# Electricity Forecasting

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# Agenda

Problem and Business Value

Project Milestones and Timeline

Data Sources

Data Preprocessing

Data Analysis

Pre-Modeling

Model

Results

Challenges and Future Steps




# Introduction

Our goal in this project is to develop accurate forecasting models for electricity consumption using the Electricity Load Diagram 20112014 data set. This is a time-series data set with 370 instances that represent the electricity consumption of each client.

# Problem

Forecasting Daily Average Electricity Consumption for All Customers

# Objective

Find deep learning models that fit and predict the dataset

# From:

March 3rd, 2023

# To:

May 3rd, 2023

# Value Creation

- Improved electricity demand forecasting
- Energy conservation
- Data-driven decision making

# Timeline

- Milestone I: Project Transition
- Milestone II: Data Exploration
- Milestone III: Data Preprocessing and Data Analysis
- Milestone IV: Predicting Model Choosing and Hyperparameter Tuning
- Deliverable: Select best model with lowest MAPE

# Data Extraction

| | MT_001 | MT_002 | MT_003 | MT_004 | MT_005 | MT_006 | MT_007 | MT_008 | MT_009 | MT_010 | ... | MT_361 | MT_362 | MT_363 | MT_364 | MT_365 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2012-01-01 00:15:00 | 3.807107 | 22.759602 | 77.324066 | 136.178862 | 70.731707 | 351.190476 | 9.609949 | 279.461279 | 75.174825 | 87.096774 | ... | 128.479657 | 28500.0 | 1729.957806 | 1704.545455 | 15.645372 |
| 2012-01-01 00:30:00 | 5.076142 | 22.759602 | 77.324066 | 136.178862 | 73.170732 | 354.166667 | 9.044658 | 279.461279 | 73.426573 | 84.946237 | ... | 127.765882 | 26400.0 | 1654.008439 | 1659.090909 | 15.645372 |
| 2012-01-01 00:45:00 | 3.807107 | 22.759602 | 77.324066 | 140.243902 | 69.512195 | 348.214286 | 8.479367 | 279.461279 | 75.174825 | 91.397849 | ... | 114.204140 | 25200.0 | 1333.333333 | 1636.363636 | 15.645372 |
| 2012-01-01 01:00:00 | 3.807107 | 22.759602 | 77.324066 | 140.243902 | 75.609756 | 339.285714 | 7.348785 | 279.461279 | 68.181818 | 88.172043 | ... | 112.062812 | 23800.0 | 1324.894515 | 1636.363636 | 15.645372 |
| 2012-01-01 01:15:00 | 5.076142 | 22.048364 | 77.324066 | 146.341463 | 73.170732 | 342.261905 | 6.783493 | 265.993266 | 69.930070 | 86.021505 | ... | 112.776588 | 23700.0 | 1118.143460 | 1659.090909 | 15.645372 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 2014-12-31 23:00:00 | 2.538071 | 22.048364 | 1.737619 | 150.406504 | 85.365854 | 303.571429 | 11.305822 | 282.828283 | 68.181818 | 72.043011 | ... | 276.945039 | 28200.0 | 1616.033755 | 1363.636364 | 29.986962 |
| 2014-12-31 23:15:00 | 2.538071 | 21.337127 | 1.737619 | 166.666667 | 81.707317 | 324.404762 | 11.305822 | 252.525253 | 64.685315 | 72.043011 | ... | 279.800143 | 28300.0 | 1569.620253 | 1340.909091 | 29.986962 |
| 2014-12-31 23:30:00 | 2.538071 | 20.625889 | 1.737619 | 162.601626 | 82.926829 | 318.452381 | 10.175240 | 242.424242 | 61.188811 | 74.193548 | ... | 284.796574 | 27800.0 | 1556.962025 | 1318.181818 | 27.379400 |
| 2014-12-31 23:45:00 | 1.269036 | 21.337127 | 1.737619 | 166.666667 | 85.365854 | 285.714286 | 10.175240 | 225.589226 | 64.685315 | 72.043011 | ... | 246.252677 | 28000.0 | 1443.037975 | 909.090909 | 26.075619 |
| 2015-01-01 00:00:00 | 2.538071 | 19.914651 | 1.737619 | 178.861789 | 84.146341 | 279.761905 | 10.175240 | 249.158249 | 62.937063 | 69.892473 | ... | 188.436831 | 27800.0 | 1409.282700 | 954.545455 | 27.379400 |

