

eledem-final

November 27, 2024

```
[4]: #!pip install -U tensorflow
```

```
[5]: import numpy as np
import pandas as pd
import math
import seaborn as sns
import xgboost as xgb
import matplotlib.pyplot as plt
import plotly.graph_objects as go
import tensorflow as tf

from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import LabelEncoder
from sklearn.svm import SVR
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
from sklearn.decomposition import PCA
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_absolute_error
from keras import Sequential
from keras import layers
from keras.models import Model
from keras.layers import LSTM, BatchNormalization, Dropout, Dense, Flatten, ␣
    ↪ Conv1D
from keras.layers import MaxPooling1D, GRU, Input, Masking, Concatenate, dot
from keras.optimizers import Adam, SGD
from keras.losses import MeanAbsoluteError
from keras.metrics import RootMeanSquaredError
from keras.callbacks import EarlyStopping
from keras.callbacks import LearningRateScheduler
```

```
[6]: file_path = 'energy_dataset.csv'
df_energy = pd.read_csv(file_path)
```

```
[7]: df_energy.head()
```

```
[7]:
```

	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]

```
[8]: df_energy.describe().T
```

```
[8]:
```

	count	mean \
generation biomass	35045.0	383.513540
generation fossil brown coal/lignite	35046.0	448.059208
generation fossil coal-derived gas	35046.0	0.000000
generation fossil gas	35046.0	5622.737488
generation fossil hard coal	35046.0	4256.065742
generation fossil oil	35045.0	298.319789
generation fossil oil shale	35046.0	0.000000
generation fossil peat	35046.0	0.000000
generation geothermal	35046.0	0.000000
generation hydro pumped storage aggregated	0.0	NaN
generation hydro pumped storage consumption	35045.0	475.577343
generation hydro run-of-river and poundage	35045.0	972.116108
generation hydro water reservoir	35046.0	2605.114735
generation marine	35045.0	0.000000
generation nuclear	35047.0	6263.907039
generation other	35046.0	60.228585
generation other renewable	35046.0	85.639702
generation solar	35046.0	1432.665925
generation waste	35045.0	269.452133
generation wind offshore	35046.0	0.000000
generation wind onshore	35046.0	5464.479769
forecast solar day ahead	35064.0	1439.066735
forecast wind offshore eday ahead	0.0	NaN
forecast wind onshore day ahead	35064.0	5471.216689
total load forecast	35064.0	28712.129962
total load actual	35028.0	28696.939905
price day ahead	35064.0	49.874341
price actual	35064.0	57.884023

	std	min \
generation biomass	85.353943	0.00
generation fossil brown coal/lignite	354.568590	0.00
generation fossil coal-derived gas	0.000000	0.00
generation fossil gas	2201.830478	0.00
generation fossil hard coal	1961.601013	0.00
generation fossil oil	52.520673	0.00
generation fossil oil shale	0.000000	0.00
generation fossil peat	0.000000	0.00
generation geothermal	0.000000	0.00
generation hydro pumped storage aggregated	NaN	NaN
generation hydro pumped storage consumption	792.406614	0.00
generation hydro run-of-river and poundage	400.777536	0.00
generation hydro water reservoir	1835.199745	0.00
generation marine	0.000000	0.00
generation nuclear	839.667958	0.00
generation other	20.238381	0.00
generation other renewable	14.077554	0.00
generation solar	1680.119887	0.00
generation waste	50.195536	0.00
generation wind offshore	0.000000	0.00
generation wind onshore	3213.691587	0.00
forecast solar day ahead	1677.703355	0.00
forecast wind offshore eday ahead	NaN	NaN
forecast wind onshore day ahead	3176.312853	237.00
total load forecast	4594.100854	18105.00
total load actual	4574.987950	18041.00
price day ahead	14.618900	2.06
price actual	14.204083	9.33

	25%	50%	75% \
generation biomass	333.0000	367.00	433.00
generation fossil brown coal/lignite	0.0000	509.00	757.00
generation fossil coal-derived gas	0.0000	0.00	0.00
generation fossil gas	4126.0000	4969.00	6429.00
generation fossil hard coal	2527.0000	4474.00	5838.75
generation fossil oil	263.0000	300.00	330.00
generation fossil oil shale	0.0000	0.00	0.00
generation fossil peat	0.0000	0.00	0.00
generation geothermal	0.0000	0.00	0.00
generation hydro pumped storage aggregated	NaN	NaN	NaN
generation hydro pumped storage consumption	0.0000	68.00	616.00
generation hydro run-of-river and poundage	637.0000	906.00	1250.00
generation hydro water reservoir	1077.2500	2164.00	3757.00
generation marine	0.0000	0.00	0.00
generation nuclear	5760.0000	6566.00	7025.00

generation other	53.0000	57.00	80.00
generation other renewable	73.0000	88.00	97.00
generation solar	71.0000	616.00	2578.00
generation waste	240.0000	279.00	310.00
generation wind offshore	0.0000	0.00	0.00
generation wind onshore	2933.0000	4849.00	7398.00
forecast solar day ahead	69.0000	576.00	2636.00
forecast wind offshore eday ahead	NaN	NaN	NaN
forecast wind onshore day ahead	2979.0000	4855.00	7353.00
total load forecast	24793.7500	28906.00	32263.25
total load actual	24807.7500	28901.00	32192.00
price day ahead	41.4900	50.52	60.53
price actual	49.3475	58.02	68.01

	max
generation biomass	592.00
generation fossil brown coal/lignite	999.00
generation fossil coal-derived gas	0.00
generation fossil gas	20034.00
generation fossil hard coal	8359.00
generation fossil oil	449.00
generation fossil oil shale	0.00
generation fossil peat	0.00
generation geothermal	0.00
generation hydro pumped storage aggregated	NaN
generation hydro pumped storage consumption	4523.00
generation hydro run-of-river and poundage	2000.00
generation hydro water reservoir	9728.00
generation marine	0.00
generation nuclear	7117.00
generation other	106.00
generation other renewable	119.00
generation solar	5792.00
generation waste	357.00
generation wind offshore	0.00
generation wind onshore	17436.00
forecast solar day ahead	5836.00
forecast wind offshore eday ahead	NaN
forecast wind onshore day ahead	17430.00
total load forecast	41390.00
total load actual	41015.00
price day ahead	101.99
price actual	116.80

```
[9]: df_energy.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

```
[10]: # columns to be removed due to all 0 or Nan values
col_names = ['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']
```

```
[11]: df_energy = df_energy.drop(col_names, axis = 1)
```

```
[12]: def check_Nans_Dups(df):
        """
        This function checks for NaNs and duplicate rows in the dataframe.

        Args:
            df: The input dataframe.

        Returns:
            None. Prints information about NaNs and duplicates.
        """
        # Check for NaNs
        num_nans = df.isna().sum().sum()
        if num_nans > 0:
            print(f"The dataframe has {num_nans} NaN values.")
            print(df.isna().sum()) # Print NaNs per column
        else:
            print("The dataframe has no NaN values.")

        # Check for duplicates
        num_dups = df.duplicated().sum()
        if num_dups > 0:
            print(f"The dataframe has {num_dups} duplicate rows.")
        else:
            print("The dataframe has no duplicate rows.")

        # Now you can call the function
        check_Nans_Dups(df_energy)
```

The dataframe has 292 NaN values.

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 forecast	0
total load actual	36
price day ahead	0

```
price actual                                0
dtype: int64
The dataframe has no duplicate rows.
```

```
[13]: df_energy['time'] = pd.to_datetime(df_energy['time'])
      df_energy = df_energy.set_index('time')
      df_energy
```

```
<ipython-input-13-c0cd3855ec4e>:1: FutureWarning: In a future version of pandas,
parsing datetimes with mixed time zones will raise an error unless `utc=True`.
Please specify `utc=True` to opt in to the new behaviour and silence this
warning. To create a `Series` with mixed offsets and `object` dtype, please use
`apply` and `datetime.datetime.strptime`
      df_energy['time'] = pd.to_datetime(df_energy['time'])
```

```
[13]:          generation biomass \
time
2015-01-01 00:00:00+01:00      447.0
2015-01-01 01:00:00+01:00      449.0
2015-01-01 02:00:00+01:00      448.0
2015-01-01 03:00:00+01:00      438.0
2015-01-01 04:00:00+01:00      428.0
...
2018-12-31 19:00:00+01:00      297.0
2018-12-31 20:00:00+01:00      296.0
2018-12-31 21:00:00+01:00      292.0
2018-12-31 22:00:00+01:00      293.0
2018-12-31 23:00:00+01:00      290.0
```

```
          generation fossil brown coal/lignite \
time
2015-01-01 00:00:00+01:00      329.0
2015-01-01 01:00:00+01:00      328.0
2015-01-01 02:00:00+01:00      323.0
2015-01-01 03:00:00+01:00      254.0
2015-01-01 04:00:00+01:00      187.0
...
2018-12-31 19:00:00+01:00          0.0
2018-12-31 20:00:00+01:00          0.0
2018-12-31 21:00:00+01:00          0.0
2018-12-31 22:00:00+01:00          0.0
2018-12-31 23:00:00+01:00          0.0
```

```
          generation fossil gas  generation fossil hard coal \
time
2015-01-01 00:00:00+01:00      4844.0      4821.0
2015-01-01 01:00:00+01:00      5196.0      4755.0
```


2015-01-01 02:00:00+01:00	4857.0	4581.0
2015-01-01 03:00:00+01:00	4314.0	4131.0
2015-01-01 04:00:00+01:00	4130.0	3840.0
...
2018-12-31 19:00:00+01:00	7634.0	2628.0
2018-12-31 20:00:00+01:00	7241.0	2566.0
2018-12-31 21:00:00+01:00	7025.0	2422.0
2018-12-31 22:00:00+01:00	6562.0	2293.0
2018-12-31 23:00:00+01:00	6926.0	2166.0

time	generation fossil oil \
2015-01-01 00:00:00+01:00	162.0
2015-01-01 01:00:00+01:00	158.0
2015-01-01 02:00:00+01:00	157.0
2015-01-01 03:00:00+01:00	160.0
2015-01-01 04:00:00+01:00	156.0
...	...
2018-12-31 19:00:00+01:00	178.0
2018-12-31 20:00:00+01:00	174.0
2018-12-31 21:00:00+01:00	168.0
2018-12-31 22:00:00+01:00	163.0
2018-12-31 23:00:00+01:00	163.0

time	generation hydro pumped storage consumption \
2015-01-01 00:00:00+01:00	863.0
2015-01-01 01:00:00+01:00	920.0
2015-01-01 02:00:00+01:00	1164.0
2015-01-01 03:00:00+01:00	1503.0
2015-01-01 04:00:00+01:00	1826.0
...	...
2018-12-31 19:00:00+01:00	1.0
2018-12-31 20:00:00+01:00	1.0
2018-12-31 21:00:00+01:00	50.0
2018-12-31 22:00:00+01:00	108.0
2018-12-31 23:00:00+01:00	108.0

time	generation hydro run-of-river and poundage \
2015-01-01 00:00:00+01:00	1051.0
2015-01-01 01:00:00+01:00	1009.0
2015-01-01 02:00:00+01:00	973.0
2015-01-01 03:00:00+01:00	949.0
2015-01-01 04:00:00+01:00	953.0
...	...
2018-12-31 19:00:00+01:00	1135.0

2018-12-31 20:00:00+01:00	1172.0
2018-12-31 21:00:00+01:00	1148.0
2018-12-31 22:00:00+01:00	1128.0
2018-12-31 23:00:00+01:00	1069.0

time	generation hydro water reservoir \
2015-01-01 00:00:00+01:00	1899.0
2015-01-01 01:00:00+01:00	1658.0
2015-01-01 02:00:00+01:00	1371.0
2015-01-01 03:00:00+01:00	779.0
2015-01-01 04:00:00+01:00	720.0
...	...
2018-12-31 19:00:00+01:00	4836.0
2018-12-31 20:00:00+01:00	3931.0
2018-12-31 21:00:00+01:00	2831.0
2018-12-31 22:00:00+01:00	2068.0
2018-12-31 23:00:00+01:00	1686.0

time	generation nuclear	generation other \
2015-01-01 00:00:00+01:00	7096.0	43.0
2015-01-01 01:00:00+01:00	7096.0	43.0
2015-01-01 02:00:00+01:00	7099.0	43.0
2015-01-01 03:00:00+01:00	7098.0	43.0
2015-01-01 04:00:00+01:00	7097.0	43.0
...
2018-12-31 19:00:00+01:00	6073.0	63.0
2018-12-31 20:00:00+01:00	6074.0	62.0
2018-12-31 21:00:00+01:00	6076.0	61.0
2018-12-31 22:00:00+01:00	6075.0	61.0
2018-12-31 23:00:00+01:00	6075.0	61.0

time	generation other renewable	generation solar \
2015-01-01 00:00:00+01:00	73.0	49.0
2015-01-01 01:00:00+01:00	71.0	50.0
2015-01-01 02:00:00+01:00	73.0	50.0
2015-01-01 03:00:00+01:00	75.0	50.0
2015-01-01 04:00:00+01:00	74.0	42.0
...
2018-12-31 19:00:00+01:00	95.0	85.0
2018-12-31 20:00:00+01:00	95.0	33.0
2018-12-31 21:00:00+01:00	94.0	31.0
2018-12-31 22:00:00+01:00	93.0	31.0
2018-12-31 23:00:00+01:00	92.0	31.0

	generation waste	generation wind onshore \
time		
2015-01-01 00:00:00+01:00	196.0	6378.0
2015-01-01 01:00:00+01:00	195.0	5890.0
2015-01-01 02:00:00+01:00	196.0	5461.0
2015-01-01 03:00:00+01:00	191.0	5238.0
2015-01-01 04:00:00+01:00	189.0	4935.0
...
2018-12-31 19:00:00+01:00	277.0	3113.0
2018-12-31 20:00:00+01:00	280.0	3288.0
2018-12-31 21:00:00+01:00	286.0	3503.0
2018-12-31 22:00:00+01:00	287.0	3586.0
2018-12-31 23:00:00+01:00	287.0	3651.0

	total load forecast	total load actual \
time		
2015-01-01 00:00:00+01:00	26118.0	25385.0
2015-01-01 01:00:00+01:00	24934.0	24382.0
2015-01-01 02:00:00+01:00	23515.0	22734.0
2015-01-01 03:00:00+01:00	22642.0	21286.0
2015-01-01 04:00:00+01:00	21785.0	20264.0
...
2018-12-31 19:00:00+01:00	30619.0	30653.0
2018-12-31 20:00:00+01:00	29932.0	29735.0
2018-12-31 21:00:00+01:00	27903.0	28071.0
2018-12-31 22:00:00+01:00	25450.0	25801.0
2018-12-31 23:00:00+01:00	24424.0	24455.0

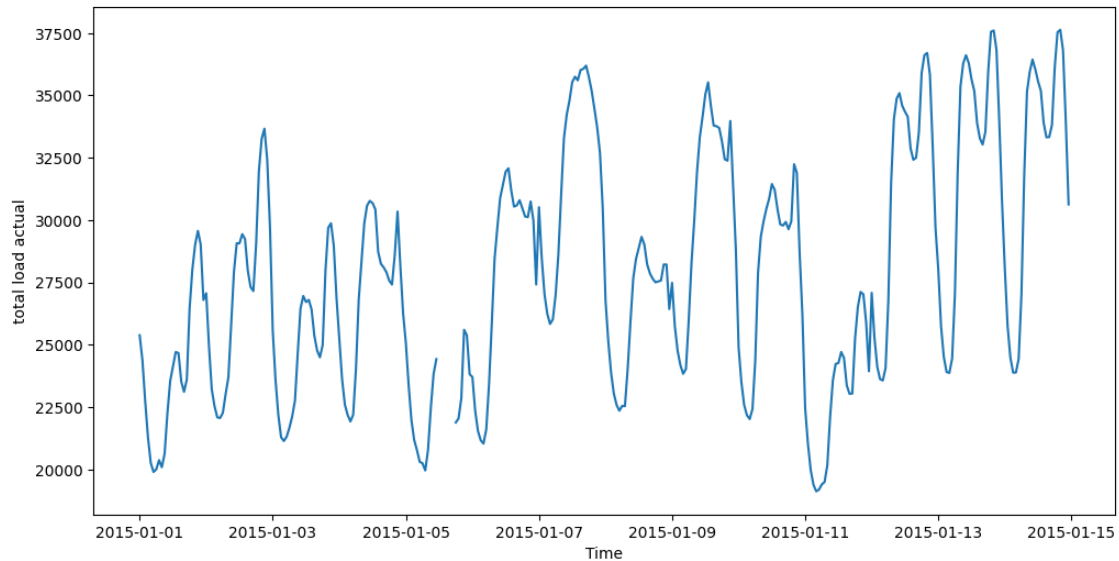
	price day ahead	price actual
time		
2015-01-01 00:00:00+01:00	50.10	65.41
2015-01-01 01:00:00+01:00	48.10	64.92
2015-01-01 02:00:00+01:00	47.33	64.48
2015-01-01 03:00:00+01:00	42.27	59.32
2015-01-01 04:00:00+01:00	38.41	56.04
...
2018-12-31 19:00:00+01:00	68.85	77.02
2018-12-31 20:00:00+01:00	68.40	76.16
2018-12-31 21:00:00+01:00	66.88	74.30
2018-12-31 22:00:00+01:00	63.93	69.89
2018-12-31 23:00:00+01:00	64.27	69.88

[35064 rows x 18 columns]

