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Empirical insights on usage trends and patterns of public fast-charging stations in Germany

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Abstract

Battery-electric vehicles (BEVs) are the most likely solution for the rapid and effective decarbonization of road transport to limit global warming. Yet, their continued adoption critically depends on the availability and usage of charging infrastructure, with inadequate coverage consistently cited as one key barrier. This study analyzes usage patterns of over N=7,500 public fast-charging stations in Germany over a two-year period, with an emphasis on utilization metrics, usage intensity, and charging patterns through data visualizations and statistical methods. The analysis confirms distinct day-night and weekday-weekend usage patterns and reveals slightly increasing utilization over time. Moreover, the study highlights how the ratio of energetic to temporal utilization differs across power classes, from one-to-five to one-to-two, and finds that station performance is more closely linked to the frequency of charging events than to rated power, charging duration, or charged energy per event. These empirical insights offer valuable guidance for optimizing the expansion and operation of a comprehensive and functional fast-charging network.

1 Introduction

Electric vehicles (EVs) are transforming the automotive industry as the most likely solution for the rapid and effective decarbonization of road transport to limit global warming, keeping touch with the Paris Climate Agreement and reaching climate neutrality by mid-century [1, 2]. In both Germany and Europe, passenger cars were responsible for about 12% of their total annual greenhouse gas (GHG) emissions by the early 2020s [3]. While global EV sales are increasing thanks to technological innovation, policy development, and investments, they remain substantially concentrated in just a few major markets [4]. At the beginning of 2025, EV sales shares reached around 20-25% in both Germany and Europe, while European CO_2 emission performance standards for new cars and vans set a 100% zero-emission vehicle (ZEV) target from 2035 onwards (Regulation (EU) 2023/851). Central to this ZEV transition are battery electric vehicles (BEVs), particularly when powered by low-carbon electricity [1].
However, the continued adoption of BEVs critically depends on the availability and usage of charging infrastructure, with inadequate coverage consistently cited as one key barrier [5, 6]. Beyond home charging, widespread BEV adoption requires reliable public charging infrastructure networks to enable day-to-day and, in particular, long-distance operations. At the beginning of 2025, Europe hosts about 150,000 public DC (direct current) fast charging points (Germany: 38,000) and about 780,000 public AC (alternating current) charging points (Germany: 131,000) [7].

In this paper, we provide a timely and comprehensive analysis of how and when public charging points (CPs) are used to improve understanding of charging behavior amid a heterogeneous market. The goal is to inform infrastructure planners and policymakers through empirical insights to improve user-centered charging infrastructure deployment strategies (site selection and sizing) and prevent systemic bottlenecks (grid stability and underutilization). Here, we address two research questions, taking Germany as our case and using long-term usage data:

Q1: What are typical occupancy durations of CPs, how much energy is charged per event, and how usage characteristics vary across CPs?

Q2: How to determine the attractiveness of CPs and what relation exists between their temporal and energetic utilization?

The remainder of this paper is organized as follows: The next subsection reviews relevant literature and summarizes key findings; Section 2 starts with introducing the dataset and data processing, and concludes with outlining the methodology; Section 3 presents the results; Section 4 discusses the findings and their implications as well as limitations of this study; and Section 5 concludes the paper.

Literature review

Several studies have already examined charging behavior and infrastructure utilization, varying in focus, approach, data source and available information, country or regional coverage, and amount of data. Among these, we highlight the following studies in chronological order:
Gnann *et al.* [5] analyzed usage data of N=224 fast charging stations in Sweden and Norway. The authors paired the empirical insights with statistical analysis, queing models, energy simulation, and driving data to create synthetic BEV fleets for Germany and Sweden and then simulated charging times, arrival-departure slots, and seasonal charging demand. They indentified right-skewed distributions (charged energy and duration) and distinct day-night charging patterns with peak usage around 11 AM to 5 PM, and highlighted seasonal variations (summer-winter and vacation-working periods).
Yang *et al.* [8] examined real-world data from N=130 BEVs in Beijing over seven months, finding that most fast charging events occurred after 10 AM, with peak usage between 1–4 PM. A regression analysis indicated that vehicle-related factors (e.g., State-of-Charge, expected trip duration and distance, or driving speed) significantly influenced the likelihood and duration of fast charging events. However, this information is usually not available for charger-derived data.
Hecht *et al.* [9] collected usage data of N=22,200 charging stations across Germany (2019-2021) to analyze usage behaviors through visualization. Their findings revealed clear differences by area type (urban, suburban, industrial) and power level, with distinct day-night and weekday-weekend patterns that are refined around typical commuting-to-business hours.
Borlaug *et al.* [10] analyzed usage data of N=3,705 charging stations in the United States (2019-2022) to identify

