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How Many Fast Charging Stations Do We Need Along the German Highway Network?

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Summary

The number of fast charging stations along highways and their concrete allocation has a strong impact on the reliability and profitability of these systems. We provide a comparison of two applied approaches – one coverage oriented approach and an optimization based method – which can be easily transferred to other regions due to comparably low data requirement. Our results identify assumptions, which have strong impacts on the allocation problem and highlight which approach is advantageous in which environment.

Keywords: charging, EVSE, fast charge, modelling, optimisation, simulation

1 Introduction

Not later than 2013, when the directive of the European Parliament and of the council on the deployment of alternative fuels infrastructure was published [1] a broad discussion on the appropriate number of fast charging stations (in the following Electric Vehicle Supply Equipment – EVSE) emerged. In this directive, 150,000 public charging stations (including fast charging stations) were requested for Germany. The calculation of this number was discussed diversely. Among others, the well-known SLAM (fast charging network for axes and metropoles) project, which is funded by the German Federal Ministry of Transport and Digital Infrastructure (BMVI) provided comprehensively based numbers [2].

The number of fast charging EVSE is key to a successful market penetration of battery electric vehicles (BEV). It does influence both, the user acceptance (e.g. range-anxiety) and therefore the market penetration rate of BEV and equally the profitability of the charging stations. Furthermore, the decision for allocating fast charging EVSE along the network is complex and touches several aspects.

In our contribution, we discuss the relevant aspects that influence the allocation of fast charging EVSE along the highway network. We consider quantitative aspects such as flow volumes, economic operation of EVSE, different service levels, different ranges of BEV, waiting times, and underlying uncertainties. Finally, we give a comprehensive methodological comparison of two current models, which are based on simple data requirements and are therefore easy applicable to other regions. One of these two approaches is based on a coverage oriented heuristic and the other one on an optimisation technique.

2 Modelling approaches for assessing the required numbers of fast charging stations along the highway

There are two main perspectives when public charging infrastructure is allocated along the highway network: either it can be placed so it is distributed as evenly as possible to guarantee a maximal geographical coverage (and high reliability for customers) or it can be placed at locations with high charging demands to enable high utilization of the charging sites (see also [14]). For an optimal placement of charging infrastructure with the aim of maximizing its utilization, often complex mathematical models are used [3]. Although these models allow for optimal solutions they show higher data requirements and consequently longer computing times. In addition, some neglect minimal geographical coverage. Therefore, a second group of studies combines different criteria, as a minimal geographical coverage, local variations in user demand or even the importance of a highway section to connect metropolitan regions [9,11,12]. While a minimal geographical coverage can be determined by allocating an EVSE every X km along the highway network, for the determination of locally diverging charging demand the use of travel data with different complexities may be applied (see e.g. [9-13] for details).

Consequently, our main methodological contribution is to compare the results from a coverage oriented approach that allocates charging sites every X km along the highway and determines in a second step the number of charging outlet at each site, which is applied in [2, 9, 12 and 13] with optimization approaches such as the flow-refuelling location model (FRLM) [3]. In addition, we discuss the flexibility of and possible adaptations for both types of approaches.

3 Coverage Oriented Approach

3.1 Data

In the covering oriented approach, we combine the aims of a geographical coverage of charging infrastructure with a heuristic determination of local charging infrastructure needs. To this end, we first determine the overall number of charging sites that are needed for geographical coverage. As long distance trips happen mainly at highways [5], we assume that fast charging infrastructure is built next to highways. We use data of the German highway network from the Federal Highway Research Institute [6] and assume potential locations at the beginning of each of the 2,570 highway segments. In total, there are 121 highways in Germany with a total network-length of 13,000 km. By dividing this total distance by the assumed range, we directly obtain the overall number of charging sites of the coverage oriented approach.

