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# Estimating the Impact of EV Charging in Chicago Based on Patterns Evidenced in a Sample Charging Facility

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**Abstract:** This study investigates the impact of commercial electric vehicle (EV) charging on electricity usage across various zones in the Chicago region, analyzing both the magnitude and distribution of demand. Using baseline charging curves, EV registrations, and charging port availability, EV electricity consumption patterns are assessed for workdays, Saturdays, and Sundays. The results reveal that workday EV charging electricity usage peaks at approximately 2,500 kWh, whereas weekend usage drops below 600 kWh. High-impact areas, defined here as zones with both high overall electricity consumption and a substantial proportion attributed to EVs, include Chicago, Evanston, Buffalo Grove, and Glenview. Geographically, the highest impacts are concentrated in downtown Chicago, the north and west suburbs, and Rochelle, Illinois.

**Keywords:** Electric Vehicles, EV charging, EV adoption, Charging infrastructure, EV Impact.

## 1. Introduction

The rapid advancement of the automotive industry toward electrification represents a significant shift in transportation and energy infrastructure. As electric vehicles (EVs) become increasingly integrated into the market, understanding and developing efficient commercial EV charging networks is critical to supporting consumer demand, managing energy independence, and maintaining U.S. leadership in automotive innovation. The demand for commercial EV charging solutions reflects growing EV adoption and a complex interrelationship [1] between technological, economic, and societal factors that warrant comprehensive investigation.

Recent studies have identified several key factors influencing EV charging demand [2], [3]. Vehicle characteristics, such as battery size and driving range, significantly determine charging frequency and duration [4]. The availability and distribution of charging infrastructure also impacts demand patterns, as more accessible and abundant charging stations can reduce the need for frequent charging. Spatial variations in EV charging demand are also an active area of study. Past research highlights that urban areas experience higher charging demand due to higher population densities and greater availability of public charging facilities [5], [6]. Spatial analyses are essential for understanding regional disparities in charging needs and planning the expansion of charging networks to ensure access across different areas [7]. In addition to spatial variations, temporal patterns in EV charging demand reveal significant fluctuations throughout the day and year. Studies show that residential charging typically peaks in the evening when users return home [8], while workplace charging sees higher usage during business hours [9]. Seasonal variations also influence demand, with increased charging during winter months due to reduced battery efficiency and greater energy consumption for heating. Understanding these patterns is crucial for optimizing infrastructure deployment and managing energy consumption effectively.

As EV infrastructure increasingly penetrates the commercial sector, its impact on the electric grid becomes a critical aero study [10], [11]. Integrating EV charging with existing energy systems presents both opportunities and challenges [12]. Smart charging technologies like time-of-use pricing and demand response programs can help manage peak demand and optimize energy use [13], [14]. These technologies enable real-time adjustments to charging schedules based on grid conditions, promoting better alignment with renewable energy sources and reducing grid strain [15]. Some researchers suggest combining EV charging infrastructure with renewable energy sources to enhance sustainability and minimize the environmental impact of increased electricity consumption [16].

Addressing these grid-related challenges, including peak demand management, infrastructure strain, and efficient integration of growing EV loads, requires careful consideration in policy and planning. A range of approaches may be explored to support the development of charging infrastructure in alignment with grid stability and efficiency. Predictive modeling has been identified as a useful method for forecasting future demand and informing decisions related to infrastructure [17]. Additionally, a variety of approaches, including incentives and regulatory measures, have been applied in different contexts to shape the development of charging infrastructure and the adoption of emerging charging technologies [18], [19]. Managing urban power distribution systems will depend largely on precise forecasting of EV charging loads' spatial and temporal distribution. This is especially critical as the growing number of EVs makes charging load distributions more complicated and unpredictable [20].

The surge in demand for commercial EV charging infrastructure presents opportunities and risks for grid performance. Understanding this demand is critical for anticipating and managing the strain that high volumes of EV charging can place on electrical grids. With consumers, commercial fleets, and businesses adopting EVs at an accelerated pace, the resulting spikes in electricity demand may challenge grid reliability and efficiency [21], [22]. This article explores the relationship between commercial EV charging demand and grid dynamics, emphasizing the need for strategic planning and technological innovation to support a stable energy future.

