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Modelling of Workplace Electric Vehicle Charging Profiles based on Trip Chain Generation

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***Abstract*— Increasing penetration of electric vehicles leads to new challenges for the power grid. Due to limited measured data the generation of charging profiles from journey data of conventional cars - called trip chain generation - is a possibility for considering them in grid planning. In this paper, the method of trip chain generation is applied to the field of workplace charging. Therefore, parameters as distances, different car models and home charging possibilities are introduced and varied. Their effects in grid planning are validated using a journey survey from Germany and a common used European MV-grid model. Simulation results show the importance of the improved modelling approach.**

Keywords*— *charging profile, electric vehicle, grid planning, journey data, trip chain, workplace charging

I. Introduction

Electric vehicles (EVs) have become increasingly important for achieving climate protection goals and reducing greenhouse gas emissions in the transport sector. However, their large-scale integration introduces new challenges in the planning and operation of power grids. To assess the effects of EV penetration on the stability, reliability and safety of the grid, it is necessary to gain more knowledge on their charging behavior and the impact in the increase of the load. Contemporary probabilistic grid planning approaches make use of time-series to perform grid analysis, allowing to include new types of loads and volatile generation with unknown simultaneity. The goal of these methods is to avoid the under- or over dimension of power grids, compared to using conventional deterministic approaches [1]. Therefore, individual load profiles of different customers, e.g. EVs, are required as input data for load flow simulations. Due to the relatively low penetration of EVs, the access to real measured data is on the one hand limited and on the other hand, the data are not yet representative enough. Therefore, the development of synthetic EV charging profiles is of growing interest, providing grid planners with new tools.

The energy demand of an EV is directly related to its movement behavior. Through trip chain generation, charging profiles of EVs can be modelled based on the driving behavior of real cars [2]. This method offers an alternative approach for modelling profiles based on limited measured data as in [3]. Based on surveys of the use of conventional cars, the expected spatial and temporal driving behavior of EVs can be derived [4]. Randomly drawn trips from historical data are recombined to form new mobility profiles. In [4]-[6], trip chain generation is applied to model charging profiles by calculating the current state of charge (SOC) of an EV based on driven distances, battery size and specific consumption of the car. While [4] focusses on analyzing the effects of diverse charging behaviors, [5] examines demands at different charging stations and [6] analyses the impact of variable charging costs. A journey survey from the UK is used in [7] to predict future EV energy demand considering consumptions depending on drive cycles.

Since EV charging devices are not yet available in every household, according to parking space situation, companies are increasingly offering charging infrastructure to employees. A realistic estimation of workplace charging requirements is a crucial aspect, not only for the companies considering a cost-optimal number of charging stations, but also for future grid planning. In the field of workplace charging, research has focused on cost-optimal charging infrastructure planning [8], maximizing renewable energy consumption [9] and energy management [10]-[11]. However, profile modelling accuracy has a significant effect on grid simulation results [12]. Hence, the method of trip chain generation is applied to assess workplace charging infrastructure planning in this paper. To generate profiles closer to reality, company features and employee data (e.g. working times) are included in trip chain modelling as new approach. This differs from [8]-[11], which use simplified modelling approaches. As driving behaviors may vary between countries, contrary to [4]-[7], journey records of the German Mobility Panel (MOP) [13] are used for the development of the charging profiles.

This paper is structured as follows: in section II the charging profile modelling approach is described. Section III presents a grid topology and the application of the charging profiles to model the load of an industrial car park. Simulation results and effects of different car park parameterizations are shown and discussed in section IV. Section V finally concludes the paper.

II. Modelling of Charging Profiles

Although the application of the trip chain concept on power systems has already been studied in [4]-[6], those studies focused mostly on EVs charging at home, and used the NHTS (National Household Trip Survey) dataset, which contains journey records from the United States [14]. In this paper, an adaptation of the concept is presented, focusing on the charging of EVs at the workplace. Based on a dataset with historical journey data in Germany, new trip chains are generated, from a European perspective. By combining a given trip chain with the specific characteristics of an EV model (e.g. range, battery capacity and specific energy consumption), a charging profile of the EV can be estimated.