In a second step, we have to determine the number of charging outlets per charging site. In the coverage oriented approach, we assume the number of charging events needed per year for the total BEV fleet being evenly distributed among the year (which is obviously not the case, but data availability is low) as well as to differ locally according to today´s traffic volumes. For the sake of harmonization, we use for the average charging demand per BEV and year the results of the optimization approach (see Section 4). However, for a sensitivity analysis, we estimate the number of needed charging events per year based on mobility data of private conventional cars from the German Mobility Panel (MOP). In this annual survey about 1,000 households report their daily travel patterns over a period of at least one week [9]. We use data from 1994 until 2010. The average annual vehicle kilometres travelled (VKT) in the dataset is 13,800 km (median 12,000 km). For deducing local differences in charging demand, we use traffic volume data of the German highway network from the Federal Highway Research Institute [6]. The data set contains average daily traffic volumes (in thousand vehicles per day) for every of the above mentioned highway segments.

Finally, we use a queuing model with the Kendall-notation M/G/s to size each charging sites. We size each charging site such that average waiting times of all users do not exceed five minutes. As discussed in Funke und Plötz 2017 [12], we analysed empirical charging data which led us to reject the assumption of exponentially distributed service times as often used in queuing models (see e.g. in [20]). We use a (truncated) normal distribution instead. In the coverage oriented approach we determine the distribution of charging times as function of the charging energy needed to continue the trip. For details see [12,16]. For a BEV with a range of 200 km (300 km) this results in a minimal charging energy of 10 kWh (12 kWh) for an additional distance of 55 km (66 km), a mean charging energy of 22.5 kWh (27 kWh) and a maximum charging energy of 28 kWh (36 kWh). Please note that energy charged publicly does not increase proportionally with vehicle range as we expect BEV users to limit the energy charged publicly to a minimum that is necessary to reach their final destination. For a range of 200 km, mean charging times are in the same magnitude of the input data for the optimisation model. However, for a range of 300 km we have to adjust our assumptions for harmonisation and use a mean charging energy of 23.5 kWh for the model comparison. We show the results of the "original" model (27 kWh mean charging energy, as shown above) separately in a sensitivity analysis. We assume a charging efficiency of 90% [12].

3.2 Method

For the geographical coverage we assume a maximum distance between two charging sites of $D_{CS} = 100\,km$ among every highway and calculate the number of needed charging sites for every highway $\#CS_{BAB}$ as function of its length l_{BAB}:

$$\#CS_{BAB} = \left\lceil \frac{l_{BAB}}{D_{CS}} \right\rceil \tag{1}$$

We assume one charging site to serve both directions of a highway (e.g. because they are allocated at highway exits).

We tried to harmonise most model assumptions of both modelling approaches. For the calculation of the average fleet charging demand, we assume the yearly number of fast charging stops of every vehicle to equal the number of days $D(L)$ on which driving distances exceed the electric range of the BEV. Following [12], we assume daily driving distances to be log-normal distributed. For every user, we use the mean μ and the standard deviation η of his logarithmised daily driving distances (see [12] for details) to calculate $D(L)$ as

$$\mathrm{D(L)} = \frac{\alpha 365}{1+\left(\frac{\mathrm{L}}{\mathrm{e}^{\mu}}\right)^{\frac{\pi}{\eta\sqrt{3}}}} \tag{2}$$

Local charging demand at each charging site is assumed to differ according to the traffic intensity TI of the particular highway-segment next to it (traffic intensity data acc. to [6], see previous section). The number of charging events demanded per year at a specific charging site i thus results from its relative traffic intensity $\frac{TI_i}{\sum_i TI_i}$, the assumed total BEV stock $\#BEV$ and the fleet average charging demand (as arithmetic mean of the user specific yearly charging demands $D_u(L)$ of all N analysed driving profiles):

$$CD_i = \frac{TI_i}{\sum_i TI_i} * \#BEV * \frac{1}{N} \sum_{u=1}^{N} D_u(L) \tag{3}$$

We assume that 10% of daily charging demand happens during rush hours (e.g. [15]) and that charging events are distributed equally over the year.