Despite growing research attention, there remains a gap in spatially explicit, city-scale estimates of commercial EV charging demand that can be developed from limited empirical data. Most existing methods rely on large-scale sensor networks or comprehensive charging records, which are rarely available across entire metropolitan regions. The research gap this study addresses is the absence of a scalable methodology for estimating zip code-level commercial EV charging electricity impacts using a single sample facility as a baseline. The main contribution of this study is a transferable demand estimation framework applied to the Chicago region, demonstrating how observed utilization and energy distributions from one commercial charging site can be extrapolated to characterize citywide impacts using publicly available EV registration and port data [23].

## 2. Data

We leverage three different datasets in this study: (1) the charging sessions and electricity usage data from the charging facility, (2) charging ports data in Chicago obtained from the Department of Energy (DOE) Alternative Fuels Data Center, and (3) EV ownership per zip code obtained from the Chicago Metropolitan Agency for Planning (CMAP) local greenhouse gases (GHG) emissions estimates data.

**Charging sessions and electricity usage data**

The charging session data originates from a partnership between Argonne National Laboratory (ANL) and a facility in Chicago. It consists of three different tables containing information on charging ports and chargers (Table 1) related by the PortID attribute, and individual charging sessions representing every time a user plugged their vehicle in one of the ports and drew energy from the charger (Table 2).

**Electricity usage**

The electricity usage of the entire facility contains time series data of 30-minute interval energy use in kWh. This consumption is the result of the operation of the chargers and all other operational electricity use required by the facility. In addition, zip code-level electricity usage from the electricity provider in Chicago is used to understand the scale of the results.

**Table 1.** Attribute descriptions for charging ports and chargers tables

| Charging Ports | | Chargers | |
|---|---|---|---|
| Variable | Description | Variable | Description |
| SessionID | Unique Session ID | PortID | Unique Port ID |
| PortID | Unique Port ID | Power (KW) | Maximum KW output the equipment is rated for |
| Session Start Time | Charging session start time | Voltage (Volts) | Maximum Voltage the equipment is rated for |
| Session End Time | Session End Time - The vehicle is unplugged from the charging port | Current (Amps) | Maximum Amperage the equipment is rated for |
| Total Charge Time | Total Time Energy is flowing from the station to the vehicle | Max Power from Facility (KW) | Maximum theoretical KW output given the facility voltage and amperage |
| | | Facility Voltage (Volts) | Maximum theoretical voltage at the facility |
| kWh | Total energy dispersed in the session | Max Current from Facility (Amps) | Maximum theoretical amperage at the facility |

**Table 2.** Attribute descriptions for the Sessions table

| Sessions | |
|---|---|
| Variable | Description |
| SessionID | Unique Session ID |
| PortID | Unique Port ID |
| Session Start Time | Charging session start time |
| Session End Time | Session End Time - The vehicle is unplugged from the charging port |
| Total Charge Time | Total Time Energy is flowing from the station to the vehicle |
| kWh | Total energy dispersed in the session |

**Charging ports**

Charging port data and locations come from The Alternative Fuels Data Center (AFDC) from the DOE. It offers valuable information, data, and tools to assist fleets, fuel providers, policymakers, cities, states, community coalitions, and other transportation stakeholders. From this source, we obtained EV charger locations, the day of start of operation, and the number of ports available at each location.

**EV registrations**

CMAP performs a regional GHG inventory to assess emissions across the seven-county area. To support communities in lowering emissions and monitoring their progress toward long-term objectives, CMAP has developed local emissions summaries for each of the region's seven counties, 284 municipalities, and 77 neighborhoods within Chicago. These summaries offer a detailed overview of emissions from the building, transportation, and waste sectors, along with related indicators such as electric vehicle registrations and tree canopy coverage.

## 3. Methods

This study applies a simple methodology supported by two fundamental assumptions. The goal is to estimate the potential impact of commercial EV charging infrastructure across Chicago by extrapolating observed patterns from a single sample facility to the broader city. This extrapolation is carried out through the following two assumptions:

1. Commercial EV charging utilization is proportional to EVs registered in the area, using the sample facility as a baseline.

2. Energy use per charging session follows the same probability distribution as the sample facility.

The utilization in the first assumption refers to the number of sessions being initiated as a percentage of the total available ports in the facility. This assumption implies that given a 30-minute utilization curve $U_s(t)$ for the sample facility s and a number $E_s$ of EVs registered in the same zip code as the sample facility, the utilization curve $U_i(t)$ for any zone i will be given by:

$$U_i(t)=\frac{E_i}{E_s}U_s(t)$$

where $E_i$ is the number of EVs registered in the zip code.

