**Public electric vehicle charging station utilization in the United States**

---We quantify the real-world EV charge acceptance ratio (i.e., the average power delivered to an EV divided by an EVSE’s rated power level) and charge idling frequency (i.e., the percent of time an EV is plugged in but not charging) from around 1.5 million unique charge sessions.

----conduct a **regression analysis** to assess the relationships between public station utilization and several contextual and environmental factors.

Data: EV WATTS by DOE access, 8.4 million sessions.

**Hotel:** hotel parking lots provided for patron use; Leisure: parks and recreation facilities, museums, sports arenas, or national parks/monuments.

**Medical/Educational:** hospital campuses, medical office parks, or educational facilities such as training centers, universities, or schools.

**Municipal:** city, county, state, or federal government facilities.

**Office:** business offices, office parks/campuses, or industrial facilities.

**Parking lot/garage:** parking lots or garages operated by private parking management companies, property management companies, or municipalities offering direct access to a variety of venues.

**Retail:** retail locations both large and small, including shopping malls, strip malls, and individual stores.

**Transit:** parking locations with direct pedestrian access to other forms of transportation such as airports, metro-rail stations, or ferry ports.

**Data Cleaning**

(1)sessions with delivered **energy >140 kWh**, since these are incompatible with the usable battery capacities of the Rivian R1T and extended-range **Ford F-150** Lighting, the two mass-market EVs with the largest batteries available through March 2022; (2) sessions with a **charge duration of 0 h or** where no energy was delivered; and (3) sessions requiring an **average charge power greater than the port’s rated power level.** These criteria filtered out 6 % of unique charging sessions for the 3,705 public stations, leaving 1,479,236 sessions for subsequent analysis.

**Data representativeness**

compare data set to national EVSE stations reported in DOE’s **Alternative Fuels Data Center (AFDC)**

**EVSE port’s rated power level**

**port’s rated power**

The majority of public L2 ports in our data set have a rated **power level** of 6.6 kW or less (97 %), and most public DCFC ports are 50 kW or less (97 %); however, the maximum power levels for L2 and DCFC ports are 16.6 kW and 170 kW, respectively.

The geographic distribution of public EVSE stations in the data set reflects the distribution of data. To show our data set is overrepresented or underrepresented. the two data sets are correlated (r = 0.4, p = 0.004)

**station utilization** as the average energy delivered by a station during a time period divided by the number of ports. This is calculated as:

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where estation,i is the energy delivered by a charging station during period i ∈ t, which is divided by pstation, the number of ports per station.

average daily basis in **kilowatt-hours per port per day** or could be **(kWh/port/hour).**

🡪Calculate average daily station utilization for the month.

The following linear equation is used to understand the factors influencing public station utilization (in kWh/port/day):



minimizes the sum of the squared differences between the observed dependent variables (**Utilstation**) and the expected values predicted by the fitted equation.

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**EV charge acceptance**

The actual rate of charging depends on multiple factors, such as ambient temperature, battery temperature, battery state of charge, and EV-specific acceptance rates. Despite this, some studies assume that EVs charge at an EVSE port’s rated power level when assessing station utilization (translating percent of time charging to energy delivered under this false assumption).

ratio of average delivered power to the port’s rated power for all charging sessions

**🡪session delivered power / rated port power**

**(<50 % for L2 ≥ 7.2 kW and DCFC > 50 kW).** This trend is explained by the current composition of

EVs on the road in the United States

**Charge idling**

when an EV is plugged into an EVSE port but not charging (poor use of resources)

🡪implement idling fees, billing customers for time spent plugged in after a charge session ends

🡪significant variance in the dependent variable that is not explained by the independent variables.

🡪following five variables to have the greatest statistically significant (0.05-level) relationship with L2 station utilization: free charging (β = 2.06, p = 2e-03), paid charging (β = -1.19, p = 4e-02), local population density (β = 4e-04, p = 1e-02), local L2 charging network size (β = -0.02, p = 2e-03), and local EV adoption (β = 0.23, p = 1e-03). Port power level, venue type, and local DCFC charging network size do not have a statistically significant relation to L2 station utilization.

 🡪The more people in an area who own EVs, the higher the demand for charging stations, n utilization are both improved by offering free charging.

🡪Surprisingly, venue type does not have a statistically significant relationship to utilization.

**Electric Vehicle Public Charging Infrastructure Planning Using Real-World Charging Data**

The data used for the analysis are the charging station availability that is accessible via different platforms in Germany 🡪21,777 charging points (CPs) 1,836,076 charging events.

* For each CP, we calculate the key performance indicators (KPIs) charging events per week and average event duration.
* We use POIs located and characterized in the OpenStreetMap (OSM) service. <https://openpoimap.org/>

🡪correlation between charging point utilization and the individual POI categories,

🡪the POIs within a certain radius r around the considered CP location are considered in the regression.