temporal utilization patterns and assess dependencies among the energetic utilization (kWh/port/hour) and contextual factors (such as charging price, venue type, population density, or local EV adoption and charger networks). Regarding temporal patterns, their findings revealed clear differences by venue type and charger type (DC fast chargers vs. Level-2) with distinct day-night and weekday-weekend patterns. However, the utilization is very heterogeneous, with a few chargers accounting for a large proportion of the total energy (highly inflected Lorenz curve). The regression results (R^2 = 0.14–0.18) showed utilization positively associated with local EV adoption and free charging, but negatively with network density; venue type had no significant effect.
Jonas *et al.* [11] evaluated usage data of N=6,700 chargers in Canada, comparing residential and public Level-2 and DC fast charger usage. Similar temporal trends (day-night and weekday-weekend) were observed for public charging, with peaks around 7:30–8:30 AM and 4–5 PM, both aligning with commuting hours.
Capeletti *et al.* [12] investigated usage data of N=10 fast charging stations in Brazil (Aug 2023-Jun 2024), confirming recurring usage patterns across area types and time (day-night and weekday-weekend), consistent with prior findings in other regions.

To summarize, real-world usage data across multiple countries consistently reveal heterogeneous but recurring EV fast charging patterns, with distinct day-night and weekday-weekend cycles and minor seasonal trends, peak usage during commuting hours, high utilization often concentrated at a small number of stations, and strong influences from location type, charger type, and local EV adoption. However, an updated analysis based on a long-term dataset, which expands on Hecht *et al.* [9], is still valuable to capture emerging trends in this rapidly evolving EV market. Plus, current literature lacks a detailed differentiation of station utilization across usage tiers (from low to high performers, and possible reasons) but focus on average considerations, and an assessment of different utilization metrices such as session counts, plug-in duration, and charged energy.

2 Data and Methods

Raw data

The data provided by the German National Center for Charging Infrastructure [13] comprise high-resolution usage data from all publicly funded fast charging stations in Germany (above 22 kW) over a two-year period (January 2022–December 2023). The data were split into four datasets and provided via the online reporting platform for charging infrastructure (called OBELIS), each representing six months of usage data. Each dataset covers millions of charging events (2,66-2,96 million) from around N=7,500 stations, with individual identifiers for each charging station (CS) and its charging points (CP). The data capture plug-in and unplug times, the charged energy (in Wh), and the rated power (in kW) per charging point and event. Furthermore, each station is characterized by one of seven general location types (i.e., parking_public, parking_garage, parking_customer, parking_park&ride, fuelingStation, fuelingStation_highway, or others), one of three general regional types (i.e., urban, rural, or undefined), and one of four predefined use cases (i.e., charging_street, charging_customer, charging_hub_corridor, or charging_hub_city). However, the dataset does not include geographical coordinates due to anonymization, vehicle-specific information (e.g., battery type, plug type, or State-of-Charge), the maximum/total power of the whole charging station, information on the charger technology (AC or DC), nor information on the total number of charging stations on site, and identifiers vary between the datasets so that station-related analyses are limited to six months.

In total, the data capture about 11.4 million charging events that are related to 211.1 GWh of charged energy and 28.5 million hours of charging duration, splitted among N= 59,545 CPs and N=30,095 CSs. ***Table 1*** provides a summary of the dataset. Note that the data also include auxiliary charging points in addition to regular ones, such as a 3.7 kW AC charging point for emergencies that supplements one or two regular charging points at a DC fast-charging station. Further information on use case and location definitions is available at [13, 14].

Table 1: Key elements of the dataset

Data Field	Description	Data Type
CP ID	Unique identifier per charging point (equal to plugs per station)	Char
CS ID	Unique identifier per charging station	Char
Timestamp	Start time (plug-in) and end time (unplug) of the charging event	Timestamptz
Charged energy	Amount of energy charged per event (in Wh)	Float
Rated power	Maximum charging power per charging point (in kW)	Float
Location	One of seven location types	Categorical
Use case	One of four predefined use cases	Categorical
Region	One of three regional types	Categorical

Data processing

Several filtering steps and assumptions were required to prepare the data for the subsequent analyses and visualizations:

