PURDUE UNIVERSITY | The Data Mine

SPRING 2022 NUVVE TEAM

NUVVE

INTRODUCTION

WHAT DOES NUVVE DO?

Nuvve is a global leader in vehicle-to-grid (V2G) technology offering high-powering charging and grid services that optimize unused and renewable energy.

WHAT ARE THEIR GOALS?

Their goal is to help decrease the ownership costs of electric vehicles. They accomplish this by returning power from the vehicle's battery to the electrical grid when the vehicle is not slated for use by the customer.

OUR GOALS

- Forecast energy needed for electric vehicles
- Forecast Plug in and Plug out times for individual vehicles
- Predict. Occupancy of charging stations.
- Explore various models such as LSTM (Long-Short term Memory), RNN (Recurrent Neural Network), GNN (Graph Neural Network) , Two-Stage Least Square (2SLS), Gaussian Process Regression (GPR), Bayesian optimization (deep learning), Multivariate linear regression, Lasso regression, Support vector regression, XGboost with time series.

For this purpose, we split ourselves into three teams.

OUR FUTURE PLANS

Ultimately, we wish to create a pipeline that would take in updated data, process and engineer it and then feed it into the model.

Other topics we wish to tap into are:

- Electric Vehicle Battery Health
- Forecasting Impact On Green House Emissions.

Group 1 – Forecast Energy Needed For Electric Vehicles

HOW DOES THIS HELP CUSTOMERS?

- Reduces excess energy given to vehicles that don't need it
- Predicts the amount of energy to request from the grid for vehicles with different use cases

RESEARCH QUESTIONS WE ARE TRYING TO ANSWER

- What variables are the best indicators of car behavior.
- How much energy does a car take per trip for different use cases on average

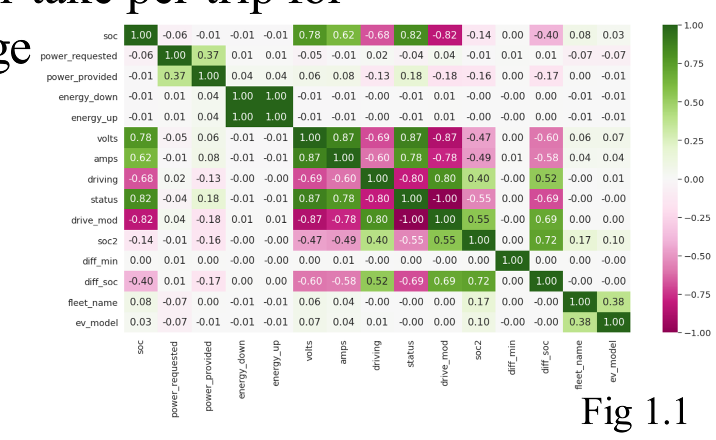

Fig 1.1

FEATURES OF OUR SOLUTION:

- Forecast model of car behavior using MLR (refer Fig 1.2-1.3), Gaussian Regression, Neural Network, and Lasso Regression
- Visualization pipeline that combines car info with plug in/out data for all Denmark fleets
- Covariance heatmap (refer fig 1.1), pairplot between features,

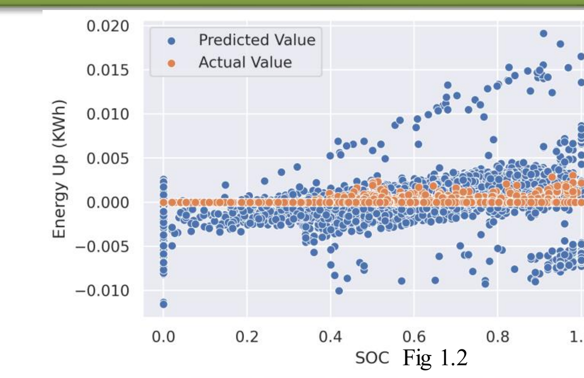

Fig 1.2

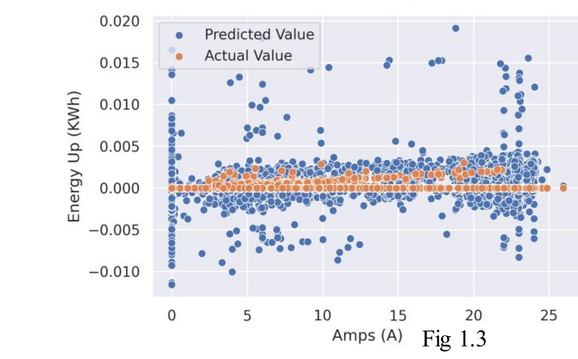

Fig 1.3

Group 2 – Forecasting Plug In and Plug Out Times for individual vehicles

HOW DOES THIS HELP CUSTOMERS?

