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Smarter charging: Power allocation accounting for travel time of electric vehicle drivers

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ABSTRACT

Growing electric vehicle (EV) dissemination will increase charging infrastructure installation at home. Similar daily routines are associated with high peak loads due to simultaneous EV charging. However, predominantly residential power transmission is not designed for such high loads, yielding charging bottlenecks and restricting future charging at home. Addressing such bottleneck situations and including the EV driver perspective, we introduce a power allocation mechanism that considers the total travel time of the upcoming trip, consisting of actual driving time and time required for charging externally (including the detour to public charging facilities). Assuming that travel time generally negatively correlates with EV driver utility, our optimization model maximizes the resulting utility of EV drivers. Avoiding unnecessary external charging stops due to an insufficient state of charge at the time of departure, our approach generates travel time savings that increase overall EV driver utility. We illustrate our approach using exemplary cases.

1. Introduction

Within the low-carbon transformation, the transport sector plays a crucial role given its high carbon dioxide emissions. Especially the substitution of vehicles with combustion engines with electric vehicles (EVs) is a promising approach to successfully reduce carbon dioxide emissions in the transport sector (Lopez-Behar et al. 2019; Bryden et al. 2018; DeForest et al. 2018; Xu et al. 2020). EV-friendly legislation in many countries, the ongoing technological progress for higher driving ranges, and decreasing costs of EVs ascended the share of EVs in recent years that is expected to significantly increase even further in the near future (Xie et al. 2016; International Energy Agency 2017). The desired dissemination of electric mobility leads to new requirements for the power grid infrastructure. On the one side, there will be an increase in the general electricity-demand level. On the other side, there will also be a growth in the demand for power transmission capacity due to the simultaneous charging of EVs. The former additional electricity demand does generally not represent a major threat to the further expansion of electric mobility due to sufficient generation capacities (Jochem et al. 2012). However, the latter rising demand for power transmission capacity to get electricity from power generators to the EVs can pose

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Nomenclature

Abbreviations

EV	electric vehicle
h	hour
km	kilometers
kW	kilowatt
kWh	kilowatt-hour
min	minutes
SoC	state of charge
t	time step

serious challenges to fulfill charging requirements.

Since charging at home is one of the most relevant options to supply EVs with power, it represents one of the major charging use cases threatened by power transmission capacity bottlenecks (Hardman et al. 2018). In particular, with the rising number of EVs, more and more EV owners equip their private parking lots with charging facilities, named wallboxes, to charge at home with up to 22 kW (Longo et al., 2016). Due to similar daily routines, especially during the week in the evening hours after work, a high share of residents connect their EVs simultaneously with the grid. Once a certain number of vehicles is connected, the energy demand can often not be satisfied by today's power transmission capacity of the residential grid infrastructure, mainly resulting from bottlenecks at coupling points (Jochem et al. 2012).

In case of a residential building with an associated parking area, already the residential grid coupling point, connecting the building to the power grid, can be the bottleneck that limits the number of EVs charging simultaneously. Using Germany as an example, the power transmission capacity of the residential grid coupling point of a building with five apartments is dimensioned for 40 kW (Baade 2007). Even if the energy consumption of the apartments themselves is neglected, the power transmission capacity can already be exceeded when charging more than one EV at the same time with a wallbox providing 22 kW. Suppose the power transmission capacity of the residential grid coupling point is not the limiting factor. In that case, a bottleneck can also occur by the transformer, which connects streets or residential areas to the distribution grid (Vasirani and Ossowski 2013). Ultimately, the residential power grid can be a limiting factor restricting simultaneous EV charging (Chung et al. 2014; Schey et al. 2012). Such bottlenecks may finally imply that the number of charging facilities for a residential building or several houses in a single street must be limited, i.e., for grid stability, not everyone who wants to install a charging facility will be allowed to do so.

A possibility to address bottleneck situations due to an insufficient power transmission capacity is the expansion of the residential power grid. However, forecasts indicate that this solution will result in enormous investments to prepare the power grid for the upcoming rise of power transmission demand (Jochem et al. 2012). Furthermore, power grid expansion not only implies a huge financial burden, but it also takes a long time, with major construction projects impacting the environment and possibly yielding public resistance. Ultimately, at least in the short run, expanding the residential power grid may not solve the possible restriction of charging facilities for residents. Therefore, alternatives to be implemented in the short run are highly needed, leading to a way to reduce high energy demand peaks caused by simultaneous EV charging instead of upgrading the grid by largescale expansions.

One possible approach to reduce high energy demand peaks is temporal power demand flexibility in EV charging. However, such charging flexibility is for instance not available at fast-charging facilities, where the foremost objective of EV drives is to charge their EV to continue their trip as fast as possible. Therefore, in this paper, we do not consider fast-charging and related public charging facilities where the EV driver only stops for recharging (Baumgarte et al. 2021; Halbrügge et al. 2020; Gupta et al. 2020). In contrast, due to the potential of the EVs' long parking time in, for instance, home charging applications, corresponding charging processes can be shifted temporally to meet grid limitations (Sachan et al. 2020; Sadeghianpourhamami et al. 2018; Brandt et al. 2017; Sundstroem and Binding 2012). As Fachrizal et al. (2020) point out, various researchers already analyze this idea with different objectives. Examples of objectives are to reduce peak load and create a more stable electricity system (Crozier et al. 2020; Amjad et al. 2018), to integrate renewable energies like photovoltaic power (Fachrizal and Munkhammar 2020; Shafie-Khah et al. 2018; van der Kam and van Sark 2015), to reduce charging costs (Nour et al. 2019; Al-Awami and Sortomme 2012), or to minimize battery degradation (Sovacool et al. 2017; Schoch 2016). They typically refer to the control of charging processes based on information exchange between the EVs and the charging infrastructure by the term smart charging (Fridgen et al. 2014; Goebel 2013). Smart charging can generally have the objective of off-peak charging, valley filling, or peak shaving (García-Villalobos et al. 2014)[1]. While corresponding allocation mechanisms may be scarcity management in the short run, they may also reduce required power grid expansions by better utilizing the capacity of the existing infrastructure in the long run. The mentioned authors demonstrate that there is a way to reduce bottlenecks by temporally shifting charging processes. First papers point out that the integration of user preferences helps to develop smart charging. Already collected information about the planned charging time can help to reduce costs and not violate the relevant technical operator constraints (Clairand et al. 2018). In addition to user preferences, bidirectional charging can improve smart charging approaches even

[1] Since we do not focus on developing a new mathematical solution algorithm in this paper, we will not provide a comprehensive review of existing algorithms in this section.

further (Al-Obaidi et al. 2021).

Thus, the smart charging approaches discussed can contribute to reducing peak load and improving grid-friendly charging. Besides, technologies such as battery storage or bidirectional charging could also contribute to the stability of the electricity system. However, the benefits and costs and, in the case of bidirectional charging, the impact on battery life are still an ongoing topic in current research (Baumgarte et al. 2020; Haupt et al. 2020; Li et al. 2020). Even more important, all these smart charging approaches cannot avoid every bottleneck situation, especially at the residential power grid (Schmidt 2017). Accordingly, even when applying a smart charging approach and, thus, using existing temporal power demand flexibility, not every EV will always reach its target state of charge (SoC) at the time of departure. This target SoC represents the necessary SoC to arrive at the planned destination without an additional charging stop. Resulting dissatisfaction and reduced mobility due to an insufficient SoC at the time of departure will, in general, negatively affect the acceptance of EVs in terms of range anxiety and long charging times (Noel et al. 2019; Bryden et al. 2018; Wagner et al. 2014; Kley et al. 2011). As a result, there is a need for smart charging approaches that handle unavoidable bottlenecks by allocating the limited power appropriately.

First approaches to manage unavoidable bottlenecks are already discussed in the literature. Some authors refer to the concept of willingness to pay (Fan 2012; Gerding et al. 2011): The driver who is willing to pay more for charging is assumed to have probably a higher utility than drivers with a lower willingness to pay and should therefore charge first. Some authors use auction mechanisms (Correa et al. 2020; Xiang et al. 2015), where the power is also allocated to the buyer who values it the most. However, such approaches are socially debatable, as it possibly favors EV drivers with higher incomes. Against this background, also smart charging power allocation mechanisms that allocate the limited power regardless of the EV driver's social status (income) are already discussed in scientific literature. Ensuring grid stability, some of these mechanisms allocate the available power by using direct measurable criteria, such as the actually allocated power in proportion to the requested power or the duration of parking time (Chung et al. 2014; Akhavan-Rezai et al. 2014; Wen et al. 2012; Phan et al. 2012). Other mechanisms use lottery scheduling to allocate the limited power (Liu and McLoone 2015; Wei et al. 2014; Vasirani and Ossowski 2013; Su and Chow 2012; Stüdli et al. 2012).

Also, there are already first papers that introduce the concept of utility of EV drivers. Utility typically depends on factors like the requested amount of energy, the battery capacity, the availability and price of power, or the EV's energy efficiency (Vasirani and Ossowski 2013; Tushar et al. 2012). However, to the best of our knowledge, none approach focuses on the impact of an insufficient SoC at the time of departure on the upcoming driving process. Therefore, existing studies neglect possible utility losses that may stem from unnecessary and avoidable external charging stops. Against this background, in this paper, we aim to extend the existing body of knowledge by including the planned driving process of the EV driver, i.e., including the travel time of the upcoming trip, in our power allocation mechanism. Considering travel time is a novel aspect of smart charging. It has been restricted to other stands of literature, e.g., literature that focuses on the selection of an external charging facility to minimize the corresponding waiting time (Cao et al. 2018; Cao et al. 2017) or to develop algorithms for route planning (Shao et al. 2017).

