AAI-530 Final Project Team 7 - Code

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1 Final Project Team 7 AAI-530

1.1 Team Members

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[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import joblib
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import LSTM, Dense
from math import sqrt
from sklearn.metrics import mean_absolute_error
from keras.callbacks import EarlyStopping, ReduceLROnPlateau
from statsmodels.tsa.arima.model import ARIMA
from pmdarima import auto_arima
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from datetime import datetime
```

1.2 Import Dataset

Import the Smart Home dataset that was downloaded from Kaggle:

https://www.kaggle.com/datasets/taranvee/smart-home-dataset-with-weather-information/data

[ ]:
```
file_path = './Dataset/Smart_Home_Dataset_with_weather_Information.csv'
df = pd.read_csv(file_path)

# Remove the last row of the dfframe
df = df.iloc[:-1]

# Convert the 'time' column from UNIX timestamp to datetime
```

```python
df['time'] = pd.to_datetime(df['time'], unit='s')
df['time'] = pd.DatetimeIndex(pd.date_range('2016-01-01 00:00',␣
 ↪periods=len(df),  freq='min'))
df.set_index('time', inplace=True)

df.head()
```

```
C:\Users\paula\AppData\Local\Temp\ipykernel_22296\2011437542.py:2: DtypeWarning:
Columns (0,27) have mixed types. Specify dtype option on import or set
low_memory=False.
  df = pd.read_csv(file_path)
C:\Users\paula\AppData\Local\Temp\ipykernel_22296\2011437542.py:8:
FutureWarning: The behavior of 'to_datetime' with 'unit' when parsing strings is
deprecated. In a future version, strings will be parsed as datetime strings,
matching the behavior without a 'unit'. To retain the old behavior, explicitly
cast ints or floats to numeric type before calling to_datetime.
  df['time'] = pd.to_datetime(df['time'], unit='s')
```

[ ]:

```
                     use [kW]  gen [kW]  House overall [kW]  Dishwasher [kW]  \
time
2016-01-01 00:00:00  0.932833  0.003483            0.932833         0.000033
2016-01-01 00:01:00  0.934333  0.003467            0.934333         0.000000
2016-01-01 00:02:00  0.931817  0.003467            0.931817         0.000017
2016-01-01 00:03:00  1.022050  0.003483            1.022050         0.000017
2016-01-01 00:04:00  1.139400  0.003467            1.139400         0.000133

                     Furnace 1 [kW]  Furnace 2 [kW]  Home office [kW]  \
time
2016-01-01 00:00:00        0.020700        0.061917          0.442633
2016-01-01 00:01:00        0.020717        0.063817          0.444067
2016-01-01 00:02:00        0.020700        0.062317          0.446067
2016-01-01 00:03:00        0.106900        0.068517          0.446583
2016-01-01 00:04:00        0.236933        0.063983          0.446533

                     Fridge [kW]  Wine cellar [kW]  Garage door [kW]  …  \
time                                                                  …
2016-01-01 00:00:00     0.124150          0.006983          0.013083  …
2016-01-01 00:01:00     0.124000          0.006983          0.013117  …
2016-01-01 00:02:00     0.123533          0.006983          0.013083  …
2016-01-01 00:03:00     0.123133          0.006983          0.013000  …
2016-01-01 00:04:00     0.122850          0.006850          0.012783  …

                     visibility  summary  apparentTemperature  pressure  \
time
2016-01-01 00:00:00        10.0    Clear                29.26   1016.91
2016-01-01 00:01:00        10.0    Clear                29.26   1016.91
2016-01-01 00:02:00        10.0    Clear                29.26   1016.91
```

```
2016-01-01 00:03:00        10.0    Clear                 29.26   1016.91
2016-01-01 00:04:00        10.0    Clear                 29.26   1016.91

                     windSpeed  cloudCover  windBearing  precipIntensity  \
time
2016-01-01 00:00:00       9.18  cloudCover        282.0              0.0
2016-01-01 00:01:00       9.18  cloudCover        282.0              0.0
2016-01-01 00:02:00       9.18  cloudCover        282.0              0.0
2016-01-01 00:03:00       9.18  cloudCover        282.0              0.0
2016-01-01 00:04:00       9.18  cloudCover        282.0              0.0

                     dewPoint precipProbability
time
2016-01-01 00:00:00      24.4                0.0
2016-01-01 00:01:00      24.4                0.0
2016-01-01 00:02:00      24.4                0.0
2016-01-01 00:03:00      24.4                0.0
2016-01-01 00:04:00      24.4                0.0

[5 rows x 31 columns]
```

2 Cleaning

- Remove the last row of data since it was garbage data
- Encode all string features
- Forward fill null values

[ ]:
```python
# replace the string cloudCover with the mean value
df['cloudCover'] = df['cloudCover'].replace('cloudCover', None)
# Convert the cloudCover column to a float
df['cloudCover'] = df['cloudCover'].astype(float)
# replace nan values with the mean of the column
df['cloudCover'] = df['cloudCover'].fillna(df['cloudCover'].mean())
# View the different strings in cloudCover
df['cloudCover'].unique()
```

[ ]:
```
array([0.22588514, 0.75      , 0.        , 1.        , 0.31      ,
       0.44      , 0.13      , 0.19      , 0.25      , 0.16      ,
       0.21      , 0.15      , 0.14      , 0.27      , 0.28      ,
       0.17      , 0.05      , 0.1       , 0.26      , 0.29      ,
       0.11      , 0.09      , 0.12      , 0.06      , 0.02      ,
       0.08      , 0.04      , 0.35      , 0.22      , 0.23      ,
       0.54      , 0.39      , 0.03      , 0.07      , 0.76      ,
       0.62      , 0.18      , 0.79      , 0.48      , 0.24      ,
       0.57      , 0.41      , 0.78      , 0.2       , 0.77      ,
       0.46      , 0.55      , 0.01      , 0.51      , 0.47      ,
       0.5       , 0.4       , 0.3       , 0.43      , 0.33      ,
```

```
       0.6       , 0.68      , 0.66      , 0.45      , 0.34      ,
       0.52      , 0.67      , 0.49      , 0.37      , 0.36      ,
       0.61      , 0.38      , 0.42      , 0.53      , 0.63      ,
       0.32      , 0.56      , 0.58      , 0.72      , 0.73      ,
       0.71      , 0.64      , 0.59      ])
```

[ ]:
```
# show the values of summary
print(df['summary'].unique())
df['summary_encoded'] = pd.factorize(df['summary'])[0]
print(df['summary_encoded'].unique())

# drop the summary column
df = df.drop(columns='summary')
```

```
['Clear' 'Mostly Cloudy' 'Overcast' 'Partly Cloudy' 'Drizzle' 'Light Rain'
 'Rain' 'Light Snow' 'Flurries' 'Breezy' 'Snow' 'Rain and Breezy' 'Foggy'
 'Breezy and Mostly Cloudy' 'Breezy and Partly Cloudy'
 'Flurries and Breezy' 'Dry' 'Heavy Snow']
[ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17]
```

[ ]:
```
print(df['icon'].unique())
df['icon_encoded'] = pd.factorize(df['icon'])[0]
print(df['icon_encoded'].unique())

# drop the icon column
df = df.drop(columns='icon')
```

```
['clear-night' 'partly-cloudy-night' 'clear-day' 'cloudy'
 'partly-cloudy-day' 'rain' 'snow' 'wind' 'fog']
[0 1 2 3 4 5 6 7 8]
```

[ ]:
```
df.describe()
```

[ ]:

	use [kW]	gen [kW]	House overall [kW]	Dishwasher [kW]	\
count	503910.000000	503910.000000	503910.000000	503910.000000	
mean	0.858962	0.076229	0.858962	0.031368	
std	1.058207	0.128428	1.058207	0.190951	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.367667	0.003367	0.367667	0.000000	
50%	0.562333	0.004283	0.562333	0.000017	
75%	0.970250	0.083917	0.970250	0.000233	
max	14.714567	0.613883	14.714567	1.401767	

	Furnace 1 [kW]	Furnace 2 [kW]	Home office [kW]	Fridge [kW]	\
count	503910.000000	503910.000000	503910.000000	503910.000000	
mean	0.099210	0.136779	0.081287	0.063556	
std	0.169059	0.178631	0.104466	0.076199	
min	0.000017	0.000067	0.000083	0.000067	

```
25%          0.020233        0.064400          0.040383       0.005083
50%          0.020617        0.066633          0.042217       0.005433
75%          0.068733        0.080633          0.068283       0.125417
max          1.934083        0.794933          0.971750       0.851267

       Wine cellar [kW]  Garage door [kW]  …  apparentTemperature  \
count     503910.000000     503910.000000  …        503910.000000
mean           0.042137          0.014139  …            48.263382
std            0.057967          0.014292  …            22.027916
min            0.000017          0.000017  …           -32.080000
25%            0.007133          0.012733  …            31.090000
50%            0.008083          0.012933  …            50.320000
75%            0.053192          0.013100  …            66.260000
max            1.273933          1.088983  …           101.120000

            pressure      windSpeed     cloudCover    windBearing  \
count  503910.000000  503910.000000  503910.000000  503910.000000
mean     1016.301625       6.649936       0.225885     202.356843
std         7.895185       3.982716       0.289890     106.520474
min       986.400000       0.000000       0.000000       0.000000
25%      1011.290000       3.660000       0.040000     148.000000
50%      1016.530000       5.930000       0.120000     208.000000
75%      1021.480000       8.940000       0.290000     295.000000
max      1042.460000      22.910000       1.000000     359.000000

       precipIntensity       dewPoint  precipProbability  summary_encoded  \
count    503910.000000  503910.000000      503910.000000    503910.000000
mean          0.002598      38.694013           0.056453         1.026771
std           0.011257      19.087939           0.165836         2.054667
min           0.000000     -27.240000           0.000000         0.000000
25%           0.000000      24.600000           0.000000         0.000000
50%           0.000000      39.030000           0.000000         0.000000
75%           0.000000      54.790000           0.000000         1.000000
max           0.191000      75.490000           0.840000        17.000000

        icon_encoded
count  503910.000000
mean        1.696803
std         1.744335
min         0.000000
25%         0.000000
50%         2.000000
75%         2.000000
max         8.000000