This chapter describes the methodology to generate the charging profiles based on the trip chain concept. First the used journey data are presented, then the adapted trip chain generation methodology is described. Finally, the conversion of trip chains to charging profiles is shown.

A. Acquisition of Journey Data

It is expected for EV drivers to follow similar driving patterns like conventional car drivers [5], as the travel destinations should not change radically by changing the vehicle technology (e.g. trip from home to work or to shopping centers, etc.). Therefore, national surveys on driving patterns can be used as an input for the trip chain generation. The behavior of the drivers may vary between countries, influenced by different factors, i.e. travelling distances, availability of public transportation. This paper uses journey records of the German Mobility Panel 2016/2017 (MOP17) [13] for the development of charging profiles. In this study, 66,109 trips performed by the members of 1,757 randomly selected German households were recorded, including driving distance, mode of transport, trip purpose, duration and departure and arrival time. For the generation of trip chains, only car trips are relevant.

B. Trip Chain Generation

To generate trip chains, data obtained directly from the journey survey are used. This differs from the approach in [4], where the spatial and temporal components are obtained from probability distributions and reduces the complexity of the preprocessing step. A car can be located at one of the following positions: home, work, other (which symbolizes leisure activities, e.g. hobby or shopping), as well as being on the way to one of these three destinations. Therefore, single car trips contained in the MOP17 dataset are first separated according to those three locations, while being differentiating between weekdays and weekends allowing the better illustration of longer weekend leisure trips and to discriminate work trips on Saturdays and Sundays. Through the methodology shown in the flow chart in Figure 1, a daily position vector for one single car in 15-minute time resolution is generated randomly from the subsets. Driven distances are saved in a distance vector as well.

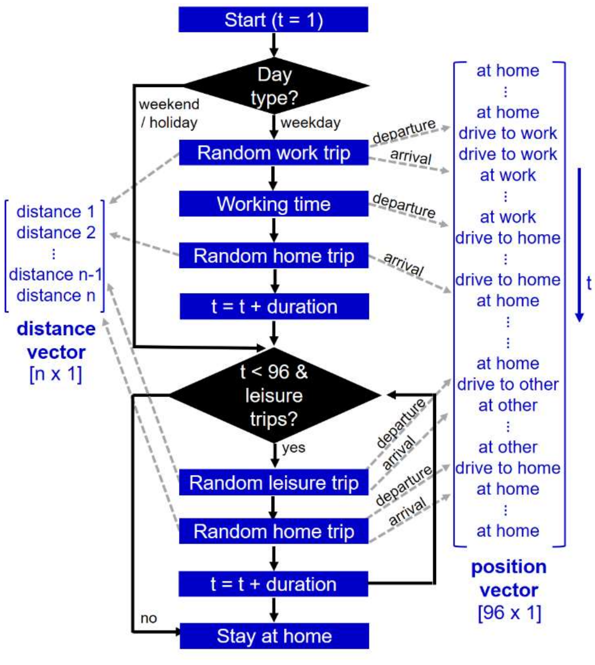

Figure 1. Flow chart of trip chain generation methodology to generate position and distance vector.

C. Electric Vehicles Charging Model

A survey of the German EV market resulted in 59 different battery EV models currently being sold to the public. By combining the trip chains from II.B with the individual EV model characteristics (driving range, battery capacity, consumption), the charging behavior of each EV can be obtained. Therefore, the charging location of the EV needs to be defined, which can be any of the three possible positions of the car (work, home, other). In this paper, the charging behavior of EVs that are only charged at work is compared to EVs additionally charging at home.

