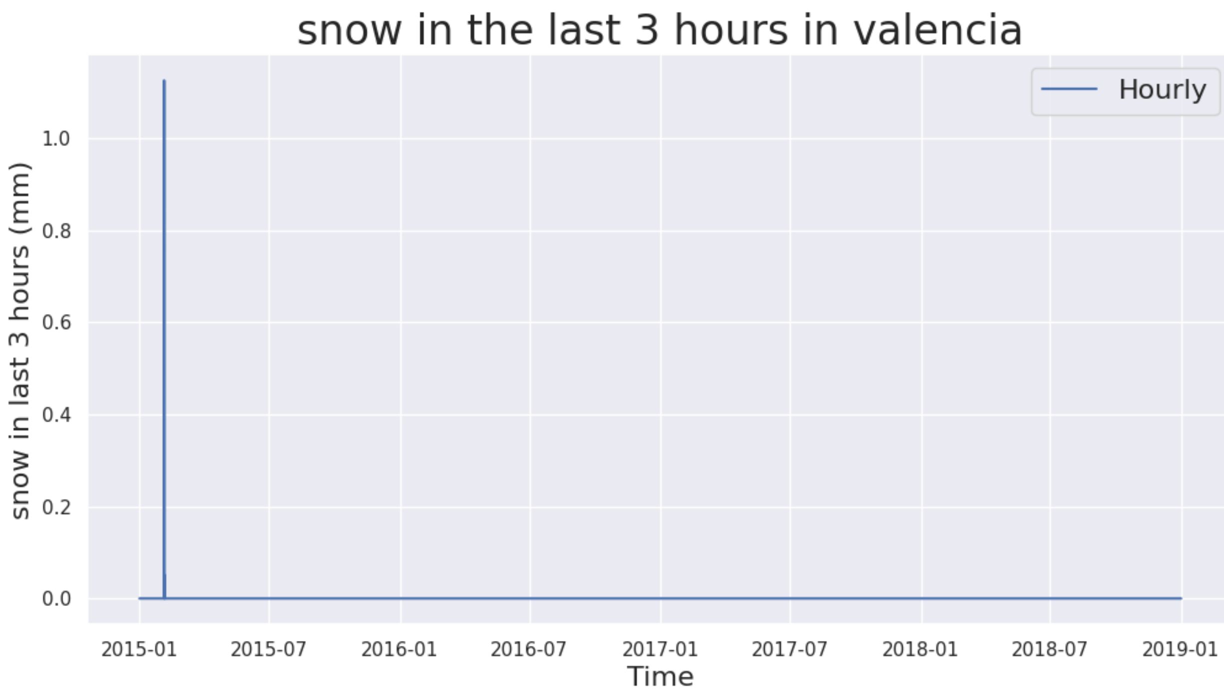

```
px = plot_series(df_weather_energy, 'snow_3h_Bilbao',
                 label='Hourly', ylabel='snow in last 3 hours (mm)',
                 title='snow in the last 3 hours in Bilbao')
plt.show()
```




```
px = plot_series(df_weather_energy, 'rain_1h_Valencia',
                 label='Hourly', ylabel='rain in last 1 hours (mm)',
                 title='rain in the last 1 hours in Valencia')
plt.show()
```

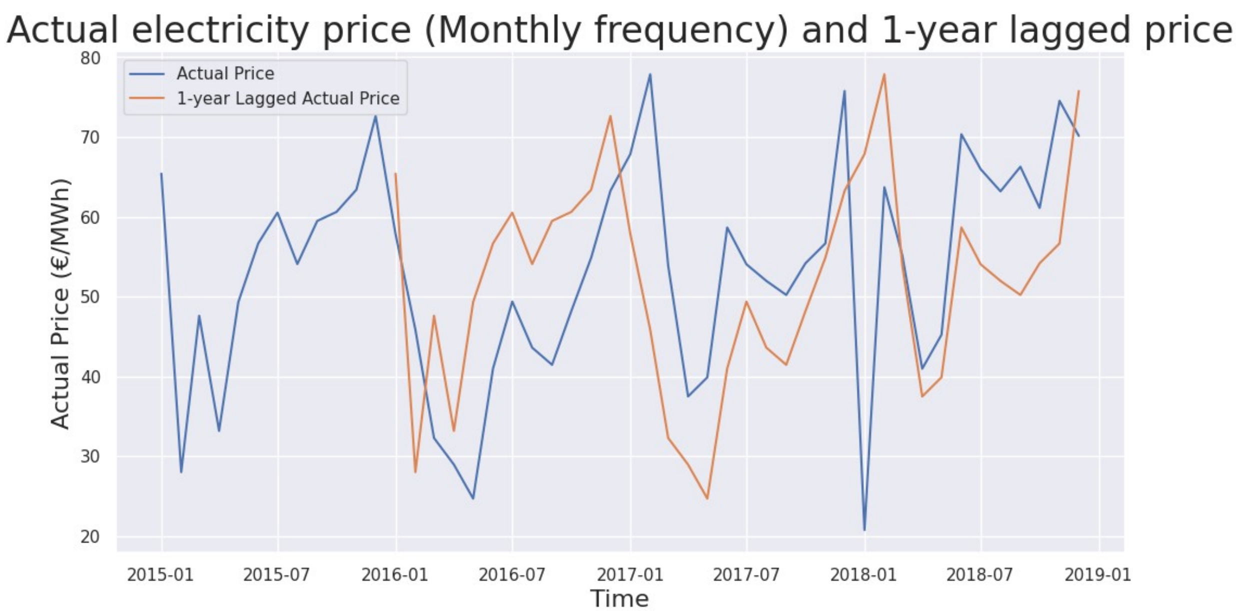


```
px = plot_series(df_weather_energy, 'snow_3h_Valencia',
                 label='Hourly', ylabel='snow in last 3 hours (mm)',
                 title='snow in the last 3 hours in valencia')
plt.show()
```




```
import plotly.graph_objects as go
from plotly.subplots import make_subplots

# Prepare data
time_index = df_weather_energy.index
price_actual = df_weather_energy["price actual"]
daily_rolling = price_actual.rolling(window=24).mean()
weekly_rolling = price_actual.rolling(window=24*7).mean()

# Create subplot
fig = make_subplots()

# Add traces for actual price, daily average, and weekly average with
custom colors
fig.add_trace(go.Scatter(x=time_index, y=price_actual, mode='lines',
name="price actual", line=dict(color='blue')))
fig.add_trace(go.Scatter(x=time_index, y=daily_rolling, mode='lines',
name="rolling window = daily ave", line=dict(color='green')))
fig.add_trace(go.Scatter(x=time_index, y=weekly_rolling, mode='lines',
name="rolling window = weekly ave", line=dict(color='orange')))

