Optimized Charging of Electric Vehicles with Regard to Battery Constraints – Case Study: Singaporean Car Park

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***Abstract*—With an increasing market share of electric vehicles (EVs) the question of additional electricity demand and its effects arises. In this context, smart charging of EVs is discussed. This paper investigates the optimization of charging strategies with cost as objective function. Thereby, battery constraints regarding the charging process are taken into account. The problem is formulated as a mixed integer linear programming problem. The model accesses detailed information on battery charging profiles, predefining charging energy amount as well as charging current and voltage. Beside the battery constraints, limitations by the EV drivers' mobility demand as well as maximum power limitations of the investigated system are considered. Within the framework of a case study for Singapore, the model is applied to a sample of EVs and to the corresponding car parks, resulting in charging power profiles for different car park types.**

***Index Terms*—Electric vehicles, Load management, Optimal scheduling, Optimization, Singapore.**

I. INTRODUCTION

The increasing market penetration of electric vehicles (EVs) stimulates the discussion about the effects of EVs on the transportation as well as on the power system. Accompanying the rise of EV market share in the individual transport, an adaption of the mobility behavior to the new circumstances, e.g., shorter range of EVs compared to conventional combustion engine vehicles, is most likely. The necessity to recharge the batteries of the EVs, dependent on the adapted EV mobility behavior, opens challenges as well as opportunities for the power system. The risk of additional load peaks, caused by uncontrolled charging of EVs, opposes the possibilities to take advantage of flexible charging processes. The control of power systems and integration of renewable energies can be simplified by flexible charging strategies [1].

At this point, intelligent charging strategies apply in order to achieve different objectives, e.g., cost minimization, grid load balancing or integration of renewable energies. This is accomplished either by shifting charging processes to most favorable times or by additionally feeding electricity back to stabilize the grid, as described in [2] and [3].

The focus of this paper lies on the optimization of charging processes with the objective of charging with minimal cost. Different charging optimization models in order to support the power system were elaborated, e.g., in [1], [4], [5] or [6]. [1] is allocating the aggregated charging load of EVs in order to minimize total cost of electricity regarding the entire power system. [4] couples an agent-based transportation simulation with a power system model with the objective of a secure power system operation while considering a power constraint of EVs. Within the charging cost minimization in [5], a simplified charging profile of a battery with two phases – a higher and a lower power level – is taken into account.

In contrast to the aforementioned models, the approach of this paper is to additionally take the constraints arising from the EV battery into account. Beside requirements of the EV drivers' mobility demand as well as maximum power limitations of the investigated system, detailed information on EV specific charging profiles are included. Deriving from this battery data, charging energy amounts, charging current, and charging voltage are predefined. Considering these constraints, the charging optimization model minimizes the charging cost.

As a case study, the charging optimization model is applied to EVs and car parks in Singapore. Therefore, a mobility model, reflecting driving and parking patterns of private vehicle drivers in Singapore, is used for simulation of EVs. For every half hour, when the Singaporean electricity price is fixed, the optimization model assigns a charging strategy to these EVs and draws a charging power profile for the car parks.

Section II elaborates the charging optimization model, while in Section III the implementation of the case study is

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described. Results thereof are analyzed and discussed in Section IV. Finally, Section V draws a conclusion and gives an outlook to future research.

II. CHARGING OPTIMIZATION MODEL

The charging optimization model aims at cost minimized charging strategies for EVs given the mobility behavior and demand of EVs over a certain time period. The problem statement is formulated as a mixed integer linear programming problem. Thereby, constraints to the charging strategies rising from the mobility demand, from the battery restrictions as well as from the power system are taken into consideration.

A. Mobility Demand

The EVs considered in the charging optimization model demand certain amounts of energy after each trip, i.e., the energy consumed during their journey. It is assumed that a car is always charged to a state of charge (SOC) of 100 % if possible in order to minimize the risk of running out of battery, prevent range anxiety and ensure the following trip can be finished. The energy demand of each EV has to be met by the proposed charging strategy for the respective parking event of the EV.

B. Battery Charging Profiles

A typical charging profile of a lithium-ion cell, as it is currently used in batteries of many commercial EVs, can be divided into two phases. First, the cell is charged with constant current while the voltage is increasing during this charging phase. This is the fastest way to charge a lithium-ion cell. This phase ends with the voltage reaching a threshold value. Afterwards, the voltage is kept constant at this value and the current is decreasing. Further increase of the cell voltage would lead to irreversible cell damage [7].

