Ecesis Assignment

May 24, 2024

1 Some Notes

Some cell outputs are truncated, for full output, please see the full notebook.

2 Assignment 1: Power Calendar function

Objective: write R/Python function which returns number of hours by iso/peak.type/period In power market, the industry defines certain hour of each day to peak type for block trading, so we need to calculate correctly how many hours belongs to certain block. Each ISO has a little different definition of it. Note: don't scrape data from the reference link. It's for reference only. You shall learn/understand the logic and calculate without access to any website.

See reference: https://www.energygps.com/HomeTools/PowerCalendar Required Function: get.hours(iso, peak.type, period) Params: (all params are required in the function) iso (character): one of PJM/MISO/ERCOT/SPP/NYISO/WECC/CAISO (see item 1 below) peak.type (character): one of onpeak/offpeak/flat/2x16H/7x8 period (character): has 4 types: "2018-2-3" as a daily, "2018Mar" as a monthly, "2018Q2" as a quarterly, "2018A" as an annually.

[1]:
```python
from datetime import datetime, timedelta
import pandas as pd

def get_hours(iso, peak_type, period):
    # defining peak hours
    peak_hours = {
        "onpeak": range(7, 23),
        "offpeak": list(range(1, 7)) + list(range(23, 25)),
        "flat": range(1, 25),
        "2x16H": range(7, 23),
        "7x8": list(range(1, 7)) + list(range(23, 25)),
    }

    # 4 different types of period formats
    if len(period) > 7:  # Daily
        startDate = datetime.strptime(period, "%Y-%m-%d")
        endDate = startDate
    elif len(period) == 7:  # Monthly
        startDate = datetime.strptime(period, "%Y%b")
```

```
        endDate = (startDate + pd.DateOffset(months=1) - timedelta(days=1)).
↪to_pydatetime()
    elif len(period) == 6:  # Quarterly
        quarter = int(period[-1])
        startDate = datetime.strptime(period[:4] + '-' + str((quarter - 1) * 3␣
↪+ 1), "%Y-%m")
        endDate = (startDate + pd.DateOffset(months=3) - timedelta(days=1)).
↪to_pydatetime()
    elif len(period) == 5:  # Annually
        startDate = datetime.strptime(period[:4] + "-01-01", "%Y-%m-%d")
        endDate = datetime.strptime(period[:4] + "-12-31", "%Y-%m-%d")

    # all dates within period
    dates = pd.date_range(start=startDate, end=endDate, freq='D')
    # of hours tracker
    numHours = 0
    for date in dates:
        if peak_type.lower() == "2x16h" and (date.weekday() >= 5 or date in␣
↪get_nerc_holidays(date.year)):
            numHours += len(peak_hours["2x16H"])
        elif peak_type.lower() == "7x8" and (date.weekday() < 5 and date not in␣
↪get_nerc_holidays(date.year)):
            numHours += len(peak_hours["7x8"])
        elif peak_type.lower() == "onpeak" and date.weekday() < 5 and date not␣
↪in get_nerc_holidays(date.year):  # Exclude saturdays and sundays
            numHours += len(peak_hours["onpeak"])
        elif peak_type.lower() != "onpeak" and date not in␣
↪get_nerc_holidays(date.year):
            numHours += len(peak_hours[peak_type.lower()])

    return {
        'iso': iso,
        'peak_type': peak_type.upper(),
        'startdate': startDate.strftime("%Y-%m-%d"),
        'enddate': endDate.strftime("%Y-%m-%d"),
        'num_hours': numHours
    }

def get_nerc_holidays(year):
    holidays = ["New Year's Day", "Independence Day", "Christmas Day",␣
↪"Memorial Day", "Labor Day","Thanksgiving Day",]
    holiday_dates = {"New Year's Day": datetime(year, 1, 1), "Independence Day":
↪ datetime(year, 7, 4),
                     "Christmas Day": datetime(year, 12, 25), "Memorial Day":␣
↪get_nth_weekday_of_month(year, 5, 0, -1),
```

```
                    "Labor Day": get_nth_weekday_of_month(year, 9, 0,␣
↪1),"Thanksgiving Day": get_nth_weekday_of_month(year, 11, 3, 4),}
    return [holiday_dates[holiday] for holiday in holidays]
def get_nth_weekday_of_month(year, month, weekday, n):
    if n > 0:
        first_day = datetime(year, month, 1)
        first_weekday = first_day + timedelta(days=(weekday - first_day.
↪weekday() + 7) % 7)
        return first_weekday + timedelta(weeks=n-1)
    else:
        last_day = datetime(year, month + 1, 1) - timedelta(days=1)
        last_weekday = last_day - timedelta(days=(last_day.weekday() - weekday␣
↪+ 7) % 7)
        return last_weekday + timedelta(weeks=n+1)

# Example Usage:
results = get_hours("ERCOT", "onpeak", "2019May")
(results)

# Matches the output provided by github
```

[1]:
```
{'iso': 'ERCOT',
 'peak_type': 'ONPEAK',
 'startdate': '2019-05-01',
 'enddate': '2019-05-31',
 'num_hours': 352}
```

[2]:
```
# testing cells to make sure calculating correctly
tmp1 = pd.date_range(start="5/1/2019", end="5/31/2019")
tmp1
```

[2]:
```
DatetimeIndex(['2019-05-01', '2019-05-02', '2019-05-03', '2019-05-04',
               '2019-05-05', '2019-05-06', '2019-05-07', '2019-05-08',
               '2019-05-09', '2019-05-10', '2019-05-11', '2019-05-12',
               '2019-05-13', '2019-05-14', '2019-05-15', '2019-05-16',
               '2019-05-17', '2019-05-18', '2019-05-19', '2019-05-20',
               '2019-05-21', '2019-05-22', '2019-05-23', '2019-05-24',
               '2019-05-25', '2019-05-26', '2019-05-27', '2019-05-28',
               '2019-05-29', '2019-05-30', '2019-05-31'],
              dtype='datetime64[ns]', freq='D')
```

[3]:
```
# testing cells to make sure calculating correctly
for i in tmp1:
    print(i.strftime('%Y-%m-%d') + " " + str(get_hours("ERCOT", "onpeak", i.
↪strftime('%Y-%m-%d'))))
```

```
2019-05-01 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-01',
```

```
'enddate': '2019-05-01', 'num_hours': 16}
2019-05-02 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-02',
'enddate': '2019-05-02', 'num_hours': 16}
2019-05-03 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-03',
'enddate': '2019-05-03', 'num_hours': 16}
2019-05-04 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-04',
'enddate': '2019-05-04', 'num_hours': 0}
2019-05-05 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-05',
'enddate': '2019-05-05', 'num_hours': 0}
2019-05-06 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-06',
'enddate': '2019-05-06', 'num_hours': 16}
2019-05-07 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-07',
'enddate': '2019-05-07', 'num_hours': 16}
2019-05-08 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-08',
'enddate': '2019-05-08', 'num_hours': 16}
2019-05-09 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-09',
'enddate': '2019-05-09', 'num_hours': 16}
2019-05-10 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-10',
'enddate': '2019-05-10', 'num_hours': 16}
2019-05-11 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-11',
'enddate': '2019-05-11', 'num_hours': 0}
2019-05-12 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-12',
'enddate': '2019-05-12', 'num_hours': 0}
2019-05-13 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-13',
'enddate': '2019-05-13', 'num_hours': 16}
2019-05-14 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-14',
'enddate': '2019-05-14', 'num_hours': 16}
2019-05-15 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-15',
'enddate': '2019-05-15', 'num_hours': 16}
2019-05-16 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-16',
'enddate': '2019-05-16', 'num_hours': 16}
2019-05-17 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-17',
'enddate': '2019-05-17', 'num_hours': 16}
2019-05-18 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-18',
'enddate': '2019-05-18', 'num_hours': 0}
2019-05-19 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-19',
'enddate': '2019-05-19', 'num_hours': 0}
2019-05-20 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-20',
'enddate': '2019-05-20', 'num_hours': 16}
2019-05-21 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-21',
'enddate': '2019-05-21', 'num_hours': 16}
2019-05-22 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-22',
'enddate': '2019-05-22', 'num_hours': 16}
2019-05-23 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-23',
'enddate': '2019-05-23', 'num_hours': 16}
2019-05-24 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-24',
'enddate': '2019-05-24', 'num_hours': 16}
2019-05-25 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-25',
```

```
'enddate': '2019-05-25', 'num_hours': 0}
2019-05-26 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-26',
'enddate': '2019-05-26', 'num_hours': 0}
2019-05-27 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-27',
'enddate': '2019-05-27', 'num_hours': 0}
2019-05-28 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-28',
'enddate': '2019-05-28', 'num_hours': 16}
2019-05-29 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-29',
'enddate': '2019-05-29', 'num_hours': 16}
2019-05-30 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-30',
'enddate': '2019-05-30', 'num_hours': 16}
2019-05-31 {'iso': 'ERCOT', 'peak_type': 'ONPEAK', 'startdate': '2019-05-31',
'enddate': '2019-05-31', 'num_hours': 16}
```

3 Assignment 2: Meter Data formatting

Objective: merge different data sources into single dataset and evaluate the dataset for anormaly (if any) For analysis purpose, we always have different data sources to merge and format. It's important to understand the data and format it correctly.

Data Files: - USA_AL_Auburn-Opelika.AP.722284_TMY3_BASE.csv This file gives hourly electricity consumptions for a resident with unit in kw (kilowatt). - new.app4.csv Assuming this is one appliance's electricity consumption minute by minute which is not captured in the previous file. The unit in the file is in watt.

Requirements: - Create script to load both files and merge. - Given the limitation of data period, try to find the overlap period and merge the data into hourly. (ignore the year but making sure the date/hour matched) - After merging the source files correctly, please create one more column in the output file to give total hourly consumption of electricity. (sum all columns) - Create plots of the data and see if there's any abnormal in the dataset and summarize any pattern observed from the data by hourl/weekday/month - Write code with clear documentation.

