Impact of Weather Conditions on Electric Vehicle Charging Behavior in an Office Context in Hungary

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Abstract: This paper explores the impact of weather conditions – particularly ambient temperature – on electric vehicle (EV) charging behavior in an office environment in Hungary. Real-world data from AC chargers and local weather records were used to analyze how temperature affects energy consumption and charging patterns. The analysis focused on energy demand and session frequency across varying temperature ranges. Results indicate that colder conditions lead to increased energy consumption, while session frequency remains relatively stable. These findings highlight that the rise in energy demand is primarily driven by higher consumption per session rather than more frequent charging. The study offers insights that can support more accurate demand forecasting.

Keywords: electric vehicle charging; weather impact; energy demand; session duration; load forecasting; charging behavior; ac chargers; smart grid

1 Introduction

The number of electric vehicles (EVs) is rapidly increasing, making optimal load management of EV chargers more critical than ever. Load management refers to the efficient distribution of available electrical power among multiple chargers to prevent system overloads (e.g., tripped fuses) and maintain a high Quality of Service (QoS). A load management system can be optimized with various objectives in mind, including efficient utilization of the power distribution grid, cost reduction, or simply meeting user demands regardless of the cost. Achieving such optimization requires comprehensive knowledge of all variables influencing the system.

This paper investigates how weather condition – particularly ambient temperature – affect EV charging behavior in a real-world office environment in Hungary. The primary objective is to first study the related literature in order to build a solid understanding of existing research in the field. This will guide the development of our own analysis, allowing for a comparison between our findings and those previously reported. Through this comparative approach, the goal is to highlight consistencies and deviations in user behavior under varying temperature conditions, ultimately demonstrating that temperature data is a critical factor to be considered in the local load management of EV chargers.

The paper is structured as follows: Section II reviews the most relevant related work concerning weather effects on EV charging and grid demand. Section III describes the datasets and methodology used in our analysis. Section IV presents the results of our empirical study, focusing on temperature- related variations in energy consumption, session frequency and session count. Finally, Section V draws conclusions and suggests implications for future forecasting and load management strategies.

2 Related Works

In general, weather has a significant influence on energy demand, and the same is observed for electric vehicles (EVs). The authors of [1] state that in cold weather, the energy needs of an EV increase due to the (pre)heating of the cabin and the heating of the battery pack to maintain its optimal operating temperature and the driver’s comfort. Additionally, due to other chemical effects discussed in [2], cold weather can reduce the available energy stored in the battery even without auxiliary loads.

2.1 Grid-Level Impacts and Their Causes

Multiple studies quantify the additional strain on the grid caused by weather-sensitive EV charging. Cold weather has been shown to raise peak load demands due to both increased charging frequency and longer charging durations. A UK-based Monte Carlo simulation by [1] demonstrated that national EV demand could rise by 630 MW during cold spells, leading to significant pressure on generation capacity and grid stability.

Similarly, [3] simulated the charging behavior of 11 million (as 11 million EVs is assumed to be on the roads by 2030) EVs under extreme winter conditions, concluding that an additional 450 MW of generation would be required. This study also noted a shift toward higher carbon intensity, as fossil-fuel generation often compensates for the increased demand.

On a more localized scale, [4] and [5] found that uncoordinated cold-weather EV charging clusters could overload distribution transformers, shortening their lifespan to less than one year in worst-case scenarios.

2.2 EV Charging Behavior and Its Consequences

From a behavioral perspective, ambient temperature influences both the timing and frequency of EV charging. [6] showed that EVs consume approximately 2.4 kWh/100 km more for every 5°C drop below 10°C. This increased demand not only impacts vehicle range but also changes charging patterns, typically resulting in longer and more frequent sessions.

Furthermore, EV users tend to adapt their schedules based on weather conditions. Authors of [7] integrated weather and traffic data into machine learning models and demonstrated a significant improvement in predicting session duration and energy usage. This underscores that cold temperatures are a critical variable in accurately modeling and forecasting EV charging behavior.

Other works, such as [8], emphasize that incorporating temperature data into short-term load forecasting improves grid readiness and infrastructure management, particularly during seasonal transitions. Additional supporting analysis from [3] further highlights grid-level risks under extreme winter charging conditions.

2.3 EV User Patterns and Grid Demand in Hungary

In Hungary, the annual mean temperature range spans approximately 30-40°C, with winter minimums falling below 0°C and summer highs reaching around 30°C [9]. A comparable climate was studied in the Umbria region of Italy in [6], which demonstrated that EV energy consumption increases by approximately 2.4 kWh/100 km for every 5°C decrease in ambient temperature.