105216 rows × 370 columns

- Data source: "Electricity Load Diagrams 2011-2014 Data Set" from UCI Machine Learning Repository
- Original dataset: ".txt" file with ";" as delimiter, 31 variables
- First column: date and time, format "yyyy-mm-dd hh:mm:ss", 15-minute intervals
- Subsequent columns: electricity consumption of individual clients in kW
- Time range: 2011-01-01 to 2015-01-01, 140,256 observations, Portuguese hours

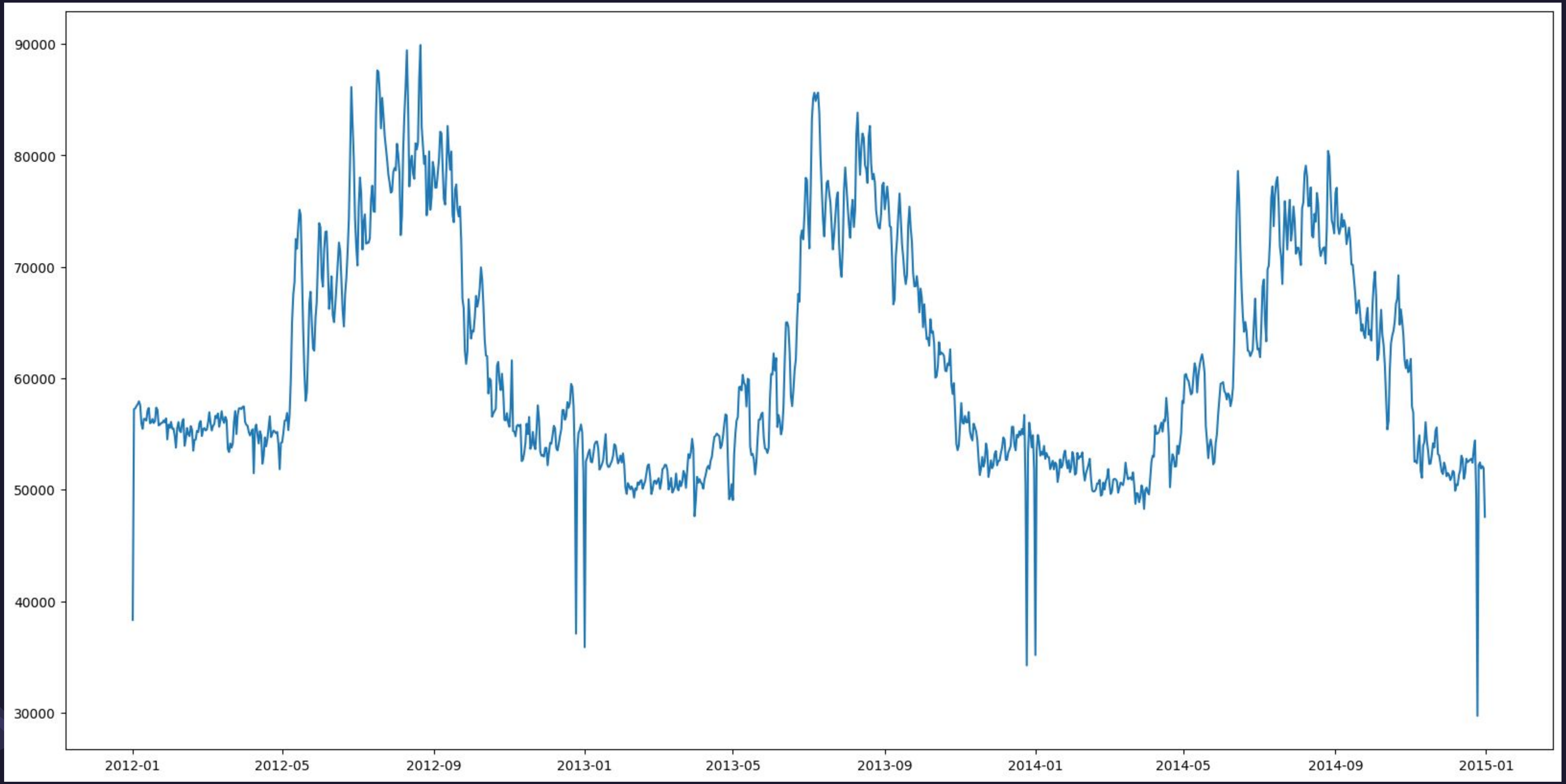
# Data Preprocessing

- Discard record for 2015-01-01
- No duplicate records, missing values, or extreme outliers
- Address minor issues:
- Focus on time range between 2012-01-01 and 2014-12-31 to account for clients established after 2011
- Exclude 40 users with late account openings
- Refined dataset: 105,216 rows and 320 columns

