TEMPORAL PATTERNS IN PUBLIC EV CHARGING: INSIGHTS FROM REAL-WORLD DATA

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Abstract
This paper investigates temporal and behavioral patterns in public electric vehicle (EV) charging based on two large-scale datasets from Czech charging providers. The analysis covers both AC and DC sessions and includes more than 490,000 charging records. Results reveal pronounced weekday–weekend asymmetries. AC sessions are typically longer but with lower energy per session, whereas DC sessions show higher variability, with Sunday standing out as the day with the highest average charging power. Statistical tests confirm that Sunday sessions are characterized by significantly lower starting and ending states of charge, suggesting deeper battery depletion after weekend travel. These findings provide novel evidence that temporal charging behavior is not only shaped by infrastructure but also by user routines, with important implications for charging station allocation, grid management, and pricing policy design.

Key words: *electric vehicles; public charging; user behavior*

INTRODUCTION
The global transition to electromobility is accelerating, with electric vehicles *(EVs)* steadily increasing their share of new registrations worldwide. This trend underscores the importance of a robust and user-centric public charging infrastructure. Early research emphasized deployment strategies, charging speeds, and spatial accessibility *(Gnann et al., 2018; Morrissey et al., 2016)*.
More recent work highlights the behavioral dimension of charging. Survey evidence and open datasets show heterogeneous mixes of home, workplace, and public charging; they also document temporal clustering by day and hour, and clear differences between AC and DC usage *(Lee et al., 2019)*. Large-scale empirical analyses further report distinct weekday–weekend patterns—AC stations peaking on weekdays/daytime, while DC fast chargers are relatively more popular on weekends—pointing to systematic temporal asymmetries that infrastructure planners should account for *(Hecht et al., 2022)*
On the technical side, the achievable charging power depends strongly on the battery's state of charge *(SOC)* and thermal conditions; field measurements and laboratory profiling consistently show high power at low SOC followed by tapering with increasing SOC *(e.g., Schaden et al., 2021)*. These dynamics shape session duration, energy delivered, and site throughput—key inputs for pricing, grid integration, and operational strategies.
Despite these advances, intra-day variability, explicit weekday–weekend asymmetries, and the SOC–power interplay in real-world public charging remains underexplored in a Central-European context. To address these gaps, this paper analyzes two large-scale datasets from Czech public charging providers and examines weekly and daily variations in session duration, energy consumption, average charging power, and SOC levels. The goal is to provide actionable insights for charging-infrastructure planning, grid management, and user-oriented pricing.

MATERIALS AND METHODS
This study employs two real-world datasets from public charging providers in the Czech Republic, representing typical public charging activity. The first dataset, referred to as Public 1, contains records from both AC and DC charging sessions, while the second dataset, Public 2, includes only DC sessions *(see in Tab. 1)*. To ensure reliability, both datasets were cleaned according to the validity criteria summarized in Tab. 2. Ultra-fast charging *(UFC, >150 kW)* is included within the DC category, as the data did not distinguish this sub-type separately. Each dataset provides detailed information on session start and end times, dates, energy consumption, and charging locations. Additionally, Public 2 includes SOC values at both the start and end of each session.

Tab. 1 Dataset description

	No. of sessions after data cleaning		Time period
	AC	**DC** *(incl. UFC)*	
Public 1	199676	215008	1/22-12/23
Public 2	-	77541	04/23-09/23; 07/24-07/25

Tab. 2 Requirement on valid session

Charging Type	**Charging duration**	**Energy consumption**
AC	1 - 1440 Min	1-100 kWh
DC *(incl. UFC)*	1-240 Min	1-100 kWh

The interpretation of the results is based on the relationship between the analyzed charging parameters, expressed by the following equations:

$$E_{ch}(T) = \int_0^T P_{ch}(t)dt \qquad (1)$$

E_{ch} *(T)* - cumulative energy in kWh delivered by the charging station in the time interval [0,T]
P_{ch} *(t)* - instantaneous charging power in kW at the station output at the time t

Or by using average values like that:

$$E_{ch} = \bar{P}_{ch} \times t_{ch} \qquad (2)$$

E_{ch} - cumulative energy in kWh delivered by the charging station
$\bar{P}_{ch}$ - average charging power in kW at the station output
t_{ch} - charging duration in min.

