Quality Differences and Similarities of EVSE Chargers: An Analysis of the EV WATTS Database

Insert Subtitle Here

Peter Minor†
Computer Science, Post Bac
University of Colorado Boulder
Boulder Colorado USA
peter.minor@colorado.edu

Shammi Pereira
Computer Science, Post Bac
University of Colorado Boulder
Boulder Colorado USA
shammi.pereira@colorado.edu

Colin McNatt
Computer Science, Post Bacc
University of Colorado Boulder
Boulder Colorado USA
comc2281@colorado.edu

1 Problem Statement

As the U.S. electric vehicle market has grown, the challenges facing it have evolved. Early experience with battery electric vehicles (BEVs) focused on access to electric vehicle supply equipment (EVSE) chargers [1]. However, as the electric vehicle market has expanded, along with the charging infrastructure, access to EVSE chargers has been overtaken by issues related to charger reliability and convenience [2] [3]. Future BEV adoption is now linked to consumers' perception of charging infrastructure and the ability to reliably obtain a sufficient charge while away from home [4]. This project proposes to mine a large national database of over 13 million charging sessions between 2019 and 2022 to identify patterns in the data for what works and what does not work.

Charging session data provides a rich source of consumers' charging experience such as failed connection, low electric transmission and point failures (no charge when a charge was expected). Additionally, the EVSE data indicates the types of venues and general location of charging stations. Our project will look for patterns in the EVSE database which can shed light on charger reliability and performance across geographical areas and venues to identify patterns of what does and does not work in the EVSE market.

2 Literature Survey

Research on EVSE reliability is a relatively recent development. The first large scale research conducted in the U.S. on EVSE availability, reliability and their impacts on EV adoption was a US Department of Energy research project in 2009-2013 [1]. Early research necessitated the installation of hardware in addition to gathering data, due to the low number of EVSE chargers and cars. Subsequent research, mainly by individual states and government organizations, learned from earlier work and refined data collection techniques and proposed early measures of EVSE reliability. The California Air Resource Board (CARB) was instrumental in conducting state and regional research into EVSE availability [5] [6]. These early research studies focused primarily on the relationship between EVSE availability and BEV adoption rates.

2.1 Importance of EVSE Charger Reliability

As the number of chargers increased across the nation, secondary concerns, such as EVSE charger reliability, are becoming a primary concern, as consumers become aware that availability, while necessary for charging, is far from sufficient to obtain a charge [2] [7] [4] [3]. EVSE reliability can be broken into several categories which include: 1) finding a charger, 2) accessing a charger, 3) starting the charger, 4) completing a charge as expected, 5) getting help and; 6) feeling safe using a charger [6]. Several of these aspects are best obtained from surveys, such as finding a charger, accessing the charger and getting help [7]. This is because charger sensors\hardware cannot monitor consumers' experience or if there are cars parked in front of charger, limiting its use. Reliability measures such as starting the charger and completing a charge can often be ascertained from the data transmitted from the charger to the charger owner [4].

2.2 Current State of EVSE Charger Reliability

Since EVSE charger reliability is a relatively recent topic of concern, few standards have been set for measuring EVSE charger reliability, as can be ascertained from the charging hardware itself. An important junction in the literature and government regulations is that a reliable charger be "up" at least 97 percent of the time. This measure has created controversy, since most EVSE chargers that the government collects data for meet this standard, even chargers which would be defined as "poor" [4]. The problem with the standard is that it is largely self-reported and just requires that power be available for delivery. When more comprehensive metrics of reliability are used, reliability measures fall to between 63 and 86 percent and worse for specific chargers [4] [2]. These numbers must be considered in contrast to consumers' expectations relative to existing gas station reliability, which exceeds 99 percent.

2.2 Measuring EVSE Charger Reliability

Early research on EVSE chargers focused on mining information contained in charger error codes, such as charger stop requests, malfunctions, and charging faults [1]. These methods were found to be inadequate since they did not comport with user experience, impacting less than three percent of charging sessions [4] [2]. Instead, Gamage et al. of UC Davis have proposed two measures of EVSE charger reliability, which do not require the use of charger error codes: 1) throttled charging events, 2) point failures. Throttled charging events occur when a user expects their vehicle to obtain electricity at the stated charger capacity but receives significantly less. The authors define a throttled charge as 70 percent of the listed charge for a single charge connector and one -half that amount for dual chargers. Point failures occur when a charging session is initiated, but the charger delivers less than 0.3 kWh of electricity. Research shows that these types of failures occur between 20 and 40 percent of the time [4] [2]. Point failures are much less common than insufficient charges but are considered to have a much greater impact on the consumer's experience, since a low charge is still better than no charge at all [2].

