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STRATEGIC PLANNING OF PUBLIC CHARGING INFRASTRUCTURE

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Abstract:

With an increasing number of electric vehicles, the strategic planning of public charging infrastructure becomes more important. In this work, the infrastructure of the charging stations in a large city is simulated. Here, various influencing factors such as number of users, charging time, charging frequency, type of the charging station and billing model are modified in order to obtain the optimal construction and operation of public charging infrastructure. The results illustrate conditions under which a system for public charging infrastructure becomes unstable as the number of users increases. In addition, it is shown, which measures should be used to improve the system characteristics. The results of the simulation reveal that with an increasing number of users a switch of the billing model can be more effective than the construction of additional charging station. Furthermore, it makes sense to construct distributed single charging points in a city at the beginning of the development phase and to switch to satellite systems with more charging points once the number of users has increased sufficiently.

Keywords:

Public charging infrastructure, billing model, user behaviour, electric vehicles, simulation.

Introduction

Electric vehicles (EVs) will play a central role in reducing CO_2-emissions in the mobility sector. With an increasing number of EVs in the future, more public charging infrastructure is needed. However, there is a lot of uncertainty about future development of market share for EVs, the battery size and the users' behaviour. Due to the high costs of building and operating a public charging infrastructure, the strategic planning of this infrastructure is important. Understanding user behaviour and its effects on charging infrastructure is helpful for optimal deployment of charging stations regarding user satisfactory and economic aspects.

The aim of this work is to study the influence of parameters such as the number of users, the number of charging points and charging frequency on the quality of a public charging infrastructure (private charging infrastructure at home or at work is not investigated in this paper). For this purpose, sensitivity analyses using an agent-based simulation model are performed on a random, large case study. Relevant parameters for the modelled city are derived from the literature (see chapter 2) and also from data of 70,000 charging processes in Munich and 580,000 charging processes of the roaming solution ladenetz.de (ladenetz.de 2021; Klosko 2020; Volk 2020). No specific city is simulated in this work to avoid biased results originating from individual circumstance. Thus, parameters for the creation of a random city are generalized. The simulation results determine the sensitivity of the system to changes of input parameters as well as required measures to improve the system characteristics. Additionally, the following questions are addressed to provide information on the construction and expansion of an exhaustive public charging infrastructure, of which the construction costs are also not insignificant:

- Should, for example, single charging stations distributed in the city be preferred over satellite systems at several central locations?
- What happens if the number of users increases significantly and the charging infrastructure is not expanded?
- When will the system reach its limits?

This paper is structured as follows. The next chapter deals with works with similar topics. Subsequently, the simulation model is presented. There, the assumptions, the parameterization and the evaluation criteria are explained. Afterwards in chapter 4, the experiments and results of the simulations are described and policy recommendations are derived. The paper ends with a conclusion.

Related work

Agent-based simulation is suitable to analyse the optimal configuration of a public charging infrastructure. These simulation models are useful to explore macro-scale behaviour as a result of micro-scale interactions between population members and their model environment (Sheppard/Harris/Gopal 2016: 175). Furthermore, behavioural changes in social systems can be investigated (van der Kam et al. 2019: 2).

Several studies addressed the applications of agent-based simulation models. Hess et al. (2012) extended the SUMO traffic simulator for EVs and charging infrastructure. In their model, the charging behaviour of EV drivers is demand driven. As soon as the EV detects a low battery warning, it receives advertisements of charging stations and navigates to a charging station. Based on simulation results for the road network of Vienna, the placement of public charging stations is optimized with Genetic Programming. Hess et al. also used charging infrastructure with satellite systems and up to 12 plugs per station.

Torres et al. (2015) simulated 2,000 EVs for a simulation period of four days. In scenarios with modified charging behaviour of EV users, they analysed effects of charging demand. An effect on the morning peak for electricity demand could be observed as a result of recharging at the workplace. Furthermore, a scenario with a heterogeneous EV fleet was calculated. In this scenario, since a capacity restriction of the charging infrastructure was not implemented, charging was always possible.

In 2016 López Hidalgo, Ostendorp and Lienkamp (2016) used the agent-based model, described by Trippe et al. (2015), to analyse both a prudent and a risky charging behaviour of users regarding failed trips. They inferred that regardless of the charging infrastructure, the risky charging behaviour leads to a noticeable number of failed trips. The battery energy efficiency in Wh/kg was also analysed in sensitivity calculations. It was revealed that this parameter has a minor impact on the number of failed trips.

Guo, Deride and Fan (2016) used a network based multi-agent optimization modelling framework to solve a business-driven charging infrastructure investment planning problem. The investment decision in charging infrastructure was made by many entities who act competitively. They concluded that a business-driven competitive market could not create a social optimal solution for a charging infrastructure. However, He et al. (2013) were able to create such a charging infrastructure with a central planning instance and the objective to maximize the social welfare.

In the same year, Sheppard et al. (2016) used the agent-based simulation model PEVI for locating public charging infrastructure in the metropolitan region Delhi. They separated the region into 53 zones to assign charging infrastructure to these zones. As expected, their results demonstrated that waiting times of EV drivers increase as more charging stations are occupied and the number of free charging stations decreases. However, this is not a linear trend. They concluded that the reduction of the waiting time by installing additional charging stations is not necessarily cost-optimal. In addition, they conclude that more charging infrastructure is needed if the battery capacity of the EV fleet decreases. They also analysed the effect of absence of home chargers. Under this scenario, as expected, additional public charging stations are required. Nevertheless, 10,000 removed home chargers only lead to 700 additional public chargers to achieve the same level of service. Furthermore, an additional energy demand for air conditioning of EVs will lead to a significant increase in additional charging infrastructure.

Hoeckstra and Hogeveen (2017) developed, the ABCD-model, a multi-level agent-based model for buying, charging and driving of EVs. They performed experiments on small regions in the Netherlands. It was shown that the number of required public charging stations significantly increases as the search radius of an EV driver to find an unoccupied charging station decreases. Furthermore, fewer charging infrastructure is needed as battery sizes of EVs increase. Hoeckstra and Hogeveen also analysed the ratio of public to private charging stations. They concluded that public charging infrastructures should not be built based on average numbers, but rather based on the individual data of neighbourhoods.

Vermeulen et al. (2019) analysed whether the current public charging infrastructures of the four largest cities in the Netherlands, namely Amsterdam, Rotterdam, The Hague and Utrecht, are capable of accommodating the EV fleet transition from plug-in hybrid electric vehicles (PHEV) with small batteries to full electric vehicles (FEV) with large batteries. They used the agent-based simulation model SEVA (Helmus 2019) and derived input parameters based on the real-world data from the IDO-laad project (University of Applied Sciences Amsterdam 2020). Charging points were clustered for each agent. A cluster has a centre and a radius with a minimum walking distance of 150 m. All charging points within this radius belong to this cluster. The results of the experiments revealed that with the same number of EVs, the demand on charging infrastructure decreases as battery sizes of these cars increase. This is according to Sheppard et al. (2016) and Sheppard, Harris and Gopal (2016). However, FEVs drivers compared to PHEV drivers have to seek more frequently for an alternative charging point because the preferred charging point is occupied. This is because PHEVs have often less incentives for charging. Thus, they are not required to use alternative charging points and their maximum walking distance of charging clusters is smaller.