Hint: - try to show smart/efficient way to merge and sum column - try not to hard code by column number or name but making the script re-usable for general data formatting

[4]:
```python
# Preliminary Data Visualization
dataAssignment2 = pd.read_csv("Documents/GitHub/GuzmanSummer2024/data/
↪Assignment 2 - new.app4.csv")
dataAssignment2.head()
```

[4]:

	Unnamed: 0	time	W_min
0	1	6/7/2013 11:04	1142.919571
1	2	6/7/2013 11:05	371.239567
2	3	6/7/2013 11:06	367.887333
3	4	6/7/2013 11:07	702.714100
4	5	6/7/2013 11:08	1655.944450

[5]:
```python
# Preliminary Data Visualization
fileUSA = pd.read_csv("Documents/GitHub/GuzmanSummer2024/data/Assignment 2 -␣
↪USA_AL_Auburn-Opelika.AP.722284_TMY3_BASE.csv")
fileUSA.head()
```

[5]:
```
           Date/Time  Electricity:Facility [kW](Hourly)  \
0   01/01  01:00:00                           0.974334
1   01/01  02:00:00                           0.796582
2   01/01  03:00:00                           0.735028
3   01/01  04:00:00                           0.727433
4   01/01  05:00:00                           0.778706

   Gas:Facility [kW](Hourly)  Heating:Electricity [kW](Hourly)  \
0                   4.452977                               0.0
1                   4.850317                               0.0
2                   5.037645                               0.0
3                   5.107562                               0.0
4                   5.270878                               0.0

   Heating:Gas [kW](Hourly)  Cooling:Electricity [kW](Hourly)  \
0                  4.425010                               0.0
1                  4.824566                               0.0
2                  5.012193                               0.0
3                  5.082468                               0.0
4                  5.246732                               0.0

   HVACFan:Fans:Electricity [kW](Hourly)  Electricity:HVAC [kW](Hourly)  \
0                               0.112709                       0.112709
1                               0.122617                       0.122617
2                               0.127099                       0.127099
3                               0.128391                       0.128391
4                               0.132549                       0.132549

   Fans:Electricity [kW](Hourly)  \
0                       0.112709
1                       0.122617
2                       0.127099
3                       0.128391
4                       0.132549

   General:InteriorLights:Electricity [kW](Hourly)  \
0                                         0.154019
1                                         0.089845
2                                         0.064175
3                                         0.064175
4                                         0.064175
```

```
   General:ExteriorLights:Electricity [kW](Hourly)  \
0                                         0.033180
1                                         0.019355
2                                         0.013825
3                                         0.013825
4                                         0.013825

   Appl:InteriorEquipment:Electricity [kW](Hourly)  \
0                                         0.092943
1                                         0.076186
2                                         0.062326
3                                         0.053976
4                                         0.065823

   Misc:InteriorEquipment:Electricity [kW](Hourly)  \
0                                         0.406035
1                                         0.373851
2                                         0.369517
3                                         0.364315
4                                         0.350553

   Water Heater:WaterSystems:Electricity [kW](Hourly)
0                                            0.158803
1                                            0.098084
2                                            0.081442
3                                            0.086107
4                                            0.135137
```

[6]:
```
print(dataAssignment2.shape)
print(fileUSA.shape)
```

```
(10846, 3)
(8760, 14)
```

[7]:
```
# Convert the 'time' column to datetime
dataAssignment2['time'] = pd.to_datetime(dataAssignment2['time'])
dataAssignment2.set_index('time', inplace=True)

# Aggregating the data from minute to hourly
hourlyData = dataAssignment2.resample('H').sum()
hourlyData.reset_index(inplace=True)
hourlyData['time'] = hourlyData['time'].dt.strftime('%m/%d %H:%M:%S')
hourlyData["W_min"] = hourlyData["W_min"].div(1000)
hourlyData.rename({'time':'Date/Time', "W_min":"kW_min"}, axis=1, inplace =␣
  ↪True)
hourlyData.drop("Unnamed: 0", axis = 1, inplace = True)
hourlyData.head()
```

```
/var/folders/vz/z83bk0kd7s5d4_3cx59yyqnw0000gn/T/ipykernel_17911/1042599370.py:6
: FutureWarning: 'H' is deprecated and will be removed in a future version,
please use 'h' instead.
  hourlyData = dataAssignment2.resample('H').sum()
```

[7]:

```
         Date/Time      kW_min
0  06/07 11:00:00   57.388943
1  06/07 12:00:00   27.227961
2  06/07 13:00:00  111.476298
3  06/07 14:00:00  109.021960
4  06/07 15:00:00    5.773963
```

We now have a dataframe that contains the aggregated hourly data, and converted from watts to kilowatts

[8]:

```
fileUSA['Date/Time'] = fileUSA['Date/Time'].str.strip().str.replace('24:00:00',␣
↪'00:00:00')
fileUSA['Date/Time'] = pd.to_datetime(fileUSA['Date/Time'], format='%m/%d %H:%M:
↪%S')
fileUSA.loc[fileUSA['Date/Time'].dt.hour == 0, 'Date/Time'] += pd.
↪DateOffset(days=1)
fileUSA['Date/Time'] = fileUSA['Date/Time'].dt.strftime('%m/%d %H:%M:%S')
fileUSA.head()
```

[8]:

```
         Date/Time  Electricity:Facility [kW](Hourly)  \
0  01/01 01:00:00                           0.974334
1  01/01 02:00:00                           0.796582
2  01/01 03:00:00                           0.735028
3  01/01 04:00:00                           0.727433
4  01/01 05:00:00                           0.778706

   Gas:Facility [kW](Hourly)  Heating:Electricity [kW](Hourly)  \
0                   4.452977                               0.0
1                   4.850317                               0.0
2                   5.037645                               0.0
3                   5.107562                               0.0
4                   5.270878                               0.0

   Heating:Gas [kW](Hourly)  Cooling:Electricity [kW](Hourly)  \
0                  4.425010                               0.0
1                  4.824566                               0.0
2                  5.012193                               0.0
3                  5.082468                               0.0
4                  5.246732                               0.0

   HVACFan:Fans:Electricity [kW](Hourly)  Electricity:HVAC [kW](Hourly)  \
0                               0.112709                       0.112709
1                               0.122617                       0.122617
```

```
2                           0.127099                      0.127099
3                           0.128391                      0.128391
4                           0.132549                      0.132549

   Fans:Electricity [kW](Hourly)  \
0                       0.112709
1                       0.122617
2                       0.127099
3                       0.128391
4                       0.132549

   General:InteriorLights:Electricity [kW](Hourly)  \
0                                         0.154019
1                                         0.089845
2                                         0.064175
3                                         0.064175
4                                         0.064175

   General:ExteriorLights:Electricity [kW](Hourly)  \
0                                         0.033180
1                                         0.019355
2                                         0.013825
3                                         0.013825
4                                         0.013825

   Appl:InteriorEquipment:Electricity [kW](Hourly)  \
0                                         0.092943
1                                         0.076186
2                                         0.062326
3                                         0.053976
4                                         0.065823

   Misc:InteriorEquipment:Electricity [kW](Hourly)  \
0                                         0.406035
1                                         0.373851
2                                         0.369517
3                                         0.364315
4                                         0.350553

   Water Heater:WaterSystems:Electricity [kW](Hourly)
0                                            0.158803
1                                            0.098084
2                                            0.081442
3                                            0.086107
4                                            0.135137
```

We now have a dataframe of the overall USA dataset that has the Date/Time column converted to match the format of the other

[9]:
```
a = hourlyData["Date/Time"][0]
a
```

[9]:
```
'06/07 11:00:00'
```

[10]:
```
tmp1 = fileUSA.iloc[3778:3779]
tmp2 = pd.DataFrame(tmp1)
tmp2
```

[10]:
```
           Date/Time  Electricity:Facility [kW](Hourly)  \
3778  06/07 11:00:00                           1.479426

      Gas:Facility [kW](Hourly)  Heating:Electricity [kW](Hourly)  \
3778                   0.018757                               0.0

      Heating:Gas [kW](Hourly)  Cooling:Electricity [kW](Hourly)  \
3778                       0.0                          0.347519

      HVACFan:Fans:Electricity [kW](Hourly)  Electricity:HVAC [kW](Hourly)  \
3778                               0.100007                       0.447526

      Fans:Electricity [kW](Hourly)  \
3778                       0.100007

      General:InteriorLights:Electricity [kW](Hourly)  \
3778                                         0.047163

      General:ExteriorLights:Electricity [kW](Hourly)  \
3778                                          0.01016

      Appl:InteriorEquipment:Electricity [kW](Hourly)  \
3778                                         0.360615

      Misc:InteriorEquipment:Electricity [kW](Hourly)  \
3778                                         0.272322

      Water Heater:WaterSystems:Electricity [kW](Hourly)
3778                                           0.324996
```

[11]:
```
a == tmp2["Date/Time"]
```

[11]:
```
3778    True
Name: Date/Time, dtype: bool
```

[12]:
```
combinedDatasetAssignment2 = fileUSA.merge(hourlyData, on='Date/Time', how =␣
 ↪"left")
combinedDatasetAssignment2
```

[12]:
```
             Date/Time  Electricity:Facility [kW](Hourly)  \
0      01/01 01:00:00                           0.974334
1      01/01 02:00:00                           0.796582
2      01/01 03:00:00                           0.735028
3      01/01 04:00:00                           0.727433
4      01/01 05:00:00                           0.778706
…                 …                                  …
8755   12/31 20:00:00                           2.601121
8756   12/31 21:00:00                           2.445630
8757   12/31 22:00:00                           2.206391
8758   12/31 23:00:00                           1.769166
8759   01/01 00:00:00                           1.335991

      Gas:Facility [kW](Hourly)  Heating:Electricity [kW](Hourly)  \
0                      4.452977                               0.0
1                      4.850317                               0.0
2                      5.037645                               0.0
3                      5.107562                               0.0
4                      5.270878                               0.0
…                           …                                …
8755                   0.044507                               0.0
8756                   0.046038                               0.0
8757                   0.044963                               0.0
8758                   0.295330                               0.0
8759                   0.636988                               0.0

      Heating:Gas [kW](Hourly)  Cooling:Electricity [kW](Hourly)  \
0                     4.425010                               0.0
1                     4.824566                               0.0
2                     5.012193                               0.0
3                     5.082468                               0.0
4                     5.246732                               0.0
…                          …                                …
8755                  0.000000                               0.0
8756                  0.000000                               0.0
8757                  0.000000                               0.0
8758                  0.256420                               0.0
8759                  0.603176                               0.0

      HVACFan:Fans:Electricity [kW](Hourly)  Electricity:HVAC [kW](Hourly)  \
0                                  0.112709                       0.112709
1                                  0.122617                       0.122617
2                                  0.127099                       0.127099
```

```
3                                             0.128391                                      0.128391
4                                             0.132549                                      0.132549
…                                                 …                                             …
8755                                          0.000000                                      0.000000
8756                                          0.000000                                      0.000000
8757                                          0.000000                                      0.000000
8758                                          0.006642                                      0.006642
8759                                          0.015653                                      0.015653

      Fans:Electricity [kW](Hourly)  \
0                          0.112709
1                          0.122617
2                          0.127099
3                          0.128391
4                          0.132549
…                              …
8755                       0.000000
8756                       0.000000
8757                       0.000000
8758                       0.006642
8759                       0.015653

      General:InteriorLights:Electricity [kW](Hourly)  \
0                                            0.154019
1                                            0.089845
2                                            0.064175
3                                            0.064175
4                                            0.064175
…                                                …
8755                                         0.743542
8756                                         0.677155
8757                                         0.570934
8758                                         0.424881
8759                                         0.298745

      General:ExteriorLights:Electricity [kW](Hourly)  \
0                                            0.033180
1                                            0.019355
2                                            0.013825
3                                            0.013825
4                                            0.013825
…                                                …
8755                                         0.160179
8756                                         0.145877
8757                                         0.122994
8758                                         0.091531
8759                                         0.064358
```

```
      Appl:InteriorEquipment:Electricity [kW](Hourly)  \
0                                             0.092943
1                                             0.076186
2                                             0.062326
3                                             0.053976
4                                             0.065823
…                                                  …
8755                                          0.349591
8756                                          0.310730
8757                                          0.293949
8758                                          0.234174
8759                                          0.151456

      Misc:InteriorEquipment:Electricity [kW](Hourly)  \
0                                             0.406035
1                                             0.373851
2                                             0.369517
3                                             0.364315
4                                             0.350553
…                                                  …
8755                                          0.646167
8756                                          0.668381
8757                                          0.652777
8758                                          0.564895
8759                                          0.490883

      Water Heater:WaterSystems:Electricity [kW](Hourly)   kW_min
0                                               0.158803      NaN
1                                               0.098084      NaN
2                                               0.081442      NaN
3                                               0.086107      NaN
4                                               0.135137      NaN
…                                                    …       …
8755                                            0.684999      NaN
8756                                            0.626843      NaN
8757                                            0.549092      NaN
8758                                            0.430399      NaN
8759                                            0.298252      NaN

[8760 rows x 15 columns]
```