2.3 Geographical and Venue differences

No surveys or databases are comprehensive of the US market. Most databases and surveys are a selection of geographical areas, which often include urban and rural areas. Research conducted by Energetics indicated distinct differences in regional utilization of EVSE chargers for the multi-dwelling unit (MUD) submarket [8]. In the case of MUDs, utilization rates of EVSE chargers in the mountain region were significantly higher than in the northeastern market area. These differences were attributed to the heterogeneity of MUD buildings and the tendency for northeast MUDs to be townhouses and condos, while the mountain region was made up more of apartment complexes, which appear to favor greater EVSE utilization.

2.4 EV Watts Database

As was mentioned earlier, EVSE research is in its early stages of development. Most early databases were limited in scope and reliability. The US DOE, therefore, sponsored the development of the EV WATTS database, which includes charging session information from over 30,000 EVSE chargers nationwide and includes data for the period 2019 to 2022. In all, there are over 13 million charging sessions included in the database [9]. The EV WATTS Database includes information on electricity transferred, session and charger details, such as length of session.

3 Proposed Work

The following sections outline the major steps in our proposed work.

3.1 Data Collection

Refer to section 4 Data Set.

3.2 Data Cleaning

In terms of data cleaning on the raw dataset, the following methods will be implemented: rename column names for better comprehension, handle duplicates, and determine missing/NaN values to remove rows and/or columns, impute mean or median values, or fill in with inference-based values.

3.3 Data Preprocessing

For data preprocessing, the following strategies will be implemented to get the dataset ready for modelling: encoding (convert categorical values to numerical values), manage noisy data through binning, regression and/or clustering techniques, and normalize data in a range of 0 to 1 using Manhattan Distance and Simple Matching Distance. Additionally, the following visualizations will aid in the data preprocessing: boxplots to determine and remove outliers, histograms to determine the probability distribution and modality of the dataset, and a correlation matrix to determine positive and/or negative correlation between the columns.

3.4 Data Integration

For data integration, the most important information is in the EV Charger Table of the EV Watts Database. This table will be joined with the sessions and vehicle trips tables, by referencing primary and foreign keys. To manage the size of the dataset, sampling or reducing the time frame might be implemented. Additionally, look up tables for charger error flags will have to be integrated. Since the database contains only the metropolitan statistical area of the charger, additional information such as population and businesses can be included from the Census Bureau[1].

3.5 Data Transformation

A key aspect of our data mining will include defining (categorizing) chargers as reliable or unreliable. Gamage et al. define charger reliability based on two factors: 1) throttled charging, and 2) point failures. = Before either of these measures can be calculated, the session records must be assigned unique alternate session IDs [4]. A high proportion of charges fall into the category of < .3kWh, not because the charge session completed with a low charge, but because the user has difficulty initiating the charge session and canceled it before significant electricity could be transferred. Frequently, a user will take two to three attempts to initiate a charge session. After a detailed analysis of charging sessions, Gamage et la determined that charging sessions within five minutes of one another were statistically likely to be the same users. Therefore, our first data transformation will require sorting the data by charger ID and charge time and assigning unique alternate session IDs, so the data can be rolled up into single charging session for multiple sessions of the same user. This will greatly reduce the number of point and throttled charging sessions from about 60 percent to about 30 percent of chargers.

Next, we will use the fields on charge transfers (kWh), charge time (seconds), type of charger (rating) to build the measures of throttled chargers and point failures. Specifically, a session's average power is defined as:

$$\frac{Energy\ dispensed\ (kWh)}{Charging\ time\ (seconds)}$$

A throttled charge is defined as any session transfer which is less than 70- percent of the power rating for the charger. When there are two charge connectors on the charger, that threshold is reduced by 50 percent.

Point failures will be categorized as any session which dispenses less than 0.3 kWh of energy.

These data on charger performance may be further transformed into a holistic reliability metric, based on probability measures (frequencies) based on Gamage et al. [4]:

$$Reliabilty = P(no\ point\ failiure) * P(no\ throttled\ charge) * P(no\ charge\ interuptions)$$

[1] https://www.census.gov/geographies/reference-maps/2020/geo/cbsa.html.

An interesting area of data mining we plan to explore is the application of this measure at the chargers, venue, and geographical levels.