| | ds | y |
|---|---|---|
| 2012-01-01 | 2012-01-01 | 38313.751557 |
| 2012-01-02 | 2012-01-02 | 57225.098775 |
| 2012-01-03 | 2012-01-03 | 57294.353754 |
| 2012-01-04 | 2012-01-04 | 57503.687632 |
| 2012-01-05 | 2012-01-05 | 57662.515150 |
| ... | ... | ... |
| 2014-12-27 | 2014-12-27 | 52452.104786 |
| 2014-12-28 | 2014-12-28 | 51899.725502 |
| 2014-12-29 | 2014-12-29 | 52114.818246 |
| 2014-12-30 | 2014-12-30 | 51946.361511 |
| 2014-12-31 | 2014-12-31 | 47560.653966 |

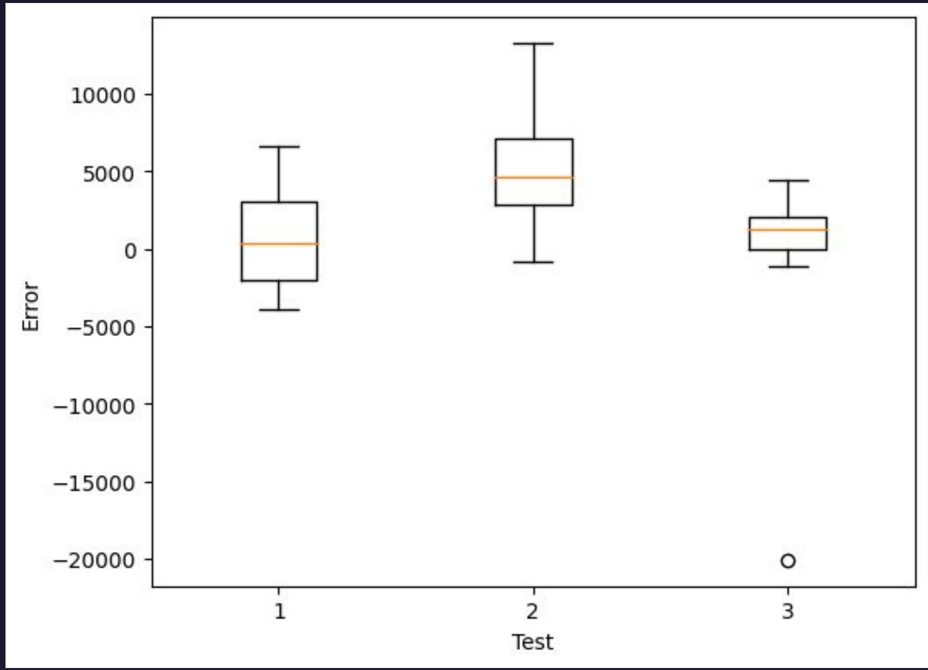