Utilizing a left join, we can merge the two datasets together based on their Date/Time column

[13]:
```
combinedDatasetAssignment2["Hourly Sum"] = combinedDatasetAssignment2.
 ↪drop('Date/Time', axis=1).sum(axis=1)
combinedDatasetAssignment2
```

```
[13]:            Date/Time  Electricity:Facility [kW](Hourly)  \
      0     01/01 01:00:00                           0.974334
      1     01/01 02:00:00                           0.796582
      2     01/01 03:00:00                           0.735028
      3     01/01 04:00:00                           0.727433
      4     01/01 05:00:00                           0.778706
      …            …                                  …
      8755  12/31 20:00:00                           2.601121
      8756  12/31 21:00:00                           2.445630
      8757  12/31 22:00:00                           2.206391
      8758  12/31 23:00:00                           1.769166
      8759  01/01 00:00:00                           1.335991

            Gas:Facility [kW](Hourly)  Heating:Electricity [kW](Hourly)  \
      0                      4.452977                               0.0
      1                      4.850317                               0.0
      2                      5.037645                               0.0
      3                      5.107562                               0.0
      4                      5.270878                               0.0
      …                          …                                …
      8755                   0.044507                               0.0
      8756                   0.046038                               0.0
      8757                   0.044963                               0.0
      8758                   0.295330                               0.0
      8759                   0.636988                               0.0

            Heating:Gas [kW](Hourly)  Cooling:Electricity [kW](Hourly)  \
      0                     4.425010                               0.0
      1                     4.824566                               0.0
      2                     5.012193                               0.0
      3                     5.082468                               0.0
      4                     5.246732                               0.0
      …                         …                                …
      8755                  0.000000                               0.0
      8756                  0.000000                               0.0
      8757                  0.000000                               0.0
      8758                  0.256420                               0.0
      8759                  0.603176                               0.0

            HVACFan:Fans:Electricity [kW](Hourly)  Electricity:HVAC [kW](Hourly)  \
      0                                  0.112709                       0.112709
      1                                  0.122617                       0.122617
      2                                  0.127099                       0.127099
      3                                  0.128391                       0.128391
      4                                  0.132549                       0.132549
      …                                     …                              …
      8755                               0.000000                       0.000000
```

```
8756                                    0.000000                                0.000000
8757                                    0.000000                                0.000000
8758                                    0.006642                                0.006642
8759                                    0.015653                                0.015653

      Fans:Electricity [kW](Hourly)  \
0                          0.112709
1                          0.122617
2                          0.127099
3                          0.128391
4                          0.132549
…                               …
8755                       0.000000
8756                       0.000000
8757                       0.000000
8758                       0.006642
8759                       0.015653

      General:InteriorLights:Electricity [kW](Hourly)  \
0                                            0.154019
1                                            0.089845
2                                            0.064175
3                                            0.064175
4                                            0.064175
…                                                 …
8755                                         0.743542
8756                                         0.677155
8757                                         0.570934
8758                                         0.424881
8759                                         0.298745

      General:ExteriorLights:Electricity [kW](Hourly)  \
0                                            0.033180
1                                            0.019355
2                                            0.013825
3                                            0.013825
4                                            0.013825
…                                                 …
8755                                         0.160179
8756                                         0.145877
8757                                         0.122994
8758                                         0.091531
8759                                         0.064358

      Appl:InteriorEquipment:Electricity [kW](Hourly)  \
0                                            0.092943
1                                            0.076186
```

```
2                                                    0.062326
3                                                    0.053976
4                                                    0.065823
…                                                        …
8755                                                 0.349591
8756                                                 0.310730
8757                                                 0.293949
8758                                                 0.234174
8759                                                 0.151456

      Misc:InteriorEquipment:Electricity [kW](Hourly)  \
0                                                    0.406035
1                                                    0.373851
2                                                    0.369517
3                                                    0.364315
4                                                    0.350553
…                                                        …
8755                                                 0.646167
8756                                                 0.668381
8757                                                 0.652777
8758                                                 0.564895
8759                                                 0.490883

      Water Heater:WaterSystems:Electricity [kW](Hourly)   kW_min  Hourly Sum
0                                                      0.158803      NaN   11.035430
1                                                      0.098084      NaN   11.496637
2                                                      0.081442      NaN   11.757447
3                                                      0.086107      NaN   11.885034
4                                                      0.135137      NaN   12.323477
…                                                          …       …           …
8755                                                   0.684999      NaN    5.230105
8756                                                   0.626843      NaN    4.920653
8757                                                   0.549092      NaN    4.441100
8758                                                   0.430399      NaN    4.086723
8759                                                   0.298252      NaN    3.926807

[8760 rows x 16 columns]
```

We now have the combined dataset, with the Hourly Sum column now integrated into the dataset as well. For visualization, it's included below.

[14]:
```python
combinedDatasetAssignment2[["Date/Time", "Hourly Sum"]]
```

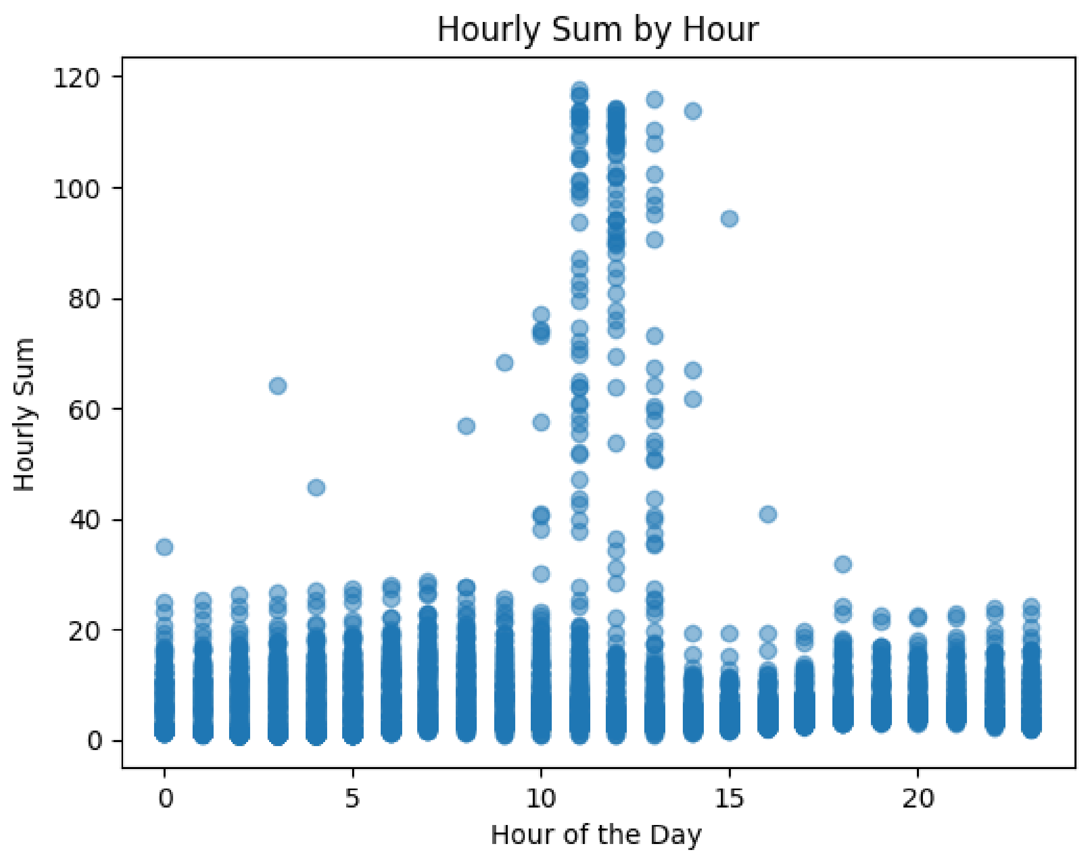
[14]:
```
           Date/Time  Hourly Sum
0     01/01 01:00:00   11.035430
1     01/01 02:00:00   11.496637
2     01/01 03:00:00   11.757447
```

```
3     01/01 04:00:00   11.885034
4     01/01 05:00:00   12.323477
…               …          …
8755  12/31 20:00:00    5.230105
8756  12/31 21:00:00    4.920653
8757  12/31 22:00:00    4.441100
8758  12/31 23:00:00    4.086723
8759  01/01 00:00:00    3.926807

[8760 rows x 2 columns]
```

[15]:
```
import matplotlib.pyplot as plt
# Convert 'Date/Time' to datetime
combinedDatasetAssignment2['Date/Time'] = pd.
 ↪to_datetime(combinedDatasetAssignment2['Date/Time'], format='%m/%d %H:%M:%S')

# Extract hour, day, and month for plotting
combinedDatasetAssignment2['Hour'] = combinedDatasetAssignment2['Date/Time'].dt.
 ↪hour
combinedDatasetAssignment2['Day'] = combinedDatasetAssignment2['Date/Time'].dt.
 ↪day
combinedDatasetAssignment2['Month'] = combinedDatasetAssignment2['Date/Time'].
 ↪dt.month
```

[16]:
```
# by hour
plt.figure()
plt.scatter(combinedDatasetAssignment2['Hour'],␣
 ↪combinedDatasetAssignment2['Hourly Sum'], alpha=0.5)
plt.title('Hourly Sum by Hour')
plt.xlabel('Hour of the Day')
plt.ylabel('Hourly Sum')
```