[8 rows x 31 columns]
```

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

[ ]:
```
use [kW]                0
gen [kW]                0
House overall [kW]      0
Dishwasher [kW]         0
Furnace 1 [kW]          0
Furnace 2 [kW]          0
Home office [kW]        0
Fridge [kW]             0
Wine cellar [kW]        0
Garage door [kW]        0
Kitchen 12 [kW]         0
Kitchen 14 [kW]         0
Kitchen 38 [kW]         0
Barn [kW]               0
Well [kW]               0
Microwave [kW]          0
Living room [kW]        0
Solar [kW]              0
temperature             0
humidity                0
visibility              0
apparentTemperature     0
pressure                0
windSpeed               0
cloudCover              0
windBearing             0
precipIntensity         0
dewPoint                0
precipProbability       0
summary_encoded         0
icon_encoded            0
dtype: int64
```

[ ]:
```
df.dtypes
```

[ ]:
```
use [kW]                float64
gen [kW]                float64
House overall [kW]      float64
Dishwasher [kW]         float64
Furnace 1 [kW]          float64
Furnace 2 [kW]          float64
Home office [kW]        float64
Fridge [kW]             float64
Wine cellar [kW]        float64
Garage door [kW]        float64
```

```
Kitchen 12 [kW]         float64
Kitchen 14 [kW]         float64
Kitchen 38 [kW]         float64
Barn [kW]               float64
Well [kW]               float64
Microwave [kW]          float64
Living room [kW]        float64
Solar [kW]              float64
temperature             float64
humidity                float64
visibility              float64
apparentTemperature     float64
pressure                float64
windSpeed               float64
cloudCover              float64
windBearing             float64
precipIntensity         float64
dewPoint                float64
precipProbability       float64
summary_encoded           int64
icon_encoded              int64
dtype: object
```

[ ]:
```
# Print the total rows with null values
print(df.isnull().sum().sum())

# Fill the null values with the forward fill method
df.fillna(method='ffill', inplace=True)
```

```
0
```

```
C:\Users\paula\AppData\Local\Temp\ipykernel_22296\1930171081.py:5:
FutureWarning: DataFrame.fillna with 'method' is deprecated and will raise in a
future version. Use obj.ffill() or obj.bfill() instead.
  df.fillna(method='ffill', inplace=True)
```

3 EDA

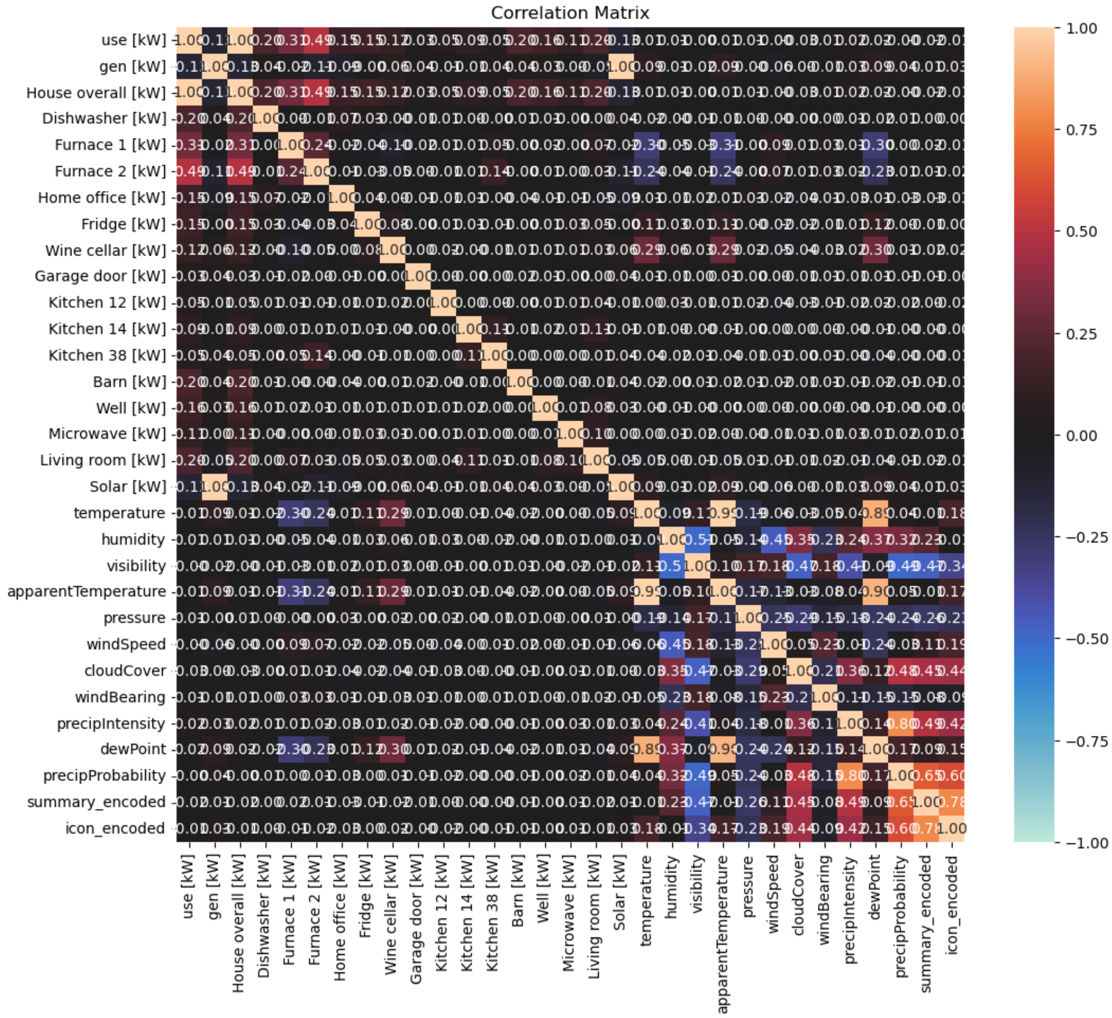
- Analyze Power and Weather features to identify correlations
- Visualize all data to identify trends
- Drop any duplicated features

[ ]:
```
# Power-related columns
power_array = [
    'use [kW]',
    'gen [kW]',
    # 'House overall [kW]',
    'Dishwasher [kW]',
```

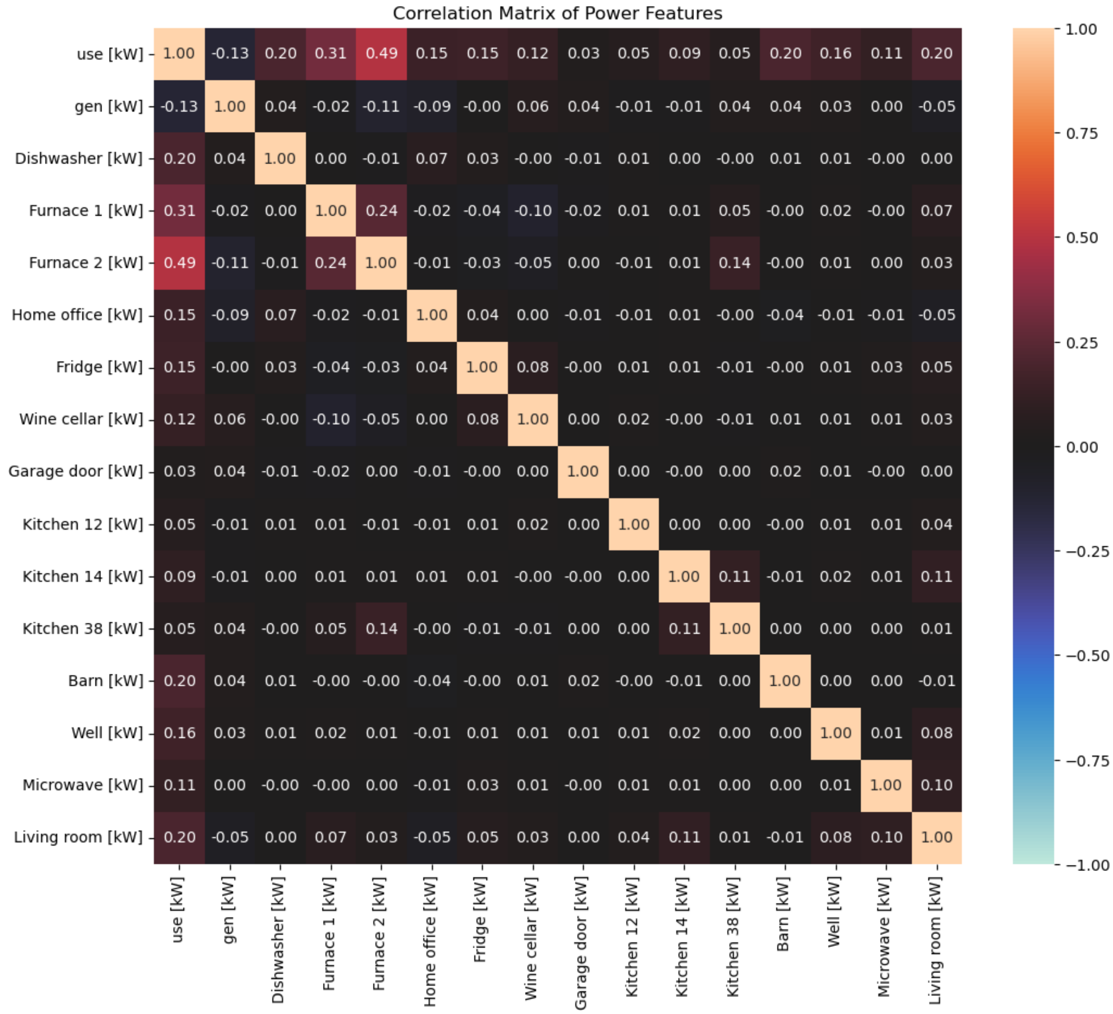
```
    'Furnace 1 [kW]',
    'Furnace 2 [kW]',
    'Home office [kW]',
    'Fridge [kW]',
    'Wine cellar [kW]',
    'Garage door [kW]',
    'Kitchen 12 [kW]',
    'Kitchen 14 [kW]',
    'Kitchen 38 [kW]',
    'Barn [kW]',
    'Well [kW]',
    'Microwave [kW]',
    'Living room [kW]',
    # 'Solar [kW]'
]

# Weather-related columns
weather_array = [
    'temperature',
    # 'icon',
    'icon_encoded',
    'humidity',
    'visibility',
    # 'summary',
    'summary_encoded',
    'apparentTemperature',
    'pressure',
    'windSpeed',
    'cloudCover',
    'windBearing',
    'precipIntensity',
    'dewPoint',
    'precipProbability'
]

