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# Optimizing the allocation of fast charging infrastructure along the German autobahn

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***Abstract*** *The allocation of fast charging stations is a severe investment for the future mobility system with electric vehicles. The allocation of the first charging stations influences the profitability of all other fast charging stations and should therefore be perfectly arranged. Hence, we applied and extended the flow-refueling location model (FRLM) developed by Capar et al. (Eur J Oper Res 227(1):142–151, 2013) to the German autobahn with a focus on the states Baden-Württemberg and Bavaria with 595 nodes and 3569 highway km. Our model extension comprehends mainly the inclusion of the access distance for traffic participants to their closest network node. In order to analyze the impact of different vehicle ranges and the desired coverage of flows we defined four scenarios. The results indicate the significance of vehicle range and the desired coverage value. 20 optimally allocated fast charging stations along the highways lead already to a coverage of about 62 % (100 km vehicle range) or even 83 % (150 km vehicle range) of all trips. A complete coverage of trips requires at least 50 (150 km vehicle range), 77 (100 km vehicle range) or even 84 (70 km vehicle range) fast charging stations. The last 30 % coverage leads to a tripling of charging stations. Furthermore, a first estimation of the corresponding surcharge for fixed costs per charging process amounts to about 20 % of the total costs for a charging process.*

***Keywords:*** *Fast charging station, Electric vehicle, Optimization, Allocation, Germany.*

*JEL Classification M20 _ C61 _ O33 _ P48*

## 1 Introduction

Electric vehicles (EV) are seen as a promising technology to mitigate greenhouse gases, to increase energy efficiency and to decrease oil dependency of the transport sector as well as to relieve mega cities from local air emissions and smog. However, their market penetration is still at the very beginning and their market success unclear. This is mainly due to their limited range and their high purchase price (Plötz et al. 2014a, b). Battery prices are currently declining significantly (Nykvist and Nilsson 2015) and the variable costs of EV are considerably lower compared to conventional vehicles for most countries. This is why EV might succeed in the future market. However, the challenge of limited range remains so far—at least for battery electric vehicles (BEV).

According to current mobility data most trips by conventional vehicles are technically replaceable by EV if a recharge at home or at the working place (at usual household sockets) is possible (Babrowski et al. 2014). However, at least once a year most of these vehicles are used for long distance trips (e.g., Chlond 2012).

Therefore, the charging at household sockets (restricted to 3.5 kW, i.e., mode 1 or 2 according to IEC 61851) and even at public charging stations (usually restricted to 22 or 43 kW, i.e., mode 3) is too time consuming for these trips. Fast charging stations (restricted to about 100 kW direct current, i.e., mode 4) allow 80 % recharge of the battery within about 15–20 min (Qian et al. 2015) and are therefore almost comparable to conventional refueling procedures (Schroeder and Traber 2012). Because fast charging processes have stronger negative effects on battery lifetime, we assume that fast charging is mainly used during long distance trips. Therefore, they should be placed along highway corridors.

A rollout of fast charging stations has already begun in several states—also in Germany (IEA 2013). Unfortunately, these stations are currently not interoperable. In Germany three competing technologies are in the market (e.g., superchargers, CHAdeMO, and combined charging system). The European Commission is supporting a rollout of fast charging stations with the combined charging system (COM (2013) 0018). The decision where fast charging stations should be allocated is serious, it has an influence on the allocation of further charging stations and it might be decisive for the market success of this technology. Furthermore, the charging infrastructure is expensive and its utilization level is going to be low for the coming years. The decision for a location is most probably final as a change of location is costly. Hence, an optimal allocation seems to be inevitable.

The objective of this paper is to optimize the allocation of fast charging infrastructure for EV along the German autobahn based on empirical vehicle flow data for different vehicle ranges and different flow covering values. For this purpose we extended the formulation of the flow-refueling location model (FRLM) developed by Capar et al. (2013) and applied it with empirical data of the German highway network. We are focusing our study on the two federal states of Germany, i.e., Baden-Württemberg, and Bavaria and give first cost estimates. Hence, our contribution to current literature is threefold: we introduce a new developed extension to the FRLM, apply it to the German highway system, and give fist estimations of the underlying costs.

We expect that plug-in hybrid electric vehicles (PHEV) and range extended electric vehicles (REEV) do not use fast charging stations and prefer petrol stations for long distance trips. We therefore focus our study on BEV. The consideration of PHEV and REEV is straightforward as long as they have a similar all electric range (they even might enlarge their range by using their combustion engine).

The structure of the paper is as follows. First, we give a literature review before we introduce our approach in Sect. 3, which includes an outline of data and the applied method. Our results (Sect. 4), discussion (Sect. 5), and conclusions (Sect. 6) complete the paper.