Project-internally measured data on the charging profile of a Samsung INR 18650-15Q cell with a $LiNi_{0.8}Co_{0.15}Al_{0.05}O_2$-based cathode and a graphite anode (NCA cell, [8]) is shown in Fig. 1. The cell with a capacity of 1.5 Ah is charged at a current of 0.75 A, i.e., at a C-rate of 0.5, until the voltage reaches 4.2 V. The typical power curve results as product of voltage and current. It is increasing to a peak during the constant current phase and decreasing during the constant voltage phase. Integration of the charging power over time yields the charging energy.

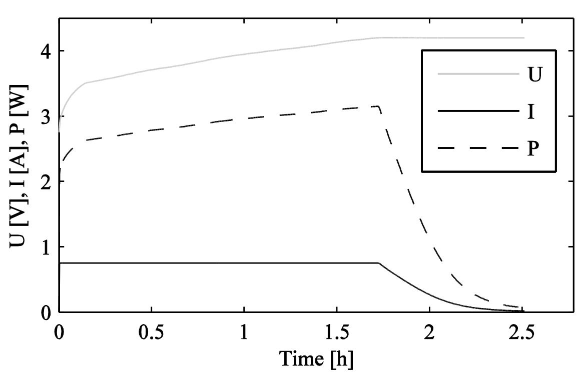

Figure 1. Charging profile at 0.5 C of 1.5 Ah NCA cell.

In addition to the charging profile shown in Fig. 1, the qualitatively resembling charging profiles for C-rates of 0.2 and 1.0 are integrated into the model calculations.

In order to conclude from cells to batteries, the current respectively voltage profiles have to be multiplied by the number of cells connected in parallel respectively in series.

C. Problem Formulation

Corresponding to the previously explicated circumstances, a system of equations was developed to describe the mixed integer linear programming problem.

Table I contains the indices, parameters, and variables of the system, where parameters are fixed values and variables are to be optimized.

TABLE I. OVERVIEW OF INDICES, PARAMETERS, AND VARIABLES.

Indices	t	Time step
	t_{ch}	Charging time step
	p_{car}	Parking event, 2-dimensional, e.g., (1,2) for 2nd parking of 1st car
Parameters	$E_{charge}(p_{car},t_{ch})$	Energy package per charging time step t_{ch} for each parking event p_{car}
	$parking(t,p_{car})$	Binary, whether car is parking or not
	dur_t	Duration of time steps t and charging time steps t_{ch}
	$pr_{el}(t)$	Electricity price
	P_{max}	Maximum power limit of the system
	$t_{help}(t)$	Value of time step t is assigned to auxiliary parameter $t_{help}(t)$
Variables	$charging(t,p_{car},t_{ch})$	Binary, whether battery is charged or not
	c	Charging cost for all EVs

The demanded energy over time for recharging the batteries to an SOC of 100 %, predefined by the charging profiles defined in Section II.B is divided into charging energy packages E_{charge} per charging time step t_{ch} for all parking events p_{car}. The binary parameter *parking* represents for every time step t whether a car is parking or not during its corresponding parking events p_{car}. Parameter dur_t reflects the duration of time steps t and charging time steps t_{ch}.

The binary variable *charging* displays whether for parking event p_{car} during time step t, charging time step t_{ch} is executed or not. This variable is optimally allocated within the scope of the optimization problem, while the objective is to minimize cost c for charging the EVs as defined in (1).

$$c = \sum_{p_{car}} \sum_t \Big(parking(t,p_{car}) \cdot \sum_{t_{ch}} \Big(charging(t,p_{car},t_{ch}) \cdot E_{charge}(p_{car},t_{ch}) \Big) \cdot pr_{el}(t) \Big) \tag{1}$$

Total cost c arises from summation over all time steps t and over all parking events p_{car} of energy charged to EVs multiplied by the electricity price pr_{el} of the respective time step t. The charging energy amounts depend on whether a vehicle is parking and charging during the respective time step, indicated by the binaries *parking* and *charging*. If both is true, the charging energy during time step t for the specific parking event p_{car} and the specific charging time step t_{ch} equals the required energy package E_{charge}, which is characterized by the charging profile of the EV's battery. Otherwise no energy is charged at specific t, p_{car} and t_{ch}.