- The rated power of each charging station (in kW) is defined as the maximum rated power among its associated charging points.
- All CPs and associated events in which the rated power of the CP does not align with that of the corresponding CS were classified as irregular events, and, thus, excluded from the analysis.
- The charging duration (in seconds) follows from plug-in and unplug times and thus corresponds to the occupation period. However, the occupation time may exceed actual charging duration due to delayed unplugging.
- Charging points were classified into six categories based on rated power to distinguish various levels of AC chargers and DC fast chargers. AC categories include: low-power ($P_{rated} < 11$ kW), medium-power (11 kW $\leq P_{rated} < 22$ kW), and high-power (22 kW $\leq P_{rated} < 50$ kW). DC categories include: low-power (50 kW $\leq P_{rated} < 100$ kW), high-power (100 kW $\leq P_{rated} < 200$ kW), and ultra-fast chargers ($P_{rated} \geq 200$ kW).
- All incomplete or erroneous charging events – primarily due to missing or invalid data – and charging points in undefined regions were excluded from the analysis.
- To exclude malfunctioning or inactive chargers, a minimum threshold of ten charging events across at least four distinct weeks per six-month period was required for each CP.

As a result, 11% of all CPs and 4% of all CSs were excluded from the analysis, representing 4-6% of the total information on duration, energy, and events. ***Table 2*** shows the composition of the processed data by splitting the charging events, energy and duration among power classes. Accordingly, DC chargers account for about 12% of all CPs and 16% of all CSs, contributing about 27% of all charging events, 38% of the total charged energy and 6% of the total charging duration.

Table 2: Sample composition by power class

Type	Power class	# CP	# CS	# Events	Charged energy	Charging duration
AC	[0,11 kW)	0.04%	0.05%	0.01%	0.00%	0.01%
	[11 kW, 22 kW)	5.19%	4.88%	2.21%	1.91%	4.10%
	[22 kW, 50 kW)	82.56%	79.55%	70.96%	60.23%	89.47%
DC	[50 kW, 100 kW)	7.17%	9.75%	11.76%	13.79%	3.43%
	[100 kW, 199 kW)	3.38%	4.30%	7.64%	11.98%	1.66%
	≥200kW	1.67%	1.48%	7.42%	12.09%	1.32%
Total		**53,021**	**28,956**	**10,702,557**	**202.26 GWh**	**27,344,621 h**

Further, note that this will focus on fast charging infrastructure so that low- and medium-power AC chargers were excluded from the analysis, while high-power AC chargers were retained due to their market relevance and presence.

Further data integration

To account for contextual factors, monthly registration data for electric vehicles (BEVs and plug-in hybrids) in Germany for January 2022 to December 2023, as well as monthly average temperatures for Germany, were incorporated from different sources. Due to the anonymized nature of the OBELIS dataset, finer spatial resolution within Germany was not feasible.

Methods

To analyze the results, both visual and statistical methods are employed. Visualizations are stratified by key parameters, while statistical analyses include contingency tables, correlation matrices, and regression modeling to assess effect strengths and the significance of contextual factors and recognize patterns. In this context, utilization rates and usage tiers were defined.

Concerning utilization rates per time period and CP, the following assumptions were applied. Note that time periods may be days, weeks, months, or half-years:

- Temporal utilization, denoted as λ_T, follows from the total occupation period (in seconds) in relation to the total time per period (in seconds).
- Energetic utilization, denoted as λ_E, follows from the actual charged energy (in Wh) in relation to the theoretically charged energy (in Wh), which is calculated from the rated power and total time per period. At the same time, the average charging power, denoted as P_{mean}, is calculated for each charging event based on charged energy and occupation period, and evaluated in relation to the rated power.

Concerning usage tiers, three tiers were defined that either use the number of charging events, total energy, or total charging time as the respective reference:

- Low performers, denoted as *bottom20*, are defined as those falling within the lowest 20% of the distribution, corresponding to values below the 20% quantile of the specified reference.
- Average performers, denoted as *mid50*, are categorized as chargers situated within the middle 20% of the distribution, corresponding to values between the 40% quantile and the 60% quantile of the specified reference.
- Top performers, denoted as *top20*, are defined as those exceeding the highest 20% of the distribution, corresponding to values above the 80% quantile of the specified reference.

3 Results

Usage intensity of public fast chargers

Usage intensity to evaluate the attractiveness can be measured in various ways, each with limitations. While simple metrics like charge events per time period ignore energy charged and session duration, time-based measures (occupation as percent of time plugged-in or actual charging time) risk either over- or underestimating actual usage. Thus, charging point operators typically prefer energy-related considerations [10], which also eases the incorporating infrastructure costs into the pricing of charging services via the levelized cost of infrastructure. However, energy-related information is usually more difficult to obtain.