## 2 Literature review

In the research field of logistics with stationary demand, node based models have been widely applied (e.g., the maximum covering location model (MCLM) by Church and ReVelle 1974). These node based models consider, however, only (weighted) nodes and not the underlying flows between nodes, which is crucial in transport demand models. This was criticized by Hodgson (1990), who proposed a flow capturing model. If a node based model is applied for our optimizing problem of allocating fast charging stations along the highway, the allocation of fast charging stations is more probable in major cities where a significant traffic volume takes place, but long distance trips might be underrepresented. Main connectors between long distant cities are attached with less weight in the calculation than in flow-based approaches, which

might lead to gaps in the network. Hence, flow based models are advantageous for our problem, but require the knowledge on traffic movements from all origins to their corresponding destinations (OD flows). This data is highly sensitive to privacy and collection is costly. Therefore, traffic planners developed the four step model to estimate these OD flows (e.g., Ortúzar and Willumsen 2011; Fotheringham and O'Kelly 1989). This model usually consists of the following four steps:
1. Traffic generation (estimation of number of trips for each node, i.e., origin),
2. Traffic distribution (choice of destination),
3. Mode choice (traffic distribution to different modes), and
4. Traffic assignment (routing).

These four steps lead to a complete OD flow matrix convenient for traffic policy evaluation or infrastructure expansion requirements etc. (Szimba 2008). In addition, research is more and more using traffic count data to estimate OD flows (cf. Willumsen 1978; Ratnayake 1988). Those OD flow matrixes are a convenient foundation for our allocation problem.

Based on the node-based MCLM by Church and ReVelle (1974), Hodgson (1990) integrated the flows into his considerations and developed the flow capturing location model (FCLM) as the first approach applicable to the allocation of refueling stations for passenger cars. An OD flow is said to be covered if a location is chosen on the path from O to D. In the FCLM a specific demand is assigned to every OD pair. To reduce the number of potential flows from $n^2$ (or even more) to $\frac{n\,(n-1)}{2}$ Hodgson made the following assumptions:

1. All flows in the network are OD flows and there are no cycles.
2. The complete flow of one OD pair follows the same path through the network.
3. OD flow matrices are symmetric. That means that the OD flow from i to j is similar to the one from j to i and therefore flows can be assumed to be undirected.
4. Flows within one zone do not need to be covered.

The model locates facilities only at the network nodes with the argument that the flows have to pass the nodes when using the corresponding arcs and nodes having the additional advantage that they might cover crossing flows.

There are several extensions of the FCLM in literature (Hodgson 1998). Hodgsonand Rosing (1992) present a hybrid model based on the p-median formulation (cf. Christofides 1975) that considers demand at arcs as well as nodes. Berman et al.(1995) propose several extensions based on the assumption that drivers are willing to take short detours in order to reach a location. The first extension allows the flows to deviate by a factor D. In a second formulation an OD flow is said to be covered if there is a location with an additional distance of D. In a third model the overall deviation D is minimized. Further extensions are Hodgson and Rosing (1996), Hodgson and Berman (1997), Hodgson et al. (1996), and Kuby and Lim (2005). To the best of our knowledge, there are only two approaches for locating petrol stations by Goodchild and Noronha (1987) and Bapna et al. (2002).

Kuby and Lim (2005) developed the flow-refueling location problem for alternative-fuel vehicles (FRLP or FRLM) which optimally locates filling stations for alternative fuel vehicles, e.g., BEV. The model incorporates the driving range of the vehicles in order to maximize the number of successfully covered trips (OD flows). An OD flow is only covered if there are sufficient fueling stations along the considered flow, which satisfy the constraint on the assumed driving range. Lim and Kuby (2010) show that the formulation of the FRLP cannot be solved for larger networks and they, therefore, propose several potential heuristics. In addition, Kuby and Lim (2007) allow in an extension of the FRLP to locate facilities on the arcs of the network. Kim and Kuby (2012) additionally included the willingness of the driver to make a small detour to reach a location. Wang and Lin (2009) and Wang und Wang (2010) reformulated the FRLP into a set-covering model to locate filling stations in order to cover 100 % of the OD flows. Capar and Kuby (2012) proposed a reformulation of the model making it dissolving even faster than the heuristics by Lim and Kuby (2010) and allowing to incorporate a large number of variables and constraints. In addition, Upchurch et al. (2009), Kuby et al. (2009), Upchurch and Kuby (2010), Shukla et al. (2011), MirHassani and Ebrazi (2013) and Capar et al. (2013) use the FRLP for strategic decision making in this research issue. However, none of them applied the model to the German highway network or made the model extensions described in the following or combined the optimization with an estimation of underlying costs per charge.

## 3 Method and data

### 3.1 Method

In this paper we are using the arc cover-path-cover model of Capar et al. (2013) as a basis. In their model they use the following assumptions.

1. The complete flow of one OD pair follows the shortest path through the network.
2. The traffic flows between two nodes of one OD-pair are known in advance.
3. The drivers have full knowledge about the locations of the refueling stations along their path and refuel sufficiently to successful overcome the roundtrip.
4. Only network nodes are used as possible locations for refueling stations.
5. All vehicles have similar identical driving ranges.
6. The fuel consumption is directly proportional to the distance traveled.
7. Refueling stations can serve an infinite number of vehicles.