The second assumption means that given the number of active sessions derived from the utilization curve and the number of available charging ports, the electricity consumed by each session is drawn randomly from the same empirical distribution observed at the sample facility. In other words, energy use per session is treated as stochastic, sampled independently from the observed distribution rather than assigned a fixed value. This approach acknowledges that individual charging events vary considerably depending on vehicle type, state of charge, and session duration. Although the resulting per-session energy values are randomly generated, the aggregate distribution of electricity use across many sessions closely mirrors the sample facility's observed distribution, which is the quantity of interest for grid impact assessment. This makes the approach useful precisely in settings where detailed session-level data are unavailable across the broader region, as it preserves statistical fidelity to real-world patterns without requiring complete observational coverage.

**Baseline demand curves**

As mentioned in the assumptions, the estimates presented in this work rely on baseline demand-related curves estimated from the sample facility. In order to capture the type of day variability, we disaggregated the utilization into three different types of the day: weekday, Saturday, and Sunday, as shown in Fig. 1. The commercial charging facility reaches peak utilization on workdays between 12:00 PM and 5:00 PM, with a peak of nearly 20%. This midday peak likely reflects the behavior of employees or visitors using workplace or commercial parking facilities during regular business hours, consistent with prior literature on workplace charging patterns [9]. On Saturdays, utilization drops substantially, never exceeding 8%, with most charging sessions occurring overnight, possibly reflecting a different user base, such as residents or shift workers accessing the facility during off-hours. Similarly, on Sunday, utilization does not exceed 7%.