# Optionally, add range slider (uncomment if needed)
# fig.update_xaxes(rangeslider_visible=True)
```

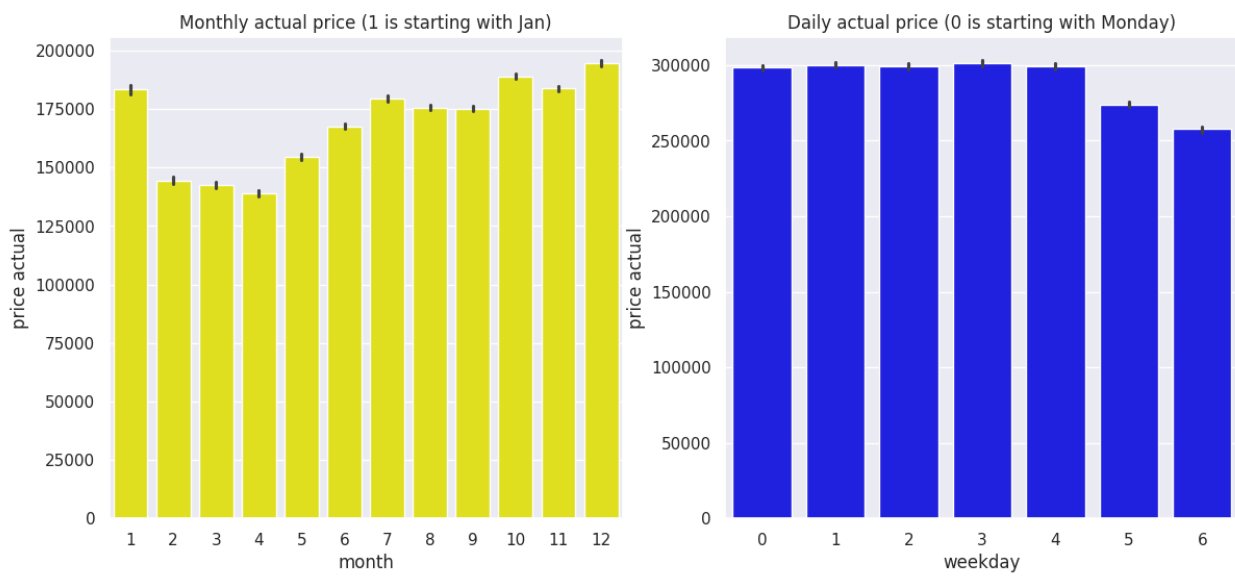
```
# Show the plot
fig.show()

monthly_price = df_weather_energy['price actual'].asfreq('ME')
ax = plot_series(series=monthly_price, ylabel='Actual Price (€/MWh)',
                 title='Actual electricity price (Monthly frequency)
and 1-year lagged price')
shifted = df_weather_energy['price actual'].asfreq('ME').shift(12)
ax.plot(shifted, label='Hourly')
ax.legend(['Actual Price', '1-year Lagged Actual Price'])
plt.show()
```




```
df_weather_energy['hour'] =
df_weather_energy.index.to_series().apply(lambda x: x.hour)
df_weather_energy['weekday'] =
df_weather_energy.index.to_series().apply(lambda x: x.weekday())
df_weather_energy['month'] =
df_weather_energy.index.to_series().apply(lambda x: x.month)
df_weather_energy['year'] =
df_weather_energy.index.to_series().apply(lambda x: x.year)

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

sns.barplot(
    x="month",
    y="price actual",
    data=df_weather_energy,
    estimator=sum,
    color='yellow',
```

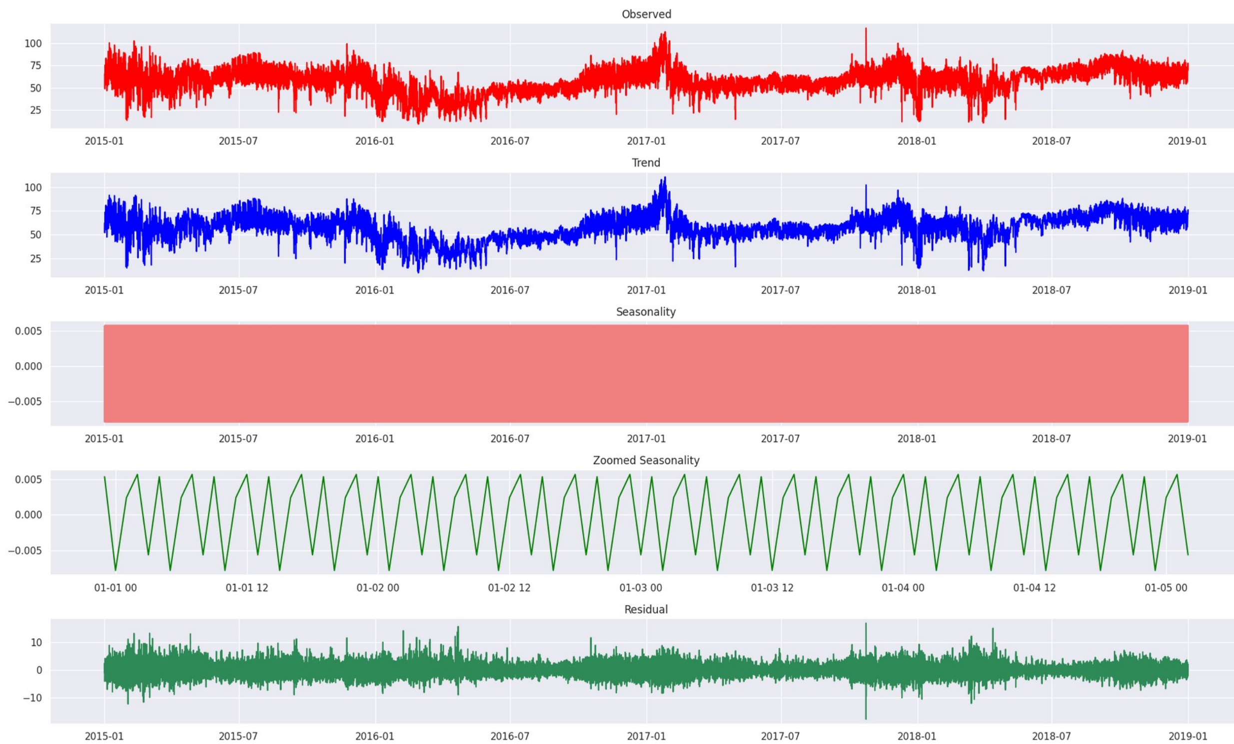
```
    ax=axes[0]);
axes[0].set_title('Monthly actual price (1 is starting with Jan)')

sns.barplot(
    x="weekday",
    y="price actual",
    data=df_weather_energy,
    estimator=sum,
    color='blue',
    ax=axes[1]);
axes[1].set_title('Daily actual price (0 is starting with Monday)')
```

```
Text(0.5, 1.0, 'Daily actual price (0 is starting with Monday)')
```




```
import matplotlib.pyplot as plt
from statsmodels.tsa.seasonal import seasonal_decompose