```
[14]: plt.figure(figsize=(12,6))
# plot total load actual for two weeks duration
plt.plot(df_energy['total load actual'][:24*7*2])
```

```
plt.xlabel('Time')
plt.ylabel('total load actual')
```

```
[14]: Text(0, 0.5, 'total load actual')
```



```
[15]: df_energy[df_energy.isna().any(axis = 1)]
```

```
[15]:
```

time	generation biomass \
2015-01-05 03:00:00+01:00	NaN
2015-01-05 12:00:00+01:00	NaN
2015-01-05 13:00:00+01:00	NaN
2015-01-05 14:00:00+01:00	NaN
2015-01-05 15:00:00+01:00	NaN
2015-01-05 16:00:00+01:00	NaN
2015-01-05 17:00:00+01:00	NaN
2015-01-19 19:00:00+01:00	NaN
2015-01-19 20:00:00+01:00	NaN
2015-01-27 19:00:00+01:00	NaN
2015-01-28 13:00:00+01:00	NaN
2015-02-01 07:00:00+01:00	449.0
2015-02-01 08:00:00+01:00	453.0
2015-02-01 09:00:00+01:00	452.0
2015-02-01 12:00:00+01:00	405.0
2015-02-01 13:00:00+01:00	402.0
2015-02-01 14:00:00+01:00	400.0
2015-02-01 15:00:00+01:00	393.0
2015-02-01 16:00:00+01:00	413.0

2015-02-01 17:00:00+01:00	465.0
2015-02-01 18:00:00+01:00	482.0
2015-02-01 19:00:00+01:00	474.0
2015-04-05 03:00:00+02:00	371.0
2015-04-16 09:00:00+02:00	NaN
2015-04-20 08:00:00+02:00	424.0
2015-04-23 21:00:00+02:00	NaN
2015-05-02 10:00:00+02:00	497.0
2015-05-29 03:00:00+02:00	569.0
2015-06-15 09:00:00+02:00	NaN
2015-10-02 08:00:00+02:00	483.0
2015-10-02 11:00:00+02:00	NaN
2015-12-02 09:00:00+01:00	NaN
2016-04-13 05:00:00+02:00	220.0
2016-04-25 05:00:00+02:00	190.0
2016-04-25 07:00:00+02:00	206.0
2016-05-10 23:00:00+02:00	348.0
2016-06-12 01:00:00+02:00	356.0
2016-07-09 22:00:00+02:00	NaN
2016-07-12 00:00:00+02:00	346.0
2016-09-28 09:00:00+02:00	347.0
2016-10-27 23:00:00+02:00	351.0
2016-11-23 04:00:00+01:00	NaN
2017-11-14 12:00:00+01:00	0.0
2017-11-14 19:00:00+01:00	0.0
2018-06-11 18:00:00+02:00	331.0
2018-07-11 09:00:00+02:00	NaN

generation fossil brown coal/lignite \

time	
2015-01-05 03:00:00+01:00	NaN
2015-01-05 12:00:00+01:00	NaN
2015-01-05 13:00:00+01:00	NaN
2015-01-05 14:00:00+01:00	NaN
2015-01-05 15:00:00+01:00	NaN
2015-01-05 16:00:00+01:00	NaN
2015-01-05 17:00:00+01:00	NaN
2015-01-19 19:00:00+01:00	NaN
2015-01-19 20:00:00+01:00	NaN
2015-01-27 19:00:00+01:00	NaN
2015-01-28 13:00:00+01:00	NaN
2015-02-01 07:00:00+01:00	312.0
2015-02-01 08:00:00+01:00	312.0
2015-02-01 09:00:00+01:00	302.0
2015-02-01 12:00:00+01:00	317.0
2015-02-01 13:00:00+01:00	317.0
2015-02-01 14:00:00+01:00	317.0

2015-02-01 15:00:00+01:00	321.0
2015-02-01 16:00:00+01:00	325.0
2015-02-01 17:00:00+01:00	321.0
2015-02-01 18:00:00+01:00	326.0
2015-02-01 19:00:00+01:00	326.0
2015-04-05 03:00:00+02:00	0.0
2015-04-16 09:00:00+02:00	NaN
2015-04-20 08:00:00+02:00	642.0
2015-04-23 21:00:00+02:00	NaN
2015-05-02 10:00:00+02:00	0.0
2015-05-29 03:00:00+02:00	756.0
2015-06-15 09:00:00+02:00	NaN
2015-10-02 08:00:00+02:00	961.0
2015-10-02 11:00:00+02:00	NaN
2015-12-02 09:00:00+01:00	NaN
2016-04-13 05:00:00+02:00	0.0
2016-04-25 05:00:00+02:00	0.0
2016-04-25 07:00:00+02:00	0.0
2016-05-10 23:00:00+02:00	960.0
2016-06-12 01:00:00+02:00	595.0
2016-07-09 22:00:00+02:00	NaN
2016-07-12 00:00:00+02:00	595.0
2016-09-28 09:00:00+02:00	594.0
2016-10-27 23:00:00+02:00	554.0
2016-11-23 04:00:00+01:00	900.0
2017-11-14 12:00:00+01:00	0.0
2017-11-14 19:00:00+01:00	0.0
2018-06-11 18:00:00+02:00	506.0
2018-07-11 09:00:00+02:00	NaN

time	generation fossil gas	generation fossil hard coal \
2015-01-05 03:00:00+01:00	NaN	NaN
2015-01-05 12:00:00+01:00	NaN	NaN
2015-01-05 13:00:00+01:00	NaN	NaN
2015-01-05 14:00:00+01:00	NaN	NaN
2015-01-05 15:00:00+01:00	NaN	NaN
2015-01-05 16:00:00+01:00	NaN	NaN
2015-01-05 17:00:00+01:00	NaN	NaN
2015-01-19 19:00:00+01:00	NaN	NaN
2015-01-19 20:00:00+01:00	NaN	NaN
2015-01-27 19:00:00+01:00	NaN	NaN
2015-01-28 13:00:00+01:00	NaN	NaN
2015-02-01 07:00:00+01:00	4765.0	5269.0
2015-02-01 08:00:00+01:00	4938.0	5652.0
2015-02-01 09:00:00+01:00	4997.0	5770.0
2015-02-01 12:00:00+01:00	5247.0	6008.0

2015-02-01 13:00:00+01:00	5449.0	6005.0
2015-02-01 14:00:00+01:00	5266.0	5995.0
2015-02-01 15:00:00+01:00	5209.0	5939.0
2015-02-01 16:00:00+01:00	5642.0	6000.0
2015-02-01 17:00:00+01:00	6127.0	5912.0
2015-02-01 18:00:00+01:00	7386.0	6002.0
2015-02-01 19:00:00+01:00	7963.0	6026.0
2015-04-05 03:00:00+02:00	5015.0	3248.0
2015-04-16 09:00:00+02:00	NaN	NaN
2015-04-20 08:00:00+02:00	5614.0	5784.0
2015-04-23 21:00:00+02:00	NaN	NaN
2015-05-02 10:00:00+02:00	5502.0	5677.0
2015-05-29 03:00:00+02:00	4239.0	4635.0
2015-06-15 09:00:00+02:00	NaN	NaN
2015-10-02 08:00:00+02:00	6545.0	8250.0
2015-10-02 11:00:00+02:00	NaN	NaN
2015-12-02 09:00:00+01:00	NaN	NaN
2016-04-13 05:00:00+02:00	3390.0	1242.0
2016-04-25 05:00:00+02:00	2969.0	886.0
2016-04-25 07:00:00+02:00	3673.0	1143.0
2016-05-10 23:00:00+02:00	6800.0	5219.0
2016-06-12 01:00:00+02:00	5719.0	6165.0
2016-07-09 22:00:00+02:00	NaN	NaN
2016-07-12 00:00:00+02:00	5951.0	6131.0
2016-09-28 09:00:00+02:00	5522.0	6272.0
2016-10-27 23:00:00+02:00	7176.0	5690.0
2016-11-23 04:00:00+01:00	4838.0	4547.0
2017-11-14 12:00:00+01:00	10064.0	0.0
2017-11-14 19:00:00+01:00	12336.0	0.0
2018-06-11 18:00:00+02:00	7538.0	5360.0
2018-07-11 09:00:00+02:00	NaN	NaN

generation fossil oil \

time	
2015-01-05 03:00:00+01:00	NaN
2015-01-05 12:00:00+01:00	NaN
2015-01-05 13:00:00+01:00	NaN
2015-01-05 14:00:00+01:00	NaN
2015-01-05 15:00:00+01:00	NaN
2015-01-05 16:00:00+01:00	NaN
2015-01-05 17:00:00+01:00	NaN
2015-01-19 19:00:00+01:00	NaN
2015-01-19 20:00:00+01:00	NaN
2015-01-27 19:00:00+01:00	NaN
2015-01-28 13:00:00+01:00	NaN
2015-02-01 07:00:00+01:00	222.0
2015-02-01 08:00:00+01:00	288.0

2015-02-01 09:00:00+01:00	296.0
2015-02-01 12:00:00+01:00	333.0
2015-02-01 13:00:00+01:00	318.0
2015-02-01 14:00:00+01:00	327.0
2015-02-01 15:00:00+01:00	345.0
2015-02-01 16:00:00+01:00	345.0
2015-02-01 17:00:00+01:00	346.0
2015-02-01 18:00:00+01:00	340.0
2015-02-01 19:00:00+01:00	343.0
2015-04-05 03:00:00+02:00	257.0
2015-04-16 09:00:00+02:00	NaN
2015-04-20 08:00:00+02:00	369.0
2015-04-23 21:00:00+02:00	NaN
2015-05-02 10:00:00+02:00	375.0
2015-05-29 03:00:00+02:00	365.0
2015-06-15 09:00:00+02:00	NaN
2015-10-02 08:00:00+02:00	385.0
2015-10-02 11:00:00+02:00	NaN
2015-12-02 09:00:00+01:00	NaN
2016-04-13 05:00:00+02:00	243.0
2016-04-25 05:00:00+02:00	151.0
2016-04-25 07:00:00+02:00	185.0
2016-05-10 23:00:00+02:00	299.0
2016-06-12 01:00:00+02:00	274.0
2016-07-09 22:00:00+02:00	NaN
2016-07-12 00:00:00+02:00	NaN
2016-09-28 09:00:00+02:00	292.0
2016-10-27 23:00:00+02:00	321.0
2016-11-23 04:00:00+01:00	269.0
2017-11-14 12:00:00+01:00	0.0
2017-11-14 19:00:00+01:00	0.0
2018-06-11 18:00:00+02:00	300.0
2018-07-11 09:00:00+02:00	NaN

generation hydro pumped storage consumption \

time	
2015-01-05 03:00:00+01:00	NaN
2015-01-05 12:00:00+01:00	NaN
2015-01-05 13:00:00+01:00	NaN
2015-01-05 14:00:00+01:00	NaN
2015-01-05 15:00:00+01:00	NaN
2015-01-05 16:00:00+01:00	NaN
2015-01-05 17:00:00+01:00	NaN
2015-01-19 19:00:00+01:00	NaN
2015-01-19 20:00:00+01:00	NaN
2015-01-27 19:00:00+01:00	NaN
2015-01-28 13:00:00+01:00	NaN

2015-02-01 07:00:00+01:00	480.0
2015-02-01 08:00:00+01:00	0.0
2015-02-01 09:00:00+01:00	0.0
2015-02-01 12:00:00+01:00	0.0
2015-02-01 13:00:00+01:00	0.0
2015-02-01 14:00:00+01:00	0.0
2015-02-01 15:00:00+01:00	0.0
2015-02-01 16:00:00+01:00	0.0
2015-02-01 17:00:00+01:00	0.0
2015-02-01 18:00:00+01:00	0.0
2015-02-01 19:00:00+01:00	0.0
2015-04-05 03:00:00+02:00	799.0
2015-04-16 09:00:00+02:00	NaN
2015-04-20 08:00:00+02:00	0.0
2015-04-23 21:00:00+02:00	NaN
2015-05-02 10:00:00+02:00	0.0
2015-05-29 03:00:00+02:00	755.0
2015-06-15 09:00:00+02:00	NaN
2015-10-02 08:00:00+02:00	0.0
2015-10-02 11:00:00+02:00	NaN
2015-12-02 09:00:00+01:00	NaN
2016-04-13 05:00:00+02:00	2270.0
2016-04-25 05:00:00+02:00	1340.0
2016-04-25 07:00:00+02:00	162.0
2016-05-10 23:00:00+02:00	0.0
2016-06-12 01:00:00+02:00	382.0
2016-07-09 22:00:00+02:00	NaN
2016-07-12 00:00:00+02:00	494.0
2016-09-28 09:00:00+02:00	0.0
2016-10-27 23:00:00+02:00	NaN
2016-11-23 04:00:00+01:00	1413.0
2017-11-14 12:00:00+01:00	0.0
2017-11-14 19:00:00+01:00	0.0
2018-06-11 18:00:00+02:00	1.0
2018-07-11 09:00:00+02:00	NaN

generation hydro run-of-river and poundage \

time

2015-01-05 03:00:00+01:00	NaN
2015-01-05 12:00:00+01:00	NaN
2015-01-05 13:00:00+01:00	NaN
2015-01-05 14:00:00+01:00	NaN
2015-01-05 15:00:00+01:00	NaN
2015-01-05 16:00:00+01:00	NaN
2015-01-05 17:00:00+01:00	NaN
2015-01-19 19:00:00+01:00	NaN
2015-01-19 20:00:00+01:00	NaN

2015-01-27 19:00:00+01:00	NaN
2015-01-28 13:00:00+01:00	NaN
2015-02-01 07:00:00+01:00	980.0
2015-02-01 08:00:00+01:00	1031.0
2015-02-01 09:00:00+01:00	1083.0
2015-02-01 12:00:00+01:00	1119.0
2015-02-01 13:00:00+01:00	1171.0
2015-02-01 14:00:00+01:00	1216.0
2015-02-01 15:00:00+01:00	1204.0
2015-02-01 16:00:00+01:00	1193.0
2015-02-01 17:00:00+01:00	1214.0
2015-02-01 18:00:00+01:00	1299.0
2015-02-01 19:00:00+01:00	1313.0
2015-04-05 03:00:00+02:00	1233.0
2015-04-16 09:00:00+02:00	NaN
2015-04-20 08:00:00+02:00	1122.0
2015-04-23 21:00:00+02:00	NaN
2015-05-02 10:00:00+02:00	1425.0
2015-05-29 03:00:00+02:00	667.0
2015-06-15 09:00:00+02:00	NaN
2015-10-02 08:00:00+02:00	1323.0
2015-10-02 11:00:00+02:00	NaN
2015-12-02 09:00:00+01:00	NaN
2016-04-13 05:00:00+02:00	1622.0
2016-04-25 05:00:00+02:00	1564.0
2016-04-25 07:00:00+02:00	1648.0
2016-05-10 23:00:00+02:00	443.0
2016-06-12 01:00:00+02:00	NaN
2016-07-09 22:00:00+02:00	NaN
2016-07-12 00:00:00+02:00	709.0
2016-09-28 09:00:00+02:00	524.0
2016-10-27 23:00:00+02:00	417.0
2016-11-23 04:00:00+01:00	795.0
2017-11-14 12:00:00+01:00	0.0
2017-11-14 19:00:00+01:00	0.0
2018-06-11 18:00:00+02:00	1134.0
2018-07-11 09:00:00+02:00	NaN

generation hydro water reservoir \

time

2015-01-05 03:00:00+01:00	NaN
2015-01-05 12:00:00+01:00	NaN
2015-01-05 13:00:00+01:00	NaN
2015-01-05 14:00:00+01:00	NaN
2015-01-05 15:00:00+01:00	NaN
2015-01-05 16:00:00+01:00	NaN
2015-01-05 17:00:00+01:00	NaN

2015-01-19 19:00:00+01:00	NaN
2015-01-19 20:00:00+01:00	NaN
2015-01-27 19:00:00+01:00	NaN
2015-01-28 13:00:00+01:00	NaN
2015-02-01 07:00:00+01:00	1174.0
2015-02-01 08:00:00+01:00	3229.0