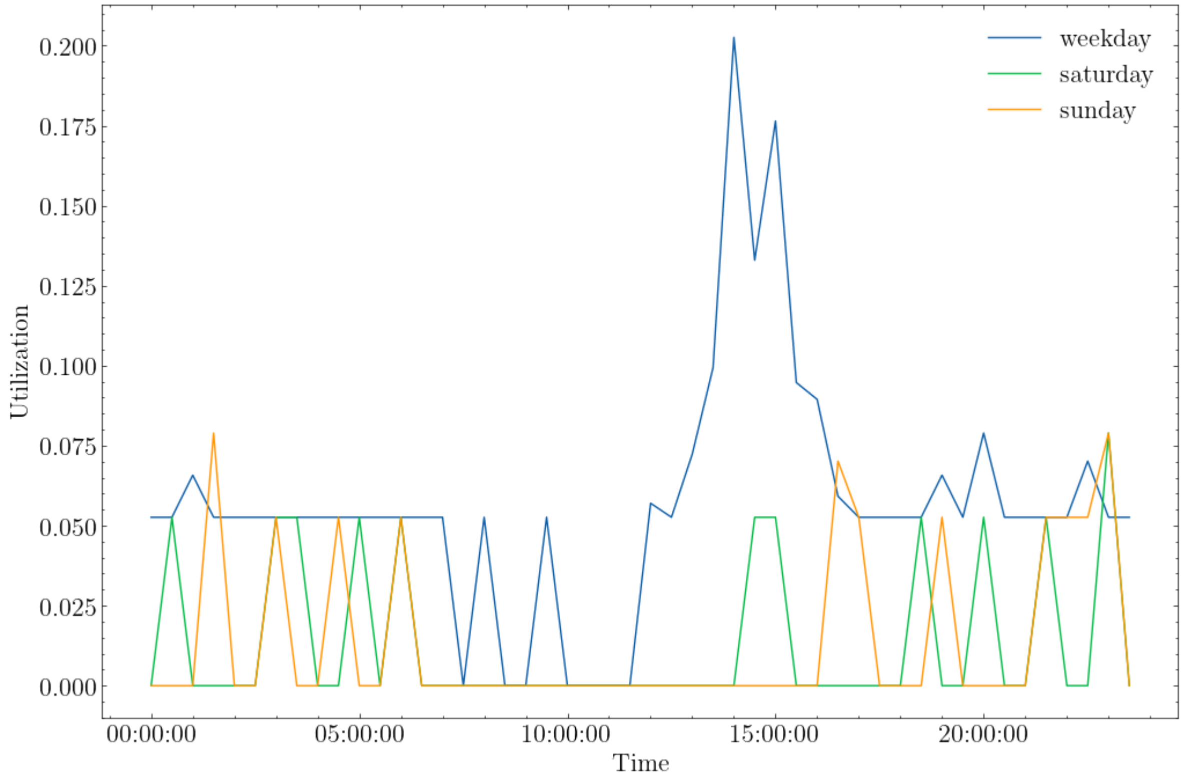


**Fig. 1.** Utilization percentage by time of day estimated from the sample facility for weekdays, Saturdays and Sundays

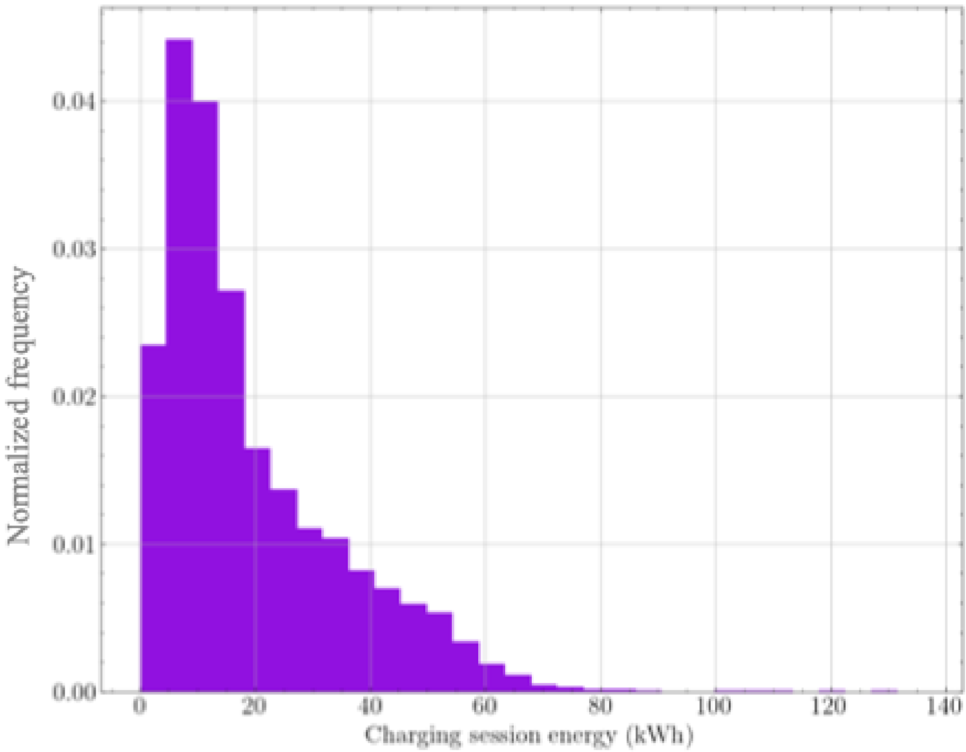


**Fig. 2.** Normalized distribution of energy used per charging session estimated from sample facility

Fig. 2 shows the empirical distribution of energy drawn per charging session at the sample facility. This distribution is included to capture the real-world variation in energy delivered per session, which depends on factors such as vehicle battery size, state of charge at arrival, and session duration. Notably, this distribution is not disaggregated by day type (weekday vs. weekend). This is intentional: the day-type variation in charging behavior is already captured by the utilization curves in Fig. 1, which govern how many sessions occur at each hour. The energy-per-session distribution therefore reflects only the magnitude of energy exchanged per event, independent of when it occurs.