By considering EV driver utility - which in our case represents the EV driver's satisfaction depending on the travel time of the upcoming trip -, we want to make smart charging even *smarter*. In particular, our approach considers the impact of an insufficient SoC at the time of departure on the travel time for the upcoming trip for each EV driver. As additional external charging, including the time for the detour to an external charging facility, is part of the travel time, we can increase the EV driver's satisfaction by avoiding such additional time for external charging. We can avoid this additional travel time if our power allocation mechanism allocates sufficient power to the driver's EV. Thereby, our power allocation mechanism can influence the *EV driver utility*.

Our chosen research methodology consists of an optimization model with the objective of maximizing the overall EV driver utility of all simultaneously connected EVs. The EV driver utility depends on the SoC at the time of departure and explicitly accounts for utility losses of unnecessary external charging time. Especially a completely avoided external charging stop significantly increases the EV driver utility, where our optimization model considers the external charging time at the charging facility and the detour to reach the charging facility. For the derivation of the EV driver utility function, we consider the relationship between a decreasing EV driver utility depending on travel time and the relationship between an increasing SoC at the time of departure and a decreasing travel time. For allocating power, we focus on the minimal technically relevant constraints of the grid coupling point, the EVs, the charging facility, and the remaining power consumption of other consumers, e.g., households connected to the same coupling point. Additional power grid constraints will restrict the power allocation even more, which will make our power allocation mechanism only more relevant. In this way, we do neither present a technically detailed network flow model nor a mathematical solution algorithm in this paper, but rather develop a first model to demonstrate the impact of a power allocation mechanism accounting for additional travel time on EV driver utility. In this paper, we also present first exemplary cases to illustrate how our power allocation mechanism can improve the overall utility of EVs with an appropriate smart charging service.

Our approach is applicable to coupling points on all layers of the power grid where a bottleneck situation can occur due to simultaneously charging EVs. The output of our optimization model is a charging schedule with the information about the allocated power for each EV at each time step. Since significant time savings may be possible by avoiding unnecessary external charging stops, our model does not only increase the satisfaction of EV drives with charging but ultimately reduces the overall number of external charging stops for the considered EVs. With the potential to avoid unnecessary external charging stops and reduce the charging time at external charging facilities, our power allocation mechanism may contribute to a more efficient use of the power grid infrastructure. Therefore, this paper positively impacts grid expansion and the need for additional external fast-charging infrastructure, which opens a broad field for future research.

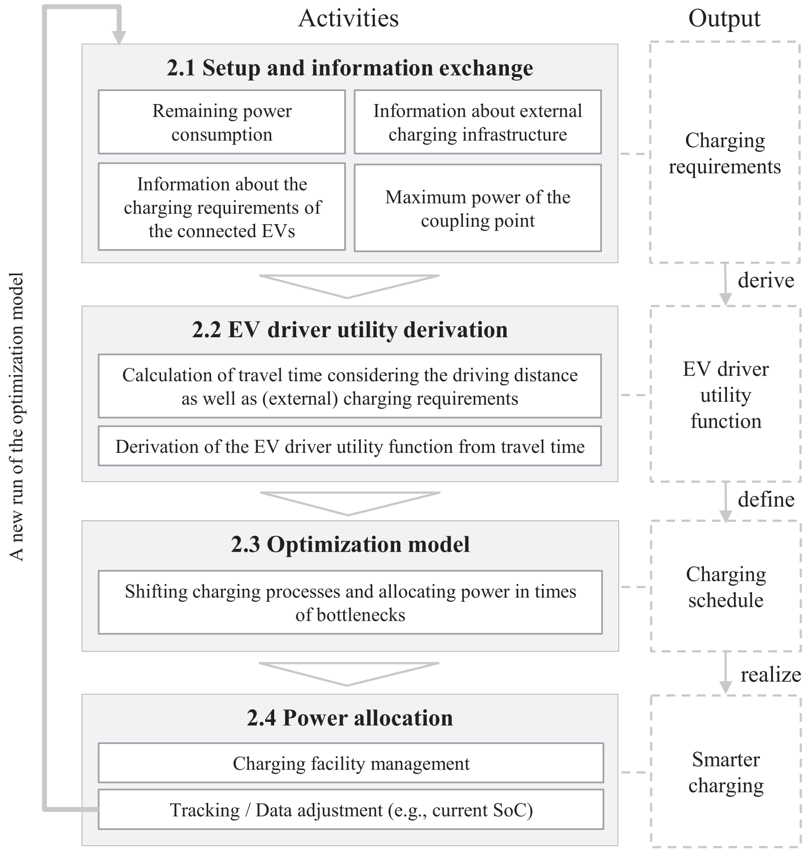


Fig. 1. The four main activities of our power allocation mechanism.

2. Developing a power allocation mechanism

In this section, we present our power allocation mechanism for *smarter charging*. The present section is divided into four subsections, where, as highlighted in Fig. 1, each subsection addresses one of the four steps that we refer to as *activities*.

2.1. Setup and information exchange

Our setup bases on $n > 1$ EV charging processes supplied with power from a central coupling point (see Fig. 2). The coupling point is typically a connection between different grid layers. Coupling points function as central nodes and can represent a bottleneck in times of peak demand. Fig. 3 illustrates the interconnection with the general power grid and highlights examples for corresponding coupling points. These coupling points may constitute a bottleneck situation for charging EVs at home at the residential grid coupling point of a residential building (I) or the transformer of a street (II), where our approach can be applied. Note that the actual power grid is not part of our setup. Instead, this paper is about allocating the limited available power at one coupling point (representing one type of grid limitation) in a way that maximizes the resulting utility of EV drivers in bottleneck situations. Therefore, in our setup, we focus on the minimum technically relevant constraints that need to be considered to analyze the effects of additional travel time due to an insufficient SoC at the time of departure. As additional constraints will lead to a bottleneck situation even faster, incorporating such technical constraints makes our power allocation mechanism only more relevant. In Fig. 3, we illustrate that we only consider the coupling point, the remaining power consumption of the house, the constraints of the charging facility, and the technical characteristics of the EV. The considered components are highlighted in black. The closely related power system constraints are not part of our actual optimization model, illustrated in gray. However, constraints of the overarching power grid and power system operation may be included in future work, e.g., to address additional questions of how EV charging may help balance power grids.

As illustrated in Fig. 2, the power transmission capacity of a coupling point limits the available power for power consumption. Since all considered charging processes are supplied by the same coupling point, the available power has to be shared, and an underlying power allocation mechanism is needed.

Each charging process (charging process *1* to n, where $n > 1$ depends on the concrete input and describes the number of connected EVs) consists of and is influenced by three components, as shown in Fig. 2. The first component (i) is the charging facility restricting the energy supply due to its technical characteristics. For the home charging scenario, a wallbox represents the charging facility. Note, that

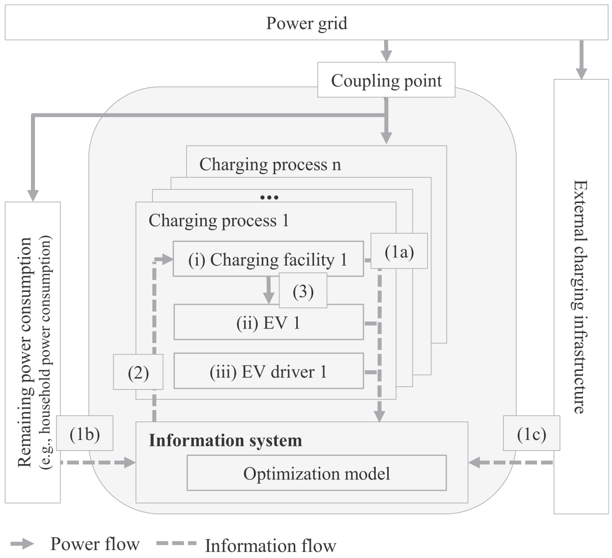


Fig. 2. Setup representation. The gray area illustrates our setup in which we allocate the power to charging processes *1* to *n* using our optimization model. $n > 1$ describes the number of charging processes considered.

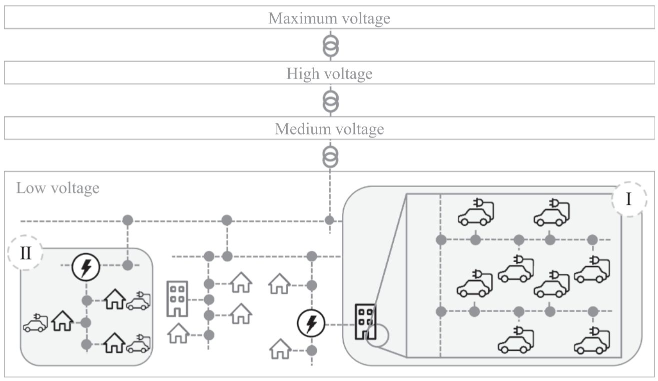


Fig. 3. The complexity of the general power grid. The gray area of (I) represents a coupling point of a residential building, and the gray area of (II) the transformer of a street, where a bottleneck situation at the low voltage grid can occur. The considered components of our optimization model (the coupling point, the remaining power consumption of the house, and the technical restrictions of the charging facility and the EV) are illustrated in black. The related power system constraints are not part of our optimization model and are illustrated in gray.

even if we introduce our approach through a home charging scenario, it is without loss of generality also applicable for simultaneous EV charging in other scenarios with long parking times of the EVs, e.g., parking at the workplace or at public charging facilities. The second component (ii) is the EV with its technical characteristics, such as battery capacity, maximum charging speed, and average energy consumption during driving. In addition to those fixed parameters, the EV provides the initial SoC at the beginning of the charging process. The third component (iii) is the EV driver that provides information about the driving distance of the upcoming trip and the departure time to leave the charging facility. This information exchange may, for example, be possible by a mobile application, an operation panel at the wallbox, or may automatically be extracted from the EV driver's calendar. Based on the driving distance, we calculate the target SoC, i.e., the minimum SoC to arrive at the destination without any unnecessary charging stop. All this information provided by the three components of a charging process to a central information system (1a) forms the basis for our approach, as illustrated in Fig. 2.

