Evaluating and Processing the Data from a Charge Point Management System for the Development of Standard Profiles of Different Charge Point Operator Types

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Abstract— **The electrification of vehicles in Germany and the planned restriction on new registrations of internal combustion engines by 2035 are increasing the pressure on the electricity grid. Accurate estimation of the current and future grid load as well as the storage potential of electric vehicles is crucial for grid planning. The development of standard profiles for different charge point operators is necessary to model charging behaviour and assess the impact on the grid. While established profiles exist for public and private charging infrastructure, profiles for corporate fleets are still sparse. However, company fleets have significant potential to contribute to grid services. The objective of this paper is to evaluate the capability of data from a charge point management system to develop standard profiles for different company fleets. Key considerations include the periodicity of the charging behaviour and the heterogeneity of a company's charging infrastructure. Employing an analytical approach, the paper determines the requirements for the data of a specific company that must be fulfilled to develop standard profiles.**

Keywords—**Bi-directional Charging, Charging Behaviour Analysis, Grid Management, Electric Vehicle Fleets, Standard Profiles**

I. INTRODUCTION

Electromobility has proven to be a key driver for the transformation of the transport sector. A central role in the process of electrification is played by company fleets. In Germany, commercial vehicles account for more than two-thirds of new registrations in 2024, while representing only 12% of passenger cars. 81% of all new plug-in hybrids and 63% of all new battery electric vehicles were registered by companies [1]. While these vehicles offer considerable potential for grid services due to their predictable operating times and fleet sizes, they also have a significant impact on the electricity grid [2], [3]. Therefore, a comprehensive understanding of their charging behaviour is essential to quantify the grid load and exploit the flexibility potential [4], [5]. However, despite the increasing number of electric vehicles standardised charging profiles for company fleets do not yet exist.

While previous studies primarily focused on public and private charging infrastructure, they often encountered challenges when analysing fleet operators due to limited data availability. Researchers like [6] typically had access to restricted datasets from only a small number of companies, with variations in origin and quality of the data. This limitation made it difficult to accurately model the unique characteristics of individual fleet operators and to generate generally applicable standard profiles.

A charge point management system (CPMS) has been identified as a possible solution to the previously mentioned challenges [4]. It offers a centralised way of accessing charge data, with a consistent database for a range of companies.

The objective of this paper is to evaluate the data from a CPMS to develop standard profiles for company fleets. It also presents the necessary steps for processing the data and specifies the requirements that must be met to successfully develop standard profiles.

The paper is structured as follows: Section II presents the current state of research and clarifies the research gap. This section also explains the interest in fleet operators and the suitability of their environment for further grid services. Section III describes the data source, data processing and methodology used to identify different user groups within a company's charging infrastructure. Section IV summarises the results of the data processing, while section V presents the conclusions drawn from the findings and outlines further steps for the development of standard profiles.

II. BACKGROUND

A. Related Work

With an increasing electrification of transportation, the need for standard profiles that include electric vehicles has become greater. Especially in the beginning of this research field, mobility studies and travel data were used to derive the impact of electric vehicles on standard profiles. The studies were used to extract relevant parameters such as arrival and departure times as well as daily mileage [6], [7], [8], [9], [10]. However, with the increase in electric vehicles and the expansion of charging infrastructure in recent years, datasets containing real charging sessions are available [4].

Nevertheless, recent research indicates that the development of realistic and feasible standard profiles for groups of plug-in electric vehicles remains a challenge. This is mainly due to uncertainties and complex dependencies between different influencing factors. Consequently, many results from previous studies are not directly applicable or limited to specific groups of charging infrastructure or users [7], [8].

To enhance the general transferability of research results on charge profiles, [6] emphasises the importance of a precise categorisation of the analysed data and user groups. It is essential to explicitly describe the data sources and user groups for which the profiles are developed, and to outline the methodologies used.

The type of charging infrastructure (public, private or semi-public) and its technical characteristics (e.g. socket type and charging power) are also relevant factors. Furthermore, user behaviour can vary significantly and is often determined by both the type of charging infrastructure and the user group. Examples of user groups include private users, commercial users, fleet and service providers, and temporary users who utilise the charging infrastructure for limited periods. The origin, quality and size of the datasets are further important factors. The type and size of the data influence the choice of the method applied to generate the profiles. This leads to the use of different approaches such as stochastic, agent-based or machine learning [6].

