Location Matters: Public EV Charging Load Curve Characteristics in Urban Settings

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Abstract: As cities worldwide accelerate their transition to electrified transport, robust insights into public EV charging demand, remain pivotal, for infrastructure development and grid reliability. This paper evaluates a high-resolution dataset from Prague, integrating geospatial and demographic indicators to uncover key spatiotemporal charging behaviors. Our findings demonstrate pronounced morning, afternoon, and evening peaks in different urban zones, highlighting the interplay between land-use patterns and grid constraints. We further discuss how incorporating predictive modeling can facilitate proactive planning, reducing bottlenecks and ensuring equitable access to charging infrastructure. Ultimately, this approach can be extended to diverse urban settings, fostering more sustainable and resilient transport systems.

Keywords: Electric Vehicles; EV Charging Patterns; Public Charging Infrastructure; Spatiotemporal Demand Analysis; Urban Mobility; Load Balancing; V2G Integration; Data-Driven Planning; Predictive Modeling; Sustainable Transport Systems

1 Introduction

The global transportation sector is undergoing a profound transformation, driven by the urgent need to mitigate climate change, reduce greenhouse gas emissions and comply with increasingly stringent environmental regulations. Across the world, policymakers, industries, and consumers are steering away from Internal Combustion Engines (ICEs) and embracing electrically powered mobility solutions, predominantly Electric Vehicles (EVs). This transition is not occurring in a vacuum; it is influenced by evolving international and regional environmental goals, economic incentives, technological advancements, and shifting public perceptions of sustainable transport. In line with this, the European Union (EU) has placed decarbonization and the development of sustainable transport systems at the forefront of its policy agenda [1]. Strategic initiatives, such as the European Green Deal and the Sustainable and Smart Mobility Strategy, emphasize not only the adoption of EVs but also the development of infrastructure that can accommodate the rising number of vehicles while ensuring grid stability, economic viability, and accessibility [2].

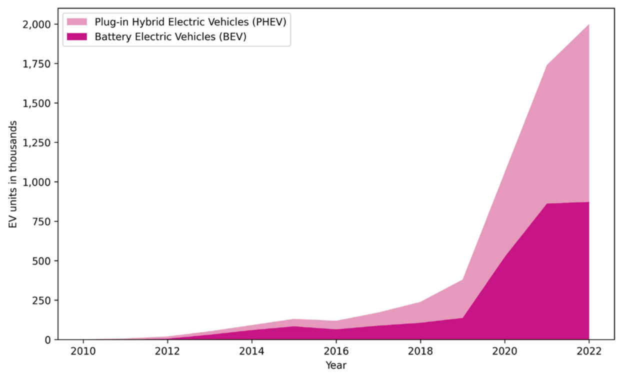

Figure 1

Electric Vehicle registrations in the EU27 have steadily increased between 2010 and 2022 [3]

This large-scale shift to EVs necessitates a parallel expansion of charging infrastructure. As registrations soar across Europe—growing by orders of magnitude in many EU states (see Fig. 1)—the geographic distribution, capacity, and sophistication of charging networks have become critical for energy planners and transportation agencies. The electrified mobility ecosystem's success hinges on strategically siting, sizing, and scaling public chargers in urban cores, residential areas, industrial hubs, and recreational sites. Such targeted deployment ensures efficient, reliable charging while enabling the grid to leverage flexible loads for improved balancing and resilience [4] [5].

However, despite these recognized needs, current approaches to deploying public charging infrastructure are often reactionary and may lack strategic foresight [6].

The emphasis has frequently been on the "low-hanging fruit"—installing chargers where it is administratively simpler or where preliminary interest exists—rather than relying on detailed data-driven methodologies that consider present and future demand profiles [7]. This gap reflects both a shortage of nuanced datasets capturing the spatio-temporal charging behavior of EV users and the complexity of deriving actionable insights from such information. For instance, while some datasets might document the increasing popularity of EV usage through the gradual temporal increase in observed charging sessions, few provide context-sensitive patterns that distinguish between charging activities in dense inner-city neighborhoods, suburban mixed-use areas, industrial hubs, or tourist-frequented recreational zones [8] [9], or lack specific localization and geographic diversity [10]. Without these differentiated insights, policymakers and grid operators risk suboptimal infrastructure investments, that could lead to underutilized chargers in some locations and excessive grid strain in others. From a system-wide perspective, efforts to expand EV charging must also account for broader market, policy, and socioeconomic forces that shape driver behavior—ranging from national incentives and electricity market structures to urban planning policies and regional travel habits [11] [12]. In doing so, researchers and practitioners can better anticipate barriers to widespread EV use, such as grid upgrade costs or inequitable charger distribution, and align infrastructure investments with evolving mobility demands.