For the purposes of this study, the factors influencing charging power are limited to the state of charge *(SOC)* of the EV; external factors are not considered. A nonlinear dependency between SOC and the maximum allowable charging power *(P max)* has been established in several studies *(e.g., Schaden et al., 2021)*.

$$P_{ch}(t) = P_{max}(s(t)) \qquad (3)$$

$P_{ch}(t)$ – charging power at the time t
P_{max} – max. charging power
s*(t)* – SOC at the time t

To compare median values of the analyzed variables across groups, non-parametric methods were applied since the data did not meet assumptions for parametric tests *(e.g., normality)*. The Kruskal–Wallis H test, a non-parametric alternative to one-way ANOVA, was used to assess differences among three or more independent groups. A significant result indicated that at least one group differed, after which Dunn's post-hoc test with p-value adjustment *(e.g., Bonferroni correction)* was conducted to identify specific group differences. This approach enabled both overall detection of group differences and the identification of the pairs responsible.

RESULTS AND DISCUSSION

1. Charging consumption over the week

Figure 1 illustrates the relative distribution of energy consumption across the week. In all datasets, Friday represents the peak day. For AC charging, there is a pronounced difference between weekdays and weekends. This can be explained by user behavior: during weekends, drivers are more frequently on longer trips and therefore rely more on DC charging. In the Public 2 DC dataset, the weekend share of energy consumption is higher than in Public 1 DC. A plausible explanation is the different structure of charging stations in the providers' portfolios. In particular, Public 2 may include a larger share of highway or petrol station chargers, which are more frequently used during weekends as people are travelling more.

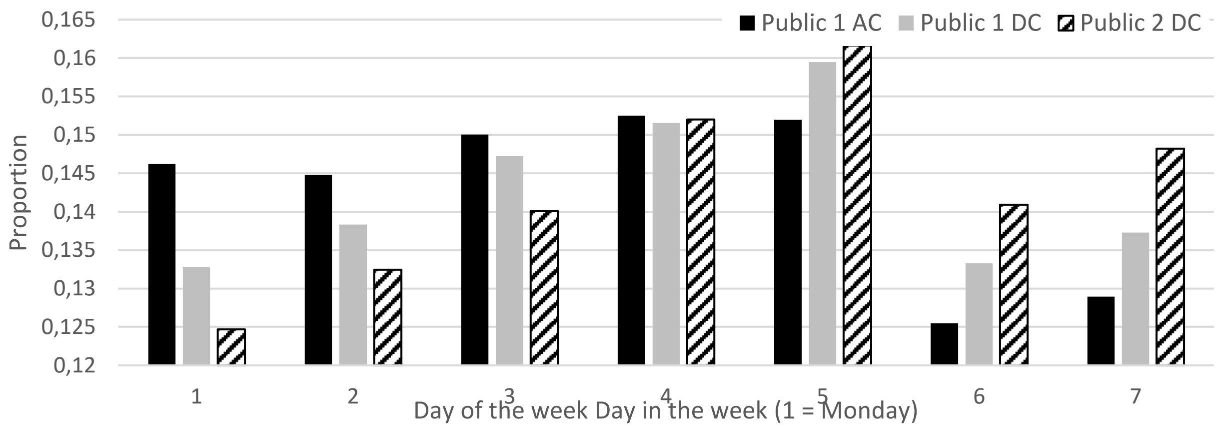

Fig. 1 Energy consumption during the week, proportion

2. Charging session characteristic over the week

2.1 Charging duration over the week

Regarding session duration, a clear distinction is observed between AC and DC charging. AC sessions are generally longer due to the lower charging power *(maximum 22 kW)*. As shown in Fig. 2, the longest average AC session occurs on Monday, while the shortest is on Friday. For both DC datasets, Thursday records the shortest average duration among weekdays, and Sunday the shortest overall. In Public 2 DC, the longest sessions occur on Monday, whereas in Public 1 DC the peak is on Wednesday, although the differences across weekdays are relatively small.