For the sizing of the each charging site, we apply a queuing model with the Kendall-notation M/G/s using normally distributed charging times such that average waiting times at all sites do not exceed five minutes during rush hours. We assume every charging site to have a maximum number of $s = 8$ charging outlets and multiple charging sites per charging site if necessary. The reasoning behind this approach is that even at charging sites with a high number of outlets there might be a single queue for one charging station with eight outlets, but not for all outlets, comparable to today´s situation at fuelling stations with multiple queues. M/G/s-Systems do not allow for analytical solutions, therefore we determine average charging waiting times based on the approximation described in [15]. The approximation is an extension of the Pollaczek-Khinchine-formula and is given as:

$$W_q^{\ M|G|s} = \frac{C^2+1}{2} * \ W_q^{\ M|M|s} \tag{4}$$

C describes the coefficient of variation of the underlying charging time distribution. For the normally distributed service times applied in this paper, $C \ll 1$, leading to lower waiting times (ceteris paribus) than for M|M|s queues.

4 Optimisation Approach

In Jochem et al. [3] a mathematical formulation for locating fast-charging stations along the German highway has been presented which is used in this paper and compared to the before explained heuristic. The formulation can be solved optimally with a standard ILP solver. For this paper IBM CPLEX was applied. The formulation determines the number and locations of EVSE that should be opened. A subsequent simulation than includes an algorithm for dimensioning the EVSE, i.e. for determining the number of outlets per EVSE. The algorithm tries to minimise waiting times, even during rush hours. It also assumes a pessimistic charging behaviour and includes that users might block the outlet longer than they are actually charging.

4.1 Data

The main input for the formulation are a flow matrix (based on www.etisplus.eu) that gives the number of cars driving from an origin O to a destination D as well as a set of possible locations for opening fast-charging stations. For determining the OD-matrix first a road network is necessary. Here we used the German highway network and the data of the Federal Highway Research Institute (Bast). We obtained the OD traffic flows by editing the data from Szimba [17] which is part of the European Transport Policy Information System (ETISplus) project, and contains traffic flows all around the European Union.

4.2 Formulation

The model ensures that a certain percentage of these OD-flows can fulfil their trip assuming an average battery capacity while minimising the number of charging sites that need to be located (set-covering model). For the comparison with the coverage oriented approach 100% of the flows are to be covered. The model can also be adapted to maximise the covered flow with a fixed number of charging sites that can be opened (maximum-covering model). Based on the results, the number of charging outlets at each site is determined and investigated in a simulation, as for example presented in [4]. For this work the set of possible charging site locations contains all existing highway service areas and highway exits.

The model assumes a set of nodes which constitute the network, denoted by $N = \{1, 2, \ldots, n\}$ and which also represent the possible locations for fast charging sites. All OD pairs are contained in the set Q. One path $q \in Q$ consists of several directional arcs $a_{j,k}$ between a starting node j and an ending node k. The set of all directional arcs on path q is denoted by A_q. f_q expresses the traffic volume on path $q \in Q$. $K_{j,k}^{q}$ denotes the set of candidate locations / nodes that can refuel the directional arc $a_{j,k}$ in A_q. The binary decision variable y_q is equal to 1 if the flow on path $q \in Q$ is recharged (and feasible), 0 else. The other binary decision variable z_i is equal to 1 if a charging site is built at node i and 0 else.

$$\min \textstyle\sum_{i \in N} z_i, \tag{5}$$

$$\text{s.t. } \textstyle\sum_{i \in K_{j,k}^{q}} z_i \geq y_q \ \forall\, q \in Q, a_{j,k} \in A_q, \tag{6}$$

$$\textstyle\sum_{q \in Q} f_q \cdot y_q \geq S = s \cdot \sum_{q \in Q} f_q, \tag{7}$$

$$y_q, z_i \in \{0, 1\} \ \forall\, q \in Q, i \in N. \tag{8}$$

The objective function (5) minimises the total number of ECSE to be installed. Constraints (6) assure that a flow is only labelled as “feasible/recharged” if every directional arc of each path q is “reachable” under the range constraint and the currently allocated facilities. Constraint (7) assures that at least the fraction s of the flow is covered by the opened EVSE. Constraints (8) are the domain constraints for the two binary decision variables.