The following constraining equation mirrors the mobility demand of the EVs. For each parking event p_{car}, the energy amounts charged to the respective EV are calculated analogous to (1). These amounts have to sum up to the energy amount required by the EV's mobility demand, i.e., the energy consumption during the last trip in order to be recharged to an SOC of 100 %.

$$\sum_t \sum_{t_{ch}} \Big(parking(t, p_{car}) \cdot charging(t, p_{car}, t_{ch}) \cdot E_{charge}(p_{car}, t_{ch}) \Big) = \sum_{t_{ch}} E_{charge}(p_{car}, t_{ch}) \quad (2)$$

The maximum power limit P_{max} of the system which the total charging power must not exceed at all times is covered by the restriction in (3). For each time step t, the sum of the charging energy amounts has to be lower than the energy amount equivalent to the power P_{max} during one time step.

$$\sum_{p_{car}} \Big(parking(t, p_{car}) \cdot \sum_{t_{ch}} \Big(charging(t, p_{car}, t_{ch}) \cdot E_{charge}(p_{car}, t_{ch}) \Big) \Big) \leq P_{max} \cdot dur_t \quad (3)$$

In order to cope with the typical charging profiles of batteries – as explained earlier – the charging energy is fixed and divided into predefined energy packages E_{charge}. These energy packages are adapted to the characteristics of each battery, e.g., cell type and circuitry, as well as of each parking event, e.g., duration and SOC at the beginning. Besides, further battery constraints have to be considered during the charging processes which are ensured by the following equations. Singleness of each charging energy package is ensured by (4) and non-simultaneity by (5). The correct chronological sequence of the charging energy packages according to the charging profiles is guaranteed by (6). Each occurrence of the binary variable *charging* as well as the subsequent occurrence are multiplied by the auxiliary time step parameter t_{help} to determine the temporal positions of the charging energy packages. These temporal positions are compared and the preceding energy package has to be executed earlier than the subsequent one.

$$\sum_t charging(t, p_{car}, t_{ch}) = 1 \quad (4)$$

$$\sum_{t_{ch}} charging(t, p_{car}, t_{ch}) \leq 1 \quad (5)$$

$$\sum_t charging(t, p_{car}, t_{ch}) \cdot t_{help}(t) < \sum_t charging(t, p_{car}, t_{ch} + 1) \cdot t_{help}(t) \quad (6)$$

III. Case Study: Optimizing Electric Vehicle Charging in a Singaporean Car Park

The optimization model for charging strategies described in Section II is applied to a car park in Singapore used by a sample of 100 EVs. Supposing a big Singaporean car park with 1,000 parking spaces with 10 % of those equipped to charge electric vehicles would meet the charging demand of 100 EVs. Furthermore, it is assumed that all 100 vehicles are parking in the same car parks throughout the modeling period of one day. Accordingly, three car parks are examined: one residential car park where the cars park mainly at night, one car park at work, and one car park where the EV drivers pursue leisure activities.

A. Simulation of Driving and Parking Behavior

The charging demands of the 100 EVs over one day derive from a mobility model, which simulates the itinerary and parking events of private vehicles in Singapore. It takes into account statistics and calculations on driven distances, average speed, working habits, employment situation, as well as duration of stay at car parks in Singapore. For each EV, the mobility model produces a sequence of driving and parking events including duration and length of trips, energy consumption during trips, parking duration as well as car park category, i.e., residential, work- or leisure-related. A more detailed description of the mobility model can be found in [1].

As a result of the mobility simulation, the occupancy of the three examined car parks can be seen in Fig. 2. At the starting point of the simulation at 12:00 AM, all 100 EVs are parked at home. In the morning, EVs begin to drive to work. During the day, some EVs drive to a leisure place for lunch, after work, or in between. At the end of the day, all EVs drive back home. Even though the simulation time period is set to one day, the simulation does not stop after 24 hours but after one complete cycle through the EV drivers' daily routine. This means, the simulation produces trips and parking events until the EV returns home in the evening respectively at night after working and/or leisure activities.