Much work has been done to model charging profiles using different data sources and methods. The research project from [8] analysed GPS data of 15 electric vehicles and driver surveys from six European countries to develop standard profiles for private vehicles charging at public infrastructure, at home and at work. Another research project, which also focused on public charging infrastructure but was based on a larger dataset, included data from 12,000 AC charge points and more than 100 DC charge points in 20 major cities over a 3-year period [11]. Standard profiles based on energy consumption and charging time profiles from a CPMS were used in [12]. In this study, the researchers noticed that the standard profiles on the public charging infrastructure were highly dependent on the charging location, and therefore profiles were created for each charging environment.

In addition to the public charging infrastructure, profiles were also developed for the private sector to analyse the impact of increasing penetration of electric vehicles on the standard load profile for households [13]. A probabilistic model using Monte Carlo simulations generated load profiles for electric vehicles in private households and assessed the impact on the distribution grid [14].

Company fleets have also been the scope of research. In [15], charging profiles for industrial consumers were modelled under the assumption that the vehicles must always be available from 6 am to 6 pm on weekdays. [16] analysed the charging behaviour of different bus depots and their potential for flexibility provision. Ambient temperature, charging method, day of the week and location (urban/rural) were identified as influencing factors. As it was not possible to develop a single standard load profile for all depots, different standard load profiles were derived for groups of depots. Furthermore, in [6] it was shown that the limited database and the dependence of charging behaviour on company-specific factors make it difficult to create generally valid standard profiles. Thus, the development of profiles is still a major challenge as the processes within and between different companies and sectors can vary greatly.

In summary, previous studies have successfully developed and validated standard load profiles for public and private charging infrastructures. Moreover, first standard profiles for specific company fleets have been developed. Nevertheless, due to the limited database and the individual characteristics of companies, ubiquitously valid and applicable results are still missing.

B. Potential of Fleet Operators

After outlining the current state of research on the development of standard profiles in electromobility, this subsection describes the interest of grid operators in fleets and their suitability for the provision of grid services.

Repetitive and predictable usage patterns combined with long charging times enable fleet operators to optimise the consumption and charging of their vehicles. Night-time and weekend operations, which are not or only partially carried out in many companies, offer considerable potential for flexibility [4], [16]. Moreover, fleet operators aggregate multiple vehicles at a single location, resulting in high connection capacities. In addition, DC charging stations with an output power of up to 350 kW per station are often installed for operators of heavy vehicles, which significantly increases the flexibility of the charging process. Furthermore, heavy electric vehicles, such as buses and trucks, generally have larger batteries compared to conventional electric cars. This results in higher energy and power demands, but also provides greater opportunities for energy supply. Another aspect is the political influence on companies. In the case of municipal companies, such as bus and city cleaning services, the authorities can determine the measures to be implemented for providing grid services [4].

In conclusion, certain fleet operators are well suited to offer both positive (increase power) and negative (reduce power) flexibility, or to provide energy as soon as bi-directional charging becomes available [16].

III. METHODOLOGY

The literature review indicated the importance of transparency regarding the origin of the data and the groups analysed when developing standard profiles. Consequently, the primary step is a precise presentation and categorisation of the data utilized for this work.

A. Database description

The data used in this paper is derived from a CPMS. A CPMS enables the communication between a Charge Point Operator (CPO) and charging stations. The Open Charge Point Protocol (OCPP) ensures a standardised communication. The protocol is an open standard that defines the method and content of the transferred messages. This allows a CPMS to integrate any charge point vendor when OCPP is implemented.

A CPMS is utilised by all types of CPOs, including private, commercial, and public operators. Consequently, the software grants access to data from multiple CPOs, encompassing various types of charging infrastructure and user groups [4].

Regarding the development of standard profiles, a CPMS proves to be a suitable data source, as the data is transmitted in a standardised format, is stored for a long period of time, and contains information on many different operator types.

Table 1 summarizes the available data for this work. The data originates from the CPMS of the distribution system operator Hamburger Energienetze GmbH, which is connected to more than 21,000 charge points throughout Germany. The information is provided in an anonymized format, indicating only the sector of the operator and the type of charging infrastructure (public, semi-public, private).