These assumptions are not as limiting as they appear for our highway network application. Especially assumptions 1–3 are the result of recent navigation systems in cars (at least in uncongested networks). Assumptions 4–7 are reliable, technical simplifications of reality. The model is even extendible to overcome assumptions 1–7 if necessary—however, with a significant increase in computing time (cf. Capar et al. 2013). The model of Capar et al. (2013) contains the same assumptions for the initial charging status of the vehicle as the original FRLM but it is implemented differently. The formulation used by Capar et al. (2013) determines the initial charging status with the help of the location of the first upstream charging station of the corresponding OD flow. If there is for example a charging station at the origin, the model starts the roundtrip with a complete state of charge (SOC = 100 %). If there is no charging station at the origin, vehicles start with the remaining SOC of the battery which has been observed at the end of the previous trip. With the assumption of constant energy consumption and roundtrips (constraint (3) and (6)) it is secured that each trip will at least start with SOC of 50 %.

The formulation of the problem is as follows.

$$Max \sum_{q \in Q} f_q y_q \tag{1}$$

Subject to (2)

$$\sum_{i \in K_{j,k}^q} z_i \geq y_q \quad \forall\, q \in Q, \qquad a_{j,k} \in A_q$$

$$\sum_{i \in N} z_i = p \tag{3}$$

$$z_i, y_q \in \{0,1\} \ \forall\, q \in Q, \qquad i \in N \tag{4}$$

Notation:

**Parameters**

| | | |
|---|---|---|
| $a_{j,k}$ | = | A directional arc starting from node j and ending at the node k |
| $A_q$ | = | Set of directional arcs on path q, sorted from origin to destination and back to origin |
| $f_q$ | = | Traffic volumes on the shortest path between OD pair q |
| $i, j, k$ | = | Indexes for potential facilities at nodes |
| $K_{j,k}^q$ | = | Set of candidate sites/nodes, which can refuel the directional arc $a_{j,k}$ in $A_q$ |
| $M$ | = | Set of OD nodes where M ⊆ N |
| $N$ | = | Set of nodes which constitute the network, N= {1,2,…n} |
| $p$ | = | The number of stations to be located |
| $q$ | = | Index of OD pairs |
| $Q$ | = | Set of OD pairs |

**Decision variables**

| | | | |
|---|---|---|---|
| $y_q$ | = | 1 | if the flow on path $q$ is recharged (and feasible) |
| | | 0 | if not |
| $z_i$ | = | 1 | if a service station is built at node $i$ |
| | | 0 | if not |

The objective function (1) of the model maximizes the flow volume of all flows that should be covered. The new approach of the model formulated by Capar et al. (2013) can be seen in the constraints (2) which allow to formulate the FRLM without the calculation of an initial refueling station-combination. The constraint (2) assures that a flow is only labeled as "feasible" if every directional arc of each path $q$ is "reachable under the range constraint and the currently allocated facilities. This is assured by a separate instance of constraint (2), which applies for all directional arcs on each path $q$. Path q is defined as the combination of arcs, which are on the shortest way from O to D and back. In other words: If every directional arc of path $q$ can be "reached" after recharging at one of the last upstream nodes, $i$, this path is ''feasible''.

Hence, the set of node combinations j, k, where charging stations should be placed in order to enable to travel the whole distance of path q ("cover sets'' cf.
Table 2) has to be calculated before the optimization model is applied. Obviously, these sets depend on the vehicle range R. Constraint (3) assures that p stations are located. The constraints (4) define the two binary decision variables, i.e., $y_q$, which indicates the feasibility of the flow on path q (depending on,$K_{j,k}^{q}$), and,$z_i$, which indicates whether a charging station is built at node i or not. This maximum covering formulation might be converted to a set-covering formulation (see below).

In our approach we used this formulation of Capar et al. (2013) and made the following two extensions: (1) we include access distances from O and D to its closest network node and (2) we use different OD data which will be explained below.
Furthermore, we applied two different versions of the FRLM: The set-covering and the maximum-covering formulation. Both of these versions contain the sets of possible node combinations$K_{j,k}^{q}$.

1. In the maximum-covering version, the objective function maximizes the aggregated OD flow-volume (total traffic flows) covered while the constraints are fixing the number of placed stations.
2. In the set-covering version the objective function minimizes the total number of stations while the constraints are fixing a specific minimum value for the aggregated OD flow-volume which has to be covered. For example a minimum percentage of 80 % of all traffic flows in Baden-Württemberg and Bavaria should be covered.

We excluded some nodes of the highway network to be considered for fast charging stations. These include, for example, highway nodes with no driveway and exit like motorway junctions or roads with only a driveway or an exit. These nodes are excluded in our model.

For the following modeling the IBM ILOG CPLEX Optimization Studio (CPLEX) is used. After the calculation of all sets of possible charging station combinations $K_{j,k}^{q}$ we transfer the data to CPLEX for model execution.