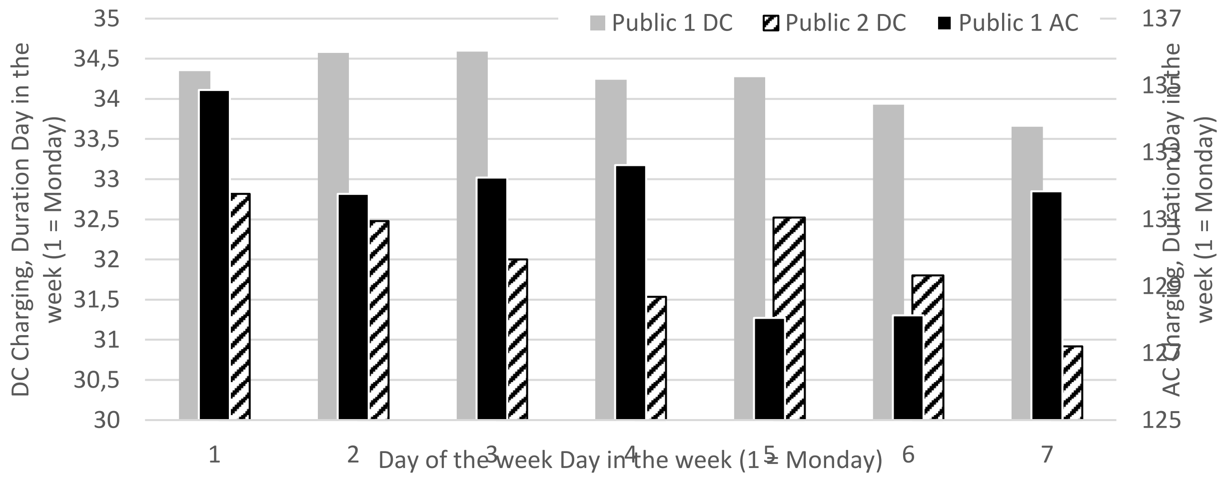

Fig. 2 Charging duration over the week, in min.

2.2 Consumption per session over the week

The distribution of energy consumption per session across the week differs from that of session duration. In *Public AC* charging, the highest average consumption per session occurs during the weekend, while the lowest is observed on Tuesday. For both DC datasets, Sunday records the highest consumption per session.