Methodology 🡪 a multiple linear regression

The geographic a POI right next to the CP has the strongest inﬂuence while vanishing with distance. To limit the effective area of POI impact to walking distances,

🡪distances between CPs and POIs are determined using the inverse haversine formula

1. Creation of a Voronoi graph that allocates areas to the nearest CS,

2. Numerical integration of the attractiveness covered within the intersection area of the walking distance radius and the Voronoi area of a CS,

3. Genetic optimization of the collected attractiveness through additional CS at new sites.

**Analysis of Electric Vehicle Charging Behavior Patterns with Function Principal Component Analysis Approach**

functional data analysis (FDA) approach

some charging stations were more frequently used and might have thousands of charging records while others might only have a few hundred. It was thus impossible to apply principal component analysis (PCA) to the charging log dataset directly because of the dimension inconsistency.

ﬁrstly represented the EV charging dataset with a continuous functional form, then performed function principal component (FPC) analysis to identify the main contributing principal components (PC) and analyzed the dataset from diﬀerent perspectives to understand EV owner’s charging behavior patterns.

🡪The ﬁrst aspect is the variability analysis of the daily usage patterns of all EV charging stations, in which the 24-hour occupancy of all charging stations in one day was treated as one continuous curve.

🡪 The second aspect is the variability analysis of the daily energy consumption of all EV charging stations, in which the total energy consumption of all charging stations in one day was treated as one continuous curve.

🡪 At the station level, the usage pattern variabilities were analyzed, in which one station’s usage over the entire observation period was treated as a continuous curve.

**Data**

The data was collected from 455 charging stations between January 2014 and November 2019 in Kansas City, Missouri (KCMO). The dataset included a total of 226,652 charging records from 4,921 users.

the proposed FDA approach considered EV charging usage as a function of time; thus, all the EV charging events that were sampled in diﬀerent scales, from diﬀerent charging stations built at diﬀerent time periods, and used with diﬀerent frequencies with diﬀerent data sizes, were all modeled uniformly by functions.

Each charging pattern to be deﬁned in Section 3.2 was treated as one functional data:

Daily Usage Occupancy.’

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24-hour time-dependent occupancy:

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ud(t) means the average occupancy of time t at day d, and J means the total number of stations on day d.

Daily energy consumption:

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the 24-hour time-dependent energy consumption:

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Station-Level Occupancy.:

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Data Smoothing:

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**B-spline expansion**

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**A data driven typology of electric vehicle user types and charging sessions**

based on 4.9 million charging transactions from January 2017 until March 2019 and 27,000 users on 7079 Charging Points the public level 2 charging infrastructure of 4 largest cities and metropolitan areas of the Netherlands.

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In this research the **Gaussian Mixture Model (GMM)** was used for clustering. The GMM is a clustering method that performs clustering based on fitting multiple Gaussian (normal) distributions on a dataset such that the sum of these distributions fits the original shape of the data. As a result, each cluster is shaped as a multivariate normal distribution that describes the input features. We hypothesized that our dataset was drawn from a mixture of probability distributions, each from an independent subpopulation of charging sessions relating to types of behavior.

Start times were normalized from 0 to 1, 1 meaning midnight (23:59 hrs), with clear morning and evening peaks. The connection duration was normalized from 0 to 48 h. The HBS value normalized from 0 to 196. For the Distances Between Sessions (DBS) first the log10 taken on the DBS in meters and then the DBS was normalized from 0 to log 152.99 10 (km).

1. Utilization Rate:
   * Calculate the utilization rate of existing charging stations by dividing the total charging time by the total available time (24 hours \* number of days \* number of ports).
   * Identify stations with high and low utilization rates to understand demand patterns.
   * Project future utilization rates based on trends in electric vehicle (EV) adoption and charging behavior.

🡪How many unique ports number for each EVSE ID

1. Energy Consumption:
   * Analyze the "Energy (kWh)" column to understand the energy consumption patterns at different charging sites.
   * Identify sites with high energy consumption, indicating high demand and potential for expansion.
2. Revenue Generation:
   * If the "Fee" column contains charging fees, calculate the revenue generated at each site.
   * Identify sites with high revenue generation, indicating potential profitability.
   * Project future revenue based on expected increases in EV adoption and charging demand.
3. Geographic Distribution:
   * Use the location data (e.g., Latitude, Longitude, City, State/Province) to visualize the spatial distribution of charging sites.
   * Identify areas with high EV adoption rates and potential gaps in charging infrastructure.
   * Plan for new charging site locations based on projected EV adoption and population growth patterns.
4. Charging Duration and Session Patterns:
   * Analyze the "Total Duration (hh:mm:ss)" and "Charging Time (hh:mm:ss)" columns to understand charging duration patterns.
   * Identify peak hours and days for charging demand.
   * Determine the need for additional charging stations or faster charging options based on session patterns.
5. Charging Station Types:
   * Use the "Port Type" and "Plug Type" columns to differentiate between Level 2 and DC fast charging sites.
   * Analyze the demand and utilization patterns for each charging type.
   * Determine the appropriate mix of Level 2 and DC fast charging stations based on user preferences and charging needs.
6. Electric Vehicle Adoption Trends:
   * Research and incorporate local, regional, and national projections for EV adoption over the next 5 years.
   * Adjust the demand and utilization projections based on expected increases in EV ownership.
7. Policies and Incentives:
   * Consider the impact of government policies, incentives, and regulations on EV adoption and charging infrastructure deployment.
   * Factor in potential changes in policies and incentives that could influence charging site viability.