Also in 2019, van der Kam et al. (2019) used an agent-based model to investigate how well different charging patterns are aligned with renewable energy production from photovoltaics and wind. Charging patterns are the result of scenarios with different renewable energy capacities, different policy interventions, limited versus unlimited charging capacities, social charging and presence and absence of a central control. Van der Kam et al. concluded that policy makers should use different incentives for different groups of EV drivers to increase sustainable charging. Furthermore, without a central control, the impact of political interventions on charging behaviour of EV drivers is small. Thus, an information and feedback campaign targeting EV drivers was recommended.

Agent-based simulation is also often used to derive the variation of the electricity demand of EVs over a day. Cui et al. (2011) used an agent-based simulation framework to calculate the future PHEV ownership distribution at the residential household level and to estimate the effect of different charging strategies on the local electrical distribution network. Acha, van Dam and Shah (2012) determined optimal charging times for EVs with an agent-based simulation. One year later, Waraich et al. (2013) used the results of an agent-based simulation model to investigate several charging schemes for EVs. Olivella-Rosell et al. (2015) applied four charging strategies at a 37-node IEEE test feeder with mobility data of Barcelona. In 2016, Hu et al. (2016) used a multi-agent system with hierarchical management structure to study the integration of EVs into the power distribution systems.

Some authors used agent-based simulation models mainly to identify EV adoption patterns based on scenarios. In 2009, Sullivan, Salmeen and Simon (2009) developed the model VAMMP to analyse the penetration of the PHEV into the U.S. car market under a variety of consumer, economic and policy conditions. Sweda and Klabjan (2011) used an agent-based model for the Chicagoland region. For Irish households, Mc Coy and Lyons (2014) found that large regional clusters of EVs could be formed, even if overall adoption is relatively low. Kangur et al. (2017) used an agent-based model for diffusion of EVs and analysed the effects of different policies on EV diffusion, e.g. tax exemption for company cars, fuel excise duties, purchasing subsidies and increase in fast charging opportunities.

In literature also, historical travel data of conventional fuel vehicles were analysed to generate insights to the optimal configuration of the EV charging infrastructure, e.g. taxi driving data of Beijing (Yuan 2010; Yuan 2011). Moreover, historical data and results of projects with EVs can be obtained from the German automobile producer BMW (BMW Group 2010) or from the U.S. Department of Energy (Wood 2017) and 'The EV Project' (INL 2021) for North America. The following research activities were done with real-world data.

Andrews et al. (2013) used publicly available data from travel surveys of Chicago and Seattle metropolitan areas to develop a charging model for generating input data for the optimal charging station location. This location problem was solved with CPLEX. Andrews et al. found that an increase in the number of charging stations lead to a significant drop in mean and maximum inconvenience experienced by EV drivers.

Xi, Sioshansi and Marano (2013) applied a simulation-optimization model to the central Ohio region. They simulated a working day and used a linear integer programming model to determine the location of the charging infrastructure. The results revealed that level one chargers with 120 V are the most economical way to build a public charging infrastructure. However, a combination of level one and level two chargers maximizes the available charging energy for EV users.

Wagner, Götzinger and Neumann (2013) studied the data on charging station usage in Amsterdam to derive a correlation between the usage of these charging stations and different categories of surrounding points of interest. They noticed that charging stations close to points of interests in the categories of food, health and museum have particularly a higher utilization level. Based on these results the placement of charging infrastructures for Amsterdam and Brussels was calculated.

In the same year, Zoepf et al. (2013) studied data of 125 PHEVs in the United States. Results of scenario analyses indicated that fast charging provides only small changes in energy consumption. Furthermore, 40 % of PHEVs that were driven on a certain day were not charged on that day, another 40 % were charged only once, 10 % were charged twice and 10 % were charged more than twice. Thus, the overall average rate of charges per day per PHEV was 0.75.

Uhrig et al. (2015) analysed data of twelve car parks in the cities of Basel, Karlsruhe and Constance (details about optimal charging strategies in car parks can be found in the paper of Gold and Günther (2011)). Based on Monte Carlo simulation, charging strategies and measures to avoid overload were analysed. Furthermore, two tariff models were compared. A time-based model in €/h and an energy-based model in €/kWh with a monthly fee. For most of the analysed car parks, the time-based tariff leads to a higher profit and more charging points can be installed due to the higher revenues.

Paffumi et al. (2015) used GPS data of 28,000 conventional fuel vehicles in the Italian provinces of Modena and Firenze. They replaced the conventional vehicles by six EV types and analysed different charging strategies regarding electricity demand, state of charge, number of successful trips and number of recharges per day.

Sun, Yamamoto and Morikawa (2015) analysed data of EVs, but only regarding fast charging processes on trips in Kanagawa prefecture in Japan. They observed that private users are willing to detour up to 1,750 m on working days and up to 750 m on non-working days to reach a fast-charging station, while commercial users, regardless of the day, are willing to detour up to 500 m. However, users prefer stations with the shortest detour and stations without a fee are only more attractive for private users traveling on working days. One year later, Sun, Yamamoto and Morikawa (2016) used the dataset of their previous work (Sun/Yamamoto/Morikawa 2015) and focused on normal charging after the last trip of the day. They concluded that the main predictors for whether an EV is charged or not are as follows: the state of charge (SOC), time until the next travel day and the expected travel kilometres on the next travel day.

Yi and Bauer (2016) solved a multi-objective optimization model for optimal placement of charging infrastructure with a mesh adaptive direct search algorithm. Experiments were made with case studies in South Bend and Chicago. The optimization criteria were maximizing the number of reachable households and minimizing the overall transportation energy cost for EVs. They concluded that transportation energy cost for EVs will increase dramatically if the charging stations are placed far away from the optimal positions. Furthermore, they demonstrated that satellite systems lead to a significant reduction in the number of used places.

Based on real-time data of taxis in Beijing, Shen et al. (2016) developed a simulation model for charging station deployment for PHEVs. Several sensitivity analyses were conducted. The results revealed that home charging should be promoted if the public charging infrastructure is not sufficient. Moreover, a mixture of slow and fast chargers should be favoured. Shen et al. also modified the number of charging points per charging station. They found under the assumption of a fixed charging power that is helpful to increase the number of charging stations and decrease the number of charging points per station.

Morrisseya, Weldona and Mahonya (2016) analysed the data of charging sessions in Ireland. Several use cases and types of charging infrastructure were identified. They found that there was a high degree of heterogeneity amongst the various use cases and types of charging infrastructure regarding charge timings, charge consumptions and charge usage frequencies. Moreover, they found that home chargers had the highest average usage frequency of 0.18 charges per day.

Motoaki and Shirk (2017) published results about user behaviour at DC fast charging stations in the United States. They compared data of a period without any charging costs with data of a later period with a fixed charging fee of $5. After the implementation of the fee, the number of users was reduced by 23 % and the number of charging processes was reduced by 43 %. The results indicated that EV users avoid charging at DC fast charging stations after the introduction of the fee because they can charge much cheaper at home. They also found that EV users used the charging stations as parking spots. Furthermore, the fee results in longer parking times at the charging stations, because users want to get more out of a charging session. However, at a DC fast charging station, the rate of charge is diminishing over time. Thus, longer charging times have a negative effect on usage efficiency of these stations. Motoaki and Shirk concluded that a pricing scheme should be used, which incentivizes the user to vacate the station for the next user after recharge.

Helmus et al. (2018) determined differences of two rollout strategies for public charging infrastructure in the Netherlands based on the data of charging sessions from EVnetNL (2021). The first strategy was demand-driven by a request of an EV user. In the second strategy, charging points were placed near to public facilities or on strategic locations. At first, Helmus et al. identified performance indicators for charging infrastructure: number of unique users, connection duration, charged kWh, charging time ratio. Based on these indicators, not one rollout strategy is favourable over the other one. They concluded that the optimal rollout strategy is a mixture of both strategies. However, in a less mature market, the demand driven strategy should be preferred while in a more mature market, differences between the strategies becomes less significant and a balanced portfolio is more attractive.