2 Motivation

Our research addresses these challenges by analyzing a unique, detailed dataset of public EV charging sessions in Prague, Czechia. Prague represents a compelling case study as a medium-sized European city, blending historical urban centers, high-density residential neighborhoods, evolving suburban communities, and industrial areas. Consequently, insights derived from Prague's charging landscape may generalize to other cities that share similar typologies and face analogous challenges in navigating the EV transition. Specifically, our work integrates charging session data with geospatial and demographic information, allowing us to characterize load curves and charging demand patterns at a granular, location-based level. By employing advanced data processing and normalization techniques, we reveal how local area types influence charging behavior, how temporal patterns emerge within specific urban morphologies, and how evolving EV charging demand aligns – or diverges – from the existing distribution of charging stations.

Such detailed insights are vital for guiding the next generation of infrastructure planning and grid management. Local utilities and distribution system operators can leverage these findings to anticipate when and where peak demands might occur, aligning resource allocation, load shaping, and potentially even dynamic pricing schemes to optimize the local and regional energy mix. For example, understanding that certain residential districts might see sharp charging demand in the early evening, or that industrial areas may experience dual peaks aligned with shift changes, can inform both operational strategies and investment decisions [13] [14]. By correlating charging behavior with urban typologies, city planners can promote more equitable and efficient infrastructure deployment, reducing range anxiety for EV owners while minimizing resources needed for grid expansion with similar utility levels [15].

A more nuanced understanding of spatiotemporal charging patterns is also essential for the effective integration of advanced charging control technologies, such as vehicle-to-grid (V2G) strategies, which allow EVs to supply power back to the grid when needed. By accurately forecasting localized demand fluctuations, grid operators can dynamically schedule V2G transactions to help balance loads, prevent distribution bottlenecks, and facilitate renewable energy integration [16]. This not only increases the overall stability and resilience of the grid but also creates potential economic benefits for both EV owners and energy providers through optimized pricing and peak-shaving measures. At a broader scale, the insights gained from analyzing Prague's public EV charging data represent an incremental but critical step towards a more holistic understanding of EV ecosystem dynamics. Pairing these localized insights with macro-level trends – such as those documented by the International Energy Agency (IEA), the European Environment Agency, and other research institutions – enables international comparisons and the development of standardized approaches to infrastructure planning [17]. State-of-the-art literature has also begun to highlight the interdependencies between EV adoption rates, battery technologies, charging station types, and power grid configurations [15] [18] [19]. Future studies can expand on this foundation by integrating policy signals, electricity market reforms, and consumer behavior models, yielding predictive tools for large-scale EV charging deployment.

This research addresses a critical gap, by revealing how public charging demand varies with spatial typologies and evolves over time. Building on holistic approaches that link transportation, urban planning, and energy systems, our findings offer improved charger siting, optimized load management, and data-informed policymaking. Ultimately, these insights pave the way for more resilient, user-friendly EV ecosystems, contributing to a cleaner, more efficient, and sustainable transportation landscape.

3 Methodology

Our research applies a multi-stage framework to analyze public electric vehicle (EV) charging demand. First, data preprocessing addresses potential inconsistencies and missing values, ensuring analyses rest on a robust foundation. Second, geospatial classification situates each charging station within a legislatively defined administrative structure, limiting bias and reflecting diverse urban morphologies. Third, normalization (e.g., feature scaling) aligns data collected under varying conditions, enabling consistent comparisons across different locales and timeframes. And finally, temporal load profiling converts discrete session data into hourly or daily load curves to pinpoint periods of elevated charging activity. Collectively, these steps facilitate the identification of core charging behaviors under distinct urban contexts and over multiple time horizons. The analysis was done in Python with ordinary scientific libraries Pandas and scikit-learn on a standard workstation.

3.1 Data Preprocessing

Data preprocessing serves as the foundational step that ensures subsequent analyses rest on reliable, high-quality information. Initially, raw session data comprising start times, end times, and total energy delivered is gathered from public charging records. However, these datasets often contain errors, inconsistencies, or missing values. Sessions may exhibit unrealistic durations, extraordinarily high or low consumption values, or unaligned timestamps due to data logging irregularities. To address these challenges, a systematic data cleaning protocol is employed. This protocol involves automated and semi-automated checks that verify temporal consistency (e.g., ensuring the end time is always after the start time), plausible energy consumption ranges based on typical EV charging power rates, and the removal of sessions that deviate substantially from expected operational boundaries.