2015-02-01 09:00:00+01:00	4574.0
2015-02-01 12:00:00+01:00	4416.0
2015-02-01 13:00:00+01:00	4475.0
2015-02-01 14:00:00+01:00	4412.0
2015-02-01 15:00:00+01:00	3403.0
2015-02-01 16:00:00+01:00	3333.0
2015-02-01 17:00:00+01:00	4684.0
2015-02-01 18:00:00+01:00	6187.0
2015-02-01 19:00:00+01:00	6895.0
2015-04-05 03:00:00+02:00	2531.0
2015-04-16 09:00:00+02:00	NaN
2015-04-20 08:00:00+02:00	4050.0
2015-04-23 21:00:00+02:00	NaN
2015-05-02 10:00:00+02:00	5289.0
2015-05-29 03:00:00+02:00	1277.0
2015-06-15 09:00:00+02:00	NaN
2015-10-02 08:00:00+02:00	5378.0
2015-10-02 11:00:00+02:00	NaN
2015-12-02 09:00:00+01:00	NaN
2016-04-13 05:00:00+02:00	4515.0
2016-04-25 05:00:00+02:00	5389.0
2016-04-25 07:00:00+02:00	6807.0
2016-05-10 23:00:00+02:00	1750.0
2016-06-12 01:00:00+02:00	1325.0
2016-07-09 22:00:00+02:00	NaN
2016-07-12 00:00:00+02:00	1215.0
2016-09-28 09:00:00+02:00	2494.0
2016-10-27 23:00:00+02:00	1295.0
2016-11-23 04:00:00+01:00	435.0
2017-11-14 12:00:00+01:00	0.0
2017-11-14 19:00:00+01:00	0.0
2018-06-11 18:00:00+02:00	4258.0
2018-07-11 09:00:00+02:00	NaN

time	generation nuclear	generation other \
2015-01-05 03:00:00+01:00	NaN	NaN
2015-01-05 12:00:00+01:00	NaN	NaN
2015-01-05 13:00:00+01:00	NaN	NaN
2015-01-05 14:00:00+01:00	NaN	NaN
2015-01-05 15:00:00+01:00	NaN	NaN

2015-01-05 16:00:00+01:00	NaN	NaN
2015-01-05 17:00:00+01:00	NaN	NaN
2015-01-19 19:00:00+01:00	NaN	NaN
2015-01-19 20:00:00+01:00	NaN	NaN
2015-01-27 19:00:00+01:00	NaN	NaN
2015-01-28 13:00:00+01:00	NaN	NaN
2015-02-01 07:00:00+01:00	7101.0	44.0
2015-02-01 08:00:00+01:00	7099.0	44.0
2015-02-01 09:00:00+01:00	7097.0	43.0
2015-02-01 12:00:00+01:00	7095.0	42.0
2015-02-01 13:00:00+01:00	7096.0	41.0
2015-02-01 14:00:00+01:00	7098.0	42.0
2015-02-01 15:00:00+01:00	7097.0	41.0
2015-02-01 16:00:00+01:00	7097.0	40.0
2015-02-01 17:00:00+01:00	7096.0	41.0
2015-02-01 18:00:00+01:00	7095.0	41.0
2015-02-01 19:00:00+01:00	7096.0	42.0
2015-04-05 03:00:00+02:00	4027.0	81.0
2015-04-16 09:00:00+02:00	NaN	NaN
2015-04-20 08:00:00+02:00	6954.0	41.0
2015-04-23 21:00:00+02:00	NaN	NaN
2015-05-02 10:00:00+02:00	6353.0	93.0
2015-05-29 03:00:00+02:00	5035.0	85.0
2015-06-15 09:00:00+02:00	NaN	NaN
2015-10-02 08:00:00+02:00	7013.0	87.0
2015-10-02 11:00:00+02:00	NaN	NaN
2015-12-02 09:00:00+01:00	NaN	NaN
2016-04-13 05:00:00+02:00	7097.0	53.0
2016-04-25 05:00:00+02:00	7094.0	50.0
2016-04-25 07:00:00+02:00	7095.0	51.0
2016-05-10 23:00:00+02:00	7002.0	50.0
2016-06-12 01:00:00+02:00	5056.0	56.0
2016-07-09 22:00:00+02:00	6923.0	NaN
2016-07-12 00:00:00+02:00	5058.0	49.0
2016-09-28 09:00:00+02:00	6997.0	61.0
2016-10-27 23:00:00+02:00	6967.0	58.0
2016-11-23 04:00:00+01:00	5040.0	60.0
2017-11-14 12:00:00+01:00	0.0	0.0
2017-11-14 19:00:00+01:00	0.0	0.0
2018-06-11 18:00:00+02:00	5856.0	52.0
2018-07-11 09:00:00+02:00	NaN	NaN

time	generation other renewable	generation solar \
2015-01-05 03:00:00+01:00	NaN	NaN
2015-01-05 12:00:00+01:00	NaN	NaN
2015-01-05 13:00:00+01:00	NaN	NaN

2015-01-05 14:00:00+01:00	NaN	NaN
2015-01-05 15:00:00+01:00	NaN	NaN
2015-01-05 16:00:00+01:00	NaN	NaN
2015-01-05 17:00:00+01:00	NaN	NaN
2015-01-19 19:00:00+01:00	NaN	NaN
2015-01-19 20:00:00+01:00	NaN	NaN
2015-01-27 19:00:00+01:00	NaN	NaN
2015-01-28 13:00:00+01:00	NaN	NaN
2015-02-01 07:00:00+01:00	75.0	48.0
2015-02-01 08:00:00+01:00	75.0	73.0
2015-02-01 09:00:00+01:00	71.0	809.0
2015-02-01 12:00:00+01:00	72.0	3817.0
2015-02-01 13:00:00+01:00	73.0	3836.0
2015-02-01 14:00:00+01:00	79.0	3701.0
2015-02-01 15:00:00+01:00	79.0	3475.0
2015-02-01 16:00:00+01:00	77.0	2742.0
2015-02-01 17:00:00+01:00	77.0	1281.0
2015-02-01 18:00:00+01:00	79.0	328.0
2015-02-01 19:00:00+01:00	82.0	161.0
2015-04-05 03:00:00+02:00	67.0	31.0
2015-04-16 09:00:00+02:00	NaN	NaN
2015-04-20 08:00:00+02:00	62.0	636.0
2015-04-23 21:00:00+02:00	NaN	NaN
2015-05-02 10:00:00+02:00	72.0	2535.0
2015-05-29 03:00:00+02:00	69.0	662.0
2015-06-15 09:00:00+02:00	NaN	NaN
2015-10-02 08:00:00+02:00	70.0	140.0
2015-10-02 11:00:00+02:00	NaN	NaN
2015-12-02 09:00:00+01:00	NaN	NaN
2016-04-13 05:00:00+02:00	69.0	150.0
2016-04-25 05:00:00+02:00	59.0	454.0
2016-04-25 07:00:00+02:00	62.0	283.0
2016-05-10 23:00:00+02:00	91.0	58.0
2016-06-12 01:00:00+02:00	86.0	30.0
2016-07-09 22:00:00+02:00	NaN	NaN
2016-07-12 00:00:00+02:00	83.0	31.0
2016-09-28 09:00:00+02:00	86.0	982.0
2016-10-27 23:00:00+02:00	91.0	70.0
2016-11-23 04:00:00+01:00	85.0	15.0
2017-11-14 12:00:00+01:00	0.0	0.0
2017-11-14 19:00:00+01:00	0.0	0.0
2018-06-11 18:00:00+02:00	96.0	170.0
2018-07-11 09:00:00+02:00	NaN	NaN

time	generation waste	generation wind onshore \
2015-01-05 03:00:00+01:00	NaN	NaN

2015-01-05 12:00:00+01:00	NaN	NaN
2015-01-05 13:00:00+01:00	NaN	NaN
2015-01-05 14:00:00+01:00	NaN	NaN
2015-01-05 15:00:00+01:00	NaN	NaN
2015-01-05 16:00:00+01:00	NaN	NaN
2015-01-05 17:00:00+01:00	NaN	NaN
2015-01-19 19:00:00+01:00	NaN	NaN
2015-01-19 20:00:00+01:00	NaN	NaN
2015-01-27 19:00:00+01:00	NaN	NaN
2015-01-28 13:00:00+01:00	NaN	NaN
2015-02-01 07:00:00+01:00	208.0	3289.0
2015-02-01 08:00:00+01:00	207.0	3102.0
2015-02-01 09:00:00+01:00	204.0	2838.0
2015-02-01 12:00:00+01:00	200.0	1413.0
2015-02-01 13:00:00+01:00	193.0	1347.0
2015-02-01 14:00:00+01:00	199.0	1345.0
2015-02-01 15:00:00+01:00	204.0	1487.0
2015-02-01 16:00:00+01:00	203.0	1648.0
2015-02-01 17:00:00+01:00	207.0	1857.0
2015-02-01 18:00:00+01:00	208.0	1864.0
2015-02-01 19:00:00+01:00	207.0	1813.0
2015-04-05 03:00:00+02:00	142.0	3153.0
2015-04-16 09:00:00+02:00	NaN	NaN
2015-04-20 08:00:00+02:00	147.0	797.0
2015-04-23 21:00:00+02:00	NaN	NaN
2015-05-02 10:00:00+02:00	205.0	10903.0
2015-05-29 03:00:00+02:00	201.0	6503.0
2015-06-15 09:00:00+02:00	NaN	NaN
2015-10-02 08:00:00+02:00	205.0	4362.0
2015-10-02 11:00:00+02:00	NaN	NaN
2015-12-02 09:00:00+01:00	NaN	NaN
2016-04-13 05:00:00+02:00	NaN	8596.0
2016-04-25 05:00:00+02:00	195.0	5989.0
2016-04-25 07:00:00+02:00	214.0	5682.0
2016-05-10 23:00:00+02:00	280.0	3311.0
2016-06-12 01:00:00+02:00	291.0	2019.0
2016-07-09 22:00:00+02:00	NaN	NaN
2016-07-12 00:00:00+02:00	309.0	2031.0
2016-09-28 09:00:00+02:00	300.0	5478.0
2016-10-27 23:00:00+02:00	299.0	3193.0
2016-11-23 04:00:00+01:00	227.0	4598.0
2017-11-14 12:00:00+01:00	0.0	0.0
2017-11-14 19:00:00+01:00	0.0	0.0
2018-06-11 18:00:00+02:00	269.0	9165.0
2018-07-11 09:00:00+02:00	NaN	NaN

total load forecast total load actual \

time		
2015-01-05 03:00:00+01:00	21912.0	21182.0
2015-01-05 12:00:00+01:00	23209.0	NaN
2015-01-05 13:00:00+01:00	23725.0	NaN
2015-01-05 14:00:00+01:00	23614.0	NaN
2015-01-05 15:00:00+01:00	22381.0	NaN
2015-01-05 16:00:00+01:00	21371.0	NaN
2015-01-05 17:00:00+01:00	20760.0	NaN
2015-01-19 19:00:00+01:00	38642.0	39304.0
2015-01-19 20:00:00+01:00	38758.0	39262.0
2015-01-27 19:00:00+01:00	38968.0	38335.0
2015-01-28 13:00:00+01:00	36239.0	NaN
2015-02-01 07:00:00+01:00	24379.0	NaN
2015-02-01 08:00:00+01:00	27389.0	NaN
2015-02-01 09:00:00+01:00	30619.0	NaN
2015-02-01 12:00:00+01:00	31357.0	NaN
2015-02-01 13:00:00+01:00	31338.0	NaN
2015-02-01 14:00:00+01:00	30874.0	NaN
2015-02-01 15:00:00+01:00	30124.0	NaN
2015-02-01 16:00:00+01:00	29714.0	NaN
2015-02-01 17:00:00+01:00	29801.0	NaN
2015-02-01 18:00:00+01:00	32257.0	NaN
2015-02-01 19:00:00+01:00	33183.0	NaN
2015-04-05 03:00:00+02:00	20016.0	NaN
2015-04-16 09:00:00+02:00	31001.0	NaN
2015-04-20 08:00:00+02:00	29287.0	NaN
2015-04-23 21:00:00+02:00	31421.0	NaN
2015-05-02 10:00:00+02:00	39644.0	NaN
2015-05-29 03:00:00+02:00	23132.0	NaN
2015-06-15 09:00:00+02:00	29899.0	30047.0
2015-10-02 08:00:00+02:00	36798.0	NaN
2015-10-02 11:00:00+02:00	38921.0	NaN
2015-12-02 09:00:00+01:00	37413.0	NaN
2016-04-13 05:00:00+02:00	23514.0	23614.0
2016-04-25 05:00:00+02:00	21471.0	NaN
2016-04-25 07:00:00+02:00	27635.0	NaN
2016-05-10 23:00:00+02:00	26641.0	NaN
2016-06-12 01:00:00+02:00	24715.0	24155.0
2016-07-09 22:00:00+02:00	34985.0	NaN
2016-07-12 00:00:00+02:00	25313.0	25103.0
2016-09-28 09:00:00+02:00	31072.0	NaN
2016-10-27 23:00:00+02:00	26423.0	26583.0
2016-11-23 04:00:00+01:00	23469.0	23112.0
2017-11-14 12:00:00+01:00	33805.0	NaN
2017-11-14 19:00:00+01:00	35592.0	NaN
2018-06-11 18:00:00+02:00	34752.0	NaN
2018-07-11 09:00:00+02:00	33938.0	NaN

time	price day ahead	price actual
2015-01-05 03:00:00+01:00	35.20	59.68
2015-01-05 12:00:00+01:00	35.50	79.14
2015-01-05 13:00:00+01:00	36.80	73.95
2015-01-05 14:00:00+01:00	32.50	71.93
2015-01-05 15:00:00+01:00	30.00	71.50
2015-01-05 16:00:00+01:00	30.00	71.85
2015-01-05 17:00:00+01:00	30.60	80.53
2015-01-19 19:00:00+01:00	70.01	88.95
2015-01-19 20:00:00+01:00	69.00	87.94
2015-01-27 19:00:00+01:00	66.00	83.97
2015-01-28 13:00:00+01:00	65.00	77.62
2015-02-01 07:00:00+01:00	56.10	16.98
2015-02-01 08:00:00+01:00	57.69	19.56
2015-02-01 09:00:00+01:00	60.01	23.13
2015-02-01 12:00:00+01:00	59.97	22.51
2015-02-01 13:00:00+01:00	59.69	23.44
2015-02-01 14:00:00+01:00	58.69	24.10
2015-02-01 15:00:00+01:00	58.13	21.12
2015-02-01 16:00:00+01:00	59.00	21.73
2015-02-01 17:00:00+01:00	59.69	25.93
2015-02-01 18:00:00+01:00	63.76	54.13
2015-02-01 19:00:00+01:00	65.01	68.53
2015-04-05 03:00:00+02:00	42.55	29.04
2015-04-16 09:00:00+02:00	56.54	67.55
2015-04-20 08:00:00+02:00	62.00	72.92
2015-04-23 21:00:00+02:00	69.49	82.57
2015-05-02 10:00:00+02:00	58.49	59.09
2015-05-29 03:00:00+02:00	45.93	55.07
2015-06-15 09:00:00+02:00	62.48	73.82
2015-10-02 08:00:00+02:00	66.19	70.13
2015-10-02 11:00:00+02:00	70.09	70.49
2015-12-02 09:00:00+01:00	75.71	80.44
2016-04-13 05:00:00+02:00	18.69	25.14
2016-04-25 05:00:00+02:00	15.00	22.65
2016-04-25 07:00:00+02:00	32.97	40.18
2016-05-10 23:00:00+02:00	51.57	39.11
2016-06-12 01:00:00+02:00	60.23	48.72
2016-07-09 22:00:00+02:00	45.72	51.72
2016-07-12 00:00:00+02:00	64.99	47.49
2016-09-28 09:00:00+02:00	49.72	56.40
2016-10-27 23:00:00+02:00	55.70	62.84
2016-11-23 04:00:00+01:00	43.19	49.11
2017-11-14 12:00:00+01:00	60.53	66.17
2017-11-14 19:00:00+01:00	68.05	75.45

2018-06-11 18:00:00+02:00	69.87	64.93
2018-07-11 09:00:00+02:00	63.01	69.79

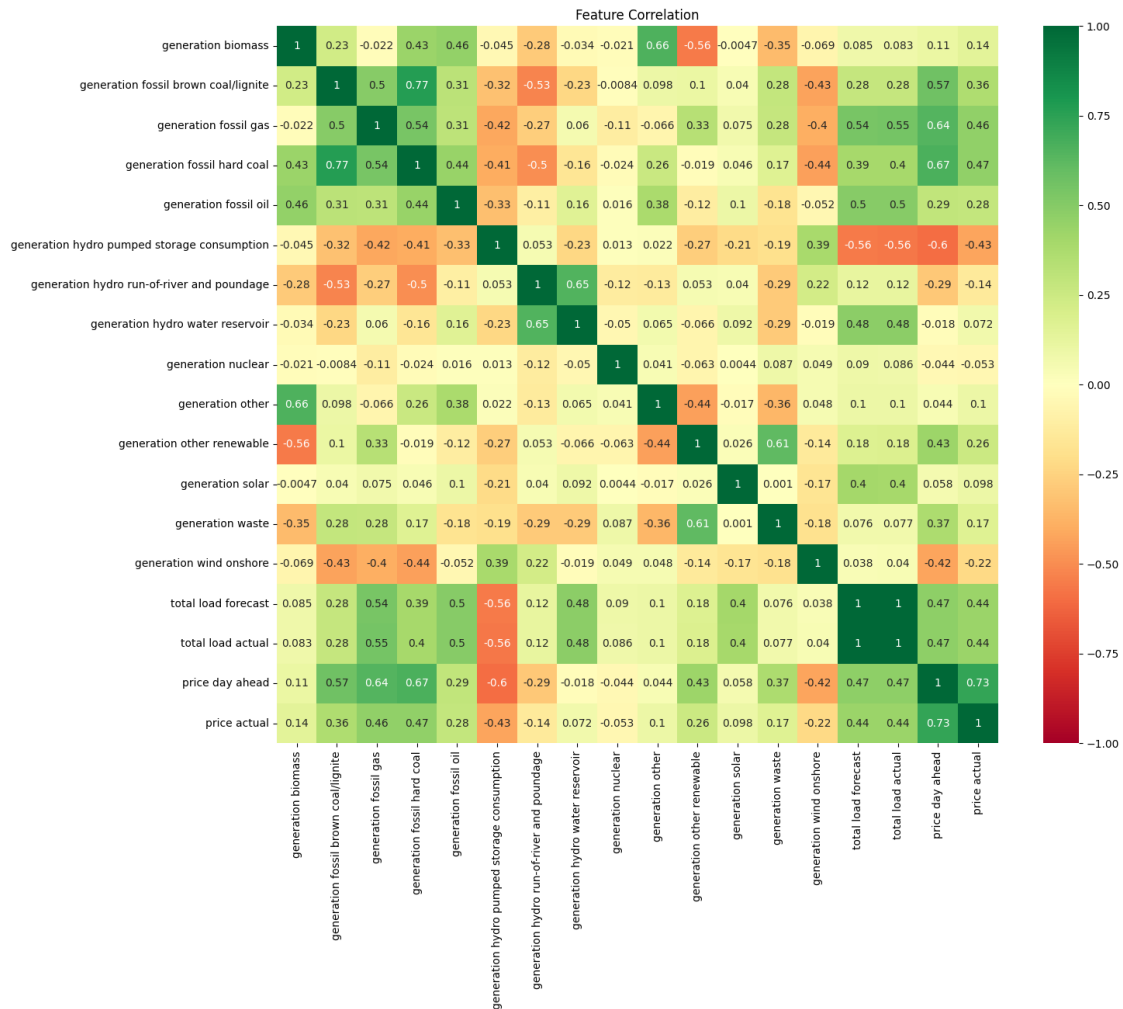
```
[16]: df_energy.isnull().sum()
```

