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Customer satisfaction at large charging parks: Expectation-disconfirmation theory for fast charging

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HIGHLIGHTS

- Addressing customer satisfaction regarding fast-charging service expectation.
- Developing an optimization model to reduce the expectation-performance gap.
- Application of the model in a real-world case and four future cases.
- Increased welfare and improved customer satisfaction by a gap reduction.
- Rising importance with further expansion of battery electric vehicles.

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ABSTRACT

Drivers of battery electric vehicles, especially along motorways, require fast-charging services and expect maximum charging power to overcome long servicing times. However, charging park operators cannot always meet customer expectations due to economic and technical restrictions. According to the expectation-disconfirmation theory, the resulting expectation-performance gap increases the dissatisfaction of vehicle drivers regarding the servicing time in a non-linear manner. Therefore, we present an optimization model with a utilitarian welfare function grounded in social choice theory. Besides a current real-world case based on a fast-charging park in Germany, we analyze further (technical) developments of electric mobility with four future cases. Compared to a uniform power allocation, our results display a reduced absolute average gap of up to 4 min (i.e., 13.3%) between expected and actual servicing time in the real-world case, thus, improving welfare by 22.9%. With an increased average gap reduction of up to 5.2 min, our future cases show the importance of addressing the expectations of battery electric vehicle drivers. Without a smart power allocation, the gap and simultaneously the dissatisfaction of vehicle drivers regarding the servicing time can increase, and potentially more hardware upgrades may be necessary.

1. Introduction

Electric mobility is considered to be vital to reduce greenhouse gases in the mobility sector [1–3]. Today, the market penetration of battery electric vehicles (BEVs) differs between countries and often depends on government incentives and transport planning policies – including the expansion of charging infrastructure [4–6]. In terms of charging infrastructure, a critical barrier to the widespread adoption of electric mobility relates to long servicing times for charging BEVs. Long servicing times can be relevant for charging at home but especially holds for charging during long-distance trips [7,8]. The fast-charging service along motorways sets out to overcome this barrier by fulfilling vehicle

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drivers' mobility needs with fast servicing times that meet customer expectations for charging at the maximum possible charging power, depending on the BEV or the charging station [9–12]. However, previous research argues that charging park operators (CPOs) do not or cannot always meet these customer expectations due to economic reasons or technical restrictions [13]. Technical restrictions such as limited grid capacities are usually set to a certain size when the charging park is built. According to expectation-disconfirmation theory (EDT), a growing gap between prior (individual) expectations and the actual performance regarding the servicing time of charging negatively impacts customer satisfaction [14,15]. Within this paper, the term "customer satisfaction" refers exclusively to the servicing time for fast charging; other aspects, such as the cost of charging or additional facilities at the charging park, which may also influence customer satisfaction during the charging process, are not considered in this paper. The expectation-performance gap regarding the servicing time will be referred to as the "gap" throughout this paper and is used as a measure of customer satisfaction. Allocating the limited available power among all charging BEVs at a charging park naively, i.e., uniformly, will not systematically address customer satisfaction in charging BEVs at a fast-charging park. This uniform power allocation potentially harms the acceptance of electric mobility.

In this regard, Halbrügge et al. [13] present a highly simplified optimization model to reallocate limited power on a minimal fast-charging park setup featuring only two charging stations to reduce the gap. In designing a satisfaction-oriented power allocation mechanism, active consideration of large charging parks, including their specific characteristics as well as the distribution of different vehicle categories, is inevitable as BEVs and their market penetration increase [16]. In particular, the construction of charging parks with a larger number of charging stations will steadily become more relevant as fixed costs per charging station decrease with an increasing number of installed charging stations [17]. Thus, large charging parks will be more economical for CPOs and as a result more common in the future. Examples of large charging parks are the charging park located along the A8 motorway near Augsburg, Germany, with 72 charging stations installed in 2021 [18,19] or the charging park at the intersection of Germany's A3 and A46 motorways near Dusseldorf, with 144 charging stations [20]. Further international examples are charging parks in Shanghai and Beijing, China, with 50 charging stations already built in 2017 by Tesla [21] and a charging park in Eidsvoll Verk in Norway with 44 superchargers [22].

Ucer et al. [23] have already shown that in large charging parks, different parameters such as the number of charging stations, the available power of the charging park, and the charging power per charging station directly affect the average waiting time as well as the charging time and thus the resulting customer satisfaction of vehicle drivers. As the installation of additional charging stations is proposed to reduce queues, the aggregated power demand of occupied charging stations may exceed the available power limited by the grid coupling point. Ucer et al. [23] highlight the urgent demand for future research to optimize power allocation. Since other research approaches either take into account that vehicle parking time allows the charging process to be shifted over time [24,25], focus on other parameters, such as price, to improve service quality [26,27], or focus on stakeholders other than the BEV driver, such as the CPO [28,29], studying larger charging parks requires more research with a focus on driver satisfaction to analyze and balance the preferences of many vehicle drivers and the CPO. As to the best of our knowledge, no research has yet presented a power allocation with the aim to increase customer satisfaction regarding welfare in a fast-charging park for immediate fast charging in a bottleneck situation, this paper deploys concepts from social choice theory to address the complex balancing of individual preferences with arising gaps in larger charging parks. This theory focuses on collective decisions by aggregating individual preferences [30,31]. Thereby, we analyze the problem at hand with a theory-grounded optimization model based on a utilitarian welfare function that explicitly accounts for gaps associated with unexpected long(er) servicing times at large charging parks. In addition, we evaluate the applicability of the derived optimization model considering the above-mentioned charging park near Augsburg as our real-world case. Here, we simulate different utilization scenarios of the investigated charging park, e.g., by varying the number of charging BEVs and the power available for BEV charging. We use BEV-related data from registered vehicle types in Germany in 2021 [32] and consider a power allocation mechanism dividing the available power uniformly across all charging stations as a benchmark to compare against. Here, we use different evaluation metrics following the applied concepts from social choice theory. Besides current BEV data, we consider future cases to evaluate the influence of possible technical changes on the smart power allocation for fast-charging services.

Summarizing, this paper sets out to contribute to the existing body of knowledge in the following four ways:

- The paper grounds the formulation of an optimization model – which improves customer satisfaction regarding servicing times from a utilitarian point of view – in social choice theory.
- The paper validates the developed optimization model by applying it to a large fast-charging park setup in Germany with BEV-related data from registered vehicle types in 2021.
- By considering future cases, we evaluate the further growing penetration of electric mobility and corresponding technological change.
- Based on our evaluation results, the first implications for investment decisions in future fast-charging infrastructure for a travel-satisfaction-oriented policy for transport planning are derived.

This paper is organized as follows: In Section 2 we first present our model setting and give relevant background information. Then, in Section 3 we introduce our formal optimization model. In Sections 4 and 5 we present our evaluation and shortly discuss our results. Finally, we conclude in Section 6 with implications, including limitations and future research.

2. Background and setting

In general, models addressing customer satisfaction with fast-charging servicing times must account for restrictions from three fields:

(1) technical and economic restrictions of the fast-charging service;
(2) the gap between service expectation and actual service performance (expectation-disconfirmation theory (EDT));
(3) the CPO's perspective, who manages power allocation and, therefore, must aggregate individual satisfaction of the vehicle drivers (social choice theory).

In this section we will describe the model context building upon existing research from all three fields and highlight their essential intersections, illustrating our paper's main contributions. Fig. 1 relates the three fields to each other. EDT (2) describes that technical and/or economic restrictions (1) cause a gap between vehicle drivers' expected and actual servicing times leading to customer dissatisfaction. This dissatisfaction regarding the servicing time for the fast-charging service exists on the level of each vehicle driver. Aiming to offer a "satisfying" charging service, the CPO must consider each vehicle driver (3) when managing the charging park and allocating the available power, i.e., aggregate the individual driver perspectives.

2.1. Technical and economic restrictions of the fast-charging service

The fast-charging service rests on the promise to charge BEVs to fulfill the mobility needs of vehicle drivers within fast servicing times for vehicle drivers, i.e. charging at the maximum possible charging power, depending on the BEV or the charging station. The available power of

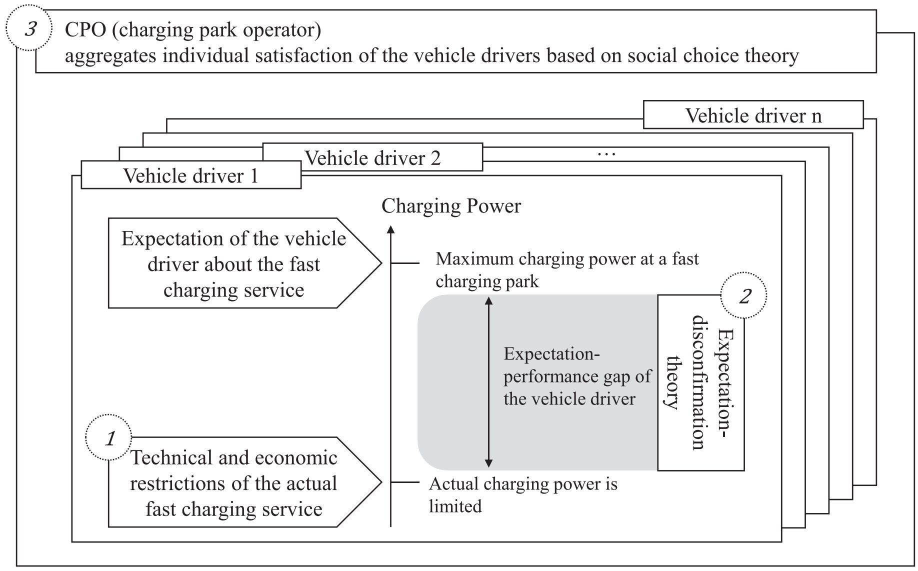

Fig. 1. Context building for our optimization model.

the charging park to fulfill the mobility needs of vehicle drivers depend on several aspects: First, the grid coupling point that connects a set of charging stations to the external electricity grid limits the available power of the charging park. The grid coupling point consists of a transformer reducing the grid's voltage as well as inverters to change the grid's alternating current to direct current. The fast-charging service is particularly relevant along motorways [11], where traffic volume varies greatly, leading to peak times [33]. Such peak times cause an uneven power demand that needs to be considered by the CPO when planning and operating a charging park. Thus, for optimal planning and operating, research literature already covers the location and sizing of fast-charging stations while considering the constraints of the electricity transportation and distribution network [34]. Upgrading or replacing an existing grid coupling point and its components comes at typically prohibitively high investments. Thus, a capacity extension to meet charging power demand at any time, as indicated by the grey dashed line in Fig. 2, is rarely economically rational due to low utilization of the additionally invested capacity. Second, there are operational costs involved with serving peak demand. Fast-charging parks face similar power tariffs to industrial consumers [35]: Energy billing consists of a payment for the energy used and a separate demand charge for peak demand. Demand charges typically represent the majority of costs for electricity [35], thus, serving peak demand is typically not economical for the CPO. For this reason, a CPO might decide to not serve all power demands with maximum charging power. Third, CPOs will typically place a sufficient number of charging stations in fear of customer queues [9]. This results in an aggregated power demand that might surpass the available power limited by the grid coupling point. Therefore, the CPOs would rather risk customers having to charge somewhat slower than forfeiting them.