3.6 Processes for Derived Data, Design and Evaluation

The derived data will be determined by conducting data aggregation by calculating the energy dispensed from chargers on a daily, monthly or yearly basis, as well as across locations. The design process includes data collecting, cleaning, preprocessing, integrating, and transforming as outlined above by incorporating the tools in section 6 Tools. The evaluation process will include testing the code with a sample of the data prior to testing it on the whole dataset, in addition to the methods outlined in section 5 Evaluation Methods.

3.7 Relation to Literature

The main goal for this project is to discover patterns for charger reliability and performance over different types of locations and venues using data mining techniques. This project will incorporate the reliability metric of two measures set by Gamage et al., which are (a) throttled charging and (b) point failures; this project will not utilize the third set measure (c) charge interruptions [6]. In terms of geographical areas, the project will aim to determine the differences in charger reliability based on urban vs rural areas. Since it has been determined that urban areas have more chargers than rural areas [3].

4 Data Set

The dataset for this project is sourced from the Livewire Data Platform (LDP), specifically the evwatts/evwatts.public database, maintained by the Livewire Data Platform. [2] It centers on the EV Charger table, which includes attributes such as charger location, power ratings (watts), error flags, and availability, complemented by linked sessions and vehicle trips tables capturing usage patterns and energy dispensation (kWh) across U.S. metropolitan statistical areas (MSAs).

[2] U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy (DOI: 10.15483/1970735, accessed 28 January 2025), https://livewire.energy.gov/ds/evwatts/evwatts.public

4.1 Supplementary Data

To deepen our analysis, we will integrate population and business density data from the U.S. Census Bureau's Core-Based Statistical Area (CBSA) reference maps. [3] This supplementary data enhances our understanding of charger deployment effectiveness relative to regional demographics. Additional data for micro and metropolitan areas may be sourced from the American Community Survey, to further refine our demographic analysis if needed.

4.2 Relevance and Storage

This dataset supports research on the optimal placement and utilization of publicly accessible EV charging stations, focusing on attributes like energy dispensed (kWh), charging time, and charger type (AC Level 2 or DC Fast Chargers [DCFC]) to derive quality metrics such as throttled charging and no5garge events. It is currently stored locally and in a shared OneDrive folder.

5 Evaluation Methods

We will evaluate charger usage based on vehicle type, location, trip session data, and charging bouts through cross-validation to ensure strong generalization and performance metrics across different conditions. Our analysis will include classification using a Confusion Matrix to assess charger type performance, regression with MAE, MSE, RMSE, and multiple linear regression for charger efficiency predictions, and clustering via the elbow method to group vehicle types, charger types, and session durations. To address potential discrepancies in validation and external benchmarks, we will implement data normalization to ensure fair comparisons and adjust for reporting bias, particularly in light of ChargerHelp's study, which found that self-reported uptime was, on average, 11% higher than actual usage logs indicated. Additionally, we will compare our findings with key external studies, including David Rempel's research on charger reliability and Powell & Johnson's work on the impact of location, grid resilience, and environmental conditions on EV

[3] https://www.census.gov/geographies/reference-maps/2020/geo/cbsa.html

charging. By leveraging these external benchmarks and refining our data validation approach, we aim to provide a comprehensive and reliable assessment of charger performance and efficiency across various stations and scenarios.

We will evaluate charger usage based on vehicle type, location, trip session data, and charging bouts through cross-validation to ensure strong generalization and performance metrics across different conditions. Our analysis will include classification using a Confusion Matrix to assess charger type performance, regression with MAE, MSE, RMSE, and multiple linear regression for charger efficiency predictions, and clustering via the elbow method to group vehicle types, charger types, and session durations. To address potential discrepancies in validation and external benchmarks, we will implement data normalization to ensure fair comparisons and adjust for reporting bias, particularly in light of ChargerHelp's study, which found that self-reported uptime was, on average, 11 percent higher than actual usage logs indicated [6]. Additionally, we will compare our findings with key external studies, including David Rempel's research on charger reliability [10] and Powell & Johnson's work on the impact of location, grid resilience, and environmental conditions on EV charging [6]. By leveraging these external benchmarks and refining our data validation approach, we aim to provide a comprehensive and reliable assessment of charger performance and efficiency across various stations and scenarios.

6 Tools

The following sections review the software tools and their mining methods we plan to employ in our research.