Beyond merely removing problematic sessions, data preprocessing also includes strategic filtering. For instance, sessions with extremely short durations (e.g., less than one minute) may represent erroneous measurements and can distort aggregate load patterns. Similarly, sessions recorded during maintenance periods or pilot testing phases are excluded to focus on genuine user-driven charging behaviors. In all cases, the overarching philosophy is to preserve data integrity and representativeness. By applying these rigorous measures, the dataset that emerges is both cleaner and more reflective of typical charging conditions, enabling more trustworthy insights later in the analysis pipeline. The resultant curated dataset is thus, a refined, high-fidelity source of truth, prepared for normalized comparisons, load curve computations and spatial-temporal correlation analyses.

3.2 Geospatial Analysis and Classification

A key element of this research is the spatial classification of charging locations. Rather than relying on subjective or manual classification schemes, we employ granularity levels and definitions that are established by national legislative frameworks, ensuring standardization and reducing bias. By anchoring the geospatial categorization to legally defined administrative units, the study attains an objective and reproducible means of classifying chargers into distinct location types. This approach aids in capturing the inherent urban complexity and heterogeneity in an unbiased manner.

For example, areas may be grouped into categories reflecting predominant land use, density, or other socio-economic factors as defined by official legislation. This ensures that each charger's surrounding environment is interpreted through a stable, nationally recognized lens, preempting the introduction of subjective criteria that could distort spatial comparisons. Although the details of the specific administrative units and their nomenclature are beyond the scope of this methodology, the principle remains that all classifications adhere to legally standardized spatial divisions.

3.3 Normalization

To address discrepancies arising from differing numbers of chargers or unequal observation periods, the data undergo normalization. Max-normalization feature scaling is employed, ensuring that all measured values that are always non-negative are placed in a [0,1] range relative to their maximum observed value, as:

$$x_i' = \frac{x_i}{\max(x)} \tag{1}$$

This scaling technique allows for valid comparisons across time (e.g., different seasons) and space (e.g., different administrative units), as it normalizes charging demand patterns to a common reference frame. This step is essential for disentangling inherent behavioral differences from mere differences in data quantity or infrastructure availability.

3.4 Transforming Charging Sessions into Hourly Load Curves

A critical step in our research is converting discrete EV charging sessions into hourly load curves, thereby revealing how charging demand unfolds during a typical 24-hour period. This transformation is essential for identifying potential bottlenecks in the distribution grid, designing time-based pricing policies, and optimizing the allocation of charging infrastructure. To capture daily charging demand dynamics, individual charging sessions are aggregated into hourly load curves, using a process described below.

3.4.1 Session-Level Distribution of Consumed Energy

The process begins with the processed session data, with each charging session, indexed by j , typically defined by the following parameters:

- $t_{start,\,j}$- session j start time
- $t_{end,\,j}$- session j end time
- E_j - total consumed energy in session j

Using the above, we can also calculate the duration Δt_j of session j as:

$$\Delta t_j = t_{end,\,j} - t_{start,\,j} \tag{2}$$

Following a commonly employed approximation in large-scale EV studies [10] [15] [20], we assume the charging power is evenly distributed over the session duration. Real-world charging profiles may exhibit ramps, tapers, or interruptions; however, in the absence of high-resolution power data, uniform distribution offers a practical first-order estimate of load contribution.

For each hour in a day, $i = 0, \ \ldots, \ 23$, we compute the energy contributed by a single charging session j during that hour by considering the width $\Delta t_{j,i}$ of the overlap between the session time window $\left[t_{start,\,j}, \ t_{end,\,j}\right]$ and the time interval corresponding to hour i . The relative energy amount $E_{j,i}$ describing the share of the total energy from charging session j allocated to hour i is thus:

$$E_{j,i} = E_j \cdot \frac{\Delta t_{j,i}}{\Delta t_j} \tag{3}$$

If a session spans multiple hours, each hour i that overlaps with the session receives a proportion of the total session energy based on the fraction of time the session occupies within that hour.