# Perform decomposition
decompose_result = seasonal_decompose(df_weather_energy['price
actual'], period=5, model='additive')

# Components to plot
components = {
    'Observed': decompose_result.observed,
    'Trend': decompose_result.trend,
    'Seasonality': decompose_result.seasonal,
    'Zoomed Seasonality': decompose_result.seasonal[:100],
    'Residual': decompose_result.resid
}
colors = ['red', 'blue', 'lightcoral', 'green', 'seagreen']

# Plot components in a loop
```

```python
fig, axes = plt.subplots(5, 1, figsize=(20, 12))
for ax, (title, data), color in zip(axes, components.items(), colors):
    ax.plot(data, color=color)
    ax.set_title(title)

fig.tight_layout()
plt.show()
```




```python
result = adfuller(df_weather_energy[['price actual']])
print('ADF Statistic:', result[0])
print('p-value:', result[1])
print('Critical Values:', result[4])
```

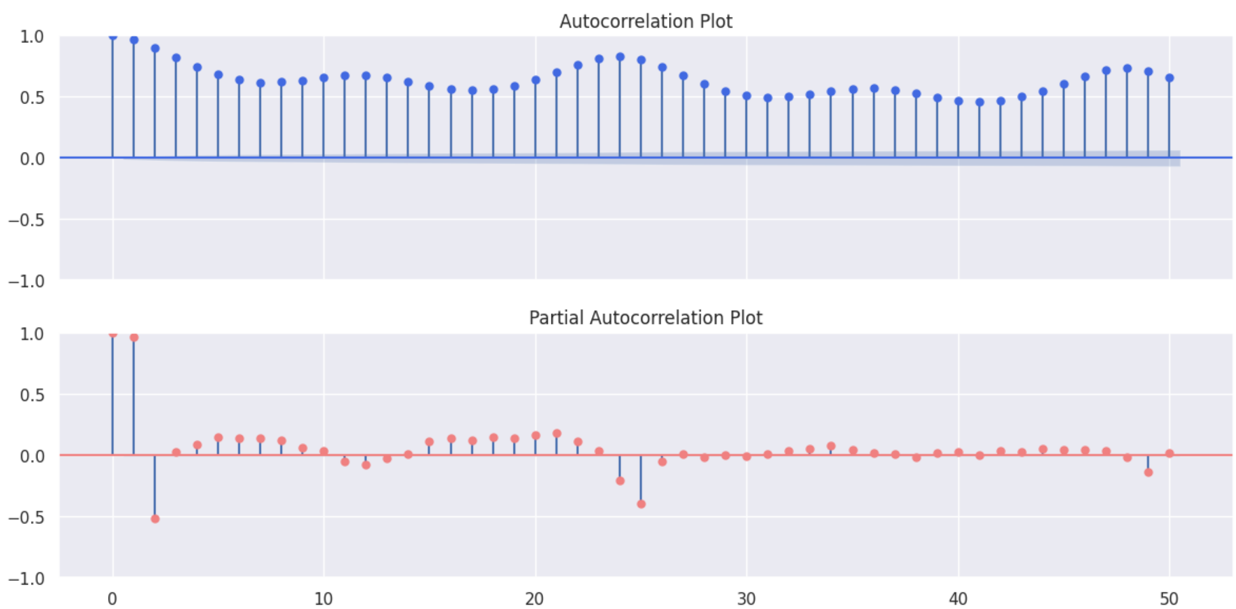
```
ADF Statistic: -9.147016232851248
p-value: 2.750493484933306e-15
Critical Values: {'1%': -3.4305367814665044, '5%': -
2.8616225527935106, '10%': -2.566813940257257}
```

```python
result = adfuller(df_weather_energy[['total load actual']])
print('ADF Statistic:', result[0])
print('p-value:', result[1])
print('Critical Values:', result[4])
```

```
ADF Statistic: -21.420315756960584
p-value: 0.0
Critical Values: {'1%': -3.43053679213716, '5%': -2.8616225575095284,
'10%': -2.566813942767471}
```

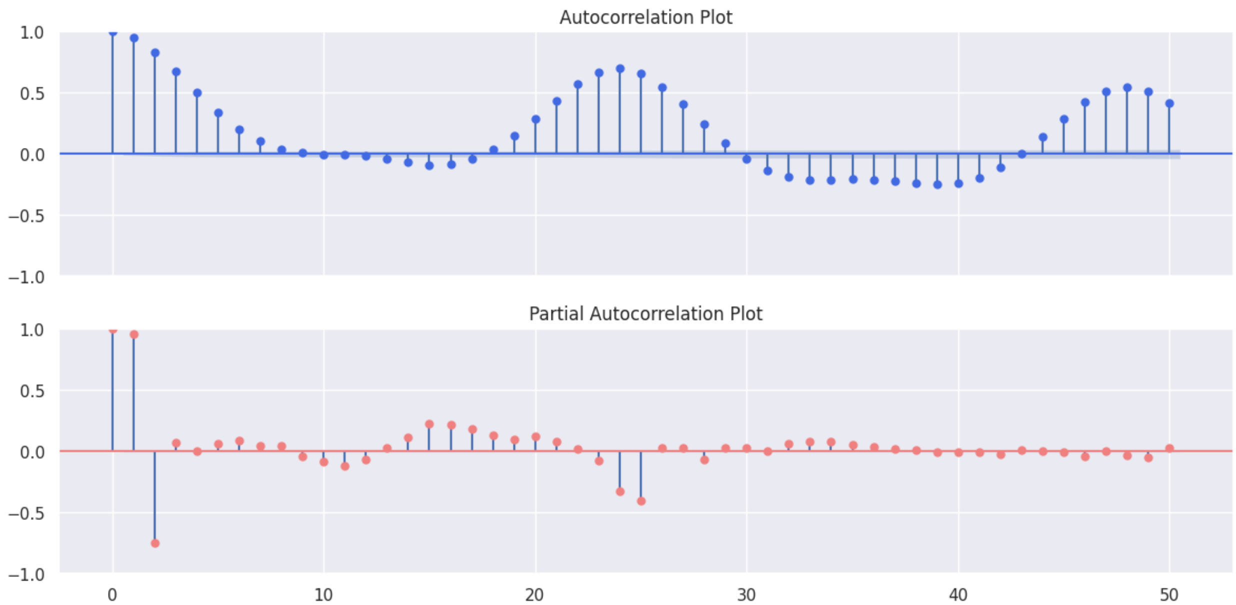
Conclusion: The time series is stationary, so no additional differencing is needed.