Furthermore, workplace EV charging data from Budapest reveals a distinct daily peak in charging activity between 7-8 AM—coinciding with the start of the workday and the broader morning load peak on the national grid [10]. Since colder temperatures both increase energy demand per vehicle and influence charging behavior, the early-morning demand spike can compound strain on already loaded grid infrastructure.

This convergence highlights the critical need for intelligent load management strategies, particularly during winter months when ambient temperatures drop and solar PV output is minimal in the early hours. Recent studies emphasize that properly designed demand-side management (DSM) and predictive scheduling, especially using user-specific behavior models and weather-informed forecasting, are key to maintaining grid stability under these conditions [11] [12] [13].

3 Methodology

For this research, two datasets were utilized: one containing electric vehicle (EV) charging session data and another comprising local weather measurements corresponding to the same time frame.

3.1 EV Dataset

To analyze electric vehicle charging behavior in response to environmental conditions, a dataset was collected from an office building equipped with 23 AC chargers, each capable of delivering up to 22 kW. These chargers are currently un-controlled, meaning that charging power is solely regulated by the vehicle's internal charging system. The user base for this infrastructure consists of 59 registered EV drivers.

Communication between the charging stations and the backend system is handled via the Open Charge Point Protocol (OCPP), an industry-standard protocol designed for EV chargers. OCPP operates over WebSocket using JSON-formatted messages. This protocol enables user authentication, charging session control, and data reporting [14]. During an active charging session, each charger transmits MeterValues messages at one-minute intervals. These reports include realtime metrics such as charging power, current, and cumulative energy delivered.

All OCPP communications are routed through a centralized backend system, which extracts relevant user and session data and forwards it to an IoT platform

(Thingsboard). This platform serves both as a telemetry database and a monitoring interface. It also provides integrated support for user authentication and access control, which was implemented via REST API due to its simplicity and wide support.

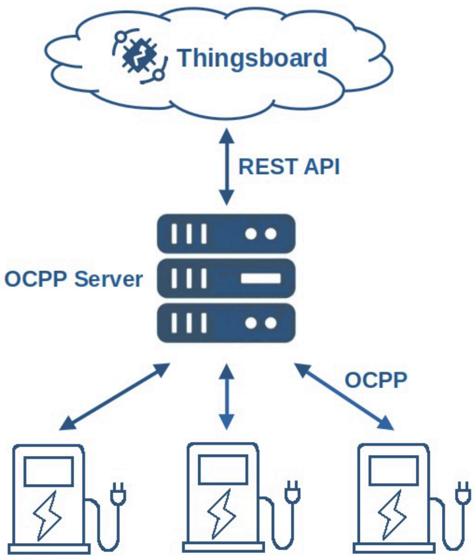

Figure 1
Simplified architecture of the system [10]

An overview of the system architecture is illustrated in Fig. 1. highlighting the connections between chargers, the OCPP server, the telemetry database.

Two key attributes were used from the dataset: deltaEnergy and sessionDuration

- sessionDuration indicates the total time the EV was connected to the charger. This includes not only the active charging period but also any idle time when the vehicle remained plugged in without drawing power.
- deltaEnergy represents the actual amount of energy delivered to the EV's battery, measured in kilowatt-hours (kWh).

3.2 Weather Dataset

The weather data was obtained from the Hungarian Meteorological Service, which provides access to historical weather records for free of charge [15]. For this analysis, the daily average temperature was primarily used as the key variable.

The two datasets were combined based on overlapping time intervals. The start date was determined by the EV charging dataset, which begins on June 29, 2024, while the end date was set by the availability of the weather data, which extended until February 28, 2025. We assumed all users were located near the office building and, accordingly, used weather data from the nearest stations to the chargers.

3.3 Data Analysis

For data analysis a Python library called NumPy was used that is an open source scientific library in Python [16].

The dataset contains some dummy charging sessions, where the user repeatedly started charging sessions within a short time period. These sessions are easily identifiable: the deltaEnergy parameter is typically 0, and the sessionDuration is very short. This user error can lead to inaccurate results, so a filter must be applied to the dataset: only sessions with a deltaEnergy value greater than 0 are accepted. Beside this, we also excluded users that have a charging record count less than 10, and sessionDuration longer than one day.

4 Results

First, we examined whether there is a correlation between temperature data and deltaEnergy. Based on related work, our assumption was that as temperature decreases, deltaEnergy increases. This assumption was supported by the data: for most users, the correlation between temperature and deltaEnergy was weak to moderate and negative (ranging from -0.004 to -0.55). Some users, however, showed a positive correlation, likely due to an insufficient amount of charging session data.

A negative correlation between temperature and charged energy was observed in 81.48% of users, suggesting that energy demand tends to decrease as temperatures rise. In Fig. 2, the weekly average energy consumption of users is shown as a function of weekly average temperature. A clear increase in energy demand can be observed at temperatures below approximately 10°C.