# all columns
all_columns = power_array + weather_array
```

3.1 View the correlations

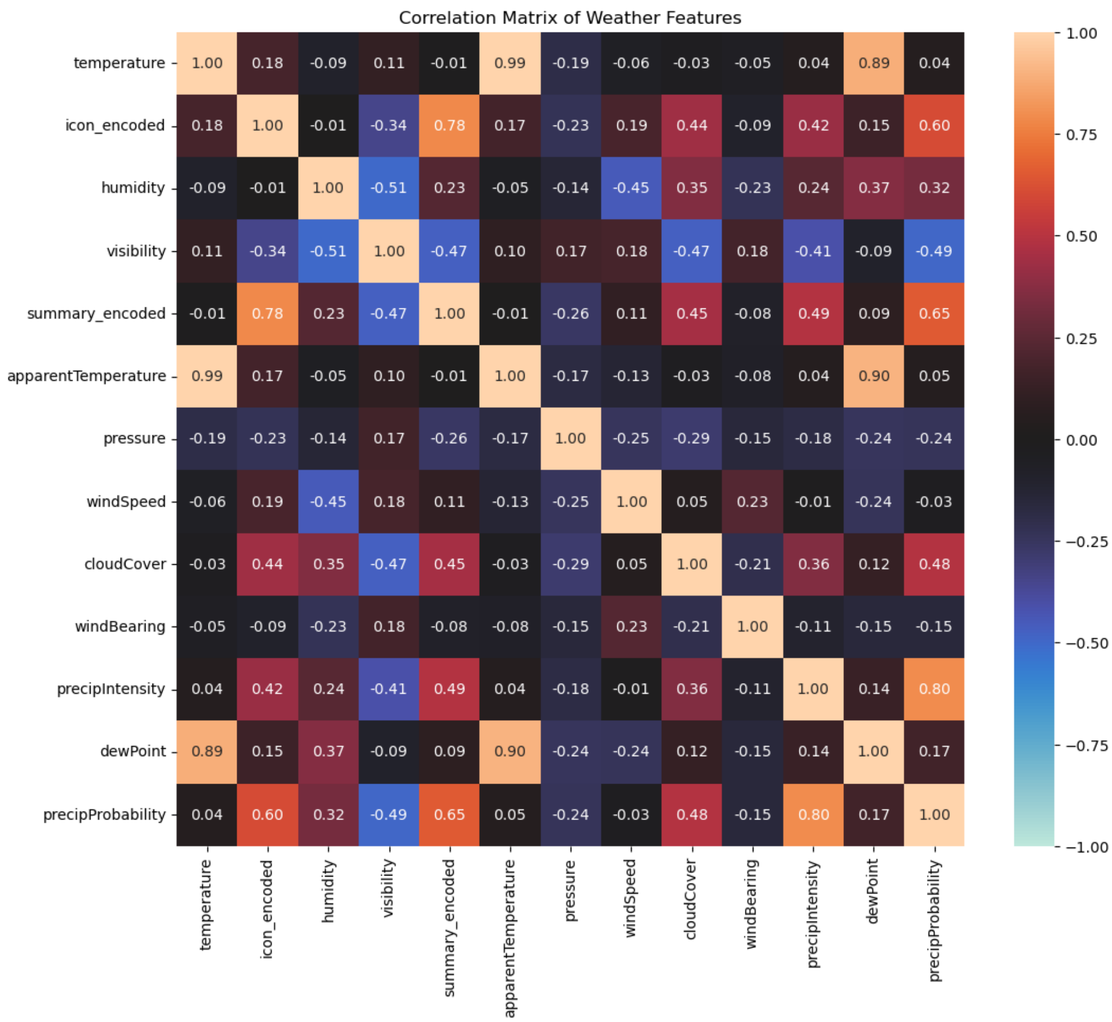
[ ]:
```
plt.figure(figsize=(12,10))
sns.heatmap(df.corr(), annot=True, fmt='.2f', vmin=-1.0, vmax=1.0, center=0)
plt.title('Correlation Matrix')
plt.show()
```




```
[ ]: # Show correlation of just the power features
plt.figure(figsize=(12,10))
sns.heatmap(df[power_array].corr(), annot=True, fmt='.2f', vmin=-1.0, vmax=1.0,
    center=0)
plt.title('Correlation Matrix of Power Features')
plt.show()
```

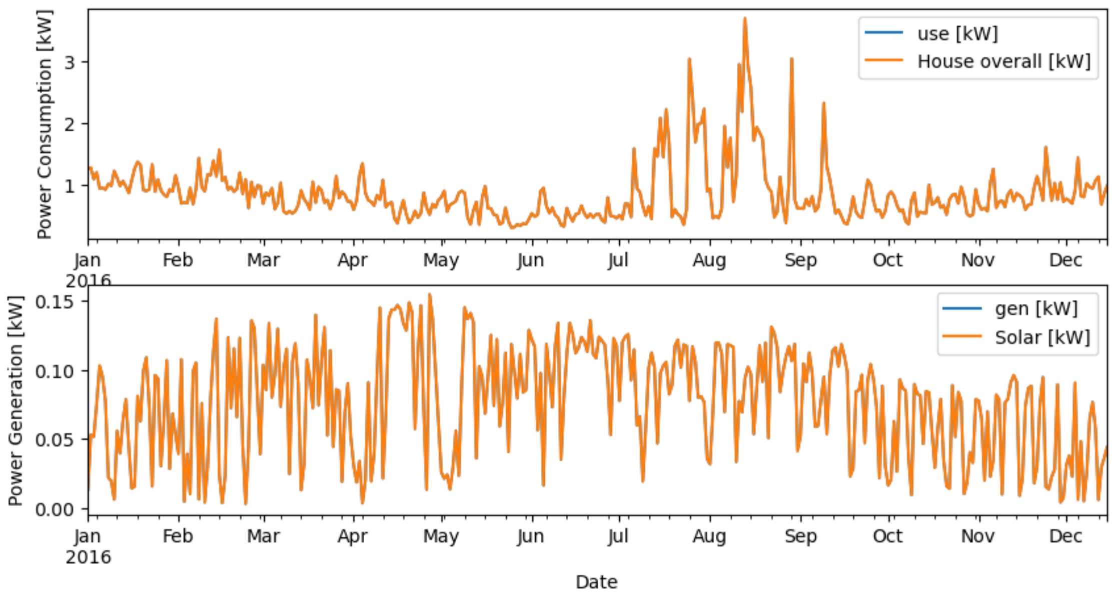


[ ]:
```
# Show correlation of just weather features
plt.figure(figsize=(12,10))
sns.heatmap(df[weather_array].corr(), annot=True, fmt='.2f', vmin=-1.0, vmax=1.
↪0, center=0)
plt.title('Correlation Matrix of Weather Features')
plt.show()
```



3.2 Check to see if use/House overall and gen/solar are identical

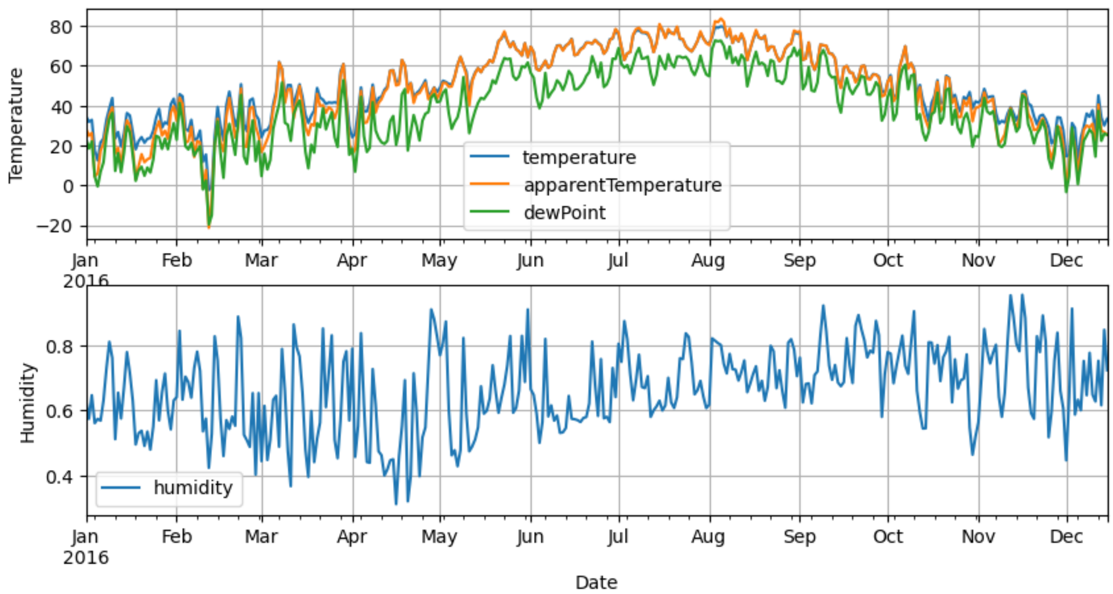
```
[ ]: #They are indeed the same df (overlaping perfectly)
     fig, axes = plt.subplots(2,1, figsize=(10,5))
     df[['use [kW]','House overall [kW]']].resample('D').mean().plot(ax=axes[0])
     axes[0].set_xlabel('Date')
     axes[0].set_ylabel('Power Consumption [kW]')
     df[['gen [kW]','Solar [kW]']].resample('D').mean().plot(ax=axes[1])
     axes[1].set_xlabel('Date')
     axes[1].set_ylabel('Power Generation [kW]')