## 3.2 Data

### *3.2.1 Road network*

For the FRLM a basic road network is required. For this purpose we chose the German highway network and used data of the Federal Highway Research Institute (Bast) (Lensing 2013) which has been edited by Herdl (2014). This data includes 2374 driveways, exits and junctions of the whole German highway network (''highway nodes'' in the following) and distances between adjacent (neighboring) nodes. With this data we calculated the shortest-path-distances from every highway node to every other highway node in the network with the Tripel-Algorithm of Floyd-Warshall (Nickel et al. 2014; Warshall 1962; Floyd 1962). Consequently, the shortest-path for each OD flow within the network including the corresponding distances have been calculated and stored.

### *3.2.2 Origin–destination Flows*

The critical data needed for the FRLM are OD traffic flows from origin to destination and back, which is, as already mentioned, difficult to obtain. In the following we use data from Szimba (2014), which is part of the European transport policy information system (ETISplus) project, and contains traffic flows all around the European Union. The data is based on several transport databases and the OD flows are generated by the classical four step model of traffic planning (see above). Among others, they contain the OD flows between the 402 German rural districts (NUTS3 regions). In contrast to the OD data used in the FRLM by Capar et al.
(2013) this OD data contains the OD flows from one rural district to another and the way back. Thus the OD matrix is not symmetric and a different algorithm is needed to generate the model input. E.g., one OD flow contains the information about how many people are driving from Stuttgart to Munich and back in 1 year.

### *3.2.3 Access distance data*

In order to obtain the flows on each highway edge, the OD flow data has been merged with the highway network data. Therefore, every rural district in Baden-Württemberg and Bavaria was assigned to the closest network node of the highway.
As a model extension (see above) we included specific access distances for each rural district to the closest highway driveway and exit. The consideration of this additional distance from the origin rural district to the next highway driveway and the distance from the highway exit to the rural district of destination is noteworthy because the whole trip distance and not only the mileage traveled on the highway is relevant for the demand for recharging.

However, it is hard to consider exact paths for every individual OD flow.
Therefore, only the distances between every district capital of the considered rural district from the OD matrix and the closest highway driveway are used in the following. These distances were measured and provided by the Federal Office for Building and Regional Planning[1] for this paper.

### 3.2.4 Data integration

We performed two main transformations of the data before the model was applied.

First, we merged the data of the highway network (cf. Sect. 3.2.1), the OD flows (cf. Sect. 3.2.2) and the access distances (cf. Sect. 3.2.3) to a single dataset. In Baden-Württemberg and Bavaria there are 140 rural districts which leads to 19,600 (140 9 140) OD flows from each rural district to each other with the corresponding access distances. Additionally, we determined the shortest path for all OD flows and all relevant data for this flow in one table (cf. Table 1). The longest path has
165 nodes.

[1] http://www.bbr.bund.de/

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**Table 1:** Table entries for the OD pair 1-4

| From | To | Flow volume [trips/Year] | Distance [km] | Access distance [km] | | Shortest path (via nodes) | Distances between nodes 1 - 2 / 2 - 3 / 3 - 4 |
|---|---|---|---|---|---|---|---|
| 1 | 4 | 45,000 | 100 | 5 | 10 | 1-2-3-4-3-2-1 | 40 / 40 / 20 |

Table 1 shows an exemplary OD pair from rural district (1) to (4). The average access distance of the origin rural district to the assigned highway node 1 is 5 km and the average distance from the destination county to highway node 4 is 10 km.

The distance from node 1 to node 4 is 100 km. The path of this OD flow shown in the table starts at node 1 and continues all the way crossing nodes 2 and 3 until it reaches node 4. After node 4 is reached the access distance at destination (10 km) is considered before the way back begins. In total 230 km are traveled. A vehicle with 100 km range would need at least 2 charging stations along this considered OD pair.

Because the resulting 19,600 OD pairs are too many for the following calculations, two additional adjustments are made. First, all OD pairs with a single distance below 40 km are excluded in our calculations as we assume that there is no need to recharge within this short distance. Second, we deleted all OD pairs with less than 5000 trips per year. As a result, the number of OD pairs is reduced to 5451 while the total flow volume is only reduced by 7 %.

Second, we define the input set $K_{j,k}^{q}$ which represents all combinations of fast charging station locations which allow a round-trip for the OD pair $q$ considering the vehicle range. Therefore, we developed the following approach based on Capar et al. (2013).

Initially we define a maximum vehicle-range to determine the minimum distance between two fast charging stations. For our main scenario we are using a range of 100km. We further assume that each trip is started with complete charged battery (SOC=100%). Now, according to Capar et al. (2013), the algorithm has to go through every OD flow. For each of the 5451 OD flows and for each directed edge of each OD flow path, the algorithm computes all possible charging station combinations.

