# Load Demand Forecasting Using State-of-the-Art Modeling Methods: Focusing on Accuracy & Explainability

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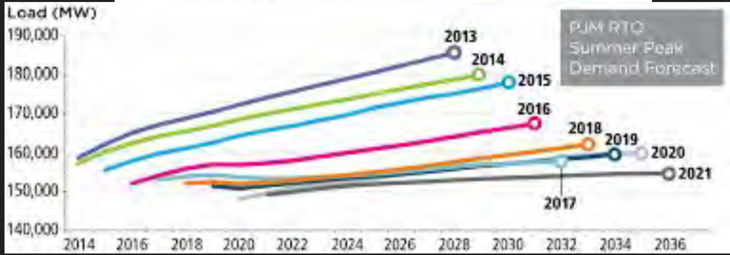
# Load Demand Forecasting

- Load demand forecasting is the process of predicting future energy consumption in a specific area.

- It is used for electricity management and stability by ensuring the supply matches the demand preventing blackouts or overloads.

- It is important to gather information related to the dataset and to then explore that data.

# Why is this important?

- The topic of predict electrical energy consumption is important since if done correctly can prevent blackouts and save money.

- If an energy prediction is wrong it could make it so that more energy is outputted than needed causing power surges which then lead blackouts.

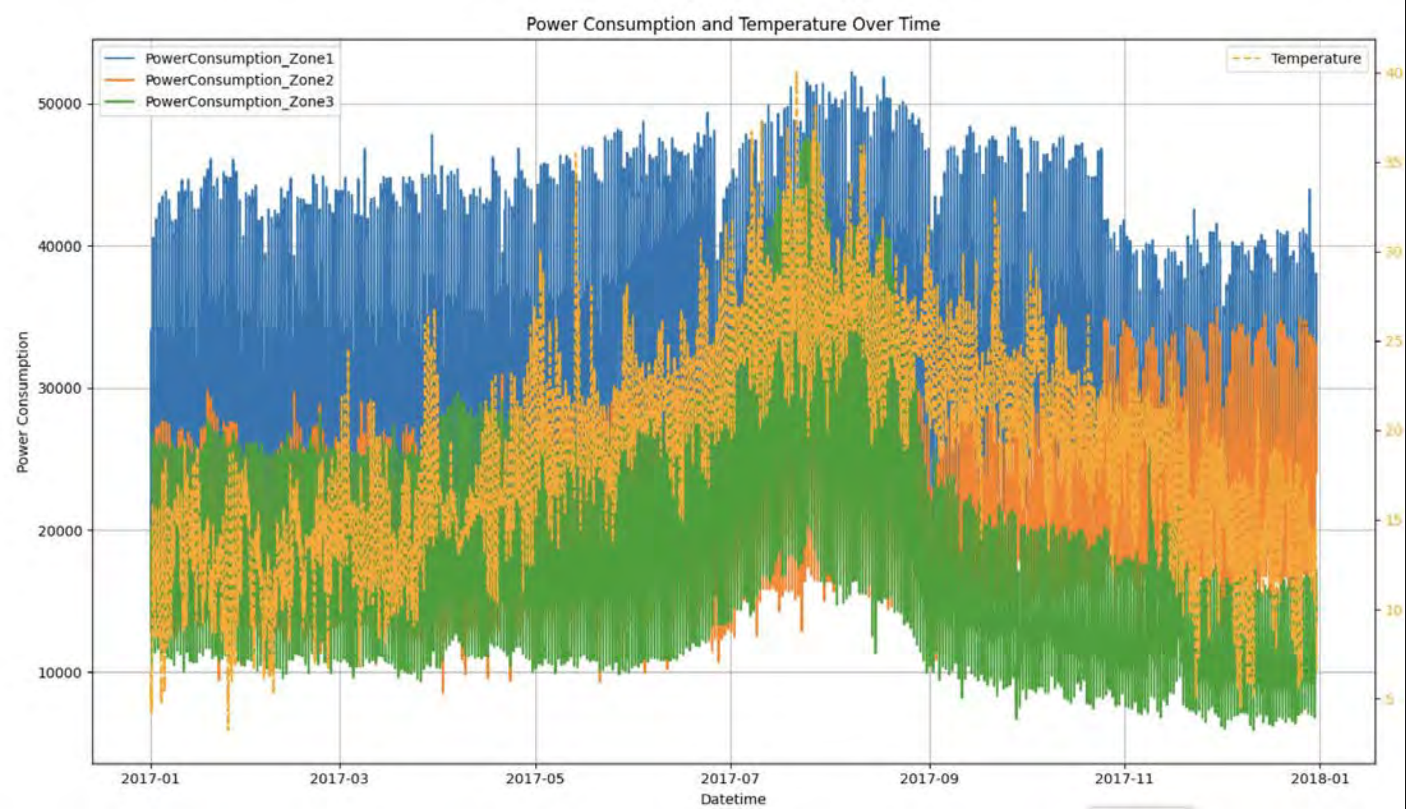
- Energy prediction can also be used to save money.