5 Results and Discussion

Our comparison of methods is supported by a general discussion of aspects, which should be considered for allocating fast charging EVSE. The results of this analysis help to identify critical assumptions made (e.g. range, maximum waiting time, coverage of all flows) and the constraints (e.g. efficiency of vehicles in changing weather conditions, holiday traffic) that need to be taken into account.

5.1 Scenarios

We have defined two test scenarios, one for 2020 with 1 million BEV (2.5% market share) and the second representing the year 2030 with an expected number of 7 million BEV (17.5% market share) in Germany. The results of both models show similar values. When applying the two approaches with harmonised assumptions, most resulting indicators of charging stations are already alike (cf. Table 1). The input data and results for the coverage oriented approach with original and therefore not harmonised assumptions, is shown in parentheses.

Table 1: Exemplary assumptions and results of the model comparison for two scenarios.

	2020 (1M BEV)		**2030 (7M BEV)**		**Model parameter**
	Optimisation model	**Coverage oriented approach**	**Optimisation model**	**Coverage oriented approach**	
BEV-Share	2.5%	2.5%	17.5%	17.5%	Input
Average BEV range	200	200	300	300	
Flow Covering	100%	100%	100%	100%	Input
Battery capacity [kWh]	ca. 36	ca. 36	ca. 54	ca. 54	Input
BEV efficiency [KWh/km]	0.18	0.18	0.18	0.18	Input
Average charging rate [kW]	50	50	130	130	Input
Average gross charging time [min]	30	30 (30)[1]	12	12 (14)	Input
Average number of charging events per BEV and year	-	19.0 (15.9)	-	9.0 (8.9)	Input[2]
Total number of EVSE	164	211-491[3] (433)	97	211-603 (653)	Output
Average number of outlets per EVSE	40	7.1-16.5[4] (6.8-13.9)	106	7.1-20.2 (7.3-22.6)	Output
Total number of outlets	6560[5] (1508)[6]	3492 (2936)	10282 (1893)	4270 (4778)	Output
Average number of chargings per EVSE and day	318	106-2474 (101-207)	1784	287-820 (261-808)	Output
Average gross charging time (incl. waiting times) [min]	34[7]	35	19	17 (19)	Output

[1] This indicates the input without hamonisation.
[2] For the harmonisation of the model inputs, the average number of charging events per BEV and year was calculated from the results of the optimisation model.
[3] The minimum number of 211 charging sites is determined by the geographical coverage. As a maximum number of eight charging outlets per site is assumed, on highway segments with high charging demand several sites could be placed at one charging site or distributed along the highway segment, thus leading to a maximum distance below the assumed 100km. The maximum number indicates the situation where every charging site consists of only one charging station with a maximum number of eight charging outlets.
[4] For an explanation of the interval see Footnote 3.
[5] The comparatively high numbers of outlets result in reducing waiting times to an absolute minimum, even for the peak times. In practice, the installed number outlets would be much closer to the minimum given below.
[6] This indicates the minimum number of outlets with a system-optimal charging behaviour.
[7] Includes a delay caused by the user by blocking the outlet longer than necessary.

From Table 1 we can follow that the optimising approach leads to fewer EVSE. This is not astonishing as in both scenarios the assumed range for the BEV exceed the maximum distance between two EVSE in the coverage oriented approach and the optimisation model will only choose the necessary locations. Note that it is also possible to force the maximum distance in the optimisation model by reducing the charging rate to e.g. 100 km. Due to less EVSE, the algorithm in the simulation that comes after solving the optimisation model locates more outlet at one EVSE. Based on queuing theory, it is beneficial for expected waiting times to have a few larger sites than more small ones. For the coverage oriented approach a minimum and a maximum number of charging sites is given as the approach locates charging sites with a maximum of 8 outlets, but often more than these 8 outlets are necessary within 100 km of a highway. It is left for the expert / practitioner to decide if one larger or several smaller sites are opened. As the simulation uses the weakly driving patterns as presented in [4] as the input, the peak on Friday afternoon basically determines the number of outlets necessary to reduce the waiting times to a predefined minimum. In the coverage oriented approach, more or less the average peak is considered and not the highest peak on Friday. This also leads to a difference in the number of charging outlets. Note that in both approaches the assumptions can be adapted.