The second type of information is the remaining power consumption of all non-EV electricity consumers supplied by the same coupling point (1b). This information is necessary to calculate the net power supply available for EV charging. For our example of charging at home with the residential coupling point as the limiting factor, the households' power consumption needs to be subtracted from the power capacity of the residential coupling point to avoid situations where EV charging negatively impacts the living habits of the residents.

Our approach also requires information on the external charging infrastructure, representing the third type of information (1c), namely the location and the maximum charging speed of (fast) charging facilities along the travel route of each plugged-in EV. With information on the upcoming driving process, our approach allows us to address EV drivers' mobility requirements better.

Subsequently, a central information system is an integral part of our approach that may be operated for the examples in Fig. 3 by the owner of the residential building (I) or by a power grid operator (II), who generally aims at the best possible utilization of the power grid infrastructure. The information system is responsible for collecting the information (1a-c) from each charging process *1* to *n*, with $n > 1$, that serves as an input for the optimization model. Already today, home energy management systems integrate and manage various consumers and generators. These systems also allow for the integration of external data via a gateway and the input of additional data via a human–machine interface system. Home energy management systems are examples of standard commercial solutions representing the required information system for our power allocation mechanism (Mahapatra and Nayyar 2019; Zhou et al. 2016). The optimization model itself calculates the actual charging schedule, i.e., the allocated power to charge the respective EV, which is then communicated. Thereby, the charging facility regulates the power flow based on the corresponding information (2). The use of arrows in Fig. 2 indicates that we only consider unidirectional charging.

To ensure the various information flows between the components and the optimization model, we assume:

Assumption 1. *The necessary information (1a-c) is available on time and correct.*

First, our optimization model needs accurate information about the charging process itself (1a). The charging process information from the considered charging facility (i) and the EV (ii) is necessary to obtain a solution for the actual real-world situation. Besides, our optimization model requires correct information about the driving distance and the departure time provided by each EV driver (iii) for the planned trip. The latter may, for instance, be habitual journeys (commute to work) or planned leisure trips. We exclude misstated information, including the strategic behavior of EV drivers, e.g., to be prioritized for charging. One example of strategic behavior of the EV driver is a misstated earlier departure time to reach the target SoC faster. Let us briefly consider a stylized example to explain the possible consequences of a misstated earlier departure time: Two simultaneously connected EVs requiring the same energy (each EV 50 kWh). The available power at the grid coupling point is 50 kW. The departure of EV1 is after 1 h, and the departure of EV2 is after 2 h. If both EVs state their correct departure time, no bottleneck occurs, and both EVs can be charged up to their desired SoC. However, if, for example, EV2 provides misstated information and communicates that it already departs after 1 h, a bottleneck situation occurs, and EV1 cannot reach its target SoC of 50 kWh. Similar arguments also hold for misstated longer driving distances. Therefore, the accuracy of the EV driver's information is crucial for the realized power allocation. Hence, applying adequate incentive schemes or penalties (Fridgen et al. 2014) may ensure correctly stated information, which underlines the validity of our approach. However, the behavior of EV drivers for specifying and stating their data (including drivers' psychological factors) is a separate field of research and not part of this paper, but certainly relevant for future work. Second, information about the external charging infrastructure is needed (1c). In this context, the information on the location and the maximum charging speed of external charging infrastructure are generally available via online map services. Third, for the remaining power consumption except EV charging (e.g., household power consumption), consumption forecasts have to be used (1b). Every time the forecasts of the remaining power consumption deviate from the actual consumption, i.e., every time data changes, the optimization model runs again with the updated data (see Fig. 1). As changes in consumption forecasts lead to either more or less available power for charging, our optimization model needs to calculate a new power allocation for the plugged-in EVs, which leads to an adjusted charging schedule. Due to the overall length of this article, we do not consider technical options for information collection in detail, which may be subject to further research.

As already described above, information on the location and the maximum charging speed of external charging facilities is available and allows to calculate the shortest travel time of the upcoming trip of each EV driver. Thereby, external charging facilities directly influence travel time. As the actual utilization of external charging infrastructure can generally change during the journey, we assume the following:

Assumption 2. *Power transmission capacity bottlenecks and waiting times at external charging infrastructure do not influence the power allocation and are therefore not considered.*

On the one hand, there are already several initiatives to develop a comprehensive external (fast) charging infrastructure. Therefore, the charging infrastructure is expected to be sufficient even for an increasing number of EVs. A prominent example is the German Federal Ministry of Transport and Digital Infrastructure funding for fast-charging infrastructure along motorways (BMVI, 2021). This trend can also be observed outside Germany, for example, by looking at the joint venture IONITY in cooperation with Shell, which aims to build 400 fast-charging facilities across Europe (Royal Dutch Shell plc 2019). On the other hand, to avoid the complexity of our optimization model, our model does not take the current utilization of external charging infrastructures into account and, in this way, does not consider a time-varying occupation of charging facilities. We only take the most essential information about how fast an EV can theoretically charge at external charging facilities along their upcoming trip into account. Possible bottlenecks that may mainly be observed at external charging infrastructure in the coming years due to other EVs are not part of our optimization model. There are smart routing approaches that incorporate the relevant data for it to identify the best charging facility along the upcoming trip. Even though we abstract from the described interdependencies at external charging facilities, our model presents a first step and may be extended to additionally consider bottlenecks and waiting times at external charging infrastructure in future research.

As range anxiety (Rauh et al. 2015) and the loss of time due to additional charging are essential for the acceptance of electric mobility, with Assumption 3, we focus on the EV driver utility depending on the travel time as our decision criterion. In this way, we want to analyze how the power allocation changes when travel time (and especially the additional travel time due to an insufficient SoC) is considered:

Assumption 3. *EV driver utility and corresponding decisions on allocating the available power depend only on the loss of time during the upcoming trip.*

This seems a strong assumption since, for example, electricity prices for charging an EV may also influence EV driver utility. However, there are currently various pricing models for charging at home and for charging at an external infrastructure (Ensslen et al. 2018; Hu et al. 2016). These circumstances show that at the moment, there is no standardized pricing model that we can consider as a general and generalizable approach. Moreover, this paper aims at explicitly focusing on the influence of time loss and isolating relevant effects from other additional effects. In this respect, it would be appropriate for further research to investigate at what point EV drivers are willing to accept a longer travel time if they pay less for charging. As in reality, some other individual factors influence the charging decision, such as weather conditions, shopping options at external charging facilities, or personal preferences, which would also be an interesting field of research to additionally consider in the context of price sensitivity. As corresponding effects will only increase the complexity of decisions, in this paper, we opted to analyze how the power allocation changes when travel time and especially the additional travel time due to an insufficient SoC are the main influencing factors. In this way, our paper provides a basis for future research.

2.2. *EV driver utility*

Utility is generally a widely used concept representing a person's satisfaction with a supplied service (Bussolon 2017). In our case, the EV driver's satisfaction depends on the (additional) travel time of the upcoming trip. As the SoC influences the (additional) travel time at the time of departure, our power allocation mechanism can directly influence EV driver satisfaction (and utility). The maximum EV driver utility is reached when the EV driver receives the target SoC, as in this case, no additional travel time is needed to arrive at the destination. Since the travel time determines EV driver utility, we first describe the various travel time components, including the additional travel time. In a second step, we derive the EV driver utility function describing the corresponding relations between travel time (with a particular focus on the additional travel time), SoC, and EV driver utility in detail.

2.2.1. *Defining the travel time*

Our model considers both the charging process and the driving process of the upcoming trip. We define the upcoming trip in such a way that a charging facility is available at the destination to charge for the later trip. In this way, the upcoming trip may also be interpreted as a round trip:

Assumption 4. *Our optimization model only considers the upcoming trip.*

This implies that EV drivers are indifferent between a situation where they receive the target SoC at the time of departure and when they get an SoC larger than the target SoC. We developed our optimization model for bottleneck situations due to peak power demand, where, first and foremost, the upcoming trip is relevant for the EV driver. Additionally, later trips and charging processes will, in fact, depend on many factors that are in general highly uncertain. In consequence of the uncertainty of the later trips and their influencing factors, whether a bottleneck situation for later charging processes will arise is not easy to answer in advance. Thus, our optimization model solves current bottleneck situations (and in this way does not address unknown later bottleneck situations, which may also be a topic for future research, e.g., in the field of stochastic optimization).

The overall travel time for the upcoming trip can be divided into four components (Fig. 4):

The *worst case travel time* specifies the travel time if the EV has to start its upcoming trip with the minimum defined SoC. The worst case travel time consists of two components: the *best case travel time* and the *additional travel time*.

The best case travel time, in turn, depends on the driving time required to cover the distance to the next destination as well as the unavoidable time for charging during the trip. The unavoidable time for charging will be strictly positive in cases where the battery capacity of the EV is too small or if the parking time is too short to charge sufficient energy to reach the destination without any charging stops. The unavoidable time for charging consists of both the time to reach the external charging facility and the charging time at the charging facility itself. Here, we consider detours to the external charging infrastructure and the possible charging speed at the external charging facility. In this way, we can directly account for the fast-charging technique used at the external charging station.

The additional travel time specifies the part of the travel time that our model can influence by allocating power to the EV. The duration of a trip extends by the additional travel time whenever the SoC at the time of departure is lower than the target SoC. The additional travel time consists of the time required to charge the missing amount of energy, which we consider by taking the maximum charging speed of the EV and the maximum power that the external charging facility can supply into account. It also comprises the time the EV needs to reach the external charging facility. The latter is determined by the length of the detour from the actual route and the time to charge the additional power required to drive the detour. Therefore, a higher SoC at the time of departure from the initial charging facility can reduce the external charging time.