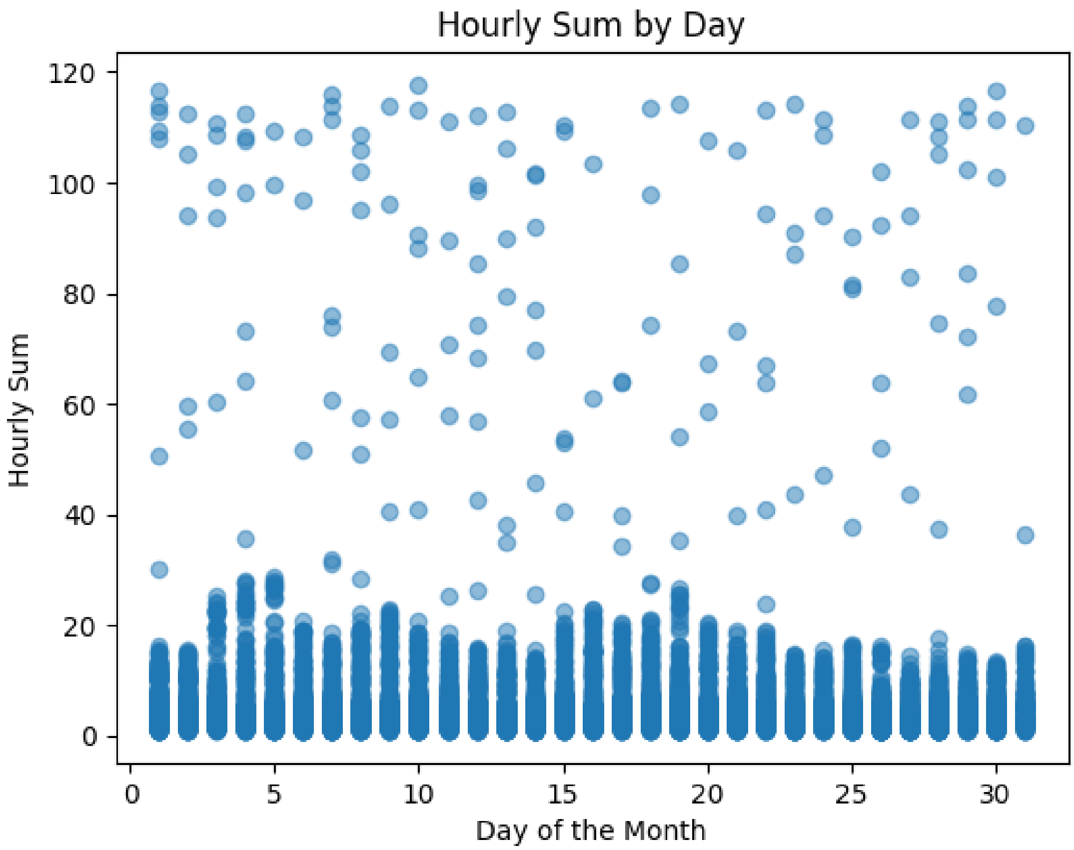
[16]:
```
Text(0, 0.5, 'Hourly Sum')
```



If we look at the graph specifically by hour of the day, we see that energy usage starts to increase from about 8am, all the way until about 7pm. This matches our expectations, as those hours are usually when the majority of people and industry are active, therefore resulting in the increased hourly energy usage during the daylight hours.

[17]:
```
# by day
plt.figure()
plt.scatter(combinedDatasetAssignment2['Day'],␣
 ↪combinedDatasetAssignment2['Hourly Sum'], alpha=0.5)
plt.title('Hourly Sum by Day')
plt.xlabel('Day of the Month')
plt.ylabel('Hourly Sum')
```

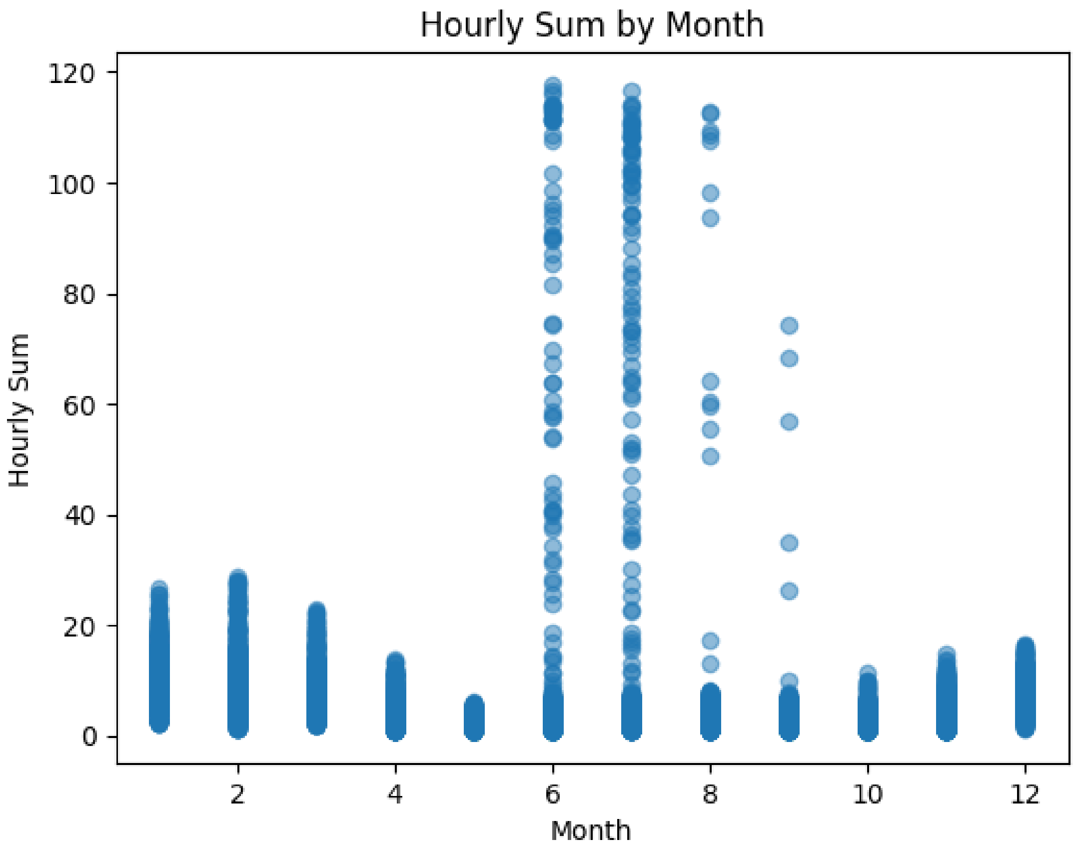
[17]:
```
Text(0, 0.5, 'Hourly Sum')
```



Unsurprisingly, there doesn't seem to be too much of a pattern between which days of the month require more energy. Generally, we might expect there to be less power use on the weekend as industry doesn't run as much.

[18]:
```
# by month
plt.figure()
plt.scatter(combinedDatasetAssignment2['Month'],␣
    ↪combinedDatasetAssignment2['Hourly Sum'], alpha=0.5)
plt.title('Hourly Sum by Month')
plt.xlabel('Month')
plt.ylabel('Hourly Sum')
```

[18]:
```
Text(0, 0.5, 'Hourly Sum')
```



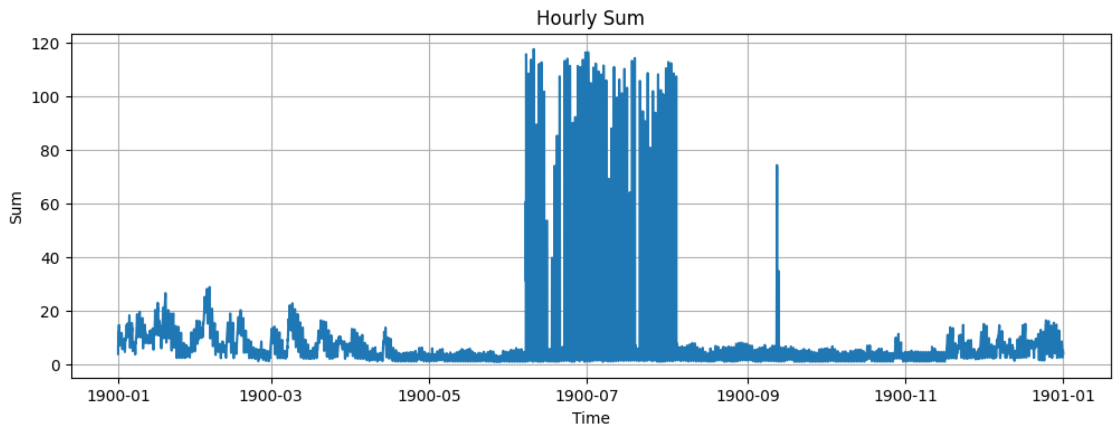
We see that usually in the summer months, as well as the winter months electricity usage tends to increase, with it being especially noticeable in the summer months. This is within expectations, as in the winter, a lot of heating is most likely due to the burning of natural gas heating, whereas in the summer, air conditioning usage is reliant on electricity, which causes electricity usage to spike significantly, as those tend to be extremely power hungry. Spring and fall tend to have lower energy usage as the climate tends to be nicer, and therefore not need climate control as much.

[19]:
```
combinedDatasetAssignment2['Date/Time'] = pd.
  ↪to_datetime(combinedDatasetAssignment2['Date/Time'])
combinedDatasetAssignment2.set_index('Date/Time', inplace=True)
hourly_data = combinedDatasetAssignment2.resample('H').sum()
daily_data = combinedDatasetAssignment2.resample('D').sum()
monthly_data = combinedDatasetAssignment2.resample('M').sum()
```

```
/var/folders/vz/z83bk0kd7s5d4_3cx59yyqnw0000gn/T/ipykernel_17911/3823209578.py:3
: FutureWarning: 'H' is deprecated and will be removed in a future version,
please use 'h' instead.
  hourly_data = combinedDatasetAssignment2.resample('H').sum()
/var/folders/vz/z83bk0kd7s5d4_3cx59yyqnw0000gn/T/ipykernel_17911/3823209578.py:5
: FutureWarning: 'M' is deprecated and will be removed in a future version,
```

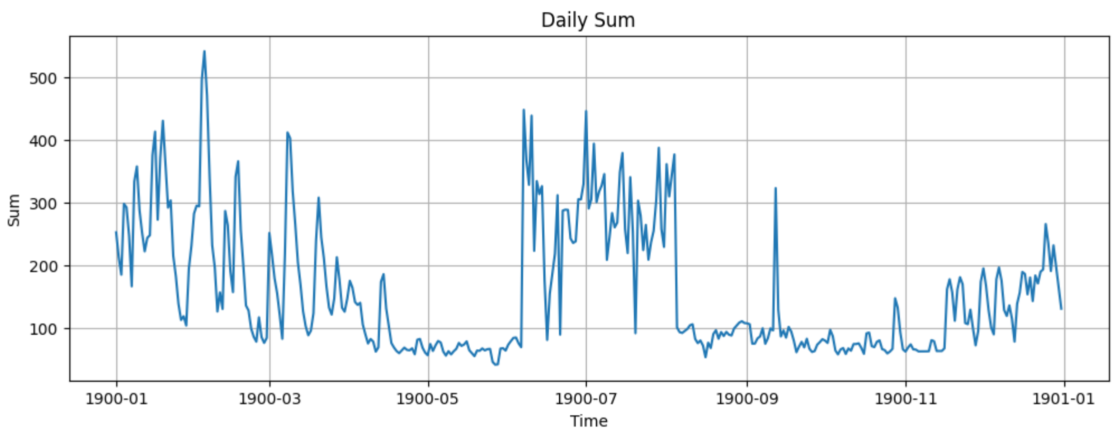
```
please use 'ME' instead.
  monthly_data = combinedDatasetAssignment2.resample('M').sum()
```

[20]:
```
plt.figure(1, figsize=(12,4))
plt.plot(hourly_data.index, hourly_data['Hourly Sum'])
plt.title('Hourly Sum')
plt.xlabel('Time')
plt.ylabel('Sum')
plt.grid(True)
```



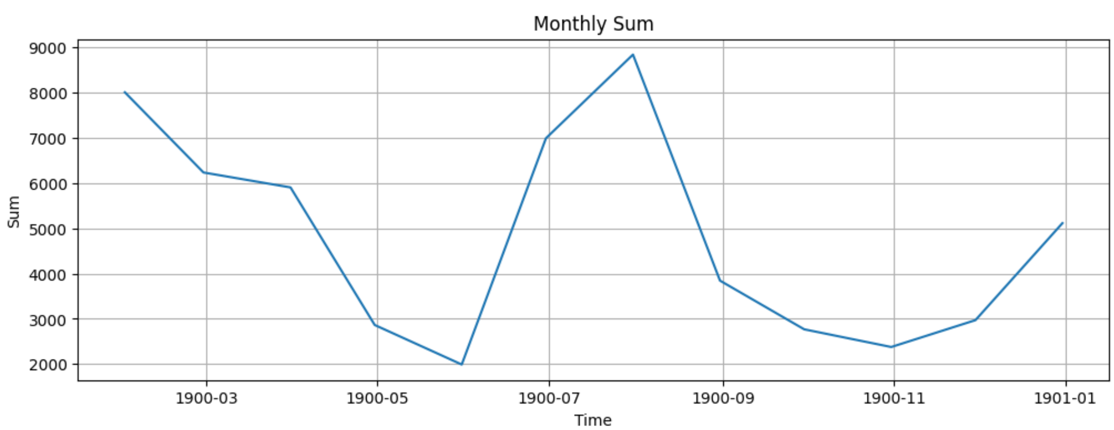
Unfortunately the index starts from 1900 due to that being the default of the DateTime package, but like before, if we look at the hourly sum across different months in time, we see that a lot more energy is consumed during the summer months, and slightly more energy is consumed during the winter. There do seem to be some outliers such as that spike in September, whether that's an outlier or a sudden weather change is unknown yet.