Figure 2 visualizes the relation among these different metrics. Each point represents a CP and its normalized ranking (with the respective minimum and maximum) when comparing events-to-energy (upper, blue) or time-to-energy (bottom, red). The diagonal provides orientation, with points below as energetically more attractive CPs (high total charged energy) despite having relatively fewer charging events or shorter charging times compared to other CPs in the sample, and vice versa for points above the diagonal. The scatters also confirms that high usage intensity often concentrates on a small number of CPs.
Concerning AC chargers, it becomes evident that charging time is a less effective metric for assessing usage intensity or attractiveness. This is likely attributed to the fact that CPs with high utilization do not necessarily correlate with a substantial number of charging events or high energy throughput. Such patterns may indicate prolonged occupation periods without active charging, particularly during overnight periods. The number of

charging events demonstrates a better alignment with the energetic perspective, indicating a more consistent but still imperfect relationship.

Concerning DC chargers, an analysis of charging events, time, and energy yields similar classifications, particularly for ultra-fast chargers. Similarly, the number of charging events demonstrates a better alignment with the energetic perspective than charging duration.

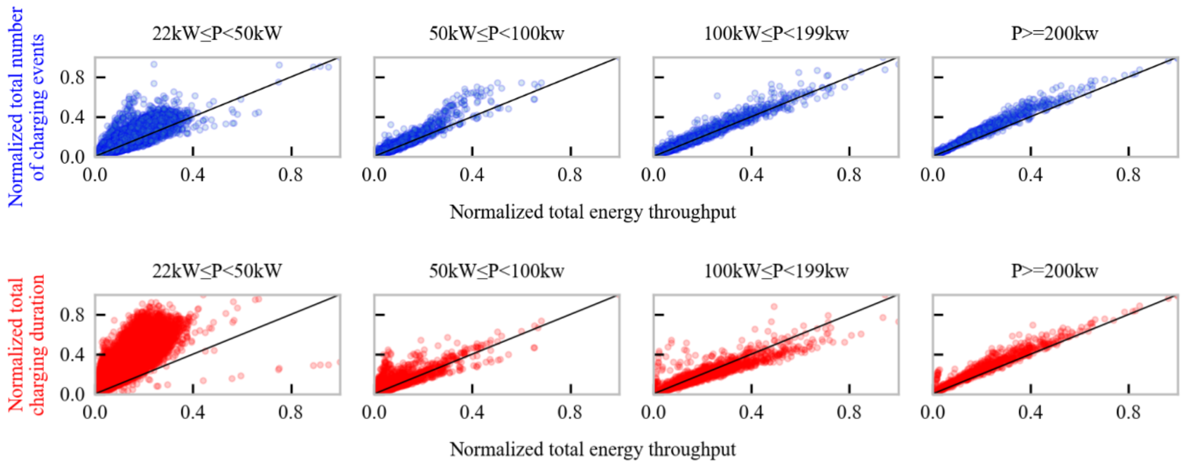

Figure 1: Usage intensity across different metrics by power class.

Utilization of public fast chargers

Figure 3 visualizes the relationship among the energetic and temporal utilization as a scatter plot across various power classes, where each point represents one CP in the stated the observation period. All plots reveal that the resulting ratios exhibit a remarkable consistency, largely independent of the observation period. Notably, AC chargers tend to exhibit the highest temporal utilization, albeit accompanied by the highest spread among all CPs, reflected by moderate R^2 values (0.67 to 0.79). However, energetic utilization is usually well below 10%. In contrast, ultra-fast DC chargers demonstrate the lowest low spread and most robust ratio, reflected by high R^2 values (~0.94). Utilization peaks are particularly noticeable for weekly scatters and are smoothed over an extended period. Specifically, high-power AC chargers demonstrate an energy-to-time utilization ratio of about 1:5, low-power DC chargers present a ratio near 1:2, high-power DC chargers present a ratio of about 1:3, and ultra-fast DC chargers exhibit a ratio of about 1:4.