```
[16]: 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
```

```
[17]: def feat_corr(input_df):
      corr = input_df.corr()
      plt.figure(figsize=(15,12))
      #plot heat map
      g=sns.heatmap(corr,annot=True,cmap="RdYlGn", vmin=-1, vmax=1)
      plt.title('Feature Correlation')

      return plt.show()
```

```
[18]: feat_corr(df_energy)
```



```
[19]: file_path = 'weather_features.csv'
df_weather = pd.read_csv(file_path)
```

```
[20]: df_weather.head()
```

```
[20]:
```

	dt_iso	city_name	temp	temp_min	temp_max	pressure	\
0	2015-01-01 00:00:00+01:00	Valencia	270.475	270.475	270.475	1001	
1	2015-01-01 01:00:00+01:00	Valencia	270.475	270.475	270.475	1001	
2	2015-01-01 02:00:00+01:00	Valencia	269.686	269.686	269.686	1002	
3	2015-01-01 03:00:00+01:00	Valencia	269.686	269.686	269.686	1002	
4	2015-01-01 04:00:00+01:00	Valencia	269.686	269.686	269.686	1002	

	humidity	wind_speed	wind_deg	rain_1h	rain_3h	snow_3h	clouds_all	\
0	77	1	62	0.0	0.0	0.0	0	
1	77	1	62	0.0	0.0	0.0	0	
2	78	0	23	0.0	0.0	0.0	0	

3	78	0	23	0.0	0.0	0.0	0
4	78	0	23	0.0	0.0	0.0	0

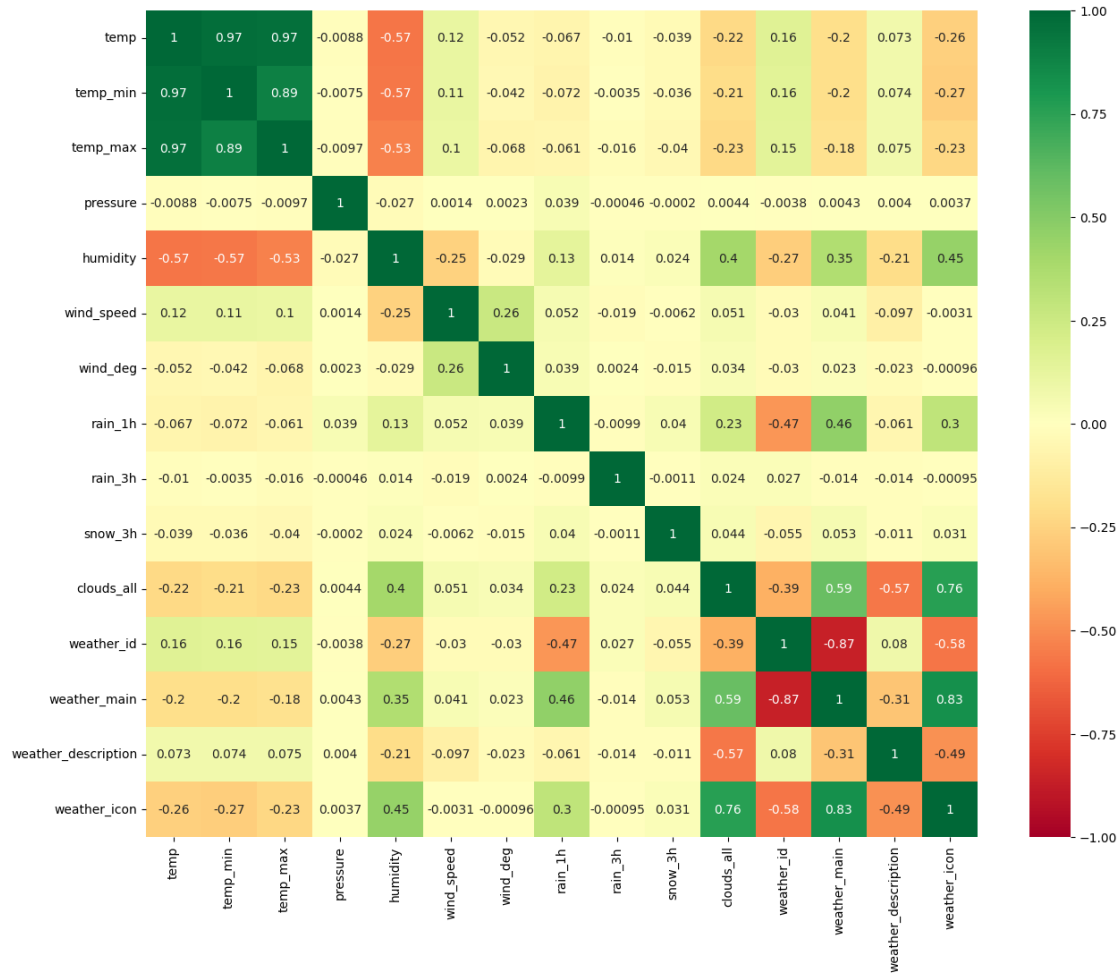
	weather_id	weather_main	weather_description	weather_icon
0	800	clear	sky is clear	01n
1	800	clear	sky is clear	01n
2	800	clear	sky is clear	01n
3	800	clear	sky is clear	01n
4	800	clear	sky is clear	01n

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

```
[22]: def feat_corr(input_df):
    # Exclude non-numeric columns before calculating correlation
    numeric_df = input_df.select_dtypes(include=np.number)

    corr = numeric_df.corr()
    plt.figure(figsize=(15, 12))
    # plot heat map
    g = sns.heatmap(corr, annot=True, cmap="RdYlGn", vmin=-1, vmax=1)
    plt.show() # This line is added to display the plot
```

```
[23]: feat_corr(df_temp)
```



```
[24]: df_weather['weather_id'].unique()
```

```
[24]: 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])
```

```
[25]: 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.drop(col_drop_name, axis = 1 , inplace = True)
```

```
[26]: check_Nans_Dups(df_weather)
```

The dataframe has no NaN values.
The dataframe has 3076 duplicate rows.