Cellular phone data of Boston were used by Vazifeha et al. (2019) to derive movement patterns and to solve the charging station deployment problem with a genetic algorithm and a greedy algorithm. The genetic algorithms always outperformed the greedy algorithm. Vazifeha et al. also made sensitivity analyses to test the robustness of the solution by modifying parameters for the EV demand. It was concluded that the obtained solution is stable in respect to changes in the charging time and the EV range.

The statements made above show that in respect to the optimal configuration of the charging infrastructure, often only single aspects were studied that were related to a specific city or region. A comprehensive, generic analyses, regardless of regional circumstances, have so far hardly been carried out.

Description of the simulation model

In this work, scenarios as they can be found in the future in cities are simulated. As shown in the previous chapter, agent-based simulation was often used to gain knowledge about the optimal configuration of a charging infrastructure. Furthermore, a simulation model is required that can map thousands of users and charging points. Thus, using queuing theory for analysis of optimal configuration of a public charging infrastructure would not be applicable (Biethahn et al. 2005: 180).

A separate simulation model was developed in C# for the experiments in this paper. The model assumes that the battery change as a fast-loading feature is not possible. This technology is too expensive and automobile manufacturers should have agreed on standardized batteries and at least on partially standardized vehicle concepts. Therefore, this aspect is neglected in the model. In addition, it is also assumed that the DC charging for public charging points is not used. DC charging is more likely to be found in motorways or at petrol stations. For a public charging infrastructure, it is possible to charge batteries with AC current of 16 A or 32 A and Voltage of 220 V (single phase) or 400 V (3-phase). In other words, each charging point has a power of 3.6 kW to 22 kW.

According to the PEVI models of Sheppard et al. (2016) and Sheppard, Harris and Gopal (2016), a discrete planning horizon is used for the simulation of an event. In this paper, an event also consists of an agent, a time and an activity, where time is split into one-hour intervals. Shorter time intervals would have increased the computational effort without a considerable gain in insights. The simulations are performed covering 365 days. The simulation does not start with a separate transition phase to reach a steady state, since this is not important for a simulation time of 24 hours a day, 365 days a year.

The research goal of this work is above all assessing the impact of changing framework conditions. Therefore, sensitivity analyses are performed. For these analyses, a baseline scenario is formulated. It is mostly based on generalized knowledge from the literature (see chapter 2), from data of Munich and from the roaming solution ladenetz.de (Klosko 2020; Volk 2020; ladenetz.de 2021). As an example, Figure 1 shows a heat map of the number of charging sessions in Munich during the workweek. It can be observed that the number of charging sessions are higher in the city centre. This is also a result of the calculation of feature importance with a random forest algorithm (Klosko 2020: 75).

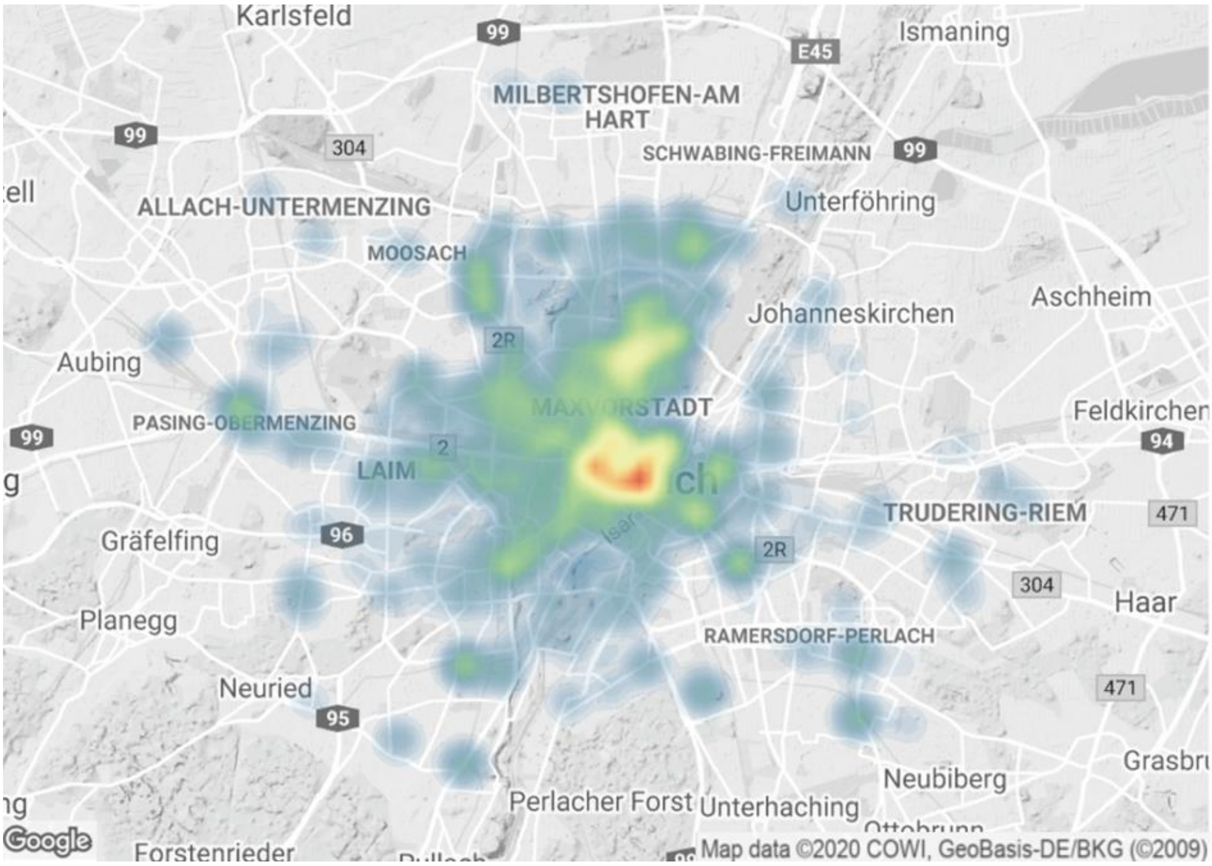

Figure 1: Charging sessions during the workweek (Klosko 2020: 47)

The baseline scenario is represented as follows:

- The random city case study is structured in a square matrix and has an area of 15,000 x 15,000 m. All assignments of charging stations and travel or charging activities of EV users are exactly geocoded in this matrix. The approach of Sheppard et al. (2016) and Sheppard, Harris and Gopal (2016) to create larger zones for locating charging infrastructure is not used in order not to lose the accuracy of the simulation results.
- The number of EV drivers (n) who use the simulated charging stations is 100,000.
- The destinations of the users are randomly distributed on the 15,000 x 15,000 m matrix. The x and y coordinates of each destination follows a normal distribution with N(7,500, 15,000/8).
- For the maximization of charging utilization, the charging infrastructure should be placed near frequently visited areas (Sweda/Klabjan 2011; Dong/Liu/Lin 2014). Klosko (2020) and Volk (2020) came to the same results when they analysed 650,000 charging processes of 29,000 users in Germany. This concept is also often used as an objective function for locating charging stations (Feng/Ge/Liu 2012). Hence, charging infrastructure in this paper is on average located close to the places where EV drivers probably want to charge their car. Thus, the public charging stations are randomly distributed on the 15,000 x 15,000 m matrix. The x and y coordinates of each charging station are also normally distributed with N(7,500, 15,000/8).
- A charging point provides the possibility to charge an EV. The number of charging points in a charging station determines the number of EVs that can simultaneously charge from that charging station. A charging station with four plugs (e.g. 2 x Schuko and 2 x IEC Type 2) in which only two vehicles can charge simultaneously is considered to have only two charging points. The number of the charging points (l) in the baseline scenario is 4,200.
- The number of public charging stations and centre of satellite systems (c) is 600.
- Usually, a single charging station has one or two charging points. In case of satellite systems, this number is ten or more charging points per centre. The average number of charging points per charging station

or centre of a satellite system (s) is seven, where s is always equal or great than one. In case of $s > 1$, the remaining charging points are distributed randomly so that the charging infrastructure remains inhomogeneous.