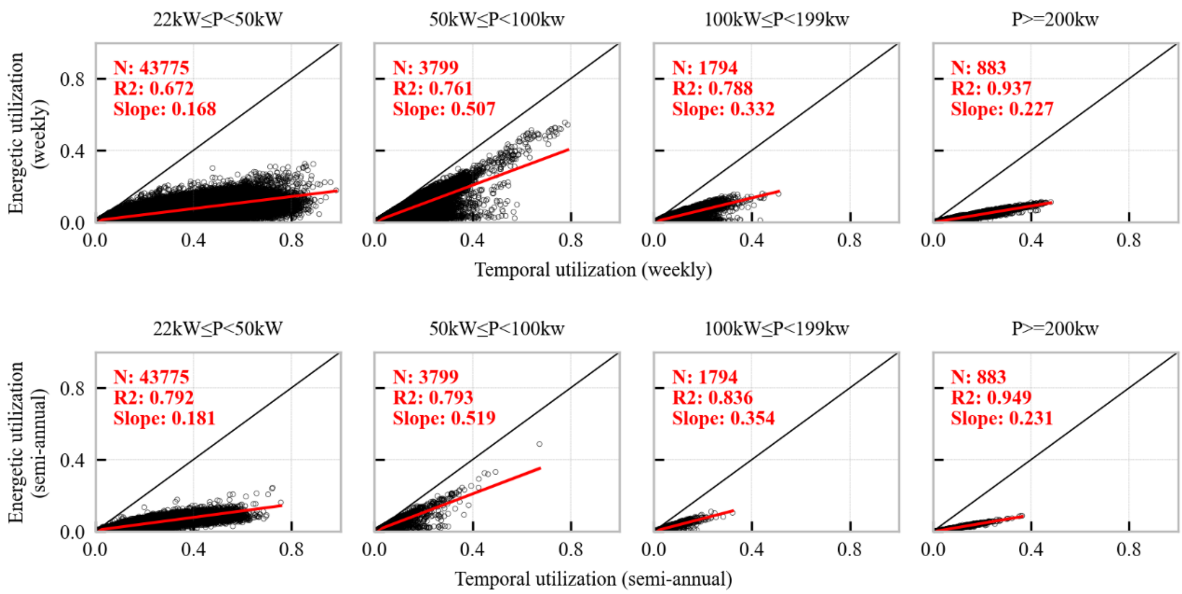

Figure 2: Charger utilization by power class.

Detailed examination of DC chargers

Figure 3 visualizes the mean charged energy (in kWh) and duration (in min) per charging event as histograms with kernel density estimators. The analysis reveals distinct variations across different power classes, while demonstrating large discrepancies for low-power DC chargers between location types but very low discrepancies for ultrafast DC chargers. Particularly, low-power chargers show shorter charging times with less charged energy at fueling stations (likely dedicated interim stops) than for parking situations for longer charging times yet similar energy levels.

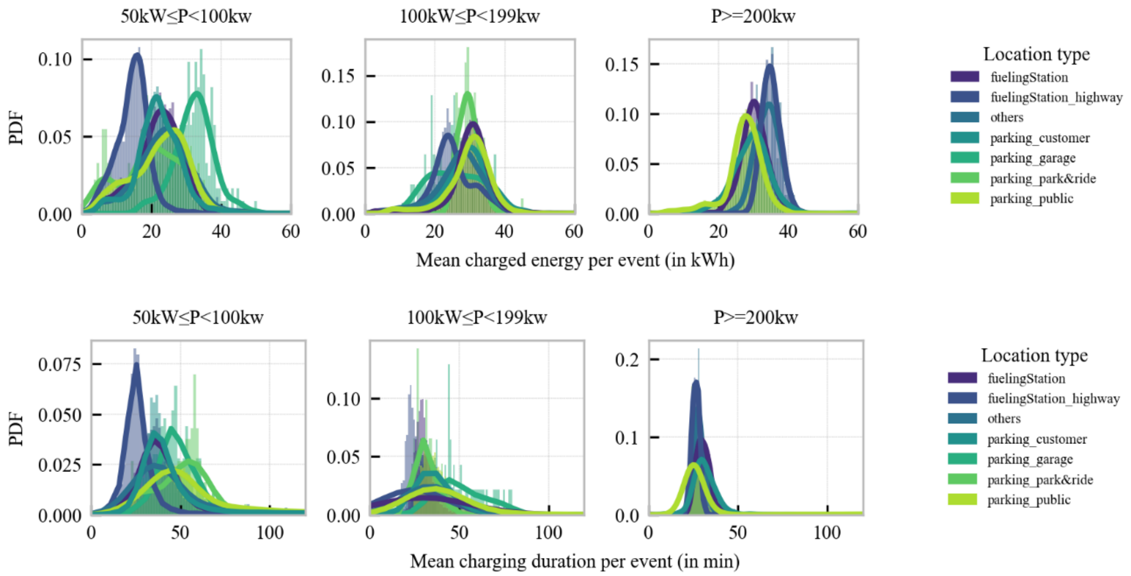

Figure 3: Evaluation of DC chargers by power class and location.

Figure 4 visualizes the average charged energy, average charging duration and average number of daily events among the three usage tiers (color-coded) and power classes as boxplots. The analysis indicates that top performers are primarily characterized by the frequency of charging events across all power classes, rather than by metrics such as charging power, charging duration, or the resultant energy throughput per event.