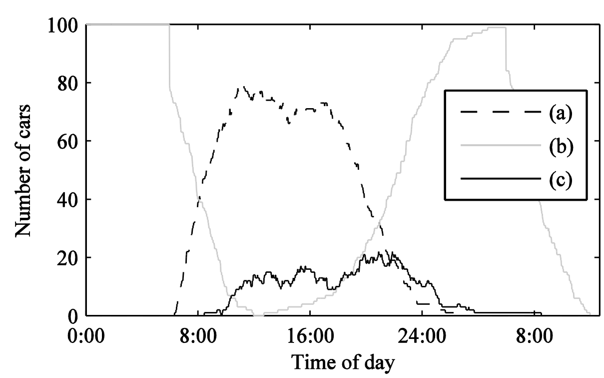

Figure 2. Occupancy by EVs of work-related (a), residential (b) and leisure-related (c) car park.

While the capacity utilization of EV parking spaces is highest at residential car parks since all vehicles park there at night, the parking time at work is more distributed because of varying working hours. At leisure-related car parks, this effect is even bigger and additionally, the average parking duration is shorter.

The binary parameter *parking* which reflects when which vehicle is parking and when not, derives from the occupancy of the three car parks.

B. General Conditions

It is assumed that each of the three car parks which the 100 EVs visit along their daily routine is equipped with 100 charging stations with 20 kW power. This results in a maximum power limit P_{max} of 2,000 kW for each car park.

The optimization model calculates with electricity price pr_{el} for each time step t. For this case study, the Uniform Singapore Energy Price (USEP) which changes every half hour is used. The USEP as well as the total electricity demand in Singapore is provided online as historical data and as forecast for 36 hours. The calculations are conducted with the electricity price data of a weekday in February 2013 [9].

The duration of time steps dur_t is set to 0.5 h since it is an optimization problem aiming minimization of charging cost for EVs and the electricity price is changing half-hourly.

C. Derivation and Calculation of Charging Energy Demand

The batteries of the EVs of the case study shall consist of the NCA cells described in Section II.B with the charging profile shown in Fig. 1. The cell and battery characteristics are displayed in Table II. Assuming a battery consisting of 3,600 of these NCA cells, the battery obtains 60 Ah, 324 V and an energy content of 19.44 kWh. Tesla is using cells of the same cell chemistry in their EVs, however, with twice that capacity [10], [11]. But as we had detailed data sets available for the 1.5 Ah cells, we used these for the case study.

TABLE II. BATTERY AND EV PROPERTIES.

Cell type[a]	Samsung INR18650-15Q cell
Cell capacity[a]	1.5 Ah
Average cell discharge voltage[a]	3.6 V
Number of cells in battery	3,600
Circuitry of cells	90 in series, 40 in parallel
Battery capacity	60 Ah
Average battery discharge voltage	324 V
Energy content of battery	19.44 kWh

a. [8]

It is assumed that the 100 EVs start their first trip in the morning, fully charged with an SOC of 100 %. The EVs' consumption during each trip is calculated assuming specific energy consumption in the range of 15 to 20 kWh / 100 km. According to this consumption, the SOC is reduced during a trip. The energy demand for the following parking event matches the consumption during the last trip. The current SOC at the beginning of the parking event is looked up in the charging profiles of Section II.B specifically for the EV. The charging time to an SOC of 100 % is calculated for C-rates of 0.2, 0.5, and 1.0. The C-rate with charging time suitable to the parking duration is chosen and according to its charging profile, the parameter E_{charge} is filled with values for the different charging time steps. In case the parking duration is too short to charge to 100 % SOC even at a C-rate of 1.0, the battery is charged for the entire parking duration at 1.0 C and the missing charging energy is added to the subsequent parking event.

The total energy demand for recharging 100 EVs can be calculated by integrating the charging power and corresponds to the area displayed in Fig. 3. If all EVs were charged with constant power as long as they are parking it would result in a power profile as shown in Fig. 3. The total charging energy correlates to 1,073 kWh and has to be optimally allocated by the charging optimization model.

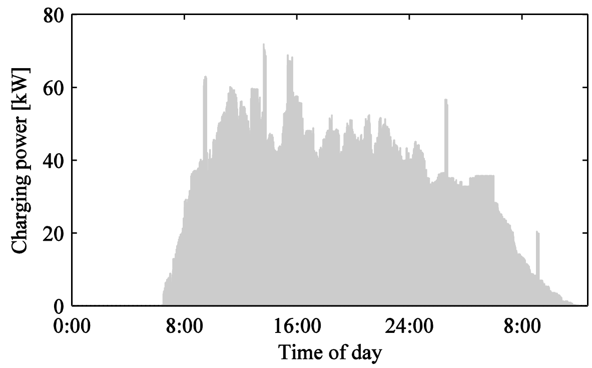

Figure 3. Energy demand for charging EVs.