     # drop duplicate columns
     df = df.drop(columns='House overall [kW]')
     df = df.drop(columns='Solar [kW]')
```



3.3 Visualize the weather correlations

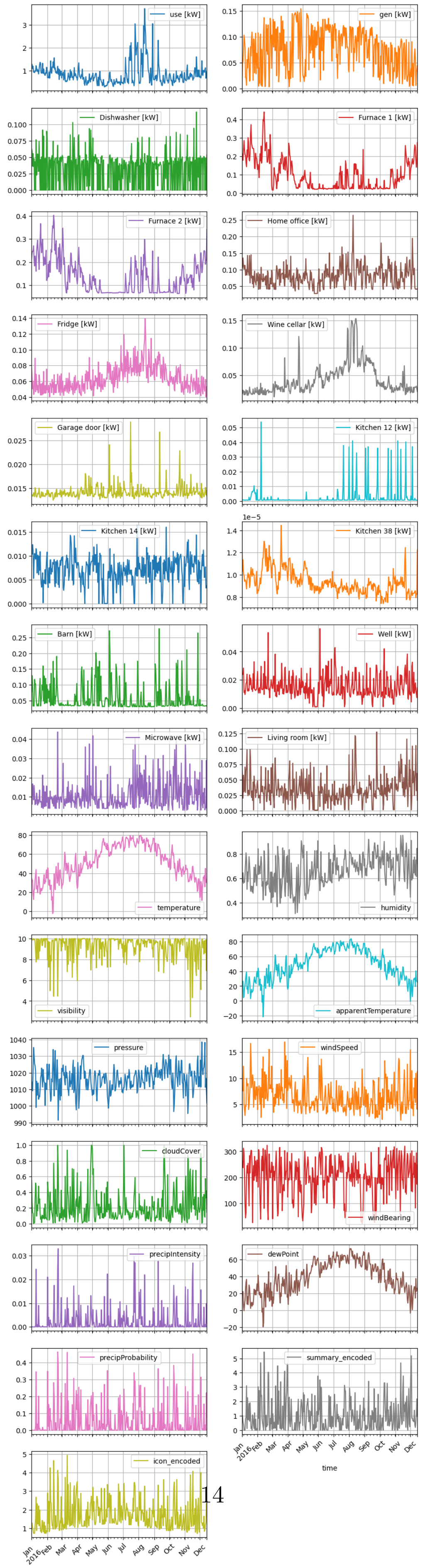
[ ]:
```
fig, axes = plt.subplots(2,1, figsize=(10,5))
df[['temperature','apparentTemperature', 'dewPoint']].resample('D').mean().
 ↪plot(ax=axes[0], grid=True)
axes[0].set_xlabel('Date')
axes[0].set_ylabel('Temperature')
df[['humidity']].resample('D').mean().plot(ax=axes[1], grid=True)
axes[1].set_xlabel('Date')
axes[1].set_ylabel('Humidity')
```

[ ]:
```
Text(0, 0.5, 'Humidity')
```

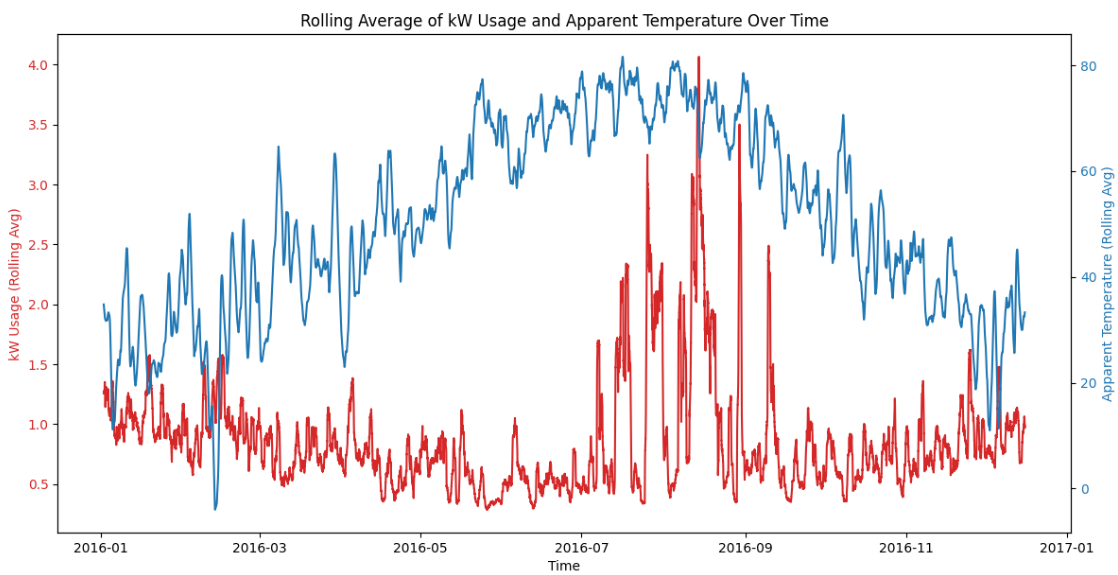


3.4 Visualizations

[ ]:
```
df.resample("D").mean().plot(subplots=True, layout=(-1, 2), figsize=(10, 40),
    grid=True, rot=45);
```

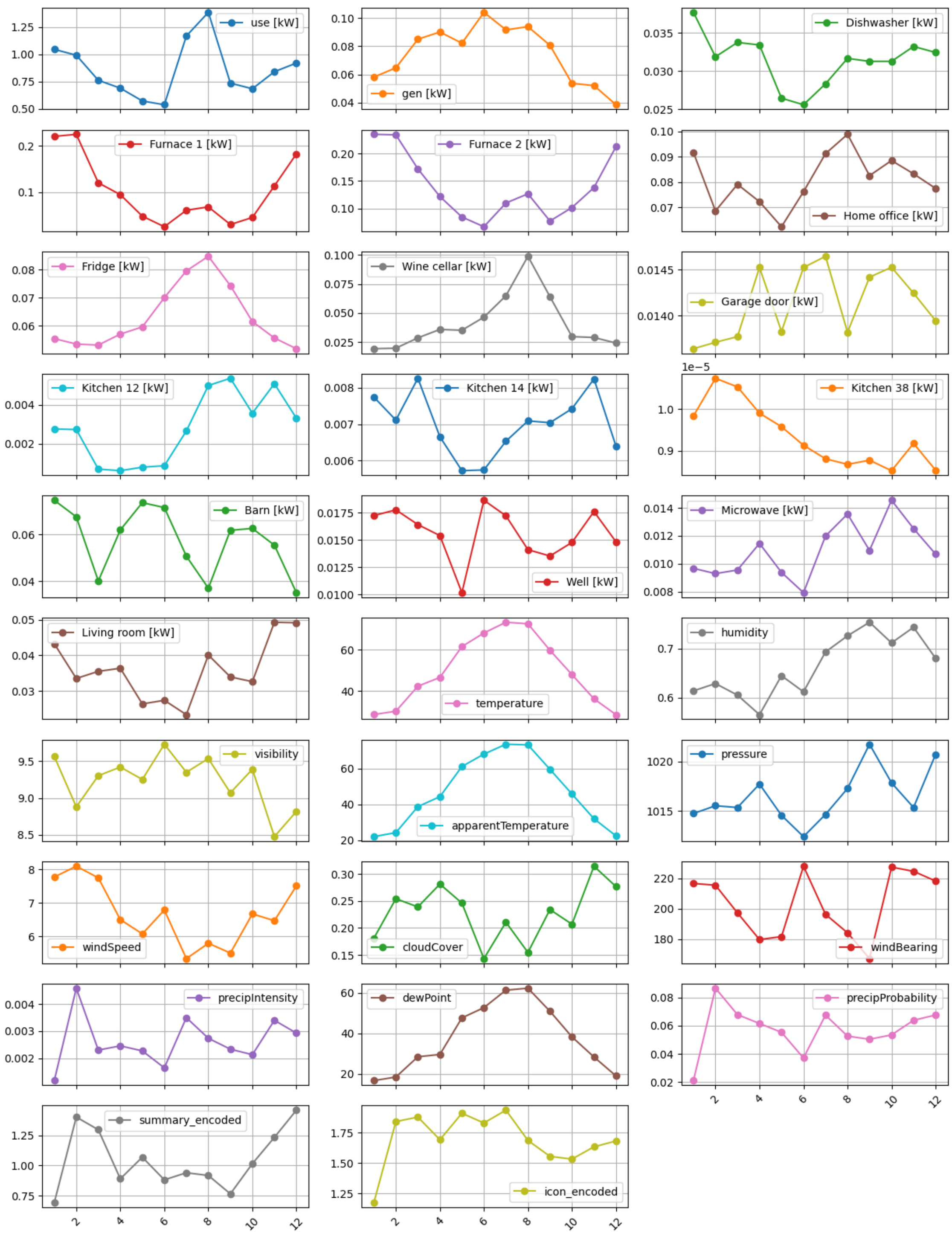

use [kW]
gen [kW]
Dishwasher [kW]
Furnace 1 [kW]
Furnace 2 [kW]
Home office [kW]
Fridge [kW]
Wine cellar [kW]
Garage door [kW]
Kitchen 12 [kW]
Kitchen 14 [kW]
Kitchen 38 [kW]
1e−5
Barn [kW]
Well [kW]
Microwave [kW]
Living room [kW]
temperature
humidity
visibility
apparentTemperature
pressure
windSpeed
cloudCover
windBearing
precipIntensity
dewPoint
precipProbability
summary_encoded
icon_encoded
Jan 2016
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
time

[ ]:
```
window_size = 60*24

# Calculate rolling averages
df['use [kW]_rolling_avg'] = df['use [kW]'].rolling(window=window_size).mean()
df['temperature_rolling_avg'] = df['temperature'].rolling(window=window_size).
    ↪mean()

fig, ax1 = plt.subplots(figsize=(12, 6))

color = 'tab:red'
ax1.set_xlabel('Time')
ax1.set_ylabel('kW Usage (Rolling Avg)', color=color)
ax1.plot(df.index, df['use [kW]_rolling_avg'], color=color)
ax1.tick_params(axis='y', labelcolor=color)

ax2 = ax1.twinx()
color = 'tab:blue'
ax2.set_ylabel('Apparent Temperature (Rolling Avg)', color=color)
ax2.plot(df.index, df['temperature_rolling_avg'], color=color)
ax2.tick_params(axis='y', labelcolor=color)

fig.tight_layout()
plt.title('Rolling Average of kW Usage and Apparent Temperature Over Time')
plt.show()
```



```
[ ]: df['month'] = df.index.month
     df['day'] = df.index.day
     df['weekday'] = df.index.day_name()
     df['hour'] = df.index.hour
     df['minute'] = df.index.minute