We take the driving process into account for the power allocation decision by converting the travel time into utility for each EV driver. Since time is limited, it is the EV drivers' objective to keep the travel time as short as possible to spend time for other activities, e.g., to earn money or to use spare time for leisure activities (Tipping 1968; Oort 1969). We also take into account that the same absolute additional travel time, e.g., 5 min, is, in general, less detrimental for an EV driver with a long best case travel time, e.g., 2 h, than it is for an EV driver with a short best case travel time, e.g., 10 min (Kahneman and Tversky 2013). Therefore, it is not sufficient to use the absolute value of travel time to calculate the EV driver utility. Instead, we consider the ratio between the additional travel time describing the time that can possibly be reduced and the worst case travel time relating to the travel time when the EV was not charged during current parking. In the following, we refer to this ratio $\frac{Additional\ \ travel\ \ time}{Worst\ \ case\ \ travel\ \ time}$ as the term *time supplement*.

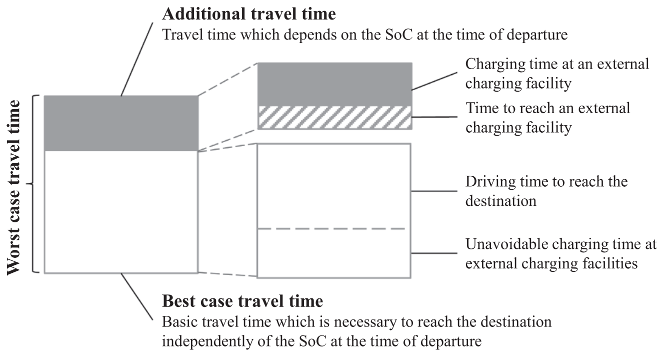


Fig. 4. The components of the travel time.

Defining the time supplement, we divide the additional travel time by the worst case travel time instead of the best case travel time to take the impact of different maximum charging speeds at external charging infrastructure into account: With the time supplement, the detour to the charging facility has a more significant impact on the EV driver utility for an EV with a fast maximum charging speed than it has for an EV with a slower maximum charging speed. The time supplement takes values in the range of [0,1). The value 1 is never reached, as the worst case travel time is always greater than the additional travel time (since the former includes the additional travel time).

2.2.2. *Deriving the EV driver utility function*

In our case, we assume that the time supplement determines utility. Function (I) in Fig. 5 defines the relationship between EV driver utility and time supplement. Since the EV driver aims shortest possible travel time (Tipping 1968; Oort 1969), the EV driver utility decreases with an increasing time supplement. As we can influence the SoC at departure with our power allocation mechanism, Function (II) depicts this relationship between time supplement and SoC at departure. The time supplement decreases with an increasing SoC at departure until the target SoC is reached. As both functions depend on the time supplement, we can derive Function (III) by substituting Function (II) in Function (I). Function (III) depicts the relationship between the EV driver utility and the SoC and builds the basis of our optimization model. Thus, the SoC at the time of departure is the variable that is chosen by our power allocation mechanism to maximize EV driver utility. In the following, we describe the three different functions in more detail.

(I). EV driver utility depending on time supplement

Function (I) represents EV driver utility depending on time supplement (Fig. 6). The EV driver utility either declines or remains constant with an increasing additional travel time. The same applies to a rising time supplement. The respective shape of the function

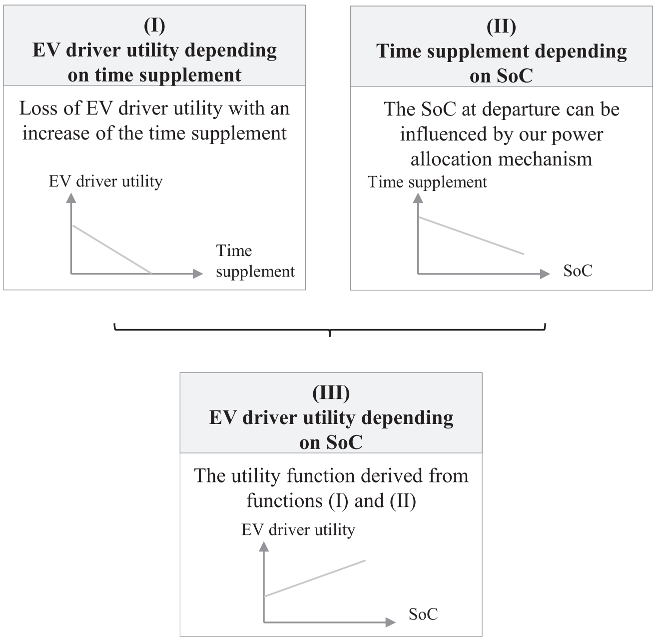


Fig. 5. The derivation of the EV driver utility function. Each function represents an example.

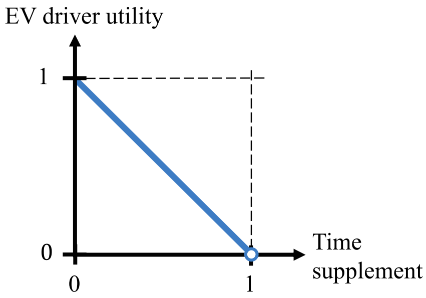


Fig. 6. EV driver utility depending on time supplement (I).

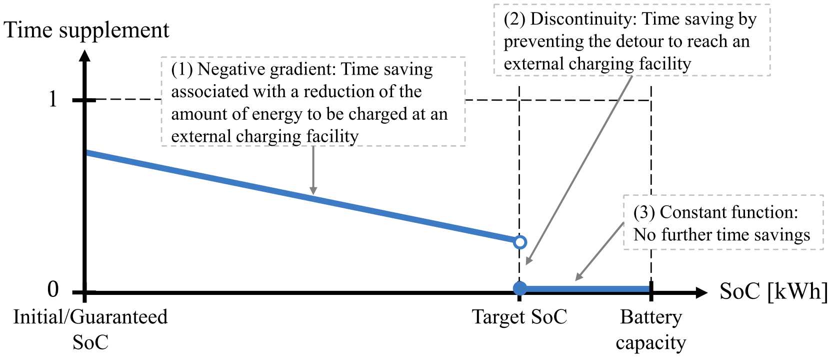


Fig. 7. Time supplement depending on SoC (II).

depends on various factors and may be individual for each EV driver. Our general model allows for different function shapes. For simplification and better understanding, we consider a linear relationship between EV driver utility and time supplement as an example for a monotonously decreasing function. Independent of the respective shape of the used function, the maximum value of EV driver utility is one as soon as the target SoC is reached, and all additional external charging stops can be avoided. The minimum value of EV driver utility depends on the individual charging process. As illustrated before, the value of time supplement can never be one. As a result, the EV driver utility can never be zero.

(II). Time supplement depending on SoC

Fig. 7 exemplarily depicts Function (II). For the sake of simplicity, in this paper, we assume a linear charging curve of the battery, i.e., a constant charging speed for the EV's battery which is independent of the current SoC.

Assumption 5. The EVs considered in our paper have a linear charging curve.

The maximum charging speed of batteries is highly complex and generally not necessarily constant. For example, the charging speed may depend on the current SoC and the temperature of the battery (Reddy and Linden 2011). Since the aim of our paper is not to present an exact model of a charging curve but rather to highlight the general possibility of a smarter charging approach, we assume a linear charging curve in line with Lindgren et al. (2014), Felipe et al. (2014), and Schneider et al. (2014). A non-linear charging curve can also be implemented in our optimization model. Still, it would make the development of the model more complex for the reader, i.e., the derivation of the EV driver utility function (see Fig. 5) or the description of the exemplary cases in Section 3. The influence of a non-linear charging curve is significant in the high SoC range when the charging speed is limited by technical constraints, e.g., by the surface ion concentration (Yin and Choe 2020). Whenever technical constraints limit the charging speed, the charging time increases. A more detailed analysis of the charging curve and corresponding effects on charging time could be further explored in future work using sensitivity analyses. In this paper, we want to highlight that the availability and the use of data considering the upcoming trip can increase overall EV driver utility, building on a linear relationship as a starting point.

As Fig. 7 depicts, Function (II) is divided into three sections.

Section (1) in Fig. 7 describes the relationship between time supplement and SoC, where a higher SoC enables a shorter charging time at an external charging facility. As a direct consequence of the linear charging curve (Assumption 5), the time supplement decreases linearly with an increasing SoC. Only values larger or equal than the minimum of the initial SoC and the EV-guaranteed SoC are feasible, where the operator may optionally further restrict the latter.

Section (2) in Fig. 7 shows a discontinuity. This discontinuity relates to the SoC, where the charged amount of energy is sufficient to avoid an external charging stop. Reaching this SoC prevents the time for the detour to reach an external charging facility and the time to charge the additional amount of energy necessary for the detour (see Fig. 4). This time saving results in a sudden reduction of the time supplement, which leads to discontinuity. Since Fig. 7 uses an example where the target SoC specifies the necessary energy to reach the destination, a discontinuity occurs at the target SoC.

Section (3) in Fig. 7 refers to a constant function between the target SoC and the battery capacity. The battery capacity represents the upper bound for the SoC at the time of departure and gives the maximum possible SoC for each EV due to technical restrictions. Once an EV reaches its target SoC, the additional travel time becomes zero, i.e., the time supplement (as the ratio of additional travel time and worst case travel time) is zero, and a further increase in SoC implies no travel time reduction.