After determining which of the three possible car positions serves as charging location, the SOC of the battery is determined from the driving distance d of the EV, its specific consumption c, its battery capacity C and the SOC of the previous timestep, initialized as 100%, according to Eq. (1).

$$\mathrm{SOC}(t)[\%] = \mathrm{SOC}(t-1)[\%] - \frac{d[\mathrm{km}] \cdot c[\frac{\mathrm{kWh}}{\mathrm{km}}]}{C[\mathrm{kWh}]} \cdot 100\% \quad (1)$$

In this work, the charging process of an EV is considered to start as soon as it reaches a charging location with a SOC below 100%. The EV stops charging once the SOC reaches 100% again, or if it leaves the charging station. The charging process is defined as a constant current / constant voltage (CCCV)-charging model. A constant voltage and thus a constant charging power up to 80% SOC is assumed in the CC-charging area. To improve profile accuracy, a decreasing charging power P in terms of CV-charging is modelled dropping following an exponential function as shown in Eq. (2). It depends on the time t after the end of CC-charging. The coefficient b is calculated according to Eq. (3) from the maximal charging power $P_{\max}$, the inverter efficiency η, the battery capacity C and the minimal charging power where charging stops p_{off} normalized to $P_{\max}$ in %. Use and benefits of a decreasing charging power were analyzed in [12], while they were not considered in [4]-[7] and [15].

$$P(t)[\mathrm{kW}] = P_{max}[\mathrm{kW}] \cdot e^{b[\frac{1}{\mathrm{h}}] \cdot t[\mathrm{h}]} \quad (t \geq 0) \quad (2)$$

$$b = \frac{P_{max}\,[\mathrm{kW}] \cdot \eta}{C\,[\mathrm{kWh}]} \cdot \frac{p_{off}[\%] - 100\%}{100\% - 80\%} \quad (3)$$

The described procedure provides a charging profile of a given EV for a defined time-frame as a result. The time-frame can be selected as an entire year, providing a more accurate individual charging behavior, which can be used for grid planning studies.

III. Case Study

To proof the practicability of the presented approach to model charging profiles, a scenario where EVs charge within a large employee car park in an industrial area was developed. The European CIGRE MV Benchmark distribution grid model is used as base for the analysis [16], [17]. For simplicity, just feeder 1 of the model is considered. With regard to distributed energy resources (DER) only photovoltaic systems (PV) are taken into consideration. The grid model is shown in Figure 2.

A. Grid Model

The total load connected to the grid model in Figure 2 is 24.99 MVA. About a quarter belongs to industrial and commercial customers. It is therefore possible to consider that there could be an industrial car park equipped with charging infrastructure connected to this grid. The car park is assumed to be connected to node 9 (Figure 2), which already contains a 675 kVA industrial load. The total PV generation amounts to a maximum of 210 kVA in the entire network. Every parameter of the described distribution grid model, as well as the peak load values are taken from [16].

The simulation period is one year, which allows to distinguish seasonal differences with regard to DER. Synthetic time-series are generated for the remaining loads. These are obtained through a linear regression based method from [18], which considers the peak loads, coincidence factors and power factors specified in [16]. The PV profiles are derived from real weather data in Germany.

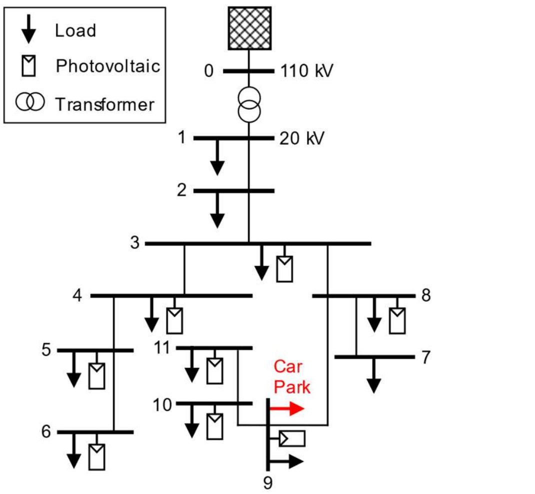

Figure 2. Topology of the European CIGRE MV Benchmark distribution grid model according to [17] with an additional car park load.