```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
import matplotlib.pyplot as plt

# Define plot settings for autocorrelation and partial autocorrelation
fig, axes = plt.subplots(2, 1, figsize=(12, 6), sharex=True)
titles = ['Autocorrelation Plot', 'Partial Autocorrelation Plot']
colors = ['royalblue', 'lightcoral']
plots = [plot_acf, plot_pacf]

# Loop through each plot type
for i, plot_func in enumerate(plots):
    plot_func(df_weather_energy['price actual'], lags=50, ax=axes[i],
color=colors[i])
    axes[i].set_title(titles[i])

plt.tight_layout()
plt.show()
```

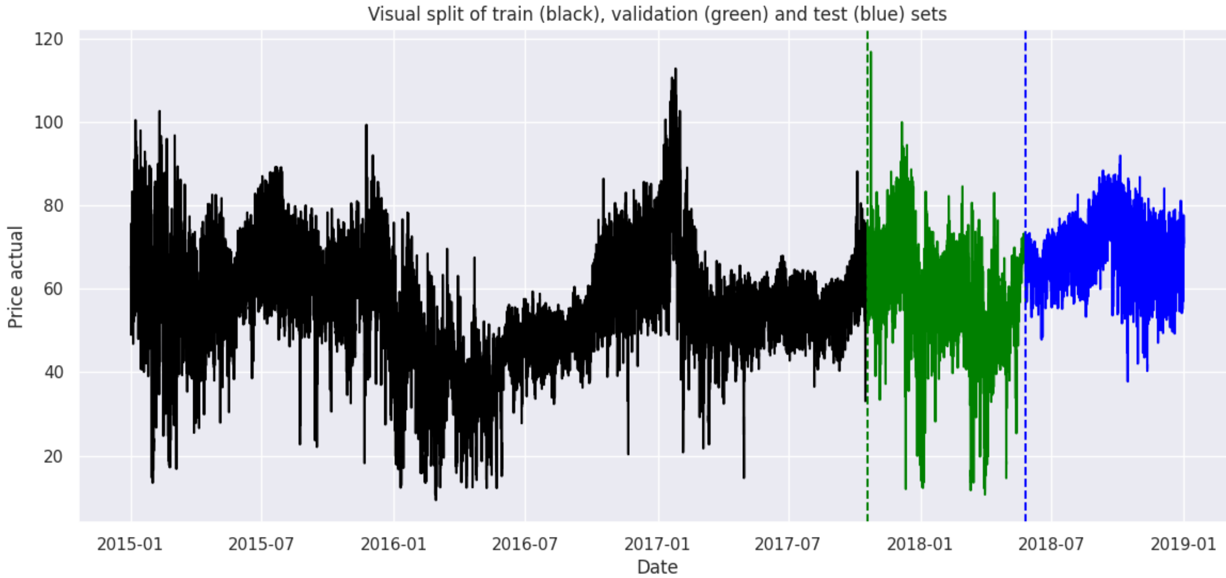



```
fig, axes = plt.subplots(2, 1, figsize=(12, 6), sharex=True)
titles = ['Autocorrelation Plot', 'Partial Autocorrelation Plot']
colors = ['royalblue', 'lightcoral']
plots = [plot_acf, plot_pacf]

# Loop through each plot type
for i, plot_func in enumerate(plots):
    plot_func(df_weather_energy['total load actual'], lags=50,
ax=axes[i], color=colors[i])
    axes[i].set_title(titles[i])
```

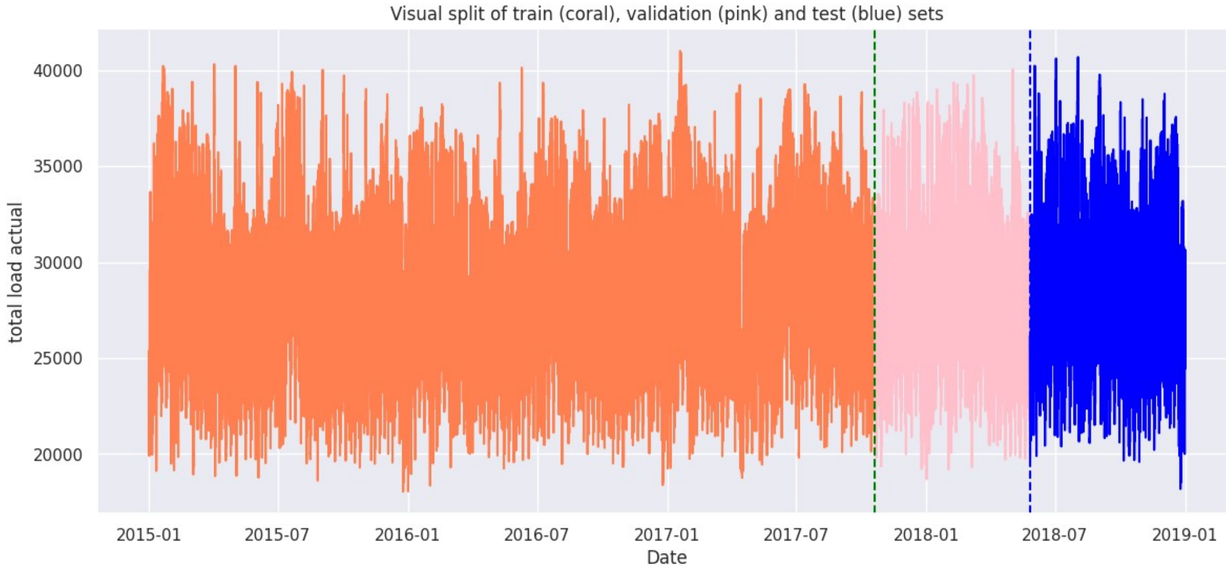
```
plt.tight_layout()
plt.show()
```




```
import matplotlib.pyplot as plt

train_cutoff = int(len(df_weather_energy) * 0.7)  # Example: 70% for
training
val_cutoff = int(len(df_weather_energy) * 0.85)  # Example: 15% for
validation (85% - 70%)

fig, axes = plt.subplots(figsize=(14, 6))
axes.plot(df_weather_energy['price actual'].iloc[:train_cutoff],
color='black')
axes.plot(df_weather_energy['price actual'].iloc[train_cutoff +
1:val_cutoff], color='green')
axes.plot(df_weather_energy['price actual'].iloc[val_cutoff + 1:],
color='blue')
axes.axvline(x=df_weather_energy.index[train_cutoff], color='green',
linestyle='--')
axes.axvline(x=df_weather_energy.index[val_cutoff], color='blue',
linestyle='--')
axes.set_title('Visual split of train (black), validation (green) and
test (blue) sets')
axes.set_xlabel('Date')
axes.set_ylabel('Price actual')
plt.show()
```




```
train_cutoff = int(len(df_weather_energy) * 0.7)  # Example: 70% for
training
val_cutoff = int(len(df_weather_energy) * 0.85)  # Example: 15% for
validation (85% - 70%)

fig, axes = plt.subplots(figsize=(14, 6))
axes.plot(df_weather_energy['total load actual'].iloc[:train_cutoff],
color='coral')
axes.plot(df_weather_energy['total load actual'].iloc[train_cutoff +
1:val_cutoff], color='pink')
axes.plot(df_weather_energy['total load actual'].iloc[val_cutoff +
1:], color='blue')
axes.axvline(x=df_weather_energy.index[train_cutoff], color='green',
linestyle='--')
axes.axvline(x=df_weather_energy.index[val_cutoff], color='blue',
linestyle='--')
axes.set_title('Visual split of train (coral), validation (pink) and
test (blue) sets')
axes.set_xlabel('Date')
axes.set_ylabel('total load actual')
plt.show()
```



XG BOOST MODEL

```
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error
import xgboost as xgb
import pandas as pd
import numpy as np

# Assuming 'df_weather_energy' is already loaded as a DataFrame
# Step 1: Prepare features (X) and target (y)
X = df_weather_energy.drop(['price actual'], axis=1)
y = df_weather_energy['price actual']

# Step 2: Train-Test Split
X_train, X_temp, y_train, y_temp = train_test_split(X, y,
test_size=0.2, random_state=42)
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp,
test_size=0.5, random_state=42)

# Step 3: Convert Data to DMatrix
dtrain = xgb.DMatrix(X_train, label=y_train)
dval = xgb.DMatrix(X_val, label=y_val)
dtest = xgb.DMatrix(X_test, label=y_test)

# Step 4: Define Parameters for XGBoost
params = {
    'objective': 'reg:squarederror',  # Regression objective
    'random_state': 42,
    'eval_metric': 'rmse',  # Metric to evaluate during training
}
```

```python
# Step 5: Train XGBoost Model with Early Stopping
evals = [(dtrain, 'train'), (dval, 'eval')]
evals_result = {}  # To store the evaluation results

xgboost_model = xgb.train(
    params=params,
    dtrain=dtrain,
    num_boost_round=500,  # Maximum number of boosting rounds
    early_stopping_rounds=10,  # Stop training if no improvement after
10 rounds
    evals=evals,
    evals_result=evals_result,  # Store evaluation results here
    verbose_eval=True
)

# Step 6: Make Predictions
y_pred = xgboost_model.predict(dtest)

# Step 7: Calculate Metrics
mae = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
mape = np.mean(np.abs((y_test - y_pred) / y_test)) * 100  # Mean
Absolute Percentage Error

# Calculate Accuracy as 1 - (Normalized MAE)
mean_actual = np.mean(y_test)
accuracy = (1 - (mae / mean_actual)) * 100

# Print Results
print(f"Mean Absolute Error (MAE): {mae}")
print(f"Root Mean Squared Error (RMSE): {rmse}")
print(f"Mean Absolute Percentage Error (MAPE): {mape:.2f}%")
print(f"Accuracy: {accuracy:.2f}%")

# Plot Results using the plot_results function
def plot_results(y_pred, y_test, evals_result, model_name):
    fig, ax = plt.subplots(2, 1, figsize=(12, 6))

    # Plotting prediction vs actual for the first 1000 observations
    ax[0].plot(y_pred[:1000], label='Prediction')