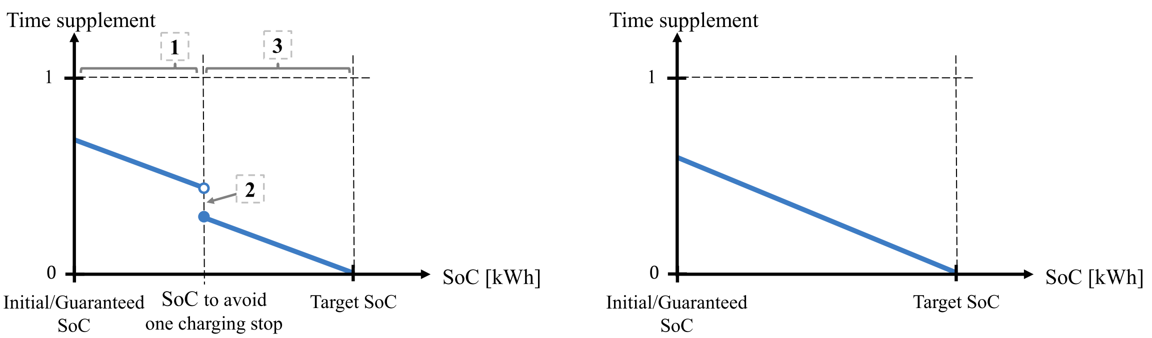
Fig. 8 depicts exemplary functions for the relation between time supplement and SoC. If an EV needs more energy to reach the destination than either the battery capacity can cover or the EV can charge during its parking time, at least one external charging stop is necessary and cannot be avoided during the upcoming trip. Ultimately, unavoidable charging stops can also lead to functions where a discontinuity does not arise at the target SoC.

Fig. 8a illustrates an example with one charging stop that can be avoided and one that cannot be avoided (Function section (2)). We present a simple numerical example for a better understanding: We consider an initial SoC of 5 kWh and a target SoC of 25 kWh, which corresponds to the battery capacity of the EV. The necessary energy to reach the next destination is 35 kWh. Since the energy demand for the trip is greater than the battery capacity (35 kWh − 25 kWh = 10 kWh), there must be at least one charging stop that cannot be avoided. Though, by reaching an SoC of 10 kWh, the unavoidable charging stop allows charging the missing amount of energy (35 kWh – 10 kWh = 25 kWh) as it corresponds to the battery capacity of 25 kWh. Therefore, for an SoC smaller than 10 kWh, two charging stops, i.e., an additional charging stop beside the unavoidable charging stop, are necessary. With an SoC greater than or equal to (2), we can avoid the additional charging stop and reduce the number of charging stops to a minimum of one (3).

Fig. 8b illustrates a function where no discontinuity occurs given that an external charging stop is unavoidable - independent of the SoC at the time of departure. The example constitutes the case where the energy to reach the destination minus the initial SoC equals the target SoC. Again, we present a small numerical example for the sake of better understanding: We assume an initial SoC of 5 kWh, a target SoC of 25 kWh (which corresponds to the battery capacity), and energy to reach the next destination of 30 kWh. Thereby, the missing energy to reach the destination equals the target SoC (30 kWh – 5 kWh = 25 kWh). Even with the target SoC which equals the battery capacity (25 kWh), the EV needs a charging stop for the remaining 5 kWh to reach the destination (30 kWh). Therefore, an increase of the SoC at departure reduces the external charging time but cannot avoid a charging stop.

(III). EV driver utility depending on SoC

The decisive Function (III), which is explicitly used in our optimization model, is the result of a combination of Function (I) and Function (II). Inserting Function (II) in Function (I), Function (III) has a positive slope. Thus, in Function (III), EV driver utility rises



(a) Energy to reach the destination is strictly larger than the target SoC

(b) Energy to reach the destination minus the initial SoC is equal to the target SoC

Fig. 8. Different exemplary functions for time supplement depending on SoC (II).

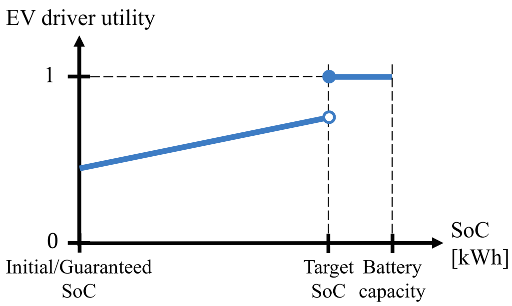


Fig. 9. EV driver utility depending on SoC (III).

with an increasing SoC. Fig. 9 illustrates an example. The respective occurrence of a discontinuity depends on the underlying Function (I).

2.3. Optimization model

2.3.1. Charging infrastructure

We will assume a residential building with an associated parking area for the residents. Each parking lot is equipped with a wallbox[2]. All wallboxes are connected to the power grid by the same residential grid coupling point with given maximum power. Each wallbox allows a maximum charging power of $\overline{w}$. The efficiency rate of each charging process is described by η and indicates the percentage of the residential grid's power that charges the EV battery. We use discrete time steps $t \in T$ with a fixed length of Δt that constitute the whole planning horizon. In each time step t, an ex-ante given amount of power denoted by $\bar{s}_t$ is available for charging the plugged-in EVs. This amount of power describes the maximum power of the residential grid coupling point minus the remaining non-EV power consumption, e.g., household power consumption.

2.3.2. Electric vehicles

We model a set of charging processes C whereby each charging process $c \in C$ is corresponding to a single EV. Each charging process $c \in C$ is described by the arrival time $t_c^a \in T$ and the departure time $t_c^d \in T$ of the corresponding EV, with $t_c^d > t_c^a$. The set $T_c = \{t_c^a, \cdots, t_c^d\}$ denotes the time periods where the EV of charging process c is plugged in and can be charged. All plugged in EVs have different technical constraints that relate to their charging process, i.e., the battery capacity $\overline{b}_c$ of the EV, which is measured in kWh and the maximum charging speed $\overline{p}_c$ which is measured in kW.

2.3.3. Charging demand

For each charging process c, the parameter SoC_c^{init} gives the initial SoC at the time of arrival. Ensuring that every EV has sufficient energy to reach at least the next charging facility or can travel short, unplanned trips (e.g., emergency trips), we set a minimum SoC that we guarantee for each charging process. This minimum SoC is denoted by the parameter $SoC_c^{\min}$. The concrete value of $SoC_c^{\min}$ can be adapted, for instance, to geographic circumstances like the distance of the considered residential building to the next external charging facility or hospital.[3] The target SoC represents the upcoming trip's mobility requirement for each EV driver. In other words, the EV's battery must be at least charged up to the target SoC to reach the EV driver's destination in the best case travel time.[4] All these parameters influence the concrete shape of the utility function, see Section 2.2. Finally, the nonnegative variable $SoC_{c,t}$ specifies the SoC of the charging process c at time step t, with SoC_{c,t_c^d} indicating the SoC at the time of departure t_c^d. We model the EV drives' mobility requirements by an individual utility function that depends on the EV's SoC at the time of departure. The EV driver utility function is denoted by $U_c : \left[SoC_c^{\min}, \overline{b}_c\right] \rightarrow (0, 1]$. The maximum EV driver utility with the value of one is achieved as soon as the target SoC is reached and the additional travel time equals zero (Assumption 4). Given the EV drivers' utility functions, the optimization model allocates power to the plugged-in EVs to maximize the overall EV driver utility. The nonnegative variable $x_{c,t} \in \mathbb{R}_0^+$ describes the amount of power allocated to the EV of charging process c in time step t.

2.3.4. Objective function and constraints

Based on the introduced model framework, we are now able to formally state our optimization model. Table 1 summarizes the relevant sets of our model, and Table 2 the corresponding input parameters. Table 3 contains a summary of the used variables.

As highlighted above, our objective function maximizes the overall EV driver utility of all charging processes, which is mathematically formulated as:

$$\max \sum_{c \in C} U_c\left(SoC_{c,t_c^d}\right) \tag{1}$$

In the above objective, U_c is a stepwise function that describes the relation between a given SoC at the time of departure (SoC_{c,t_c^d}) and the corresponding utility of the EV driver of charging process c (see Section 2.2).

The following constraint ensures that the allocated power for each charging process c does not exceed the maximum charging speed of the considered EV at each time step $t \in T_c$ the EV is plugged in. The calculation corresponds to Assumption 5 of a linear charging curve which implies that the maximum charging speed is independent of the current SoC. Also, we account for the maximum power that the wallbox can supply:

$$\min(\overline{p}_c; \overline{w}) \geq x_{c,t} \quad \forall c \in C, t \in T_c. \tag{2}$$

[2] Note that the charging facility does not have to be a wallbox, it simply describes the technical restriction of any charging facility.

[3] The calculation of the guaranteed SoC depends on the parking time of each EV as well as on the available power transmission capacity which has to be shared between all the plugged in EVs.

[4] The target SoC is calculated from the average energy consumption of each EV as well as the driving distance to reach the destination. The EV driver provides the information about the destination to the system.

Table 1
Sets.

Symbol	Description
C	Set of charging processes
T	Set of time steps
$T_c \subseteq T$	Set of time steps where the EV of charging process $c \in C$ is plugged in

Table 2
Input parameters.

Symbol	Description	Unit
Δt	Fixed time-step length	h
$\bar{s}_t$	Maximum power available for EV charging at time step $t \in T$	kW
$\overline{w}$	Maximum charging power that the wallbox can supply	kW
η	The efficiency of the charging process	%
$\overline{b}_c$	The battery capacity of the EV of charging processc $\in C$	kWh
$\overline{p}_c$	Maximum charging speed of the EV of charging process $c \in C$	kW
SoC_c^{init}	Initial SoC of the EV of charging process $c \in C$ at arrival time	kWh
SoC_c^{min}	Minimum SoC of the EV that we guarantee for charging process $c \in C$	kWh

Table 3
Variables.