- According to the results during the pilot test in Berlin, charging is carried out on average about three times a week (BMW Group 2010; Vattenfall 2011: 67). The probability distribution of the number of charging processes per user and week is distributed normally with N(2.98, 2.36). In a chi-squared test with $\alpha = 0.1$ for checking the validity of the normal distribution for the empirical data, the alternative hypothesis that the data does not have a normal distribution can be rejected. In addition, it is known from the pilot test that only 25 % of all charging processes are performed at a public charging point (BMW Group 2010). In the discrete-time simulation model with one-hour intervals, the probability of charging (w_p) for each user in the baseline scenario is therefore, 0.4 %. For orientation: according to work of Vermeulen et al. (2019: 9) 30 % of FEVs and 49 % of PHEVs are disconnected from a charging station by more than one day.
- In the discrete-time simulation model with one-hour intervals, the probability (w_f) that a user stops a charging process is 13 % in each hour in the baseline scenario. It should be noted that in practice cars will also be parked relatively long: overnight or for several days at a certain charging point, even if the charging itself takes only a few hours. Sometimes, an EV user only seeks for a free parking position and uses a parking position with a charging station.

The process of the simulation is as follows: In each time interval, first, it is checked whether a user who is currently using a charging point will continue to charge or will leave the charging point. This occurs using a probability distribution function in the background. Subsequently, using another probability distribution function, it is determined if a user of an EV who reach a randomly set destination and is currently not using a charging point will charge his vehicle. In this case, the user is assigned to the closest free charging point of his original planned destination. If there is no free charging point currently available, the user cannot charge his vehicle. Based on these data, the specified evaluation criteria listed below can be calculated.

In order to evaluate and compare the parameterization of the simulation model in the different scenarios, evaluation criteria are introduced. On the one hand, the number of required charging processes is used. Since possibly not every charging process can be carried out, the performed and non-performed charging processes are counted separately. A non-performed charging process is a situation in which a user wants to charge his vehicle; however, there is no free public charging point available in the entire city. The charging process, therefore, does not take place at one of the simulated public charging points. The charging infrastructure should be available in a way that the user has a free charging point nearby once it is needed. To evaluate this, the Euclidean distance in meters between the destination and the closest free charging points is introduced as a walking distance for the EV user. In the papers of Andrews et al. (2013), Baouche et al. (2013), Vazifeha et al. (2019) and Vermeulen et al. (2019) the criterion of a walking or driving distance was used as well.

Experiments and Results

Results for the base case

The parameters of the baseline scenario for sensitivity analyses were introduced in the previous chapter. At this point, in order to obtain a better understanding of the baseline scenario, the values of the evaluation criteria are discussed. All analyses for the scenarios are carried out with 30 replications due to the stochastic nature of the simulation model, provided that the random placement of charging stations in each replication is done newly.

Table 1 shows the results for the baseline scenario. None of the nearly four million charging processes had to be omitted because there was no free charging point. This suggests a well-developed charging infrastructure. With a total of 1,077,306 km, it seems that the additional total distance between the travel destination and the charging point used seems to be quite long. However, it should be considered that this value is for a simulation period of one year and for 100,000 users. This appears also in the average walking distance per process of charging, which with 287 m is relatively low.

Table 1: Assessment criteria for the baseline scenario

criterion	result
required charging processes	3,759,420
performed charging processes	3,759,420
performed charging processes	0
overall walking distance	1,077,306 km
average walking distance per performed charging processes	287 m

Overall, the parameterization of this scenario can be described as 'very good' with regard to the used evaluation criteria. Low distances and short travel times per each process of charging are a result of the exhaustive developed charging infrastructure with 4,200 charging points for 100,000 users. This corresponds to an average of approx. 24 users per charging point.

In the next section, the effects of charging frequency, consumption duration and the number of users are investigated. This is followed by the study of the effects of different expansion levels and expansion variants of the charging infrastructure.

User types and frequency of use

The majority of all charging processes in the baseline scenario does not take place at public charging infrastructure. However, the prerequisite for this is that the users have private parking places with charging points and possibly access to charging points at the workplace. Otherwise, the user is a 'street parker', which is dependent on public charging infrastructure.

In its final report, the e-connected initiative states that around 70 % of all vehicles are parked on the street in urban centres (Klima- und Energiefonds 2009). In the case of Munich it is known that 78 % of all vehicle owners park in a private car park within the 'Mittlerer Ring' although it is not known what type of car park it is (Mauch et al. 2010). Depending on the number of private parking spaces and their design, as well as depending on charging options at the workplace, there are different requirements for the charging infrastructure. In the simulation model, the user type can be mapped among all with the parameter w_p. This parameter specifies the probability with which a user visits a public charging point in the currently simulating time interval. For many users with a charging point in private parking lots and at work, this value is lower than for many street parkers.

Figure 2 illustrates the effect of the charging probability w_p on the number of required charging processes, the number of performed charging processes and the number of non-performed charging processes while fixing other parameters of the baseline scenario. Further to the left on the x-axis, are rather the scenarios for street parkers. It can be seen that the graphs for the required and non-performed charging processes rise with a higher frequency of use while the number of performed charging processes from w_p > 0.5 % running parallel to the x-axis. With w_p = 0.5 % or less, all charging processes can always be carried out. Figure 2 reveals that doubling the frequency of use, approximately doubles the required charging processes and also increases the non-performed charging processes. This has a negative impact on the amount of financial resources required to expand the charging infrastructure. If the user of an EV also has a private parking space, it is highly recommended to equip this parking space with a charging device so that w_p is as low as possible. This means that considerably fewer public charging points are required.

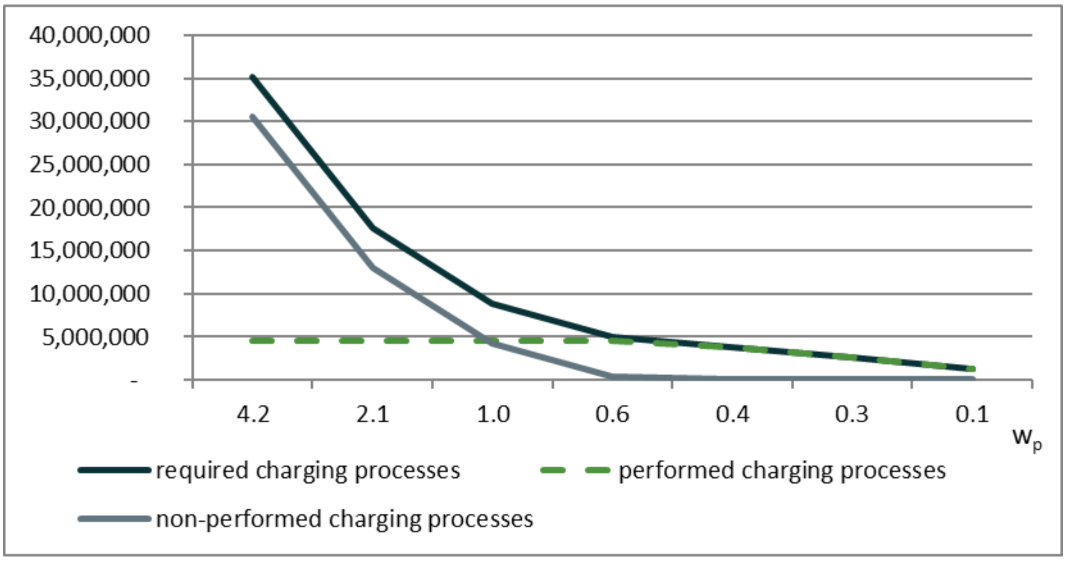

Figure 2: Impact of the using frequency on the required, performed and non-performed charging processes