```
[27]: df_weather = df_weather.reset_index().drop_duplicates()
```

```
[28]: df_weather['time'] = pd.to_datetime(df_weather['dt_iso'])
df_weather.drop(["dt_iso"], axis = 1, inplace = True)
df_weather = df_weather.set_index('time')
df_weather.drop(["index"], axis = 1, inplace = True)
```

<ipython-input-28-f2d592ef1b17>:1: FutureWarning: In a future version of pandas, parsing datetimes with mixed time zones will raise an error unless `utc=True`. Please specify `utc=True` to opt in to the new behaviour and silence this warning. To create a `Series` with mixed offsets and `object` dtype, please use `apply` and `datetime.datetime.strptime`

```
df_weather['time'] = pd.to_datetime(df_weather['dt_iso'])
```

```
[29]: df_weather
```

```
[29]:
```

	city_name	temp	pressure	humidity	wind_speed	\
time						
2015-01-01 00:00:00+01:00	Valencia	270.475	1001	77	1	
2015-01-01 01:00:00+01:00	Valencia	270.475	1001	77	1	
2015-01-01 02:00:00+01:00	Valencia	269.686	1002	78	0	
2015-01-01 03:00:00+01:00	Valencia	269.686	1002	78	0	
2015-01-01 04:00:00+01:00	Valencia	269.686	1002	78	0	
...	
2018-12-31 19:00:00+01:00	Seville	287.760	1028	54	3	
2018-12-31 20:00:00+01:00	Seville	285.760	1029	62	3	
2018-12-31 21:00:00+01:00	Seville	285.150	1028	58	4	
2018-12-31 22:00:00+01:00	Seville	284.150	1029	57	4	
2018-12-31 23:00:00+01:00	Seville	283.970	1029	70	3	

	wind_deg	rain_1h	rain_3h	snow_3h	clouds_all
time					
2015-01-01 00:00:00+01:00	62	0.0	0.0	0.0	0
2015-01-01 01:00:00+01:00	62	0.0	0.0	0.0	0
2015-01-01 02:00:00+01:00	23	0.0	0.0	0.0	0
2015-01-01 03:00:00+01:00	23	0.0	0.0	0.0	0
2015-01-01 04:00:00+01:00	23	0.0	0.0	0.0	0
...
2018-12-31 19:00:00+01:00	30	0.0	0.0	0.0	0
2018-12-31 20:00:00+01:00	30	0.0	0.0	0.0	0
2018-12-31 21:00:00+01:00	50	0.0	0.0	0.0	0
2018-12-31 22:00:00+01:00	60	0.0	0.0	0.0	0
2018-12-31 23:00:00+01:00	50	0.0	0.0	0.0	0

[178396 rows x 10 columns]

```
[30]: df_energy
```

[30]:

```

generation biomass \
time
2015-01-01 00:00:00+01:00      447.0
2015-01-01 01:00:00+01:00      449.0
2015-01-01 02:00:00+01:00      448.0
2015-01-01 03:00:00+01:00      438.0
2015-01-01 04:00:00+01:00      428.0
...
2018-12-31 19:00:00+01:00      297.0
2018-12-31 20:00:00+01:00      296.0
2018-12-31 21:00:00+01:00      292.0
2018-12-31 22:00:00+01:00      293.0
2018-12-31 23:00:00+01:00      290.0

```

```

generation fossil brown coal/lignite \
time
2015-01-01 00:00:00+01:00      329.0
2015-01-01 01:00:00+01:00      328.0
2015-01-01 02:00:00+01:00      323.0
2015-01-01 03:00:00+01:00      254.0
2015-01-01 04:00:00+01:00      187.0
...
2018-12-31 19:00:00+01:00          0.0
2018-12-31 20:00:00+01:00          0.0
2018-12-31 21:00:00+01:00          0.0
2018-12-31 22:00:00+01:00          0.0
2018-12-31 23:00:00+01:00          0.0

```

```

generation fossil gas  generation fossil hard coal \
time
2015-01-01 00:00:00+01:00      4844.0      4821.0
2015-01-01 01:00:00+01:00      5196.0      4755.0
2015-01-01 02:00:00+01:00      4857.0      4581.0
2015-01-01 03:00:00+01:00      4314.0      4131.0
2015-01-01 04:00:00+01:00      4130.0      3840.0
...
2018-12-31 19:00:00+01:00      7634.0      2628.0
2018-12-31 20:00:00+01:00      7241.0      2566.0
2018-12-31 21:00:00+01:00      7025.0      2422.0
2018-12-31 22:00:00+01:00      6562.0      2293.0
2018-12-31 23:00:00+01:00      6926.0      2166.0

```

```

generation fossil oil \
time
2015-01-01 00:00:00+01:00      162.0
2015-01-01 01:00:00+01:00      158.0
2015-01-01 02:00:00+01:00      157.0

```

2015-01-01 03:00:00+01:00	160.0
2015-01-01 04:00:00+01:00	156.0
...	...
2018-12-31 19:00:00+01:00	178.0
2018-12-31 20:00:00+01:00	174.0
2018-12-31 21:00:00+01:00	168.0
2018-12-31 22:00:00+01:00	163.0
2018-12-31 23:00:00+01:00	163.0

time	generation hydro pumped storage consumption \
2015-01-01 00:00:00+01:00	863.0
2015-01-01 01:00:00+01:00	920.0
2015-01-01 02:00:00+01:00	1164.0
2015-01-01 03:00:00+01:00	1503.0
2015-01-01 04:00:00+01:00	1826.0
...	...
2018-12-31 19:00:00+01:00	1.0
2018-12-31 20:00:00+01:00	1.0
2018-12-31 21:00:00+01:00	50.0
2018-12-31 22:00:00+01:00	108.0
2018-12-31 23:00:00+01:00	108.0

time	generation hydro run-of-river and poundage \
2015-01-01 00:00:00+01:00	1051.0
2015-01-01 01:00:00+01:00	1009.0
2015-01-01 02:00:00+01:00	973.0
2015-01-01 03:00:00+01:00	949.0
2015-01-01 04:00:00+01:00	953.0
...	...
2018-12-31 19:00:00+01:00	1135.0
2018-12-31 20:00:00+01:00	1172.0
2018-12-31 21:00:00+01:00	1148.0
2018-12-31 22:00:00+01:00	1128.0
2018-12-31 23:00:00+01:00	1069.0

time	generation hydro water reservoir \
2015-01-01 00:00:00+01:00	1899.0
2015-01-01 01:00:00+01:00	1658.0
2015-01-01 02:00:00+01:00	1371.0
2015-01-01 03:00:00+01:00	779.0
2015-01-01 04:00:00+01:00	720.0
...	...
2018-12-31 19:00:00+01:00	4836.0
2018-12-31 20:00:00+01:00	3931.0

2018-12-31 21:00:00+01:00	2831.0
2018-12-31 22:00:00+01:00	2068.0
2018-12-31 23:00:00+01:00	1686.0

time	generation nuclear	generation other \
2015-01-01 00:00:00+01:00	7096.0	43.0
2015-01-01 01:00:00+01:00	7096.0	43.0
2015-01-01 02:00:00+01:00	7099.0	43.0
2015-01-01 03:00:00+01:00	7098.0	43.0
2015-01-01 04:00:00+01:00	7097.0	43.0
...
2018-12-31 19:00:00+01:00	6073.0	63.0
2018-12-31 20:00:00+01:00	6074.0	62.0
2018-12-31 21:00:00+01:00	6076.0	61.0
2018-12-31 22:00:00+01:00	6075.0	61.0
2018-12-31 23:00:00+01:00	6075.0	61.0

time	generation other renewable	generation solar \
2015-01-01 00:00:00+01:00	73.0	49.0
2015-01-01 01:00:00+01:00	71.0	50.0
2015-01-01 02:00:00+01:00	73.0	50.0
2015-01-01 03:00:00+01:00	75.0	50.0
2015-01-01 04:00:00+01:00	74.0	42.0
...
2018-12-31 19:00:00+01:00	95.0	85.0
2018-12-31 20:00:00+01:00	95.0	33.0
2018-12-31 21:00:00+01:00	94.0	31.0
2018-12-31 22:00:00+01:00	93.0	31.0
2018-12-31 23:00:00+01:00	92.0	31.0

time	generation waste	generation wind onshore \
2015-01-01 00:00:00+01:00	196.0	6378.0
2015-01-01 01:00:00+01:00	195.0	5890.0
2015-01-01 02:00:00+01:00	196.0	5461.0
2015-01-01 03:00:00+01:00	191.0	5238.0
2015-01-01 04:00:00+01:00	189.0	4935.0
...
2018-12-31 19:00:00+01:00	277.0	3113.0
2018-12-31 20:00:00+01:00	280.0	3288.0
2018-12-31 21:00:00+01:00	286.0	3503.0
2018-12-31 22:00:00+01:00	287.0	3586.0
2018-12-31 23:00:00+01:00	287.0	3651.0

total load forecast	total load actual \
---------------------	---------------------

time		
2015-01-01 00:00:00+01:00	26118.0	25385.0
2015-01-01 01:00:00+01:00	24934.0	24382.0
2015-01-01 02:00:00+01:00	23515.0	22734.0
2015-01-01 03:00:00+01:00	22642.0	21286.0
2015-01-01 04:00:00+01:00	21785.0	20264.0
...
2018-12-31 19:00:00+01:00	30619.0	30653.0
2018-12-31 20:00:00+01:00	29932.0	29735.0
2018-12-31 21:00:00+01:00	27903.0	28071.0
2018-12-31 22:00:00+01:00	25450.0	25801.0
2018-12-31 23:00:00+01:00	24424.0	24455.0

	price day ahead	price actual
time		
2015-01-01 00:00:00+01:00	50.10	65.41
2015-01-01 01:00:00+01:00	48.10	64.92
2015-01-01 02:00:00+01:00	47.33	64.48
2015-01-01 03:00:00+01:00	42.27	59.32
2015-01-01 04:00:00+01:00	38.41	56.04
...
2018-12-31 19:00:00+01:00	68.85	77.02
2018-12-31 20:00:00+01:00	68.40	76.16
2018-12-31 21:00:00+01:00	66.88	74.30
2018-12-31 22:00:00+01:00	63.93	69.89
2018-12-31 23:00:00+01:00	64.27	69.88

[35064 rows x 18 columns]

```
[31]: df_weather.describe().round(2)
```

```
[31]:
```

	temp	pressure	humidity	wind_speed	wind_deg	rain_1h	\
count	178396.00	178396.00	178396.00	178396.00	178396.00	178396.00	
mean	289.62	1069.26	68.42	2.47	166.59	0.08	
std	8.03	5969.63	21.90	2.10	116.61	0.40	
min	262.24	0.00	0.00	0.00	0.00	0.00	
25%	283.67	1013.00	53.00	1.00	55.00	0.00	
50%	289.15	1018.00	72.00	2.00	177.00	0.00	
75%	295.15	1022.00	87.00	4.00	270.00	0.00	
max	315.60	1008371.00	100.00	133.00	360.00	12.00	

	rain_3h	snow_3h	clouds_all
count	178396.00	178396.00	178396.00
mean	0.00	0.00	25.07
std	0.01	0.22	30.77
min	0.00	0.00	0.00
25%	0.00	0.00	0.00

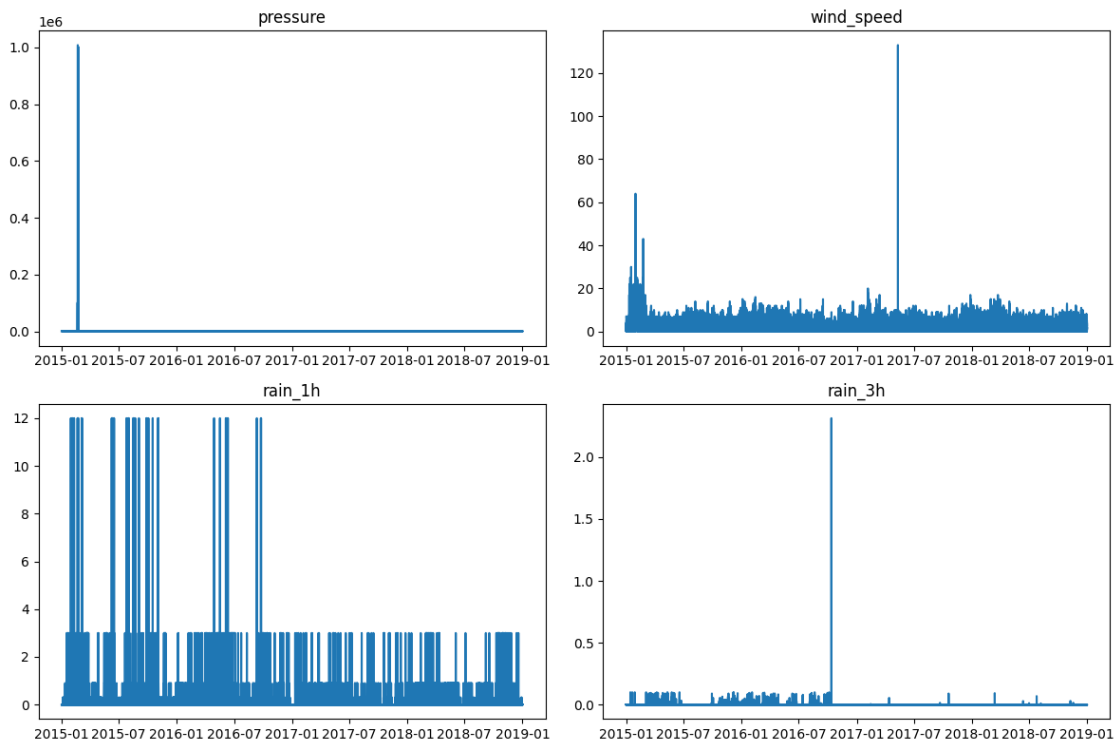
50%	0.00	0.00	20.00
75%	0.00	0.00	40.00
max	2.32	21.50	100.00

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

# select the columns to plot
columns_to_plot = ['pressure', 'wind_speed', 'rain_1h', 'rain_3h']

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



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

# select the columns to plot
```

