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Development and Applications of Electric Vehicle Charging Profiles

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Abstract. The aim of this paper is to present a methodology for generating electric vehicle (EV) charging profiles based on real-world data. The approach dynamically adjusts charging behaviour to daily travel needs and available charging time. A battery cycle counting method is introduced to track charge and discharge cycles. Case study results demonstrate the method's ability to simulate realistic charging scenarios. The paper also discusses practical applications, including grid impact analysis, household energy optimization, and analysis of new grid fee tariffs.

Key words. electric vehicle, charging profile, cycle counting.

1. Introduction

Advancements in battery technology and the broader shift toward low-carbon technologies are accelerating the electrification of transportation. Enhanced energy density, faster charging capabilities, and improved battery longevity have made electric vehicles (EVs) more viable and attractive for widespread adoption. However, the increasing number of EVs and their charging requirements introduce new challenges for the power grid.

Unlike conventional loads, EV charging demand is highly variable, influenced by user behaviour and other external factors. As EV adoption grows, the intermittent and often unpredictable nature of charging patterns can lead to fluctuations in demand for electrical energy, grid congestion, and potential power quality issues.

Charging profiles play a crucial role in understanding and managing EV charging behaviour. By modelling and optimizing these profiles, it becomes possible to gain deeper insights into their impact on the power grid and develop strategies to mitigate adverse effects. Well-defined charging profiles can also support demand-side management strategies, enabling smarter and more sustainable energy use. As the transition to electric mobility continues, the development and application of charging profiles will be essential for ensuring a reliable and efficient power system.

The adoption of EVs has steadily increased over the past decade. In Slovenia, the first registrations of EVs as personal vehicles appeared in 2012. By the end of 2024, the number of registered EVs in the country had already reached 16,000 [1], reflecting significant growth driven by consumer interest and government subsidies for EV purchases. On a broader scale, Europe saw over 1.4 million battery electric vehicles (BEVs) registered in 2024 alone [2], accounting for approximately 14 % of all new car sales [3]. This figure excludes hybrid and plug-in hybrid (PHEV) models. Supporting this shift, the European charging infrastructure has also expanded, with more than 755,000 EV charging stations installed across the continent by end of 2023 [4]. These trends underscore the substantial transformation of the transport sector and the growing need for further research into EV charging dynamics.

The increasing adoption of BEVs has been widely recognized and anticipated by numerous researchers. A common challenge highlighted in the literature is the lack of statistical data on EV charging behaviour, which is essential for determining typical electrical energy demand profiles during vehicle charging. At the same time, researchers emphasize the need to predict charging behaviour accurately [5]. Consequently, many studies rely on existing mobility statistics, which are predominantly based on conventional internal combustion engine vehicles [6].

EVs exhibit unique characteristics, particularly in terms of charging duration and driving range. Key parameters for modelling EV charging behaviour include the number of charging sessions per day, the start time of charging, and the state of charge (SoC) before charging. As expected, studies indicate that 93 % of weekday trips follow a simple loop between two locations [6]. The findings in [7] suggest that 70 % of EVs are charged only once per day, primarily at home. Interestingly, the average user rarely allows the battery's SoC to drop below 16.7 % [7], with most drivers initiating charging when the SoC reaches 50 % [8]. Furthermore, most home charging sessions occur overnight [9].

Studies often rely on measurements from BEVs of various manufacturers, battery capacities, and power ratings to determine charging power profiles. In [5], the authors compared seven different vehicles, finding that charging profiles remain mostly constant, except for a power reduction toward the end of the charging process. During charging, the battery's state of charge increases linearly.

It is important to note that actual charging power is not solely limited by the charging station's capacity but is also constrained by the vehicle's battery itself [8]. Although most public charging stations operate at 11 kW, real-world charging rarely reaches this maximum power due to vehicle-specific limitations [5].

The reviewed studies present charging profiles with varying temporal resolutions, but a common approach is carrying the battery’s SoC from one increment to the next. The SoC is updated by subtracting the energy consumed during driving and adding the energy supplied during charging [6]. This paper follows the same methodological principles.

The development of the charging profile in this paper is based on data from a single charging station, which is among the most commonly used in Slovenian households. Additionally, during the research, access was provided to only one EV, which serves as the object of the study and is representative of the mid-range segment in Slovenia in terms of price and driving range. However, the methodology, built upon these findings, provides an easily replicable approach applicable to various vehicle types. Therefore, it is argued that data limitations do not pose a significant issue, and the work remains a valuable contribution, demonstrating practical applicability.

Most researchers recognize the suitability of charging profile modelling methodologies for grid analysis, and the methodology presented in this paper has similarly been applied for these purposes. It has proven valuable in various contexts, including the development of graphical user interfaces to support investors in making informed decisions about vehicle adoption, as well as in calculations related to the revision of the grid fee tariff system. These EV charging profiles have been successfully implemented and applied in these areas, demonstrating their practical applicability and value.