The course of the overall walking distance of the whole year is shown in Figure 3. As w_p decreases from 4.2, the graph is relatively flat. The reduction in the frequency of use has therefore less impact at first, because there are still too many non-performed charging processes. Only if $w_p \leq 0.6$ %, the graph sinks more sharply and begins to approach the x-axis asymptotically. Therefore, measures to reduce the using frequency are not helpful with regard to the walking distance at very low w_p.

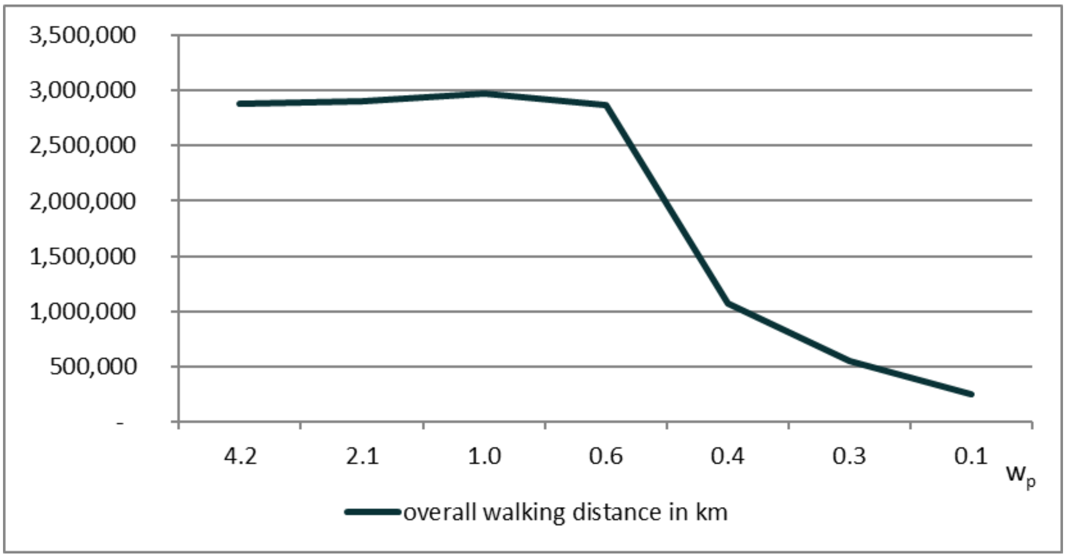

Figure 3: Impact of the using frequency on the overall walking distance

The impact of w_p on the average walking distance per performed charging processes is depicted in Figure 4. In comparison to Figure 3 small changes can be observed, because fewer charging processes are needed with $w_p \leq$ 0.5 %. Thus, the number of performed charging processes (see Figure 2) and the average walking distance are decreasing.

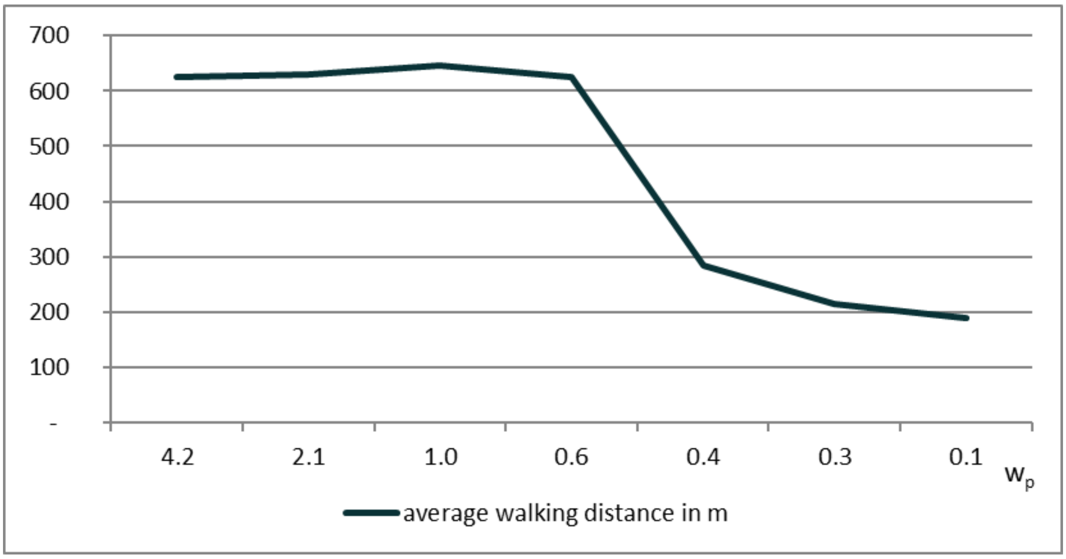

Figure 4: Impact of the using frequency on the average walking distance per performed charging processes

In general, it must be said that a w_p > 0.5 % should be avoided in the baseline scenario. If the frequency of use is too high, situations arise in which there is no free charging point available in the entire city. This can lead to considerable user complaints.

Billing model and parking duration

Basically, four billing models can be distinguished, which have the following characteristics:

- Flat rate: This is the simplest form of billing. It will probably dominate in the initial development phase since this billing variant does not require a costly connection to the existing IT systems of the charging station operators. A flat rate model supports the frequent use of the charging stations, which is highly desirable by policymakers in the initial phase of electric mobility, where there are few EVs on the streets. Since the flat rate leads to a long blocking of charging points, it is unsuitable for a larger number of EVs.
- Lump sum payment per usage: Here, the user pays a fixed amount for each charging process, regardless of the amount of energy charged and the duration of the charging process. Once paid, the user can theoretically charge and park for an unlimited amount of time. This billing variant leads to less blocking of the charging points than the flat rate. Since every charging process has to be paid, a user will not start charging if the battery is almost full. However, if the user only seeks for a parking position, this billing model can still be very attractive for him. Thus, the operator of the charging infrastructure should avoid parking without charging by usage rules.
- Billing on used kWh: The exact billing of the used energy puts high demands on the operator of the charging infrastructure. The difficulties arise among all due to regulatory and legal requirements, the effort for the connection to existing IT systems and due to requirements of calibration law, data protection and data security. With this billing variant, it can be expected that charging will only take place if it is necessary. The frequency of use of the charging points is lower compared to the previous two variants, if a parking without charging can be avoided.

- Billing on parking time: In contrast to billing on used kWh, the operator of the charging infrastructure can enforce higher margins with billing on parking time. Because users are more used to relatively high parking fees rather than to kWh prices, which are higher than the household electricity prices. In the case of a parking space that has been upgraded by a charging point, higher parking fees can be easily argued. The billing of parking time shows the lowest frequency of use of the charging infrastructure of all billing variants. However, this depends on the amount of the parking fee.