1096 rows × 2 columns

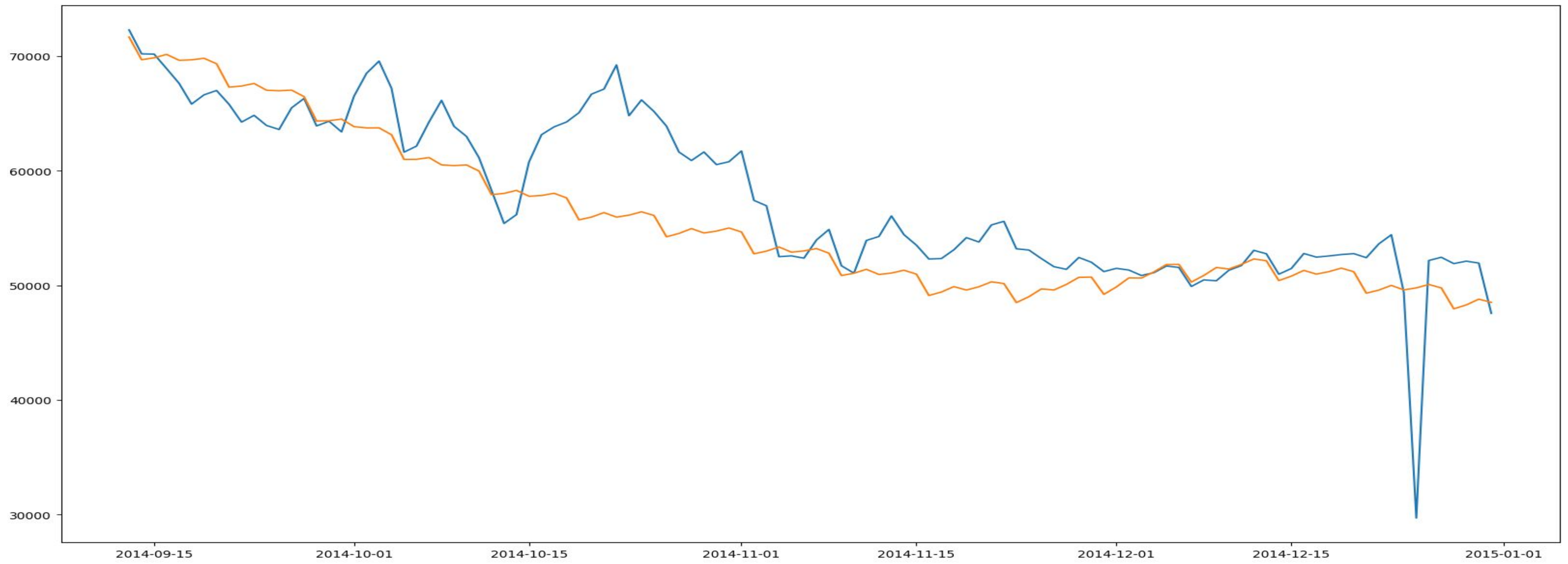
# Data Exploration



# Model

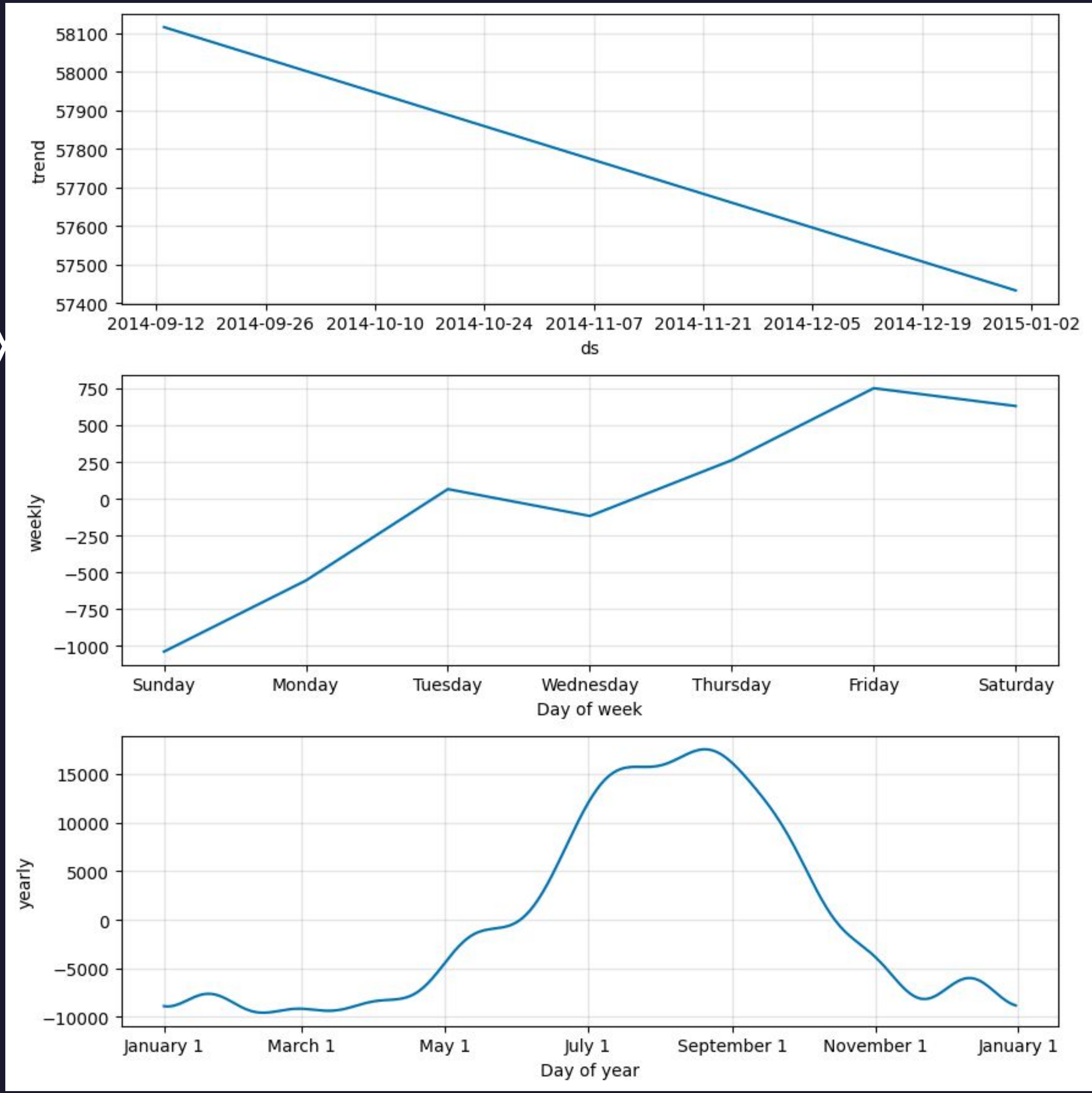
- The Facebook Prophet can make the prediction which very close to the true value by its ability to handle seasonality, holiday, trend, and errors
- After hyper-parameter tuning, the MAPE is close to 0.056728
- From the line plot below, in the middle part the predicted value is close to the real-value
- The boxplot on the right shows the distribution of the error for each part of testing data