     ##Averge consuption per month
     mean_month = df.groupby('month').agg({col: 'mean' for col in df.columns if col␣
      ↪in all_columns})
     num_columns = len(mean_month.columns)
     num_rows = -1
     columns_per_row = 3
     mean_month.plot(subplots=True, layout=(num_rows, columns_per_row), figsize=(15,␣
      ↪20),
                     grid=True, rot=45, xlabel='', marker='o')
```

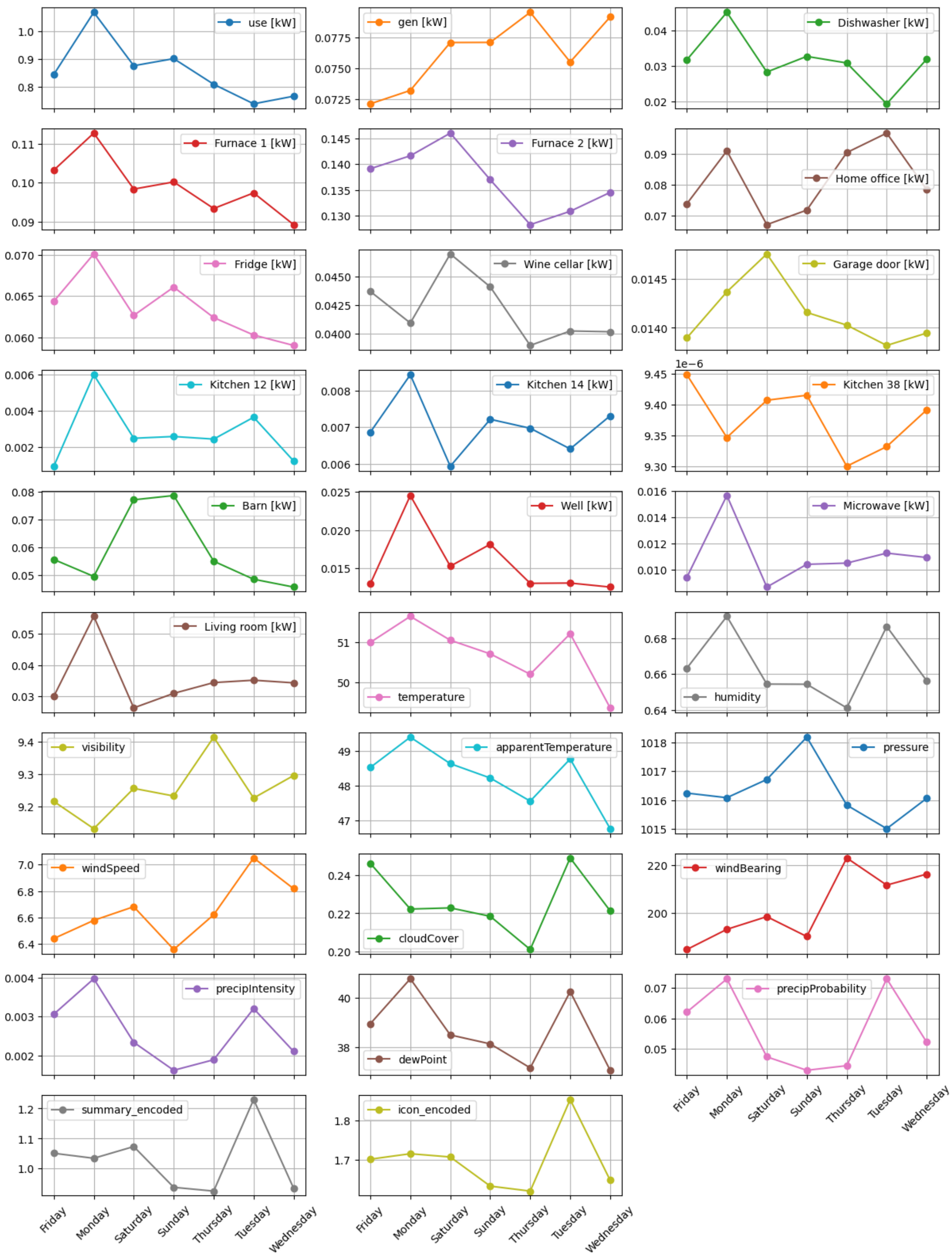
```
[ ]: array([[<Axes: >, <Axes: >, <Axes: >],
            [<Axes: >, <Axes: >, <Axes: >],
            [<Axes: >, <Axes: >, <Axes: >],
            [<Axes: >, <Axes: >, <Axes: >],
            [<Axes: >, <Axes: >, <Axes: >],
            [<Axes: >, <Axes: >, <Axes: >],
            [<Axes: >, <Axes: >, <Axes: >],
            [<Axes: >, <Axes: >, <Axes: >],
            [<Axes: >, <Axes: >, <Axes: >],
            [<Axes: >, <Axes: >, <Axes: >]], dtype=object)
```



[ ]:
```
#Averge consuption per day of the week
days = [ 'Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday',␣
↪'Sunday']
```

```
mean_weekday = df.groupby('weekday').agg({col: 'mean' for col in df.columns if␣
↪col in all_columns})
num_columns = len(mean_weekday.columns)
num_rows = -1
columns_per_row = 3
mean_weekday.plot(subplots=True, layout=(num_rows, columns_per_row),␣
↪figsize=(15, 20),
                grid=True, rot=45, xlabel='', marker='o')
```

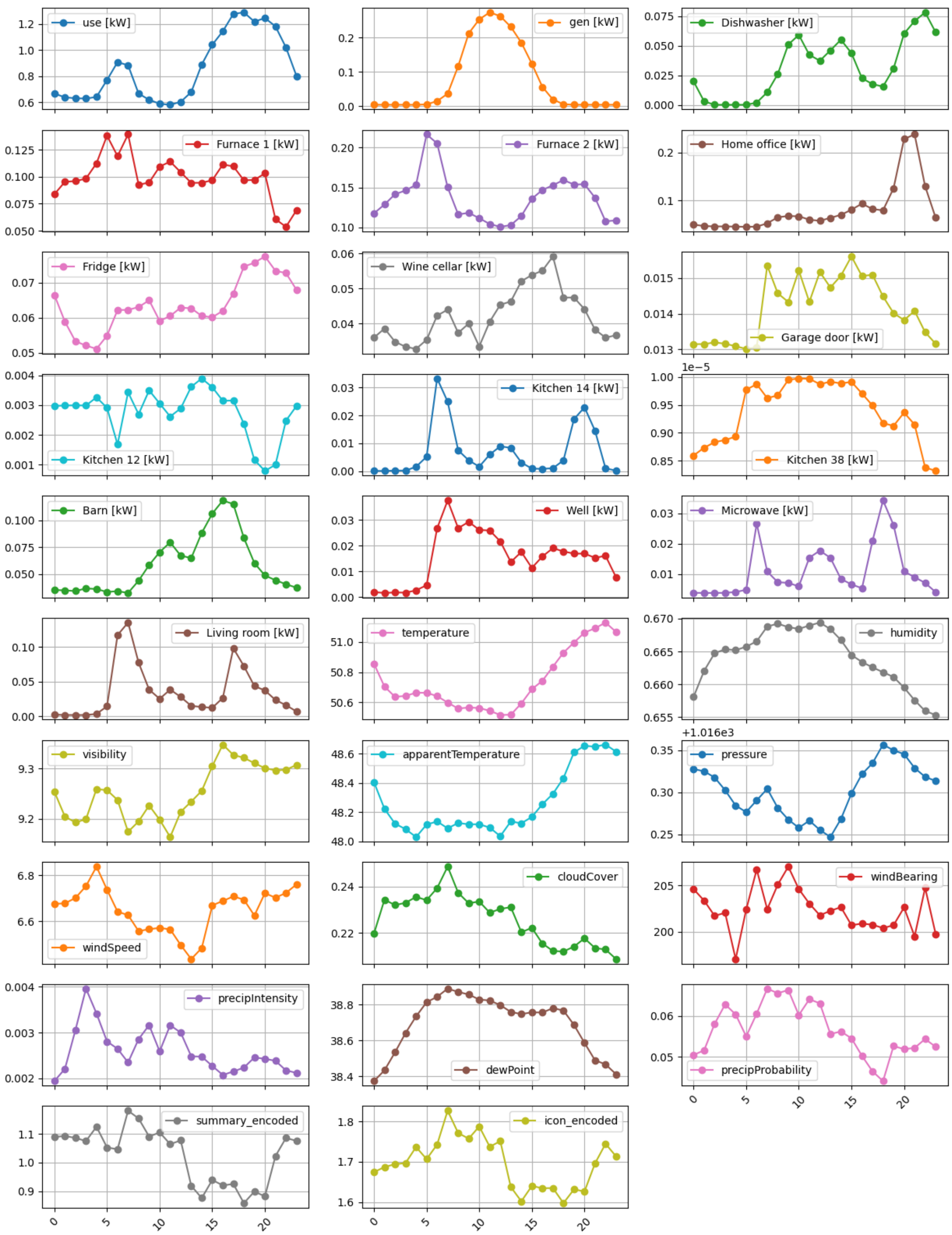
[ ]:
```
array([[<Axes: >, <Axes: >, <Axes: >],
       [<Axes: >, <Axes: >, <Axes: >],
       [<Axes: >, <Axes: >, <Axes: >],
       [<Axes: >, <Axes: >, <Axes: >],
       [<Axes: >, <Axes: >, <Axes: >],
       [<Axes: >, <Axes: >, <Axes: >],
       [<Axes: >, <Axes: >, <Axes: >],
       [<Axes: >, <Axes: >, <Axes: >],
       [<Axes: >, <Axes: >, <Axes: >],
       [<Axes: >, <Axes: >, <Axes: >]], dtype=object)
```




```
[ ]: #Averge consuption per hour
     mean_hour = df.groupby('hour').agg({col: 'mean' for col in df.columns if col in
      ↪all_columns})
```

```
num_columns = len(mean_hour.columns)
num_rows = -1
columns_per_row = 3
mean_hour.plot(subplots=True, layout=(num_rows, columns_per_row), figsize=(15,␣
↪20),
                grid=True, rot=45, xlabel='', marker='o')
```

```
[ ]: array([[<Axes: >, <Axes: >, <Axes: >],
            [<Axes: >, <Axes: >, <Axes: >],
            [<Axes: >, <Axes: >, <Axes: >],
            [<Axes: >, <Axes: >, <Axes: >],
            [<Axes: >, <Axes: >, <Axes: >],
            [<Axes: >, <Axes: >, <Axes: >],
            [<Axes: >, <Axes: >, <Axes: >],
            [<Axes: >, <Axes: >, <Axes: >],
            [<Axes: >, <Axes: >, <Axes: >],
            [<Axes: >, <Axes: >, <Axes: >]], dtype=object)
```



4 Model Training

- Build the LSTM for Power usage

- Build the Linear Regression for Temperature

Initially, the first month of data was used for fast iteration training. After a baseline model was developed we trained on all of the data. Training took a long time so a stop early feature was added to save time once a good model had been trained.

[ ]:
```
### Constants
MINUTES_AHEAD_TO_PREDICT = 10
```

[ ]:
```
## Drop the columns created for EDA usage
df = df.drop(columns=['use [kW]_rolling_avg', 'temperature_rolling_avg',␣
↪'month', 'day', 'weekday', 'hour', 'minute'])
```

[ ]:
```
df['hour_of_day'] = df.index.hour
```

[ ]:
```
# Filter the df down to just the first week from every month
# df = df[df.index.day <= 7]

# Filter to just january
# df = df[df.index.month == 1]
```

4.0.1 LSTM Model for Predicting Energy Consumption ('use [kW]')

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

[ ]:
```
                     use [kW]  gen [kW]  Dishwasher [kW]  Furnace 1 [kW]  \
time
2016-01-01 00:00:00  0.932833  0.003483         0.000033        0.020700
2016-01-01 00:01:00  0.934333  0.003467         0.000000        0.020717
2016-01-01 00:02:00  0.931817  0.003467         0.000017        0.020700
2016-01-01 00:03:00  1.022050  0.003483         0.000017        0.106900
2016-01-01 00:04:00  1.139400  0.003467         0.000133        0.236933