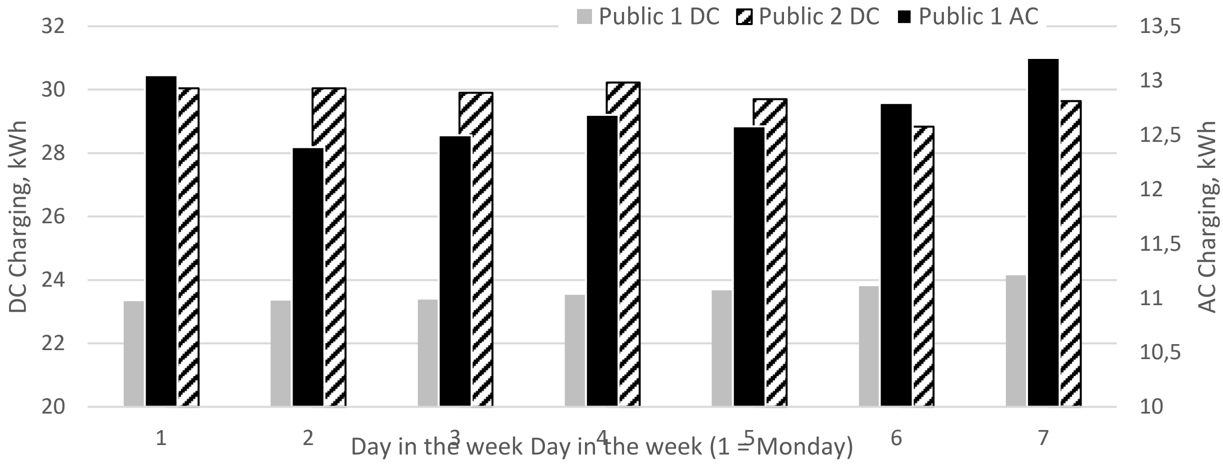

Fig. 3 Consumption per session over the week, in kWh

2.3 Charging power over the week

The charging speed, expressed as the average charging power per session, is determined by the ratio of energy consumption to session duration, as shown in Equation *(2)*. Across all datasets, Sunday exhibits the highest average charging power of the week *(Fig. 3)*. This phenomenon can be explained by both external and behavioral factors. One possible reason is the reduced industrial demand on Sundays, which may improve grid conditions and indirectly support higher charging performance. A more likely explanation, however, relates to user behavior: drivers returning from weekend trips are more likely to charge at high-power highway hubs and to arrive with lower battery SOC levels, which enables charging at higher power levels *(e.g., Schaden et al., 2021)*. This hypothesis is supported by the results shown in Fig. 5, where both the starting and ending SOC values on Sundays are lower compared to other days of the week.