# Electric Power Consumption Dataset

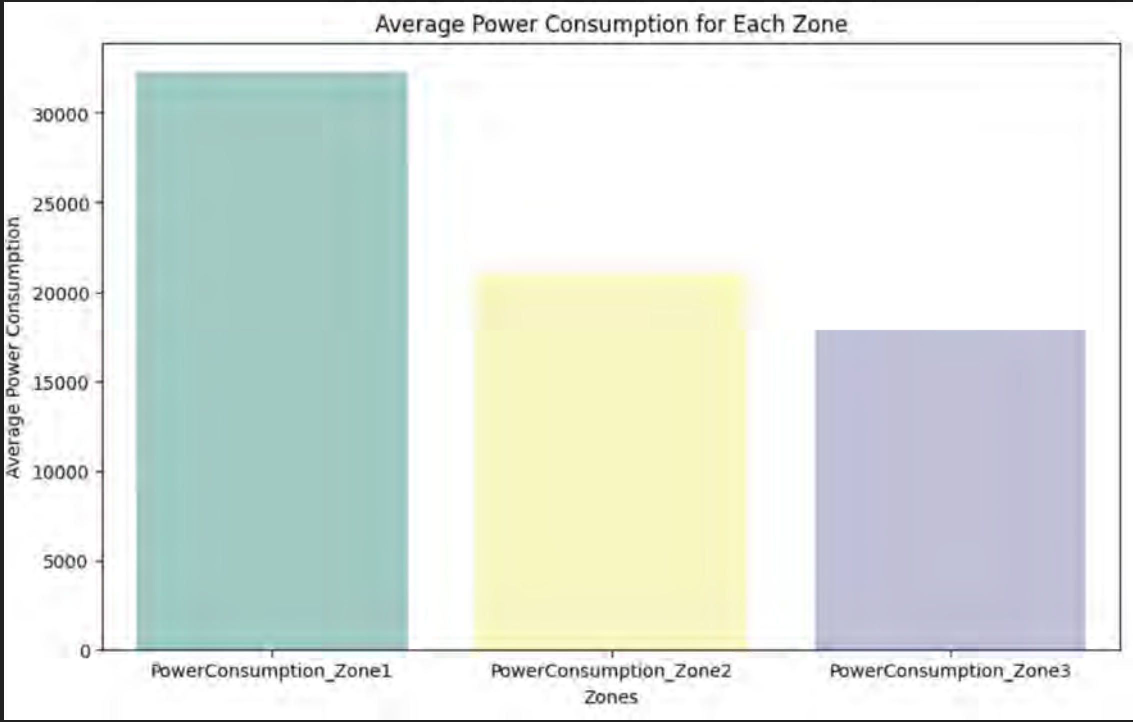
- Energy consumption for the city of Tetouan in morocco in 2017.
- The capacity is measured in kilowatts per hour.
- There are 52,416 observations of energy consumption on a 10 minute windows.