## 4. Results

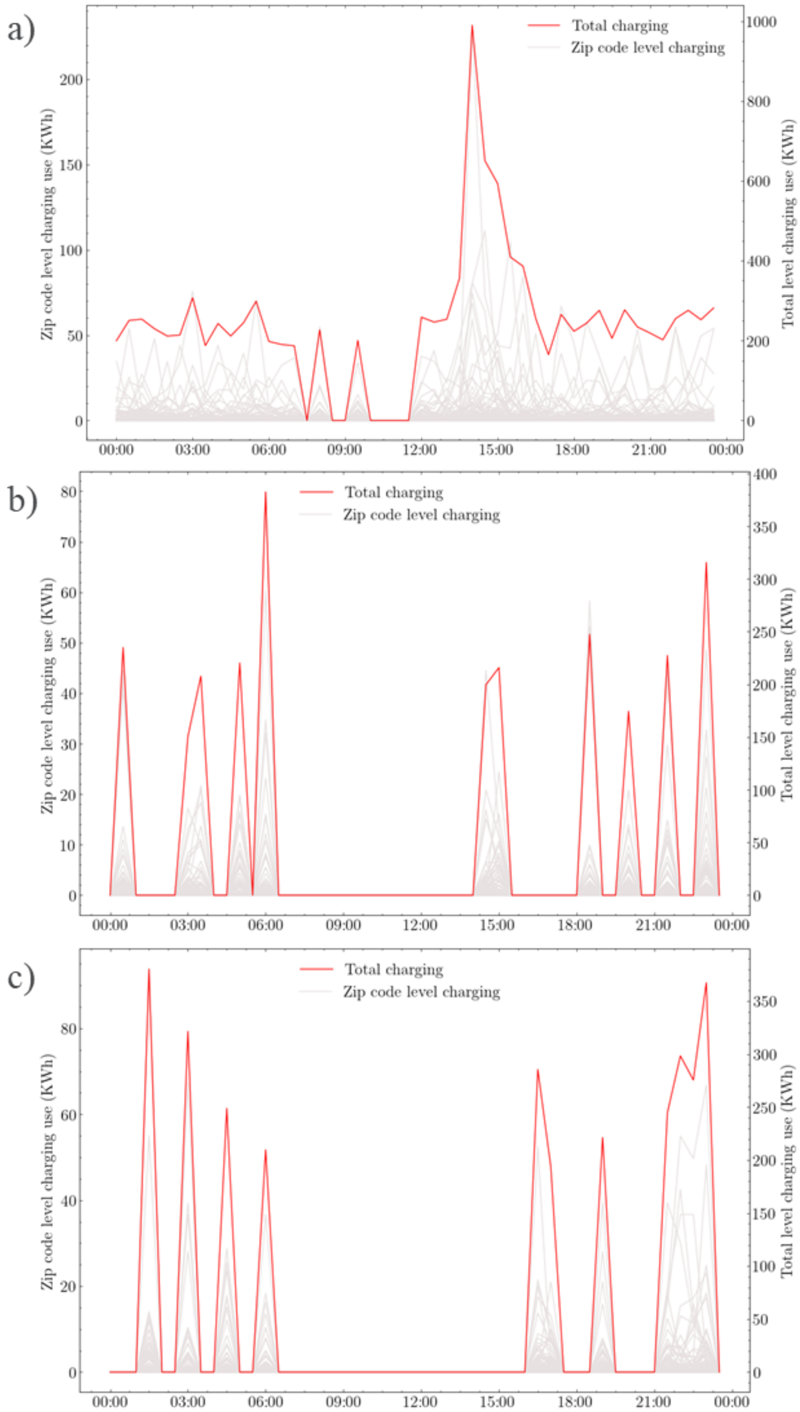


**Fig. 3.** Estimated commercial EV charging electricity usage per zip code for a) workdays, b) Saturdays, and c) Sundays. Each color represents a different zip code

After obtaining the baseline curves presented in the previous section, we applied our assumptions at the zip code level based on EV registrations and charging port availability, as shown in [9]. Consistent with the assumptions, each of the estimated curves follows similar utilization shapes to those in Fig. 1. The figures also illustrate variations in magnitude across zip codes. Workday usage reaches up to 200 kWh per zip code, whereas weekend usage remains below 100 kWh. This substantial difference is consistent with the utilization patterns in Fig. 1: workdays exhibit prolonged midday peaks driven by regular commercial activity and employee charging, while weekend utilization is sparse and concentrated overnight. The lower weekend values reflect reduced commercial operations and fewer vehicles accessing public and workplace chargers during non-business days.

To contextualize the results in terms of what these electricity loads mean at the zip code level, we obtained the aggregated electricity consumption at each zip code. We determined the potential impact of commercial EV charging proportional to the total energy usage per zone that can be attributed to EV charging according to our results. To highlight areas where EV charging has the most pronounced impact, results are filtered to display only those zip codes where EV charging corresponds to at least 0.01% of total electricity usage, as shown in Fig. 4. The area with the highest EV charging demand as a fraction of total electricity consumption is located in Plainfield, Illinois, where EV charging approaches 1% of total usage. However, this result should be interpreted cautiously: Plainfield has the lowest total electricity consumption among the zip codes analyzed, meaning that even a modest absolute level of EV charging appears disproportionately large in relative terms. Plainfield is a rapidly growing outer suburb of Chicago with a predominantly residential character and high rates of newer housing stock: factors associated with higher EV adoption among affluent households [7]. The presence of commercial chargers serving a relatively low-consumption area may reflect early infrastructure investment ahead of demand maturation. In contrast, areas in the city of Chicago, Evanston, Buffalo Grove, and Glenview represent high-impact zones in an absolute sense: they combine both high overall electricity consumption and a substantial proportion attributable to EV charging, making them priority candidates for grid planning and infrastructure investment.