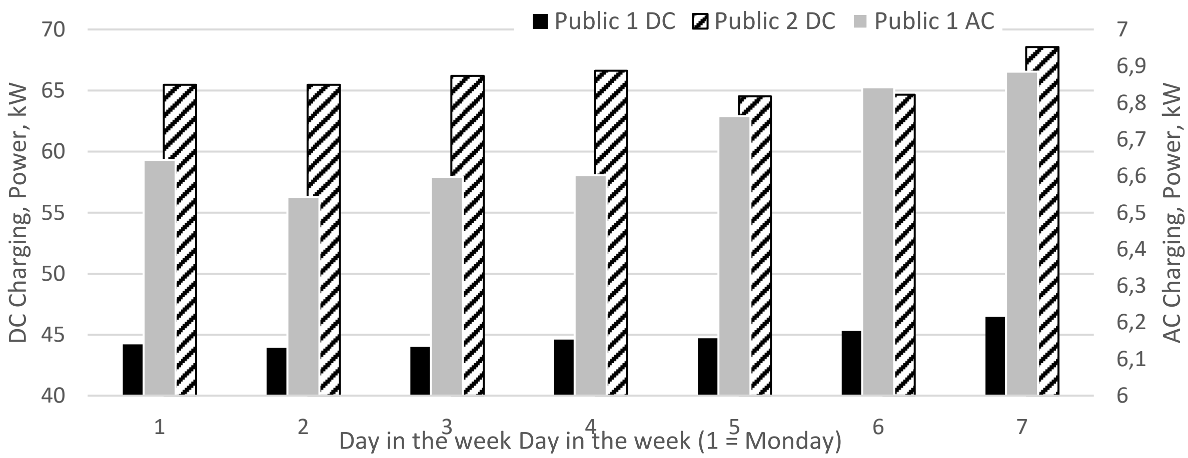

Fig. 4 Charging power over the week, in kW

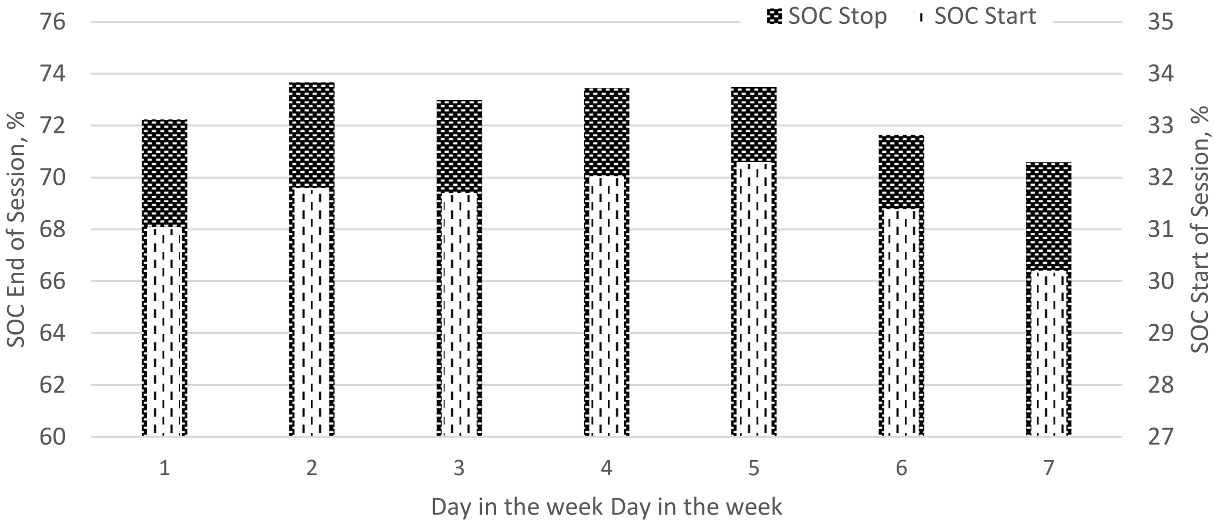

Fig. 5 SOC Start / Stop of the session, dataset Public 2 DC

The post-hoc Kruskal–Wallis test confirmed significant differences between Sunday and all other days of the week in both the starting and ending SOC values *($p < 0.05$)*, as shown in Fig. 6. These results indicate that EV user behavior on Sundays differs systematically from that observed on other days of the week.

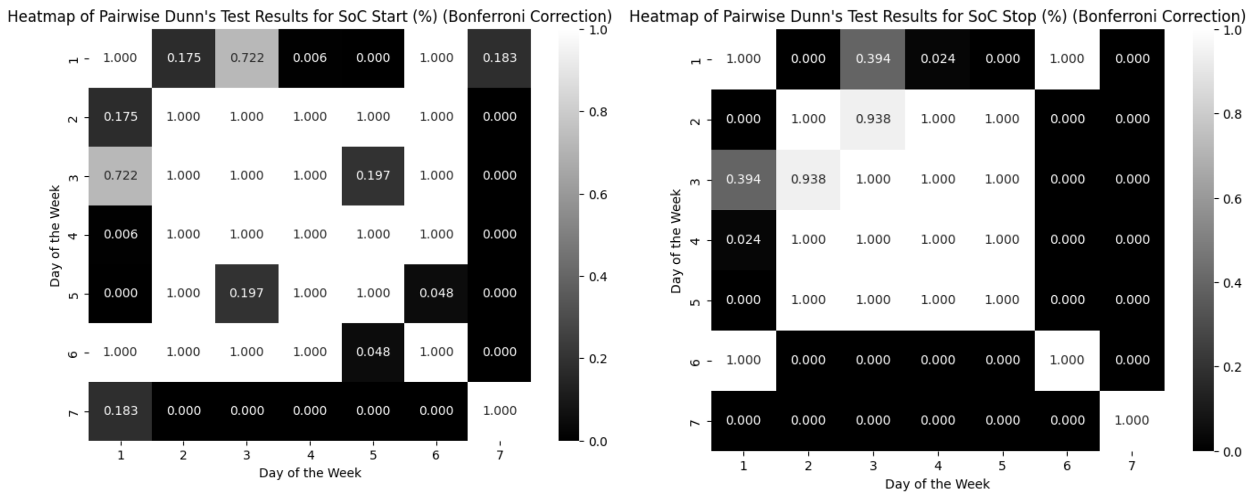

Fig. 6 Post-hoc Kruskall-Wallis test, dependency SOC Start & SOC Stop vs. Day of the week *(1 = Monday)*

ISBN 978-80-213-3541-7

CONCLUSIONS

This study analyzed large-scale datasets from two Czech public charging providers to identify behavioral patterns in electric vehicle *(EV)* charging. The results reveal clear temporal variations across the week. For AC charging, total daily energy consumption is higher on weekdays compared to weekends. Similar findings are reported by *(Hecht et al., 2022)* for Germany and *(Lucas et al., 2018)* for the Netherlands. *(Jonas et al., 2023)* further observed that the number of AC sessions in Canada is higher on weekdays, with a peak on Thursday, a pattern consistent with results from *(Siddique et al., 2022)* based on U.S. data.