In numerical terms, the average energy consumption difference between values below and above 10°C threshold is as follows:

- The energy demand increased for 65.45% of the users at temperatures below 10°C.
- 27.27% of users showed a decrease in energy demand in colder conditions.
- 7.27% of users had insufficient data (i.e., no charging sessions in either the cold or warm period).

- For users whose energy demand increased, the average growth was 6.25 kWh.
- For users whose energy demand decreased, the average reduction was 2.49 kWh.

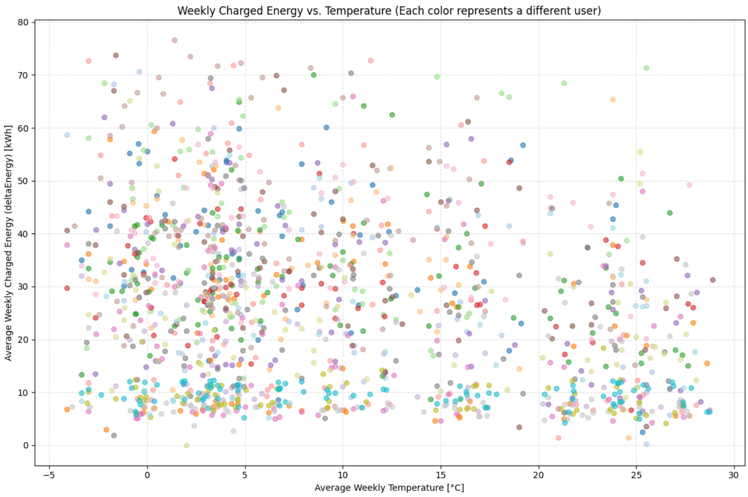

Figure 2
Average weekly energy need vs. average weekly temperature

Some individual users' data were also examined. We fitted both linear and third-order polynomial models to each user's data points, this can be seen in Figure 3. The resulting models show that the intercepts vary, due to differences in battery capacities, while the slopes reflect trends in energy consumption relative to the independent variable.

However, in most cases, the coefficient of determination (R^2) was relatively low even when using actual (non- averaged) data instead of weekly averages. The R^2 values are indicated in the legends. These plots clearly demonstrate high variance in the data, resulting in poor model fits. Consequently, the regression curves may not yield reliable or meaningful predictions.

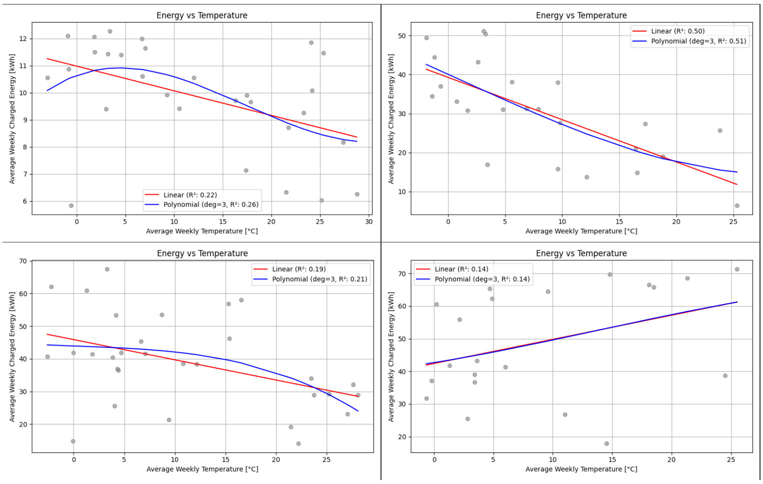

Figure 3

Individuals' average weekly energy consumptions vs. average weekly temperature

To determine whether the increased energy demand in colder temperatures is due to higher energy consumption per session or simply more frequent charging, we examined the average session count. As shown in Fig. 4 the average number of sessions per week does not differ significantly above and below the threshold. The overall change in session count is minimal, with both increases and decreases observed among users.

Figure 4

Average weekly session count vs. average weekly temperature

In Fig. 5 some examples of individual users' charging session count can be observed. In most cases, the average session count shows similarity in both cold and warm weather.