IV. RESULTS AND DISCUSSION

The optimization model is executed for each of the three car parks. The resulting charging strategies for cost minimized charging of 100 EVs yield the charging power profiles pictured in Fig. 4.

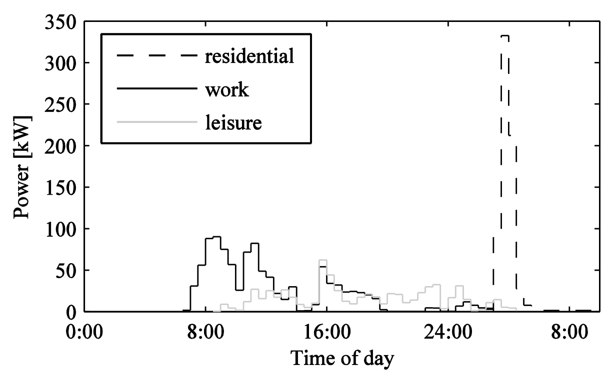

Figure 4. Charging power profiles for three car parks.

The charging profiles must be examined together with the flexibility of the charging options, which can be derived from Fig. 5. It shows how many EVs are parking respectively charging at the particular car park. The larger the difference between the areas beneath the parking curve and the charging curve, the larger is the flexibility for optimizing the charging processes. Regarding the work-related car park, the charging power in the morning is high due to relatively low electricity price (see Fig. 6 (c)). In the afternoon, another peak can be identified because the EVs of people having lunch somewhere else need to be recharged before they leave in the evening and prices are still lower than in the evening. Such an obvious pattern cannot be recognized at the leisure car park. Since the average parking durations are shorter, charging options are not so flexible, as can be seen in Fig. 5 (c), and hence, the charging processes cannot be shifted very much. While the EVs return home in the evening to park there at night, they are charged mainly between 3:00 AM and 5:00 AM when electricity prices are lowest. This is possible because of the high flexibility for the allocation of the charging processes at residential car parks (see Fig. 5 (a)).

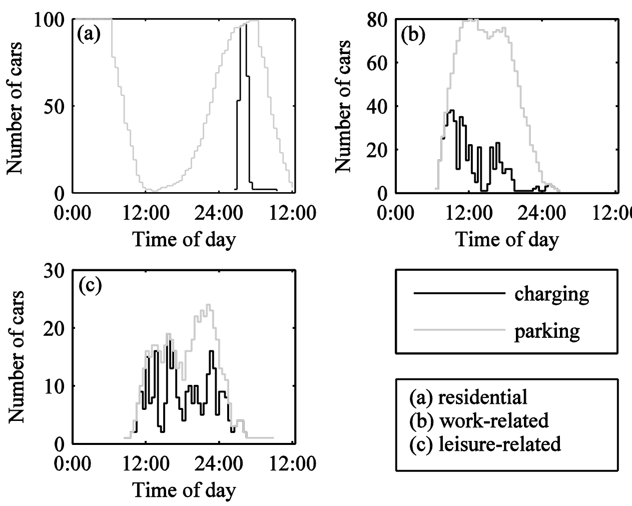

Figure 5. Parking and charging utilization for three car parks.

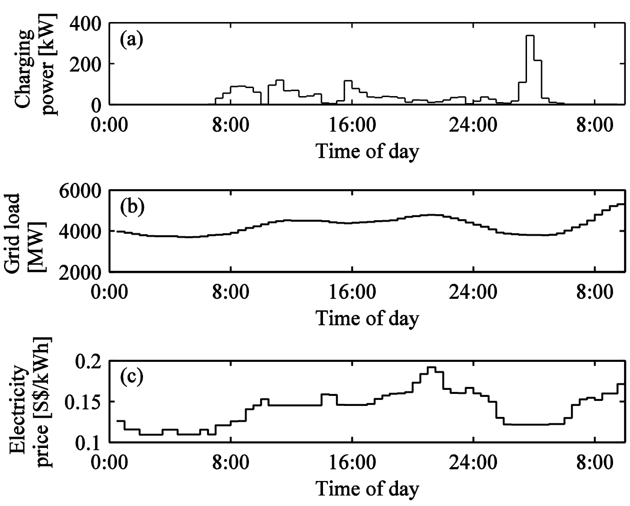

Figure 6. Charging power (a), grid load (b), and electricity price (c).