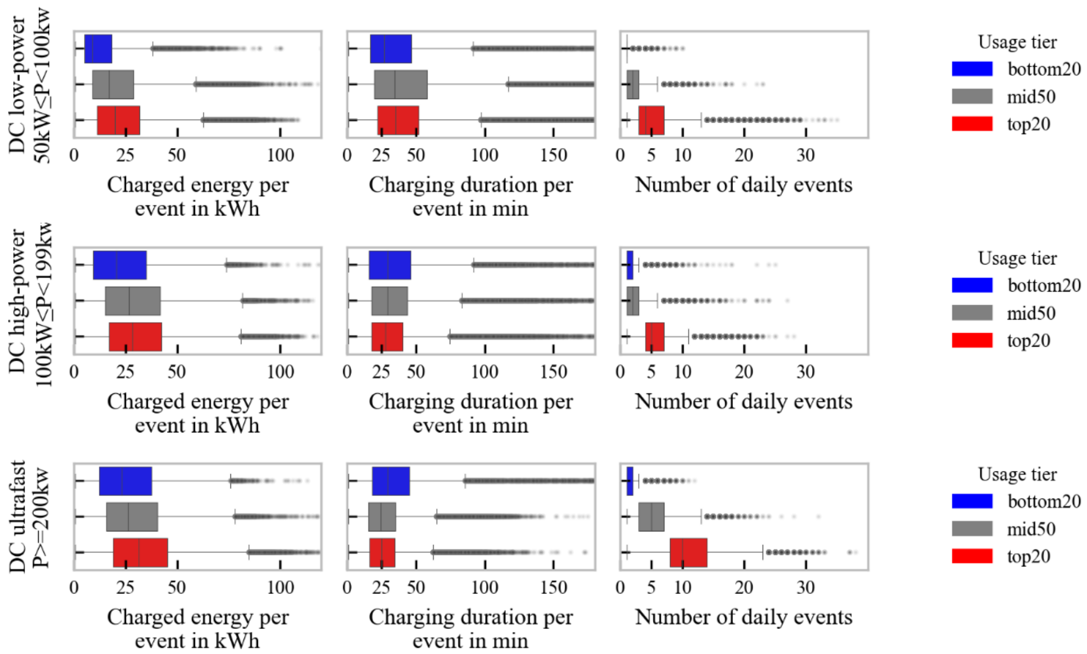

Figure 4: Evaluation of DC chargers by power class and usage tiers

Ultrafast DC chargers: Usage and occupancy patterns

The following section provides a detailed examination of ultrafast DC chargers only. ***Table 3*** shows the contingency table of all ultrafast chargers, and the relationship between usage tiers and contextual factors (location, use case, and region). Values in brackets indicate the correlation among the variables. In addition, Cramér’s V test are conducted to evaluate the strength of association between the categorical variables. Given the moderate to strong association of location, use case and usage tier, top performers benefit from being located at transport corridors (likely highways), supporting high energy throughput or transit-oriented charging behavior. Low performers cluster around customer parking spots.

Table 3: Contingency table with correlation values for ultrafast DC chargers

Location	**Fueling station**	**Highway fueling station**	**others**	**Parking customer**	**Parking public**
bottom20	1% (-0.202)	0% (-0.189)	0% (-0.059)	23% (0.615)	9% (-0.194)
mid50	10% (0.148)	2% (-0.064)	1% (0.064)	2% (-0.346)	18% (0.195)
top20	5% (-0.056)	14% (0.383)	0% (-0.034)	0% (-0.254)	15% (-0.012)

Location - Cramér's V = 0.600

Use case	**Customer charging**	**City charging hub**	**Corridor charging hub**	**Street charging**
bottom20	24% (0.452)	0% (-0.026)	4% (-0.463)	5% (0.079)
mid50	7% (-0.232)	1% (-0.024)	22% (0.215)	4% (0.014)
top20	2% (-0.278)	0% (-0.068)	29% (0.304)	2% (-0.044)

Use case - Cramér's V = 0.472

Region	**city**	**rural**
bottom20	26% (0.033)	7% (-0.033)
mid50	23% (-0.07)	10% (0.07)
top20	29% (0.145)	4% (0.145)

Region - Cramér's V = 0.184

Figure 5 presents the development of temporal (left) and energetic (right) utilization over time, differentiated by usage tier, with monthly trends (top) and comparisons to the growth of the EV stock in Germany (bottom). The analysis reveals a moderate positive correlation between utilization and the expanding EV stock, although substantial variance and distinct patterns across usage tiers are evident. Seasonal fluctuations between summer and winter appear relatively minor. With respect to energetic utilization, each additional percentage point increase in EV stock is associated with a 0.6 percentage point increase for average-performing stations (mid50) and a 1.1 percentage point increase for top-performing stations (top20). For temporal utilization, the effects are more pronounced, with each additional percentage point in EV stock corresponding to a 2.46 percentage point increase for mid50 and a 4.46 percentage point increase for top20 stations.