The geographic allocation of charging sites is presented in Figures 1 and 2. The results of the coverage oriented approach were mapped to the list of possible locations (highway exists) used for the optimisation model. It can be seen that not only the number and sizes of EVSE differ, but also their locations. On some highway connections the optimisation model allocates more EVSE (highways with high flow volumes such as A8 in southern Germany) than the coverage oriented model and in other areas (mainly with low flow volumes) the opposite is the case. Also, it becomes clear again that the optimisation model needs significantly less EVSE for the expected flows in 2030. It can be assumed that with an increasing battery capacity and charging rate many of the EVSE located by the coverage approach will not be necessary and might therefore not be used to capacity, but can help reducing the range anxiety, for example. Note that when the optimisation model is run with a maximum distance of 100 km for the year 2020, 339 EVSE must be opened.

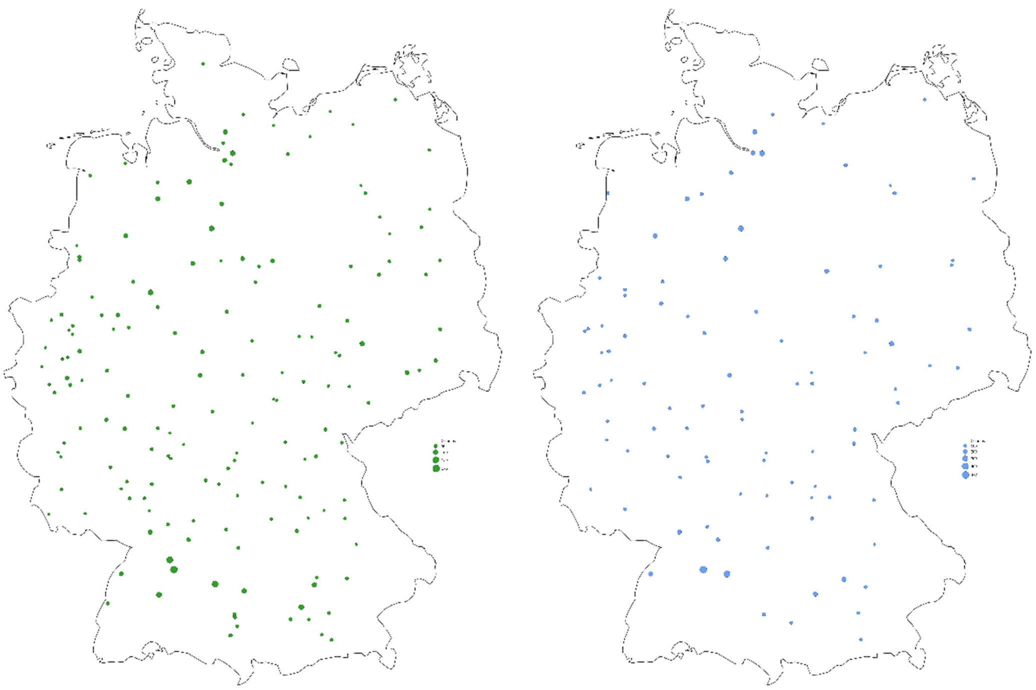

Figure 1: Results of the optimisation model for 2020 (left) and 2030 (right).