Consequently, due to economic considerations and technical restrictions in times of peak demand, an "actively dimensioned bottleneck" will occur (illustrated by the red line in Fig. 2). This implies that the CPO will typically not provide the aggregated maximum charging power (as advertised by car manufacturers) at every time for each charging station. Fig. 2 illustrates the aggregated demand for maximum charging power. In the following, we refer to these situations as bottleneck situations.

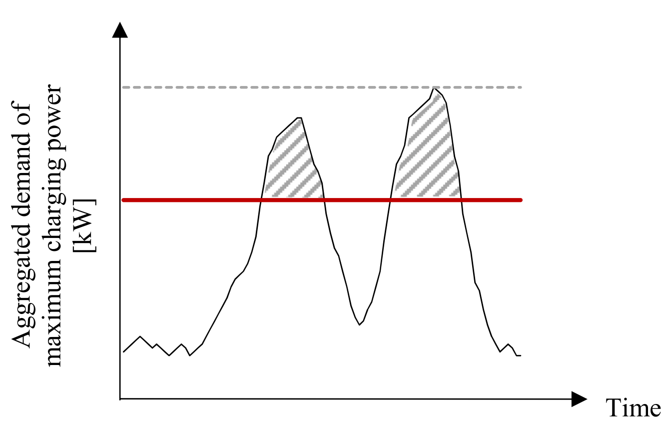

Fig. 2. Schematic power demand curve of a charging park. The grey dashed line represents the bottleneck dimensioned to meet power demand at any time, the red line gives the bottleneck dimensioned under technical and economic restrictions, and the grey dashed area describes bottleneck situations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2.2. Expectation-disconfirmation theory

Given car manufacturers' advertisements of the shortest technically possible servicing times for charging BEVs with maximum charging power, customers often have high expectations about charging service [36]. However, as described in the previous section, bottleneck situations constrain the maximum charging power, which results in a gap between servicing time expectations and actual performance. Previous literature already identified that the gap between prior expectations and actual performance plays a central role in influencing customer satisfaction regarding fast-charging service [13]. In other research areas, such highly relevant gaps have been studied particularly concerning waiting time. For example, Thomson and Yarnold [37], as well as Cassidy-Smith et al. [38], consider the gap in the context of waiting time of hospital or emergency department patients and Davis and Heineke [39] in the context of waiting times for fast food. EDT suggests that a customer's pre-purchase expectation and the subjective after-purchase evaluation can lead to possibly high (dis)satisfaction [14,15]. In the context of fast-charging service, customer satisfaction will generally be lower the larger the gap. In addition, the relationship between the gap and the resulting satisfaction appears to be non-linear. According to Lin et al. [40], this non-linear correlation seems to especially hold for negative service-expectation deviations. This implies that the more the duration of the charging process deviates from a customer's expectation, the increasingly less satisfied the customer will be with the charging service.

2.3. Social choice theory

Based on the previous two sections, typically not all customer expectations can be met at the same time, which results in customer dissatisfaction. Against this background, CPOs generally have two non-exclusive options to influence the gap: adjustment of expectations or adjustment of actual servicing performance. Changing expectations is generally difficult for customers even for the very same charging park due to, e.g., non-transparent power bottlenecks for customers and endogenous factors affecting the current charging situation like the charging power of other simultaneously charging BEVs. Therefore, this paper focuses on the service-performance side.

In general, the CPO decides on the realized power allocation (among the BEVs) and might – due to the respective power bottleneck situation – allocate less power than the BEV can be charged with. By applying energy-quantity-based pricing for the charging service [19], reallocating the same overall amount of power at one point in time between different BEVs does not change a CPO's costs. This is because power reallocation at one point in time does not increase demand peaks and, thus, the paid demand charges. Consequently, the CPO may benefit from reallocating power to address and improve overall customer satisfaction without (negative) effects on its costs. In other words, the CPO is indifferent between a given set of feasible power allocations from a cost perspective, which directly enables a reallocation of power to increase the aggregated vehicle driver satisfaction.

The allocation of a limited resource is also known as the "bankruptcy problem" in game theory. There are several established methods to address this problem, including equal distribution, proportional distribution, and priority-based distribution [41]. However, allocating power in proportion to the requested charging power may result in a bias toward less expensive BEVs with lower charging capacities. Similarly, priority selection proves challenging and potentially discriminatory in a charging park with a primary demand for immediate fast charging. Overall, for CPOs, equal distribution, i.e., uniform power allocation, seems to be the simplest way to (re)allocate power, as every vehicle driver is treated equally and there is no need to make "complex" calculations. For this reason, and in conjunction with research that has used uniform power allocation to compare newly developed power allocation approaches, we also use the uniform allocation as our benchmark power allocation [8,42,43]. The uniform power allocation is carried out through an iterative process, as illustrated in Fig. 3. The process first checks whether a uniformly allocated charging power, i.e., allocation power $Pow_d = \frac{power\ bottleneck}{\#BEVs}$, would exceed the maximum charging power of any plugged-in BEV ($Pow_d > PowMax_s^{\mathrm{BEV}}$). For those charging stations where $PowMax_s^{\mathrm{BEV}}$ of any plugged-in BEV is below the uniformly allocated charging power Pow_d, only the maximum charging power of the respective BEV is allocated. Following, to fully utilize the power bottleneck, the uniformly allocated Pow_d is recalculated by considering the remaining power and the remaining number of BEVs. The iterative process restarts and checks again if any $PowMax_s^{\mathrm{BEV}}$ is below the newly calculated and slightly increased Pow_d. The iterative process ends under two possible conditions: i) the maximum charging power of all remaining BEVs exceeds the uniform allocation of the remaining charging power ($Pow_d \leq PowMax_s^{\mathrm{BEV}}$) or ii) every BEV is allocated a charging power. This approach guarantees maximum utilization of available power while ensuring equitable treatment to all BEV drivers.

Uniform power allocation does not take into account the resulting gap between expected and actual servicing time. BEVs with lower maximum charging power tend to experience smaller gaps because they receive the (almost) expected power allocation. Conversely, BEVs with higher maximum charging power receive considerably less charging power than expected, resulting in a larger gap. Consequently, there is a spectrum of customers with small and considerably large gaps, respectively. According to EDT, specifically, large gaps lead to a high level of customer dissatisfaction. Moreover, the interdependency with other concurrently charging BEVs in the charging park introduces a notable degree of variability and uncertainty for BEV drivers across multiple charging events, further aggravating their dissatisfaction [44]. Hence, we challenge the hypothesis that allocating power uniformly is socially desirable and argue that a CPO can optimize the power allocation to increase vehicle drivers' satisfaction. All allocations will be Pareto efficient in a bottleneck situation, i.e., no vehicle drivers' satisfaction can be improved without harming another driver (as there is no temporal flexibility to shift charging processes in case of fast charging). In this context, social choice theory builds on welfare economics and aggregates the preferences/behaviors of individuals, resulting in the concept of social welfare. The possibility to aggregate, e.g., summing up, individual satisfaction is subject to interpersonal comparability. There are different ways how social welfare can be defined. One possibility is, to sum up each satisfaction and treat each individual equally. Maximizing the social welfare of equally treated individuals (i.e., in a non-discriminatory way) refers to the utilitarian welfare function, also called the Benthamite welfare function [31].

2.4. Power allocation related work

After presenting the theoretical background in the previous subsections, we will now delve into the related work to highlight our contribution in this area. In general, the allocation of limited power to different charging stations falls into the broad research area of smart charging, which serves a variety of goals such as maximizing profits, improving resilience, increasing the share of renewable energy, and

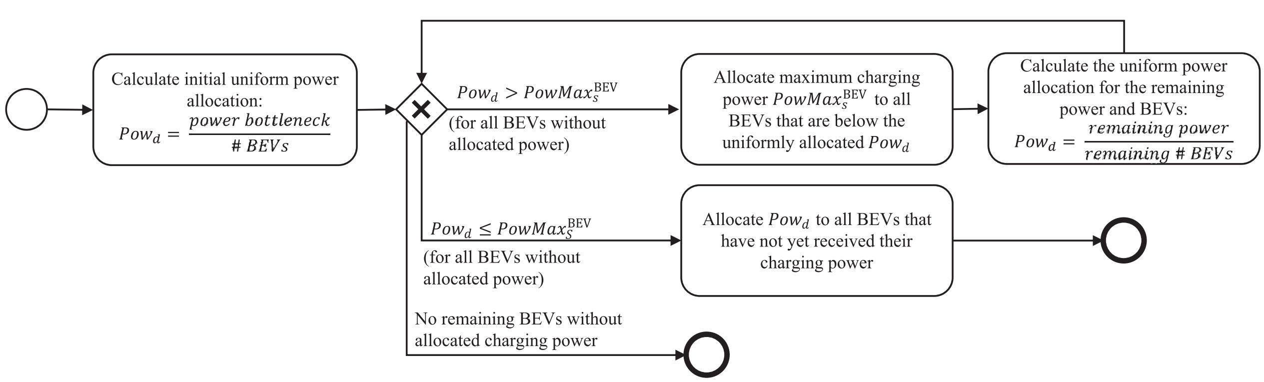

Fig. 3. Uniform power allocation process (in the above figure, Pow_d describes the allocated charging power and $PowMax_s^{\mathrm{BEV}}$ describes the maximum charging power of BEV s).

minimizing operating costs, power losses, or emissions [45]. In many cases, smart charging helps to make better use of available resources to avoid bottleneck situations in the first place so that each BEV driver gets the power they demand [24,25].