3.4.2 Aggregation Across Chargers and Sessions

To construct system-level (or network-level) hourly load curves, we extend the summation across all chargers, indexed by k , and all their respective sessions, indexed by j . Let N_k be the total number of charging sessions recorded at charger k . We denote the total number of chargers in the dataset as M . The aggregated load X_i at hour i is:

$$X_i = \sum_{k=1}^{M} \sum_{j=1}^{N_k} \left(E_{k,j} \cdot \frac{\Delta t_{k,j,i}}{\Delta t_{k,j}} \right), \ \forall i = 0, \ \ldots, \ 23 \tag{4}$$

where:

- $E_{k,j}$ is the total energy consumed in session j at charger k
- $\Delta t_{k,j} = t_{end,k,j} - t_{start,k,j}$ and is the total absolute duration of the j th session at charger k
- $\Delta t_{k,j,i}$ denotes the relative portion of the j -th session at charger k that overlaps with hour i

This formulation ensures that every session from every charger that intersects hour i contributes proportionally to the load at that hour. The result is a load profile $\{X_0, X_1, \dots, X_{23}\}$ that captures how total charging demand evolves over a 24-hour cycle. Aggregating load curves in this manner offers multiple advantages for both researchers and practitioners. First, grid operators can use these system-level profiles to assess total load impacts on local feeders and substations, informing decisions about transformer capacity, distribution upgrades, or congestion management strategies. Second, city planners and policy-makers gain insights into the collective intensity and timing of demand, helping them anticipate potential hotspots where additional charging sites may be required to accommodate surges in EV usage. Third, analysts can easily scale this approach to larger geographical regions or specific subsets of chargers (for example, by area type), enabling flexible inquiries into how drivers' charging behaviors might shift across different land-use contexts or varying penetration levels of EV adoption. Finally, the aggregator can be iterated over multiple days, weeks, or months to capture seasonal trends or emerging usage patterns, thus providing an evolving picture of how charging demand develops over time. Used in conjunction with geospatial and demographic overlays, this aggregated viewpoint becomes a powerful tool for conducting scenario analyses, designing fair pricing policies, and ensuring that infrastructure expansions remain responsive to real-world driver behavior.

3.4.3 Practical Implementation and Computational Workflow

Below is an example of pseudocode illustrating the above-described construction of a daily load curve for all chargers:

```
# Let M = number of chargers in the dataset.
# Let sessions[k] = list of sessions for charger k.

initialize total_load[0..23] = 0

for k in range(1 to M):                     # loop over all chargers
for each session s in sessions[k]:          # loop over all sessions for charger k
E_total = s.E                               # total energy consumed in this session
session_duration = s.end - s.start
start_hour = extract_hour(s.start)
end_hour   = extract_hour(s.end)

for i in range(start_hour to end_hour):
hour_start = datetime_of(i)
hour_end   = datetime_of(i + 1)

# Compute overlap (in hours) between session s and hour i
overlap_duration = intersection([s.start, s.end], [hour_start, hour_end])
if session_duration > 0:
# Distribute energy proportionally
total_load[i] += E_total * (overlap_duration / session_duration)


# At this point, total_load[i] contains the load (in kWh or Wh) for hour I across
all chargers in the dataset.
```

The calculated `total_load[i]` represents the accumulated energy consumption during hour from all chargers under consideration. In practice, these calculations are batch-processed over extended periods – days, months, or years – enabling advanced time-series analyses. For tailored metrics, such as average daily or peak loads, aggregated profiles can be further refined.

3.4.4 Advantages and Limitations

While the uniform distribution model simplifies calculations and is widely used [10] [15] [20], it can obscure details such as power tapering toward the end of a session or variable charging power levels. Future work could incorporate more detailed power-curve data for each session to enhance fidelity. Nevertheless, this approach robustly captures the overall shape and magnitude of load, providing a valuable first-order assessment of temporal charging demands. By aggregating data in this manner, one gains practical insights into how infrastructure usage accumulates over the course of a day, which hours may experience peak draw on the distribution grid, and how these trends evolve seasonally or in response to changes in EV adoption. Ultimately, this foundation supports deeper analyses, such as identifying load-shifting opportunities, thus serving both academic research and real-world applications in energy systems planning.

3.5 Analytical Tools and Visualizations

Once refined load data is assembled, various analytical and visualization techniques extract actionable insights. Beyond basic descriptive statistics, methods like clustering, time series decomposition, and correlation analysis uncover subtle charging patterns and group chargers by similar load profiles. These techniques reveal socioeconomic, traffic, and accessibility factors influencing demand. Visualization enhances interpretation of temporal variations. Line charts, heatmaps, and violin plots highlight daily peaks, weekday versus weekend variations, and seasonal trends. Overlaying contextual data, such as electricity prices or weather, enriches this analysis, clarifying how diverse factors shape charging behaviors. These tools allow grid operators and city planners to allocate resources more strategically, ensuring efficient and sustainable infrastructure deployment.