    ax[0].plot(y_test[:1000].values, label='Actual')
    ax[0].legend(loc='upper left')
    ax[0].set_title(f'Prediction vs Actual for 1000 observations in
Test Set ({model_name})')
    ax[0].set_xlabel('Observation')
    ax[0].set_ylabel('price actual')

    # Extract training and validation RMSE from evals_result
    train_rmse = evals_result['train']['rmse']
    val_rmse = evals_result['eval']['rmse']
```

```python
    # Plot RMSE for training and validation
    ax[1].plot(train_rmse, label='Training RMSE')
    ax[1].plot(val_rmse, label='Validation RMSE')

    ax[1].legend()
    ax[1].set_title(f'Training and Validation RMSE ({model_name})')
    ax[1].set_xlabel('Iteration')
    ax[1].set_ylabel('RMSE')

    fig.tight_layout()
    plt.show()

# Call the function to plot results
plot_results(y_pred, y_test, evals_result, 'XGBoost')
```

```
[0]	train-rmse:11.38927	eval-rmse:11.33749
[1]	train-rmse:9.49666	eval-rmse:9.54363
[2]	train-rmse:8.24840	eval-rmse:8.37787
[3]	train-rmse:7.38621	eval-rmse:7.60264
[4]	train-rmse:6.77502	eval-rmse:7.03955
[5]	train-rmse:6.33795	eval-rmse:6.64540
[6]	train-rmse:5.95068	eval-rmse:6.31109
[7]	train-rmse:5.65098	eval-rmse:6.05233
[8]	train-rmse:5.34229	eval-rmse:5.78414
[9]	train-rmse:4.98549	eval-rmse:5.45353
[10]	train-rmse:4.83535	eval-rmse:5.31613
[11]	train-rmse:4.70675	eval-rmse:5.21496
[12]	train-rmse:4.52258	eval-rmse:5.04659
[13]	train-rmse:4.40622	eval-rmse:4.93890
[14]	train-rmse:4.31609	eval-rmse:4.86779
[15]	train-rmse:4.23425	eval-rmse:4.79228
[16]	train-rmse:4.16175	eval-rmse:4.72743
[17]	train-rmse:4.04820	eval-rmse:4.62982
[18]	train-rmse:3.95808	eval-rmse:4.56161
[19]	train-rmse:3.89846	eval-rmse:4.50902
[20]	train-rmse:3.84802	eval-rmse:4.45727
[21]	train-rmse:3.81566	eval-rmse:4.43067
[22]	train-rmse:3.77556	eval-rmse:4.38767
[23]	train-rmse:3.72363	eval-rmse:4.34813
[24]	train-rmse:3.66229	eval-rmse:4.30377
[25]	train-rmse:3.62402	eval-rmse:4.27363
[26]	train-rmse:3.56306	eval-rmse:4.23637
[27]	train-rmse:3.52139	eval-rmse:4.21152
[28]	train-rmse:3.47709	eval-rmse:4.18282
[29]	train-rmse:3.41014	eval-rmse:4.12289
[30]	train-rmse:3.37630	eval-rmse:4.09194
[31]	train-rmse:3.34253	eval-rmse:4.06087
[32]	train-rmse:3.31469	eval-rmse:4.03975
[33]	train-rmse:3.29060	eval-rmse:4.01448
```

```
[34]	train-rmse:3.26279	eval-rmse:3.99697
[35]	train-rmse:3.23069	eval-rmse:3.96667
[36]	train-rmse:3.19139	eval-rmse:3.94352
[37]	train-rmse:3.15114	eval-rmse:3.92578
[38]	train-rmse:3.13272	eval-rmse:3.91372
[39]	train-rmse:3.09996	eval-rmse:3.89237
[40]	train-rmse:3.08979	eval-rmse:3.88515
[41]	train-rmse:3.05480	eval-rmse:3.86289
[42]	train-rmse:3.03801	eval-rmse:3.85157
[43]	train-rmse:3.02373	eval-rmse:3.83911
[44]	train-rmse:2.99663	eval-rmse:3.82250
[45]	train-rmse:2.97765	eval-rmse:3.80438
[46]	train-rmse:2.95221	eval-rmse:3.78888
[47]	train-rmse:2.93800	eval-rmse:3.78084
[48]	train-rmse:2.90555	eval-rmse:3.76316
[49]	train-rmse:2.88388	eval-rmse:3.75126
[50]	train-rmse:2.87536	eval-rmse:3.74451
[51]	train-rmse:2.86244	eval-rmse:3.73523
[52]	train-rmse:2.84467	eval-rmse:3.72077
[53]	train-rmse:2.83743	eval-rmse:3.71625
[54]	train-rmse:2.82206	eval-rmse:3.71254
[55]	train-rmse:2.79395	eval-rmse:3.68943
[56]	train-rmse:2.78174	eval-rmse:3.68493
[57]	train-rmse:2.76171	eval-rmse:3.67586
[58]	train-rmse:2.73933	eval-rmse:3.66392
[59]	train-rmse:2.72369	eval-rmse:3.65446
[60]	train-rmse:2.72036	eval-rmse:3.65288
[61]	train-rmse:2.70256	eval-rmse:3.64514
[62]	train-rmse:2.67449	eval-rmse:3.63448
[63]	train-rmse:2.66749	eval-rmse:3.63247
[64]	train-rmse:2.64816	eval-rmse:3.62332
[65]	train-rmse:2.63071	eval-rmse:3.61405
[66]	train-rmse:2.61008	eval-rmse:3.60517
[67]	train-rmse:2.59011	eval-rmse:3.59473
[68]	train-rmse:2.56816	eval-rmse:3.57831
[69]	train-rmse:2.55043	eval-rmse:3.56364
[70]	train-rmse:2.52969	eval-rmse:3.54701
[71]	train-rmse:2.51953	eval-rmse:3.54579
[72]	train-rmse:2.51578	eval-rmse:3.54461
[73]	train-rmse:2.49932	eval-rmse:3.53537
[74]	train-rmse:2.47578	eval-rmse:3.52025
[75]	train-rmse:2.45465	eval-rmse:3.50653
[76]	train-rmse:2.43914	eval-rmse:3.49404
[77]	train-rmse:2.42670	eval-rmse:3.48207
[78]	train-rmse:2.40762	eval-rmse:3.47160
[79]	train-rmse:2.39953	eval-rmse:3.46805
[80]	train-rmse:2.38679	eval-rmse:3.45782
[81]	train-rmse:2.37203	eval-rmse:3.44599
[82]	train-rmse:2.36705	eval-rmse:3.44041
```

```
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[405]	train-rmse:0.79553	eval-rmse:2.93525
[406]	train-rmse:0.79358	eval-rmse:2.93462
[407]	train-rmse:0.79091	eval-rmse:2.93424
[408]	train-rmse:0.79043	eval-rmse:2.93400
[409]	train-rmse:0.78876	eval-rmse:2.93424
[410]	train-rmse:0.78755	eval-rmse:2.93412
[411]	train-rmse:0.78599	eval-rmse:2.93433
[412]	train-rmse:0.78363	eval-rmse:2.93374
[413]	train-rmse:0.78037	eval-rmse:2.93306
[414]	train-rmse:0.77928	eval-rmse:2.93328
[415]	train-rmse:0.77820	eval-rmse:2.93321
[416]	train-rmse:0.77631	eval-rmse:2.93345
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[419]	train-rmse:0.77204	eval-rmse:2.93380