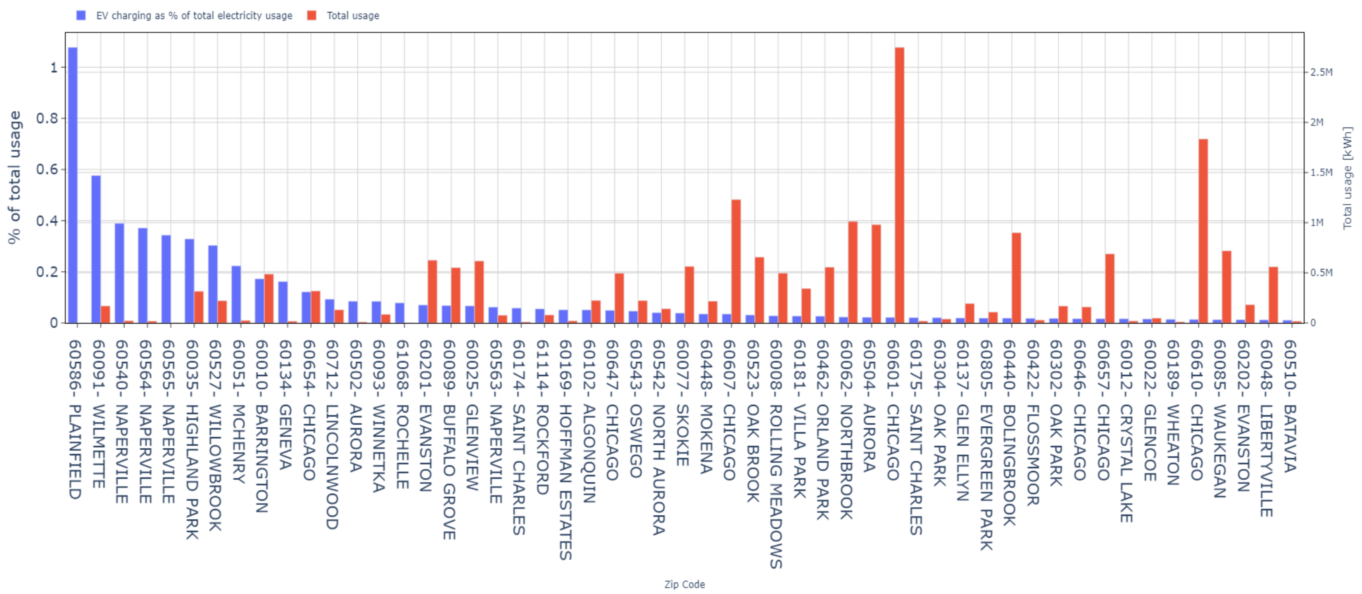


**Fig. 4.** EV charging demand per zip code as a percentage of the total electricity consumption. Results displayed correspond to those where the percentage is at least 0.01%