Symbol	Description	Unit
$SoC_{c,t}$	SoC of the EV of charging process $c \in C$ at time step $t \in T_c$	kWh
$x_{c,t}$	Power allocated to charging process $c \in C$ at time step $t \in T_c$	kW
U_c	EV driver utility of charging process $c \in C$	EUR

According to Equation (3), only plugged in EVs can be charged:

$$x_{c,t} = 0 \;\; \forall c \in C, t \in T \setminus T_c. \tag{3}$$

Furthermore, the aggregated power that is allocated to all EVs must not be larger than the maximum power available for EV charging at time step t:

$$\bar{s}_t \geq \sum_{c \in C} x_{c,t} \;\; \forall t \in T. \tag{4}$$

The SoC at time step t is calculated as the sum of the power for charging process c up to time step t and the initial SoC:

$$SoC_{c,t} = SoC_c^{\text{init}} + \sum_{i=1}^{t} x_{c,i} \cdot \eta \cdot \Delta t \;\; \forall c \in C, t \in T_c. \tag{5}$$

The battery's SoC of charging process c at time step t must not exceed the battery capacity of the EV:

$$\overline{b}_c \geq SoC_{c,t} \;\; \forall c \in C, t \in T_c. \tag{6}$$

As the operator may decide to guarantee a minimum SoC for each charging process c, Constraint (7) ensures that at least this minimum SoC is reached for every charging process:

$$SoC_c^{\text{min}} \leq SoC_{c,t_c^d} \;\; \forall c \in C. \tag{7}$$

2.4. Power allocation

After the optimization model has derived an optimal charging schedule, the last activity of our approach refers to the actual power allocation. The charging facilities receive the information about the allocated power and charge the EVs appropriately, represented by the gray dashed arrow (2) in Fig. 2 that lead from the information system to the charging facility. The input data for the optimization model can change every time step, e.g., if a new EV is plugged in or, as mentioned above, the non-EV power consumption does not match with the forecast. In such a case, the model generates a new charging schedule each time a change occurs and takes the new information into account. To ensure that all the required information for a new calculation is available, the model processes and stores the updated information appropriately.

3. Evaluation

In this section, we evaluate our presented approach by describing different exemplary cases for the occurrence of a bottleneck. To calculate the achievable time savings, we evaluate our power allocation, named *smarter charging allocation*, with a naive comparative power allocation (Halbrügge et al. 2020; Lindgren et al. 2014), referred to as *equal allocation*. The equal allocation allocates the power equally to the plugged-in EVs unless the maximum battery capacity is reached. We note that a comparison with other established mechanisms like allocating the power in proportion to the requested power would lead to similar results as the equal allocation used in our paper. With these power allocations, no EV reaches its target SoC, and the travel time doesn't specifically pay into it.

3.1. Evaluation setup

To keep our examples as simple as possible, we limit our evaluation setup to two simultaneously plugged-in EVs connected via wallboxes to the same residential grid coupling point of a residential building. We assume an identical EV driver utility function for the two drivers and consider a linear relationship between time supplement and EV driver utility.

The parameters of the residential charging infrastructure, i.e., the maximum charging power of the wallbox and the power supply of the residential grid coupling point, are identical in all presented exemplary cases. The maximum power of the residential grid coupling point reduced by the power required for the households results in the power available for charging. Taking Germany as an example, the maximum power of the residential grid coupling point for a two-family house is about 24 kW (Baade 2007). We assume a power supply of 6 kW for each household to not restrict the household's power consumption by charging the EVs. Since a single clothes dryer, for instance, can consume up to 6 kW, this assumption is rather conservative (Pipattanasomporn et al. 2014). Ultimately, this results in a power supply for EV charging of 12 kW in our evaluation setup. The power the wallbox can supply is 11 kW (Müller et al. 2017; Wolbertus et al. 2018). For the sake of simplicity, the efficiency rate corresponds to 100%. Besides, the guaranteed SoC is already covered by the initial SoC (5 kW) and is therefore not taken into further consideration for all exemplary cases. The different time steps are defined on a per minute basis, i.e., $\frac{1}{60}$h. The technical EV data is based on the car model of a Nissan LEAF, one of the most common electric car models in Germany (Bach 2019). The corresponding vehicle-specific data comprise the maximum charging speed of 50 kW, the battery capacity of 40 kWh, as well as the energy consumption of 16 kWh/100 km (Bach 2019). For the calculation of the travel time, we assume an average driving speed of 60 km/h. The time to reach an external charging facility is set to 10.0 min for both EVs, named detour.

3.2. Exemplary case 1: different driving distances

In the first exemplary case, we consider a scenario where only the parameter of the driving distance, and thus the required energy to reach the destination differs. The driving distance of the EV driver of EV1 ex-ante provided to the information system is 200 km (which results in required energy of 32 kWh), and the driving distance of the EV driver of EV2 is 150 km (which equals the required energy of 24 kWh). For both EVs, the energy demand is lower than the battery capacity (40 kWh), and the departure times, which the EV drivers also provide, allow to charge the respective amount of energy. Therefore, the amount of energy to reach the destination equals the target SoC for both EVs. Table 4 summarizes the used input data.

Fig. 10 presents the EV driver utility function for each EV. With their target SoC, both EVs reach their destination in the best case travel time, i.e., without an additional charging stop. As the mobility requirements of the EV drivers are fully met with the target SoC, the EV drivers' utility cannot increase any further. For each SoC smaller than the target SoC, each EV driver has to interrupt the trip for

Table 4
Exemplary Case 1: Input data.

	Initial SoC [kWh]	Charging speed [kW]	Arrival time	Departure time	Detour [min]	Required energy (trip) [kWh]	Target SoC [kWh]
EV1	5	50	0	180	10.0	32	32
EV2	5	50	0	180	10.0	24	24

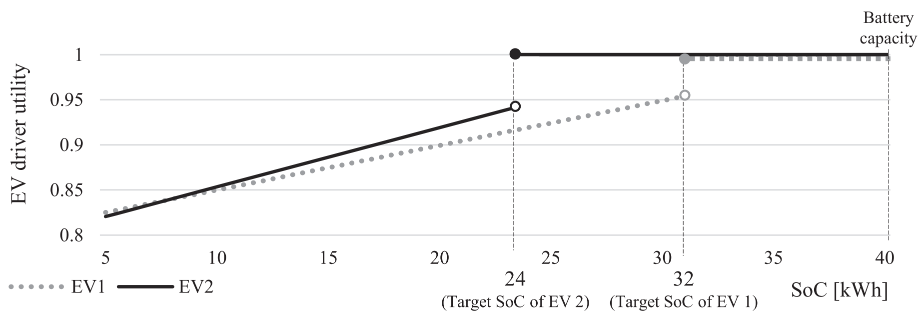


Fig. 10. Exemplary Case 1: EV driver utility functions.

Table 5
Exemplary Case 1: Equal allocation.

	SoC at departure [kWh]	Charging stop avoided?	Additional travel time [min]	Best case travel time [min]	Relative additional travel time
EV1	23	No	20.8	200.0	10.4%
EV2	23	No	11.2	150.0	7.5%
Additional travel time in total [min]			**32.0**		

Table 6
Exemplary Case 1: Smarter charging allocation.

	SoC at departure [kWh]	EV driver utility	Charging stop avoided?	Additional travel time [min]	Best case travel time [min]	Relative additional travel time
EV1	22	0.91	No	22.0	200.0	11.0%
EV2	24	1.00	Yes	0.0	150.0	0.0%
Additional travel time in total [min]				**22.0**		

an additional charging stop. The external charging time increases with a decreasing SoC, and the utility drops accordingly. The discontinuity results from the fact that the target SoC leads to external charging time savings, and the time to reach an external charging facility can be avoided.

When applying the equal allocation mechanism, the available power is equally divided among the EVs, i.e., both EVs are supplied with the same amount of power as long as they are simultaneously connected and not fully charged. Since the two EVs have the same arrival and departure time, the equal allocation allows the vehicles to charge with 6 kW during the entire charging period. The same initial SoC, applying the equal allocation, results for both EVs in the same insufficient SoC at the time of departure (23 kWh). Thus, neither the first nor the second EV can reach the desired target SoC of 32 kWh (EV1) or 24 kWh (EV2), i.e., for both EV drivers, the SoC of their EVs is not sufficient to reach their destination without an external charging stop. The additional charging stop at external charging facilities extends the travel time of the upcoming trip by the additional travel time (please compare with Fig. 4 in Section 2.2.1). The additional travel time comprises the time for the detour (10.0 min for both EVs) and the time for charging the additionally required energy (10.8 min for EV1 and 1.2 min for EV2). This results in a total additional travel time of 20.8 min for EV1 and 11.2 min for EV2 (Table 5). Consequently, the overall additional travel time for both EVs results in 32.0 min at external charging infrastructure.

In comparison to the equal allocation, our smarter charging approach reduces the additional travel time. The corresponding optimization model prioritizes the charging of EV2 to reach the highest possible time reduction. EV2 is charged preferentially, as the same amount of power results for EV2 in a greater reduction of the time supplement as for EV1. The resaon for this differentiation is that the additional travel time carries more weight for the shorter worst case travel time of EV2 (182.8 min) as compared to the longer worst case travel time of EV1 (242.4 min). Thus, charging EV2 leads to a higher increase in overall EV driver utility. Accordingly, EV2 is charged up to the target SoC of 24 kWh to avoid an additional charging stop. As a result, the driver of EV2 reaches the destination in the best case travel time, i.e., the additional travel time is reduced to zero (Table 6).

Since EV2 reaches the target SoC applying the smarter charging allocation, the SoC at the time of departure of EV1 (22 kWh) is lower than the SoC resulting from the equal allocation (23 kWh). Consequently, the driver of EV1 has to stop during the trip for a longer time, which results from a higher additional time required for charging (12.0 min). With the time for the detour to reach the external charging infrastructure (10.0 min), the additional travel time is 22.0 min. Accordingly, when applying our smarter charging approach instead of the equal allocation, the driver of EV1 reaches the destination later, but only by 1.2 min (Table 6).