For DC charging, both Czech datasets display different distributions of energy consumption across the week, but with a consistent peak on Friday. In dataset Public 1, weekend consumption is significantly lower than during weekdays, whereas in dataset Public 2 Sunday consumption exceeds that of some weekdays. In comparison, *(Jonas et al., 2023)* found the peak number of sessions in Canada on Saturday, with Sunday usage above almost all weekdays, and *(Hecht et al., 2022)* confirmed a similar weekend peak in Germany. These differences likely reflect country-specific conditions, particularly the availability and distribution of charging infrastructure.

We further examined session-level characteristics over the week. In terms of session duration, distinct weekly patterns were observed for AC and DC charging. AC charging sessions are longest on Mondays and shortest on Fridays, while DC sessions are shortest on Sundays, with peaks for longest sessions differing across the two datasets. No comparable studies reporting on this parameter were identified in the literature.

The distribution of average charging power across the week largely mirrors that of charging duration. However, in two cases *(Public 1 AC and Public 1 DC)*, the highest average power was recorded on Sundays. In contrast, *(Tian et al., 2023)* reported higher average session-level consumption on weekdays than weekends in China.

Calculated charging power also peaks on Sundays in all datasets. One possible explanation lies in the SOC levels at the beginning and end of charging sessions: statistical testing suggests that vehicles typically arrive more deeply discharged after weekend travel. *(Tian et al., 2023)* reported similar user behavior in Chinese data.

These findings highlight the importance of incorporating temporal and behavioral dynamics into charging infrastructure planning and pricing strategies. Recognizing that weekend usage, particularly on Sundays, differs systematically from weekday behavior can support more efficient charger allocation, improved grid management, and better-informed user guidance. Future work should integrate external factors such as grid conditions, station location types, and seasonal variation to provide a more comprehensive understanding of public EV charging behavior.

REFERENCES

1. Gnann, T., Funke, S., Jakobsson, N., Plötz, P.,Sprei, F., & Bennehag, A. (2018). Fast charging infrastructure for electric vehicles: Today's situation and future needs. Transportation Research Part D: Transport and Environment, 62, 314–329. https://doi.org/10.1016/j.trd.2018.03.004
2. Hall, D., & Lutsey, N. (2017). EMERGING BEST PRACTICES FOR ELECTRIC VEHICLE CHARGING INFRASTRUCTURE.
3. Hecht, C., Figgener, J., & Sauer, D. U. (2022). Analysis of electric vehicle charging station usage and profitability in Germany based on empirical data. iScience, 25(12), 105634. https://doi.org/10.1016/j.isci.2022.105634
4. Jonas, T., Daniels, N., & Macht, G. (2023). Electric Vehicle User Behavior: An Analysis of Charging Station Utilization in Canada. Energies, 16(4), 1592. https://doi.org/10.3390/en16041592
5. Lee, Z. J., Li, T., & Low, S. H. (2019). ACN-Data: Analysis and Applications of an Open EV Charging Dataset. Proceedings of the Tenth ACM International Conference on Future Energy Systems, 139–149. https://doi.org/10.1145/3307772.3328313
6. Charging Infrastructure Using Exploratory Data Analysis. Energies, 11(7), Article 7. https://doi.org/10.3390/en11071869
7. Morrissey, P., Weldon, P., & O'Mahony, M. (2016). Future standard and fast charging infrastructure planning: An analysis of electric vehicle charging behaviour. Energy Policy, 89, 257–270. https://doi.org/10.1016/j.enpol.2015.12.001
8. Schaden, B., Jatschka, T., Limmer, S., & Raidl, G. R. (2021). Smart Charging of Electric Vehicles Considering SOC-Dependent Maximum Charging Powers. Energies, 14(22), 7755. https://doi.org/10.3390/en14227755
9. Siddique, C., Afifah, F., Guo, Z., & Zhou, Y. (2022). Data mining of plug-in electric vehicles charging behavior using supply-side data. Energy Policy, 161, 112710. https://doi.org/10.1016/j.enpol.2021.112710
10. Tian, H., Sun, Y., Hu, F., & Du, J. (2023). Charging Behavior Analysis Based on Operation Data of Private BEV Customers in Beijing. Electronics, 12(2), Article 2. https://doi.org/10.3390/electronics12020373

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