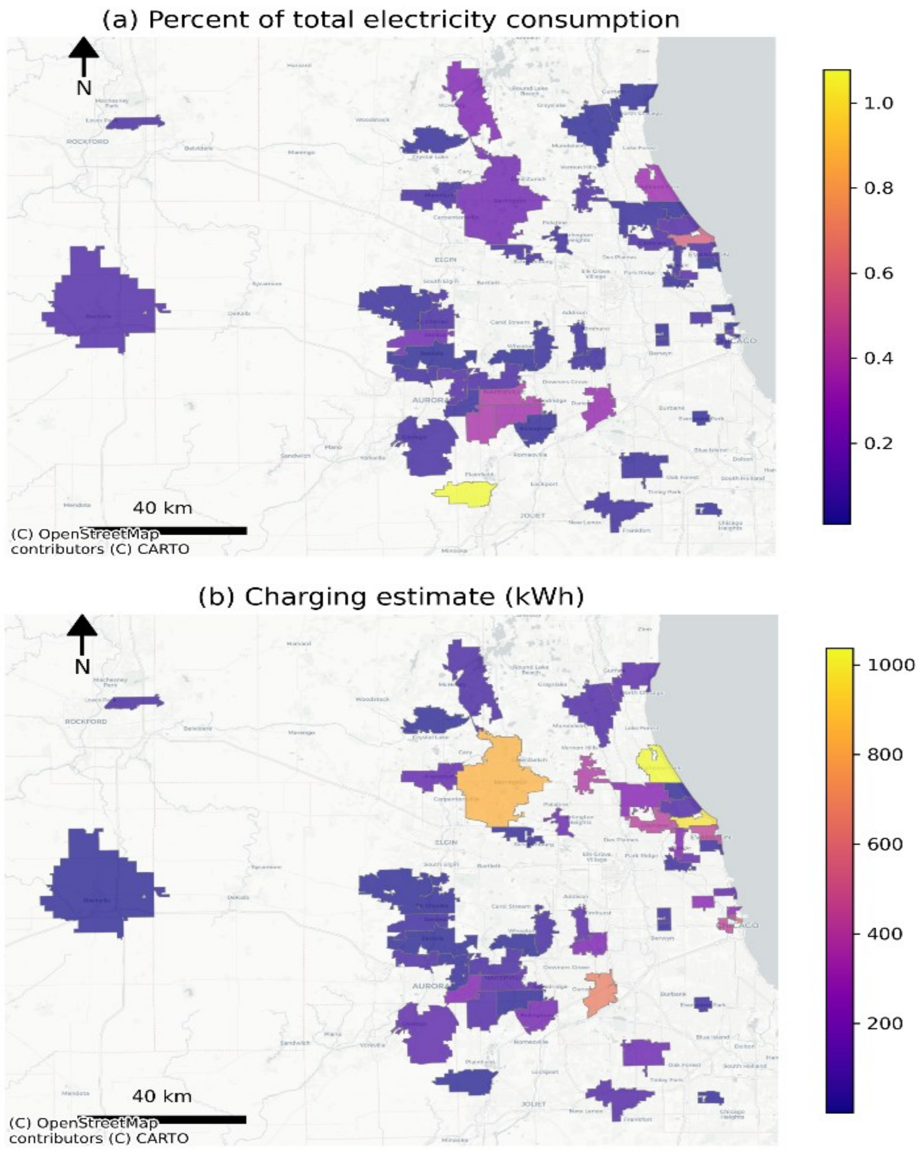


**Fig. 5.** Zip codes in the Chicago region with the highest (a) EV charging as a percentage of the total electricity consumption in the area. The showcased areas have EV charging demand of 0.01% or more of the total electricity usage. (b) displays total energy use destinated to EV charging

Finally, we present the geographical distribution of the high impact of EV charging based on the percentages presented in Fig. 4. The maps in Fig. 5 show that the areas where the EV charging impact is expected to be the highest are downtown Chicago, the suburbs in the north and west, as well as Rochelle IL.

**5. Discussion**

The analysis offers insights into the spatial distribution and impact of commercial EV charging on electricity usage at the zip code level. The data illustrated in Fig. 3 through 5 reveal distinct patterns in electricity consumption driven by EV charging across different days of the week and highlight areas of varying impact intensity. The baseline curves in Fig. 3 align with expected utilization patterns. Workday electricity usage peaks at approximately 2,500 kWh, reflecting the higher demand during weekdays driven by commercial activity and regular business hours. In contrast, weekend usage remains significantly lower, under 600 kWh, reflecting reduced commercial operations and less frequent charging activity. This variation suggests the need for dynamic grid management strategies to accommodate fluctuating weekly demand. While

EV charging currently constitutes less than 1% of total electricity consumption in any given zip code, this finding does not diminish its policy relevance. Grid infrastructure is sized to handle peak loads, not average demand; even small but temporally concentrated charging loads, particularly the midday workday peaks observed here, can stress local transformers and distribution infrastructure [22]. Moreover, EV adoption is growing rapidly, and the current low share makes this an opportune moment to proactively plan grid adaptations before EV charging loads become a more acute operational challenge.