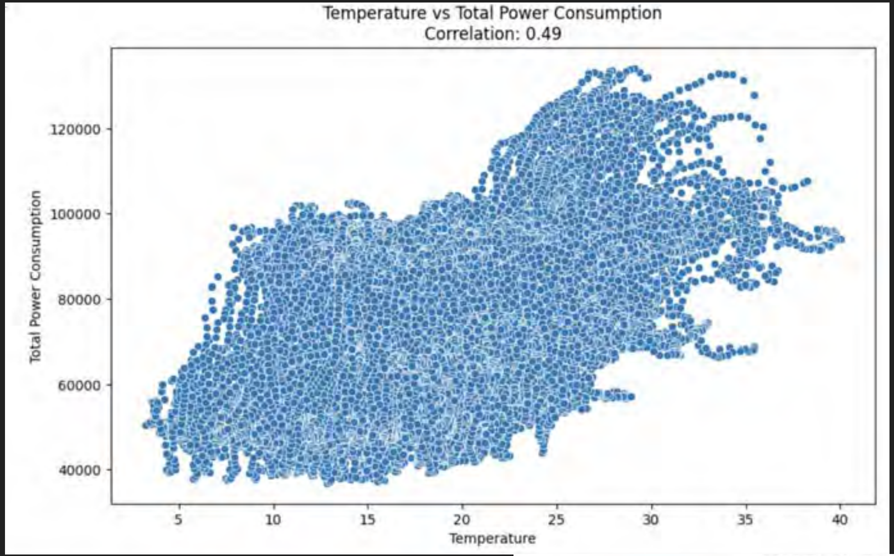
Source:

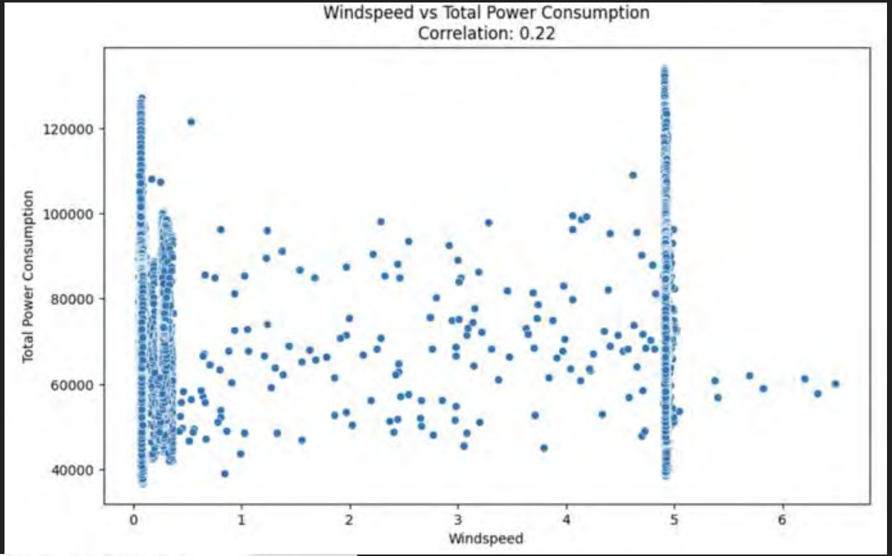
https://www.kaggle.com/datasets/fedesoriano/electric-power-consumption/data