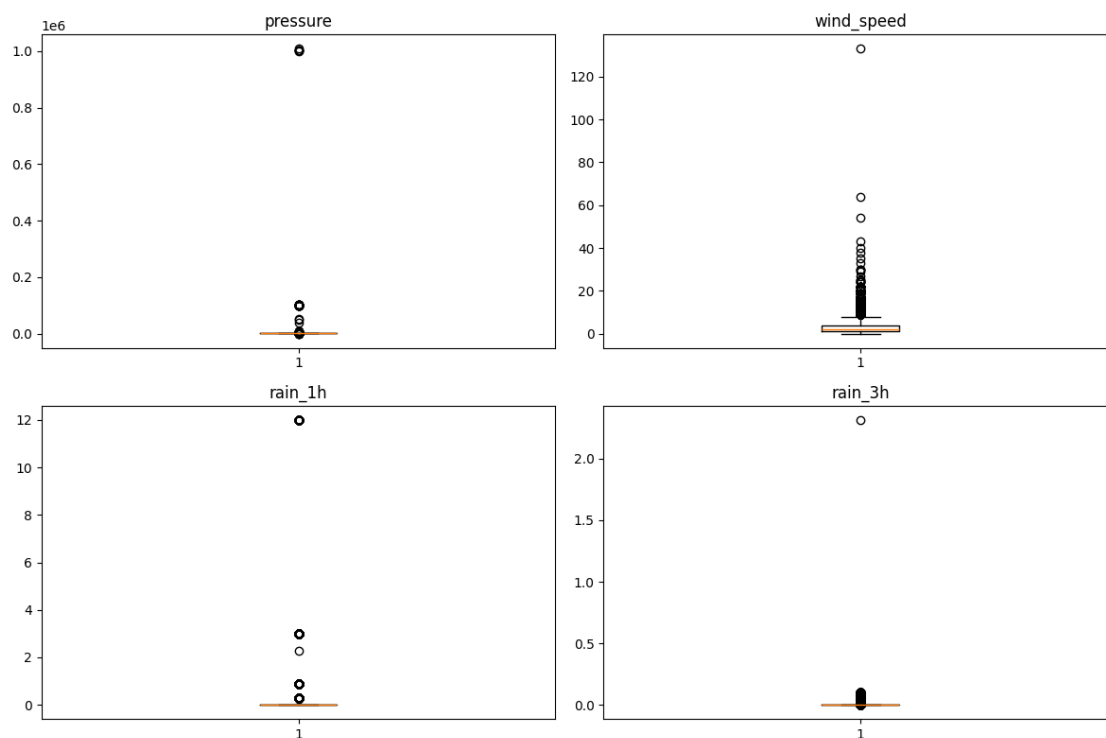
```

columns_to_plot = ['pressure', 'wind_speed', 'rain_1h', 'rain_3h']

# loop through the subplots and plot each column
for i, ax in enumerate(axes.flat):
    if i < len(columns_to_plot):
        ax.boxplot(x = df_weather[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() # display the plot

```



```

[34]: df_weather.loc[df_weather['pressure'] > 1080, 'pressure'] = np.nan
df_weather.loc[df_weather['pressure'] < 870, 'pressure'] = np.nan
df_weather.loc[df_weather['wind_speed'] > 113, 'wind_speed'] = np.nan

df_weather.interpolate(method='linear', limit_direction='forward', inplace =
↪ True)

```

<ipython-input-34-e09d3d1c477d>:5: FutureWarning: DataFrame.interpolate with object dtype is deprecated and will raise in a future version. Call obj.infer_objects(copy=False) before interpolating instead.

```

df_weather.interpolate(method='linear', limit_direction='forward', inplace =

```

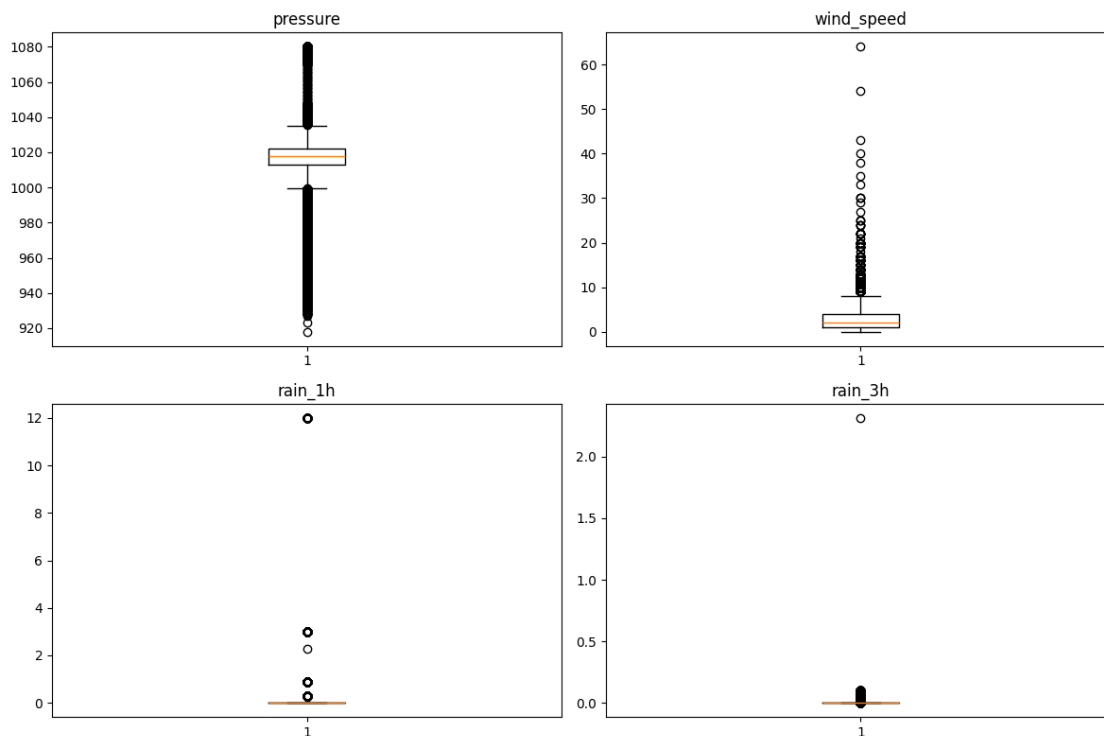
True)

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

# select the columns to plot
columns_to_plot = ['pressure', 'wind_speed', 'rain_1h', 'rain_3h']

# loop through the subplots and plot each column
for i, ax in enumerate(axes.flat):
    if i < len(columns_to_plot):
        ax.boxplot(x = df_weather[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() # display the plot
```



```
[36]: # be sure to drop rain_h3
df_weather.drop(['rain_3h'], axis = 1 , inplace = True)
```

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

city_list = df_weather['city_name'].unique()
```

```
grouped_weather = df_weather.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 35145
 Number of samples in df_weather in Madrid is 36267
 Number of samples in df_weather in Bilbao is 35951
 Number of samples in df_weather in Barcelona is 35476
 Number of samples in df_weather in Seville is 35557

```
[38]: df_weather_cleaned = df_weather.reset_index().drop_duplicates(subset=['time',
    ↪'city_name'], keep='first').set_index('time')
```

```
[39]: df_weather_cleaned
```

```
[39]:
```

	city_name	temp	pressure	humidity	wind_speed	\
time						
2015-01-01 00:00:00+01:00	Valencia	270.475	1001.0	77	1.0	
2015-01-01 01:00:00+01:00	Valencia	270.475	1001.0	77	1.0	
2015-01-01 02:00:00+01:00	Valencia	269.686	1002.0	78	0.0	
2015-01-01 03:00:00+01:00	Valencia	269.686	1002.0	78	0.0	
2015-01-01 04:00:00+01:00	Valencia	269.686	1002.0	78	0.0	
...	
2018-12-31 19:00:00+01:00	Seville	287.760	1028.0	54	3.0	
2018-12-31 20:00:00+01:00	Seville	285.760	1029.0	62	3.0	
2018-12-31 21:00:00+01:00	Seville	285.150	1028.0	58	4.0	
2018-12-31 22:00:00+01:00	Seville	284.150	1029.0	57	4.0	
2018-12-31 23:00:00+01:00	Seville	283.970	1029.0	70	3.0	
	wind_deg	rain_1h	snow_3h	clouds_all		
time						
2015-01-01 00:00:00+01:00	62	0.0	0.0	0		
2015-01-01 01:00:00+01:00	62	0.0	0.0	0		
2015-01-01 02:00:00+01:00	23	0.0	0.0	0		
2015-01-01 03:00:00+01:00	23	0.0	0.0	0		
2015-01-01 04:00:00+01:00	23	0.0	0.0	0		
...		
2018-12-31 19:00:00+01:00	30	0.0	0.0	0		
2018-12-31 20:00:00+01:00	30	0.0	0.0	0		
2018-12-31 21:00:00+01:00	50	0.0	0.0	0		
2018-12-31 22:00:00+01:00	60	0.0	0.0	0		
2018-12-31 23:00:00+01:00	50	0.0	0.0	0		

[175320 rows x 9 columns]

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

city_list = df_weather['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

[41]: df_weather_all_cities = [grouped_weather.get_group(x) for x in grouped_weather.
    ↪groups]

[42]: df_weather_all_cities[0]
```

```
[42]:
```

	city_name	temp	pressure	humidity	\
time					
2015-01-01 00:00:00+01:00	Barcelona	281.625	1035.0	100	
2015-01-01 01:00:00+01:00	Barcelona	281.625	1035.0	100	
2015-01-01 02:00:00+01:00	Barcelona	281.286	1036.0	100	
2015-01-01 03:00:00+01:00	Barcelona	281.286	1036.0	100	
2015-01-01 04:00:00+01:00	Barcelona	281.286	1036.0	100	
...	
2018-12-31 19:00:00+01:00	Barcelona	284.130	1027.0	71	
2018-12-31 20:00:00+01:00	Barcelona	282.640	1027.0	62	
2018-12-31 21:00:00+01:00	Barcelona	282.140	1028.0	53	
2018-12-31 22:00:00+01:00	Barcelona	281.130	1028.0	50	
2018-12-31 23:00:00+01:00	Barcelona	280.130	1028.0	100	

	wind_speed	wind_deg	rain_1h	snow_3h	clouds_all
time					
2015-01-01 00:00:00+01:00	7.0	58	0.0	0.0	0
2015-01-01 01:00:00+01:00	7.0	58	0.0	0.0	0
2015-01-01 02:00:00+01:00	7.0	48	0.0	0.0	0
2015-01-01 03:00:00+01:00	7.0	48	0.0	0.0	0
2015-01-01 04:00:00+01:00	7.0	48	0.0	0.0	0
...	
2018-12-31 19:00:00+01:00	1.0	250	0.0	0.0	0
2018-12-31 20:00:00+01:00	3.0	270	0.0	0.0	0
2018-12-31 21:00:00+01:00	4.0	300	0.0	0.0	0
2018-12-31 22:00:00+01:00	5.0	320	0.0	0.0	0

```
2018-12-31 23:00:00+01:00      5.0      310      0.0      0.0      0
```

```
[35064 rows x 9 columns]
```

```
[43]: df_weather_energy = df_energy

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)
```

```
[44]: df_weather_energy.columns
```

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

```
[45]: check_Nans_Dups(df_weather_energy)
```

The dataframe has 292 NaN values.