This marginal loss of EV1 has advantages for the overall system and other plugged-in EVs, in this exemplary case for EV2. In particular, our approach enables EV2 to prevent an additional charging stop. Therefore, in contrast to the equal allocation, a total travel time saving of 10 min can be realized. In addition to the time saving, reducing the number of external charging stops, our approach can have additional implications for the occupancy rate of the external charging infrastructure.

3.3. *Exemplary case 2: different maximum charging speed*

In Exemplary Case 2, the maximum charging speed of the two EVs differs. EV1 can only charge with a maximum charging speed of 25 kW. EV2 has again a charging speed of 50 kW. In comparison to Exemplary Case 1, both EVs have the same driving distance of 150 km, i.e., require the same energy of 24 kWh to reach the destination in the best case travel time (Table 7). The initial SoC, the parking time, the time to reach the external charging facility, and the vehicle-specific data besides the maximum charging speed are identical to Exemplary Case 1.

The (relevant part of the) EV driver utility functions of EV1 and EV2 are depicted in Fig. 11. Since the target SoC is equal for both EVs, the discontinuity occurs at the same SoC and corresponds to the target SoC of the two vehicles. Due to the different maximum charging speeds of both EVs, the utility function differs in three parameters. The first parameter is the EV driver utility at the initial SoC, which corresponds to 0.73 for EV1 and 0.82 for EV2. The second parameter is the slope: an increasing SoC leads to a higher increase in utility for EV1 than for EV2. The last parameter is the improvement of the utility at the discontinuity, which is slightly greater for EV2 (0.06) than it is for EV1 (0.05).

Table 7
Exemplary Case 2: Input data.

	Initial SoC [kWh]	Charging speed [kW]	Arrival time	Departure time	Detour [min]	Required energy (trip) [kWh]	Target SoC [kWh]
EV1	5	25	0	180	10.0	24	24
EV2	5	50	0	180	10.0	24	24

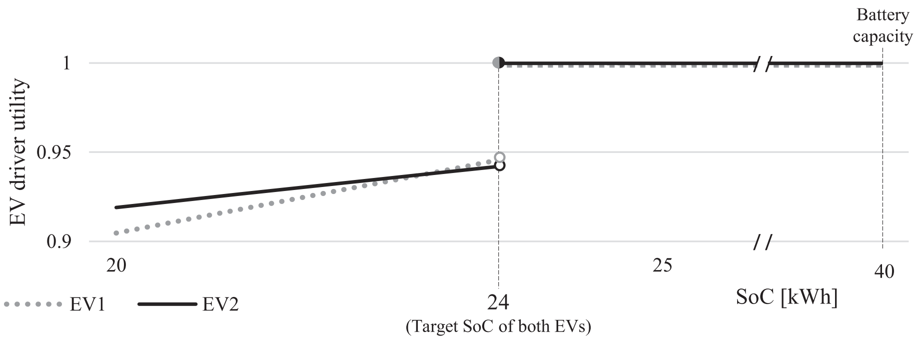


Fig. 11. Exemplary Case 2: EV driver utility functions.

Table 8
Exemplary Case 2: Equal allocation.

	SoC at departure [kWh]	Charging stop avoided?	Additional travel time [min]	Best case travel time [min]	Relative additional travel time
EV1	23	No	12.4	150.0	8.3%
EV2	23	No	11.2	150.0	7.5%
Additional travel time in total [min]			**23.6**		

Table 9
Exemplary Case 2: Smarter charging allocation.

	SoC at departure [kWh]	EV driver utility	Charging stop avoided?	Additional travel time [min]	Best case travel time [min]	Relative additional travel time
EV1	24	1.00	Yes	0.0	150.0	0.0%
EV2	22	0.93	No	12.4	150.0	8.3%
Additional travel time in total [min]				**12.4**		

With the equal allocation both EVs have the same SoC at the time of departure (23 kWh), which again resembles the results of Exemplary Case 1. Therefore, both EV drivers have to charge during their trip given the insufficient SoC. Due to the different maximum charging speeds of the two EVs, the time for charging the same amount of power up to the target SoC results in 2.4 extra minutes for EV1 and 1.2 extra minutes for EV2. With the detour of 10.0 min (Table 7), this results in a total additional travel time of 12.4 min for EV1 and 11.2 min for EV2 (Table 8). As a consequence, the overall additional travel time for both EVs is 23.6 min.

In Exemplary Case 2, our smarter charging model allocates more power to EV1 to reach the vehicle's target SoC of 24 kWh. EV1 is charged up to the target SoC because the same amount of power results in a greater reduction of time supplement due to the slower maximum charging speed. Thus, charging EV1 leads to a higher increase of the EV driver utility. Consequently, EV2 reaches a lower SoC at the time of departure (22 kWh) compared to the equal allocation (23 kWh). However, the additional travel time of EV2 only increases from 11.2 min to 12.4 min, which corresponds to an absolute time loss of 1.2 min (see Table 9).

Exemplary Case 2 demonstrates that prioritizing EVs with slower maximum charging speed may reduce the time that external charging facilities are occupied.

3.4. Exemplary case 3: one unavoidable charging stop for both EVs

In the third exemplary case, both EVs again have a maximum charging speed of 50 kW, but the driving distances for the two EVs differ. To create an exemplary case where one charging stop is unavoidable and the SoC to prevent a charging stop does not correspond to the target SoC, the driving distance is set to 350 km for EV1 and 360 km for EV2. Due to the longer driving distances, the required energy to reach the destination is 56 kWh for EV1 and 57.6 kWh for EV2. The target SoC is only 27 kWh for both EVs since the maximum charging speed of the wallbox (11 kW) and the limited parking duration (which is only 120 min) restrict the maximum possible SoC at the time of departure (Table 10).

As the target SoC is not sufficient to reach the destination, both EVs cannot avoid one charging stop during the trip. However, with

Table 10
Exemplary Case 3: Input data.

	Initial SoC [kWh]	Charging speed [kW]	Arrival time	Departure time	Detour [min]	Required energy (trip) [kWh]	Target SoC [kWh]
EV1	5	50	0	120	10.0	56.0	27
EV2	5	50	0	120	10.0	57.6	27

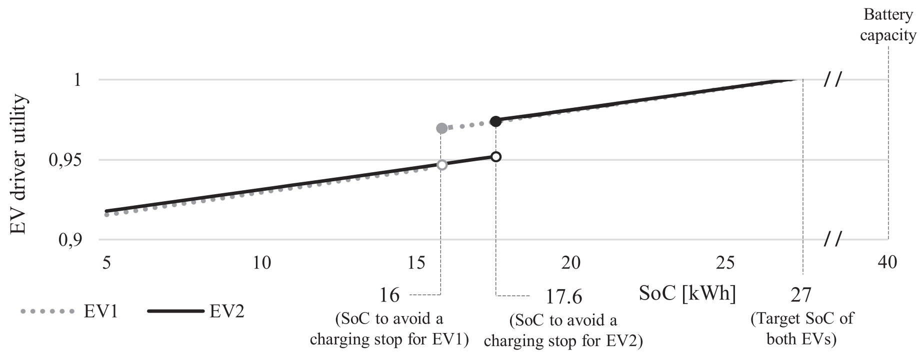


Fig. 12. Exemplary Case 3: EV driver utility functions.

Table 11
Exemplary Case 3: Equal allocation.

	SoC at departure [kWh]	Charging stop avoided?	Additional travel time [min]	Best case travel time [min]	Relative additional travel time
EV1	17.0	Yes	12.0	394.8	3.0%
EV2	17.0	No	22.0	406.7	5.4%
Additional travel time in total [min]			**34.0**		

Table 12
Exemplary Case 3: Smarter charging allocation.

	SoC at departure [kWh]	EV driver utility	Charging stop avoided?	Additional travel time [min]	Best case travel time [min]	Relative additional travel time
EV1	16.4	0.97	Yes	12.7	394.8	3.2%
EV2	17.6	0.97	Yes	11.3	406.7	2.8%
Additional travel time in total [min]				**24.0**		

an SoC lower than the SoC of 16 kWh for EV1 and 17.6 kWh for EV2, even two charging stops will be necessary (see Fig. 12). The SoC that avoids the unnecessary charging stop corresponds to the energy to reach the destination minus the battery capacity described in Section 2.2.2.

Applying the equal allocation mechanism results for both EVs in the same SoC at the time of departure (17 kWh) as the available power for EV charging is allocated equally (Table 11). With an SoC at the time of departure of 17 kWh, only EV1 can avoid the second additional charging stop and thus the time for the detour (10 min). This SoC at the time of departure results in an additional travel time of 12 min for EV1. EV2 still needs a second additional charging stop which results in an additional travel time of 22 min.

The detour to the external charging facility is related to a loss of EV driver utility. Therefore, our utility-maximization approach tries to avoid the detour through a reduction of charging stops. The available power is sufficient to charge 16 kWh (EV1) and 17.6 kWh (EV2). As a result, the additional charging stop for both EVs can be avoided (Table 12). Allocating 11 kWh to EV1 and 12.6 kWh to EV2 to reach their SoC avoiding an additional external charging stop, the remaining 0.4 kWh of the available power for EV charging (24 kWh) are allocated to EV1. The reason is that it has the smaller best case travel time (compare Exemplary Case 1). Finally, this results in a power allocation of 16.4 kWh for EV1 and 17.6 kWh for EV2.

To sum up, this exemplary case highlights that reaching the target SoC for one EV is not always worthwhile. In contrast, both EV drivers can save the detour of 10 min by avoiding two external charging stops.