When it comes to allocating limited power to multiple charging stations, academic literature already elaborates on allocation limited power to multiple charging stations by developing a variety of approaches. For example, Kumar et al.'s [46] prioritization approach is based on information about the state of charge (SoC), the available slack time for charging, and the energy already charged, which are weighted individually for each use case. Another approach is to consider the user's parking time by proposing a new policy called Least Laxity Ratio in the use case of a parking garage with longer parking times [42], or to identify the essential power needs during a power outage with a corresponding evaluation using an adapted fairness index [43]. Furthermore, a smart charging algorithm allocates the limited power by considering the travel time of the upcoming trip [8]. For this branch of research, it is essential to emphasize that the optimal power allocation is always highly dependent on the specific charging use case. In this context, most research has considered smaller charging stations without fast charging. Additionally, it is often assumed that at least a certain proportion of BEV drivers will have longer parking times that allow them to postpone the charging process. Therefore, the existing literature does not take into account the need for immediate charging with maximum charging power due to the location along the motorway.

A related stream of research focuses on the Quality of Service to increase customer satisfaction, which is, for example, determined by the achieved SoC of the BEV, service delay, BEV arrival rates, or pricing [26,27,47]. While here the Quality of Service is optimized individually for the BEV driver, the aggregated welfare view is often neglected.

The stream of research dealing with welfare maximization pursues a more holistic approach. Huang et al. [26], for example, consider the arrival rate of BEVs, the pricing scheme, and the quality of service to increase welfare. Other studies integrate additional stakeholders besides the BEV driver, such as the charging station operator or power generation facilities [28,29,48]. To calculate the associated welfare these studies include, for example, electricity consumption or the charging price. Various theories and approaches have been used to maximize welfare, such as non-cooperative game pricing strategy [29], individual cost functions to account for inconvenience [48], or the development of various utility functions [28]. The utilitarian welfare function is a well-established social welfare function in the electric mobility domain. For example, Stein et al. [49] address a scheduling problem for charging services. Rahimi-Eichi and Chow [50] study an auction-based energy management to allocate resources between customers with different budgets by maximizing utilitarian welfare. Further, Zhao et al. [51] use utilitarian welfare as a criterion to analyze the results of their energy and reserve management. So far, however, the utilitarian welfare function has not been applied to reduce the gap between BEV drivers' expectations and the actual performance of charging services.

Summarizing existing literature, to the best of our knowledge, no research study has yet developed an optimal power allocation model to increase customer satisfaction in a fast-charging park for immediate fast charging in a bottleneck situation by maximizing welfare with an average gap reduction between expected and actual servicing time.

3. Optimization model

Based on prior research that uses a simplified power-allocation model with only two charging stations [13], in this paper, we develop an optimization model that is capable of managing service performance in bottleneck situations, considering the gap for an arbitrary number of BEVs. As introduced before, our model addresses the gap by grounding it in social choice theory and allows us to apply a corresponding power management system on real-world charging parks as they exist along motorways. In the following, we first present the model setting and corresponding model components in Section 3.1 to Section 3.3. Then, we introduce the complete mathematical problem formulation in Section 3.4.

3.1. General economic and technical model setting

The model considers a public charging park with fast-charging technology. The charging park comprises different system components, i.e., a grid coupling point, charging stations, connected BEVs, eventually further power demanding or generating components, and a power management system. The CPO, as the relevant decision maker, allocates the power to the charging stations and aims to satisfy the charging demand of all customers. Within the scope of this paper, our objective is to enhance welfare through optimized power allocation while operating at a pre-defined power bottleneck. Hence, our optimization model is the final layer in a holistic control system for the charging park that allocates the available power in real-time to the charging stations with plugged-in BEVs in bottleneck situations, as shown in Fig. 4.

In particular, our model setting considers a set of different vehicle drivers D that are currently charging their BEV at the charging park. The charging park consists of multiple charging stations S with a maximum charging power of $PowMax_s^{\mathrm{CS}}$. As mentioned before, the grid coupling point is the physical connection to the public electricity grid, which limits the power for all charging stations of the charging park technically or economically. This limit is described by the parameter $PowMax$ that can be either fixed or variable over time due to economic reasons. The different stations are accessible to all BEVs. Each station is either occupied by a BEV or vacant. Since our model allocates power in real-time, only the currently charging BEVs are considered. A new power allocation is determined by the optimization model every time relevant circumstances change, such as when a BEV initiates or terminates a charging process or the available power $PowMax$ varies. The optimization model communicates the power allocation to the power management system, which is located at the grid coupling point and initiates the actual power flow. As the CPO of the charging park of our real-world case, we model energy-quantity-based pricing for the charging service for a specific power range, i.e., each vehicle driver pays the same price per kWh regardless of the applied power allocation within the respective power range [19]. Considering that pricing can also affect customer satisfaction, and that these power ranges vary, it would be interesting for future research to consider pricing when optimizing power allocation, which could mean that the price depends on the charging power.

3.2. Expected servicing time

The expected servicing time $Time_d^{\mathrm{exp}}$ of a vehicle driver d reflects and is based on information available to the respective vehicle driver. In our setting, each vehicle driver d is aware of the initial SoC, SoC_d^{init}, as information given by the vehicle. In addition, each driver knows the target SoC, SoC_d^{target}, as the intended charging target based on the remaining distance to drive and the consumption of the BEV. The battery capacity BC_d and the maximum charging power $PowMax_d^{\mathrm{BEV}}$ of the BEV are technical information and relate to the car model. Information about the maximum charging power of the charging station s, denoted by $PowMax_s^{\mathrm{CS}}$, is listed in directories of charging stations today [33] and is known when the BEV connects to the charging station at the latest. Both the initial and the target SoC are given in percent of the battery capacity. For this reason, the (absolute) required electricity for vehicle driver d to reach the target SoC is given by the product of the SoC charged (in percentage) and the battery capacity, formally described by

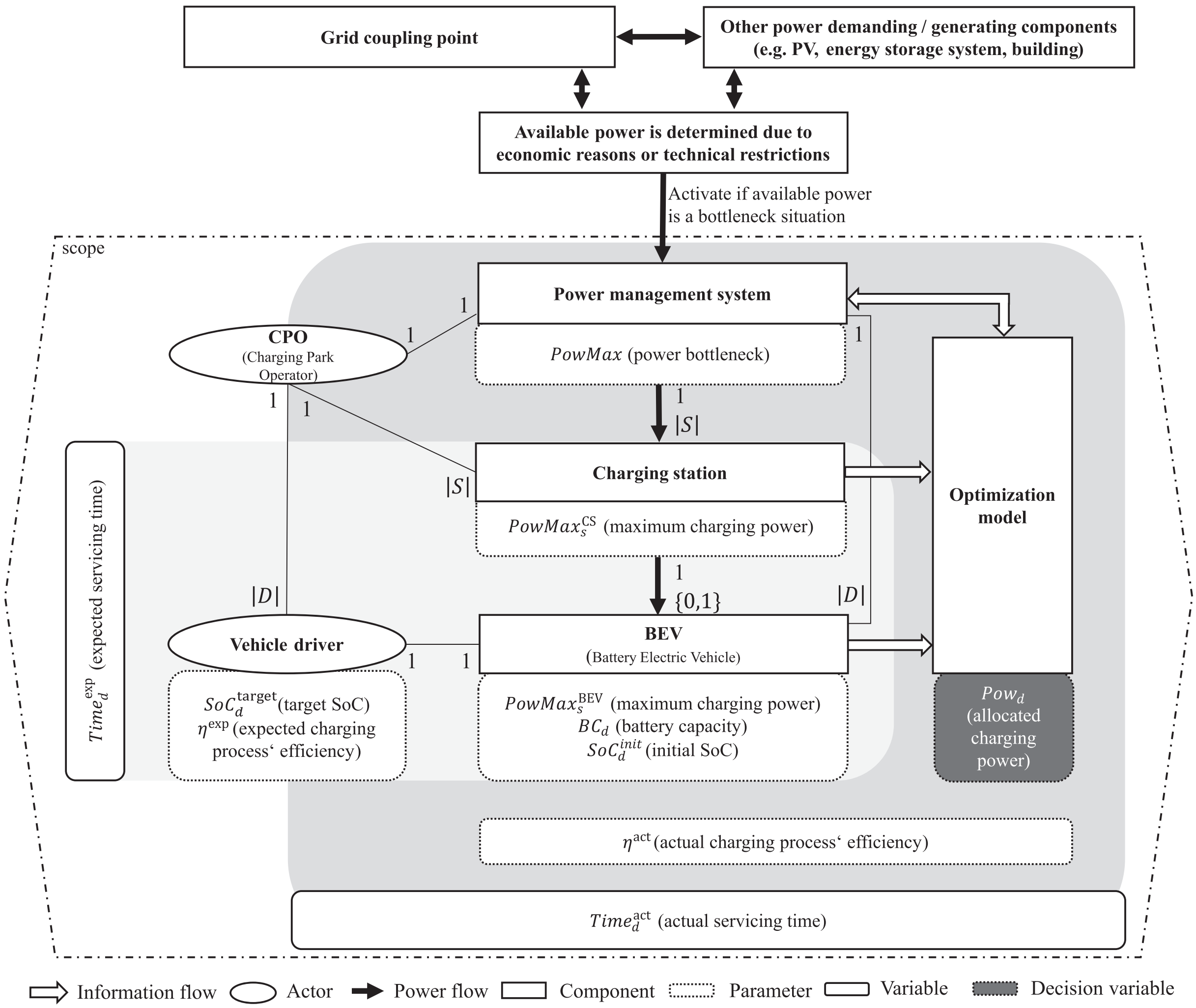

Fig. 4. Model setting based on Halbrügge et al. (2020). The stated numbers along the different lines indicate the number of components or actors that are connected.