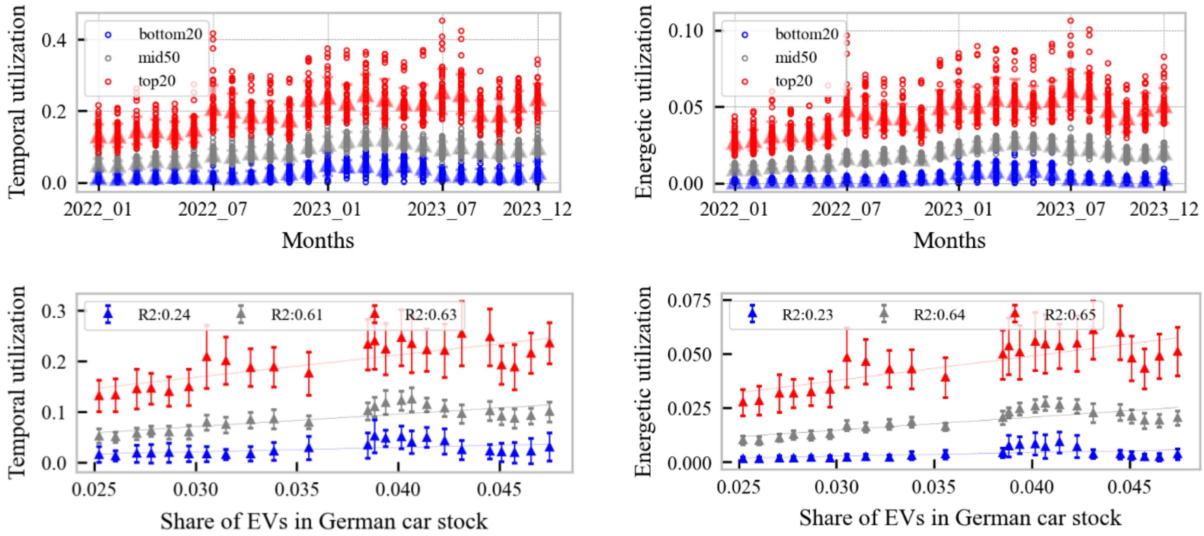

Figure 5: Evaluation of ultrafast DC chargers by usage tiers

Figure 6 illustrates the occupancy probability over a representative week, shown in 15-minute intervals, and differentiated between average-performing charging points (CPs) (upper, gray) and top-performing CPs (lower, red). Each thin line represents an individual CP, while the black line indicates the mean occupancy at each time step. A pronounced day-night cycle is observed, with peak occupancy during typical commuting hours, and only a marginal increase in utilization during weekends. Average-performing stations exhibit daily occupancy rates between 10–15%, whereas top-performing stations reach 20–25% on average. The most-frequented CPs achieve maximum weekly occupancy rates of approximately 30–35%, compared to peak values of only around 20% for average-performing stations. These patterns highlight the concentration of demand among a few high-frequented stations and the strong temporal patterns of charging activity.