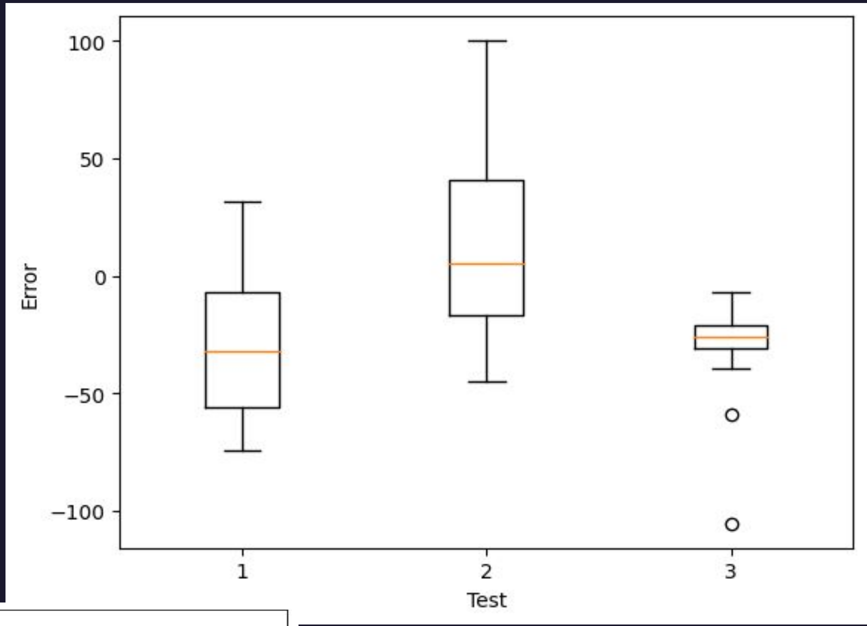
# Model - PROPHET

- The plot shows the trend, weekly seasonality, and yearly seasonality.
- The yearly seasonality shows that the peak of the year appears between July and september and we assume that this high amount of electricity usage is caused by the air-conditioning.
- The weekly seasonality shows that the peak of the week appears on Friday.