$\left(SoC_d^{\text{target}} - SoC_d^{\text{init}}\right) \cdot BC_d$. As we model an energy-quantity-based pricing for the charging service, vehicle drivers do not have monetary incentives to slow down charging processes. Therefore, for each vehicle driver we model the expected servicing time on a rule of proportion basis [33], where the mathematical operator $\delta(d)$ gives the station s where vehicle driver d is currently charging at. The calculation of the expected servicing time $Time_d^{\text{exp}}$ is based on all charging restrictions observable by vehicle driver d. In particular, Eq. (1) uses the minimum of both the BEV's maximum charging power and the maximum charging power of the charging station to determine the expected servicing time for each vehicle driver d. As customers adapt their expectations according to experiences [52], we assume that vehicle drivers may know or "learn" the charging process' efficiency η_d^{exp}.

$$Time_d^{\text{exp}} = \frac{\left(SoC_d^{\text{target}} - SoC_d^{\text{init}}\right) \cdot BC_d}{\min\left\{PowMax_d^{\text{BEV}}, PowMax_{\delta(d)}^{\text{CS}}\right\} \cdot \eta_d^{\text{exp}}} \quad \forall d \in D. \tag{1}$$

3.3. Actual servicing time

In contrast to the expected servicing time, the actual servicing time $Time_d^{\text{act}}$ represents the actual time between the initiation and the termination of a vehicle driver d's charging process. The relevant information to calculate the actual servicing time for a vehicle driver d consists of the initial SoC_d^{init} of its BEV, the target SoC_d^{target}, the battery capacity BC_d, the allocated charging power Pow_d of the CPO and the actual charging efficiency η^{act}, as described in Eq. (2) [33].[1] In a large charging park and especially at peak demand times, relevant circumstances may change as other BEVs initiate or terminate their charging process, leading to a newly optimized power allocation. Thus, we note that in a real-world application of our optimization model, the actual servicing time is only known after the BEV driver terminates the charging process. During the charging process, the optimization model may decide multiple times on the then time-dependent actual power allocation Pow_d^t with updated SoC_d^t (the calculation is based on the prior power allocation Pow_d^{t-1} and the time passed).). However, in a model analysis over time, the charging processes of newly arriving BEVs overlap with still-charging BEVs, complicating the analysis of the direct impact on welfare for each power allocation, power bottleneck, and charging BEVs. Thus, a resulting analysis may provide less detailed insights on the observed effects. Further, possible combinations of BEV types and charging demand variations increase rapidly due to the subsequent BEVs. Since this study

[1] We note that additional restrictions that slow down the charging process (e.g., due to restrictions on the side of the BEVs or the charging station) and which are not considered in our simulation, only extend actual servicing times. Such extended servicing times will imply an increase of the gap, as customers' expectations will typically not change due to additional technical restrictions that are non-transparent to the customer, in our case the vehicle driver. Therefore, we deliberately constrain power allocations by the necessary minimum of technical restrictions.

examines the general potential of optimized real-time power allocation to maximize welfare, we focus on a power allocation at one point in time for further analysis. We conduct a sensitivity analysis by varying input parameters to compare various combinations and identify when our optimization model is most beneficial (see Section 4).

$$Time_d^{act}(Pow_d) = \frac{\left(SoC_d^{target} - SoC_d^{init}\right)\cdot BC_d}{Pow_d \cdot \eta^{act}} \qquad \forall d \in D. \tag{2}$$

3.4. Customer satisfaction and utilitarian welfare function

The CPO – as the relevant decision maker – aims at maximizing social welfare of all vehicle drivers who are currently charging their BEVs at the charging park. To treat each vehicle driver equally (i.e., in a non-discriminatory way), we apply the utilitarian welfare function and thereby account for individual satisfaction [31]. Bentham [31] and Mill [53] initially considered utility as a measure of satisfaction and pleasure. As EDT can infer vehicle driver's satisfaction, vehicle drivers are supposed to form a preference relation on the continuum of feasible charging alternatives. As stated by Debreu [54], these relations can be formalized as a utility function under certain conditions. Concerning the given feasible charging alternatives, we note that they are typically defined to a large extent by the BEV, e.g., in the form of the maximum charging power and, most importantly, by the CPO when it comes to bottleneck situations.

Based on EDT, the gap between service expectation and actual service performance is at the core of each vehicle driver's evaluation of the servicing process. Thus, we measure satisfaction with a charging process by the gap between actual and expected servicing time for each vehicle driver d, i.e., $\Delta Time_d = Time_d^{act}(Pow_d) - Time_d^{exp}$. Maximizing the vehicle driver's satisfaction, this gap needs to be minimized. A vehicle driver is (completely) satisfied if the actual servicing time is equal to or even less than the expected servicing time, i.e., $\Delta Time_d \leq 0$. If the actual servicing time is longer than the expected servicing time, i.e., $\Delta Time_d > 0$, the vehicle driver is dissatisfied with the charging service. The more the actual servicing time exceeds the expected servicing time, the increasingly less satisfied the vehicle driver tends to be. Here, the utilitarian welfare function uses preference orders over the set of alternatives to describe the vehicle driver's (dis)satisfaction. When assuming that a vehicle driver expects maximum charging power, the continuum of feasible alternatives is defined over all gaps in the interval $[0, \infty[$ measured in time units, e.g., minutes. In the following, we additionally assume that the satisfaction of a given vehicle driver d does not only decrease monotonously with an increasing servicing gap $\Delta Time_d$ (or equivalently with an increasing actual servicing time $Time_d^{act}(Pow_d)$), but define (dis-)satisfaction to be non-positive $u(\Delta Time_d) \leq 0$ for all $\Delta Time_d \geq 0$. Here, $u(\Delta Time_d)$ gives the actual customer (dis-)satisfaction of vehicle driver d for a gap of $\Delta Time_d$.

As described in Section 2 and in line with Lin et al. [40], customer satisfaction might decrease non-linear with a growing servicing gap $\Delta Time_d$. Therefore, we use monomials to model the effect that stronger forms of aversion lead to larger gaps: $\Delta Time_d{}^q$, with $q > 1$ indicating some form of dissatisfaction aversion. Note that for all integer q, the corresponding monomials $\Delta Time_d{}^q$ have a joint intersection point at $(1,-1)$, as shown in Fig. 5. This directly leads to an inversion of the effect of an increasing gap on satisfaction for different exponents q: For $0 \leq \Delta Time_d < 1$, the higher the exponent q, the higher the customer satisfaction for the given gap. On the opposite, for a gap in the range of $]1, \infty[$, the higher the exponent q, the lower the customer satisfaction for the given gap. As an example, we consider a gap of 0.5 h for two different vehicle drivers A and B: Vehicle driver A has $q = 2$ and vehicle driver B has $q = 3$. Then, we have $u_A(0.5) = -(0.5)^2 = -0.25 < -0.125 = -(0.5)^3 = u_B(0.5)$ and paradoxically would conclude that B is less unsatisfied despite the larger aversion (see marking in Fig. 5). To avoid such situations, we model the satisfaction of a vehicle driver by the function $u(\Delta Time_d) = -(\Delta Time_d + 1)^q$, with $q > 1$ and $\Delta Time_d \geq 0$. As can be seen in Fig. 6, this shifts the corresponding functions $u(\Delta Time_d)$ to the left and, in this way, indeed avoids such paradoxical situations.

Following the social choice theory, we aggregate individual utilities using a utilitarian welfare function $W(Pow_1, \ldots, Pow_{|D|})$:

$$W(Pow_1, \ldots, Pow_{|D|}) = -\sum_{d \in D} (\Delta Time_d + 1)^q \tag{3}$$

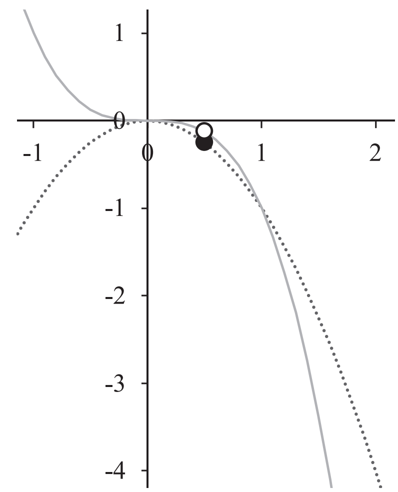

Fig. 5. Function before adjustment. The dashed line represents the function $f_2(x) = -(x)^2$ and the grey line the function $f_3(x) = -(x)^3$. The black dot visualizes the exemplary value $x = 0.5$ for vehicle driver A before adjustment and indicates that vehicle driver B is less unsatisfied despite the larger aversion (visualized by the white dot).

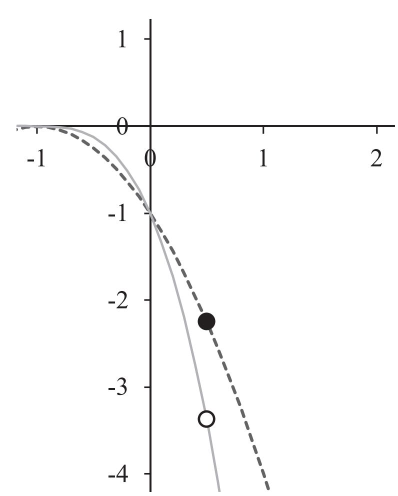

Fig. 6. Function after adjustment. The dashed line represents the function $f_2(x) = -(x+1)^2$ and the grey line the function $f_3(x) = -(x+1)^3$. The black dot visualizes the exemplary value $x = 0.5$ for vehicle driver A after adjustment and indicates that vehicle driver B is more unsatisfied in line with the larger aversion (visualized by the white dot).

3.5. Complete welfare-maximization problem

In total, our final welfare maximization problem writes as follows:

$$\max\, W(Pow_1,\dots,Pow_{|D|}) = -\sum_{d\in D}(\Delta Time_d + 1)^q \tag{4a}$$

$$\Delta Time_d = Time_d^{act}(Pow_d) - Time_d^{exp} \qquad \forall d \in D. \tag{4b}$$

$$Pow_d \le \min\left\{PowMax_d^{BEV}, PowMax_{\delta(d)}^{CS}\right\} \qquad \forall d \in D. \tag{4c}$$

$$Pow_d \ge PowMin_s^{CS} \qquad \forall d \in D. \tag{4d}$$

$$\sum_{d\in D} Pow_d \le PowMax \tag{4e}$$

The above constraints ensure that an optimal solution satisfies the relevant technical and service constraints: First, the power that each vehicle driver d's BEV is charged with must be non-negative. It cannot exceed the charging station's maximum charging power and the maximum charging power of the BEV according to Eq. (4c). Note that we defined a minimum charging power of each charging station s $PowMin_s^{CS}$ in Eq. (4d), as a minimum charging power should be guaranteed for every BEV connected to a charging station. Finally, the sum of the power allocated to all charging BEVs must account for the given maximum power available for charging (see Eq. (4e)).

4. Evaluation

We evaluate our model using an exemplary fast-charging park near Augsburg, Germany. For the evaluation, we distinguish between five cases: one real-world case and four future cases that consider the further growing penetration of electric mobility and the corresponding technological changes. Within each case, we perform a sensitivity analysis, resulting in corresponding scenarios that vary with respect to the number of charging BEVs and power bottlenecks. Across all cases and scenarios, the characteristics of the charging park remain consistent.