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[422]	train-rmse:0.76715	eval-rmse:2.93259
[423]	train-rmse:0.76586	eval-rmse:2.93213
[424]	train-rmse:0.76447	eval-rmse:2.93169
[425]	train-rmse:0.76357	eval-rmse:2.93139
```

```
[426]	train-rmse:0.76090	eval-rmse:2.93079
[427]	train-rmse:0.76029	eval-rmse:2.93090
[428]	train-rmse:0.75820	eval-rmse:2.92996
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[431]	train-rmse:0.75124	eval-rmse:2.92871
[432]	train-rmse:0.74926	eval-rmse:2.92811
[433]	train-rmse:0.74761	eval-rmse:2.92799
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[435]	train-rmse:0.74240	eval-rmse:2.92699
[436]	train-rmse:0.74051	eval-rmse:2.92704
[437]	train-rmse:0.73803	eval-rmse:2.92641
[438]	train-rmse:0.73575	eval-rmse:2.92537
[439]	train-rmse:0.73413	eval-rmse:2.92538
[440]	train-rmse:0.73254	eval-rmse:2.92488
[441]	train-rmse:0.72935	eval-rmse:2.92459
[442]	train-rmse:0.72792	eval-rmse:2.92422
[443]	train-rmse:0.72593	eval-rmse:2.92380
[444]	train-rmse:0.72477	eval-rmse:2.92271
[445]	train-rmse:0.72389	eval-rmse:2.92252
[446]	train-rmse:0.72141	eval-rmse:2.92246
[447]	train-rmse:0.72010	eval-rmse:2.92260
[448]	train-rmse:0.71782	eval-rmse:2.92224
[449]	train-rmse:0.71558	eval-rmse:2.92209
[450]	train-rmse:0.71367	eval-rmse:2.92167
[451]	train-rmse:0.71170	eval-rmse:2.92117
[452]	train-rmse:0.70975	eval-rmse:2.92157
[453]	train-rmse:0.70847	eval-rmse:2.92147
[454]	train-rmse:0.70664	eval-rmse:2.92121
[455]	train-rmse:0.70481	eval-rmse:2.92148
[456]	train-rmse:0.70230	eval-rmse:2.92123
[457]	train-rmse:0.70144	eval-rmse:2.92071
[458]	train-rmse:0.70035	eval-rmse:2.91999
[459]	train-rmse:0.69920	eval-rmse:2.91920
[460]	train-rmse:0.69709	eval-rmse:2.91818
[461]	train-rmse:0.69553	eval-rmse:2.91805
[462]	train-rmse:0.69284	eval-rmse:2.91794
[463]	train-rmse:0.69120	eval-rmse:2.91807
[464]	train-rmse:0.68898	eval-rmse:2.91789
[465]	train-rmse:0.68807	eval-rmse:2.91790
[466]	train-rmse:0.68583	eval-rmse:2.91790
[467]	train-rmse:0.68363	eval-rmse:2.91774
[468]	train-rmse:0.68101	eval-rmse:2.91686
[469]	train-rmse:0.67943	eval-rmse:2.91640
[470]	train-rmse:0.67705	eval-rmse:2.91635
[471]	train-rmse:0.67508	eval-rmse:2.91629
[472]	train-rmse:0.67393	eval-rmse:2.91601
[473]	train-rmse:0.67168	eval-rmse:2.91551
[474]	train-rmse:0.66940	eval-rmse:2.91495
```
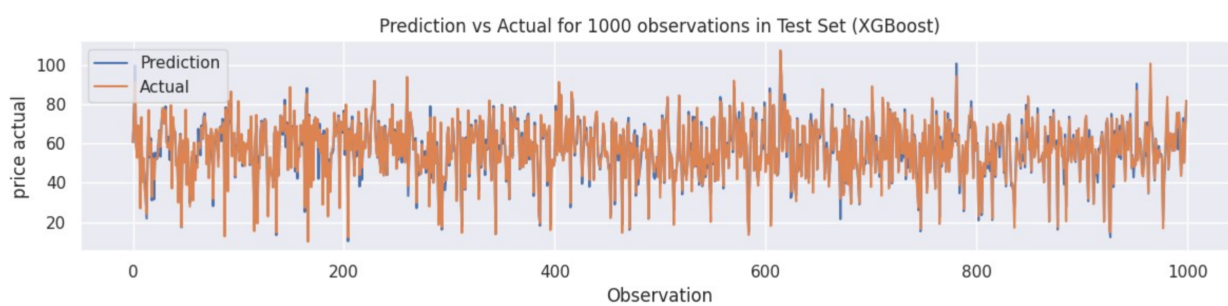

```
[475] train-rmse:0.66754    eval-rmse:2.91464
[476] train-rmse:0.66614    eval-rmse:2.91376
[477] train-rmse:0.66401    eval-rmse:2.91313
[478] train-rmse:0.66176    eval-rmse:2.91296
[479] train-rmse:0.66110    eval-rmse:2.91318
[480] train-rmse:0.65895    eval-rmse:2.91257
[481] train-rmse:0.65762    eval-rmse:2.91236
[482] train-rmse:0.65611    eval-rmse:2.91235
[483] train-rmse:0.65415    eval-rmse:2.91219
[484] train-rmse:0.65238    eval-rmse:2.91182
[485] train-rmse:0.65021    eval-rmse:2.91169
[486] train-rmse:0.64942    eval-rmse:2.91172
[487] train-rmse:0.64727    eval-rmse:2.91106
[488] train-rmse:0.64477    eval-rmse:2.91041
[489] train-rmse:0.64360    eval-rmse:2.91016
[490] train-rmse:0.64232    eval-rmse:2.90971
[491] train-rmse:0.64166    eval-rmse:2.90959
[492] train-rmse:0.63998    eval-rmse:2.90933
[493] train-rmse:0.63953    eval-rmse:2.90914
[494] train-rmse:0.63821    eval-rmse:2.90917
[495] train-rmse:0.63626    eval-rmse:2.90963
[496] train-rmse:0.63600    eval-rmse:2.90956
[497] train-rmse:0.63452    eval-rmse:2.91008
[498] train-rmse:0.63331    eval-rmse:2.90986
[499] train-rmse:0.63169    eval-rmse:2.90935
Mean Absolute Error (MAE): 2.124053182436049
Root Mean Squared Error (RMSE): 3.067974857555092
Mean Absolute Percentage Error (MAPE): 4.25%
Accuracy: 96.30%
```



```
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error
import xgboost as xgb
import pandas as pd
import numpy as np

# Assuming 'df_weather_energy' is already loaded as a DataFrame
# Step 1: Prepare features (X) and target (y)
X = df_weather_energy.drop(['total load actual'], axis=1)
y = df_weather_energy['total load actual']

# Step 2: Train-Test Split
X_train, X_temp, y_train, y_temp = train_test_split(X, y,
test_size=0.2, random_state=42)
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp,
test_size=0.5, random_state=42)

# Step 3: Convert Data to DMatrix
dtrain = xgb.DMatrix(X_train, label=y_train)
dval = xgb.DMatrix(X_val, label=y_val)
dtest = xgb.DMatrix(X_test, label=y_test)

# Step 4: Define Parameters for XGBoost
params = {
    'objective': 'reg:squarederror',  # Regression objective
    'random_state': 42,
    'eval_metric': 'rmse',  # Metric to evaluate during training
}

# Step 5: Train XGBoost Model with Early Stopping
evals = [(dtrain, 'train'), (dval, 'eval')]
evals_result = {}  # To store the evaluation results

xgboost_model = xgb.train(
    params=params,
    dtrain=dtrain,
    num_boost_round=500,  # Maximum number of boosting rounds
    early_stopping_rounds=10,  # Stop training if no improvement after
10 rounds
    evals=evals,
    evals_result=evals_result,  # Store evaluation results here