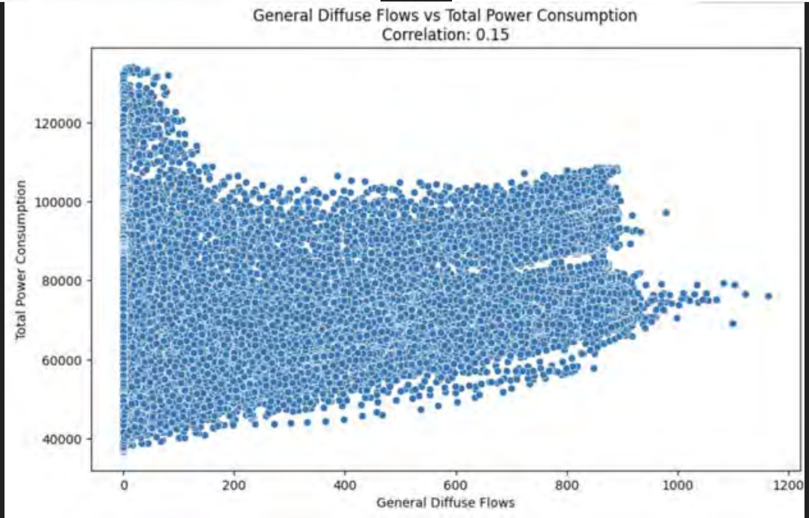


Power Consumption and Temperature Over Time
PowerConsumption_Zone1
PowerConsumption_Zone2
PowerConsumption_Zone3
Temperature
Power Consumption
50000
40000
30000
20000
10000
40
35
30
25
20
15
10
5
2017-01
2017-03
2017-05
2017-07
2017-09
2017-11
2018-01
Datetime

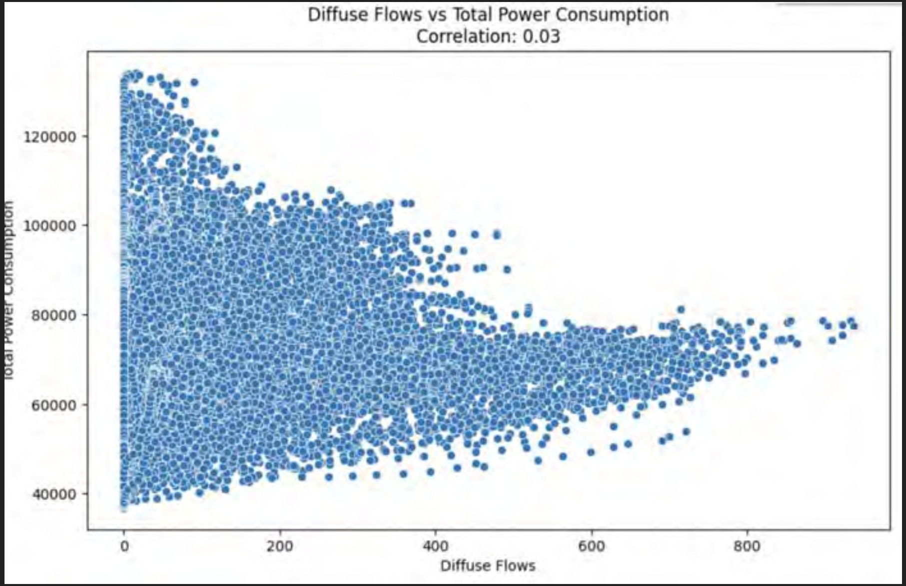

Average Power Consumption for Each Zone
Average Power Consumption
30000
25000
20000
15000
10000
5000
0
PowerConsumption_Zone1
PowerConsumption_Zone2
PowerConsumption_Zone3
Zones