4.1. Parameterization of the cases: BEV characteristics and market shares

The five cases, illustrated in Table 1, differ in the characteristics of the BEVs and the associated market shares. For the real-world case, we refer to the currently registered BEVs in Germany and their corresponding market shares. Since >75 different vehicle types of fast-charging-capable BEVs with different battery capacities and with different maximum charging power were already registered in Germany in 2021, we assign the vehicle types to a corresponding vehicle category (according to the Electric Vehicle Database [55], cf. Table 1). For each vehicle category, we determine the mean value for the battery capacity (BC) and the mean value for the maximum charging power ($PowMax^{BEV}$). Further, to determine the market share of each vehicle category, we utilize the number of registered BEVs for each vehicle type [32,55] and aggregate it to the market share of each vehicle category. Thus, we determine the likelihood of occurrence for a BEV belonging to a given vehicle category at the simulated charging park using a discrete distribution function. This means the market shares define the probable combination of BEVs with different characteristics charging at the same time at the charging park.

In future case 1, we investigate how adjusted vehicle category market shares affect our results compared to the considered real-world case. Since the development and commercialization of BEVs are still in the ramp-up phase, the market shares of the vehicle categories are strongly influenced by the current supply. Thus, the distribution of BEVs is highly distorted compared to the distribution of combustion engine vehicles [32]. We expect a full transition to electric mobility will lead to a similar BEV distribution as we see today for combustion engine vehicles. This assumption is based on the fact that the choice of vehicle category largely depends on individual circumstances, including neighborhood design, travel disposition, personality, lifestyle, mobility, and socio-demographic characteristics [56,57]. Thus, a currently used combustion engine vehicle is substituted by a BEV of the same vehicle category for the entire population. The distribution of vehicle categories published by the German Federal Motor Transport Authority in 2022 [32] is, therefore, applied to the BEV vehicle category market shares. Note that the technical characteristics of SUVs vary widely and cannot be assigned to one of our vehicle categories. Therefore, the market share of SUVs was excluded from the calculation, and the remaining market share values were scaled up proportionately. The mapping to our vehicle categories for calculating market shares is listed in Table A.1 in the appendix.

Additionally to future case 1, we consider three more cases for further (technical) developments. Since electric mobility is still undergoing extensive development, significant technological changes will occur in

Table 1
Parameterization of vehicle categories including market shares.

		Vehicle category			
		Mini and small vehicles	Middle and compact-class vehicles	Upper-middle-class and upper-class vehicles	Commercial vehicles
Real-world case	BC	34	64	92	50
	$PowMax^{BEV}$	56	127	180	75
	Market share in %	50	44	5	1
Future case 1 with adjusted market shares of vehicle categories	BC	34	64	92	50
	$PowMax^{BEV}$	56	127	180	75
	Market share in %	29	57	7	7
Future case 2 with adjusted market shares of vehicle categories and technical changes (I)	BC	40	70	95	55
	$PowMax^{BEV}$	60	140	190	80
	Market share in %	29	57	7	7
Future case 3 with adjusted market shares of vehicle categories and technical changes (II)	BC	40	75	100	60
	$PowMax^{BEV}$	60	150	200	90
	Market share in %	29	57	7	7
Future case 4 with adjusted market shares of vehicle categories and technical changes (III)	BC	40	80	105	65
	$PowMax^{BEV}$	60	160	210	100
	Market share in %	29	57	7	7

the coming years. Two main trends can be observed: The first trend relates to decreasing battery costs leading to larger batteries and, thus, higher battery capacities [58–60]. The second trend relates to the fact that energy density has already reached a plateau at present, which is why an upper limit may be reached in terms of battery capacity, especially for mini and small vehicles where the size of the battery is primarily limited [61,62]. To investigate these trends in further future cases, we increased the values for battery capacity and maximum charging power depending on the vehicle category. We made a higher adjustment for the mean value of maximum charging power compared to the battery capacity because the maximum charging power of a BEV is already up to 270 kW, and the charging stations installed today can charge up to 300 kW. Thus, after the first adjustment in future case 2, we further increased the mean values of the battery capacity by 5kWh and the mean value of the maximum charging power by 10 kW. The exception here is the mini and small vehicles category, which, due to the plateaued energy density, probably already reached their maximum. The adaptions for the future cases also fall within the range of forecast values from 2019 [60]. The BEV characteristics and market shares of all cases are displayed in Table 1.

4.2. Parameterization of the scenarios: Charging park and BEV drivers

In August 2022, the real-world charging park near Augsburg serves 72 fast-charging stations with exactly one charger per station [18,19]. Further fast-charging stations are planned up to a total number of 144. All 72 installed charging stations have a maximum charging power of 140 kW. In addition, 12 of the 72 charging stations at the charging park have a maximum charging power of up to 300 kW [19]. However, only a few BEVs can charge >140 kW, so in this case study, we set the maximum charging power $PowMax^{CS}$ at 140 kW for all 72 charging stations in the simulated charging park. To ensure at least the minimum charging power that is defined as fast charging (≤22 kW is defined as normal charging), we set the minimum charging power of each charging station, $PowMin_s^{CS}$, to 23 kW [63].

With the defined charging park consisting of 72 charging stations, each with a minimum and maximum charging power, and the maximum charging power per vehicle category, it is now possible to identify bottleneck situations, i.e., the scenarios for our sensitivity analysis. In a bottleneck situation the available power for charging is limited by economic or technical restrictions. Such sensitivity analysis of the available power allows us to quantify the benefit of our model for different fast-charging park setups and charging demand. As technical as well as economic restrictions of the charging park are not publicly available, we define bottleneck situations based on the charging park characteristics: To be more precise, given the minimum charging power of 23 kW and the maximum charging power of 140 kW for each of the 72 charging stations, we vary $PowMax$ between 1,656 kW ($= 23kW{\cdot}72$) and 10,080 kW ($= 140kW{\cdot}72$). Within these bounds, we consider 200 kW increments, i.e., from 1,800 kW to 10,000 kW. Simultaneously with an increasing $PowMax$, the minimum number of charging BEVs must also increase to analyze bottleneck situations. Therefore, we divide $PowMax$ by the maximum charging power (140 kW) to get the minimum number of BEVs that could lead to a bottleneck situation. The maximum number of BEVs for the evaluation is always 72 BEVs, i.e., all charging stations are occupied. In summary, for each of the five cases presented in the previous section, we conduct a sensitivity analysis with increasing $PowMax$ from 1,656 kW to 10,080 kW and increasing number of charging BEVs, starting at the lowest number to create a potential bottleneck situation. This results in 1,340 analyzed scenarios per case and a total of 6,700 simulations with 350 runs each, illustrated in Fig. 7.

In terms of the actual charging process efficiency η^{act}, we refer to the built-in technology on the charging park and set it to 98% [64]. Regarding the expected servicing time (which in turn depends on the expected charging efficiency), most countries still face the problem that a major part of the population has little or no experience with charging

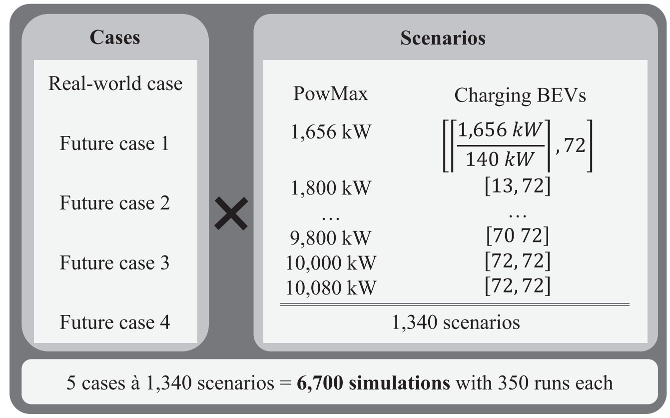

Fig. 7. Overview of simulated cases and scenarios.

BEVs. Especially when vehicle drivers charge at a public (fast) charging park for the first time, they might either not be aware of the underlying physics or refrain from the computational hassle of getting information on the actual efficiency. In addition, car manufacturers are advertising maximum charging power. Therefore, we use an efficiency of $\eta^{exp} = 1$ as a starting point for calculating the expected servicing time by the vehicle driver in absence of detailed empirical data. In order not to favor or disadvantage any driver, we use the same η^{exp} for all vehicle drivers. Finally, we note that as the experience of BEV drivers increases, the expected efficiency may indeed adjust toward the actual efficiency. With this in mind, this value may be further investigated in future work and can easily be adjusted in our model.

To create realistic charging setups, we combine real-world data from the charging park with information from a database about vehicle types registered in Germany in 2021 [32,55]. To determine the appropriate distribution functions of the different SoCs at the start and end of a charging process, we utilize real-world data regarding SoC^{init} and SoC^{target} [2] provided by the charging park over three months. Since the SoC is given in percent, the corresponding SoC in kWh can be calculated for all vehicle categories. For the final dataset, there were 1,448 charging processes available for the calculation. The final dataset represents a filtered data basis, i.e., charging processes where SoC^{init} is equal to or higher than SoC^{target} were filtered out. Further, we did not consider charging processes where SoC^{init} equals 0%, as we assume that the BEVs arrive at the charging park with a small “buffer” SoC^{init} to avoid stopping beforehand. In addition, we detected and eliminated outliers utilizing the interquartile range method. Afterward, we tested over 100 distribution functions with the python fitter package and selected the one with the lowest residual sum of squares respectively for SoC^{init} and SoC^{target}.

Table 2 summarizes the parameterization of the charging park and simulated BEV drivers.

Finally, following Lin et al. [40], we consider the effect that customer satisfaction decreases non-linearly with a growing servicing gap with $q > 1$. But we do not take into account that vehicle drivers may have different levels of customer satisfaction concerning servicing time. Analyzing how different levels of customer satisfaction might affect

[2] Note: The real- world data here refers to the actual SoC reached at the end of the charging process, not the SoC^{target} desired by the vehicle driver. Due to a change of mind triggered by external circumstances, the desired SoC^{target} may differ from the SoC actually achieved. However, we assume that the possible difference between the desired SoC^{target} and the SoC actually achieved is moderate across the large number of customers in the data set and is, therefore, a sufficiently close approximation for the parameterization of our model. Nevertheless, for our power allocation, as well as for many other smart charging approaches, it would be very helpful to know the desired SoC^{target} of the vehicle drivers (see Section 6).

Table 2
Parameterization.