[21]:
```
# Daily Data
plt.figure(1, figsize=(12,4))
plt.plot(daily_data.index, daily_data['Hourly Sum'])
plt.title('Daily Sum')
plt.xlabel('Time')
plt.ylabel('Sum')
plt.grid(True)
```



As expected, if we look at the daily sum instead, then the trend becomes much more smooth. We see that there's actually almost comparable peaks in the winter months to the summer months, with some of the highest peaks actually belonging to about February. This tells me that even though the hourly sum clearly shows a lot of energy being consumed in summer, significant variance is actually presence, therefore when we aggregate, the peaks aren't actually that much different than the winter months

[22]:
```
plt.figure(1, figsize=(12,4))
plt.plot(monthly_data.index, monthly_data['Hourly Sum'])
plt.title('Monthly Sum')
plt.xlabel('Time')
plt.ylabel('Sum')
plt.grid(True)
```



Like before, when we look at a monthly rolling sum instead, we see that the trend becomes even more smooth. Compared to the previous graphs, the seasons of spring and fall still consume the least amount of energy, but the winter and summer months have almost comparable energy peaks now, with the summer months only being slightly higher (9000 vs 8000). This supports the trend that while summer does tend to have higher energy usage, the variance present is also significantly higher.

4 Assignment 3: EDA and forecast model

Objective: create EDA and forecast model to predict RTLMP We need to analyze and create predictive modeling in daily basis as quantitive analyst. Create EDA using the data and make your model to predict RTLMP from the data.

Data Files: In the data file timeseries_data.xlsx, you can find following timeseries (hourly): - RTLoad: ERCOT real-time hourly actual load - WIND_RTI: ERCOT real-time hourly wind generation - GENERATION_SOLAR_RT: ERCOT real-time solar generation - RTLMP: ERCOT North hub real-time price

Requirements: - Create Exploratory Data Analysis (EDA) - Create forecast model to predict RTLMP

Hint: - Notice the timestamps between independent and explanatory variables

[23]:
```
#pip install openpyxl
```

[24]:
```
#pip install seaborn
```

[25]:
```
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")

timesSeriesData = pd.read_excel('Documents/GitHub/GuzmanSummer2024/data/
 ↪Assignment 3 - timeseries_data.xlsx')
timesSeriesData['ERCOT (WIND_RTI)'].fillna(timesSeriesData['ERCOT (WIND_RTI)'].
 ↪median(), inplace=True)
timesSeriesData['ERCOT (GENERATION_SOLAR_RT)'].fillna(timesSeriesData['ERCOT␣
 ↪(GENERATION_SOLAR_RT)'].median(), inplace=True)
timesSeriesData['hour'] = timesSeriesData['DATETIME'].dt.hour
timesSeriesData['dayofweek'] = timesSeriesData['DATETIME'].dt.dayofweek
timesSeriesData['month'] = timesSeriesData['DATETIME'].dt.month

# Exploratory Data Analysis (EDA)
# Descriptive Statistics
descriptive_stats = pd.DataFrame(timesSeriesData.describe())
descriptive_stats
```

[25]:
```
                           DATETIME  HB_NORTH (RTLMP)  ERCOT (WIND_RTI)  \
count                         14987      14987.000000      14987.000000
```

```
mean   2017-11-09 06:41:09.340094720          25.766417       7532.352547
min              2017-01-01 01:00:00         -17.860000         54.440000
25%              2017-06-06 04:30:00          18.041250       4138.390000
50%              2017-11-09 06:00:00          20.057500       7281.445000
75%              2018-04-14 09:30:00          25.030000      10851.280000
max              2018-09-17 12:00:00        2809.357500      20350.400000
std                              NaN          46.361945       3992.221308

       ERCOT (GENERATION_SOLAR_RT)  ERCOT (RTLOAD)    HOURENDING  \
count                  14987.000000    14987.000000  14987.000000
mean                     291.917695    42371.673703     12.495763
min                        0.000000    25566.511248      1.000000
25%                        0.000000    35431.636526      6.000000
50%                       22.150000    39934.007113     12.000000
75%                      608.580000    47873.100786     18.000000
max                     1257.540000    73264.662123     24.000000
std                      370.891286     9874.339631      6.922309

                           MARKETDAY          YEAR          hour  \
count                          14987  14987.000000  14987.000000
mean   2017-11-08 18:11:24.593314304   2017.415493     11.496497
min              2017-01-01 00:00:00   2017.000000      0.000000
25%              2017-06-06 00:00:00   2017.000000      5.000000
50%              2017-11-09 00:00:00   2017.000000     11.000000
75%              2018-04-14 00:00:00   2018.000000     17.000000
max              2018-09-17 00:00:00   2018.000000     23.000000
std                              NaN      0.492823      6.921750

          dayofweek         month
count  14987.000000  14987.000000
mean       3.001802      5.814706
min        0.000000      1.000000
25%        1.000000      3.000000
50%        3.000000      6.000000
75%        5.000000      8.000000
max        6.000000     12.000000
std        2.002983      3.195156
```

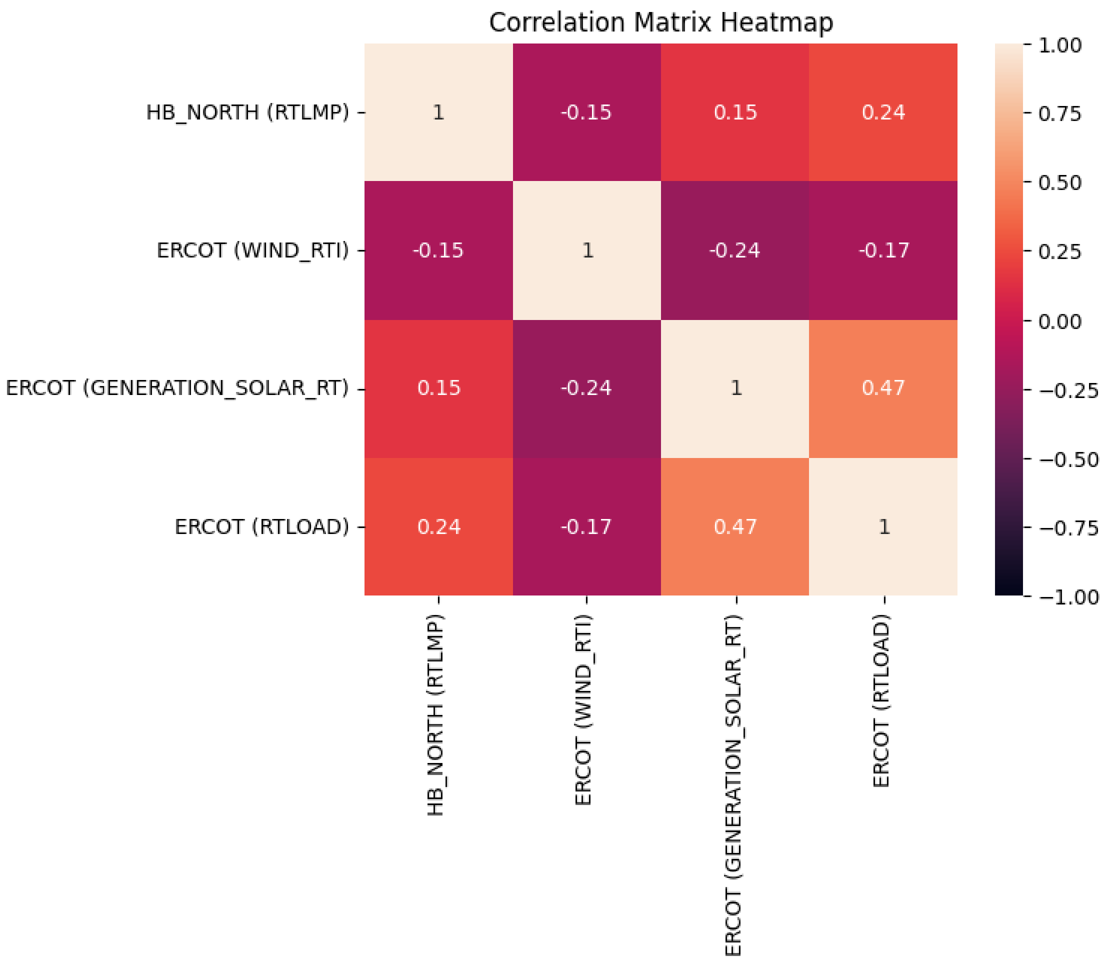
Before analysis, I imputed the median of several columns to replace the nan - it's a more robust metric than the mean, which may not be ideal for our purposes if we're trying to find our value at risk or our 99% CVAR. If we look at the different columns, it's obvious that some metrics are meaningless, ie taking the mean of DATETIME or MARKETDAY. However, there's some more interesting statistics elsewhere. For example, we note that Wind generates significantly more energy than solar across all metrics. Whether this is due to more wind turbines and wind based electricity generation compared to few solar sources or if wind is just that much more productive will need to be deduced through other datasets and contextual knowledge.