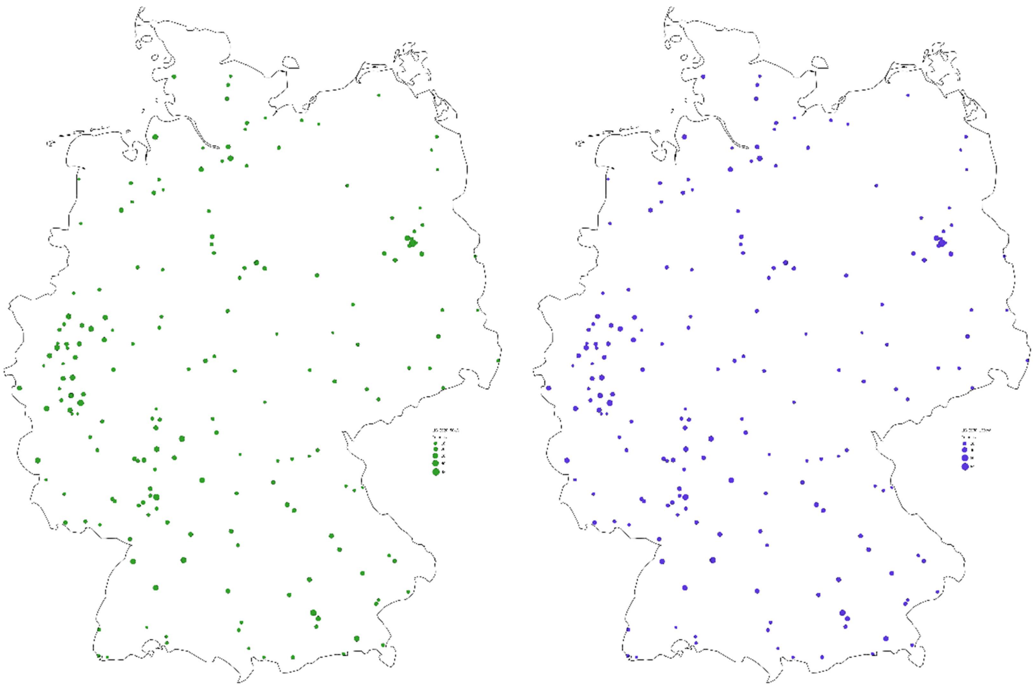

Figure 2: Results of the coverage oriented approach for 2020 (left) and 2030 (right).

5.2 Modell comparison

In Table 2 five characteristics are qualitatively compared for the two approaches. The main advantages of the coverage oriented approach are the publicly available data and the high adaptability due to relatively low complexity of the model use as well as the low computation time. However, as consequence of the intended model logic to place charging sites according to the simple criterion of a maximum distance between two charging sites, the results does not optimize the placement of the charging sites according to potential charging demand. In addition, the model solution is given as highway segment and not as a specific charging site. On the one hand, the end of a highway segment could be predestined for location charging sites, e.g. as it might be accessible from both sites of the highway. On the other hand, the lack of an optimal charging site might be used as an interface to the optimisation model, in a sense that the coverage oriented approach is used for a first assessment of suitable highway segments – for a given maximum distance of the charging sites –, while the optimisation approach uses the information gained from the coverage oriented approach for the determination of optimal charging sites. Note that this will probably still lead to non-optimal solutions compared to solving the optimisation model in the first place.

While implementing and solving the optimisation model is straightforward, it is perceived as difficult by many practitioners. The main advantage is that the model can be solved optimally and therefore determines the optimal locations for fast charging EVSE. It is also easy to adapt the model, for example by adding additional constraints, changing the objective function or including one or more additional objectives leading to a multi-criteria problem. As all the input parameters can be separated from the model itself, it is also simple to change parameters and rerun the model. The optimisation model determines the solution in only a few minutes. The simulation then needs significantly longer with around an hour. Still, computation times are practical and allow for several runs within a day.

Table 2: Comparison of the two methods.

	Optimisation model	Coverage oriented approach
Complexity	o	o
Optimality of the solution	+	o/-
Data input	o	+
Flexibility / Adaptability	+	+
Computation time	o/+	+

To sum up, due to their flexibility both approaches are suited for the testing of a magnitude of influencing factors on charging infrastructure demand. While the optimisation model is perceived as being more complex, it determines the optimal solution for a defined input within minutes. On the other hand, the coverage oriented approach determines solutions fast and only needs public data as input.

5.3 Main influences and sensitivity analysis

The results of both approaches directly depend on the assumptions on charging behaviour. In this section we give an overview over the most important factors influencing charging demand and discuss their effects on charging infrastructure demand in the context of a sensitivity analysis of the presented results. Table 3 shows influencing factors on charging infrastructure demand and how they are addressed in both approaches.

Table 3: Influencing factors of charging infrastructure demand and how they are addressed in both models.