Parameter	Data values	Source
$\lvert S\rvert$	72	[18,19]
$PowMax^{CS}$	140 kW	[65]
$PowMin^{CS}$	23 kW	[63]
$PowMax$	Depending on $\lvert S\rvert$and $PowMax^{CS}$:Sensitivity analysis for the values between [1,656, 10,080]	[18,19,65]
$\lvert D\rvert$	Depending on $\lvert S\rvert$and $PowMax^{CS}$:Sensitivity analysis for the values between $[\frac{PowMax}{140kW}, 72]$	[18,19,65]
η^{act}	0.98	[64]
η^{exp}	1.00	Own assumption
SoC^{init}	Johnson's S_B-distribution over [0.01, 0.96]	Based on real-world data
SoC^{target}	Beta distribution over [0.04, 1.00]	Based on real-world data
BC	Depending on the vehicle category and the case, see Table 1	[32,55,60]
$PowMax^{BEV}$	Depending on the vehicle category and the case, see Table 1	[32,55,60]

power allocation is subject to future research. Since the magnitude of the deviation is not crucial for the allocation, we set $q = 2$ in the following.

4.3. Evaluation metrics

In our evaluation, we compare the power allocation of our optimization model – in the following called "optimized power allocation" – with a benchmark power allocation. The benchmark power allocation reflects a uniform power allocation among all charging BEVs. We then compare the optimized power allocation with the benchmark power allocation using different metrics as described below.

The central concept of this study is the utilitarian welfare function. This metric is a utilitarian construct that focuses on the welfare of a collective by giving equal weight to all individual satisfaction levels. It will serve as the primary metric in this paper. In each scenario, we expect non-negative welfare gains when comparing the benchmark with the optimized power allocation, i.e., an improvement through the optimization. In the following, we present both absolute and relative gains in welfare.

As welfare (gain) is an abstract measure, we also analyze two measures that are may be more "intuitive" from the perspective of a vehicle driver: (1) The average gap in minutes between expected and actual servicing time for each combination of bottlenecks and number of BEVs that is in line with EDT as introduced in Section 2. (2) As the literature suggests that uncertainty in outcomes additionally negatively affects satisfaction [44], we decided to capture the uncertainty of the gap by its average standard deviation.

4.4. Results

Looking at the welfare results for the real-world case and comparing the benchmark with the optimized power allocation, we find that when the utilization rate of the charging park is low (e.g., a low number of charging BEVs) or the bottleneck is very high (i.e., every BEV will get its maximum charging power), the welfare values of both power allocations are nearly identical for all cases. Theoretically, the maximum level of welfare can be observed when every vehicle driver's expectations can be met and, therefore, no gap exists between actual and expected servicing time. In this sense, the maximum level of welfare will be zero. For our case study, however, such a maximum level of welfare only theoretically exists due to the difference between expected and actual charging efficiency. Further, we only analyze scenarios in which a bottleneck situation can arise, and thus the available power capacity does not meet the demand. At a low charging park utilization or high available power, there is a low probability that an actual bottleneck occurs. Thus, the welfare is close to the maximum level of welfare (see Fig. 8). Nevertheless, as mentioned before, a low utilization rate of a charging park or a grid coupling point with too much connected power is not in the interest of the CPO for economic reasons. Therefore, in this paper, we focus on bottleneck situations where the optimization model can improve welfare. We identify several findings regardless of the type of power allocation (benchmark or optimized). First, welfare decreases with an increasing number of BEVs, while in contrast, welfare increases with an increasing bottleneck value and, thus, more available power for charging. Second, welfare decreases increasingly faster as the number of BEVs increases and the available power decreases. The absolute minimum welfare, i.e., the minimum of the aggregated vehicle drivers' satisfaction, can be observed for 72 BEVs and a bottleneck of 1,656 kW over all cases. Here, each vehicle only receives the minimum amount of 23 kW.

When turning to differences between the benchmark and the optimized power allocation, welfare is generally higher in all scenarios and cases when applying the optimized power allocation. This is best demonstrated by the following two examples of our real-world case. First, the scenario (3,000 kW, 54 BEVs) for the benchmark power allocation and the scenario (3,000 kW, 60 BEVs) for the optimized power allocation lead to the same welfare of approximately −21. This suggests that 6 more BEVs can be served at the same welfare level using the optimized power allocation. Second, the scenario (3,000 kW, 72 BEVs) for the benchmark power allocation and the scenario (2,600 kW, 72 BEVs) for the optimized power allocation lead to the same welfare of approximately −56. This suggests that using the optimized power allocation, 72 BEVs can be served at the same level of welfare in a situation with 400 kW less available power. Fig. 8 illustrates the levels of welfare for all scenarios of the real-world case and both the benchmark and the optimized power allocation graphically.

Turning to welfare gains for the real-world case generated by the optimized instead of the benchmark power allocation (Fig. 9), we find that for our real-world case the absolute gains range from 0 (where there is no bottleneck situation, i.e., no improvement possible) to 24.07 under the scenario of 2,000 kW available power and 72 BEVs. The higher the bottleneck, the more charging BEVs are needed to generate a welfare gain without the optimization model, i.e., until some BEVs no longer receive their maximum charging power. Interestingly, however, the largest absolute welfare gain is not observed when the available power is scarcest, i.e., 1,656 kW and a full utilization rate of 72 BEVs. This is because in the latter case, power is so scarce that each BEV gets the minimum of 23 kW charging power, and our model cannot find any more efficient reallocation(s) compared to the benchmark. When looking at the relative welfare

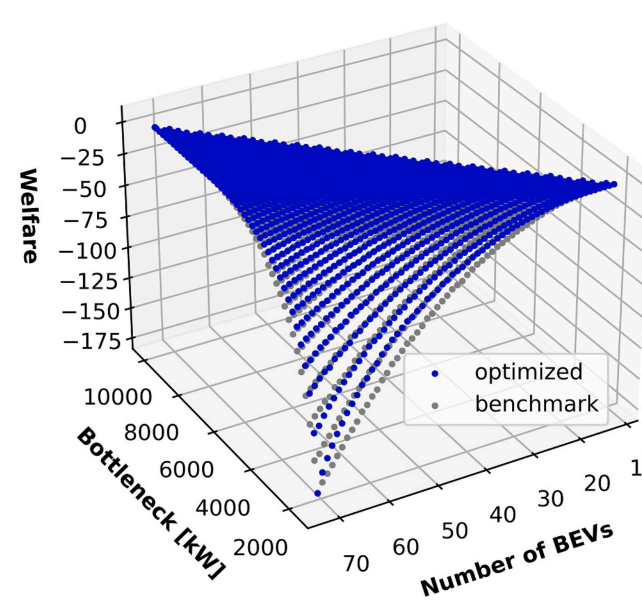

Fig. 8. Levels of welfare for all scenarios – Real-world case.

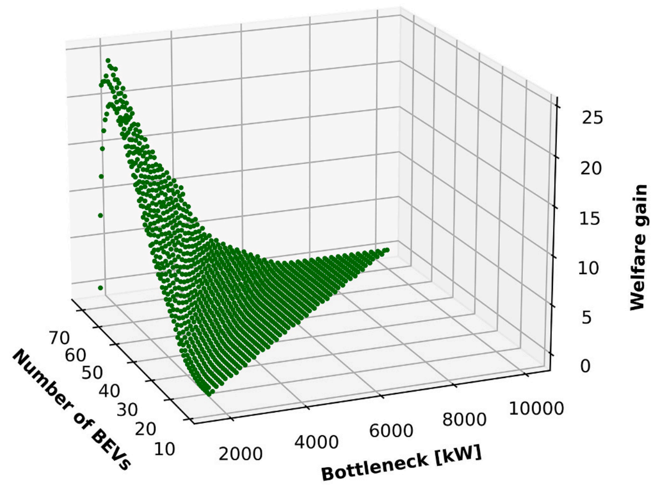

Fig. 9. Absolute welfare gain for each scenario – Real-world case.

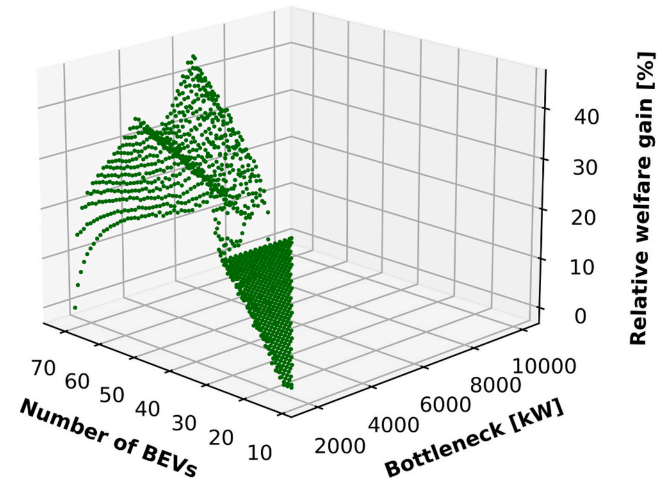

Fig. 10. Relative welfare gain for each scenario - Real-world case.

gains from the optimized to the benchmark power allocation, it is evident that they do not align with the absolute welfare gains (Fig. 10). The power bottleneck of 6,000 kW and 70 BEVs resulted in a maximum relative welfare gain of 44.2%, with an absolute welfare gain of only 1.23. On the other hand, the highest absolute welfare gain of 24.07 only yields a relative improvement of 20%. At a highly limited power availability, the resulting gaps are considerably larger. Consequently, a higher absolute reduction is achievable but with only a moderate relative impact. The greatest relative welfare gains occur in cases with considerably more degrees of freedom and smaller gaps.

Regarding future cases 1 to 4, the basic pattern of the welfare gain does not change (see Fig. 11, Fig. 12, Fig. 13 and Fig. 14). However, the optimization model can considerably improve welfare for a higher number of scenarios. Likewise, the magnitude of the maximum welfare gain increases up to 38.2. In future case 1, the adjusted market share of vehicle categories causes a decline in the mini and small vehicles and a significantly higher market share in middle and compact-class vehicles. Thus, this case results in a higher demand for maximum charging power and battery capacity. The incremental technical changes in future cases 2 to 4 further accelerate this development and increase the spread between minimum and maximum required charging power and battery capacity. Fig. 11, Fig. 12, Fig. 13 and Fig. 14 illustrate that all future cases cause effects in the same direction. First, the optimization model already achieves a welfare gain with fewer BEVs since there is a higher demand for charging power. Second, the realized maximum welfare gain increases for each case. Interestingly, the maximum welfare gain can be achieved across all cases at a bottleneck of 2,000 kW.