4 Dataset Description

This study is underpinned by three major categories of data, each contributing a complementary perspective on the public electric vehicle (EV) charging landscape in Prague, Czechia. These categories include two datasets cataloging individual charging sessions, a comprehensive body of geospatial information, and a set of demographic indicators that, taken together, delineate the complex spatial and temporal dynamics of charging demand. In this study, the data has been processed to establish direct linkages based on geographic information, specifically utilizing individual charger addresses, as illustrated in a data linkage overview in Fig. 2.

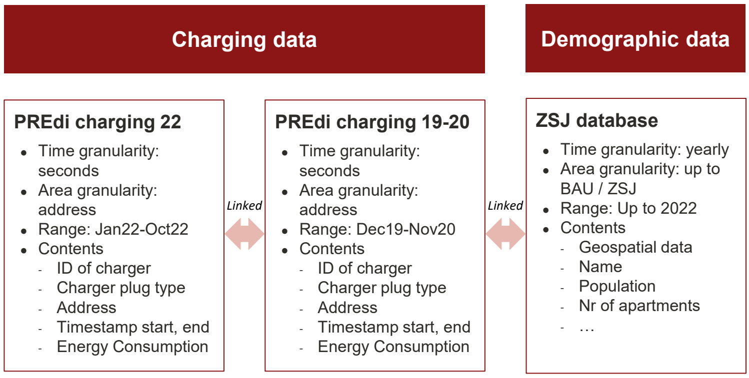

Figure 2
Overview of the analyzed datasets

4.1 Charging Session Data

A central feature of this work are two extensive datasets documenting public EV charging sessions, generously provided by PREdistribuce, a.s., the largest public charging point provider in Prague [21]. The first dataset spans December 2019 to November 2020, and the second covers January 2022 to October 2022. Each record specifies session start and end times along with total energy delivered, enabling precise hourly load curve calculations, as well as insights into consumption patterns, peak demand, and temporal trends. The datasets encompass AC and DC charging events, reflecting diverse real-world scenarios. AC stations typically handle moderate power levels, common in residential and commercial areas, while DC stations, offering higher power rates, are often located at major transport hubs. This composition supports comparative analysis of charging behavior, revealing variations in location-specific infrastructure usage and demand evolution over time.

4.2 Geospatial and Demographic Data

Complementing session-focused information, robust geospatial and demographic data are critical for elucidating the contextual factors that shape charging behavior. In this regard, the study draws upon Basic Administrative Units (Základní sídelní jednotka, ZSJ) curated by the Czech Statistical Office [22]. These units constitute Prague's most granular form of local administrative division, with the city subdivided into 948 unique ZSJ areas. The ZSJ framework is legislatively established and segregates the municipality into twelve classifications based on primary usage. Table 1 illustrates the standardized naming conventions and color coding assigned to these categories.

Table 1
Basic Administrative Units (ZSJ) categories

Original Czech Name	English translation	Color
Obytná plocha v kompaktní zástavbě	Compact residential area	Purple
Městská a příměstská smíšená plocha	Urban and suburban mixed area	Red
Obytně rekreační plocha	Residential and recreational area	Teal
Odloučená obytná plocha	Separated residential area	Violet
Dopravní areál	Transportation infrastructure area	Orange
Areál občanské vybavenosti	Civic amenities area	Blue
Rekreační plocha	Recreational area	Coral
Ostatní účelová plocha	Urban and suburban mixed area	Lime
Průmyslový areál	Industrial area	Pink
Rezervní plocha	Reserve area	Yellow
Zemědělská plocha	Agricultural area	Brown
Lesní plocha	Forest area	Gree

Fig. 3 illustrates the spatial distribution of ZSJ types across Prague using consistent color coding. Linking chargers to their respective ZSJ ensures a standardized and objective classification, avoiding subjective delineations. The associated demographic and infrastructural profiles, such as population density and land use, provide deeper insights into how local environmental factors influence EV charging patterns. This multi-layer geospatial approach forms a robust basis for statistical and visual analyses of charging demand.