We give an example here for the first OD pair out of Table 1, i.e., from node 1–4. The algorithm starts at the first directed edge on the path from O to D (i.e., the edge from node 1 to node 2) and proves, whether this directed edge is reachable with the assumed range of 100 km. As the battery is completely charged at the beginning of each trip, the edge from node 1 to node 2 is easily reached (SOC = 55 % at node 2). Afterwards the algorithm checks at which (past) nodes of the OD flow a charging station is required in order to reach the end of his edge under consideration of the assumed vehicle range (here 100 km). Between the origin and node 4, the distance is already 105 km (5 km access distance plus 40 plus 40 plus 20 km). Therefore, a charging station is required in order to reach node 4 and correspondingly this edge is the first entry (OD01041) in Table 2. The algorithm identifies the corresponding nodes, which allows the vehicle to reach at least node 4. Hence, at least one charging station should be allocated to one of the following nodes: 1, 2 or 3 (cf. Table 2). Hereafter, the algorithm takes the next node of this OD pair and defines the corresponding potentially allocated charging station locations, which allows to reach this node. In our example, it is again node 4, but on the way back (i.e., edge between node 4 and 4R).

In order to enable a drive from node 1 to node 4 and back, at least one charging station has to be placed in each row of the table (OD01041–OD01046). If, for example, a station is only placed at node 3, all required links for this OD flow are enabled (cf. Table 2). An allocation only in node 1 leads to a cancellation of the considered OD relation due to all restrictions besides row one.

Our assumption regarding the availability of charging stations at origins and destinations is based on our own experiences in numerous fleet tests with BEV. At the origin we assume [in contradiction to Capar et al. (2013)] always a complete charged battery. At the destination the situation is considerably more uncertain. We, therefore, assume a pessimistic user, which plans its trip without disposability of charging stations at all destinations. Hence, the algorithm has to include the distances from the origin rural district to the assigned highway node and the distance from the destination node to the corresponding destination rural district and back. Correspondingly this procedure results in 211,483 rows in the matrix which includes all 5451 OD pairs and information on the possible combinations for all OD flows to enable a trip from one rural district to all other without running out of electricity.

## 4 Results

In our calculations we modified two parameters for our scenario analysis. These are the vehicle range of an average BEV and the percentage of the total traffic flows covered. In our first scenario we assume a minimal vehicle range of 100 km between each fast charging station to enable a car with a range of somewhat above 100 km to overcome this distance. In the following we are focusing on four different scenarios:

**Table 2** Required charging stations for enabling the OD flow 1-4 $\boldsymbol{K_{j,k}^{0104}}$ (range: 100 km)

| | Possible locations for charging stations (at least one is necessary) … | | | … to reach node | $\boldsymbol{K_{j,k}^{q}}$ |
|---|---|---|---|---|---|
| $OD0104_1$ | 1 | 2 | 3 | 4 | $\boldsymbol{K_{3,4}^{0104}}$ |
| $OD0104_2$ | 2 | 3 | 4 | 4R | $\boldsymbol{K_{4,4R}^{0104}}$ |
| $OD0104_3$ | 2 | 3 | 4 | 3R | $\boldsymbol{K_{3,4R}^{0104}}$ |
| $OD0104_4$ | 3 | 4 | | 2R | $\boldsymbol{K_{2,3R}^{0104}}$ |
| $OD0104_5$ | 2 | 3 | 4 | 1R | $\boldsymbol{K_{1,2R}^{0104}}$ |
| $OD0104_6$ | 1 | 2 | 3 | Origin | $\boldsymbol{K_{0,1R}^{0104}}$ |

Set-covering formulation of the FRLM:

1. In the first scenario we assume a vehicle range of 100 km and fix the number of stations to 20.
2. In the second scenario we assume a vehicle range of 150 km and fix the number of stations to 20.

Maximum-covering formulation of the FRLM:

3. In the third scenario we assume a vehicle range of 100 km and calculate the required number of charging stations in order to cover 80 % of all flows.

4. In the fourth scenario we assume a vehicle range of 100 km and calculate the required number of charging stations in order to cover 100 % of all flows.

In the following, our results for all four scenarios are described and illustrated in maps[2] before an overview of all conducted calculation can be seen in Table 4.

### 4.1 Set-covering problem—scenario 1 and 2

In the first two scenarios the number of charging stations within the highway network of Baden-Württemberg and Bavaria with 595 nodes and 3569 km is fixed to 20 stations and the vehicle range is restricted to 100 or 150 km. A range of 100 km (scenario 1) leads to a coverage of 62 % of the 257 thousand considered flows on the highway per day, whereas a range of 150 km (scenario 2) increases this value even to 83 % of total traffic flows covered.

