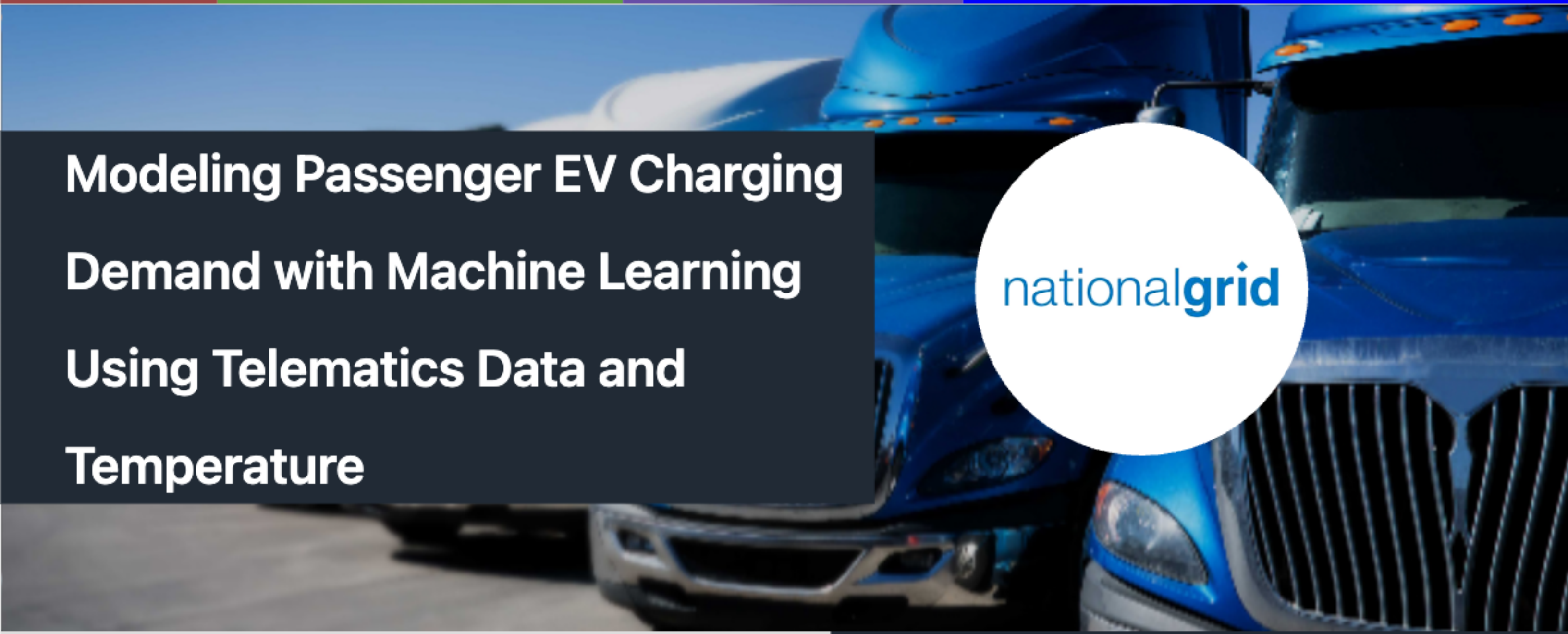
Operations | Transportation and logistics | Predictive forecasting | Ensemble-based (bagging, boosting, stacking)



Modeling Passenger EV Charging Demand with Machine Learning Using Telematics Data and Temperature

BUSINESS PROBLEM

The purpose of this research was to analyze passenger EV charging data from National Grid's Massachusetts EV Off-Peak Charging Program, the largest service-territory-specific EV charging data set the Company possessed , and determine whether scalable supervised machine learning models could be built to predict EV charging demand, and further determine the lowest geographic granularity of such models. This research and the resultant models aim to support more deliberate distribution infrastructure planning, inform electricity rate design, and improve managed EV charging programs to mitigate the impact of EV proliferation on peak energy demand.