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
temp_Barcelona	0
pressure_Barcelona	0
humidity_Barcelona	0
wind_speed_Barcelona	0
wind_deg_Barcelona	0
rain_1h_Barcelona	0
snow_3h_Barcelona	0
clouds_all_Barcelona	0
temp_Bilbao	0
pressure_Bilbao	0
humidity_Bilbao	0
wind_speed_Bilbao	0
wind_deg_Bilbao	0
rain_1h_Bilbao	0
snow_3h_Bilbao	0
clouds_all_Bilbao	0
temp_Madrid	0
pressure_Madrid	0
humidity_Madrid	0
wind_speed_Madrid	0
wind_deg_Madrid	0
rain_1h_Madrid	0
snow_3h_Madrid	0
clouds_all_Madrid	0
temp_Seville	0
pressure_Seville	0
humidity_Seville	0
wind_speed_Seville	0
wind_deg_Seville	0
rain_1h_Seville	0
snow_3h_Seville	0
clouds_all_Seville	0
temp_Valencia	0
pressure_Valencia	0
humidity_Valencia	0
wind_speed_Valencia	0


```
wind_deg_Valencia          0
rain_1h_Valencia           0
snow_3h_Valencia           0
clouds_all_Valencia        0
dtype: int64
The dataframe has no duplicate rows.
```

```
[46]: df_weather_energy['hour'] = df_weather_energy.index.map(lambda x : x.hour)
df_weather_energy['weekday'] = df_weather_energy.index.map(lambda x : x.
    ↪weekday())
df_weather_energy['month'] = df_weather_energy.index.map(lambda x : x.month)
df_weather_energy['year'] = df_weather_energy.index.map(lambda x: x.year)
```

```
[47]: df_weather_energy.columns
```

```
[47]: Index(['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 forecast',
'total load actual', 'price day ahead', 'price actual',
'temp_Barcelona', 'pressure_Barcelona', 'humidity_Barcelona',
'wind_speed_Barcelona', 'wind_deg_Barcelona', 'rain_1h_Barcelona',
'snow_3h_Barcelona', 'clouds_all_Barcelona', 'temp_Bilbao',
'pressure_Bilbao', 'humidity_Bilbao', 'wind_speed_Bilbao',
'wind_deg_Bilbao', 'rain_1h_Bilbao', 'snow_3h_Bilbao',
'clouds_all_Bilbao', 'temp_Madrid', 'pressure_Madrid',
'humidity_Madrid', 'wind_speed_Madrid', 'wind_deg_Madrid',
'rain_1h_Madrid', 'snow_3h_Madrid', 'clouds_all_Madrid', 'temp_Seville',
'pressure_Seville', 'humidity_Seville', 'wind_speed_Seville',
'wind_deg_Seville', 'rain_1h_Seville', 'snow_3h_Seville',
'clouds_all_Seville', 'temp_Valencia', 'pressure_Valencia',
'humidity_Valencia', 'wind_speed_Valencia', 'wind_deg_Valencia',
'rain_1h_Valencia', 'snow_3h_Valencia', 'clouds_all_Valencia', 'hour',
'weekday', 'month', 'year'],
dtype='object')
```

```
[48]: fig = make_subplots()

fig.add_trace(
    go.Line(x=df_weather_energy.index, y=df_weather_energy["price actual"],
        name="price actual"))

fig.add_trace(
    go.Line(x=df_weather_energy.index,y=df_weather_energy.rolling(window=24).
    ↪mean()["price actual"],
```

```

name="rolling window = daily ave"))
fig.add_trace(
    go.Line(x=df_weather_energy.index,y=df_weather_energy.rolling(window=24*7).
    ↪mean()["price actual"],
name="rolling window = weekly ave"))
# fig.update_xaxes(rangeslider_visible=True)
fig.show()

```

/usr/local/lib/python3.10/dist-packages/plotly/graph_objs/_deprecations.py:378:
DeprecationWarning:

plotly.graph_objs.Line is deprecated.

Please replace it with one of the following more specific types

- plotly.graph_objs.scatter.Line
- plotly.graph_objs.layout.shape.Line
- etc.

```

[49]: 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='royalblue',
    ax=axes[0]);
axes[0].set_title('Monthly actual price (1 is Jan)')

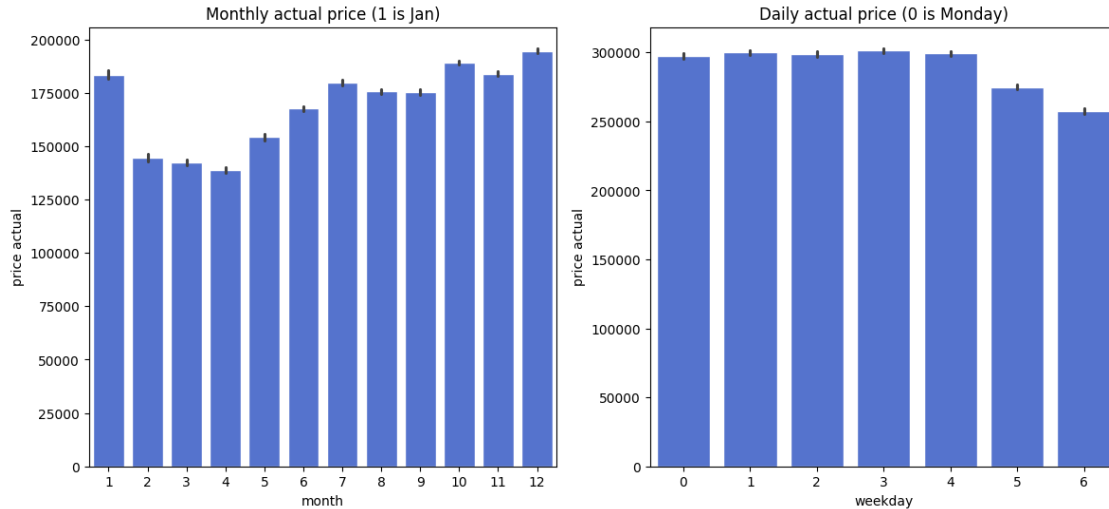
sns.barplot(
    x="weekday",
    y="price actual",
    data=df_weather_energy,
    estimator=sum,
    color='royalblue',
    ax=axes[1]);
axes[1].set_title('Daily actual price (0 is Monday)')

```

```

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

```



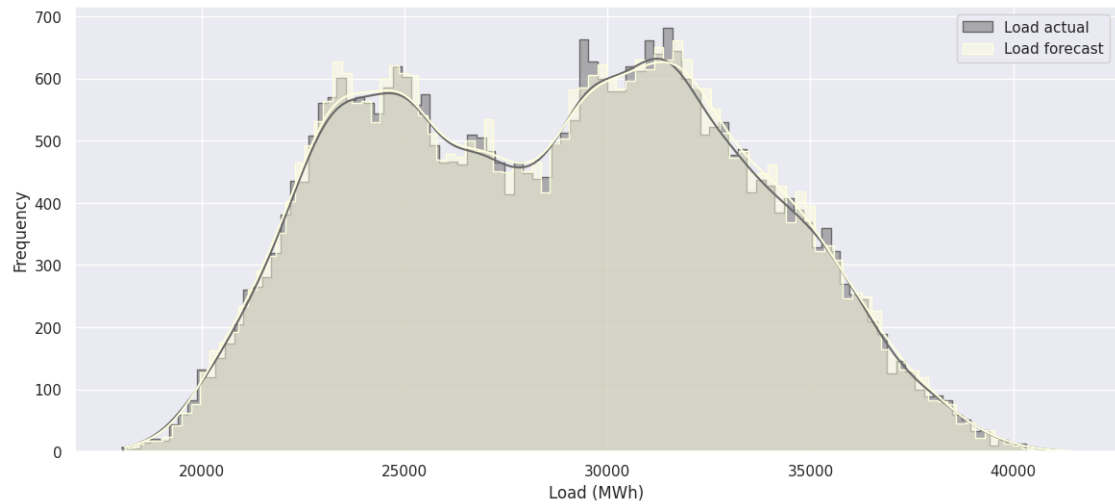
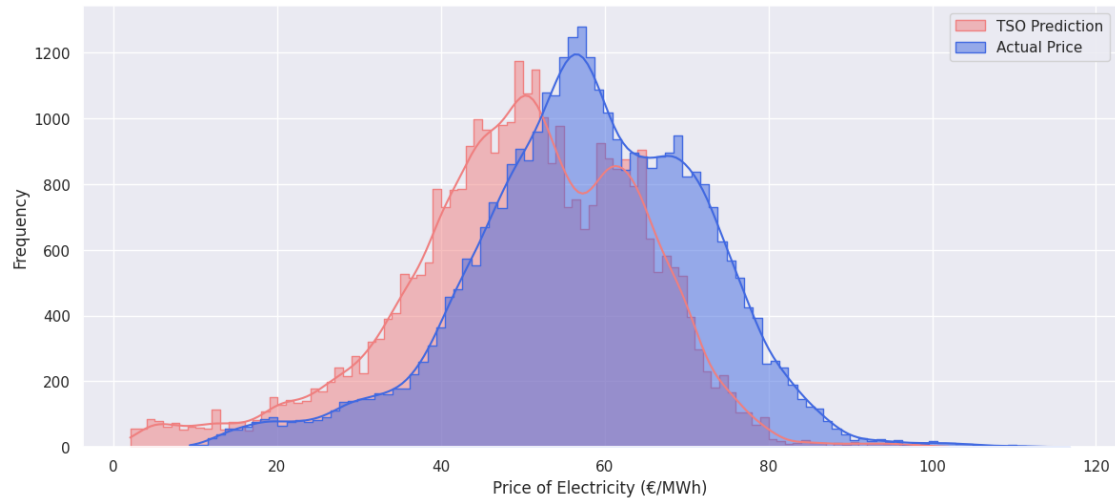
```
[50]: plt.figure(figsize=(14,6))

gr = sns.histplot(df_weather_energy['price day ahead'], bins=100, label='TSO_
↳Prediction', element="step", color='lightcoral', kde = True)
gr = sns.histplot(df_weather_energy['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(df_weather_energy['total load actual'], bins=100, label='Load_
↳actual', element="step", color='dimgrey', kde = True)
gr = sns.histplot(df_weather_energy['total load forecast'], bins=100,
↳label='Load forecast', element="step", color='lightyellow', kde = True)

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



```
[51]: y_scaler_actual = MinMaxScaler()
y_scaler_dayahead = MinMaxScaler()

train_cutoff = int(0.8*df_weather_energy.shape[0])
val_cutoff = int(0.9*df_weather_energy.shape[0])

y_price_actual = df_weather_energy[['price actual']]
y_price_dayahead = df_weather_energy[['price day ahead']]

y_scaler_actual.fit(y_price_actual[:train_cutoff])
actual_norm = y_scaler_actual.transform(y_price_actual)

y_scaler_dayahead.fit(df_weather_energy[['price day ahead']][:train_cutoff])
```

```

dayahead_norm = y_scaler_dayahead.transform(y_price_dayahead)

print(f' mean absolute error for normalized acutal price and TSO predcition is :
↪ {round(mean_absolute_error(actual_norm, dayahead_norm),3)}')

```

mean absolute error for normalized acutal price and TSO predcition is : 0.071

```

[52]: df_weather_energy.drop(['total load forecast'], axis = 1, inplace = True)

```

```

[53]: fig, axes = plt.subplots(5, 1, figsize=(20, 12))
decom_data = df_weather_energy[['price actual']].copy()

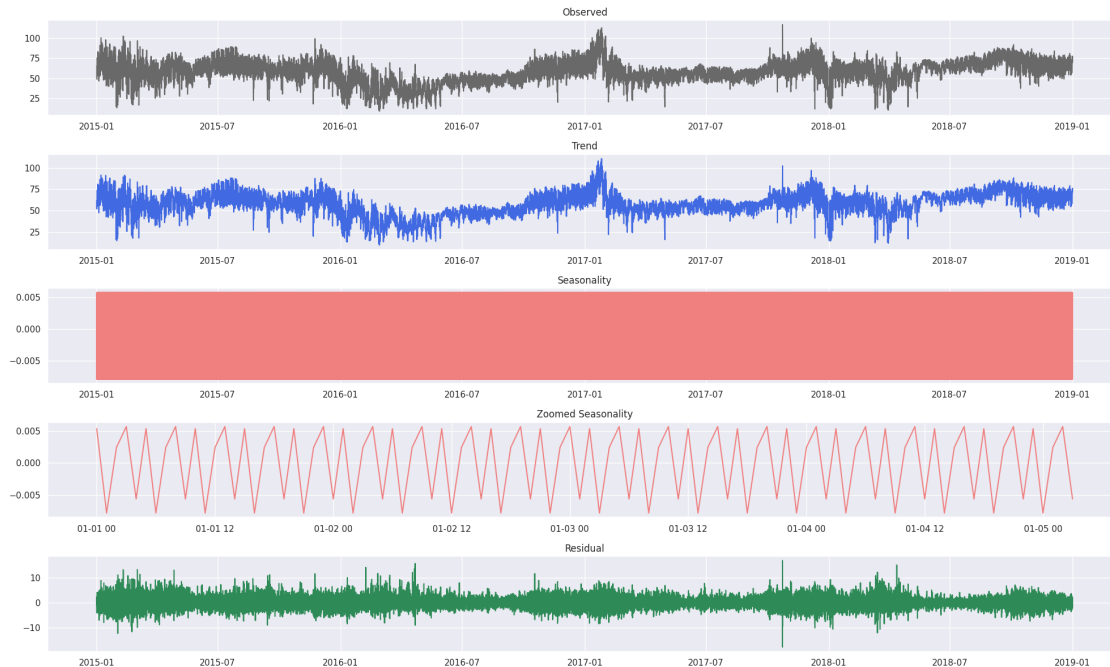
decompose_result = seasonal_decompose(decom_data, period =5, model='additive')

observed    = decompose_result.observed
trend       = decompose_result.trend
seasonal     = decompose_result.seasonal
residual     = decompose_result.resid

axes[0].plot(observed, color='dimgrey')
axes[0].set_title('Observed')
axes[1].plot(trend, color='royalblue')
axes[1].set_title('Trend')
axes[2].plot(seasonal, color='lightcoral')
axes[2].set_title('Seasonality')
axes[3].plot(seasonal[:100], color='lightcoral')
axes[3].set_title('Zoomed Seasonality')
axes[4].plot(residual, color='seagreen')
axes[4].set_title('Residual')

fig.tight_layout()
plt.show()

```



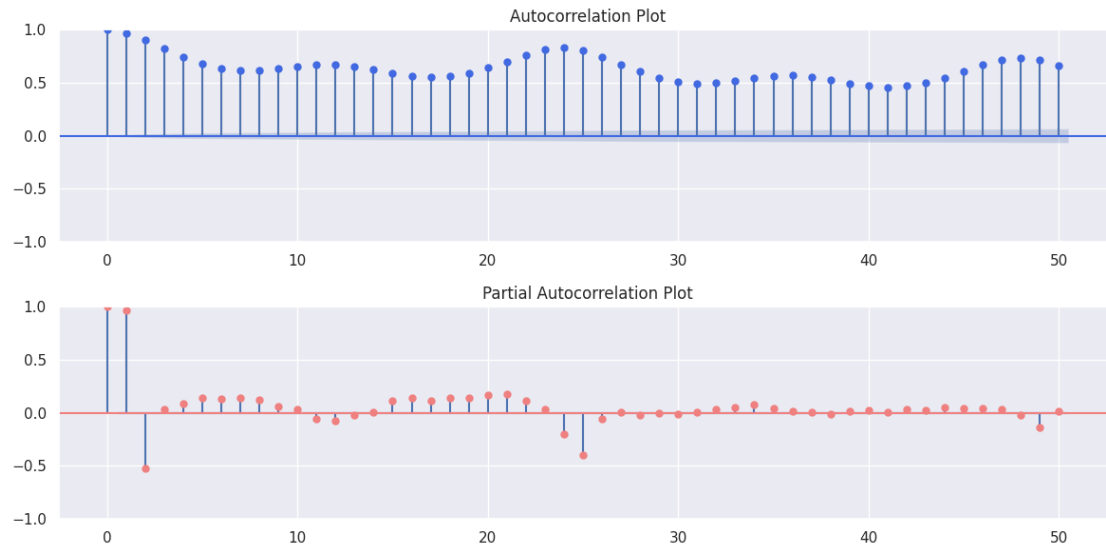
```
[54]: result = adfuller(df_weather_energy[['price actual']])
print('ADF Statistic:', result[0])
print('p-value:', result[1])
print('Critical Values:', result[4])
```

ADF Statistic: -9.147016232851248

p-value: 2.750493484933306e-15

Critical Values: {'1%': -3.4305367814665044, '5%': -2.8616225527935106, '10%': -2.566813940257257}