We now focus on the vehicle driver perspective and discuss the average gap and gap reduction between expected and actual servicing time for each scenario as well as the average standard deviation of this gap for the real-world case. The pattern across all scenarios of the average gap is analogous to the pattern of the previously explained welfare. Only the axis labeling of the Figure changes from “welfare” to “average gap”, with a value between 0 (no improvement since there was no optimization possible) and −45 min (see Fig. B.1). The gap increases with a growing number of BEVs or decreasing power availability of the bottleneck. In line with the identified welfare gains, the highest absolute gap reduction occurs at a power bottleneck of 2,000 kW. Interestingly, however, the scenario with the largest absolute average gap reduction of 4 min occurs in the scenario with 64 BEVs, whereas the largest welfare gain occurs in the scenario with 72 BEVs. Nevertheless, the overall course of the average gap reduction resembles the welfare gain with minor deviations as the model optimizes for welfare gain (see Fig. B.2). Similarly, the relative gap reduction resembles the relative welfare gain with 13.3% improvement at the largest absolute average gap reduction and 43.6% highest relative improvement with an absolute gap reduction of 0.5 min (see Fig. B.3).

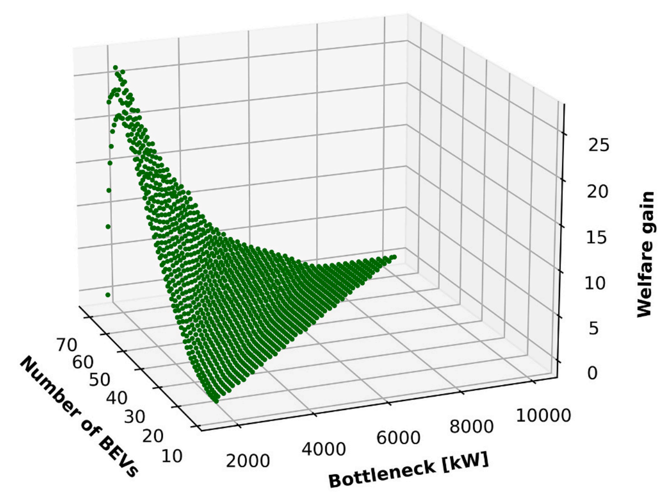

Fig. 11. Welfare gain for each scenario - Future case 1 with adjusted market shares of vehicle categories.

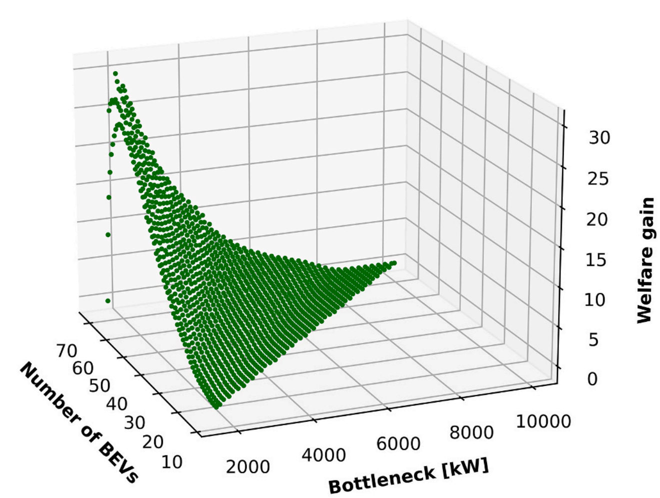

Fig. 12. Welfare gain for each scenario - Future case 2 with adjusted market shares of vehicle categories and technical changes (I).

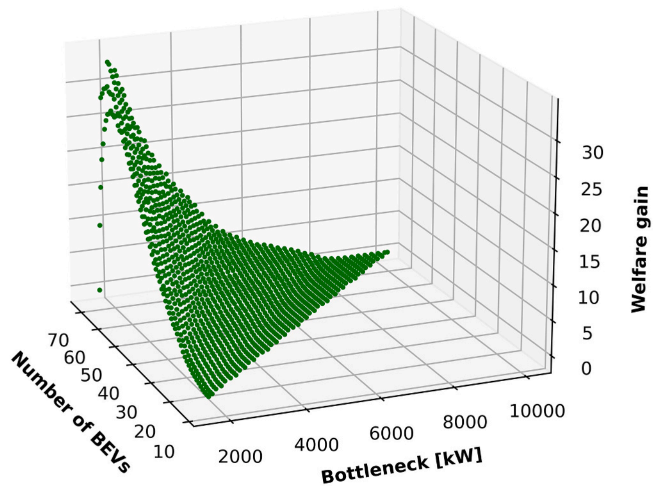

Fig. 13. Welfare gain for each scenario – Future case 3 with adjusted market shares of vehicle categories and technical changes (II).

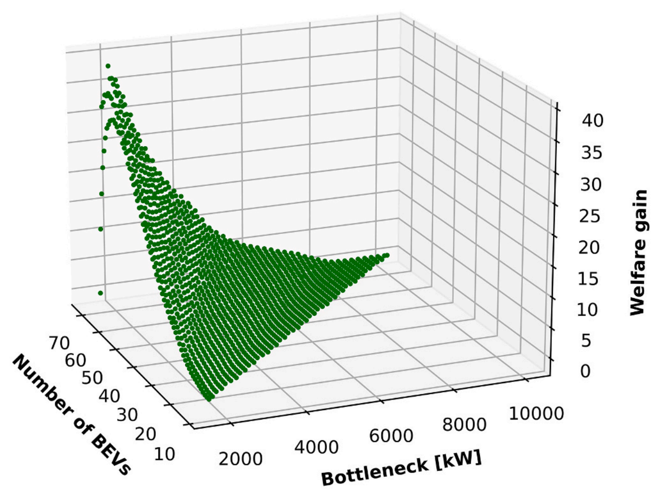

Fig. 14. Welfare gain for each scenario – Future case 4 with adjusted market shares of vehicle categories and technical changes (III).

Turning to the average standard deviation of the gap, the optimized power allocation results in a considerably lower standard deviation at bottleneck situations compared to the benchmark power allocation (see Fig. 15).

While the benchmark and the optimization model allocate the same amount of power to charging stations within the charging park, the optimization model achieves improvements across all evaluation metrics. The following underlying effect drives such improvements: Section 2.3 describes the uniform power allocation with BEV drivers experiencing small gaps as well as BEV drivers experiencing substantial gaps between expected and actual servicing times. Following EDT, large gaps lead to higher individual dissatisfaction (in this paper, parameterized through a quadratic formulation), resulting in lower welfare. The optimization model allocates the available power to minimize the occurrence of large, substantial gaps, albeit at the expense of small gaps now appearing for customers with lower charging power expectations — consequently, overall welfare increases. The same principle underlies the reduction of the average gap in minutes. Extreme values of large gaps significantly impact the calculation of the average gap for all BEV drivers in the charging park. Hence, applying the optimization model reduces the average gap over all customers. For clarity, Table B.1 exemplifies this principle. In addition, variability and uncertainty across multiple charging events decrease, further contributing to dissatisfaction mitigation. In summary, welfare enhancement is not achieved by

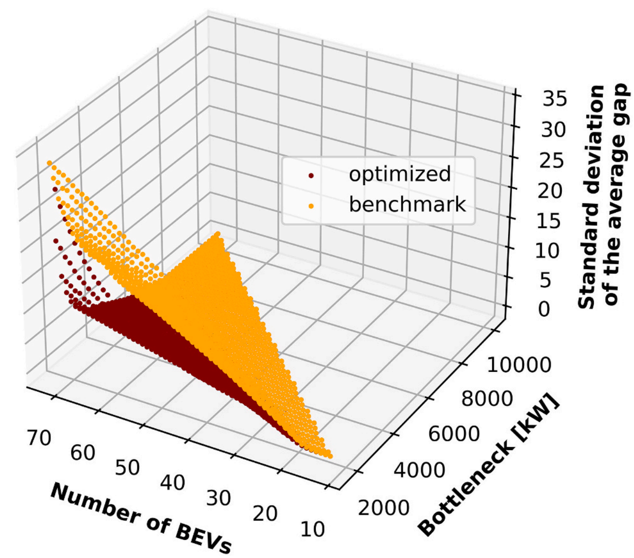

Fig. 15. Standard deviation of the average gap between expected and actual servicing times for all scenarios – Real-world case.

shortening the overall servicing time – which is technically unattainable with constant available power – but rather by reallocating charging power and avoiding extreme gaps for some customers.

5. Discussion

Our model and the optimized power allocation indicate improvements compared to the benchmark power allocation mechanism. This is not only reflected in improving overall customer satisfaction (see the increased welfare gain) but also at the individual vehicle driver's level (see the reduction of the average gap in minutes). Improvements for individual vehicle drivers can especially be realized concerning decreasing standard deviations of servicing times, as uncertainty additionally negatively affects satisfaction. It should be emphasized that welfare gains of our model – associated with generally reduced gaps – increase with a scarcer average available power per BEV compared to the benchmark power allocation, as long as there are sufficient planning degrees of freedom. Such effects may be considered "positive" as they add the more welfare, the more critical the bottleneck. However, the absolute level of welfare generally declines the stronger, the scarcer the available power per BEV. We can, therefore, conclude that our model will generally utilize resources more "efficiently" than a uniform power allocation between all charging BEVs (i.e., our benchmark power allocation). However, our model may not overcompensate for poor charging park planning, where power bottlenecks appear to be very large [34]. This may be the case when such a big gap between expected and actual servicing time results that the vehicle driver cannot recognize an improvement due to the optimized power allocation. Overall, we quantitatively support the initial hypothesis that allocating power uniformly across all charging stations is not optimal concerning customer satisfaction using a utilitarian welfare function.

