



Predicting EV Charging in Apartment Buildings

Introduction

In a world moving towards sustainability, as traditional fuel resources depleting and environmental worries grow, there is a notable shift towards electric solutions. More individuals are opting for electric vehicles (EVs), and countries are actively planning to fully embrace the reliance on EVs for a more sustainable future.



Problem Statement

Challenges of energy consumption and load prediction
in the context of residential electric vehicle (EV)
charging in apartment buildings



Dataset

Residential EV Charging Data



What does the Data look like:

Dataset 1: EV charging reports

Dataset 2: Hourly EV charging loads and idle capacity, for all sessions and users individually

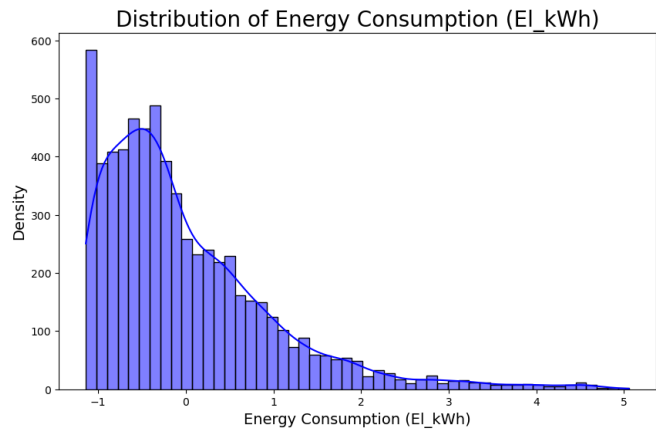
Dataset 3 and 4: Hourly EV charging loads and idle capacity, aggregated for private or shared CPs