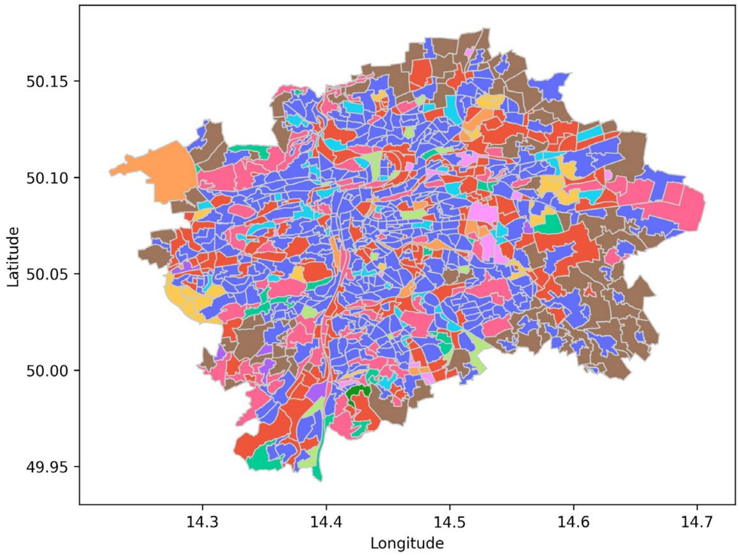

Figure 3
Prague proper split into ZSJ units classified per area type

4.3 Integration of Multiple Data Layers

Combining the charging session records with geospatial and demographic variables yields a multifaceted dataset that illuminates the interplay between infrastructure, user behavior, and urban form. For instance, evaluating the relationships between session counts, total energy delivered, or peak usage hours and the classified ZSJ areas sheds light on localized disparities in demand.

These analyses can also help detect how certain neighborhoods—especially dense urban centers or peripheral industrial zones—may exhibit unique utilization patterns. Fig. 4, for example, portrays the total recorded charging load across the spatial extent of Prague, thereby providing a macroscopic perspective on how charging demand is distributed among different localities.

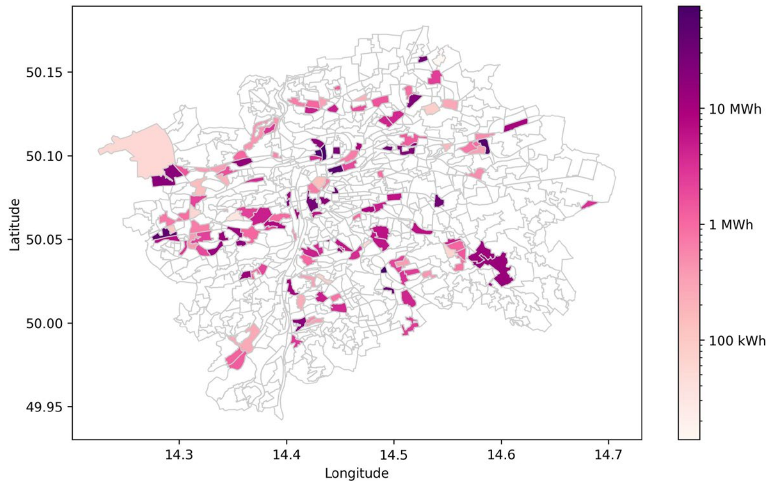

Figure 4
Total charging load per Prague ZSJ in W/h across the whole dataset. Note the logarithmic scale.

Such integrative data processing not only allows for purely descriptive visualizations but also informs more advanced modeling techniques. Researchers can draw on this layered dataset to build predictive models of future charging demand or to identify potential stress points in the electric grid. As the share of EVs continues to grow, understanding how geographic, demographic, and infrastructural features converge in shaping driver charging preferences becomes increasingly vital for municipal planners, grid operators, and policy experts. By offering a richly contextualized depiction of Prague's public charging ecosystem, these data thereby represent a significant step forward in comprehensively analyzing, forecasting, and optimally guiding EV infrastructure development.

5 Results and Insights about Public Charging

The data in this study provides a comprehensive analysis of the spatial and temporal patterns shaping public EV charging behavior in Prague. While overall charging volumes increase with rising EV adoption, this section highlights granular trends shaped by factors like time, location type, and infrastructure characteristics.

5.1 Intra-week Charging Demand

An analysis of charging frequency across the week reveals workweek-centric usage patterns. As shown in Fig. 5, charging demand during weekends (Saturday and Sunday) is approximately 21% lower than on weekdays, suggesting that public chargers are primarily used for work-related commutes and associated errands. December 2019 is treated as an outlier due to its brief observation window and deviation from trends seen in 2020 and 2022.