```
[55]: fig, ax = plt.subplots(2, 1, figsize=(12, 6))
plot_acf(df_weather_energy['price actual'], lags=50, ax=ax[0],
        color='royalblue')
ax[0].set_title('Autocorrelation Plot')
plot_pacf(df_weather_energy['price actual'], lags=50, ax=ax[1],
        color='lightcoral')
ax[1].set_title('Partial Autocorrelation Plot')
plt.tight_layout()
plt.show()
```



```
[56]: #DIMENSIONALITY REDUCTION
```

```
X = df_weather_energy.drop(['price actual'], axis = 1)
y= df_weather_energy[['price actual']]
```

```
[57]: def apply_PCA(X_input, cum_variance, if_apply):
```

```
    if if_apply:
```

```
        pca = PCA(n_components = cum_variance)
        # make pipeline to first standardize then apply PCA on data
        scaler_pca = make_pipeline(MinMaxScaler(), pca)
        X_pca = scaler_pca.fit(X_input).transform(X_input)
```

```
        return X_pca
```

```
    else:
```

```
        return np.array(X_input)
```

```
[58]: !pip install scikit-learn
```

```
import numpy as np
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import MinMaxScaler
from sklearn.decomposition import PCA
from sklearn.impute import SimpleImputer # Import SimpleImputer

def apply_PCA(X_input, cum_variance, if_apply):
```

```

if if_apply:
    # Create an imputer to replace NaN with the mean of the column
    imputer = SimpleImputer(strategy='mean')

    # Apply imputation to the input data
    X_input_imputed = imputer.fit_transform(X_input)

    pca = PCA(n_components=cum_variance)
    # make pipeline to first standardize then apply PCA on data
    scaler_pca = make_pipeline(MinMaxScaler(), pca)

    # Apply the pipeline to the imputed data
    X_pca = scaler_pca.fit(X_input_imputed).transform(X_input_imputed)

    return X_pca

else:

    return np.array(X_input)

```

Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-packages (1.5.2)

Requirement already satisfied: numpy>=1.19.5 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.26.4)

Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.13.1)

Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.4.2)

Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (3.5.0)

```

[59]: params_pca = {'cum_variance' : 0.8, 'if_apply' : True }
      X_pca = apply_PCA(X, **params_pca)
      X_pca.shape

```

[59]: (35064, 15)

```

[60]: def windowing(X_input,y_input, history_size):

      data = []
      labels = []
      for i in range(history_size, len(y_input)):
          data.append(X_input[i - history_size : i, :])
          labels.append(y_input[i])

      return np.array(data), np.array(labels).reshape(-1,1)

```



```

[61]: train_cutoff = int(0.8*X_pca.shape[0])
      val_cutoff   = int(0.9*X_pca.shape[0])

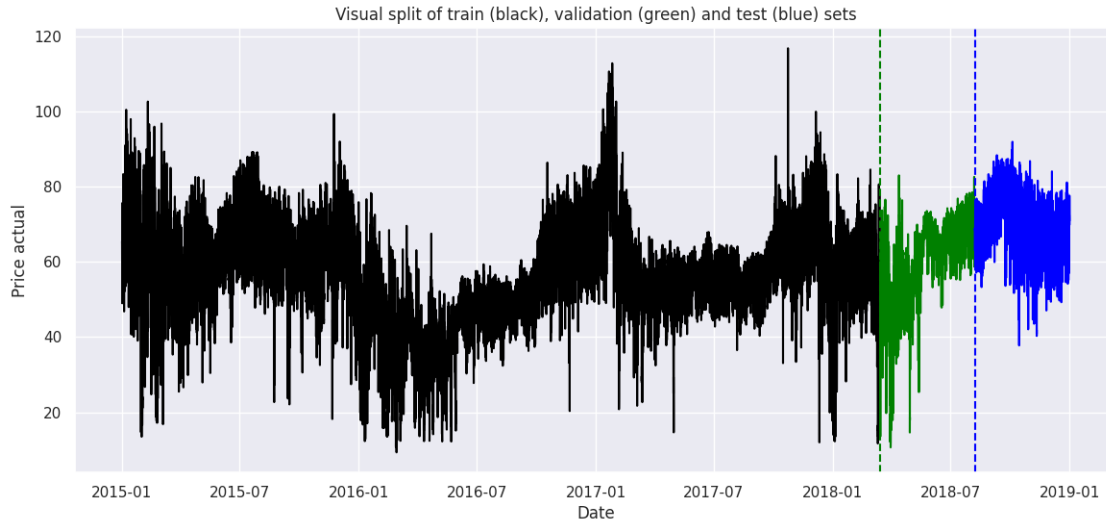
      scaler_y = MinMaxScaler()
      scaler_y.fit(y[:train_cutoff])
      y_norm = scaler_y.transform(y)

[62]: hist_size= 24
      data_norm = np.concatenate((X_pca,y_norm), axis = 1)

      X_train, y_train = windowing(data_norm[:train_cutoff,:],data_norm[:
      ↪train_cutoff,-1], hist_size)
      X_val, y_val      = windowing(data_norm[train_cutoff :val_cutoff,:
      ↪],data_norm[train_cutoff:val_cutoff,-1], hist_size)
      X_test, y_test    = windowing(data_norm[val_cutoff :,:],data_norm[val_cutoff:
      ↪,-1], hist_size)

[63]: fig, axes = plt.subplots(figsize = (14,6))
      axes.plot(df_weather_energy['price actual'].iloc[:train_cutoff], color = 'black')
      ↪('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')
      ↪('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()

```



```
[64]: from tensorflow.keras.optimizers import Adam # Importing the Adam optimizer
```

```
def base_model_cnn():
```

```
    model = Sequential()
```

```
    model.add(Conv1D(filters=32, kernel_size=3, activation='relu',
```

```
    ↪input_shape=X_train.shape[-2:]))
```

```
    model.add(Flatten())
```

```
    model.add(Dense(128, activation='relu'))
```

```
    model.add(Dropout(0.1))
```

```
    model.add(Dense(1))
```

```
    return model
```

```
cnn_model = base_model_cnn()
```

```
optimizer = Adam() # Assigning Adam optimizer to the variable 'optimizer'
```

```
cnn_model.compile(optimizer = optimizer , loss = 'mean_absolute_error')
```

```
cnn_model.summary()
```

```
/usr/local/lib/python3.10/dist-
```

```
packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning:
```

Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.

```
Model: "sequential"
```

Layer (type)	Output Shape	
Param #		
conv1d (Conv1D)	(None, 22, 32)	
↳1,568		
flatten (Flatten)	(None, 704)	
↳ 0		
dense (Dense)	(None, 128)	
↳90,240		
dropout (Dropout)	(None, 128)	
↳ 0		
dense_1 (Dense)	(None, 1)	
↳129		

Total params: 91,937 (359.13 KB)

Trainable params: 91,937 (359.13 KB)

Non-trainable params: 0 (0.00 B)

```
[65]: # Define the 'epoch' and 'batch_size' variables
epoch = 40 # Example: Set the number of epochs to 10
batch_size = 128 # Example: Set the batch size to 32
# Define the callback, or remove it if not needed
from tensorflow.keras.callbacks import EarlyStopping
callback = EarlyStopping(monitor='val_loss', patience=40) # Example early
↳stopping callback

# Now run the fit method
history = cnn_model.fit(X_train, y_train, validation_data=(X_val, y_val),
                        epochs=epoch, batch_size=batch_size, callbacks=[callback])
```

```
Epoch 1/40
219/219          4s 8ms/step -
loss: 0.0974 - val_loss: 0.0532
Epoch 2/40
219/219          2s 7ms/step -
loss: 0.0482 - val_loss: 0.0495
Epoch 3/40
```

```

219/219          1s 7ms/step -
loss: 0.0403 - val_loss: 0.0383
Epoch 4/40
219/219          3s 7ms/step -
loss: 0.0369 - val_loss: 0.0381
Epoch 5/40
219/219          1s 6ms/step -
loss: 0.0335 - val_loss: 0.0315
Epoch 6/40
219/219          4s 12ms/step -
loss: 0.0319 - val_loss: 0.0390
Epoch 7/40
219/219          4s 6ms/step -
loss: 0.0300 - val_loss: 0.0390
Epoch 8/40
219/219          3s 7ms/step -
loss: 0.0285 - val_loss: 0.0364
Epoch 9/40
219/219          2s 6ms/step -
loss: 0.0277 - val_loss: 0.0425
Epoch 10/40
219/219          1s 3ms/step -
loss: 0.0265 - val_loss: 0.0390
Epoch 11/40
219/219          2s 6ms/step -
loss: 0.0258 - val_loss: 0.0321
Epoch 12/40
219/219          1s 4ms/step -
loss: 0.0246 - val_loss: 0.0342
Epoch 13/40
219/219          1s 3ms/step -
loss: 0.0235 - val_loss: 0.0306
Epoch 14/40
219/219          1s 4ms/step -
loss: 0.0230 - val_loss: 0.0253
Epoch 15/40
219/219          1s 4ms/step -
loss: 0.0231 - val_loss: 0.0275
Epoch 16/40
219/219          1s 4ms/step -
loss: 0.0221 - val_loss: 0.0323
Epoch 17/40
219/219          1s 4ms/step -
loss: 0.0216 - val_loss: 0.0326
Epoch 18/40
219/219          1s 4ms/step -
loss: 0.0211 - val_loss: 0.0248
Epoch 19/40

```

```

219/219          1s 4ms/step -
loss: 0.0205 - val_loss: 0.0250
Epoch 20/40
219/219          1s 4ms/step -
loss: 0.0199 - val_loss: 0.0258
Epoch 21/40
219/219          1s 4ms/step -
loss: 0.0195 - val_loss: 0.0270
Epoch 22/40
219/219          2s 6ms/step -
loss: 0.0195 - val_loss: 0.0247
Epoch 23/40
219/219          2s 4ms/step -
loss: 0.0191 - val_loss: 0.0252
Epoch 24/40
219/219          1s 4ms/step -
loss: 0.0190 - val_loss: 0.0274
Epoch 25/40
219/219          1s 4ms/step -
loss: 0.0185 - val_loss: 0.0291
Epoch 26/40
219/219          1s 4ms/step -
loss: 0.0182 - val_loss: 0.0252
Epoch 27/40
219/219          1s 3ms/step -
loss: 0.0180 - val_loss: 0.0244
Epoch 28/40
219/219          1s 4ms/step -
loss: 0.0180 - val_loss: 0.0238
Epoch 29/40
219/219          1s 4ms/step -
loss: 0.0177 - val_loss: 0.0248
Epoch 30/40
219/219          1s 4ms/step -
loss: 0.0172 - val_loss: 0.0218
Epoch 31/40
219/219          1s 3ms/step -
loss: 0.0176 - val_loss: 0.0235
Epoch 32/40
219/219          2s 6ms/step -
loss: 0.0171 - val_loss: 0.0227
Epoch 33/40
219/219          2s 3ms/step -
loss: 0.0170 - val_loss: 0.0246
Epoch 34/40
219/219          1s 4ms/step -
loss: 0.0172 - val_loss: 0.0215
Epoch 35/40

```

```

219/219          1s 4ms/step -
loss: 0.0169 - val_loss: 0.0211
Epoch 36/40
219/219          1s 4ms/step -
loss: 0.0172 - val_loss: 0.0219
Epoch 37/40
219/219          1s 4ms/step -
loss: 0.0168 - val_loss: 0.0205
Epoch 38/40
219/219          1s 4ms/step -
loss: 0.0164 - val_loss: 0.0205
Epoch 39/40
219/219          1s 4ms/step -
loss: 0.0161 - val_loss: 0.0185
Epoch 40/40
219/219          1s 4ms/step -
loss: 0.0162 - val_loss: 0.0217

```

```

[68]: import matplotlib.pyplot as plt
import numpy as np
from sklearn.metrics import mean_absolute_error

def plot_results(y_pred, y_true, history, model_name):
    fig, axes = plt.subplots(figsize=(12, 8), nrows=2, ncols=1)

    # Predictions vs Actual Values
    axes[0].plot(y_true, label='Actual')
    axes[0].plot(y_pred, label='Predictions')
    axes[0].set_title(f'{model_name} Predictions vs Actual Values')
    axes[0].set_xlabel('Time')
    axes[0].set_ylabel('Value')
    axes[0].legend()

    # Training History
    if history is not None: # Check if history is provided
        axes[1].plot(history.history['loss'], label='Training Loss')
        axes[1].plot(history.history['val_loss'], label='Validation Loss')
        axes[1].set_title(f'{model_name} Training History')
        axes[1].set_xlabel('Epoch')
        axes[1].set_ylabel('Loss')
        axes[1].legend()
    plt.tight_layout()

    # Predict on the test set and inverse transform to get actual values
    y_pred = cnn_model.predict(X_test)
    y_pred_actual = scaler_y.inverse_transform(y_pred) # Inverse transform
    ↪ predictions

```

```

y_test_inv = scaler_y.inverse_transform(y_test)      # Inverse transform actual
↳ values

print('')
print('')
print('-----')
print(f'CNN MAE for test set :␣
↳ {round(mean_absolute_error(y_pred_actual,y_test_inv),3)}') # Use
↳ y_pred_actual and y_test_inv
print('-----')
print('')
plot_results(y_pred_actual, y_test_inv, history,'CNN') # Use y_pred_actual and
↳ y_test_inv

```

109/109

0s 1ms/step

CNN MAE for test set : 2.643