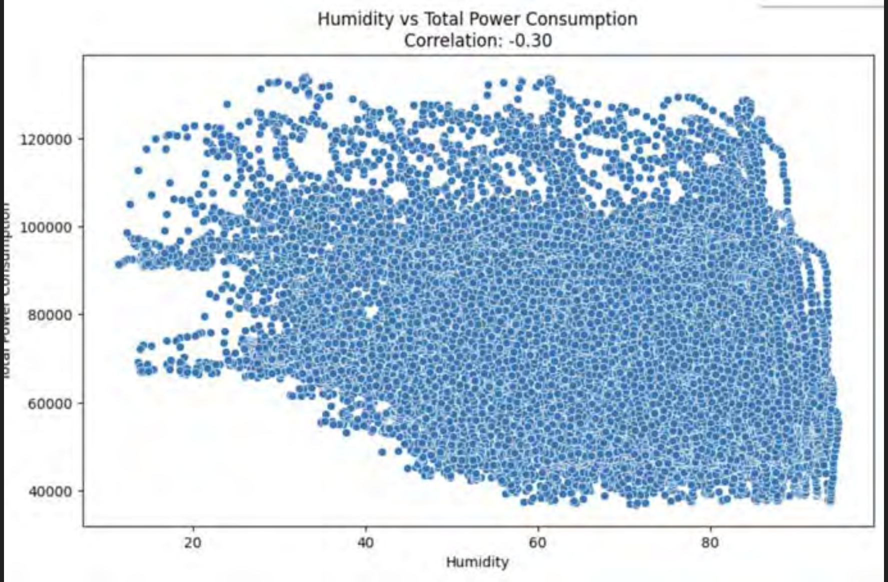

Temperature vs Total Power Consumption
Correlation: 0.49
Total Power Consumption
Temperature


Windspeed vs Total Power Consumption
Correlation: 0.22
Total Power Consumption
Windspeed


General Diffuse Flows vs Total Power Consumption
Correlation: 0.15
Total Power Consumption
General Diffuse Flows

# Features that will not be present



# Training/Testing Sets For DNN Model

## Training

Training set:

| Datetime | Temperature | WindSpeed | GeneralDiffuseFlows | Hour \ |
|---|---|---|---|---|
| 2017-06-08 00:00:00 | 20.670000 | 0.068167 | 0.046333 | 0.0 |
| 2017-06-08 01:00:00 | 20.388333 | 0.070167 | 0.039000 | 1.0 |
| 2017-06-08 02:00:00 | 20.076667 | 0.077000 | 0.051333 | 2.0 |
| 2017-06-08 03:00:00 | 19.960000 | 0.075500 | 0.051167 | 3.0 |
| 2017-06-08 04:00:00 | 20.273333 | 0.072167 | 0.050167 | 4.0 |

| Datetime | Temperature | WindSpeed | GeneralDiffuseFlows | Hour |
|---|---|---|---|---|
| 2017-08-14 19:00:00 | 24.953333 | 4.907167 | 83.050000 | 19.0 |
| 2017-08-14 20:00:00 | 23.750000 | 4.906500 | 2.004333 | 20.0 |
| 2017-08-14 21:00:00 | 23.298333 | 4.905667 | 0.092500 | 21.0 |
| 2017-08-14 22:00:00 | 22.731667 | 4.905167 | 0.099833 | 22.0 |
| 2017-08-14 23:00:00 | 21.715000 | 4.907167 | 0.096167 | 23.0 |

**Training set is from June 8th all the way to August 14th.**

## Testing

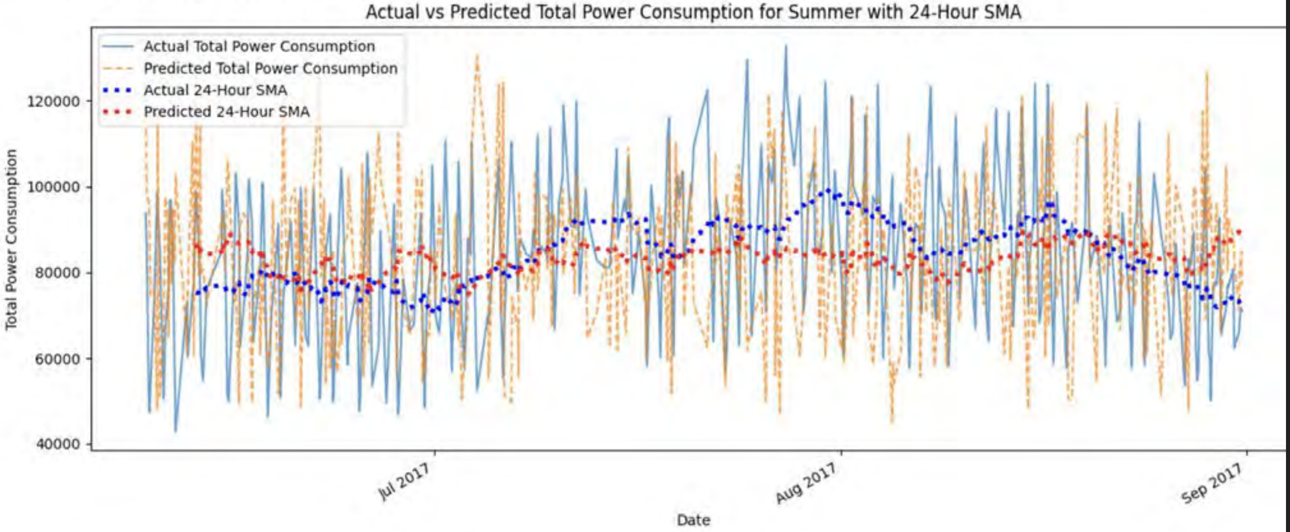
Testing set:

| Datetime | Temperature | WindSpeed | GeneralDiffuseFlows | Hour \ |
|---|---|---|---|---|
| 2017-08-15 00:00:00 | 21.155000 | 4.906167 | 0.075333 | 0.0 |
| 2017-08-15 01:00:00 | 21.300000 | 4.908333 | 0.074167 | 1.0 |
| 2017-08-15 02:00:00 | 21.725000 | 4.904167 | 0.086500 | 2.0 |
| 2017-08-15 03:00:00 | 21.081667 | 4.904000 | 0.091333 | 3.0 |
| 2017-08-15 04:00:00 | 20.708333 | 4.904333 | 0.084000 | 4.0 |

| Datetime | DayOfWeek | Month | Lag1 | Lag24 \ |
|---|---|---|---|---|
| 2017-08-31 19:00:00 | 3.0 | 8.0 | 77547.325070 | 97360.696422 |
| 2017-08-31 20:00:00 | 3.0 | 8.0 | 95241.605187 | 96906.782785 |
| 2017-08-31 21:00:00 | 3.0 | 8.0 | 95799.335722 | 94923.632710 |
| 2017-08-31 22:00:00 | 3.0 | 8.0 | 93825.287503 | 89811.500048 |
| 2017-08-31 23:00:00 | 3.0 | 8.0 | 88423.131125 | 80760.137647 |

**Testing set is from August 15th all the way to August 31st**

Train Score ($R^2$): 0.997378697432035
Test Score ($R^2$): 0.9846271998426246
Mean Absolute Percentage Error (MAPE): 0.018434531630178 27




Root Mean Squared Error (RMSE): 2278.7300457895853
Mean Absolute Error (MAE): 1503.21
Mean Absolute Percentage Error (MAPE): 1.84%