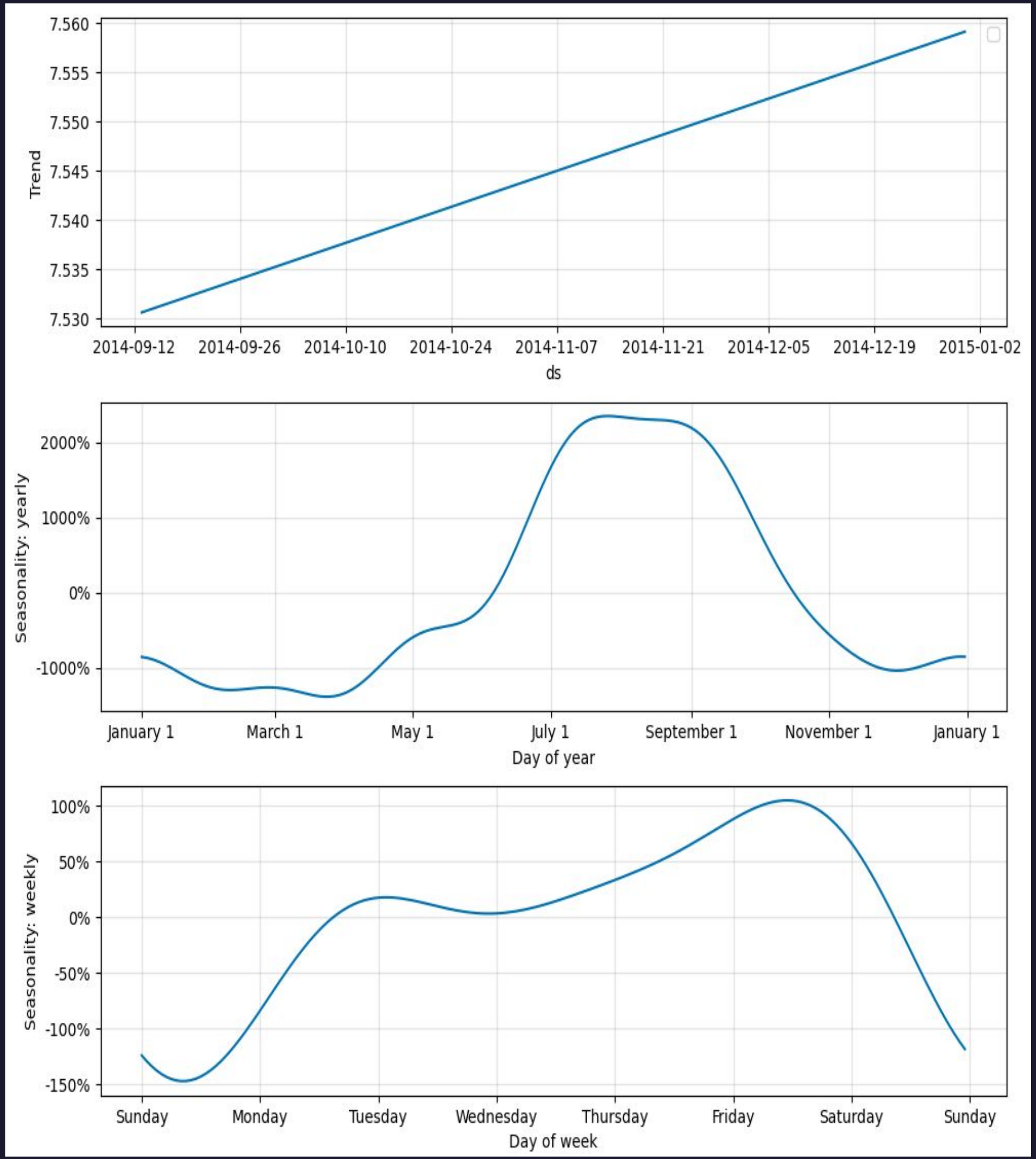
# Model Neural Prophet

- The neural prophet is a model based on neural network and inspired by Facebook Prophet and AR-Net
- After hyper-parameter tuning, the MAPE is close to 0.0524
- The Neural Prophet has a better performance on this dataset than Facebook Prophet.