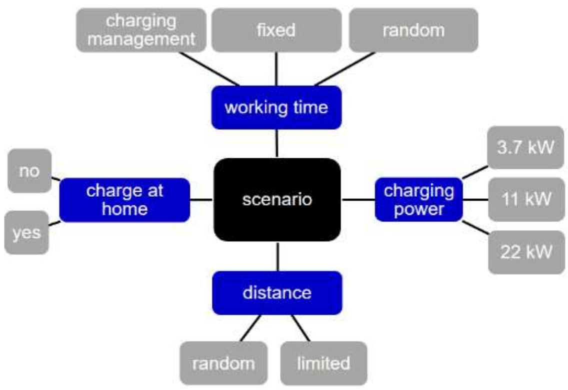

Figure 3. Varied parameters in different charging scenarios.

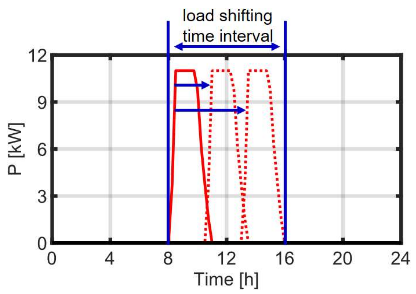

Figure 4. Time shifting through load management.

B. Car Park Parameterization

The introduced EV charging modelling approach allows a variation of several charging parameters in order to construct realistic models of employee car parks. Because of this the local conditions can be varied and different car parks could be modelled. These parameters depend on the characteristics of each establishment (e.g. working times or available charging infrastructure) and data of the employees (e.g. driving distance to workplace, opportunity to charge at home or owned car model). An overview on the considered set of parameters and their allowed values is shown in Figure 3.

An employee car park with 100 spaces is modelled. Every parking space is equipped with charging infrastructure for 3.7 kW, 11 kW and 22 kW. A simple EV load management system is considered and shown in Figure 4, in which the charging start time is determined randomly considering working times and EV energy requirement to reduce simultaneity within charging processes.

IV. Simulation Results

Based on the parameter variation of the proposed model for EV charging profiles, different scenarios are defined in this section. Their impact on the defined grid model will be verified using time-series based load flow calculations. A car park with 100 EVs is considered in all presented scenarios.

A. Charging Power

An AC charging power of 11 kW is particularly common in the field of workplace charging in Germany, therefore it is compared to other possible charging powers (3.7 kW, 22 kW). The average, minimum and maximum load of the car park on a weekday for different charging powers can be seen in Figure 5. The load profiles are generated using the same trip chains for each charging power. This is a clear advantage of the modelling approach and improves comparability. Table I shows the results for peak power and the coincidence factor g of the load profiles obtained for each charging power based on Eq. (4).

$$g(P_{i,t}) = \frac{\max_t(\sum_i P_{i,t})}{\sum_i \max_t(P_{i,t})} \tag{4}$$

TABLE I. Peak Power and Coincidence Factor for Different Charging Powers

Charging Power	3.7 kW	11 kW	22 kW
Peak power [kW]	321.2	648.9	839.6
coincidence factor g	0.87	0.59	0.38

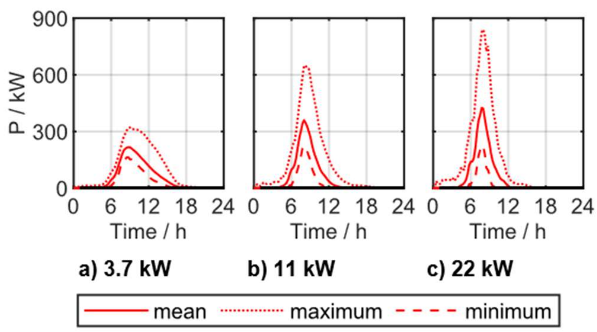

Figure 5. Mean, maximum and minimum aggregated workplace charging load for charging power 3.7 kW (a), 11 kW (b) and 22 kW (c).