3.5. *Exemplary case 4: three EVs and different arrival and departure times*

To demonstrate the potential of our model using existing temporal power demand flexibility, we create an exemplary case with three EVs connected to the grid in overlapping time periods. Since with a grid bottleneck and two plugged-in EVs, either no EV or only one EV can reach its target SoC, power allocation among three vehicles offers more temporal flexibility. The technical requirements of

Table 13
Exemplary Case 4: Input data.

	Initial SoC [kWh]	Charging speed [kW]	Arrival time	Departure time	Detour [min]	Required energy (trip) [kWh]	Target SoC [kWh]
EV1	5	50	0	300	10.0	24	24
EV2	5	50	0	120	10.0	24	24
EV3	5	50	60	240	10.0	32	32

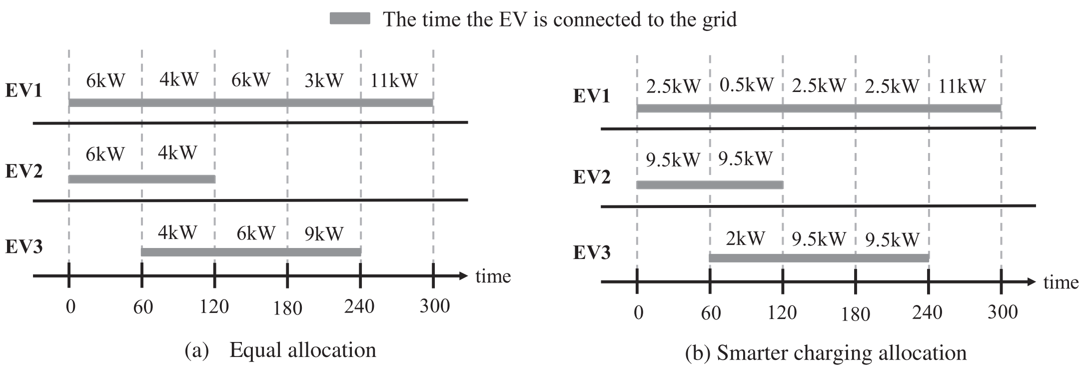


Fig. 13. Exemplary Case 4: Graphical illustration of the power allocations.

Table 14
Exemplary Case 4: Equal allocation.

	SoC at departure [kWh]	Charging stop avoided?	Additional travel time [min]	Best case travel time [min]	Relative additional travel time
EV1	35	Yes	0.0	150.0	0.0%
EV2	15	No	20.8	150.0	13.9%
EV3	24	No	19.6	200.0	9.8%
Additional travel time in total [min]			**40.4**		

Table 15
Exemplary Case 4: Smarter charging allocation.

	SoC at departure [kWh]	EV driver utility	Charging stop avoided?	Additional travel time [min]	Best case travel time [min]	Relative additional travel time
EV1	24	1.00	Yes	0.0	150.0	0.0%
EV2	24	1.00	Yes	0.0	150.0	0.0%
EV3	26	0.93	No	17.2	200.0	8.6%
Additional travel time in total [min]				**17.2**		

all three EVs are the same and correspond to our base car model of a Nissan LEAF. Only the arrival and departure times, as well as the driving distance of the EVs, differ. Table 13 summarizes all input data.

As the initial SoC, the driving distance, and the target SoC of the three EVs are identical to the values of the two EVs in Exemplary Case 1, the utility functions of EV1 and EV2 exactly correspond to the utility function of EV2 in Fig. 10; the utility function of EV3 is equal to the one of EV1 in Fig. 10. The gray bars in Fig. 13 depict the time each EV is connected to the grid. Fig. 13a illustrates the power allocation using the equal allocation mechanism. Between time steps 0 to 60, two EVs are connected to the grid. Each of the two EVs is supplied with 6 kW, half of the total power available for EV charging (12 kW). Between time steps 60 to 120, three vehicles are connected to the grid, and each of the EVs is supplied with 4 kW. Between time steps 180 to 240, the power allocation for the two plugged-in EVs (EV1 and EV2) is unequal: The power supply for EV1 is 3 kW, sufficient to reach its target SoC; EV3 can charge 9 kW. Between time steps 240 to 300, EV1 is supplied with 11 kW, which corresponds to the maximum charging power of the wallbox because no other vehicle is connected to the grid, and EV1 still has sufficient battery capacity to charge this amount of power. The results in Table 14 indicate that only EV1 reaches the target SoC to avoid an additional external charging stop, leading to a total additional charging time of 40.4 min for EV2 (20.8 min) and EV3 (19.6 min).

In contrast to the equal allocation, there are several optimal power allocations of our smarter charging approach that fulfill the underlying technical restrictions, i.e., the optimal solution is nonunique. Fig. 13b illustrates one possible optimal power allocation. The SoC at the time of departure for each EV is presented in Table 15. Given the underlying grid bottleneck, two EVs instead of one EV reach the target SoC when applying the smarter charging allocation. Similar to Exemplary Case 1, the smarter charging allocation charges the EVs with the lower driving distance and therefore with the lower worst case travel time up to their target SoC. For this reason, EV1 and

EV2 with a driving distance of 150 km reach their target SoC, and EV3 with a driving distance of 200 km does not. Our smarter charging approach considers that EV1 can charge 11 kW between time steps 240 to 300. As a result, EV1 needs less power in the previous time steps to reach the target SoC. Thus, EV3 can charge the remaining power to reach an SoC at the time of departure closer to the target SoC, which implies that its charging time at an external charging facility can be reduced.

In summary, this exemplary case shows that our approach may positively impact the total travel time aggregated over all EVs as well as the travel time for each EV.

4. Conclusion

Given an increase in the number of EVs, its impact on the power grid infrastructure, especially at peak times with many simultaneously plugged-in EVs, is a frequently discussed topic. By using smart charging approaches such as temporally shifting charging processes, scientific literature already addresses some of the arising challenges. However, existing contributions do not focus on the driving process and especially not on the travel time of the upcoming trip. Consequently, no account is taken of the possible travel time savings that can be achieved by allocating power while avoiding unnecessary external charging stops. Since travel time is perceived as a loss of time that could be spent for other activities e.g., to earn money or spare time, a reduction in travel time will generally represent an increase in utility (Tipping 1968).

Our smarter charging approach considers the relationship between the utility of an EV driver and the travel time. We developed a power allocation mechanism that maximizes the EV driver utility via an optimization model. With the objective function maximizing the EV driver utility, our optimization model reduces the number of additional charging stops, which may positively impact the fulfillment of EV drivers' mobility requirements. Including travel time in a smarter charging approach may address challenges such as range anxiety and long charging or waiting times. By avoiding unnecessary external charging stops and reducing the charging time at external charging facilities, our model contributes to a more efficient use of the power grid infrastructure and may positively impact grid expansion and the need for additional external fast-charging infrastructure. Also, a reduced number of detours for additional external charging stops may save energy needed to reach the external charging facility and, in this way, contribute to a more efficient energy use. Depending on the electricity mix, a decrease in carbon dioxide emissions may be achieved.

However, there are some limitations of this paper that may be addressed by future research. Presenting a power allocation mechanism applied to first exemplary cases, we aim to illustrate how the consideration of travel time can influence travel satisfaction (i.e., utility). We note that the developed model generally represents a mixed-integer program, which is a hard class of optimization problems (Pochet and Wolsey 2006; Cook et al. 1990; van Roy and Wolsey 1987). Therefore, developing adequate mathematical solution approaches for large-scale real-world applications is, in fact, a highly relevant and interesting field for future research. Focusing on travel time, we did not consider price differences between charging at home and charging at external charging facilities. Nevertheless, pricing is an essential aspect of customer acceptance (Ensslen et al. 2018), making pricing important to address in more detail in future research. With regard to the charging process, we do not take unplanned departure times (that deviate from the announced departure time) into account. For an earlier departure time, the EV driver needs to notify the information system as soon as possible: Only with the new departure time, the optimization model can create a new charging schedule. Since the optimization model requires correct and timely information to calculate the charging schedule, it is important to consider adequate incentive schemes for EV drivers such that they actually provide all the information faithfully in future research (Zhang et al. 2018). As described before, our optimization model decides which EV does not reach its target SoC in bottleneck situations. Thereby, correct information about the planned trips is a prerequisite for reducing bottleneck situations. In this context, the information the EV driver states for its upcoming planned trip does not cover unplanned trips as well as unplanned detours. In our paper, however, we already included a minimum SoC, which is guaranteed for every EV, to allow for unplanned short trips, emergency trips, or generally the way to the next charging facility. Nevertheless, this paper neither addresses how an appropriate minimum SoC is defined nor how more advanced planning instruments from stochastic optimization can also be used. Therefore, these aspects could be interesting for future research. We also note that our approach allocates power based on the utility of each EV driver. Further research may also deal with how to get the information about the individual relation between EV driver utility and time supplements. Also, as power consumption, e.g., of households, influences the available power for charging EVs, future research could include the integrated control of household appliances such as dishwashers and washing machines. By shifting the operation of these devices to times where no EV wants to charge, more power is available for charging EVs. As we currently focus on unidirectional charging, bidirectional charging (vehicle-to-grid) can be considered to further increase the temporal power demand flexibility potential (Xie et al. 2016). Finally, fairness considerations may be included in our smarter charging approach. As we have already discussed, among other things, the concept of willingness to pay is socially debatable when used for allocating power. Therefore, it would be interesting to consider the power allocation across multiple charging processes of an EV driver (e.g., multiple charging processes over a week) and analyze whether one EV is disadvantaged in every (or many) bottleneck situations due to technical characteristics or requirements. To address possible disadvantages (e.g., measured by the aggregated additional travel time of an EV over one week), there are different fairness schemes including proportional fairness or max–min fairness, where disadvantages of the most disadvantaged EV is minimized (Bertsimas et al. 2011). Building on the results of our paper, all of these future research directions may contribute to a successful low-carbon future transportation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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