- This can help Nuvve know customer behavior better and plan their grid accordingly.
- Planning grid accordingly can help save money (for the customer and company)

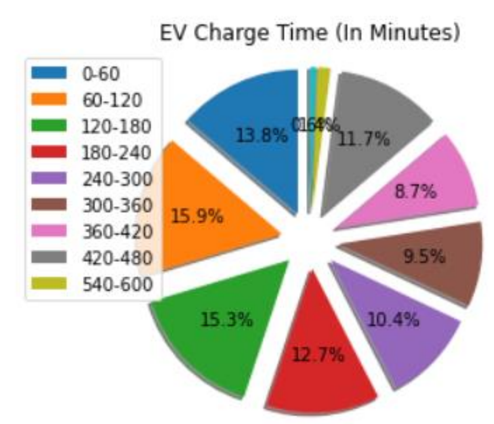

Fig 2.1

RESEARCH QUESTIONS WE ARE TRYING TO ANSWER

- What independent variables are influencing plug-in and plug-out? At what coefficient?
- When do customers typically plug-in (or plug-out) their EV (i.e., what are the most active charging times)?
- How does state of charge (SOC) affect plug in and plug out times?

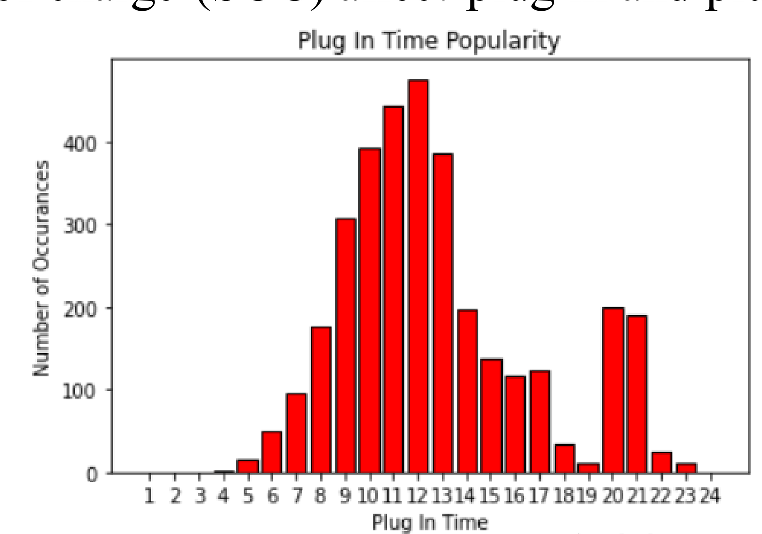

Fig 2.2

PROCESSING , VISUALIZATIONS AND MODEL DEVELOPMENT

- Through our analysis of the data, we prepared visualizations to display:

1) EV Charge time in vehicles (Ref fig 2.1)
2) Plug in time popularity (Ref fig 2.2)
3) Correlation matrix

- Feature Engineering:

1) Adding meaningful variables
2) Creating time delta objects
3) Creating the data frames that are relevant to our model.

- Model Development: We are focusing on KNN and Polynomial Regression

Group 3 – Predicting occupancy of charging stations

HOW DOES THIS HELP CUSTOMERS?

- The number of cars charging directly influences how much Nuvve can contribute back to the electric grid through V2G technology.
- Knowing/predicting how many cars remain at a charging station at a given time allows Nuvve to more precisely assess grid/vehicle energy availability.