Table 1: Description of the database

Data	**Description**
Origin	Charge point management system
Type	Static and dynamic data from charge points
Format	Open Charge Point Protocol
No. charge points	21,000
Location	Germany
Collection time	4 years
Operator types	Public, semi-public, private (company fleets)
Charge point operators	364
Charge point vendors	38
Charge point types	AC, DC

Over a period of four years, static information on the charge points, as well as time series data on charging sessions from various operator types, has been collected. Depending on the individual configuration of the charging stations, the time series data is recorded at intervals with a maximum resolution of 30 seconds and a minimum resolution of 5 minutes.

B. Research question and approach

Based on the conducted literature review this study assumes that standardised charging profiles can be developed for fleet operators due to regular usage patterns in their charging behaviour. These profiles enable the modelling of different types of fleet operators from various sectors. Furthermore, common standard profiles can be defined for fleet operators that follow similar charging patterns, even though they are from different industry sectors.

However, the evaluation and processing of the used data is a crucial preparatory step to enable the derivation of reliable standardised charging profiles. Herein it is possible to determine and rate certain conditions that the data, as well as the companies and their fleets, must fulfil. This assessment is fundamental to evaluate the suitability of the data for the development of standardised profiles and to verify the applicability of these profiles to other fleet operator groups.

C. Data processing

The following subsection describes the individual steps of data preparation and evaluation. The study focussed on operators with at least one full year of available data. In addition, only operators with a certain fleet size were considered. Operators with less than ten different vehicles charged per week were excluded.

Data inconsistency*:* To ensure a high level of plausibility in the observed charging patterns, additional data from the CPMS (OCPP-status, web socket connections, CPMS logs) were provided. The data allows a precise analysis and categorisation of anomalies that may explain drops in charging infrastructure usage. Hence, fleet operators' actual changes in charging behaviour can be differentiated from technical problems.

By analysing the OCPP-defined error messages, specific hardware problems can be identified. Hardware problems at charging stations can cause charging processes to fail. This leads to a discontinuity in the usage of the charging infrastructure. Therefore, the analysis of the OCPP status messages enables the determination whether charging at a charge point was technically possible during the analysed time.

The CPMS itself can also be a source of failure. In terms of software issues, data received from charging stations may not be processed correctly, leading to further inconsistencies.

In addition, the type of communication between the charging stations and the CPMS contributes to possible data gaps. In many cases, charging stations are connected to the CPMS via a mobile phone network. Therefore, a breakdown of the mobile phone network impacts data transmission, resulting in either delayed or absent data.

By analysing the available OCPP status messages, CPMS logs and web socket connections, the causes of interruptions in time series data can be identified and categorised accordingly.

Temperature: Another factor influencing the charging behaviour of vehicles and users is temperature. Therefore, the data has been analysed and adjusted when necessary.

Data from Germany's national meteorological service (Deutscher Wetterdienst, DWD) was used to gather ambient temperature measurements of 83 weather stations in Germany [17]. The time series data was mapped to the operator's location. By calculating the correlation of ambient temperature, charged energy, and number of charging sessions, an analysis of the relationship between charging patterns and temperature was done. Linear regression analysis was then used to separate the effects of temperature from the actual charging patterns.

Public holydays, strikes and operational disruptions: Holidays, strikes and operational disruptions have significant impact on charging behaviour. Therefore, holidays were added to the dataset as a feature and time series analysis was applied to identify anomalies that could not be explained by the previously described data inconsistencies. The affected weeks were corrected by averaging the charging behaviour of the previous and the following week for these days and replacing them accordingly. This approach enables the creation of weekly profiles under normal operating conditions and allows a separate analysis of days affected by holidays, strikes and interruptions, thus improving the understanding of their impact on charging behaviour.

Periodicity: Periodicity is a key feature for the development of standard profiles. It describes the repetitive charging behaviour of individual companies. By calculating the autocorrelation of the charging behaviour, the extent to which the charging processes follow regularly recurring patterns is examined. This analysis identifies whether and how significantly charging processes align with temporal cycles, such as daily, weekly, or monthly intervals.

Charging infrastructure groups within a company: As charging behaviour can vary between groups of charging infrastructure within a company, as shown schematically in Figure 1, a cluster analysis of the charging infrastructure was carried out for each operator.