The remainder of this paper is organized as follows: section 2 presents the methodology, detailing the collected charging data and the algorithm used to create EV charging profiles, along with an algorithm for counting battery cycles, which is not commonly addressed in the existing literature. Section 3 presents the results of the case study, demonstrating an example of input data and the corresponding outcomes. Section 4 explores the potential applications of charging profiles, providing a discussion of their practical uses in various contexts. Finally, section 5 concludes the paper, summarizing the main findings and their broader implications.

2. Methodology

The methodology presented in this paper is based on data collected from a real charging station and an EV. These data are described in subsection 2. *A*, form the basis for developing the charging profiles. This includes details of the charging station, the vehicle used and key features relevant to profile development. Subsection 2. *B* outlines the algorithm employed to generate the charging profiles, while Subsection 2. *C* introduces the method for battery cycle counting.

A. Charging station and EV data overview

Power measurements on the charging station were conducted at various times between October 13 and November 23, 2024, during which the charging station was in use. The measurements were taken at 15-minute intervals, aligning with the data resolution proposed for the charging profile methodology.

The charging station offers two distinct charging power levels, referred to as "high power" and "low power," corresponding to the "fast" and "eco" charging modes. The nominal power of the charging station is 22 kW, while the electric vehicle is limited to a charging power of 11 kW. During high-power charging, the actual power is typically around 8 kW on average. Power fluctuations during charging are depicted in Figure 1, which shows several charging sessions at high power. At the beginning of the charging cycle, the power starts higher, fluctuating around an average value of 8 kW. The duration of the charging process varies due to the initial SoC of the battery.

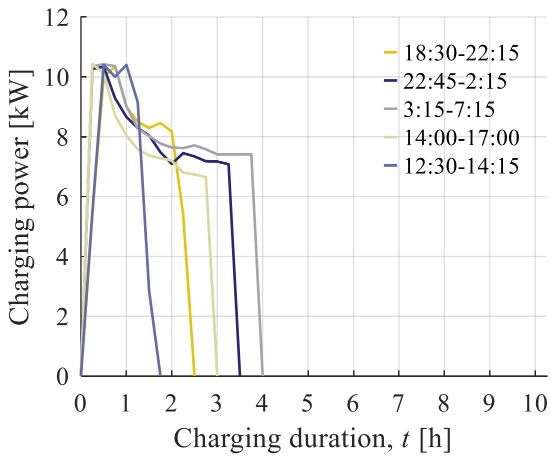

Fig. 1. High-power charging sessions

Figure 2 shows several low-power charging sessions, with power fluctuations around an average value of 4 kW. As with high-power charging, the duration of the charging process varies based on the initial SoC of the EV’s battery.

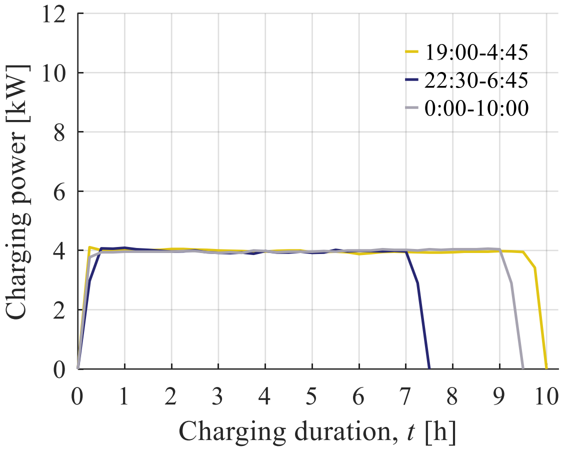

Fig. 2. Low-power charging sessions

The key characteristics of the charging station and EV are summarized in Table I.

Table I. – Charging Station and Vehicle Specifications

Charging station type	AC, three-phase
Charging station nominal power	22 kW
EV charging power limit	11 kW
EV nominal battery capacity	50 kWh
EV nominal range	350 km

B. EV charging algorithm

This subsection presents the algorithm developed for generating the charging profiles. The algorithm considers various factors, such as the vehicle's required energy for daily travel, the availability of charging time, and the power levels offered by the charging station. It iterates over a period of one year, adjusting the SoC of the vehicle based on daily driving requirements and available charging periods.

The decision to use low- or high-power charging is made dynamically, considering the availability of consecutive charging hours and the energy required to meet the vehicle's daily travel needs. The algorithm distinguishes between workdays and weekends, as the driving distance and charging availability may vary.

The input data required for the algorithm include charging station and vehicle specifications which are listed in Table I. Additionally, the distances travelled on workdays and weekends, as well as the charging availability periods for both workdays and weekends. These inputs serve as the foundation for simulating the charging profile and will be used to initialize the charging process throughout the entire year.