Fig. 4 further contextualizes the impact of EV charging by presenting it as a proportion of total electricity consumption per zip code. The analysis identifies Plainfield, Illinois, as having the highest percentage of electricity usage attributable to EV charging at nearly 1%. However, this result is influenced by Plainfield's relatively low total electricity consumption, which makes even a small amount of EV charging more pronounced in percentage terms. In contrast, high-impact areas in Chicago, Evanston, Buffalo Grove, and Glenview display a significant EV charging footprint, reflecting both high overall electricity consumption and a substantial proportion attributed to EV chargers. These findings highlight that while some areas have a high percentage impact, it is often in conjunction with high total electricity usage, which may necessitate more focused grid planning and infrastructure investment.

The geographical distribution of high EV charging impact, as shown in Fig. 5, indicates that the most significant effects are concentrated in downtown Chicago, the north and west suburbs, and Rochelle, Illinois. This spatial pattern suggests that urban centers and densely populated suburban areas, with their higher overall electricity consumption and potentially greater number of commercial EV chargers, are most affected by the integration of EV charging infrastructure. The concentration of high impact in these areas suggests the need for targeted strategies to manage and optimize grid resources, ensuring that the growing demand for EV charging does not lead to potential disruptions or inefficiencies. From a policy perspective, these findings call for a multifaceted approach to grid management, infrastructure investment, and regulatory design. High-impact zip codes should be prioritized for grid capacity upgrades, especially as peak charging loads could threaten local transformers and substation reliability. Urban zoning laws could also evolve to mandate EV-ready developments in dense commercial districts, facilitating future-proof infrastructure deployment.

The strong weekday demand pattern observed—concentrated during mid-morning hours—points to the importance of demand-side management tools, including time-of-use pricing and smart charging systems. These solutions could shift charging demand to off-peak periods, flattening the demand curve and reducing peak loads. Integrating these tools with renewable energy sources could further amplify sustainability outcomes while promoting grid stability. Moreover, the observation that certain lower-consumption areas like Plainfield exhibit disproportionate impacts from EV charging highlights important questions on the actual user behavior exhibited in this area. The observations here may be just an artifact of our assumptions and further investigation into the dynamics of this outlying region should be investigated.

Overall, the results highlight the importance of considering both the magnitude and distribution of EV charging impacts when planning for grid infrastructure and energy management. As commercial EV adoption continues to rise, understanding these patterns will be crucial for developing effective policies and solutions to balance the increased demand on the electric grid. Future work should focus on refining these spatial analyses and exploring additional factors, such as time-of-day variations and seasonal impacts, to further enhance grid management strategies and support sustainable energy systems.

We recognize that these results are built upon two strong assumptions, which raises questions about the reliability of the results. We consider that the availability of data needed to validate these results fully would eliminate the need for this methodology in the first place. The reason is that this procedure is helpful in instances where such data is not available at large scales, so we can make use of these simple yet useful estimates to derive more informed estimates and decisions.

## 6. Conclusion

In conclusion, the analysis of commercial EV charging impacts at the zip code level reveals significant variations in electricity usage patterns and highlights areas of high impact. The results suggest that while workday usage peaks significantly, weekend demand remains relatively low, indicating the need for adaptive grid management strategies. Areas such as downtown Chicago and its surrounding suburbs, which exhibit both high overall electricity consumption and a substantial proportion of that consumption attributed to EV charging, could benefit from further investigation to evaluate the actual need for strategic planning and infrastructure interventions. As the adoption of commercial EVs continues to grow, understanding these dynamics will be critical for developing strategies that ensure grid stability and support the joint growth of the transportation and energy markets. Future research should continue to refine these insights by incorporating additional socio-economic variables (e.g., household income, vehicle fleet composition, land use type, and charging rate classifications) and temporal factors (e.g., seasonal variation in battery efficiency and charging demand, and peak vs. off-peak period differentiation) to better characterize the spatial and temporal heterogeneity of commercial EV charging impacts across metropolitan regions.

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**Author contributions**

The authors confirm their contribution to the paper as follows: study conception and design: Acosta-Sequeda Juan; data collection: Auld, J,, Verbas O.; analysis and interpretation of results: Acosta-Sequeda Juan, U. Sutradhar, F. Allahakbari, A. Bansal, Derrible, S, Auld, J,, Verbas O; draft manuscript preparation: Acosta-Sequeda Juan, U. Sutradhar, F. Allahakbari, A. Bansal, Derrible, S, Auld, J,, Verbas O. All authors reviewed the results and approved the final version of the manuscript.

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