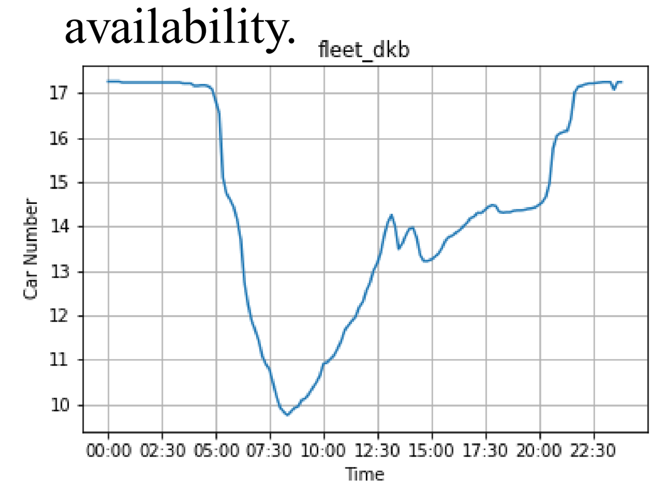

Fig 3.1

RESEARCH QUESTIONS WE ARE TRYING TO ANSWER

- Are there specific days/times that have a majority of the fleet remaining at the charging stations? (Ref fig 3.1)
- What differences are there in the behavior of different fleets?

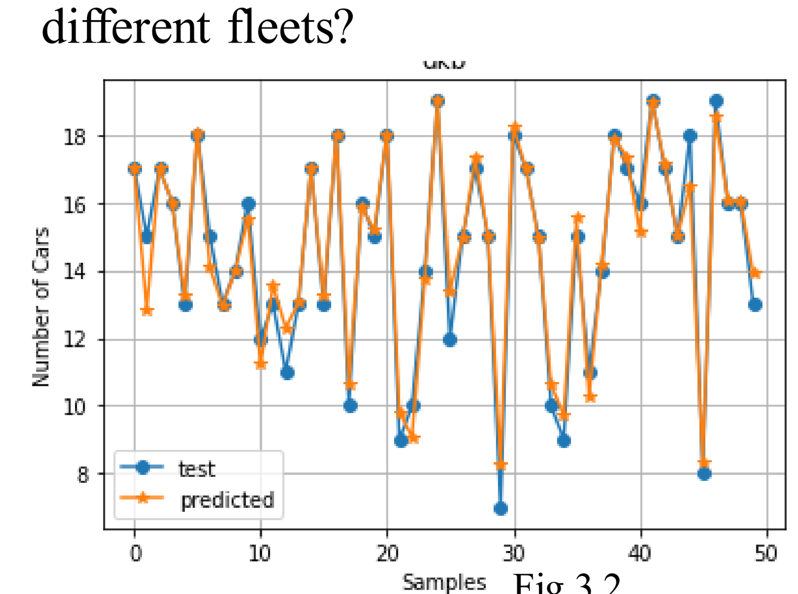

Fig 3.2

MODEL DEVELOPMENT AND OUTCOMES

- For our model we chose a Random Forest using Sci Kit Learn.
- We trained it on data including the time, day of the week, month, car battery charge level, temperature, humidity, and precipitation level
- Our model achieved an R2 value of .92, shown on the left is a graph of some of its predictions on untouched test data versus the actual values. (Ref fig 3.2)

DATA PIPELINE AND MODEL AUTOMATION

- In the future we look to add automation to our work
- A data pipeline will be able to automatically take new data, process, format, and feed it to our premade model on a scheduled timeline

ACKNOWLEDGEMENTS:

Special thanks to Dr. Ward, Nuvve and our mentors – Ted Smith and Hamza Lamsaddek, David Glass and the Data Mine faculty for their continued guidance and support.

OUR TEAM

Alan Bare, Angela Joseph, Aniket Mahajan, Ben Roath, Daniel Patel, Jack Brewer, Jayanth Palamand, Joo Wan Lim, Jordan Plymale, Luz Maria Agudelo Urrego, Mikaylah Poli, Mohammed Ayaz Naick, Nivedha Kumar, Prabhpreet Dhir, Salil Kulkarni, Yili Jin, Yuanhao Cheng, Yuhang Fang, Zhongkun Zhan, Zuhal Cakir

TA : Mihika Ghaisas