	Optimisation model	Coverage oriented approach
Charging behaviour	"Rational" charging behaviour deduced from driving behaviour.	
Share of BEV	Model uncertainty.	
Locally diverging charging demand	Given by OD matrix.	Proportional to traffic intensity on highway segments.
User specific vehicle range	Not addressed, but can be included relatively easy when the information is available.	Not addressed.
Rush hours	Included in the flow pattern over the week.	Increased demand during rush hours (10% of daily charging demand).
Yearly variation of charging demand	Not addressed.	
Charging power	Addressed by the two scenarios and the sensitivity analysis.	
Psychological aspects	Can be included by reducing the range, also in the simulation for modelling the charging behaviour.	Implicitly addressed by coverage orientation.

Public fast charging infrastructure demand depends on 1) share of BEV, 2) actual charging behaviour and 3) the level of service to be guaranteed.

In both our models, we assume "rational" charging behaviour. That means, we determine charging needs based on actual driving behaviour of conventional vehicles and assume that individuals charge the amount of energy needed to finish their trip. In addition, we assume charging demand to differ locally according to today´s driving. These assumptions come with the following uncertainties. First, the driving behaviour of BEV users could be different from conventional car users as BEV need high mileages to economise against conventional vehicles, thus leading to higher charging demand than predicted. Second, although the fast charging of BEV might be economic, users might have to substitute fast charging needs by conventional driving thus leading to lower charging infrastructure demands (ceteris paribus). Third, actual charging behaviour might differ from "rational" charging demand, e.g. due to range anxiety. This might lead to users recharging more often than needed [19]. We analyse this effect in a sensitivity analysis shown in Table 4 exemplary for the coverage oriented approach.

Charging infrastructure demand further depends on the level of service to be guaranteed. That means sizing charging sites for maximum demand, e.g. during vacation, would lead to low waiting times for the users all over the year implying a high infrastructure demand. However, the infrastructure operator will aim at a high occupation rate to maximize his profit.

To show the influence of the assumptions on the results, we conducted a sensitivity analysis for the coverage oriented approach. We analysed the effects of a higher geographic coverage, a higher charging power as well as the effect of a charging behaviour, where users charge more often but recharge a lower amount of energy. The results are shown in Table 4.

Table 4: Sensitivity analysis for the coverage oriented approach.

	Scenario 1 Mio BEV		**Scenario 7 Mio BEV**	
Parameter variation	**No of charging outlets**	**No of charging sites**	**No of charging outlets**	**No of charging sites**
D_{CS} **= 25 km**	+10%	+42%	+5%	+28%
D_{CS} **= 50 km**	+3%	+14%	+1%	+8%
Charging power doubled	-51%	-42%	-52%	-44%
Charging energy halved, charging events doubled	-7%	-3%	-6%	-5%

Shown are the changes in the number of needed charging sites as well as in the sum of necessary charging outlets. For both the tendencies are the same, however, the changes are lower for the number of charging outlets in most of the cases. Due to the high demand of 1 Mio BEV, the effects of halving the maximum distance of two charging sites to $D_{CS} = 50$ km are comparatively low. The effect of charging power is as expected. By doubling charging power and thus halving charging time, charging infrastructure demand increases proportionally with regard to charging outlets and almost proportionally for charging sites. This means that increasing the charging power might be a lever to lower charging infrastructure demand, although the higher cost must be taken into account. Finally, a change of charging behaviour ("charging energy halved, charging events doubled") leads to a reduction of charging infrastructure demand of about 5%. This underlines the importance of short charging times, however, the overall effect is limited.

6 Conclusions and Outlook

The contribution of this paper is twofold. First critical assumptions when allocating fast charging EVSE along the highway are identified and, second, results from a coverage oriented approach that allocates EVSE every 100 km along the highway with those from a more sophisticated mathematical optimisation approach are compared and the advantages of each method are highlighted. For both approaches most assumptions have a significant impact on the results.

One key result is that especially in the beginning market diffusion of BEV, an optimal allocation of (fewer) fast charging EVSE will increase their profitability significantly.

The optimisation model has additional potential for adaptations. One aspect that will be investigated in future research is the sizing of charging sites within the model instead of within the subsequent simulation.

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