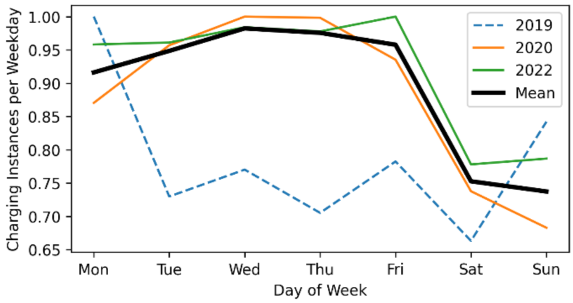

Figure 5
Weekday normalized average charging demand

5.2 Charging Demand Development Split per Area Type

Temporal trends in charging demand differ significantly across geographic zones. Figure 6 shows monthly relative shares of charging instances and installed charging points between December 2019 and October 2022, categorized by ZSJ types. Data gaps between December 2020 and December 2021 are interpolated and marked. Compact residential areas show a growing share of charging sessions, reflecting increased EV adoption in densely populated zones. Agricultural and Industrial areas also display modest growth. In contrast, Civic amenities, Urban and suburban mixed, and Recreational areas experience a decline in usage, possibly due to changing travel patterns or evolving local infrastructure. These shifts suggest that demand is influenced by more than the availability of chargers, pointing to evolving user behavior and broader urban trends.

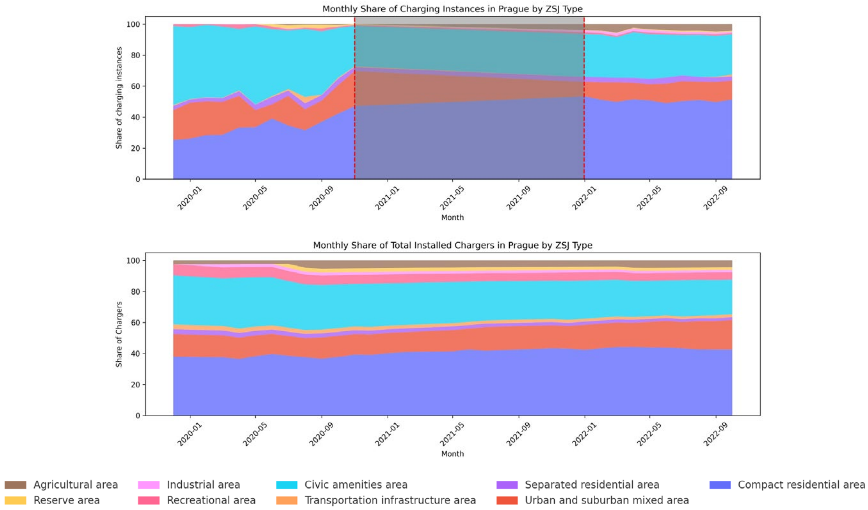

Figure 6

Temporal relative share development analysis for charging instances and installed chargers in Prague, classified per ZSJ type. Note that the red-bordered, gray fill area in the upper chart of charging instances corresponds to the interpolated region of unavailable data. The lower chart is the number of installed chargers distribution including chargers put into operation before the span of the timeline.

5.3 Location Based Parameters of Demand Curves

Extending the geographic inquiry, the study explored heterogeneity in charging demand curves by area classification. Fig. 7 plots the normalized average load curve profile for each type of administrative unit, revealing four overarching profiles:

1. *Sustained single peak*: Areas such as Compact residential, Urban and suburban mixed, and Civic amenities exhibit a steady increase in demand, culminating in a single, protracted peak. These high-density or multifunctional zones appear to maintain a relatively stable baseline of charging activity throughout the day.
2. *Morning single peak*: Transportation and Recreational areas show a surge in demand in the morning, driven by early-day visitors.
3. *Evening single peak*: Separated residential and Agricultural areas reach peak usage around 17:00, suggesting that drivers who lack immediate home-charging options may rely on these chargers when returning from work or other daytime activities.
4. *Double peak*: Reserve and Industrial areas display both a morning and evening peak, albeit sometimes offset by an hour. This phenomenon could reflect commuting patterns (morning arrivals and evening departures) in industrial job sites and larger logistical facilities.