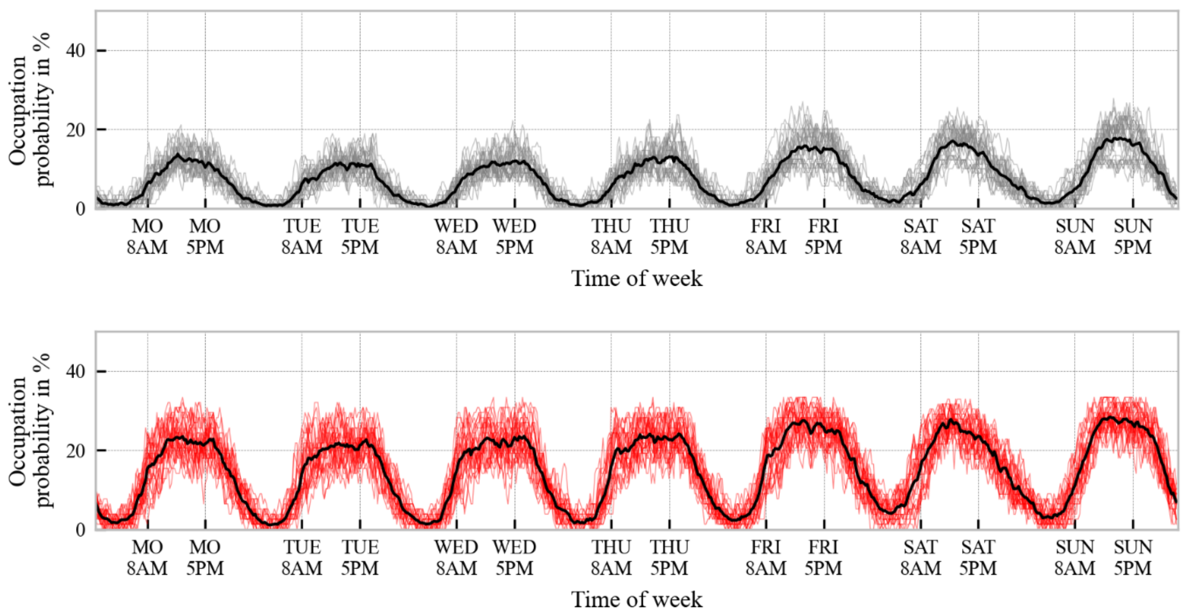

Figure 6: Evaluation of ultra-fast DC chargers by usage tiers

4 Discussion

The present study analyzed the usage patterns of public fast-charging stations in Germany, based on a two-year dataset covering more than N=7,500 charging stations. Particular emphasis was placed on a differentiated assessment of utilization metrics, considering both energy throughput and time-based occupancy, alongside measures of usage intensity and patterns. While the results are broadly in line with findings from existing literature, they also reveal new nuances specific to the German market and the dataset's characteristics. Nevertheless, several limitations must be acknowledged, which may influence the generalizability of the conclusions and point to important directions for future research.

First, we acknowledge a potential sampling bias as our sample covers only a fraction of the German market, and only subsidized stations. Usage patterns and performance measures from purely commercial stations may differ, because their selected locations are more attractive so that no funding was requested. This could supported by the fact that many of the low-performing stations are hardly used, which could make them difficult to operate economically.

Second, there are technical challenges in matching charging points to charging stations. Although a CP might have a nominal rated power (e.g., 150 kW), the actual available power during a session often depends on the station and the number of simultaneous charging events. Typically, two CPs share one station's power output, effectively limiting the power available for each individual session, regardless of the CP's theoretical capability. This issue affects the calculated energetic utilization.

Third, data limitations affect the depth of this study. Important information such as the SOC at start and end, the true end of the charging session, or precise geographic coordinates was missing. This lack of detail restricts a finer-grained regional analysis and prevents a full understanding of charging behavior at individual sites.

For future research, it would be valuable to expand the sample with data from non-subsidized charging stations and expand the analysis to include all power classes. Other modeling techniques, such as multinomial logit regression might be used to identify detailed interaction patterns across categories (e.g., usage tier × power class × location × region × use case) as partially indicated for ultrafast DC chargers. Plus, semi-annual data for 2024 is expected to become available too. This extension could help to better identify seasonal trends (e.g., temperature effects on usage patterns) and assess the impact of growing EV adoption rates on station performance over a longer time period. Last, further operational data like location-specific information including waiting and queing times or charging prices would allow for a more nuanced understanding of what drives station performance.

5 Conclusion and Implications

The present study analyzed the usage patterns of over N=7,500 public fast-charging stations in Germany over a two-year period, with a focus on utilization metrics, usage intensity, and charging behavior through a combination of data visualization and statistical methods.

Addressing the first research question, we find that occupancy durations and energy charged per event vary substantially across charging points, with the greatest variability observed among lower-power AC chargers. Typical energy-to-time utilization ratios range from approximately 1:5 for high-power AC chargers, to 1:2 for low-power DC chargers, 1:3 for high-power DC chargers, and 1:4 for ultra-fast DC chargers. Different metrics - such as number of events, occupancy time, and energy throughput - capture different aspects of usage intensity, each with inherent limitations. From an economic standpoint, however, energy throughput is the most critical indicator, as it directly influences the amortization of infrastructure investments.

Regarding the second research question, our results show that temporal and energetic utilization are closely related, particularly for DC chargers. Nevertheless, the number of charging events emerges as a more reliable proxy for station performance than occupancy time alone, especially at ultra-fast charging stations, where sessions are typically short but involve high energy transfer. Top-performing stations are primarily distinguished by a high frequency of charging events, and are frequently located along transport corridors facilitating high-throughput via transit-oriented charging.

Finally, the analysis highlights the importance of considering the skewed distribution of station usage, meaning that a small number of top-performing stations account for a disproportionate share of total energy throughput, largely driven by favorable location factors. Consequently, evaluating infrastructure performance based solely on average values can lead to misleading conclusions, underscoring the need for more granular performance assessments.

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