                     Furnace 2 [kW]  Home office [kW]  Fridge [kW]  \
time
2016-01-01 00:00:00        0.061917          0.442633     0.124150
2016-01-01 00:01:00        0.063817          0.444067     0.124000
2016-01-01 00:02:00        0.062317          0.446067     0.123533
2016-01-01 00:03:00        0.068517          0.446583     0.123133
2016-01-01 00:04:00        0.063983          0.446533     0.122850

                     Wine cellar [kW]  Garage door [kW]  Kitchen 12 [kW]  …  \
time                                                                      …
2016-01-01 00:00:00          0.006983          0.013083         0.000417  …
2016-01-01 00:01:00          0.006983          0.013117         0.000417  …
2016-01-01 00:02:00          0.006983          0.013083         0.000433  …
2016-01-01 00:03:00          0.006983          0.013000         0.000433  …
2016-01-01 00:04:00          0.006850          0.012783         0.000450  …
```

```
                     pressure  windSpeed  cloudCover  windBearing  \
time
2016-01-01 00:00:00   1016.91       9.18    0.225885        282.0
2016-01-01 00:01:00   1016.91       9.18    0.225885        282.0
2016-01-01 00:02:00   1016.91       9.18    0.225885        282.0
2016-01-01 00:03:00   1016.91       9.18    0.225885        282.0
2016-01-01 00:04:00   1016.91       9.18    0.225885        282.0

                     precipIntensity  dewPoint  precipProbability  \
time
2016-01-01 00:00:00              0.0      24.4                0.0
2016-01-01 00:01:00              0.0      24.4                0.0
2016-01-01 00:02:00              0.0      24.4                0.0
2016-01-01 00:03:00              0.0      24.4                0.0
2016-01-01 00:04:00              0.0      24.4                0.0

                     summary_encoded  icon_encoded  hour_of_day
time
2016-01-01 00:00:00                0             0            0
2016-01-01 00:01:00                0             0            0
2016-01-01 00:02:00                0             0            0
2016-01-01 00:03:00                0             0            0
2016-01-01 00:04:00                0             0            0

[5 rows x 30 columns]
```

[ ]:
```
# check df for null values
df.isnull().sum()
```

[ ]:
```
use [kW]              0
gen [kW]              0
Dishwasher [kW]       0
Furnace 1 [kW]        0
Furnace 2 [kW]        0
Home office [kW]      0
Fridge [kW]           0
Wine cellar [kW]      0
Garage door [kW]      0
Kitchen 12 [kW]       0
Kitchen 14 [kW]       0
Kitchen 38 [kW]       0
Barn [kW]             0
Well [kW]             0
Microwave [kW]        0
Living room [kW]      0
temperature           0
```

```
humidity               0
visibility             0
apparentTemperature    0
pressure               0
windSpeed              0
cloudCover             0
windBearing            0
precipIntensity        0
dewPoint               0
precipProbability      0
summary_encoded        0
icon_encoded           0
hour_of_day            0
dtype: int64
```

[ ]:
```
correlation_matrix = df.corr()
target_correlation = correlation_matrix['use [kW]']

# Filter based on the threshold
# We use .abs() to handle both positive and negative correlations
filtered_features = target_correlation[(target_correlation >= 0.3) |␣
↪(target_correlation <= -0.3)]

# If you want to exclude the target variable itself from the list, assuming␣
↪it's included
# filtered_features = filtered_features.drop('use [kW]', errors='ignore')

# Get the list of feature names
feature_list = filtered_features.index.tolist()
feature_list
```

[ ]:
```
['use [kW]', 'Furnace 1 [kW]', 'Furnace 2 [kW]']
```

[ ]:
```
feature_columns = feature_list

# Select features and target
features = df[feature_columns]
target = df['use [kW]']

# Scale features
scaler_features = MinMaxScaler(feature_range=(0, 1))
scaled_features = scaler_features.fit_transform(features)

scaler_target = MinMaxScaler(feature_range=(0, 1))
scaled_target = scaler_target.fit_transform(target.values.reshape(-1, 1))
```

[ ]:
```
def create_sequences(input_data, output_data, sequence_length, time_ahead):
    X, y = [], []
    for i in range(len(input_data) - sequence_length - time_ahead):
        X.append(input_data[i:(i + sequence_length)])
        y.append(output_data[i + sequence_length + time_ahead])
    return np.array(X), np.array(y)

sequence_length = 10  # 10 minutes
time_ahead = MINUTES_AHEAD_TO_PREDICT  # Predict the next minute
X, y = create_sequences(scaled_features, scaled_target, sequence_length,␣
 ↪time_ahead)

split_index = int(len(X) * 0.8)
X_train = X[:split_index]
X_test = X[split_index:]
y_train = y[:split_index]
y_test = y[split_index:]

# print the shape of the training and testing data
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(403112, 10, 3) (100778, 10, 3) (403112, 1) (100778, 1)
```

[ ]:
```
# Example check for NaNs or infinite values in your dataset
print(np.any(np.isnan(X)), np.any(np.isnan(y)))  # Check for NaN values
print(np.any(np.isinf(X)), np.any(np.isinf(y)))  # Check for infinite values
```

```
False False
False False
```

4.1 LSTM

[ ]:
```
lstm_model = Sequential()
lstm_model.add(LSTM(50, activation='relu', input_shape=(sequence_length, X.
 ↪shape[2])))
# lstm_model.add(Dense(1))
lstm_model.add(Dense(1, kernel_initializer='glorot_uniform'))
lstm_model.compile(optimizer='adam', loss='mean_squared_error')

early_stopping = EarlyStopping(
    monitor='val_loss',  # Monitor the validation loss
    patience=5,          # Number of epochs with no improvement after which␣
 ↪training will be stopped
    verbose=1,
    restore_best_weights=True  # Restore model weights from the epoch with the␣
 ↪best value of the monitored metric
)
```

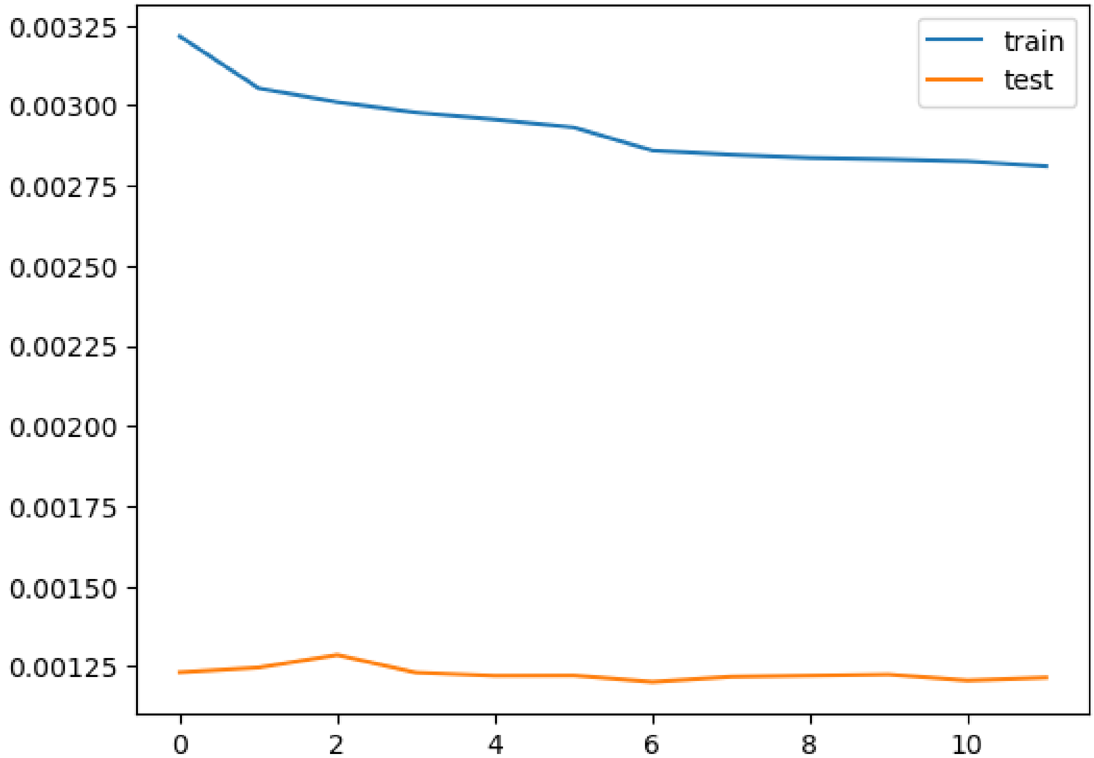
```
reduce_lr = ReduceLROnPlateau(
    monitor='val_loss',  # Monitor the validation loss
    factor=0.2,          # Factor by which the learning rate will be reduced.␣
 ↪new_lr = lr * factor
    patience=5,          # Number of epochs with no improvement after which␣
 ↪learning rate will be reduced
    verbose=1,
    min_delta=0.001,     # Threshold for measuring the new optimum, to only␣
 ↪focus on significant changes
    cooldown=0,          # Number of epochs to wait before resuming normal␣
 ↪operation after lr has been reduced
    min_lr=0.0001        # Lower bound on the learning rate
)


history = lstm_model.fit(
    X, y,
    epochs=100,  # Set a higher number of epochs; EarlyStopping will halt␣
 ↪training when necessary
    batch_size=32,
    validation_split=0.1,
    verbose=2,
    callbacks=[early_stopping, reduce_lr]  # Include the callbacks here
)

# save the model
lstm_model.save('./model.h5')
```

```
WARNING:tensorflow:Layer lstm will not use cuDNN kernels since it doesn't meet
the criteria. It will use a generic GPU kernel as fallback when running on GPU.
Epoch 1/100
14172/14172 - 251s - loss: 0.0032 - val_loss: 0.0012 - lr: 0.0010 - 251s/epoch -
18ms/step
Epoch 2/100
14172/14172 - 257s - loss: 0.0031 - val_loss: 0.0012 - lr: 0.0010 - 257s/epoch -
18ms/step
Epoch 3/100
14172/14172 - 258s - loss: 0.0030 - val_loss: 0.0013 - lr: 0.0010 - 258s/epoch -
18ms/step
Epoch 4/100
14172/14172 - 255s - loss: 0.0030 - val_loss: 0.0012 - lr: 0.0010 - 255s/epoch -
18ms/step
Epoch 5/100
14172/14172 - 249s - loss: 0.0030 - val_loss: 0.0012 - lr: 0.0010 - 249s/epoch -
18ms/step
Epoch 6/100
```