In both scenarios the stations are aligned in uniform distances and mainly along the highway A8 from Karlsruhe in the north-east to Munich in the south-west and along the adjacent highways (cf. Figs. 1, 2). This result has several reasons. The main reason is the high traffic volumes on these relations, which is confirmed by empiric traffic count data of the Federal Highway Research Institute (Bast) (Lensing 2013) (cf. Table 3). Hence, the alignment of charging stations in scenario 1 is focused on the four OD flows with the highest traffic volumes. These relations are the highways A9 (Munich-Nuremberg), A81 (Lake Constance-Stuttgart-Heilbronn),A5 (Freiburg-Heidelberg/Mannheim) and A8 (Karlsruhe-Munich).

Additionally, we have to take into consideration that we only regard the traffic flows of the states Baden-Württemberg and Bavaria. Traffic flows from outside are not included in our calculations. This fact might explain the missing stations on the A81 north of Heilbronn and the A3 from Frankfort (Hesse) and around Nuremberg (Bavaria).

Concluding, the distribution of the fast charging stations is coherent to the traffic count data along the highways and the distances between the charging stations are sufficiently large.

[2] For the maps the website http:/-/umap.openstreetmap.fr/ is used.

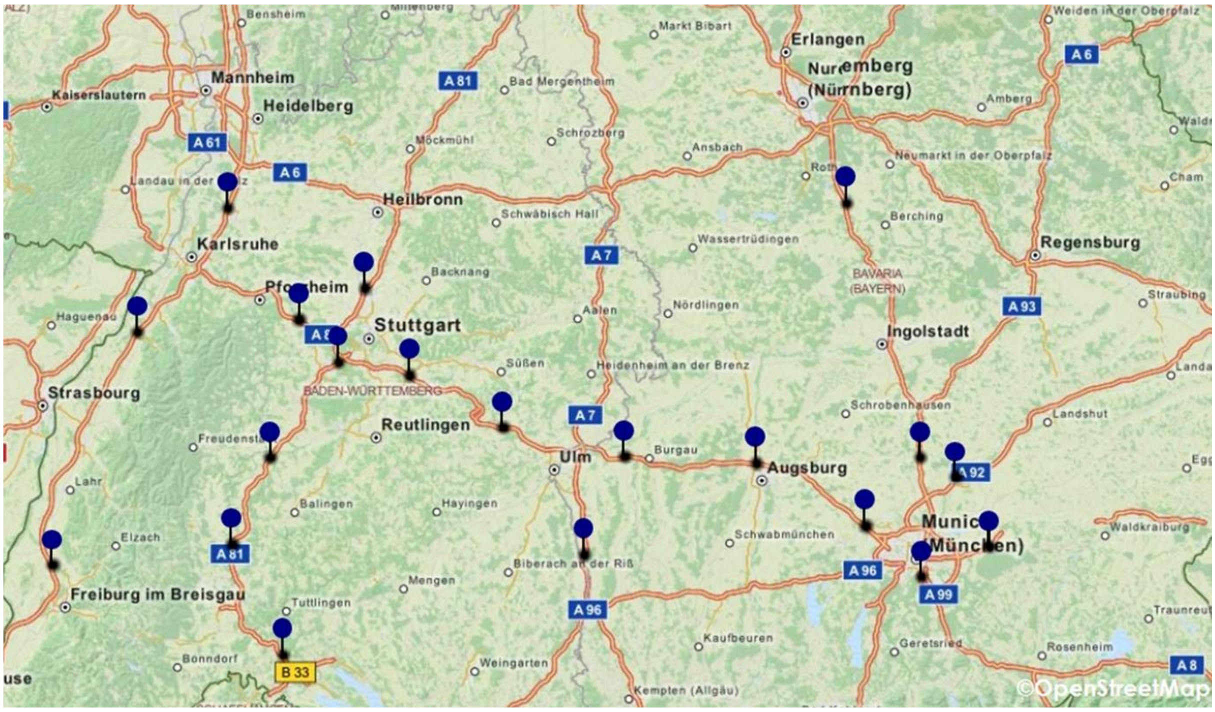


**Fig. 1** Allocation of fast charging stations in scenario 1 (100 km range, 20 charging stations placed)

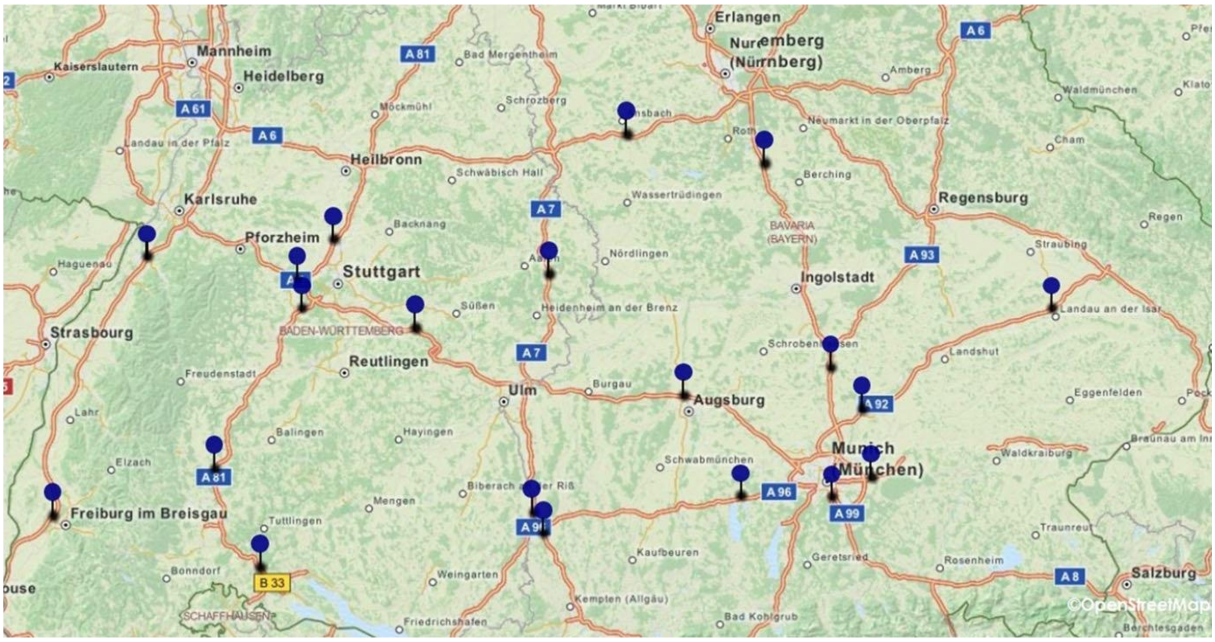


**Fig. 2** Allocation of fast charging stations in scenario 2 (150 km range, 20 charging stations placed)

### 4.2 Maximum-covering problem—scenario 3 and 4

In these two scenarios we calculated the amount of fast charging stations needed to cover a percentage of 80 and 100 % of the total traffic flows in Baden-Württemberg and Bavaria. In the scenario 3 with 100 km range, 34 fast charging stations were distributed to cover 80 % of the flows and in the scenario 4 with 100 km range, 77 fast charging stations are required to cover 100 % of the flows.