[26]:
```python
# Correlation Analysis: Calculate and plot the correlation matrix
corr_matrix = timesSeriesData[['HB_NORTH (RTLMP)', 'ERCOT (WIND_RTI)', 'ERCOT␣
↪(GENERATION_SOLAR_RT)', 'ERCOT (RTLOAD)']].corr()
pd.DataFrame(corr_matrix)
```

[26]:
```
                            HB_NORTH (RTLMP)  ERCOT (WIND_RTI)  \
HB_NORTH (RTLMP)                    1.000000         -0.151160
ERCOT (WIND_RTI)                   -0.151160          1.000000
ERCOT (GENERATION_SOLAR_RT)         0.151931         -0.235345
ERCOT (RTLOAD)                      0.238509         -0.166730

                            ERCOT (GENERATION_SOLAR_RT)  ERCOT (RTLOAD)
HB_NORTH (RTLMP)                               0.151931        0.238509
ERCOT (WIND_RTI)                              -0.235345       -0.166730
ERCOT (GENERATION_SOLAR_RT)                    1.000000        0.466339
ERCOT (RTLOAD)                                 0.466339        1.000000
```

[27]:
```python
sns.heatmap(corr_matrix, annot=True, vmin=-1, vmax=1)
plt.title('Correlation Matrix Heatmap')
```

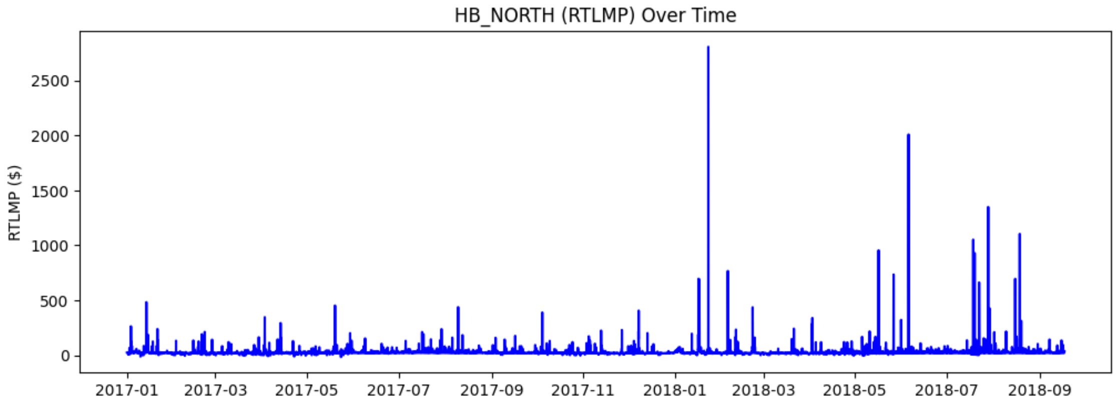
[27]:
```
Text(0.5, 1.0, 'Correlation Matrix Heatmap')
```



When we look at the correlation matrix, we see that the correlations in finance terms are surprisingly large, with correlations between Solar and RTLOAD at 0.47, and many of the other correlations being in the range of 0.15 to 0.24 in absolute value terms.

[28]:
```
plt.figure(1, figsize=(12,4))
plt.plot(timesSeriesData['DATETIME'], timesSeriesData['HB_NORTH (RTLMP)'],␣
↪color='blue')
plt.title('HB_NORTH (RTLMP) Over Time')
plt.ylabel('RTLMP ($)')
```

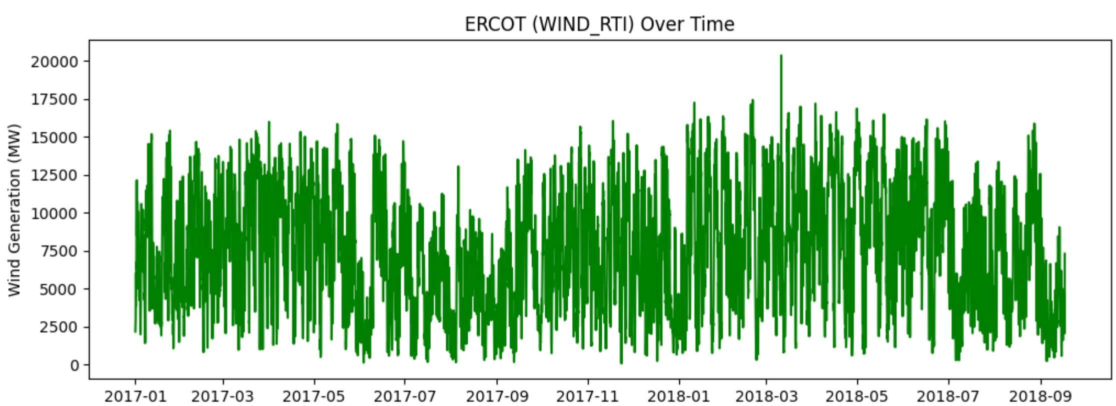
[28]: Text(0, 0.5, 'RTLMP ($)')



When we look at this data over time, we see that there are definitely years that contribute more - notably after 2018 there was a lot more value being generated here. Previous to 2018, RTLMP almost seemed to be consistently cyclical in nature.

[29]:
```
# Plotting ERCOT (WIND_RTI)
plt.figure(1, figsize=(12,4))
plt.plot(timesSeriesData['DATETIME'], timesSeriesData['ERCOT (WIND_RTI)'],␣
 ↪color='green')
plt.title('ERCOT (WIND_RTI) Over Time')
plt.ylabel('Wind Generation (MW)')
```

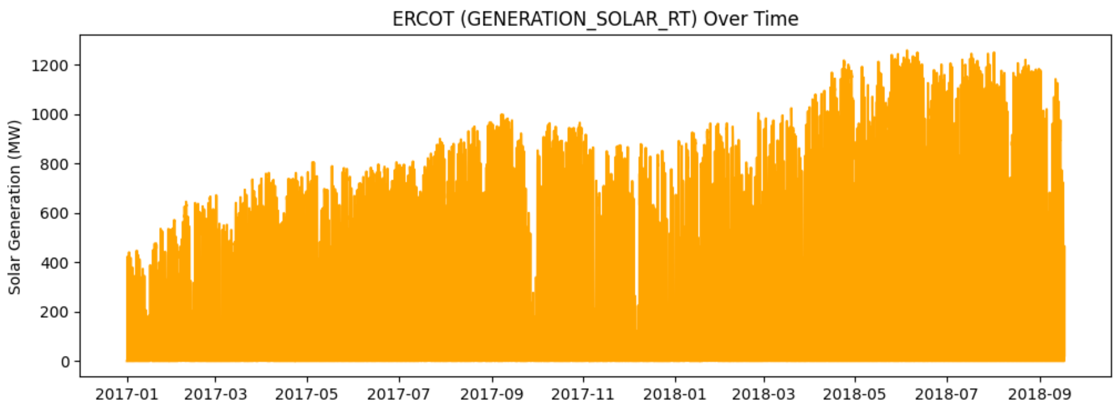
[29]:
```
Text(0, 0.5, 'Wind Generation (MW)')
```



Wind RTI seems to be pretty constantly fluctuating over time, there might be some patterns to be gleaned from it, as it does seem to have “bumps” - 2017-01 to 2017-09 definitely looks like a bump happened, and then another bump happened from 2017-09 to 201801, and the third from 2018-01 to 2018-09. It would be worth looking into it more closely in the future to separate out noise from an actual trend.

[30]:
```
# Plotting ERCOT (GENERATION_SOLAR_RT)
plt.figure(1, figsize=(12,4))
plt.plot(timesSeriesData['DATETIME'], timesSeriesData['ERCOT␣
↪(GENERATION_SOLAR_RT)'], color='orange')
plt.title('ERCOT (GENERATION_SOLAR_RT) Over Time')
plt.ylabel('Solar Generation (MW)')
```

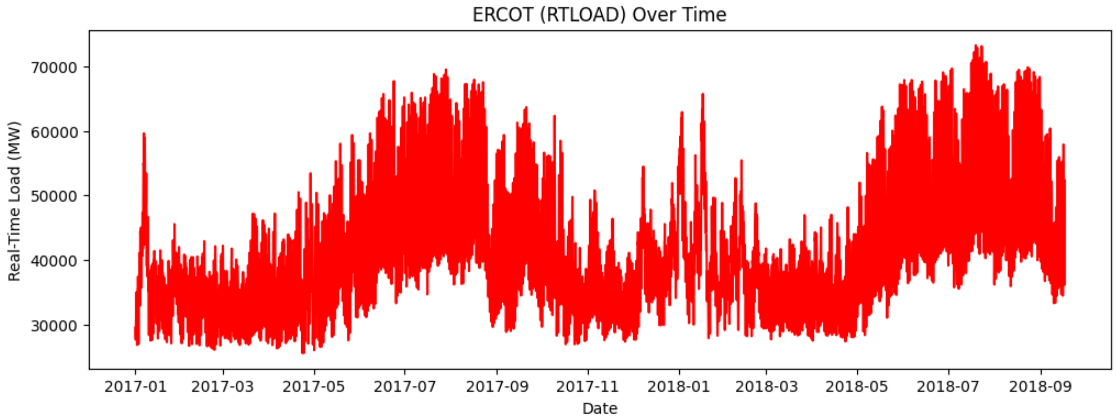
[30]:
```
Text(0, 0.5, 'Solar Generation (MW)')
```



Solar generation looks like it's pretty consistently increased over time, and the generation does seem to appear to be relatively cyclical as well, every few months there's a notable drop. Whether this is from weather patterns or maintence to temporarily take solar farms off line, or if it's just noise requires further analysis. However, it is clear that solar power has grown, and most likely will continue to grow.

[31]:
```
# Plotting ERCOT (RTLOAD)
plt.figure(1, figsize=(12,4))
plt.plot(timesSeriesData['DATETIME'], timesSeriesData['ERCOT (RTLOAD)'],␣
↪color='red')
plt.title('ERCOT (RTLOAD) Over Time')
plt.ylabel('Real-Time Load (MW)')
plt.xlabel('Date')
```

[31]:
```
Text(0.5, 0, 'Date')
```



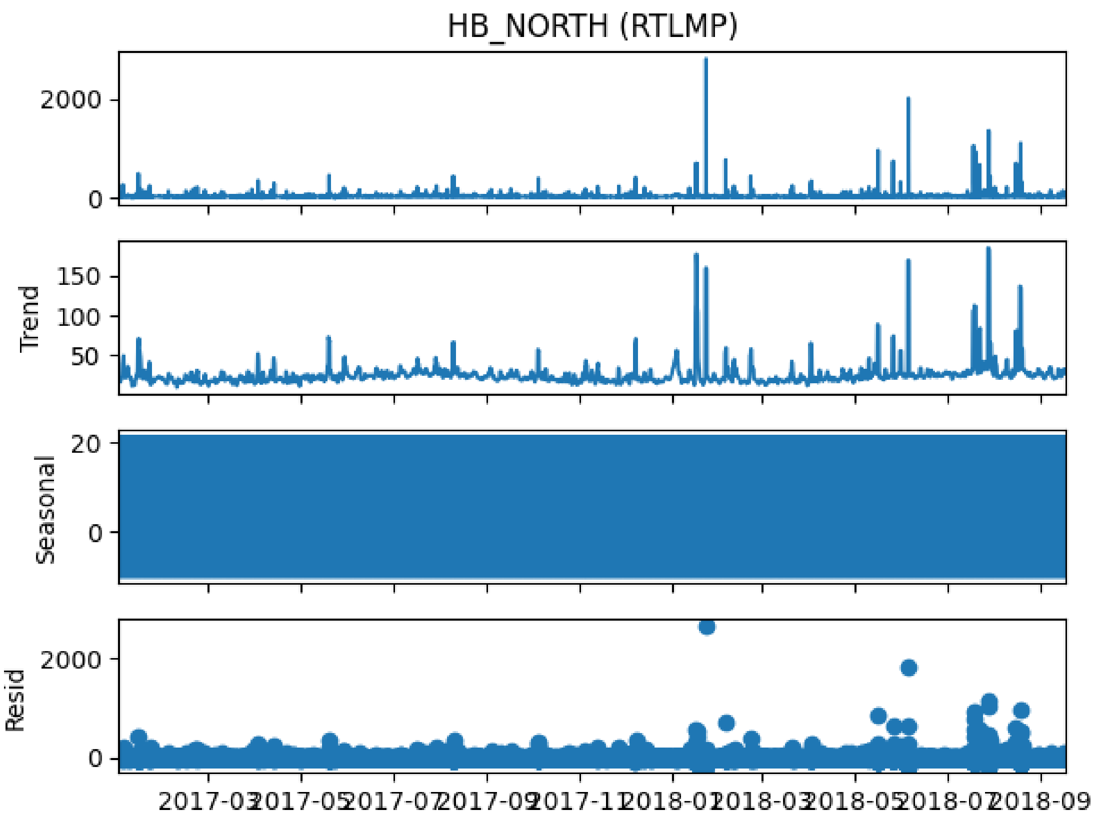
RT Load seems to be very cyclical in nature, just the not even 2 years data that we have here already show two pretty big increases, and both starting in May. There's a peak in 2018-01, and it looks to be similar to the peak that occured in 2017-01. However, we lack the data to further analyze this and determine if it's a true effect or random chance alone.