Dataset 5: Hourly smart meter data from garage BI2

Dataset 6: Local traffic density

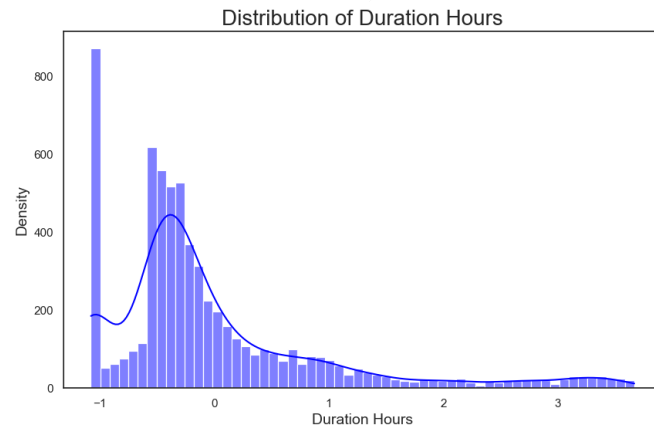
Dataset 7: Weather Data

EDA



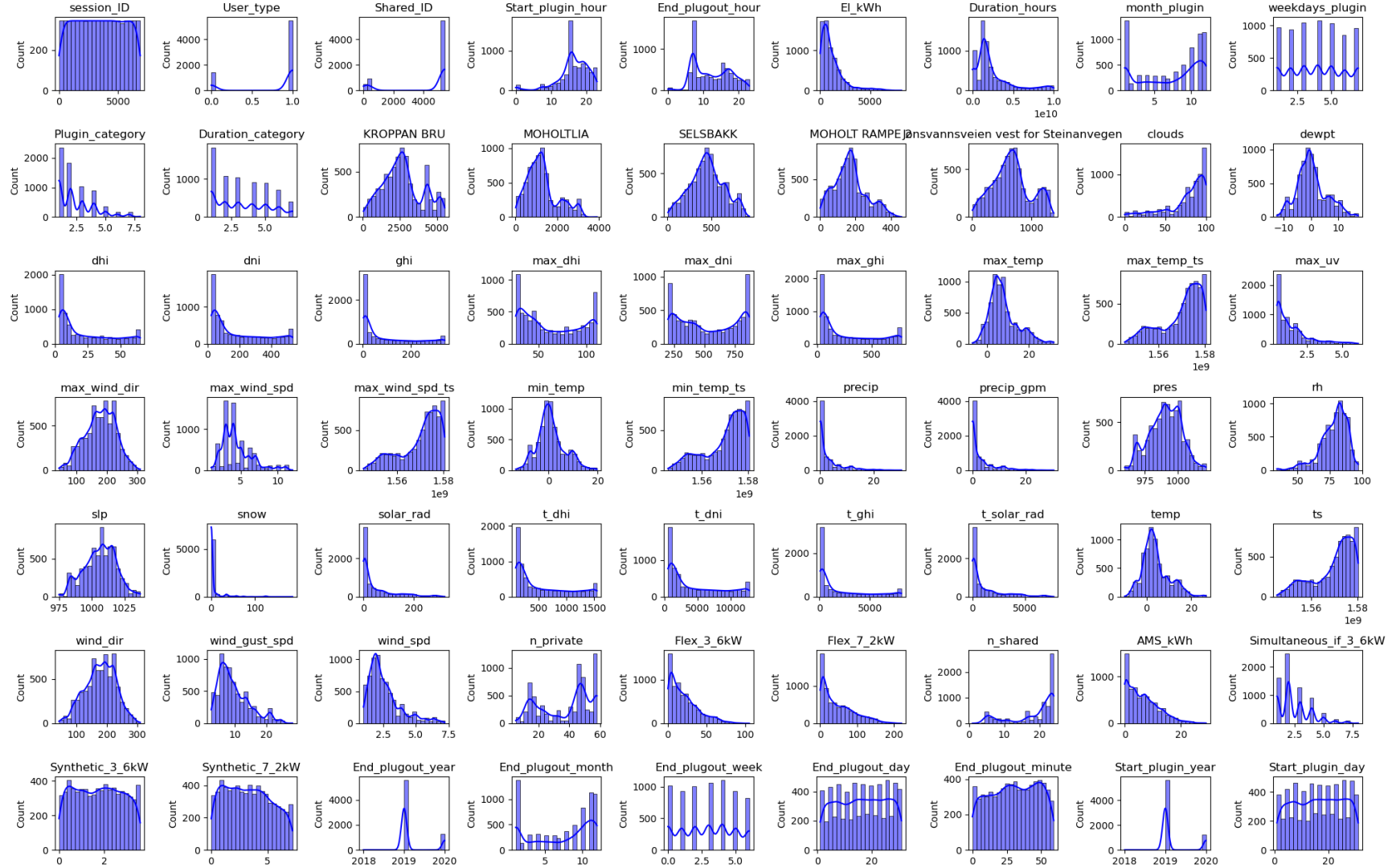
Target Variable

The amount of electrical energy consumed, measured in kilowatt-hours (kWh)



Independant Feature

Is the amount of time that a vehicle is connected to a charging station to replenish its battery



Feature Engineering

Techniques

Date and Time Features:

- Hour/day/week/month/year

Feature Scaling:

- Standardization or normalization of numerical features

Outlier Handling:

- Identification and handling of outliers

Missing Data Handling:

- Imputation or removal of missing data

Encoding Categorical Variables

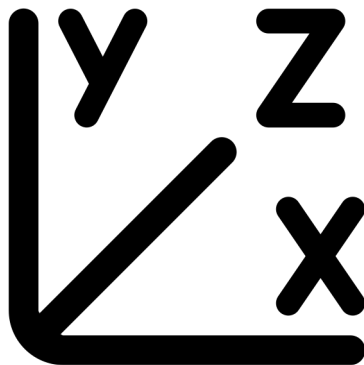
- Utilized one-hot encoding



Baseline Models



Random Forest Regressor



Linear Regression



Gradient Boosting Regression

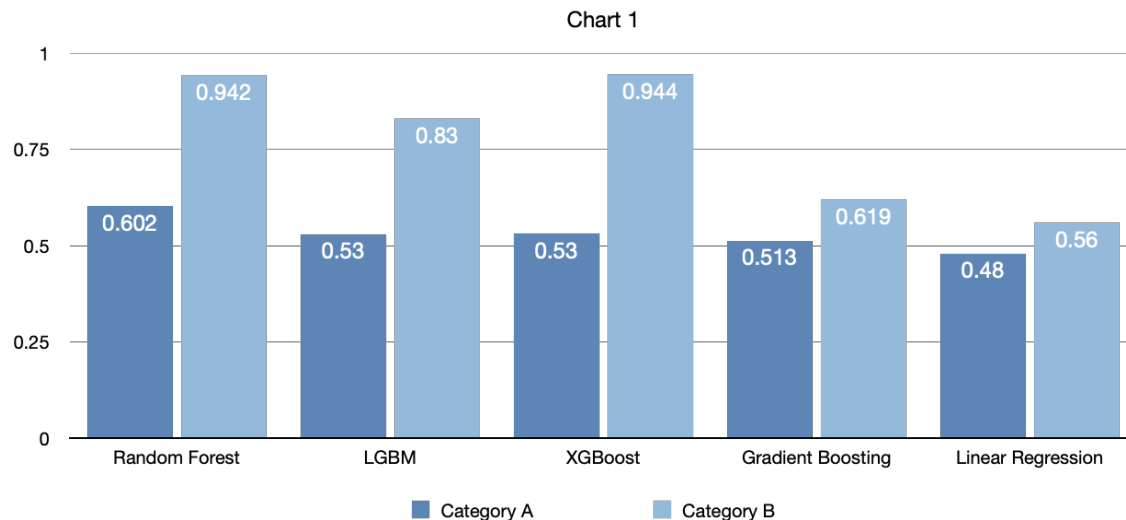
Baseline Models Comparison

Results

Random Forest has both the highest R-squared (R^2) score on validation and train set, it strengthens the evidence in favor of its performance.

Results interpretation

- Non-Linear Patterns:
- High Feature Correlation:
- Multicollinearity Mitigation:
- Robust Against Outliers:

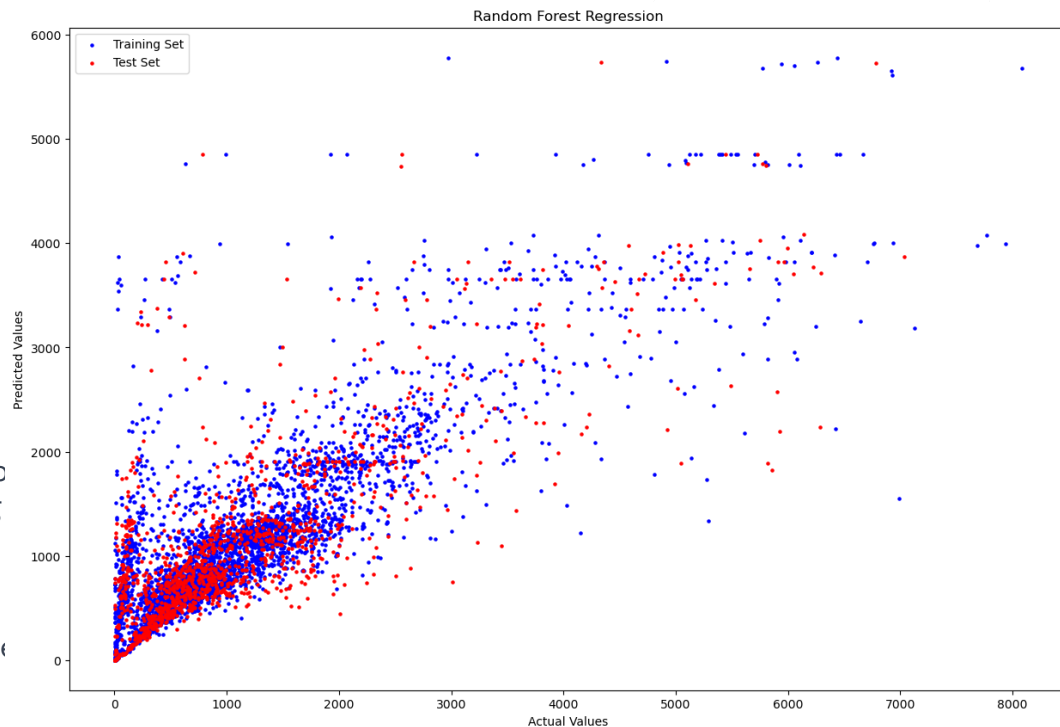


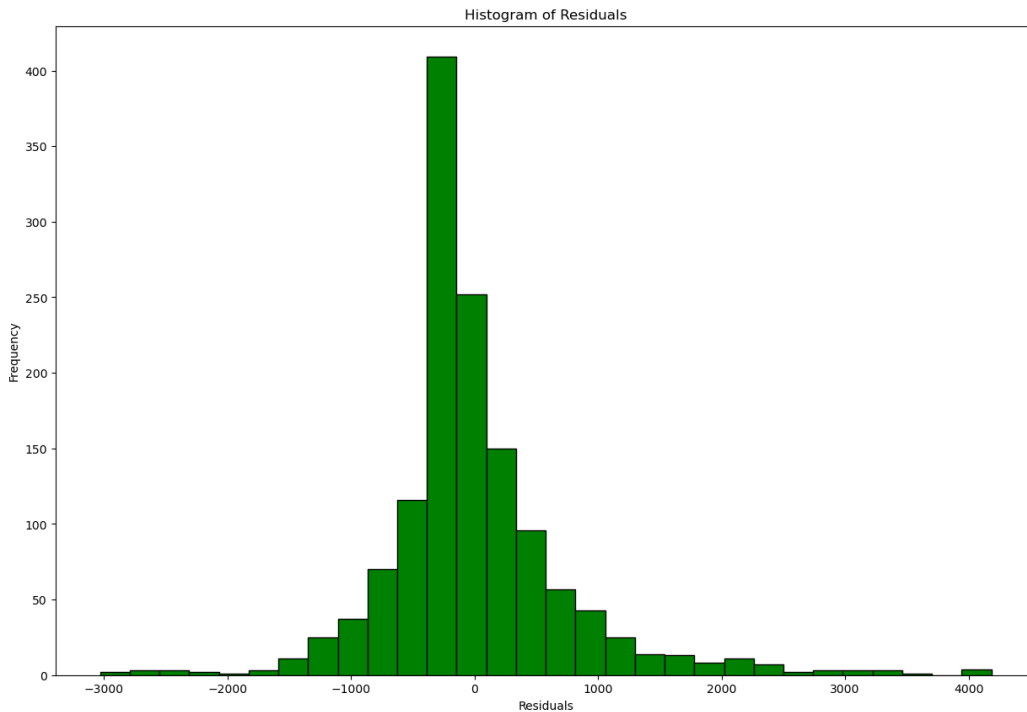
Random Forest Regression Model Results

The scatter plot visually examines the model's predictions on the test and validation sets. The proximity of points to the diagonal line reflects the alignment of predictions with the actual values. R-squared (R^2) scores of 0.61 for the Test set and 0.70 for the Train set indicate a reasonably strong fit, capturing substantial portion of the variance in both datasets.

Conclusion:

The outcomes from the random forest regression model suggest that approximately 56–57% of the features effectively predict energy consumption.





Residuals

Observation:

- The residuals are spread relatively evenly across the range of predicted values, it suggests homoscedasticity.
- The errors are normally distributed.
- The residuals that are centered around zero represent a well-fitted model.
- Outliers in the residuals may indicate data points that the model is not capturing well. Will need to be investigated.

Conclusion

Firstly, at a societal level, optimizing energy consumption in residential EV charging can contribute to overall energy efficiency and sustainability. From a business standpoint, property managers and energy providers can gain from implementing efficient energy management, leading to reduced costs, optimized infrastructure investments, and an improved charging experience for EV users.



Next Step:

Go back to EDA

Feature Engineering

Model Evaluation and Fine-Tuning

Deep learning models

Reinforcement learning to optimize energy consumption

A quote

“If you torture the data long enough, it will confess to anything”

Ronald Coase