    verbose_eval=True
)

# Step 6: Make Predictions
y_pred = xgboost_model.predict(dtest)

# Step 7: Calculate Metrics
mae = mean_absolute_error(y_test, y_pred)
```

```python
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
mape = np.mean(np.abs((y_test - y_pred) / y_test)) * 100  # Mean
Absolute Percentage Error

# Calculate Accuracy as 1 - (Normalized MAE)
mean_actual = np.mean(y_test)
accuracy = (1 - (mae / mean_actual)) * 100

# Print Results
print(f"Mean Absolute Error (MAE): {mae}")
print(f"Root Mean Squared Error (RMSE): {rmse}")
print(f"Mean Absolute Percentage Error (MAPE): {mape:.2f}%")
print(f"Accuracy: {accuracy:.2f}%")

# Plot Results using the plot_results function
def plot_results(y_pred, y_test, evals_result, model_name):
    fig, ax = plt.subplots(2, 1, figsize=(12, 6))

    # Plotting prediction vs actual for the first 1000 observations
    ax[0].plot(y_pred[:1000], label='Prediction')
    ax[0].plot(y_test[:1000].values, label='Actual')
    ax[0].legend(loc='upper left')
    ax[0].set_title(f'Prediction vs Actual for 1000 observations in
Test Set ({model_name})')
    ax[0].set_xlabel('Observation')
    ax[0].set_ylabel('Total Load')

    # Extract training and validation RMSE from evals_result
    train_rmse = evals_result['train']['rmse']
    val_rmse = evals_result['eval']['rmse']

    # Plot RMSE for training and validation
    ax[1].plot(train_rmse, label='Training RMSE')
    ax[1].plot(val_rmse, label='Validation RMSE')

    ax[1].legend()
    ax[1].set_title(f'Training and Validation RMSE ({model_name})')
    ax[1].set_xlabel('Iteration')
    ax[1].set_ylabel('RMSE')

    fig.tight_layout()
    plt.show()

# Call the function to plot results
plot_results(y_pred, y_test, evals_result, 'XGBoost')
```

```
[0]	train-rmse:3223.45802	eval-rmse:3247.51617
[1]	train-rmse:2280.16447	eval-rmse:2302.82134
[2]	train-rmse:1627.23376	eval-rmse:1649.82824
[3]	train-rmse:1180.38659	eval-rmse:1204.05018
```

```
[4]	train-rmse:879.86241	eval-rmse:906.13044
[5]	train-rmse:683.60161	eval-rmse:712.63274
[6]	train-rmse:560.72581	eval-rmse:592.44403
[7]	train-rmse:486.45202	eval-rmse:520.86192
[8]	train-rmse:442.20571	eval-rmse:479.34657
[9]	train-rmse:415.27903	eval-rmse:454.56851
[10]	train-rmse:398.29575	eval-rmse:437.67499
[11]	train-rmse:386.37849	eval-rmse:426.42089
[12]	train-rmse:376.95510	eval-rmse:418.64664
[13]	train-rmse:368.77415	eval-rmse:411.59055
[14]	train-rmse:361.27884	eval-rmse:405.95663
[15]	train-rmse:355.99736	eval-rmse:402.29231
[16]	train-rmse:350.14027	eval-rmse:396.42569
[17]	train-rmse:346.25532	eval-rmse:394.40096
[18]	train-rmse:341.48924	eval-rmse:390.65301
[19]	train-rmse:337.67796	eval-rmse:387.01968
[20]	train-rmse:334.32903	eval-rmse:384.12726
[21]	train-rmse:330.43209	eval-rmse:379.58460
[22]	train-rmse:326.44989	eval-rmse:377.31836
[23]	train-rmse:322.63927	eval-rmse:375.08381
[24]	train-rmse:320.34407	eval-rmse:373.92342
[25]	train-rmse:316.55530	eval-rmse:371.25287
[26]	train-rmse:315.04865	eval-rmse:370.53741
[27]	train-rmse:310.86390	eval-rmse:368.04975
[28]	train-rmse:307.83893	eval-rmse:366.03314
[29]	train-rmse:305.05817	eval-rmse:363.49304
[30]	train-rmse:302.49913	eval-rmse:361.57088
[31]	train-rmse:299.96419	eval-rmse:360.22626
[32]	train-rmse:298.00610	eval-rmse:358.63855
[33]	train-rmse:295.38414	eval-rmse:355.98190
[34]	train-rmse:293.16310	eval-rmse:354.27693
[35]	train-rmse:290.69570	eval-rmse:352.15991
[36]	train-rmse:287.88470	eval-rmse:349.92237
[37]	train-rmse:285.62469	eval-rmse:348.22948
[38]	train-rmse:283.76141	eval-rmse:346.94857
[39]	train-rmse:281.69572	eval-rmse:345.91711
[40]	train-rmse:279.34233	eval-rmse:344.97726
[41]	train-rmse:277.09168	eval-rmse:344.06711
[42]	train-rmse:274.45140	eval-rmse:342.67339
[43]	train-rmse:271.99143	eval-rmse:341.78846
[44]	train-rmse:270.62794	eval-rmse:341.04953
[45]	train-rmse:268.38909	eval-rmse:339.82841
[46]	train-rmse:267.49667	eval-rmse:339.24613
[47]	train-rmse:265.73578	eval-rmse:338.20682
[48]	train-rmse:263.92930	eval-rmse:337.05187
[49]	train-rmse:262.09739	eval-rmse:336.59458
[50]	train-rmse:260.34705	eval-rmse:335.61718
[51]	train-rmse:259.09789	eval-rmse:334.83762
[52]	train-rmse:256.70379	eval-rmse:333.82348
```

```
[53]	train-rmse:254.66352	eval-rmse:333.18993
[54]	train-rmse:253.02151	eval-rmse:332.15605
[55]	train-rmse:251.53814	eval-rmse:331.00930
[56]	train-rmse:249.20678	eval-rmse:329.18847
[57]	train-rmse:247.24644	eval-rmse:328.36958
[58]	train-rmse:246.07892	eval-rmse:327.56316
[59]	train-rmse:243.85230	eval-rmse:326.68492
[60]	train-rmse:241.51642	eval-rmse:325.39876
[61]	train-rmse:240.30438	eval-rmse:325.06884
[62]	train-rmse:239.97924	eval-rmse:325.01255
[63]	train-rmse:238.76363	eval-rmse:324.05233
[64]	train-rmse:237.27469	eval-rmse:323.22162
[65]	train-rmse:236.04262	eval-rmse:322.73509
[66]	train-rmse:234.91258	eval-rmse:322.02842
[67]	train-rmse:233.31813	eval-rmse:321.10199
[68]	train-rmse:231.51256	eval-rmse:320.32465
[69]	train-rmse:230.24194	eval-rmse:319.52275