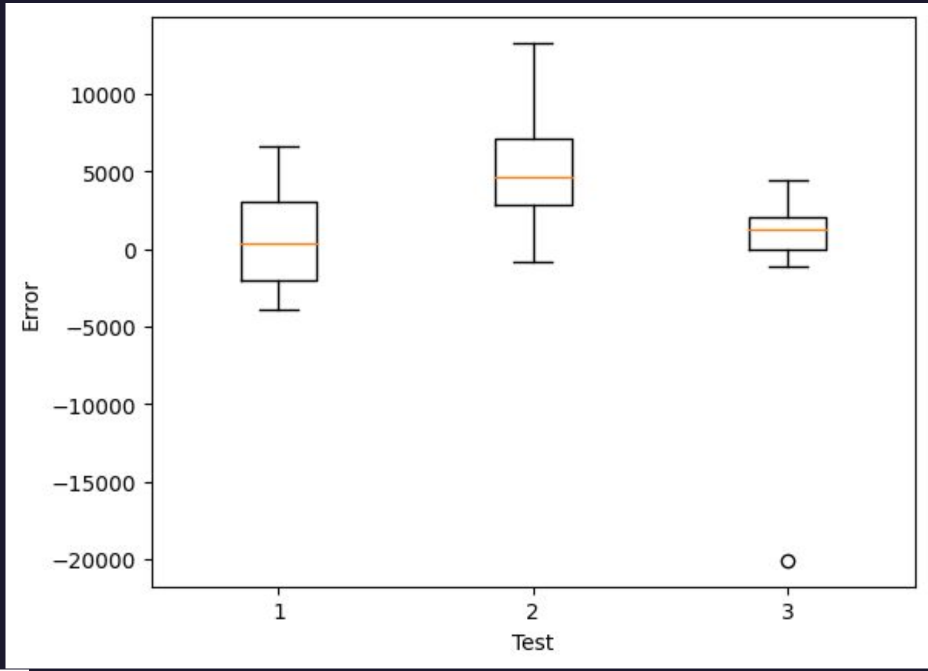

# Model - Neural Prophet

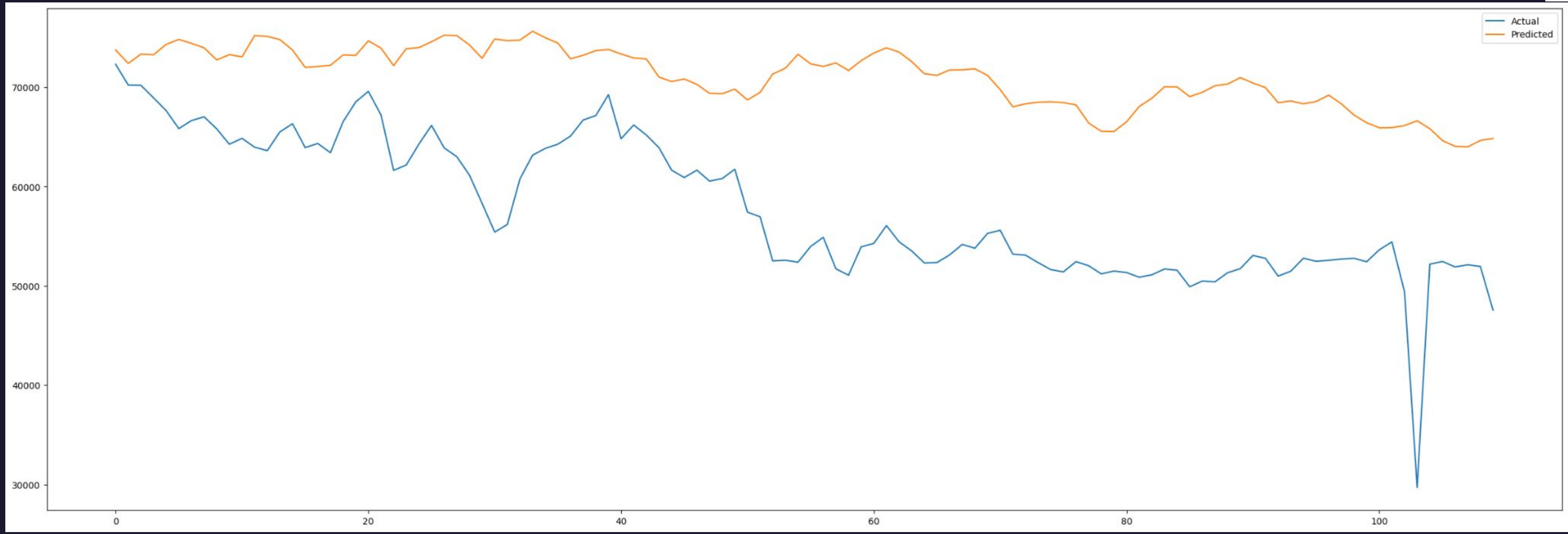
- The plot shows the trend, weekly seasonality, and yearly seasonality.
- The yearly seasonality shows that the peak of the year appears between July and september and we assume that this high amount of electricity usage is caused by the air-conditioning.
- The weekly seasonality shows that the peak of the week appears between friday and saturday.



# Model - DeepAR

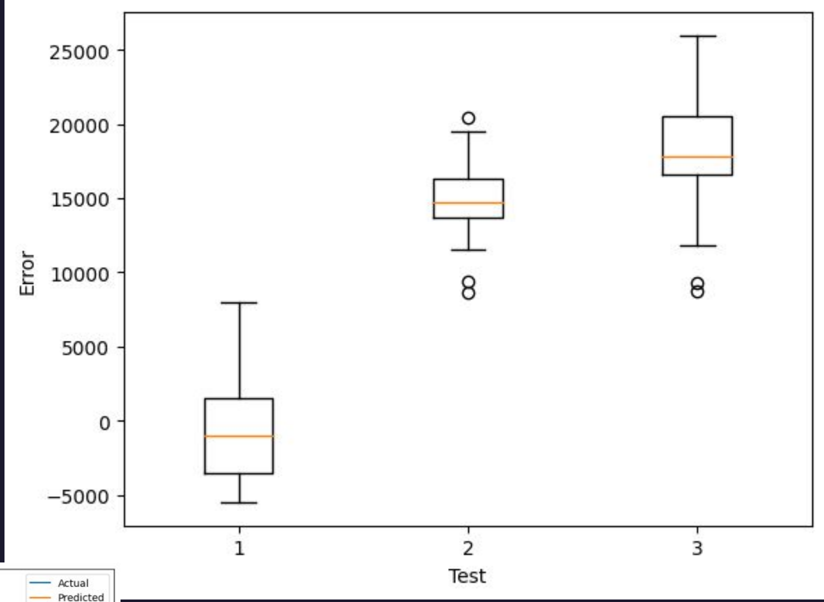
- The DeepAR model does not fit well for this dataset
- After hyper-parameter tuning, the MAPE is close to 0.24418
- The line plot below clearly shows its bad performance.
- The boxplot on the right shows the distribution of the error for each part of testing data