In the third scenario there are more routes covered than in scenario 1 with only 20 fast charging stations. Additionally, to the covered highways in scenario 1, the highways A96 (Memmingen-Munich), A73 (Bamberg-Nuremberg), A92 (Munich-Northeast) and A6 (Mannheim-Nuremberg) are fully covered with fast charging infrastructure. These results are also coherent to the traffic flow data in Table 3. On the map of scenario 3 (Fig. 3) one can see that there is no charging station assigned to the highway A81 between Würzburg and Ulm which seems to be a mistake. But, again, the missing stations on this route can be explained with Table 3. This highway only exhibits an average traffic flow of 25.000 cars per day between Würzburg and Ulm.

**Table 3** Average traffic flows along the most important highways in Baden-Württemberg and Bavaria (excluding city highways)

| Autobahn | Average traffic volume [Passenger vehicles/24h] | OD relation |
|---|---|---|
| A 9 | 66,212 | Munich-Nuremberg |
| A 81 | 62,664 | Lake Constance-Stuttgart-Heilbronn |
| A 5 | 60,916 | Freiburg-Heidelberg/Mannheim |
| A 8 | 60,833 | Karlsruhe-Munich |
| A 3 | 46,186 | Frankfort-Nuremberg |
| A 7 | 43,922 | Memmingen-Ulm |
| A 96 | 43,006 | Memmingen-Munich |
| A 73 | 42,122 | Bamberg-Nuremberg |
| A 92 | 37,476 | Munich-Northeast |
| A 6 | 36,693 | Mannheim-Nuremberg |
| A 95 | 34,762 | Munich-Southwest |
| A 94 | 33,877 | Munich-East |
| A 93 | 31,170 | Munich-Regensburg |
| A 7 | 25,004 | Ulm-Würzburg |


**Fig. 3** Allocation of fast charging stations in scenario 3 (100 km range, 80 % coverage)

Average distances between charging stations on the highways depend strongly on the traffic flows. On highways with only few flows (e.g., A93), one charging station for 243 km is allocated whereas at highly frequented highways (e.g., A8 with 391 km total length) with several intersections in average each 43 km a charging station can be found (maximum distance is 84 km and minimum about 25 km).

Additionally, in scenario 3 there are no charging stations at the A3 from Frankfort to Nuremberg or the A5 from Frankfort to Karlsruhe. This is again due to the border between Hesse and Baden-Württemberg where traffic flows from Frankfort and other cities are not included in the model, but in the empiric values (Table 3). We assume that an inclusion of all other German federal states would lead to further allocations of fast charging stations along the highways to the north, but will not drastically affect the allocation within central and southern Baden- Württemberg and Bavaria. Figure 4 shows the charging station distribution for 100 % coverage. It can be seen that there are many additional stations needed to obtain full coverage of 100 %.