It can be seen that the different billing variants lead to a different usage duration of the charging infrastructure. This effect was also observed by Motoaki and Shirk (2017), as a fixed fee per charge was introduced. This situation can be represented in the simulation model with the parameter w_f. It is used to model the duration of blocking a charging point. Beside the tariff, also the charging technique can affect the parking duration (w_f) of an EV. For example, a DC fast charging point with 60 kW can charge a depleted 24 kWh battery in 24 minutes. A slow charging point with 1.2 kW needs 20 hours (He/Yin/Lawphongpanich 2014: 309).

Figure 5 shows the number of the required, performed and non-performed charging processes. Further into the left on the x-axis are scenarios with the billing on parking time. With w_f = 100 %, the charging point is only blocked for one hour. At w_f = 50 %, the charging process ends with a probability of 50 % in each hour. Further into the right on the x-axis are scenarios with a flat rate. With the exception for w_f, other parameters of the baseline scenario are kept constant (w_f = 13 % corresponds to the baseline scenario). It can be clearly seen that the number of required charging processes decreases slightly as w_f decreases since the user spends more time to charge or park his vehicle. The number of non-performed charging increases significantly from w_f < 13 % and approaches the number of required charging asymptotically. With $w_f \geq$ 13 %, all charging processes can always be carried out. It becomes clear that the flat rate or a lump sum per use are less suitable in the baseline scenario. The charging points are blocked for too long and therefore, the charging infrastructure would have to be expanded. In such situations, the billing on used kWh or ideally, the billing on parking time would be more suitable.

The billing model also has an effect on w_p. The probability to charge or park at a charging point is lower with pay per kWh or with pay per hour than with a flat rate. The results in Figure 2 and Figure 5 reveal that the usage duration w_f has a less distinct impact on the number of required and non-performed charging processes than w_p. Nevertheless, in addition to the usage duration, the frequency of use should be kept to a certain low level if low investment in the charging infrastructure is desired.

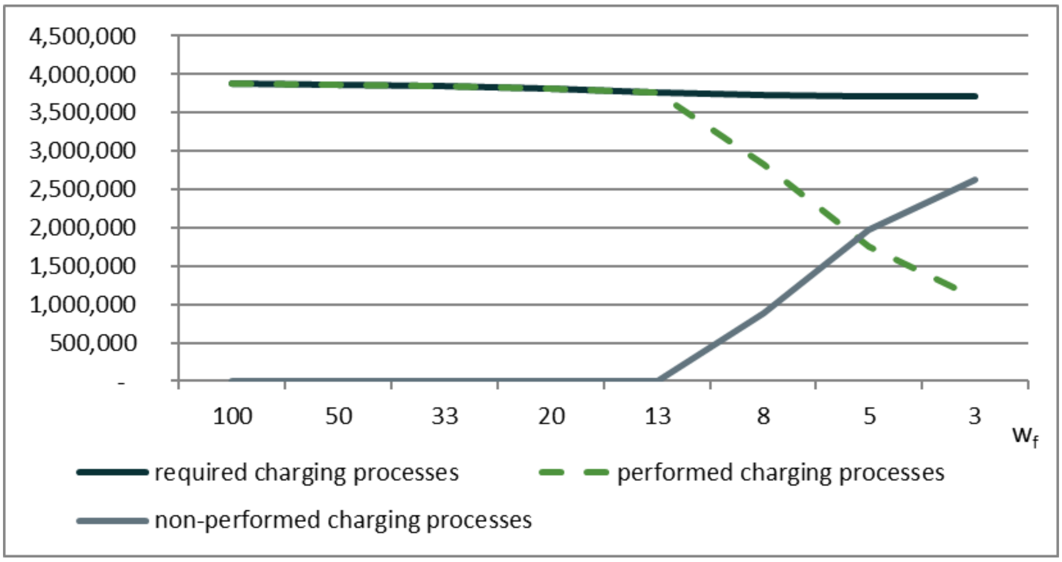

Figure 5: Impact of the charging duration on the required, performed and non-performed charging processes

Figure 6 also shows the course of the overall walking distance. With $w_f \leq$ 8 % the graph drops. This seems unusual; however, it can be justified by the fact that an increasing number of charging processes cannot be carried out at all as the charging infrastructure is not sufficiently dimensioned for these scenarios. This means that fewer trips to free charging stations are required. The graph in Figure 6 would have theoretically reached the x-axis if there was a satellite system on every square meter of the city with $l = n$. In practice, however, this is unrealistic. In an existing charging infrastructure with good values of the walking distance, measures to reduce the usage duration are only effective to a limited extent.

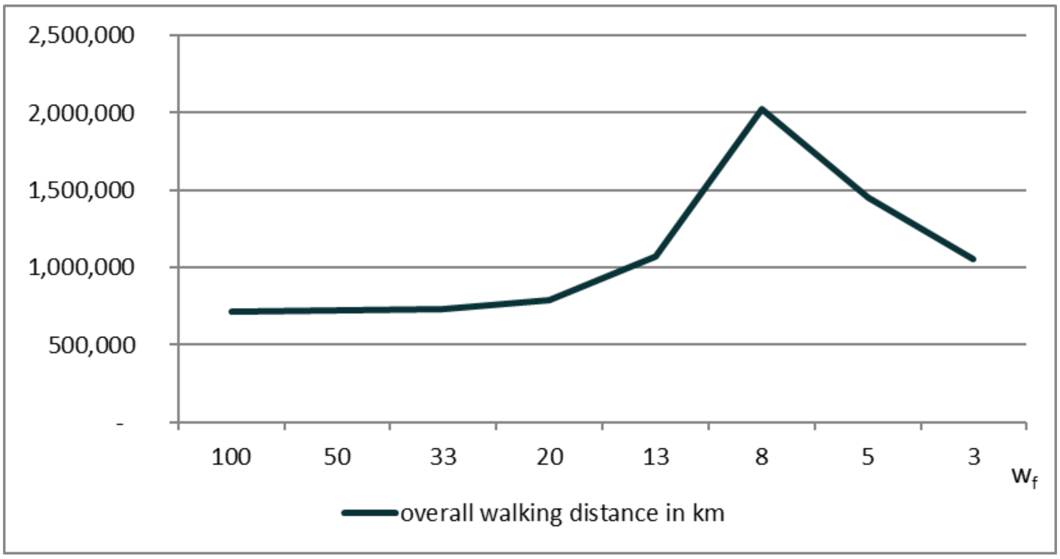

Figure 6: Impact of the charging duration on the overall walking distance

The impact of the charging duration on the average walking distance per performed charging processes is depicted in Figure 7. As stated above, all charging processes can always be carried out with $w_f \geq 13$ % (see Figure 5). This is the reason why the graph in Figure 7 is at fist relatively flat. With $w_f < 13$ %, the number of performed charging processes decreases and the graph in Figure 7 is increasing.