```
Epoch 6: ReduceLROnPlateau reducing learning rate to 0.00020000000949949026.
14172/14172 - 256s - loss: 0.0029 - val_loss: 0.0012 - lr: 0.0010 - 256s/epoch -
18ms/step
Epoch 7/100
14172/14172 - 252s - loss: 0.0029 - val_loss: 0.0012 - lr: 2.0000e-04 -
252s/epoch - 18ms/step
Epoch 8/100
14172/14172 - 251s - loss: 0.0028 - val_loss: 0.0012 - lr: 2.0000e-04 -
251s/epoch - 18ms/step
Epoch 9/100
14172/14172 - 252s - loss: 0.0028 - val_loss: 0.0012 - lr: 2.0000e-04 -
252s/epoch - 18ms/step
Epoch 10/100
14172/14172 - 250s - loss: 0.0028 - val_loss: 0.0012 - lr: 2.0000e-04 -
250s/epoch - 18ms/step
Epoch 11/100

Epoch 11: ReduceLROnPlateau reducing learning rate to 0.0001.
14172/14172 - 255s - loss: 0.0028 - val_loss: 0.0012 - lr: 2.0000e-04 -
255s/epoch - 18ms/step
Epoch 12/100
Restoring model weights from the end of the best epoch: 7.
14172/14172 - 256s - loss: 0.0028 - val_loss: 0.0012 - lr: 1.0000e-04 -
256s/epoch - 18ms/step
Epoch 12: early stopping
```

[ ]:

```
# plot loss
plt.plot(history.history['loss'], label='train')
plt.plot(history.history['val_loss'], label='test')
plt.legend()
plt.show()
```

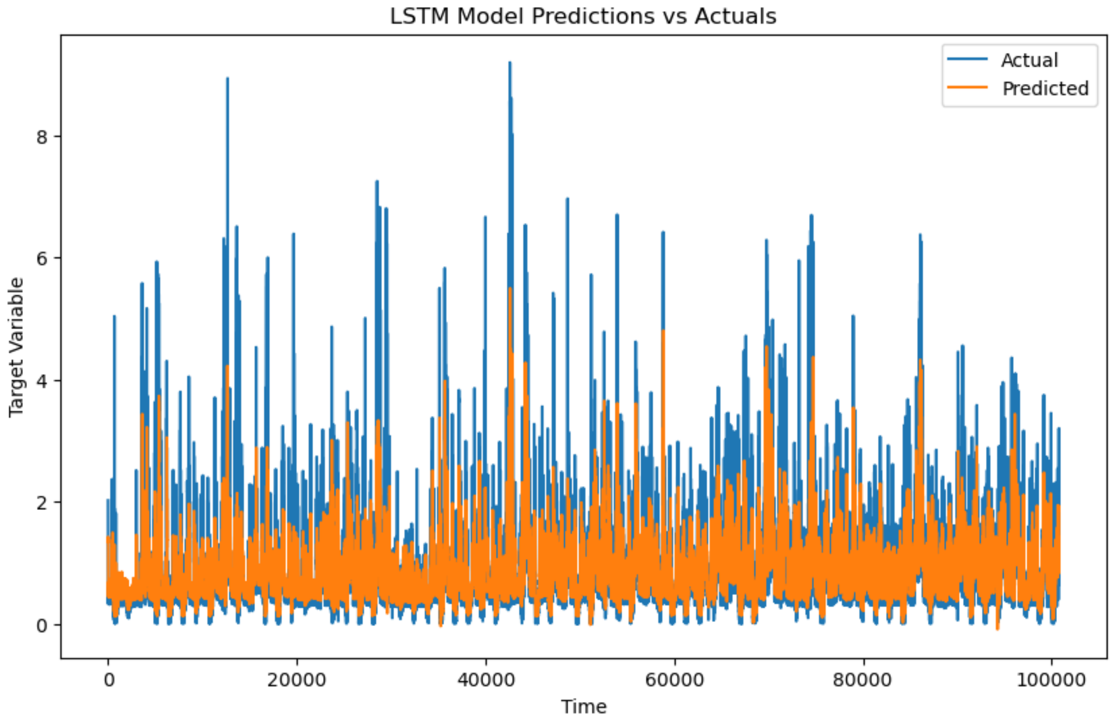


[ ]:
```
test_predictions = lstm_model.predict(X_test)
test_predictions_rescaled = scaler_target.inverse_transform(test_predictions)
test_y_rescaled = scaler_target.inverse_transform(y_test.reshape(-1, 1))

mse = mean_squared_error(test_y_rescaled, test_predictions_rescaled)
rmse = sqrt(mse)
mae = mean_absolute_error(test_y_rescaled, test_predictions_rescaled)

print(f"MSE: {mse}")
print(f"RMSE: {rmse}")
print(f"MAE: {mae}")
```

```
3150/3150 [==============================] - 17s 5ms/step
MSE: 0.2506907470532965
RMSE: 0.5006902705798232
MAE: 0.31568480847868097
```

[ ]:
```
plt.figure(figsize=(10, 6))
plt.plot(test_y_rescaled, label='Actual')
plt.plot(test_predictions_rescaled, label='Predicted')
plt.title('LSTM Model Predictions vs Actuals')
plt.xlabel('Time')
```

```
plt.ylabel('Target Variable')
plt.legend()
plt.show()
```



4.1.1 Linear Regression Model for Forecasting Temperature

[ ]:
```
# Calculate the correlation matrix
corr_matrix = df[weather_array].corr()

# Focus on correlations with temperature
temp_corr = corr_matrix['temperature']

# Filter features based on correlation threshold
highly_correlated_features = temp_corr[(temp_corr.abs() >= 0.3) & (temp_corr.
 ↪index != 'temperature') & (temp_corr.index != 'apparentTemperature')].index.
 ↪tolist()

print("Features highly correlated with temperature:",␣
 ↪highly_correlated_features)
```

```
Features highly correlated with temperature: ['dewPoint']
```

[ ]:
```python
# include temperature in the list of features since we are attempting to
↪predict future temperature
highly_correlated_features.append('temperature')

df['temperature_next'] = df['temperature'].shift(-MINUTES_AHEAD_TO_PREDICT)
df = df[:-MINUTES_AHEAD_TO_PREDICT]  # Remove the last row as it now has NaN
↪for 'temperature_next'

X = df[highly_correlated_features]
y = df['temperature_next']

# Split the data into training and testing sets
# split based on the first 80% of the data

split_index = int(len(X) * 0.8)
X_train = X[:split_index]
X_test = X[split_index:]
y_train = y[:split_index]
y_test = y[split_index:]
```

[ ]:
```python
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)

predictions = lr_model.predict(X_test)
mse = mean_squared_error(y_test, predictions)
rmse = np.sqrt(mse)

print(f"Test MSE: {mse}")
print(f"Test RMSE: {rmse}")

# store model
joblib.dump(lr_model, 'temperature_model.pkl')
```

```
Test MSE: 0.5496897499889629
Test RMSE: 0.7414106486886757
```

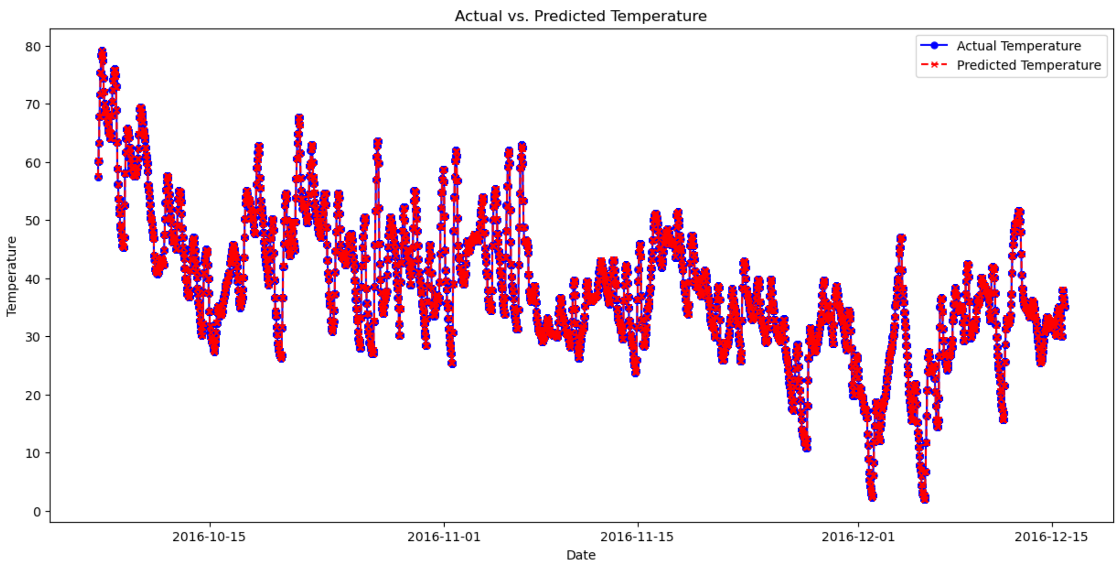
[ ]: ['temperature_model.pkl']

[ ]:
```python
feature_importance = pd.Series(lr_model.coef_, index=highly_correlated_features)
print("Feature Importance:\n", feature_importance)
```

```
Feature Importance:
 dewPoint       0.004216
temperature    0.995174
dtype: float64
```

[ ]:
```python
comparison_df = pd.DataFrame({'Actual': y_test, 'Predicted': predictions},
↪index=y_test.index)
```

```
plt.figure(figsize=(15, 7))
plt.plot(comparison_df.index, comparison_df['Actual'], label='Actual␣
↪Temperature', color='blue', marker='o', linestyle='-', markersize=5)
plt.plot(comparison_df.index, comparison_df['Predicted'], label='Predicted␣
↪Temperature', color='red', marker='x', linestyle='--', markersize=5)

plt.title('Actual vs. Predicted Temperature')
plt.xlabel('Date')
plt.ylabel('Temperature')
plt.legend()

plt.show()
```



5 Dataset creation for Dashboard

- Save all of the predicted values to be used in our dashboard

```
[ ]: # Rename temperature_next to temperature_next_MINUTES_AHEAD_TO_PREDICT_minutes
df.rename(columns={'temperature_next':␣
↪f'temperature_next_{MINUTES_AHEAD_TO_PREDICT}_minutes'}, inplace=True)

# create a column for the predicted use [kW] from the LSTM model
df[f'use_[kW]_next_{MINUTES_AHEAD_TO_PREDICT}_minutes'] = df['use [kW]'].
↪shift(-MINUTES_AHEAD_TO_PREDICT)
```