[70]	train-rmse:228.89590	eval-rmse:318.84657
[71]	train-rmse:227.89987	eval-rmse:318.46617
[72]	train-rmse:226.42091	eval-rmse:317.60857
[73]	train-rmse:224.99314	eval-rmse:316.97440
[74]	train-rmse:224.23121	eval-rmse:316.90428
[75]	train-rmse:222.64241	eval-rmse:315.91318
[76]	train-rmse:221.74452	eval-rmse:315.58945
[77]	train-rmse:220.50470	eval-rmse:314.76526
[78]	train-rmse:219.50465	eval-rmse:314.19790
[79]	train-rmse:218.24037	eval-rmse:313.53473
[80]	train-rmse:217.48076	eval-rmse:313.32533
[81]	train-rmse:215.85348	eval-rmse:312.29923
[82]	train-rmse:214.87251	eval-rmse:312.05040
[83]	train-rmse:214.20848	eval-rmse:311.83342
[84]	train-rmse:213.75122	eval-rmse:311.68815
[85]	train-rmse:212.26016	eval-rmse:311.20887
[86]	train-rmse:211.03939	eval-rmse:310.92337
[87]	train-rmse:210.17760	eval-rmse:310.55841
[88]	train-rmse:209.56694	eval-rmse:310.40097
[89]	train-rmse:209.03689	eval-rmse:310.21633
[90]	train-rmse:208.33951	eval-rmse:309.95642
[91]	train-rmse:207.48732	eval-rmse:309.68739
[92]	train-rmse:205.94881	eval-rmse:308.86746
[93]	train-rmse:205.09422	eval-rmse:308.40228
[94]	train-rmse:203.82815	eval-rmse:307.84083
[95]	train-rmse:202.86984	eval-rmse:307.48715
[96]	train-rmse:202.09819	eval-rmse:307.19847
[97]	train-rmse:200.72338	eval-rmse:306.48979
[98]	train-rmse:199.70640	eval-rmse:306.04835
[99]	train-rmse:198.50090	eval-rmse:305.34014
[100]	train-rmse:197.58081	eval-rmse:305.22192
[101]	train-rmse:196.55189	eval-rmse:304.48591
```

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[102]	train-rmse:195.56340	eval-rmse:304.05271
[103]	train-rmse:195.02162	eval-rmse:303.75581
[104]	train-rmse:194.29210	eval-rmse:303.44303
[105]	train-rmse:193.69860	eval-rmse:303.20166
[106]	train-rmse:192.84628	eval-rmse:302.87531
[107]	train-rmse:192.01813	eval-rmse:302.72371
[108]	train-rmse:190.95316	eval-rmse:302.08483
[109]	train-rmse:189.85129	eval-rmse:301.46702
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[111]	train-rmse:188.67012	eval-rmse:301.10548
[112]	train-rmse:187.73792	eval-rmse:300.52070
[113]	train-rmse:187.05957	eval-rmse:300.25409
[114]	train-rmse:186.05944	eval-rmse:299.96178
[115]	train-rmse:184.90429	eval-rmse:299.65009
[116]	train-rmse:184.24610	eval-rmse:299.68154
[117]	train-rmse:183.42392	eval-rmse:299.26088
[118]	train-rmse:182.80316	eval-rmse:298.73278
[119]	train-rmse:181.72619	eval-rmse:298.47628
[120]	train-rmse:181.18014	eval-rmse:298.43631
[121]	train-rmse:179.98692	eval-rmse:297.84965
[122]	train-rmse:179.27006	eval-rmse:297.48281
[123]	train-rmse:178.21927	eval-rmse:297.02209
[124]	train-rmse:177.60691	eval-rmse:296.86864
[125]	train-rmse:176.89527	eval-rmse:296.79588
[126]	train-rmse:176.26115	eval-rmse:296.61736
[127]	train-rmse:175.16103	eval-rmse:296.17871
[128]	train-rmse:174.55099	eval-rmse:295.97999
[129]	train-rmse:173.82134	eval-rmse:295.75394
[130]	train-rmse:173.18966	eval-rmse:295.57321
[131]	train-rmse:172.22835	eval-rmse:295.12982
[132]	train-rmse:171.56627	eval-rmse:294.99578
[133]	train-rmse:170.76321	eval-rmse:294.43152
[134]	train-rmse:170.00900	eval-rmse:294.16723
[135]	train-rmse:169.56228	eval-rmse:294.01125
[136]	train-rmse:168.65604	eval-rmse:293.59036
[137]	train-rmse:168.12747	eval-rmse:293.11453
[138]	train-rmse:167.12981	eval-rmse:292.65202
[139]	train-rmse:166.63437	eval-rmse:292.39134
[140]	train-rmse:166.17592	eval-rmse:292.31037
[141]	train-rmse:165.64342	eval-rmse:291.89953
[142]	train-rmse:164.78046	eval-rmse:291.56721
[143]	train-rmse:164.13178	eval-rmse:291.13305
[144]	train-rmse:163.57274	eval-rmse:290.74291
[145]	train-rmse:162.90890	eval-rmse:290.49952
[146]	train-rmse:162.12088	eval-rmse:290.15305
[147]	train-rmse:161.56819	eval-rmse:289.69499
[148]	train-rmse:160.81289	eval-rmse:289.23995
[149]	train-rmse:160.55283	eval-rmse:289.16233
[150]	train-rmse:159.57585	eval-rmse:288.61040
```

```
[151] train-rmse:158.90931  eval-rmse:288.40035
[152] train-rmse:158.23858  eval-rmse:288.00974
[153] train-rmse:157.41004  eval-rmse:287.81162
[154] train-rmse:156.95968  eval-rmse:287.44138
[155] train-rmse:156.67902  eval-rmse:287.22790
[156] train-rmse:155.97504  eval-rmse:287.08471
[157] train-rmse:155.36836  eval-rmse:286.79603
[158] train-rmse:154.77151  eval-rmse:286.20203
[159] train-rmse:154.02272  eval-rmse:285.99222
[160] train-rmse:153.73455  eval-rmse:285.83035
[161] train-rmse:153.11894  eval-rmse:285.67774
[162] train-rmse:152.65837  eval-rmse:285.36191
[163] train-rmse:151.90450  eval-rmse:285.03264
[164] train-rmse:151.11442  eval-rmse:284.91459
[165] train-rmse:150.23118  eval-rmse:284.39505
[166] train-rmse:149.87124  eval-rmse:284.47405
[167] train-rmse:149.66708  eval-rmse:284.42387
[168] train-rmse:149.21613  eval-rmse:284.38542
[169] train-rmse:148.65983  eval-rmse:284.08019
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[499] train-rmse:58.29402   eval-rmse:264.38921
Mean Absolute Error (MAE): 194.73541898098645
Root Mean Squared Error (RMSE): 334.0486547952177
Mean Absolute Percentage Error (MAPE): 0.69%
Accuracy: 99.32%
```