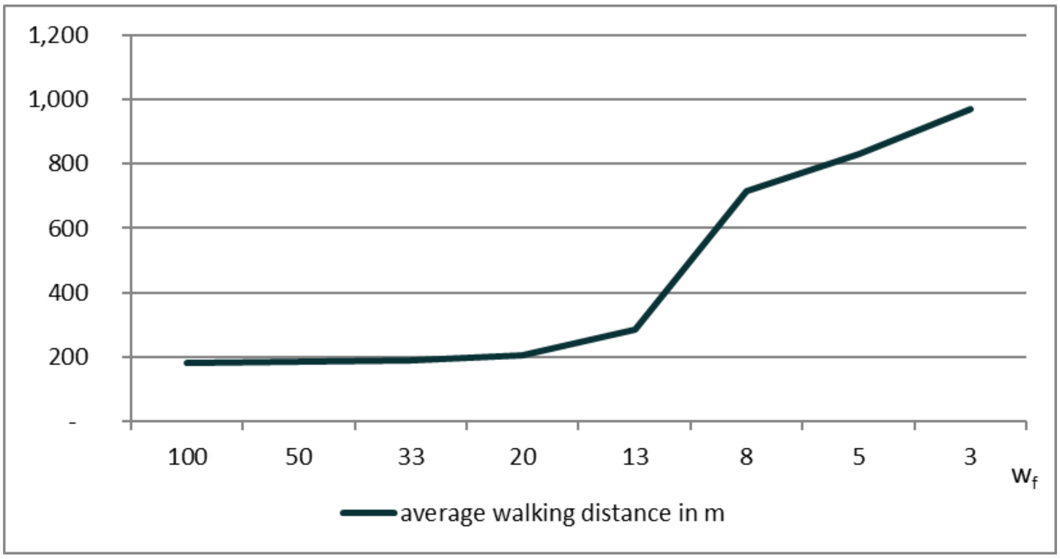

Figure 7: Impact of the charging duration on the average walking distance per performed charging processes

In the baseline scenario, a charging point in the immediate vicinity of the destination is almost always free with $w_f = 13$ %. Further expansion of the charging infrastructure would make little sense. However, it should be noted that the baseline scenario is on a critical point. A small increase in the usage duration will lead to non-performed charging processes. Thus, in practice the system should be monitored carefully.

Expansion of the charging infrastructure

A fundamental question is to which extend the charging infrastructure should be expanded with an increasing number of users. An extremely fast expansion leads to unnecessary costs because the charging points are hardly used. Extremely slow expansion, on the other hand, leads to user dissatisfaction and, in the worst case, can hamper the development of electric mobility in the city.

According to research from DLR and KIT, 33 public and semi-public charging points per 1,000 EVs are needed in 2020 (approx. 30 EV users per charging point) (Anderson 2016: 42). Other publications suggest much more charging points. The German 'National Platform for Electric Mobility' expects 14 to 16.5 EV users per public AC charging point (Nationale Plattform Elektromobilität 2018: 53). In the baseline scenario of this paper 100,000 users and 4,200 charging points are assumed which results in 23.8 EV users for each public charging point. In comparison: 30 EV users per charging point would result in 3,333 and 14 EV users in 7,143 public charging points in this paper. This shows that a variety of scenario exists for the number of required charging points.

Figure 8 shows the influence of the number of charging points with constant parameters of the baseline scenario with regard to the charging processes. As expected, the number of required charging processes remains almost constant and only drops slightly in the range from 700 to 3,500 charging points since in this range, the number of non-performed charging processes decreases. This is because a user who is already charging cannot charge again in this time interval. With 3,500 charging points and more, all charging processes can always be carried out. With 3,500 charging points and 100,000 users, the ratio is 28.6 users per charging point.

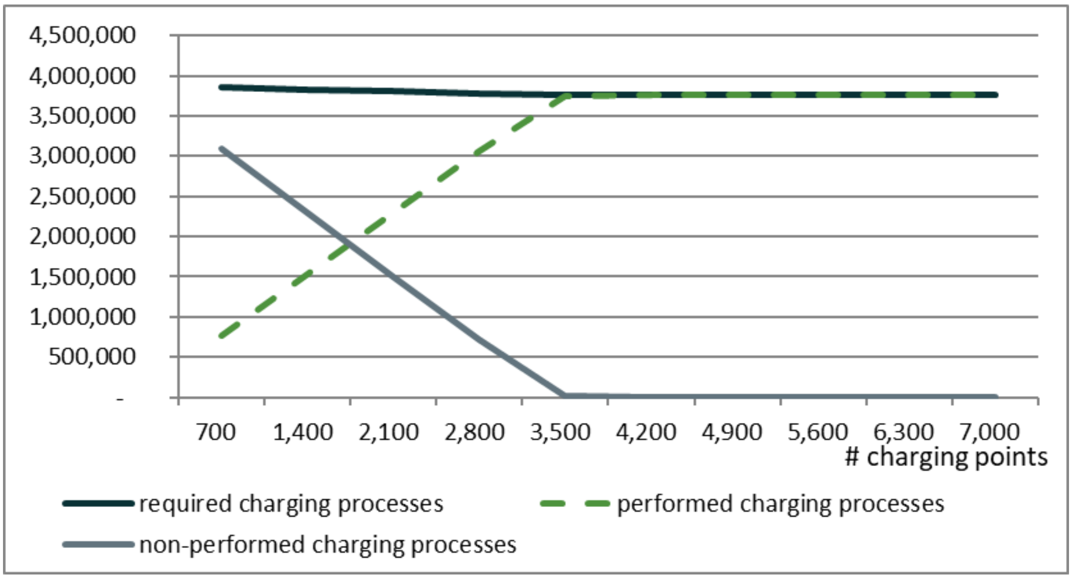

Figure 8: Impact of the number of charging points on the required, performed and non-performed charging processes

Figure 9 shows the course of the overall walking distance for the entire simulation period of one year. Here, the number of charging points is varied only. All other parameters of the baseline scenario are kept constant. Firstly, the graph rises since the number of non-performed charging processes decreases. The graph only sinks again from around 2,800 charging points (36 users per public charging point) because the higher number of available charging points means that free charging points are now more often located near the customer's destination.

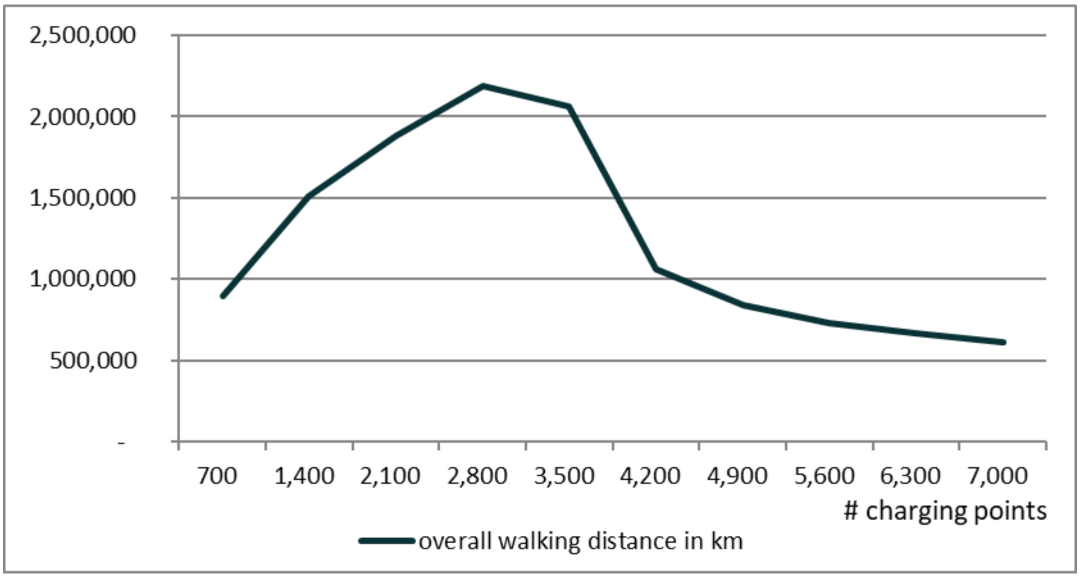

Figure 9: Impact of the number of the charging points on the overall walking distance

The course of the average walking distance per performed charging process is visualized in Figure 10. The curve drops relatively sharply up to 4,200 charging points. After that, the improvement slows down. According to Sheppard et al. (2016), a further expansion of the charging infrastructure only leads to a limited improvement and is not necessarily cost-optimal.