While the causes of these distinctive load curves remain only partially explained, certain patterns are evident. Group 1 (sustained single peak) aligns with commuting trends, complementing residential charging profiles that peak later in the evening. Morning spikes in Group 2 reflect leisure commutes, while Group 3's late-afternoon peaks coincide with post-work arrivals in less urbanized areas. Group 4's dual peaks indicate shift-based schedules in industrial zones. This heterogeneity has practical implications for grid balancing, which has long been a potential in EV adoption [13]. For example, mid-day or morning demand in urban neighborhoods can offset heavier evening residential loads [14] [15]. Distributing chargers across multiple location types may therefore help moderate overall consumption peaks.

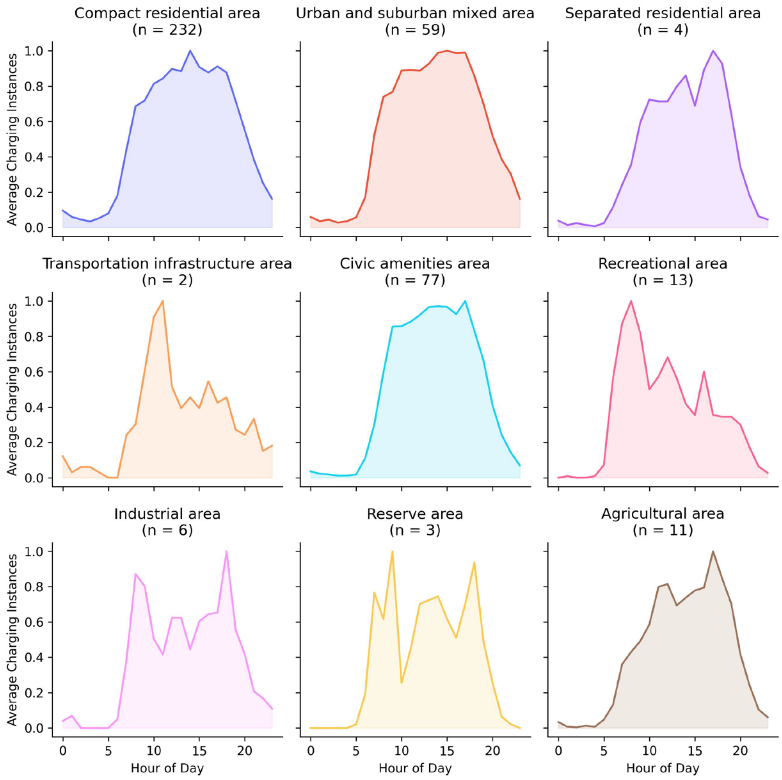

Figure 7

Normalized demand curves for ZSJ types with chargers present in the dataset

Considering these findings, strategic initiatives – such as dynamic capacity allocation – appear merited [23]. Time-of-use pricing might incentivize off-peak charging, and combined with deploying chargers strategically, stakeholders can enhance grid stability while addressing localized demand effectively.

6 Limitations

This study's reliance on data from a single public charging provider limits the representativeness of findings. Expanding datasets to include private and multi-provider sessions could offer a more comprehensive view of EV behavior [24] [25]. Translating site-level load profiles to substation or feeder-level impacts is another challenge, as grid operators prioritize nodal or feeder-based metrics for capacity planning [26]. Integrating granular session data with network-level structures will improve overload risk identification and enable proactive asset management. Disparate charging intensities across Prague's spatial clusters highlight the influence of factors such as alternative station availability, private chargers, traffic flows, and socio-economic conditions [14] [27]. Extending analyses to different regions would clarify broader patterns and refine predictive models that address diverse regulatory, climatic, and infrastructural conditions [28] [29]. Future research should employ machine learning models trained on high-resolution charging data to forecast usage in unobserved areas. These models could combine time series analytics, spatial factors, and user behavior to optimize siting, capacity planning, and load balancing [30]. Refining these algorithms is essential for anticipating system-level stresses and guiding effective infrastructure deployment.

Conclusions

This study enhances our understanding of urban public EV charging by illustrating how charger location, reshapes intra-week load patterns. Prague's data reveals significant public charging growth with distinct temporal and spatial variations. Compact residential areas see gradual day usage, recreational areas experience morning peaks, peripheral zones peak in the afternoon and industrial areas demonstrate multi-peak behavior.

These insights stress the need for aligning infrastructure with localized demand trends. Leveraging midday activity in some locations can offset evening residential ramps, while dynamic pricing and capacity allocation may ease congestion and encourage off-peak charging [23] [31].

Future directions of this research include considering grid capacity in the context of growing EV adoption and using modelling techniques to process available datasets to model locations and situations not present in source data.

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