The algorithm first calculates the required energy for each day based on the distance travelled. It then checks whether the vehicle's current SoC is sufficient to cover the daily energy needs. The algorithm triggers the charging process if the SoC is below the required energy or falls below 50 % of the nominal capacity.

During charging, the algorithm evaluates the available charging time. If enough consecutive time is available for low-power charging, it opts for the slower charging mode. Otherwise, it uses high-power charging to ensure that the vehicle reaches its full capacity as quickly as possible. The charging process continues until the SoC reaches the nominal capacity of the battery, after which no further charging is required for that day.

The charging decision is influenced by both the required energy and the availability of charging time throughout the day, which is split into 15-minute time blocks for workdays and weekends. The algorithm iterates through these steps daily, updating the SoC based on the energy consumed for driving and the energy added during charging, ensuring the vehicle remains adequately charged for the next day's journey.

Charging algorithm

```
for n = 1 : 365
  if n == workday
       1. distance travelled on workdays
       2. charging availability periods
       on workdays

  else
       1. distance travelled on weekends
       2. charging availability periods
       on weekends

       if SoC(n-1) < (required energy ||
       50 % nominal capacity)

         for h = 1 : 96

              if max. consecutive
              charging availability >=
              low power charging time

                start low-power charging

              else

                start high-power charging

                     if SoC == nominal
                     capacity

                       break

                     end

              end

         end

       end

  end

SoC(n) = SoC (n-1) - required energy +
charging

end
```

C. *Battery cycle counting algorithm*

Each battery is expected to complete a certain number of cycles (known as cycle life) over its lifetime. A cycle refers to one full charge and discharge of the battery, although in practice, most charging and discharging events are partial, representing only a portion of a full cycle. Many authors highlight the difficulty of defining a complete cycle, as real-world batteries are rarely charged and discharged to their full capacity. Most charge and discharge events are partial, contributing only a fraction of a full cycle [10, 11]. Despite the cycle not being fully completed, each partial charge or discharge still contributes to the battery's strain.

The cycle counting method used in this paper is inspired by the approach outlined in [12]. Charging and discharging cycles are calculated daily, as the input data provide only the total daily energy required for travel without details on the exact timing of discharging events throughout the day. The proposed battery cycle counting method is illustrated by the Cycle counting algorithm below. If the change in battery SoC during a given period is positive, it contributes to the charging increment, while a negative change in SoC corresponds to the discharging increment. One full charge or discharge cycle is counted when the total charging or discharging reaches the usable battery capacity. Over a longer period, the total number of cycles is calculated as the average of the charging and discharging cycles.

Cycle counting algorithm

```
for n = 1 : 365
  dSoC = charging – required energy

  if dSoC > 0
       charge = charge + dSoC

  elseif dSoC < 0
       discharge = discharge + dSoC

  end

  if charge == nominal capacity
       plus cycles = plus cycles + 1
       charge = 0
  end

  if discharge == – nominal capacity
       minus cycles = minus cycles + 1
       discharge = 0
  end

  charge cycles (n) = plus cycles
  discharge cycles (n) = minus cycles

end

cycles = (charge + discharge cycles)/2
```

3. Case results

In this section, a charging profile is generated for a specific case study. The input parameters used in the simulation are consistent with those defined in Table I, with additional case-specific parameters summarized in Table II. These inputs define the vehicle's daily driving distances and available charging periods, forming the basis for the generated charging profile.

Table II. – Case input data

Distance travelled on workdays	100 km
Distance travelled on weekends	50 km
Charging availability periods on workdays	0:00-4:00, 15:00-17:00, 21:00-23:59
Charging availability periods on weekends	0:00-8:00, 15:00-23:59

Figure 3 presents the charging power profile over the course of one month. A one-month period is selected for improved readability of the graph. The alternation between low and high charging power levels is clearly visible, with high-power charging occurring more frequently. This pattern reflects the dynamic decision-making process of the algorithm, which adapts charging power based on availability and required energy for the daily travelled distance. Although the figure displays data for a single month, the same pattern repeats consistently throughout the entire year.

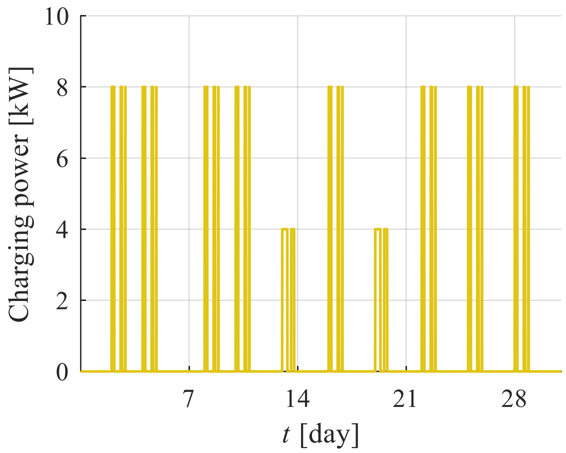

Fig. 3. Charging power profile over one month

Figure 4 presents the SoC of the EV battery over one month. The SoC fluctuates between approximately 20 % and 100 %, reflecting daily energy consumption and subsequent charging events. A repeating pattern is observed, indicating that the battery is regularly recharged before depleting to low levels.