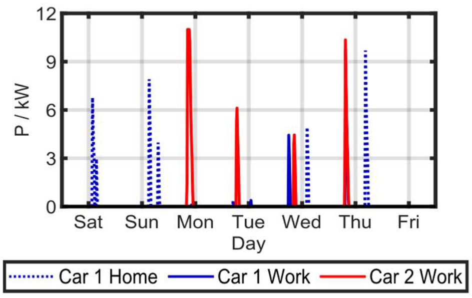

Figure 6. Weekly load profiles of two cars and charging infrastructure of 11 kW depending on charging locations.

With increasing charging power, the coincidence factors decrease, but even when the average energy consumption is similar in all cases, the peak power differs significantly. This shows that depending on the application a charging power of 11 kW is not always necessary. Charging with 3.7 kW can also be sufficient in an employee car park in order to provide enough energy to charge the vehicles in the available time.

B. *Home Charging*

The charging profile generation methodology in this paper allows a differentiation between charging locations and their influence on energy requirement in workplace charging. Having charging infrastructure at home, employees are not forced to charge at work, but can choose the charging location. In Figure 6 the weekly charging profile of an EV charging at home and at work (Car 1) is compared to one charging only at workplace with 11 kW (Car 2) assuming that charging starts as soon as the car reaches home or workplace with a SOC below 100%. The dashed lines symbolize home charging processes after work or at the weekend. As a result, a vehicle only recharges the distance travelled to work or the energy it could not recharge at home when arriving at work.

Through additional home charging infrastructure, a reduction of 66% of the mean recharged energy at workplace on weekdays is observed. Moreover, there is an increased energy requirement on Mondays for cars without home charging infrastructure, as they need to recharge their whole energy consumption from leisure trips at the weekend. This also leads to a strongly increasing peak power of the car park in this case study from 189 kW with to 649 kW without home charging infrastructure.

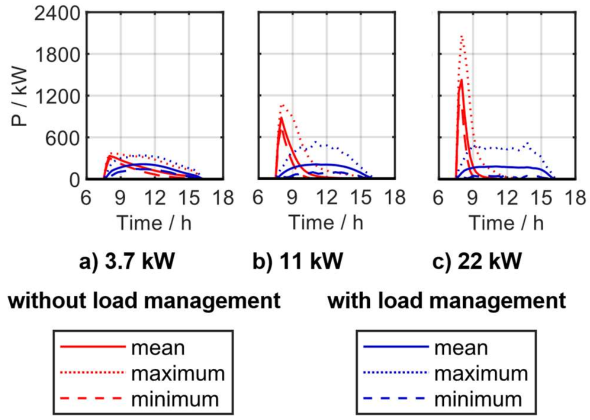

Figure 7. Mean, maximum and minimum aggregated workplace charging load [kW] with and without load management for fixed working times and charging power 3.7 kW (a), 11 kW (b) and 22 kW (c).

C. *Distance to work*

Similar to the availability of home charging infrastructure, the employees' distance to work also impacts the energy requirements of EVs in workplace charging. A consideration of this employee characteristic in the charging profile modelling approach can be achieved through filtering work trips from the MOP17 according to a maximum value before using them in trip chain generation. An exemplary reduction of work trip distances to a maximum of 30 km is compared to randomly drawn distances without limitation. Combined with additional home charging infrastructure, this strongly affects the recharged energy at work. Through this an energy requirement reduction at workplace of 36% can be achieved in this paper. Car park peak power is reduced to 128 kW for 11 kW charging infrastructure.

D. *Working Times and EV Load Management*

An accidental arrival such as the random drawing of working times from the mobility survey can be quite suitable for a large employee car park, if the company has different working time models or even flextime. In the manufacturing industry, however, companies can also specify fixed shift times, which all employees must keep. On the one hand this means that considerably more employees arrive at the workplace at the same time and coincidence factors increase. On the other hand, this scenario also offers a good starting point for a simple EV load management system (Figure 4). Figure 7 shows the aggregated workplace charging load for fixed working times from 8:00 am to 4:00 pm with and without EV load management for different charging powers.