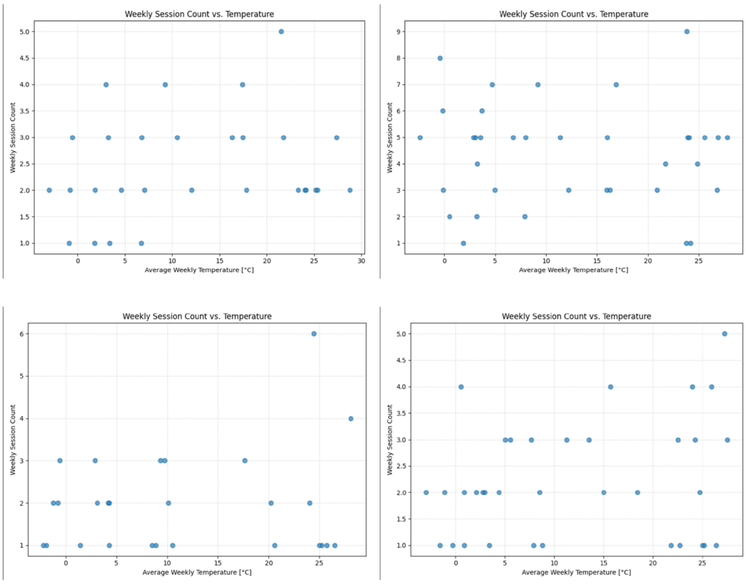

Figure 5
Average weekly session count vs. average weekly temperature

Compared to the previous results of delta energy, the session count is divergent:

- The session count increased for 50.9% of the users at temperatures below 10°C.
- 41.82% of users showed a decrease in session count in colder conditions.
- 7.27% of users had insufficient data (i.e., no charging sessions in either the cold or warm period).
- For users whose session count increased, the average growth was 0.42 sessions per week.
- For users whose session count decreased, the average reduction was 0.49 sessions per week.

Finally, we examined how the session duration depends on the temperature, this is illustrated in Fig. 6. As session duration is not equal to the charging time, we expect that session duration will bring the same tendency like the session count, there will be no significant change. If we calculate the differences beneath and over the 10°C threshold value we got the following results:

- 63.64% of users had an increase in session duration in cold weather.

- 29.09% of users had a decrease in session duration in cold weather.
- 7.27% of users had insufficient data to evaluate session duration changes.
- Among users with increased session duration, the average growth was 68.97 minutes.
- Among users with decreased session duration, the average reduction was 43.33 minutes.

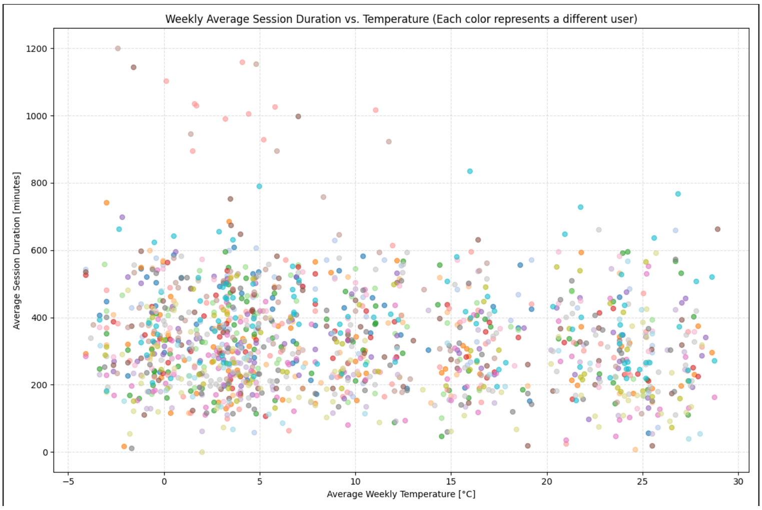

Figure 6

Average weekly session duration vs. average weekly temperature

On the plot we can see that in case of some users, the session duration is significantly increased, but for the rest it is basically remained the same.

Conclusion

This study examined the relationship between ambient temperature and EV charging behavior in an office environment in Hungary. The results consistently showed that colder temperatures lead to increased energy consumption per session, while the frequency of charging sessions remains largely unchanged. This is consistent with previous studies from the related literature, where increased energy demand in cold weather is attributed to battery heating and cabin conditioning requirements [1], [2], [6]. None of the related works explicitly examine the impact of weather on the number of charging sessions. However, our findings suggest that in fixed-schedule office environments, increased demand due to cold weather is reflected primarily in higher energy per session rather than an increased number of sessions.

Furthermore, our findings reinforce conclusions from other research efforts [7], [8], which demonstrated that incorporating temperature data into forecasting models improves predictive accuracy. In our case, this holds true even in a localized and behaviorally stable environment, such as a workplace charging scenario.

Given the significant influence of temperature on energy consumption, it is evident that weather conditions – especially temperature – should be factored into EV load management systems. Doing so not only improves forecasting and scheduling but also helps mitigate risks of grid overload during cold periods. These insights underscore the importance of weather-aware demand-side management strategies in both local and national grid contexts.

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