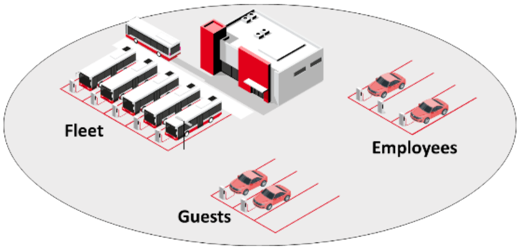

Figure 1. Schematic representation of different charging infrastructure groups within a company

The scope of the analysis was to identify different user behaviours at charge point groups. For example, groups such as the company fleet, external visitors or employees with private cars were expected. A k-means algorithm was applied on the distribution of charging times for each charging station. Cluster centres were randomly initialised, and 100 iterations were run for cluster numbers between 2 to 10. The Silhouette, Calinski-Harabasz and Davies-Bouldin evaluation methods were used to determine the optimal number of clusters. The process was repeated for each fleet operator and the optimal number of clusters was defined as the number resulting the best scores in at least two of the three methods. After applying the cluster analysis, the charging infrastructure groups were separated. Therefore, the aggregated profiles for the entire company were decomposed into charging profiles for each group. This process enables a more detailed pattern analysis of the individual user groups. The process also increases comparability with other companies that may have similar charging behaviour for their company fleet but do not provide charging stations for employees and their private cars or for guests.

Fleet and charging infrastructure size: To ensure the comparability of charging profiles across different operators and to identify similar patterns in their charging behaviour, it is essential to normalize the data. The Z-Score normalization was used ensuring a mean value of 0 and a standard deviation of 1. The normalization minimizes distortions and allows for an analysis of charging behaviour that is independent of absolute values, such as the size of the fleet or the charging infrastructure.

IV. RESULTS

The data processing identified 81 suitable operators that met the specified criteria. These operators were categorized according to the economic sector codes [18]. As shown in Figure 2, 14 out of 21 defined sectors are represented by at least one company.

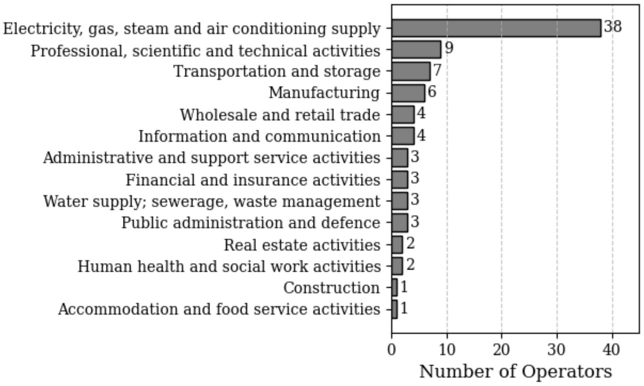

Figure 2: Distribution of operators by industry sector

Data inconsistencies were identified and corrected using the information from the CPMS. A web socket connection between the charging stations and the CPMS was provided 99% of the time. In the event of problems with mobile phone networks, data transmission was only delayed. As soon as a connection to the CPMS could be re-established, the data was sent to the system. The analysis thus showed that this problem only led to data problems in a few cases and that these could be corrected with the available data.

Another source of inconsistent data was hardware failure, which was analysed using the OCPP status messages. On average, charging stations had an OCPP error state 0.2% of the time. However, in the event of an error, which disabled charging, the data was corrected using the averaged behaviour of the previous weeks.

Furthermore, the temperature adjustment indicated that temperature has less influence on the number of charging sessions of vehicles for fleet operators than for public or semi-public charging infrastructure. While more charging sessions tend to take place at lower temperatures at public charging points, no significant correlation was found between temperature and plugging behaviour for fleet operators. However, a negative correlation was observed between the amount of energy charged and extreme temperatures, both at very low and very high values.

The clustering analysis of the charging infrastructure within a company resulted in a further separation for 15 operators. Specific groups of charging infrastructure for employees and company fleets were identified. For companies that operate specialised vehicles for their core business, such as passenger transport, parcel delivery, city cleaning or waste collection, an additional distinction was made between vehicles for the core business and vehicles for office and service staff.

Figure 3 illustrates an example of the plug-in and plug-out times throughout the day for a fleet operator with three identified charging station clusters. It was concluded that Group A is used by employees and their private vehicles, while Group B is utilized by fleet vehicles from office or service staff. Group C, consisting mainly of fast chargers, is identified as the core business fleet.