[32]:
```
#pip install keras
```

[33]:
```
#pip install tensorflow
```

[34]:
```
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.statespace.sarimax import SARIMAX

warnings.filterwarnings("ignore")
timesSeries = pd.read_excel('Documents/GitHub/GuzmanSummer2024/data/Assignment␣
↪3 - timeseries_data.xlsx')
timesSeries['ERCOT (WIND_RTI)'].fillna(timesSeries['ERCOT (WIND_RTI)'].
↪median(), inplace=True)
timesSeries['ERCOT (GENERATION_SOLAR_RT)'].fillna(timesSeries['ERCOT␣
↪(GENERATION_SOLAR_RT)'].median(), inplace=True)
timesSeries.set_index('DATETIME', inplace=True)

# Seasonality
result = seasonal_decompose(timesSeries['HB_NORTH (RTLMP)'], model='additive',␣
↪period=24)
result.plot()
plt.show()

train_data = timesSeries['HB_NORTH (RTLMP)'][:int(0.8*len(timesSeries))]
test_data = timesSeries['HB_NORTH (RTLMP)'][int(0.8*len(timesSeries)):]

# Fit the SARIMA model
```

```
sarima_model = SARIMAX(train_data, order=(1, 1, 1), seasonal_order=(1, 1, 1,␣
↪24))
sarima_result = sarima_model.fit()
forecast = sarima_result.predict(start=len(train_data),␣
↪end=len(train_data)+len(test_data)-1, dynamic=False)

# Evaluate the model
mae = mean_absolute_error(test_data, forecast)
mse = mean_squared_error(test_data, forecast)
print(f'MAE: {mae}, MSE: {mse}')
```

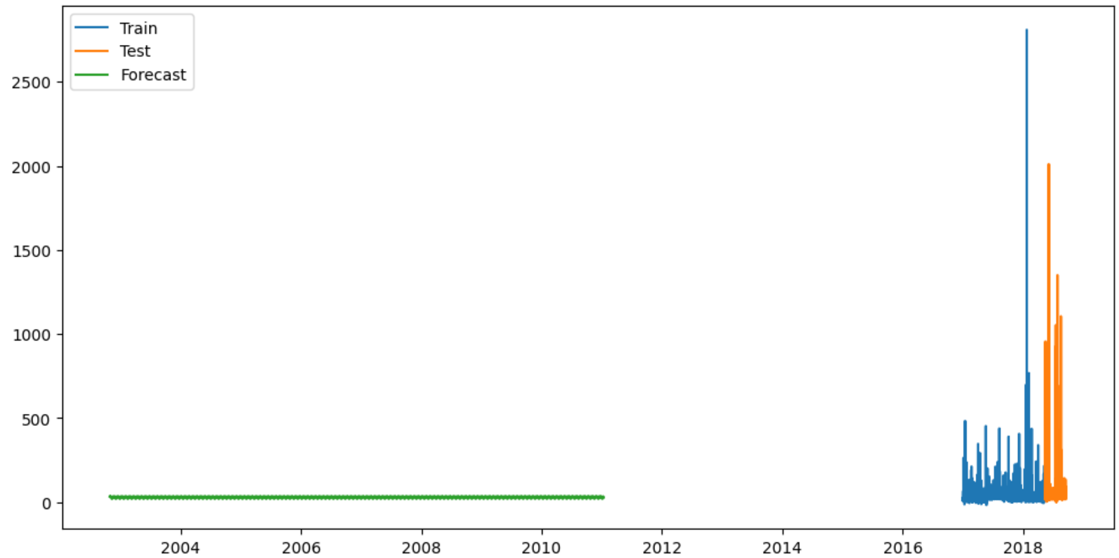



```
RUNNING THE L-BFGS-B CODE

           * * *

Machine precision = 2.220D-16
 N =            5     M =           10

At X0         0 variables are exactly at the bounds

At iterate    0    f=  5.11042D+00    |proj g|=  8.08484D-02
```

```
 This problem is unconstrained.

At iterate    5    f=  5.03118D+00    |proj g|=  2.04819D-02

At iterate   10    f=  4.90522D+00    |proj g|=  1.36895D-02

           * * *

Tit   = total number of iterations
Tnf   = total number of function evaluations
Tnint = total number of segments explored during Cauchy searches
Skip  = number of BFGS updates skipped
Nact  = number of active bounds at final generalized Cauchy point
Projg = norm of the final projected gradient
F     = final function value

           * * *

   N    Tit     Tnf  Tnint  Skip  Nact     Projg        F
    5     14     17      1     0     0   3.105D-05   4.905D+00
  F =   4.9049448630240375

CONVERGENCE: REL_REDUCTION_OF_F_<=_FACTR*EPSMCH
MAE: 13.530740318415798, MSE: 5730.33521088294
```

[35]:

```
# Plot the results
plt.figure(figsize=(12, 6))
plt.plot(train_data, label='Train')
plt.plot(test_data, label='Test')
plt.plot(forecast, label='Forecast')
plt.legend()
plt.show()
```



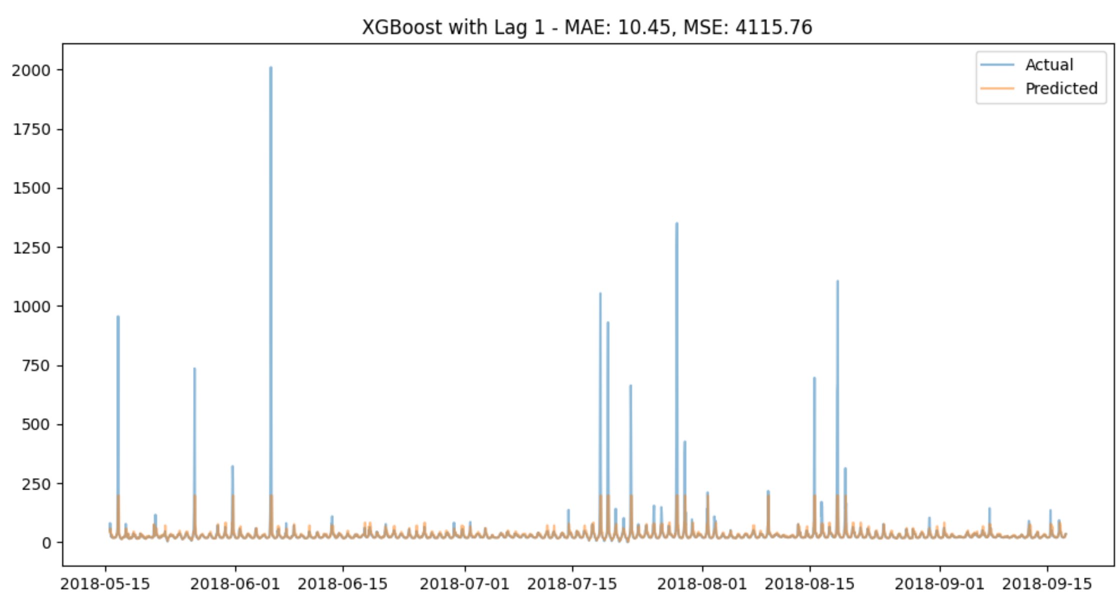
SARIMAX is one of the more commonly used tools for times-series analysis, being able to decompose the data into several metrics like seasonality, which is important for us as we expect and have shown greater energy usage during summer and winter when compared to the other months.

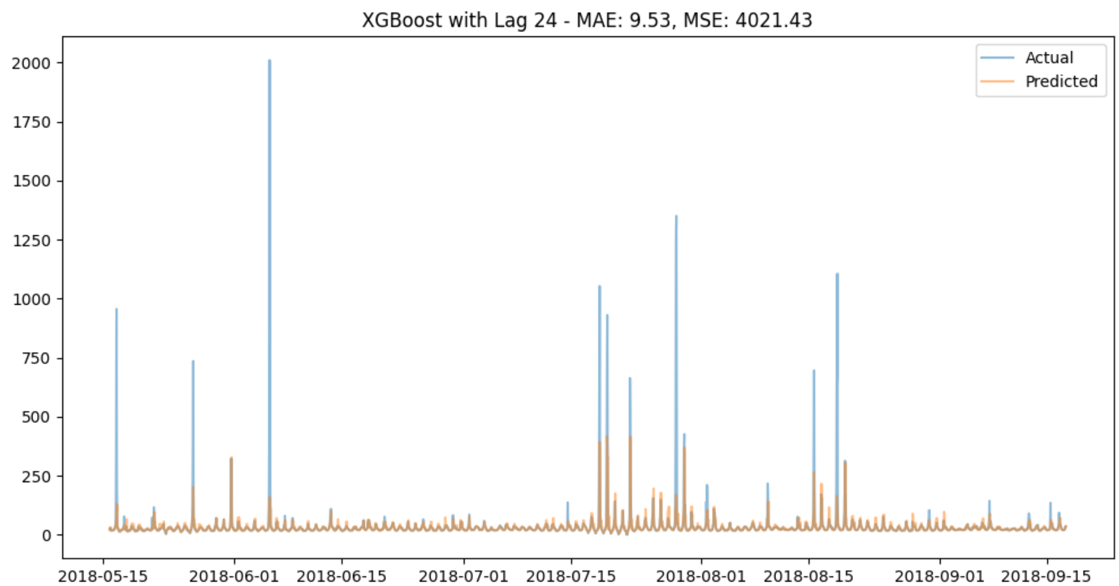
However, some of it looks off, therefore I've decided to utilize an XGBoost tree algorithm with varied lookback periods to see if it will be a better model.