6.1 Python and Libraries

Python will be utilized in the Jupyter Notebooks development environment, along with many of its libraries. The Pandas library will be used for data cleaning, preprocessing, integrating, and transforming since it can handle large datasets. The Numpy library will be used for statistical analysis since it can handle numerical computations. The libraries Matplotlib and Seaborn will be used to create visualizations such as boxplots, histograms, and correlation matrices, to aid in further data analysis. If needed, the libraries Plotly and Plotly Dash will be used to create an interactive dashboard for data exploration. The Sci-Kit Learn library will be used to implement machine learning and data mining techniques, such as classification, regression, and clustering.

6.2 Machine Learning and Data Mining Techniques

Classification can be used to determine the performance of different charger types (L2 vs DCFC) based on various factors such as charging session duration, amount of energy delivered, port availability, charger location, etc. Regression can be used to predict the efficiency of chargers based on the dependent variable being the amount of energy delivered and the independent variables being charging session duration, port availability, charger location, etc. Clustering can be used to group charger types and session durations to discover patterns between differing charger types and session durations.

6.3 Additional Tools

The version control system that will be implemented for collaboration is Git, with GitHub. Various MS OneDrive tools (MS Word, MS Excel, MS PowerPoint) will be used to store project information, datasets, and to create presentations.

7 Milestones

- March 3, 2025 (Proposal Paper)

Complete proposal development, finalizing the problem statement, literature survey, proposed work (including cleaning, preprocessing, and integration plans), dataset details, tools, and evaluation methods. Submit the Part 2 proposal in ACM SIG format.

- March 17, 2025 (Progress Report)

Clean the dataset (rename columns, remove duplicates, impute missing values) and preprocess (encode variables, normalize with Manhattan/Simple Matching Distance, generate boxplots, histograms, and correlation matrices). Integrate the EV Charger

Table with sessions, vehicle trips, Census data using charger IDs and session IDs, adding error flag look-up tables. Implement the EVSE quality index (Gamage et al.'s measures: throttled charging < 70% rated power, no-charge events < 0.3 kWh) [4]. Submit the Part 3 report with initial findings.

- April 7, 2025

Conduct data mining, building and testing models (e.g., clustering, regression) with Sci-Kit Learn on the integrated dataset to explore charger utilization and quality patterns, drafting preliminary results.

- April 21, 2025

Finalize analysis, complete model evaluation (per Cassandra's methods), refine visualizations with Matplotlib/Seaborn or Plotly, and prepare the final report, code, and presentation materials as a team.

- April 28, 2025 (Final Deliverables)

Submit all components: the 10–12-page Part 4 report, Part 5 code with README (via GitHub), Part 6 video and slides, and individual Part 7 peer evaluations to Moodle.

REFERENCES

[1] Idaho National Labratory, "What Can be Learned From The EV Project to Inform Other Who May be Interested in a Similar Study?," Idaho National Labratory, Idaho Falls, ID, 2015.

[2] Energetics Clean Energy Consulting, "Electric Vehicle Charging Station Reliability," Energetics Clean Energy Consulting, 2024.

[3] C. W. Quinn, S. Cardinali, J. Clifford, K. Houck, K. Moriarty, M. Savargaonkar, J. G. Smart, D. E. Smith and B. J. Varghese, "Customer-Focused Key Performance Indicators for Electric Vehicle Charging," Idaho National Laboratory, Idaho Falls, 2024.

[4] T. Gamage, A. Jenn and G. Tal, "Reliability of Corridor DC Fast Chargers and the Prevalence," in *36th International Electric Vehicle Symposium and Exhibition (EVS36)*, Sacramento, 2023.

[5] California Air Resource Board, "Electric Vehicle Supply Equipment Standards Technology Review," California Air Resource Board, Sacramento, CA, 2022.

[6] B. Powell and C. Johnson, "Impact of Electric Vehicle Charging Station Reliability, Resilience, and Location on Electric Vehicle Adoption," Renewable Energy Laboratory, Golden, CO, 2024.

[7] J.D. Power, "Public Charging Issues May Short-Circuit EV Growth," J.D. Power, 2023.

[8] Energetics Clean Energy Consulting, "Multi-Unit Dwelling Station Utilization," Energetics Clean Energy Consulting, 2023.

[9] Yash Pavuluri, "EV Watts Public Database," US Department of Energy, USA, 2025.

[10] D. Rempel, C. Cullen, M. M. Bryan and G. V. Cezar, "Reliability of Open Public Electric Vehicle Direct Current Fast Chargers," 7 April 2022. [Online]. Available: https://ssrn.com/abstract=4077554.