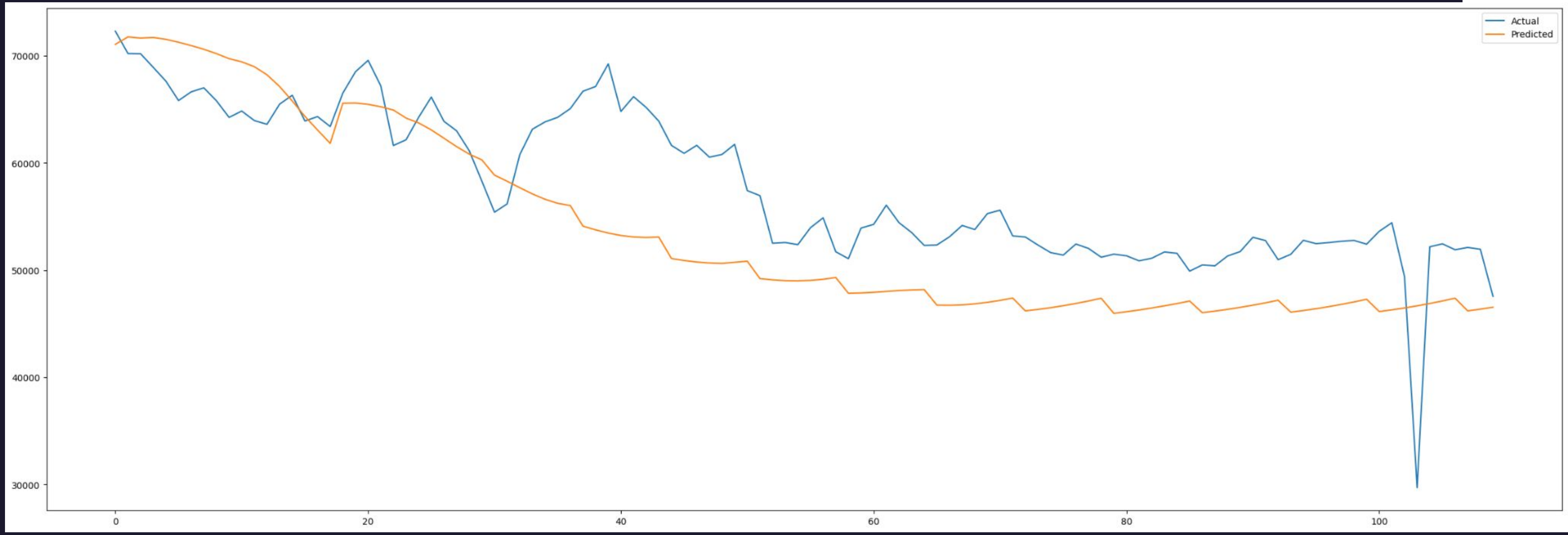


# Model - Temporal Fusion Transformer

- The TFT make the prediction slightly worse than Neural Prophet but it successfully captures the trend and seasonality of the dataset
- After hyper-parameter tuning, the MAPE is close to 0.09775
- From the line plot below, in the middle part the predicted value is close to the real-value
- The boxplot on the right shows the distribution of the error for each part of testing data



# Table

| Model | Prophet | Neural Prophet | TFT | DeepAR |
|---|---|---|---|---|
| Testing1 | 0.03953 | 0.03905 | 0.04652 | |
| Testing2 | 0.08385 | 0.06411 | 0.13411 | |
| Testing3 | 0.04634 | 0.03541 | 0.11127 | |
| Average MAPE | 0.05678 | 0.04501 | 0.09775 | 0.24418 |

# Challenge & Future Steps

In the future, we will try to change different ways of cleaning the data and feature engineering. Also, more hyperparameter tuning and predicting models will be implemented.