Our results generally point out that applying our optimization model to a charging park for the allocation of charging power can improve customer satisfaction. However, for implementation in reality, it is essential to recognize that the added value depends on the occurring power bottlenecks, the maximum charging power of the charging BEVs, and the overall utilization rate of the charging park. Thereby, our model complements a holistic control system of the charging park (see Section 3.1 and Fig. 4), which often includes further components such as a photovoltaic (PV) and an energy storage system (ESS) [66]. A PV system provides low-cost and emission-free power. However, it is highly volatile and delivers only limited power during the early morning and evening hours, when traffic and charging demand are still high. Therefore, PV systems can relieve the grid coupling point during the day, however, power bottlenecks will still occur during bad weather days or at night. An ESS can perform various functions within holistic control systems of charging parks. The highly fluctuating load from BEVs plugging and unplugging at high charging power can affect power quality, which can be mitigated by an ESS connected directly ahead of the grid coupling point [67–70]. In addition, an ESS can significantly reduce operational costs, which consist of power consumed (per kWh) and monthly peak demand costs (highest power peak per kW) [71,72]. Sizing the ESS to match the configuration of the charging park can reduce peaks and, in turn, reduce these peak demand costs. However, optimizing the size of an ESS for cost reduction is complex and depends on investment costs, uncertain electricity consumption and peak demand costs, as well as charging demand [73,74]. Haupt et al. [74] demonstrated that charging parks with a high proportion of immediate charging demand require large ESS, which would only be economically viable with meager ESS investment costs. Furthermore, predicting long-term charging requirements is challenging, as the forecasts for the deployment of electric vehicles still vary significantly [75]. To conclude, even with optimal planning in the design phase, it is foreseeable that bottleneck situations will continue to occur. Therefore, managing customer satisfaction during peak demand periods is necessary due to changing circumstances and fluctuating PV generation. Our optimization model is the last layer in the holistic charging park control system. It receives the input parameter *PowMax* after the power management system determines the optimal energy flow from the grid coupling point, PV, and ESS. Regardless of the other components, the customer satisfaction effects investigated in this study remain constant. Therefore, the parameters of each charging station need to be considered to decide if the investment for implementing our optimization model including a power management system is worthwhile. However, with technological progress (which our future cases account for) and an additional increase in the number of BEVs on roads, it is important to emphasize that our approach is becoming increasingly relevant as bottleneck situations will occur even faster and more frequently.

6. Conclusion and future research

In this paper, we develop a welfare-maximization model addressing service performance gaps of fast charging, which we explicitly ground in social choice theory. The developed optimization model is evaluated using data from a large charging park in Augsburg, Germany. Our evaluation of the real-world case shows that the developed model serves up to six more BEVs with the same power bottleneck at the same level of welfare as compared to a uniform power allocation mechanism – the latter constitutes our benchmark. Second, we can serve the same number of BEVs at the same level of welfare even at an up to 400 kW smaller bottleneck. Both findings potentially suggest reduced investments for hardware upgrades such as transformers, inverters, etc. Looking at additional future cases we analyzed in this paper, we can see that corresponding results are only becoming even more relevant. Increasing volatile power generation from on-site renewable energy installations, such as photovoltaics, further increases demand for a smart power allocation. These results and trends underline the need for a travel-satisfaction-oriented policy for transport planning and highlight their relevance for the future of electric mobility.

However, this study is also subject to some limitations. A more detailed charging curve would identify the resulting gap for each BEV more accurately since, at high SoC values, the maximum charging power of the BEV can no longer be fully utilized. However, as we focus on the average gap, the results should only vary slightly. Further, we only consider a maximum charging power of 140 kW, whereas charging parks often offer several different charging power products. The analysis of multiple charging power products requires further research on how different charging prices can be incorporated into this model. Additionally, while this paper focuses on managing service performance, it remains an open topic to study the expectation side of the considered gap, i.e., the expectations of vehicle drivers. Since advertisements often set inflated customer expectations [36], like car manufacturers typically advertise the shortest technically possible servicing times, addressing the expectation side would be a relevant topic for further research. To adequately model the expected servicing time, the expectations of each vehicle driver must be known. In this context, artificial intelligence could be a relevant approach for future considerations, as argued by Baumgarte et al. [76]. Apart from the expected servicing time, the target SoC is also a key factor. A limitation of our work is that we used the actual SoC at the end of the charging process for the parameterization of our model. To avoid such limitation, it would be crucial for our power allocation, as well as for other smart charging approaches, to know the target SoC desired by the vehicle drivers. Since the target SoC is difficult to predict due to many different influencing parameters, the target SoC would have to be asked at the beginning of the charging process. Additionally, integrating our model into a holistic charging park control system that includes PV, ESS, and varying power bottleneck over time could provide further interesting insights. This would allow for a temporal analysis of individual customer satisfaction and welfare over a day or year. Power allocation would be re-optimized at each change on the supply or demand side, and specific circumstances with significant potential for enhancing welfare may be identified. Finally, it might also be important to consider the potential improvement of waiting conditions, e.g. by offering additional services that could be used during the charging process such as open working spaces, or using expectation management by displaying and explaining waiting or servicing time [39,77,78]. These extensions of our current research will open up several opportunities to further increase the acceptance of electric mobility and fast charging in specific.

CRediT authorship contribution statement

Jessica Bollenbach: Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Writing-Review & Editing. **Stephanie Halbrügge:** Writing – original draft, Methodology, Conceptualization. **Lars Wederhake:** Software, Methodology, Conceptualization. **Martin Weibelzahl:** Supervision, Formal analysis, Conceptualization. **Linda Wolf:** Writing – original draft, Project administration, Methodology, Investigation, Data curation, Writing-Review & Editing.

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.

Data availability

The data that has been used is confidential.

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Appendix A. Additional parameterization

Table A.1
Calculation of market shares.

Vehicle category [55]	German Federal Motor Transport Authority vehicle categories [32]		Market Shares
Mini and small vehicles	Mini vehicles	6.9%	28.7%
	Small vehicles	18.2%	
Middle and compact-class vehicles	Compact-class vehicles	24.2%	57.5%
	Middle-class vehicles	12.3%	
	Mini-Vans	3.9%	
	Vans	4.0%	
	Off-road vehicles	6.0%	
Upper-middle-class and upper-class vehicles	Upper-middle-class vehicles	3.8%	7.2%
	Sport car	1.9%	
	Upper-class vehicles	0.6%	
Commercial vehicles	Utilities	4.2%	6.6%
	Camper	1.6%	
		87.6%	**100%**

Appendix B. Additional Results

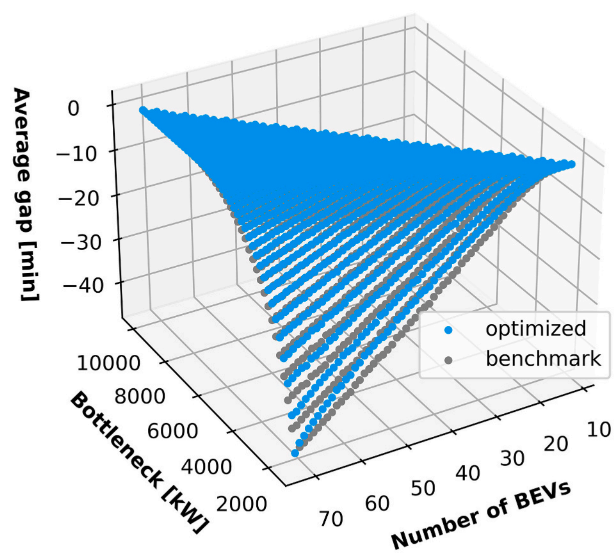

Fig. B.1. Average gap between expected and actual servicing times for all scenarios - Real-world case.

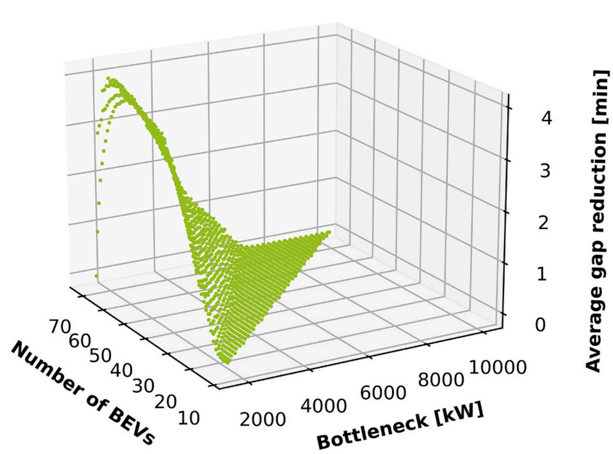

Fig. B.2. Absolute average gap reduction - Real-world case.

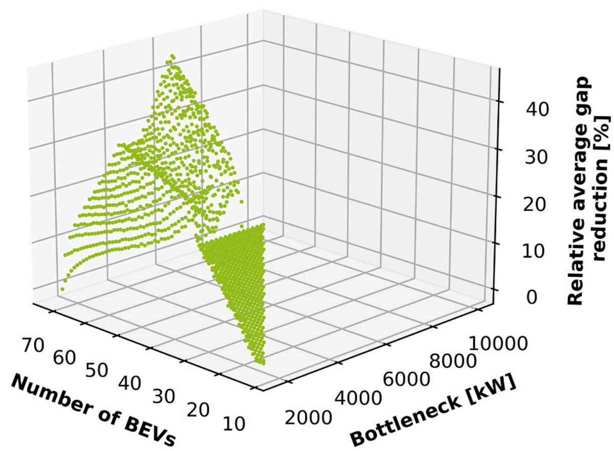

Fig. B.3. Relative average gap reduction - Real-world case.

Table B.1
Exemplary illustration of the average gap and welfare reduction in a charging park with a 180 kW bottleneck situation and two charging stations.

	BEV driver 1	BEV driver 2	Average gap and welfare
Characteristics	$SoC_1^{\text{init}} = 0.5$ $SoC_1^{\text{target}} = 0.8$ $BC_1 = 64$ kWh $PowMax_1^{\text{BEV}} = 127\ kW$	$SoC_2^{\text{init}} = 0.2$ $SoC_2^{\text{target}} = 0.9$ $BC_2 = 64$ kWh $PowMax_2^{\text{BEV}} = 127\ kWh$	
Expected servicing time	$\frac{64\cdot(0.8-0.5)}{\min\{127,140\}\cdot 1} = 0.15\ [h]$	$\frac{64\cdot(0.9-0.2)}{\min\{127,140\}\cdot 1} = 0.35\ [h]$	
Actual servicing time with uniform power allocation	$\frac{64\cdot(0.8-0.5)}{90\cdot 0.98} = 0.22\ [h]$	$\frac{64\cdot(0.9-0.2)}{90\cdot 0.98} = 0.51\ [h]$	
Gap	$0.15 - 0.22 = -0.07\ [h]$	$0.35 - 0.51 = -0.16\ [h]$	Average gap of −6.9 min; Welfare = −2.48
Actual servicing time with optimized power allocation	$\frac{64\cdot(0.8-0.5)}{72\cdot 0.98} = 0.27\ [h]$	$\frac{64\cdot(0.9-0.2)}{108\cdot 0.98} = 0.42\ [h]\Big]$	
Gap	$0.15 - 0.27 = -0.12\ [h]$	$0.35 - 0.42 = -0.07\ [h]$	Average gap of −5.7 min; Welfare = −2.41
			Gap reduction of 1.2 min (17%)

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