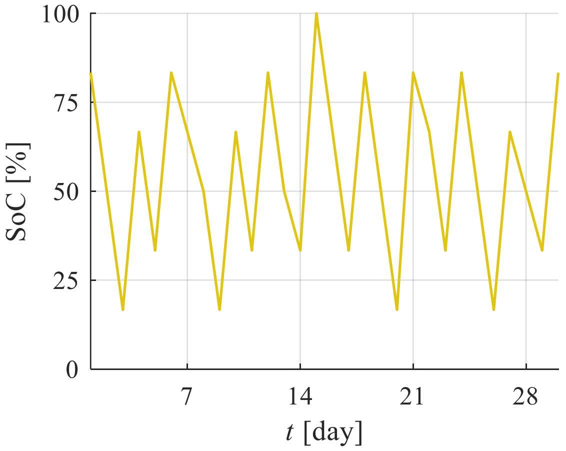

Fig. 4. EV battery SoC over one month

Figure 5 presents the number of charge and discharge cycles recorded over one month. The graph shows a stepwise increase in both charge and discharge cycles, reflecting periodic charging and usage patterns. By the end of the month, the total number of cycles reaches five. Over the course of the year, the total number of cycles amounts to 73.

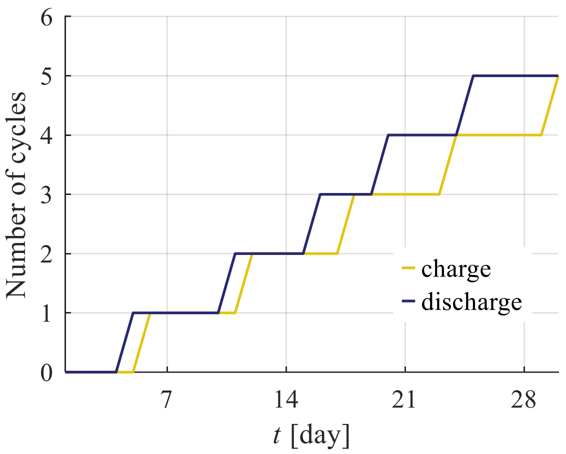

Fig. 5. Number of charge and discharge cycles over one month

4. Discussion on applications

The most prevalent application of EV charging profiles is in grid impact analysis, where they are integrated into simulation models of electrical distribution grids. These models are designed to assess the effects of distributed energy resources and various low-carbon technologies, including EVs and their associated charging infrastructure. By simulating EV charging behaviour, we can evaluate their potential impact on the grid, considering factors such as demand fluctuations, load distribution, and grid stability. This approach enables more accurate forecasting of future grid conditions, providing grid operators with valuable insights to optimize infrastructure planning and capacity management.

Another key application of the presented methodology is the development of a graphical user interface (GUI) designed to guide investors in their decision to purchase EVs and in optimizing the overall electrical energy consumption of their households. The GUI utilizes 15-minute smart meter data, making the 15-minute resolution of the EV charging profiles particularly well-suited for this purpose. This interface requires user input, as detailed in section 3, allowing for personalized vehicle preferences and recommendations based on individual traveling patterns. By integrating these profiles with real-time household energy data, the tool offers valuable insights, enabling users to make informed EV adoption choices and effectively manage their electrical energy consumption.

The presented methodology has also been applied to analyse a new grid fee tariff system, where it plays a crucial role in assessing the financial implications for EV owners. By incorporating 15-minute resolution smart meter data, this analysis enables a detailed understanding of how different charging behaviours impact overall energy costs. With the use of EV charging profiles, potential and current EV owners can better visualize the costs associated with their vehicle usage patterns and anticipate future energy expenditures.

5. Conclusion

This paper presents a methodology for generating EV charging profiles based on real-world charging data and an algorithm that dynamically adjusts charging behaviour according to daily travel needs and charging availability. Additionally, the proposed cycle counting method offers valuable insights into battery usage patterns, revealing a balanced progression of charge and discharge cycles over time.

The paper also outlines several practical applications of the EV charging profiles, demonstrating their real-world applicability, as some have already been successfully implemented. Well-defined charging profiles are essential for understanding and managing EV charging behaviour. Future work should expand this study by incorporating a broader dataset, considering multiple vehicle types and different charging infrastructures.

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