```
[ ]: # filter df to only the test data
     df = df[split_index:]
```

```
[ ]: # find the smallest length of df, test_predictions_rescaled, and predictions
     min_length = min(len(df), len(test_predictions_rescaled), len(predictions))
     print(f"Smallest length: {min_length}")
     # trim all down to smallest length
     df = df[:min_length]
     test_predictions_rescaled = test_predictions_rescaled[:min_length]
     predictions = predictions[:min_length]
```

```
Smallest length: 100778
```

```
[ ]: # add the lstm predictions to the df
     # drop the last row of the test_predictions_rescaled
     df[f'lstm_prediction_use_kw_next_{MINUTES_AHEAD_TO_PREDICT}_minutes'] =␣
      ↪test_predictions_rescaled

     # add the linear regression predictions to the df
     df[f'linear_regression_prediction_temperature_next_{MINUTES_AHEAD_TO_PREDICT}_minutes']␣
      ↪= predictions
```

```
[ ]: # write out df to a csv
     df.to_csv('./predictions.csv')
```

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

```
[ ]:                      use [kW]  gen [kW]  Dishwasher [kW]  Furnace 1 [kW]  \
     time
     2016-10-06 22:40:00  0.887600  0.004933         0.046300        0.020433
     2016-10-06 22:41:00  1.914867  0.004917         1.019900        0.018583
     2016-10-06 22:42:00  2.283350  0.004900         1.355867        0.017933
     2016-10-06 22:43:00  2.265800  0.004900         1.352700        0.017883
     2016-10-06 22:44:00  2.218167  0.004817         1.343200        0.017750

                          Furnace 2 [kW]  Home office [kW]  Fridge [kW]  \
     time
     2016-10-06 22:40:00        0.063267          0.070900     0.005083
     2016-10-06 22:41:00        0.069350          0.065533     0.004400
     2016-10-06 22:42:00        0.070567          0.063767     0.004183
     2016-10-06 22:43:00        0.070267          0.063933     0.004183
     2016-10-06 22:44:00        0.070283          0.063500     0.004200

                          Wine cellar [kW]  Garage door [kW]  Kitchen 12 [kW]  …  \
     time                                                                      …
     2016-10-06 22:40:00          0.129250          0.012917         0.000833  …
     2016-10-06 22:41:00          0.127983          0.011833         0.000950  …
     2016-10-06 22:42:00          0.127517          0.011467         0.001017  …
```

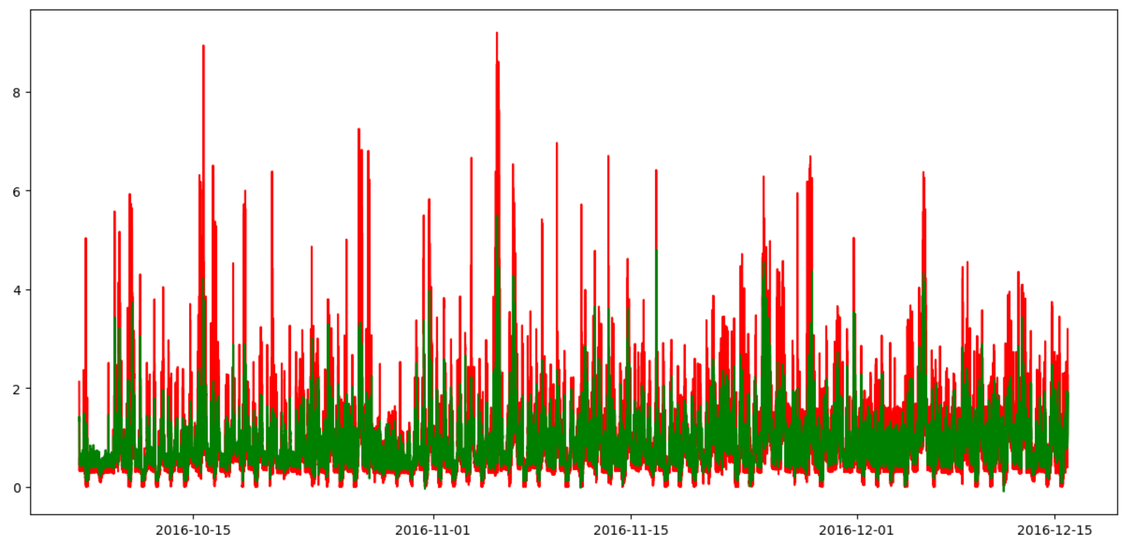
```
2016-10-06 22:43:00         0.127267         0.011450         0.001067  …
2016-10-06 22:44:00         0.127217         0.011367         0.001050  …

                     precipIntensity  dewPoint  precipProbability  \
time
2016-10-06 22:40:00              0.0     56.53                0.0
2016-10-06 22:41:00              0.0     56.53                0.0
2016-10-06 22:42:00              0.0     56.53                0.0
2016-10-06 22:43:00              0.0     56.53                0.0
2016-10-06 22:44:00              0.0     56.53                0.0

                     summary_encoded  icon_encoded  hour_of_day  \
time
2016-10-06 22:40:00                0             2           22
2016-10-06 22:41:00                0             2           22
2016-10-06 22:42:00                0             2           22
2016-10-06 22:43:00                0             2           22
2016-10-06 22:44:00                0             2           22

                     temperature_next_10_minutes  use_[kW]_next_10_minutes  \
time
2016-10-06 22:40:00                        57.49                  2.131200
2016-10-06 22:41:00                        57.49                  2.129683
2016-10-06 22:42:00                        57.49                  2.019767
2016-10-06 22:43:00                        57.49                  1.839867
2016-10-06 22:44:00                        57.49                  1.848200

                     lstm_prediction_use_kw_next_10_minutes  \
time
2016-10-06 22:40:00                                1.340331
2016-10-06 22:41:00                                1.411025
2016-10-06 22:42:00                                1.422542
2016-10-06 22:43:00                                1.409162
2016-10-06 22:44:00                                1.394071

                     linear_regression_prediction_temperature_next_10_minutes
time
2016-10-06 22:40:00                                          57.538057
2016-10-06 22:41:00                                          57.538057
2016-10-06 22:42:00                                          57.538057
2016-10-06 22:43:00                                          57.538057
2016-10-06 22:44:00                                          57.538057

[5 rows x 34 columns]
```

[ ]:
```
df.columns
```

[ ]: Index(['use [kW]', 'gen [kW]', 'Dishwasher [kW]', 'Furnace 1 [kW]',
       'Furnace 2 [kW]', 'Home office [kW]', 'Fridge [kW]', 'Wine cellar [kW]',
       'Garage door [kW]', 'Kitchen 12 [kW]', 'Kitchen 14 [kW]',
       'Kitchen 38 [kW]', 'Barn [kW]', 'Well [kW]', 'Microwave [kW]',
       'Living room [kW]', 'temperature', 'humidity', 'visibility',
       'apparentTemperature', 'pressure', 'windSpeed', 'cloudCover',
       'windBearing', 'precipIntensity', 'dewPoint', 'precipProbability',
       'summary_encoded', 'icon_encoded', 'hour_of_day',
       'temperature_next_10_minutes', 'use_[kW]_next_10_minutes',
       'lstm_prediction_use_kw_next_10_minutes',
       'linear_regression_prediction_temperature_next_10_minutes'],
      dtype='object')

[ ]:
```
# plot use_[kW]_next_10_minutes and lstm_prediction_use_kw_next_10_minutes
plt.figure(figsize=(15, 7))
plt.plot(df.index, df[f'use_[kW]_next_{MINUTES_AHEAD_TO_PREDICT}_minutes'],␣
 ↪label=f'Actual Use [kW]', color='red')
plt.plot(df.index,␣
 ↪df[f'lstm_prediction_use_kw_next_{MINUTES_AHEAD_TO_PREDICT}_minutes'],␣
 ↪label=f'Predicted Use [kW] (LSTM)', color='green')
```

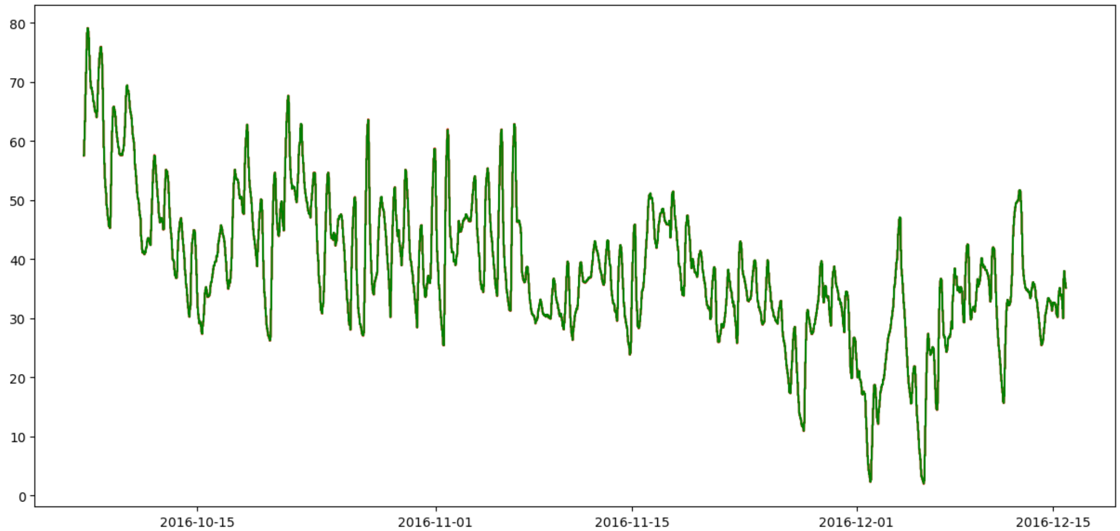
[ ]: [<matplotlib.lines.Line2D at 0x1b004067310>]



[ ]:
```
# plot temperature_next_10_minutes and␣
 ↪linear_regression_prediction_temperature_next_10_minutes
plt.figure(figsize=(15, 7))
plt.plot(df.index, df['temperature'], label=f'Actual Temperature', color='red')
```

```
plt.plot(df.index,␣
↪df[f'linear_regression_prediction_temperature_next_{MINUTES_AHEAD_TO_PREDICT}_minutes'],␣
↪label=f'Predicted Temperature (Linear Regression)', color='green')
```

[ ]: [<matplotlib.lines.Line2D at 0x1b005292eb0>]



[ ]:
```
# print df min date
print(df.index.min())
# print df max date
print(df.index.max())
```

```
2016-10-06 22:40:00
2016-12-15 22:17:00
```