Fig. 6 pictures the correlation between EV charging power, grid load, and electricity price in Singapore. The total charging power for 100 EVs over the modeling time period of one day is shown in Fig. 6 (a) with a maximum of 338 kW between 3:00 AM and 5:00 AM. The maximum charging power for 100 EVs is in the magnitude of merely 0.01 % of the grid load in Singapore (see Fig. 6 (b)). Nevertheless, it can be seen that the cost minimizing charging strategies produce a power profile favoring the grid load as peaks of the charging power profile coincide with times of low demand of the rest of the system in most of the times. Scaling up these results to 50,000 EVs, which would account for 10% of all private vehicles in Singapore [12], the peak charging power would rise to approximately 150 MW equaling 3 to 4 % of the grid load.

The charging cost for the 100 EVs, minimized by the charging optimization model, are listed in Table III. It has to be pointed out that the listed charging cost include only electricity cost for charging, but not cost for charging infrastructure. Charging at home is cheapest with an average cost per parking event of 0.42 S$. This can be inferred from the very low electricity price at night. Charging at work- and leisure-related car parks lies in the same price range but is more expensive than parking at residential car parks since it is charged mainly during the day.

TABLE III. CHARGING COST PER CAR PARK.

Charging cost [S$][a]	**100 EVs during one day**	**Average per parking event**
Residential	41.72	0.42
Work-related	71.72	0.51
Leisure-related	50.29	0.50
All car parks	163.73	0.48

a. currency exchange rate as of 2013-02-28: 1 US$ = 1.2363 S$ [13]

For comparison, a cost minimizing charging optimization excluding the battery constraints, described in the equations formulated in (4)-(6) as well as through parameter E_{charge} in Section II.C, was calculated for the same 100 EVs. The charging cost for all car parks in this case is 161.62 S$, a decrease of 2.11 S$. Per EV, the charging is 0.02 S$ cheaper for one day. Given a lifetime of an EV of 5 years, an amount of 39 S$ could be saved when charging without battery constraints. The peak power between 3:00 AM and 5:00 AM increases to 696 kW for charging without battery constraints. This would more than double the maximum power compared to the scenario with battery constraints if it is not restricted otherwise. Even though the charging cost with regard to battery constraints are slightly higher, it is beneficial to take them into account, because these charging strategies guarantee charging processes adapted to battery restrictions. The upper charging voltage limit is not exceeded and this leads to longer lifetime of batteries and enhances safety [7].

This can be summarized to two main advantages of cost optimized charging including battery constraints compared to charging without battery constraints. First, the slightly higher charging cost is compensated by longer lifetime and increased battery safety. Based on cost in the range of 15,000 S$ for a new battery [13], [14], the additional amount of 39 S$ for battery adjusted charging for 5 years is amortized as soon as the battery experiences a longer lifespan of only 5 days. Secondly, the significantly higher peak power of charging without battery constraints, as it appears between 3:00 AM and 5:00 AM, is assumed to have effects on the power supply system in scenarios with a larger amount of EVs and especially if photovoltaic systems play an important role in the power system.

V. Conclusion and Outlook

An optimization model for EV charging strategies considering battery constraints with the objective to minimize charging cost was developed. As case study for Singapore, it was applied to a sample of 100 EVs, which are parking and charging in Singaporean car parks. The cost minimized charging processes occur mainly during load valleys and hence have a positive effect on the grid load. Moreover, the charging strategies consider battery restrictions and thereby ensure battery lifetime and safety, which overcompensates the slightly higher charging cost compared to charging without battery constraints.

Future research will consider valley filling of the grid load as objective and compare it to the model elaborated here. Furthermore, the cost for charging infrastructure and demand for charging stations will be included. The model can be extended to larger systems as districts, cities or even larger areas. In addition, various battery types with corresponding battery profiles can be integrated to cover the diversity of the EV market. Moreover, charging profiles for higher C-rates can be implemented in order to include fast charging options. Thus, a comprehensive view on future large scale EV charging can be given.

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