APPROACH

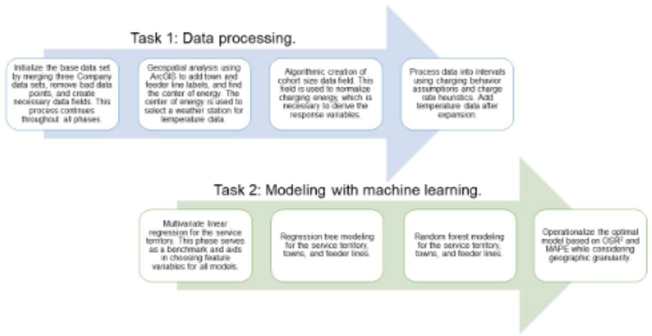
Modeling employed supervised machine learning methods with random forests being deemed optimal. This research was novel in its charge rate estimation methodology, normalization of charging energy to a per-vehicle basis, accounting for charging energy demand flowing into and out of the system being studied, and the addition of ambient air temperature as a feature variable.

DATA SOURCES

1.) Data from National Grid's Massachusetts EV Off-Peak Charging Program. 2.) Temperature data from Independent System Operator - New England (ISO-NE). 3.) Feeder line shape file from National Grid. 4.) Energy utility and town bound shape file from MassGIS.

Data Types and Format

All data was structured and processed locally as .csv files.



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IMPACT

Understanding when customers charge their EVs and how much energy they consume better enables the Company and other electric utilities to provide more reliable and affordable energy to all customers while aiding the transition to clean transportation. Ultimately, this research successfully created and operationalized an acceptably-accurate random forest model at the service territory level and illuminated the challenges associated with utilizing telematics data for demand modeling. The operationalized model was packaged into a save file which is loaded by an executable demonstration program that predicts passenger EV charging demand based on a temperature data file designated by the user. The program requests the number of EVs to scale its prediction and outputs the peak energy demand magnitude and time of year, along with graph that shows predicted demand by hour of year. The program can be used to generate lagging or forecasting demand predictions depending on the user's needs.

DRIVERS

Interviews with several stakeholders, ranging from managed EV charging customer program leads to data scientists, provided a detailed cross-functional view of how data are generated and analyzed within the Company. With a fresh perspective on the problem and guidance from several subject matter experts, an innovative approach and solution were generated.

BARRIERS

The telematics-based nature of the data and the lack of separation of charging energies into time intervals made this research very challenging. The vast majority of time was spent on data manipulation and preparing variables for modeling. However, after the data were organized and the preferred machine learning method, random forests, was identified, the modeling process went very smoothly.

ENABLERS

Employees in the Company were highly communicative and easy to approach. Answers to critical questions and mentorship were easily found throughout the internship by simply sending a meeting invitation and preparatory email. Feedback on research was timely and highly detailed.

ACTIONS

The operationalized model was packaged into a save file which is loaded by an executable demonstration program that predicts passenger EV charging demand based on a temperature data file designated by the user. Additionally, the data manipulation and modeling processes were carefully recorded to support future work.

INNOVATION

1.) Utilizes heuristics to estimate charge rates and uses the estimates to divide the data into equal time intervals. 2.) Charging energy is normalized on a per-vehicle basis in order to create scalable models. 3.) The models generated attempted to account for the influx of vehicles into the system and the efflux of vehicles out of the system. 4.) Ambient air temperature was added as a feature variable to increase model accuracy.

IMPROVEMENT

The Company now has an additional modeling tool based on highly specific and relevant data. More importantly, a process and set of recommendations were codified to enable better model design in the future.

BEST PRACTICES

1.) Request interval data that displays normalized energy consumption. 2.) Allow data to become more dense, perhaps over course of one additional year. 3.) Experiment with unsupervised learning methods. 4.) Temperature should be sustained as a feature in future predictive modeling for EVs. 5.) Incorporate more environmental features, such as precipitation, or temporal features that are easily derivable from a date, such as day of year or month.

OTHER APPLICATIONS

Given the niche application of the solution, it is not likely that the exact approach would work for a dissimilar problem. However, other electric utilities could utilize this research to create their own models from telematics data.