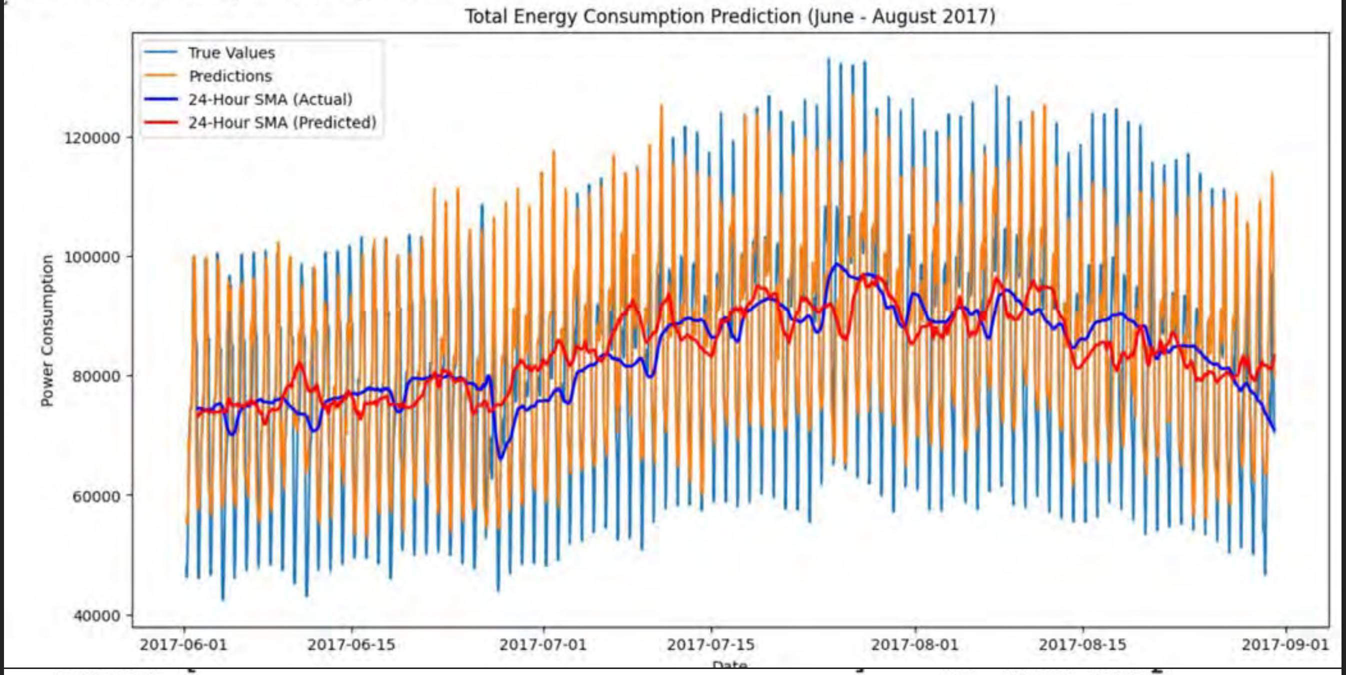
# Training/Testing Sets for RNN Model

```
Training Data Datetime Range:
Start: 2017-06-01 05:00:00 End: 2017-08-12 20:00:00
3629    2017-06-01 05:00:00
3630    2017-06-01 06:00:00
3631    2017-06-01 07:00:00
3632    2017-06-01 08:00:00
3633    2017-06-01 09:00:00
                ...
5368    2017-08-12 16:00:00
5369    2017-08-12 17:00:00
5370    2017-08-12 18:00:00
5371    2017-08-12 19:00:00
5372    2017-08-12 20:00:00
```

```
Testing Data Datetime Range:
Start: 2017-08-12 21:00:00 End: 2017-08-31 00:00:00
5373    2017-08-12 21:00:00
5374    2017-08-12 22:00:00
5375    2017-08-12 23:00:00
5376    2017-08-13 00:00:00
5377    2017-08-13 01:00:00
                ...
5804    2017-08-30 20:00:00
5805    2017-08-30 21:00:00
5806    2017-08-30 22:00:00
5807    2017-08-30 23:00:00
5808    2017-08-31 00:00:00
```

**Training Set is from June 1st all the way to August 12th**

**Testing set is from August 12th all the way to August 30th**




```
Mean Squared Error (MSE): 88378182.96527651
Mean Absolute Error (MAE): 7242.885332785741
Mean Absolute Percentage Error (MAPE): 0.0912816843714211 9
```

# Conclusion

Used the RNN and DNN model to try to predict energy consumption as accurate as possible.

Got close to accurate results with the DNN model.

Discovered that summer tends to be the month where energy consumption is at its highest.

# Future Work

Expand the scope of the trained model by testing it on diverse datasets or scenarios. For example, evaluate its performance on the energy consumption levels for the entire FAU campus or analyze the energy usage patterns of buildings in different urban areas.

This approach not only verifies the model's robustness but also provides insights into its adaptability and potential applications in broader contexts.


# Works Cited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