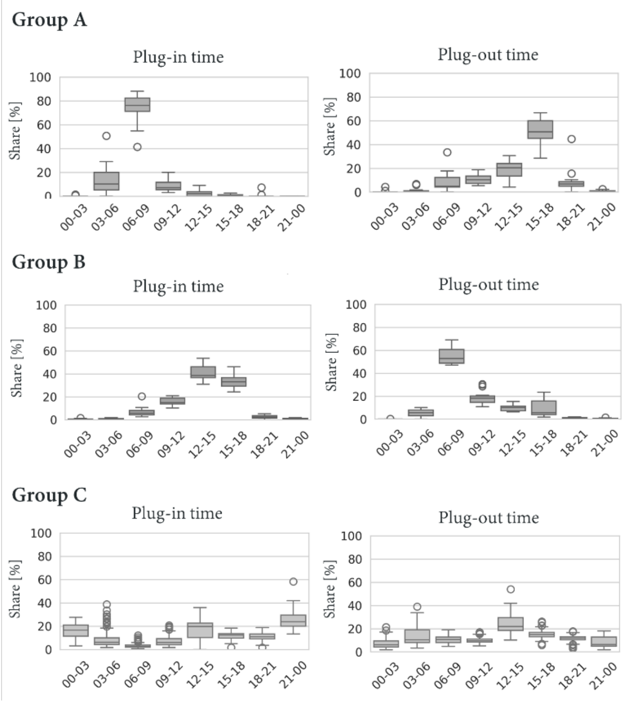

Figure 3: Example of a fleet operator with three identified charging station clusters

The analysis of the data indicated that all fleet operators have a significantly different charging behaviour on weekdays compared to weekends. This observation led to the decision to use weekly profiles to better capture these differences.

When analysing the periodicity between the weekly profiles per CPO, it was determined that 41 operators had an autocorrelation greater than 0.5. Figure 4 provides an example of the week profiles from three different CPOs with an overlay of 18 weeks.

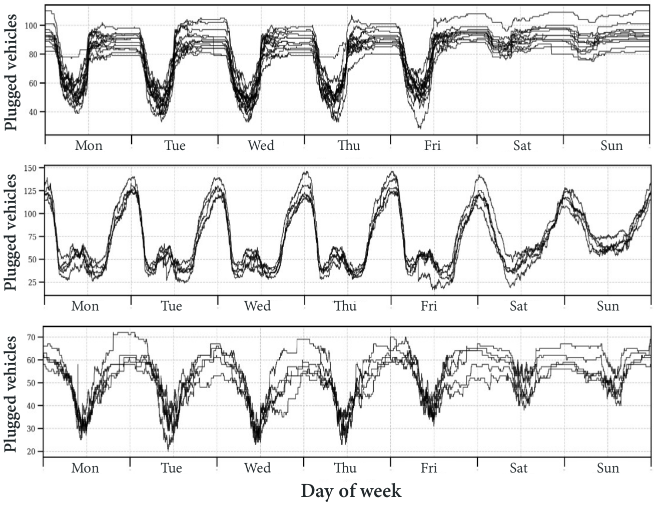

Figure 4: Weekly profiles of the connected vehicles for three exemplary companies with an overlay of 18 weeks

V. CONCLUSION

The paper presented a method for evaluating data from a CPMS to develop standard profiles for different types of CPOs. The proposed approach focuses on preparing and analysing data to ensure its quality and to understand the operational and industry-specific characteristics of a fleet operator.

The findings of the study demonstrate that using OCPP status data, web socket connection information and CPMS logs improves data quality and enable the identification, analysis and correction of data inconsistencies. This approach ensures that the investigation examines the operator's charging behaviour, while technical problems that cause data inconsistencies have no impact on the analysis. Additionally, the paper shows that performing a cluster analysis on a company's charging infrastructure allows segmentation and identification of different groups of charging stations within a company. The analysis enhances the understanding of the charging behaviour of various user groups and disaggregates the overall charging profile. This method also improves the fleet operator modelling as charging patterns can be developed modularly. Furthermore, it improves the comparability between different fleet operators as individual charging groups can be compared separately. The high periodicity of CPOs observed proves the reliability and feasibility of developing standard profiles for specific fleet operators.

In conclusion, the data from a CPMS has been demonstrated to be a suitable solution to the challenges previously identified in related studies. Standard profiles can be developed for different types of fleet operators using data from a CPMS.

In future research, a methodology with a time-optimised clustering algorithm will be used to identify similar behaviour of different charge point operators. This enables the identification of companies from different sectors that exhibit similar charging behaviour. The aim is to produce standard profiles that can be used for specific sectors and operator types.

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