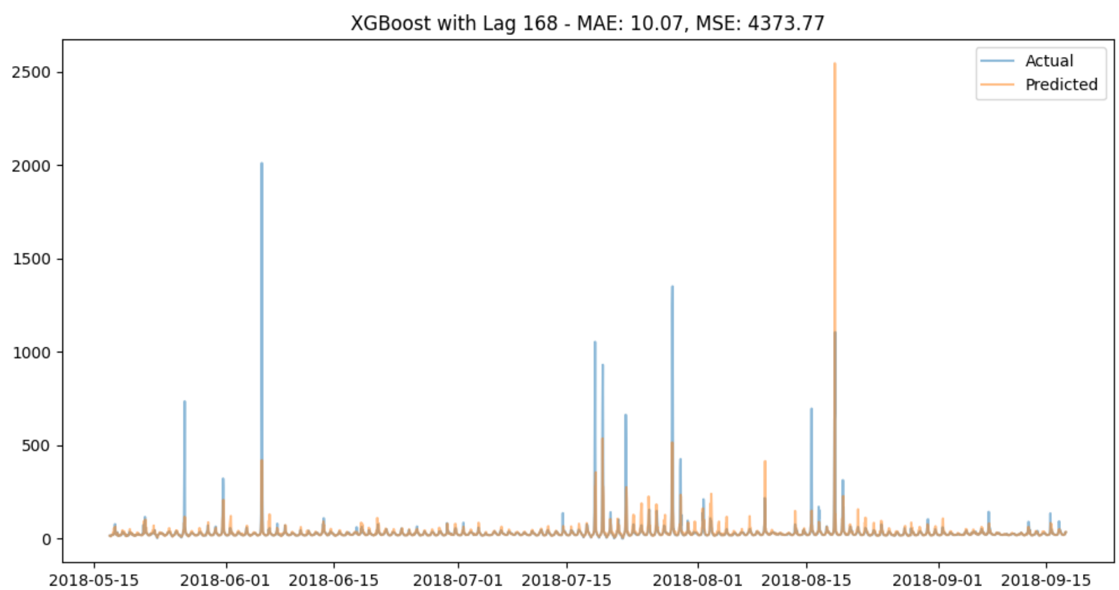
[36]:
```
#pip install xgboost
```

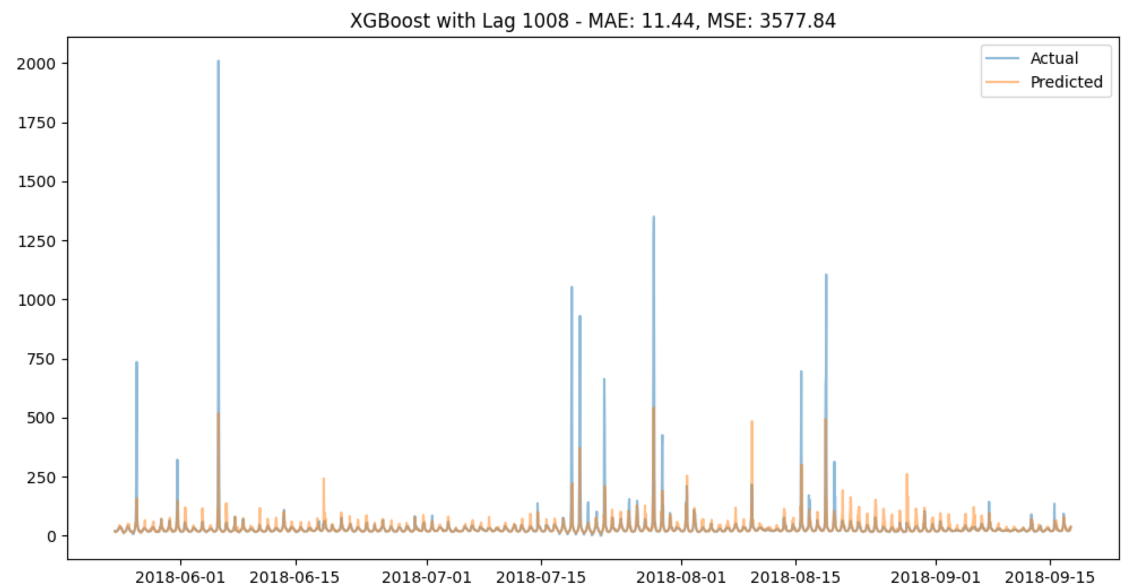
[37]:
```
import numpy as np
from sklearn.preprocessing import MinMaxScaler
import xgboost as xgb
warnings.filterwarnings("ignore")

forecast = timesSeries[['HB_NORTH (RTLMP)']]
def create_lag_features(data, lags):
    for lag in lags:
        data[f'lag_{lag}'] = data['HB_NORTH (RTLMP)'].shift(lag)
    return data.dropna()

# Define different lag periods
lag_periods = [1, 24, 168, 1008] # hourly, daily, montly, half-month

results = {}
for lag in lag_periods:
    data_with_lags = create_lag_features(forecast.copy(), range(1, lag + 1))


    train_size = int(len(data_with_lags) * 0.8)
```

```
    train_data = data_with_lags[:train_size]
    test_data = data_with_lags[train_size:]
    X_train = train_data.drop(columns=['HB_NORTH (RTLMP)'])
    y_train = train_data['HB_NORTH (RTLMP)']
    X_test = test_data.drop(columns=['HB_NORTH (RTLMP)'])
    y_test = test_data['HB_NORTH (RTLMP)']

    # Scale the data - compare apples to apples, make sure scale isn't causing␣
 ↪spurious correlations
    scaler = MinMaxScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_scaled = scaler.transform(X_test)

    model = xgb.XGBRegressor(objective='reg:squarederror', n_estimators=100,␣
 ↪learning_rate=0.1)
    model.fit(X_train_scaled, y_train)
    y_pred = model.predict(X_test_scaled)
    mae = mean_absolute_error(y_test, y_pred)
    mse = mean_squared_error(y_test, y_pred)
    results[lag] = {'MAE': mae, 'MSE': mse}

    plt.figure(figsize=(12, 6))
    plt.plot(test_data.index, y_test, label='Actual', alpha = 0.5)
    plt.plot(test_data.index, y_pred, label='Predicted', alpha = 0.5)
    plt.title(f'XGBoost with Lag {lag} - MAE: {mae:.2f}, MSE: {mse:.2f}')
    plt.legend()
    plt.show()

for lag, metrics in results.items():
    print(f'Lag {lag}: MAE = {metrics["MAE"]:.2f}, MSE = {metrics["MSE"]:.2f}')
```




XGBoost with Lag 24 - MAE: 9.53, MSE: 4021.43
Actual
Predicted
2000
1750
1500
1250
1000
750
500
250
0
2018-05-15
2018-06-01
2018-06-15
2018-07-01
2018-07-15
2018-08-01
2018-08-15
2018-09-01
2018-09-15


XGBoost with Lag 168 - MAE: 10.07, MSE: 4373.77
Actual
Predicted
2500
2000
1500
1000
500
0
2018-05-15
2018-06-01
2018-06-15
2018-07-01
2018-07-15
2018-08-01
2018-08-15
2018-09-01
2018-09-15




```
Lag 1: MAE = 10.45, MSE = 4115.76
Lag 24: MAE = 9.53, MSE = 4021.43
Lag 168: MAE = 10.07, MSE = 4373.77
Lag 1008: MAE = 11.44, MSE = 3577.84
```

We see that in general, the longer the lookback period is, the better the model is able to predict. However, the model still doesn't perform as extreme as the original data, we see several peaks where the model is extremely off, and requires further refinement.

5 Assignment 4 (Optional): Learn products of Futures

Objective: self-learning of market products and create hedging method This assignment will give some information to guide you to learn U.S. Power Futures market products. The goal is to demonstrate self-learning skill and passion to explore/learn new market/products.

Products: - Product 1: Power Futures - ERN https://www.theice.com/products/6590337/ERCOT-North-345KV-Real-Time-Peak-Fixed-Price-Future - Product 2: Natural Gas Futures - H https://www.theice.com/products/6590258/Henry-LD1-Fixed-Price-Future - Product 3: Heat Rate Futures - XPR https://www.theice.com/products/27998706/ERCOT-North-345KV-Physical-HR-Peak-HE-0700-2200-Future

Data Files: - dataset.xlsx the file provides the time series of daily settlement prices for same strip (December 2016 product).

Requirements: - create understanding of the products from the links provided. (do more research with uncleared concepts) - assume Product 1 has no liquidation in the market and we are holding the physical power (same settlement as Product 1), how to use Product 2 & 3 to hedge our exposure to physical power (again, same settlement as Product 1)? - create Excel file model with weekly rebalance of your positions (only rebalance Product 2) to try to achieve hedging. within the Excel file, use parameter to decide your rebalance and summarize the efficiency of hedging.

Hint: - make your own assumptions and explain in summary report - notice contract size limit

[38]:
```
dataAssignment4 = pd.read_excel("Documents/GitHub/GuzmanSummer2024/data/
 ↪Assignment 4 - dataset.xlsx")
dataAssignment4
```

[38]:
```
       Time Series Function Contract=ERN,Strip=12/1/2016  \
0                      NaN                Settlement_Price
1                      NaN                             NaN
2     Date (America/Chicago)                            NaN
3        2016-11-28 00:00:00                         27.77
4        2016-11-25 00:00:00                         26.51
..                       …                               …
217      2016-02-01 00:00:00                         24.56
218      2016-01-29 00:00:00                         24.88
219      2016-01-28 00:00:00                         24.43
220      2016-01-27 00:00:00                          24.5
221      2016-01-26 00:00:00                         24.62

    Contract=H,Strip=12/1/2016 Contract=XPR,Strip=12/1/2016
0             Settlement_Price             Settlement_Price
1       "Henry, NG LD1 Futures"                         NaN
2                          NaN                          NaN
3                        3.232                     8.592203
4                        3.085                     8.593193
..                           …                            …
217                        2.7                     9.096296
218                      2.742                     9.073669
219                      2.692                     9.075037
220                        2.7                     9.074074
221                      2.713                     9.074825

[222 rows x 4 columns]
```

5.1 Understanding of the links provided:

There's three different links provided:

The first link: ERCOT Power Future This is a derivatives future contract that allows buyers and sellers to lock in the price of 1 megawatt of electricity certain time in advance. Notably, this is cash settled as opposed to physical delivery.

The second link: Henry LD1 Fixed Price Future Like before, this is also a cash settled derivative futures contract on natural gas instead of electricity, trading specifically in 2500 MMBtu's.

The third link: Physical HR Peak HE This unlike the previous two, appears to be a forward derivatives contract instead. It's traded OTC, and also has a daily settlement term labelled on it, which are usually more standard for forwards contracts. We would have to be careful of trading these products as it may be more likely for there to be less liquidity for these products when compared to futures, which are traded on exchanges.

5.2 Assume Product 1 has no liquidation in the market and we are holding the physical power (same settlement as Product 1), how to use Product 2 & 3 to hedge our exposure to physical power (again, same settlement as Product 1)?

If we are holding the physical power, then we want to sell contracts of product 1 - in the future, the buyer agrees to pay us however much we agree on, scaled by the amount of MW we want to sell. However, since we know that product 1 has no liquidity, it implies that the bid-ask spread will be large. However, we also have Products 2 and 3, which although are not electricity specifically, are similar in the sense that they are both energy products. Therefore, we could sell the physical power that we do have (Product 1), and then buy Product 2 and 3 to hedge our exposure to the physical power directly by using these alternative energy assets that most likely will be correlated.

[ ]:

```

```