Fixed working times lead to high peaks in the morning when all employees arrive. The load profile decreases towards noon due to the reduced charging power for CV-charging and different energy requirements of the vehicles. The higher the charging power, the higher is the maximum reduction potential of using load management, since shorter charging times reduce simultaneity. Similar mean charging profiles can be achieved for all three charging powers using a management system. This clarifies that, depending on the application, lower charging powers should also be taken into consideration for workplace charging infrastructure planning.

E. *Load flow simulation results*

As shown in the previous subsections, different car park parameterization influences the total load and energy requirements of the car park significantly. A proper consideration of the parameters of the charging profiles can help to define the most suitable charging infrastructure for a car park. However, the parameterization of the car park model may not only have an impact on its load profile, but also have significant impact in the loading of the grid. Therefore, the generated charging profiles are used in a time-series-based Newton Raphson load flow calculation.

Table II shows an overview of the load flow results without EV charging in the MV grid presented in Section III. In this initial state, the network is already stressed especially considering nodal voltages which exceed acceptable limits. The results of a time-series-based load flow calculation over one year show the effects on nodal voltages as well as line and transformer loadings. Maximal and minimal differences to the initial state are shown in Table III. It compares the differences in the maximum and mean network parameters between the different parameterizations. The minimum values remain unchanged.

TABLE II. OVERVIEW OF GRID PARAMETERS IN THE INITIAL STATE

Parameter	Value
Max. transformer loading [%]	83.9
Max. line loading [%]	34.1
Min. nodal voltage [p.u.]	0.938

TABLE III. MAXIMAL AND MINIMAL DIFFERENCES OF LOAD FLOW RESULTS BETWEEN BASE SCENARIO AND SCENARIO WITH CAR PARK

Value	Transformer loading [%]		Line loadings [%]		Nodal voltages [p.u.]	
	scenario		scenario		scenario	
	min	max	min	max	min	max
Maximum	0	0	0	+4.27	0	0
Mean	+0.05	+0.14	+0.12	+0.40	0	|- 0.0007|

The maximum car park load, which occurs in the morning hours when the employees arrive, does not occur at the same time as of the industrial and domestic loads. This means that the maximum transformer loading is not changed. The largest differences between the modelling parameterizations can be seen in the maximum line loadings. While the maximum for charging at 22 kW is 4.27% above the initial state, it does not change when home charging is considered. The mean transformer loadings are increased by 0.14% when charging with 22 kW and fixed shift times without load management, and by a minimum of 0.05% when home charging is available. The influence of the modelling approach on the nodal voltages is even smaller in this case study and is therefore not shown.

Summarizing, the influence of various car park parameterizations can be noticed in both the aggregated car park load and in the load flow simulations. With a car park size of 100 parking slots, as examined in this paper, however, the effects of employee charging on the grid are still relatively low. This may be due to the fact that the maximum employee charging load is small compared to the maximum load of the entire network, and that the simultaneity of these two maxima is low due to the arrival at work in the morning. When considering growing EV penetration in industrial areas the connection of more employee car parks equipped with charging infrastructure to the grid, differences may become clearer. The same effect could also have the consideration of a feeder to which exclusively industrial customers are connected by what means coincidence between conventional loads and the employee car park load will increase.

V. CONCLUSIONS

In this paper a methodology for generating charging profiles from trip chains is adapted to the case of workplace charging. Variable car park parameters such as working time, distance to work, home charging possibility and charging power are considered to allow a more accurate estimation of employee charging. The effects of those parameters in grid planning are analyzed using a European MV-grid model.

It is shown, that a variation of the parameters, especially home charging infrastructure and driving distances, can significantly change the modelled charging profiles in terms of consumed energy and peak power. The approach allows an evaluation of the individual charging infrastructure needs of each company and a generation of more realistic charging profiles with many degrees of freedom in modelling. Therefore, there are advantages for both grid customers and distribution system operators. In the field of car park load modelling using trip chain generation, a validation of the annual charging profiles, for example by measured data, is necessary. In addition, a further starting point could be the investigation of the grid effects of considerably larger car parks on the MV grid.

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