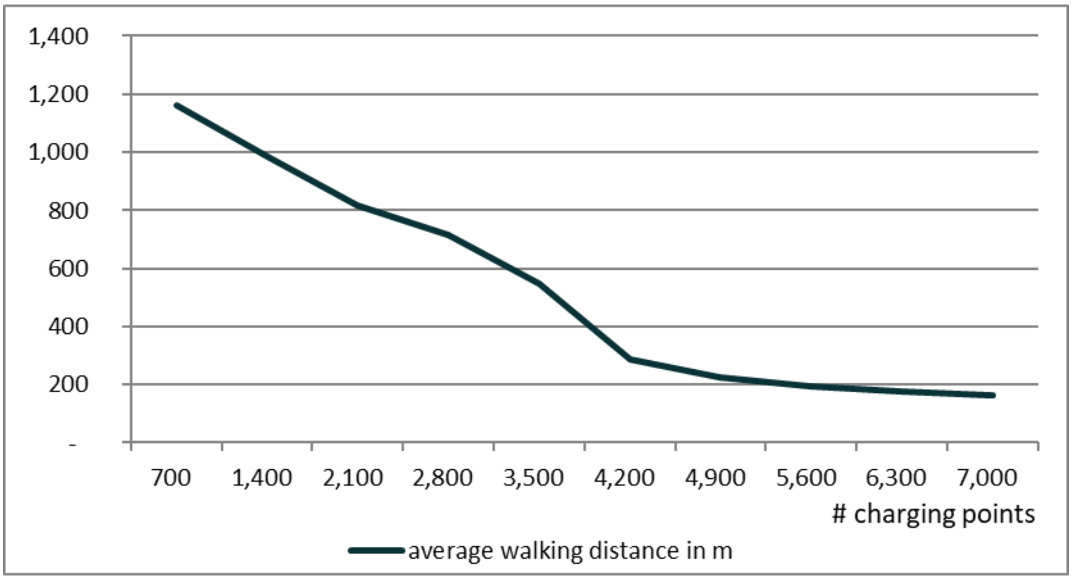

Figure 10: Impact of the number of the charging points on the average walking distance per performed charging processes

Type of charging stations

With regard to the types of charging stations, simple single charging stations can be distinguished from satellite systems. Satellite systems consist of a centre with up to four integrated charging points and additional connected satellites, which often only contain one charging point.

While a well-equipped single charging station costs around $5,000 (Sheppard et al. 2016: 11), a centre of a satellite system costs around $8,000. A satellite system becomes attractive when a larger number of satellites are connected to the centre since a satellite is very simple and therefore very cheap. In addition, the average installation costs per charging point are lower for satellite systems. As a result, it makes sense to choose a suitable charging station type for each usage scenario.

In contrast to single charging stations, satellite systems combine a large number of charging points in one place. With satellite systems, it is therefore more expensive to cover a large area in a way that the distance from the destination to the nearest free charging point is as short as possible. An exhaustive coverage of charging points can be realized more cost-effectively with single charging stations. It can be seen in Figure 11 that the overall walking distance is with an increasing number of charging points always lower with the extensive use of single charging stations in comparison compared to satellite systems. Only in the case of an extremely large number of satellite systems, which is anyway financially not viable, the graphs meet at one point (this area is not shown in Figure 11).

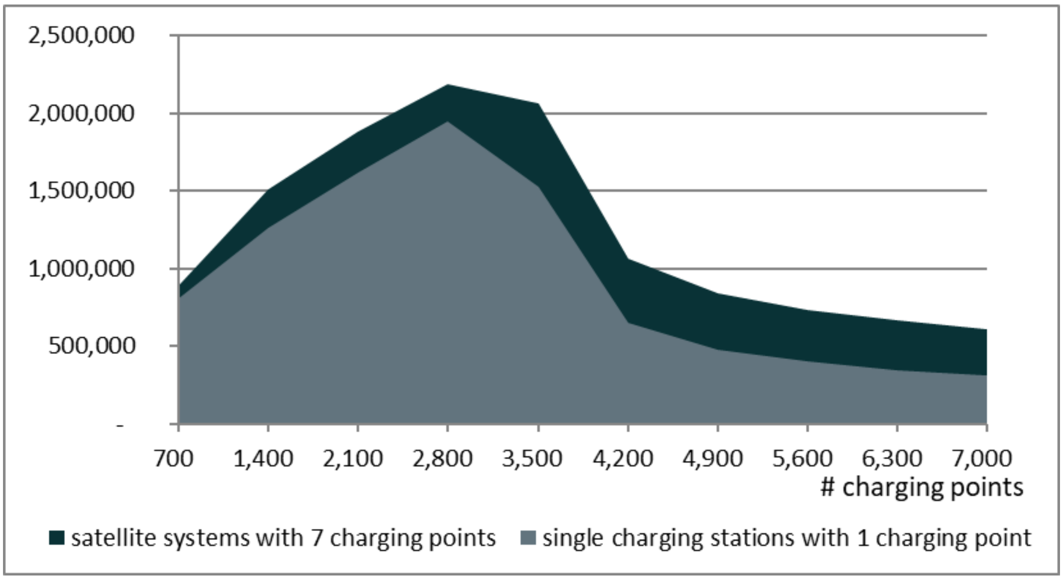

Figure 11: Comparison of charging station types based on the overall walking distance with a modifying number of charging points

However, as described above, a charging point at a single charging station is more expensive than a charging point at a satellite system. Since there are budget limits in practice, first of all, a comprehensive charging infrastructure with individual charging stations should be set up. One can start at an early stage to find centres in attractive locations such as in parking garages. Only with a rapidly increasing number of users should the centres be expanded to include satellites, if possible, and then only satellite systems should be set up.

Conclusions

On the basis of numerous experiments, in which various parameters of the baseline scenario were varied, derivations for the construction and expansion of a charging infrastructure could be identified. In addition, statements regarding the suitable billing methods and the optimal charging station types were made. The following key findings have been obtained:

- The simulation model is very sensitive to changes in the average usage frequency of the charging points; however, less sensitive to changes in the average charging duration in a charging point.
- A large number of street parkers can put a heavy load on the system. Therefore, users with an own parking place should equip it with a charging point if possible.

- With a rising number of users, billing at a flat rate quickly necessitates an expansion of the charging infrastructure. By changing the billing model (e.g. to billing based on parking time), an expansion can partly be avoided.
- If there are unfavourable shifts in the probability of occurrence for the usage duration and the usage frequency in areas where these probabilities are close to the limit of possible charging processes, the system tilts very quickly. The system is very instable in these areas.
- The sole establishment of single charging stations (one charging point per charging station) is optimal with regard to the evaluation criteria of this work. However, this variant is very expensive for a larger number of users. For this reason, individual charging stations should first be installed in order to cover a basic demand for charging infrastructure. Centres of satellite systems can be set up in a timely manner, which can be expanded to include satellites as required.

In the future, there will be extensions to the simulation model. Different user types should exist in parallel in the model with individual behaviour regarding the days of the week and the hours of the day. It is also planned to analyse the effect of charging processes in different scenarios on the electricity grid.

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