**4.3 Findings**

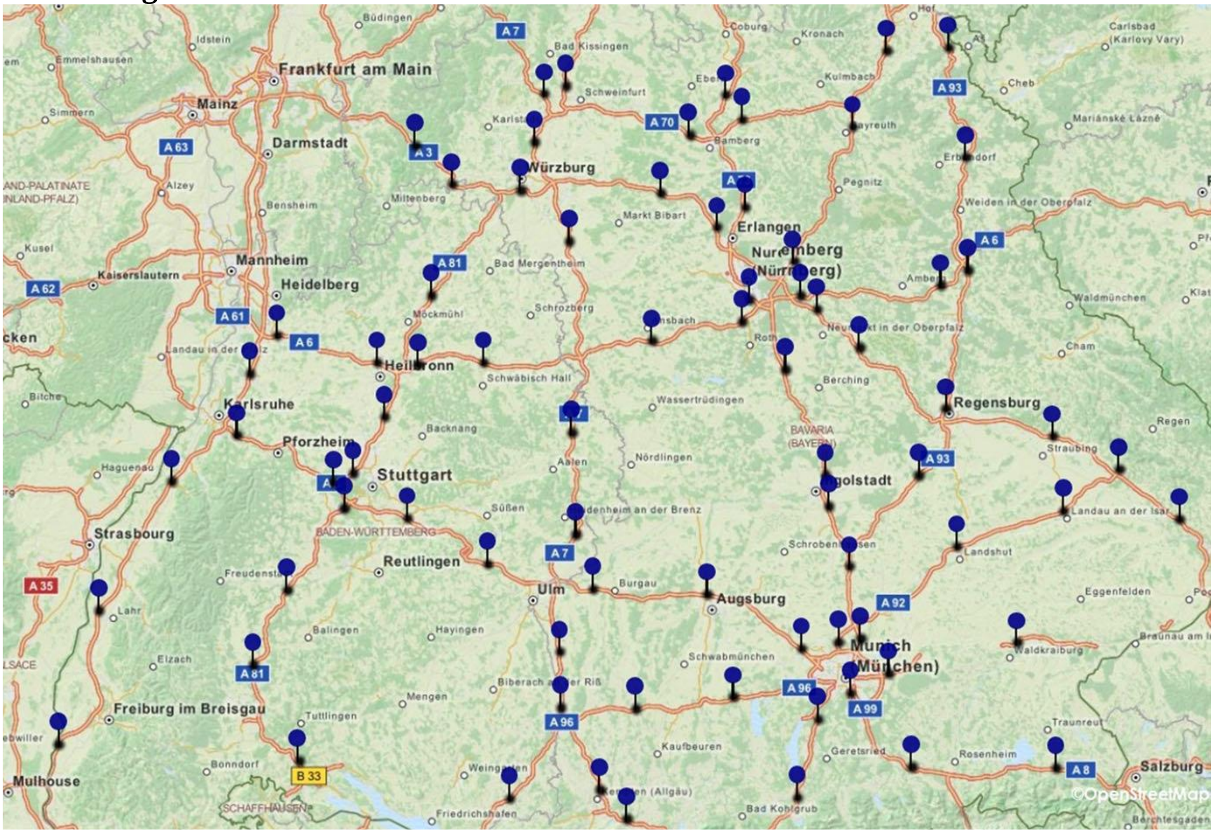


**Fig. 4** Allocation of fast charging stations in scenario 4 (100 km range, 100 % coverage)

In the four scenarios the optimization model of Capar et al. (2013) and the extensions in this paper qualify well for the allocation of fast charging infrastructure for EV along the German autobahn in Baden-Württemberg and Bavaria. With the traffic flows between the rural districts we identified optimal locations for fast charging stations while considering a specific vehicle range and a specific coverage percentage. In addition, we included several realistic aspects about the potential locations like the exclusion of highway junctions as a potential charging location and the consideration of the access distance from each rural district to the closest highway node.

In the different scenarios we changed both the percentage of total flows covered and fixed the number of charging stations to be placed. As a result we indicated that for a vehicle range of 100 km only 25 charging stations are required to cover about 70 % of all flows. For a complete coverage, a disproportionate number of additional fast charging stations is required (cf. Capar et al. 2013). In our scenario, this increase in coverage leads to a tripling of required fast charging stations (cf.
Fig. 5).

Finally, a comparison of the results from our scenarios and with a further differentiation of vehicle range shows significant differences (cf. Table 4). A unique range of 70 km (150) for all BEV leads to an installation of about 10–60 % additional (35–49 % fewer) fast charging stations compared to a unique vehicle range of 100 km. 20 fast charging stations in Baden-Württemberg and Bavaria cover already between 47 % (70 km range) up to 83 % (150 km range) of all OD flows. A complete coverage requires between 50 (150 km range) to 84 (70 kmrange) fast charging stations along the German autobahn in Baden-Württemberg and Bavaria.

### 4.4 Cost Estimation for 2020

As mentioned earlier, the investment for allocating fast charging stations is significant. The profitability of this investment depends strongly on its

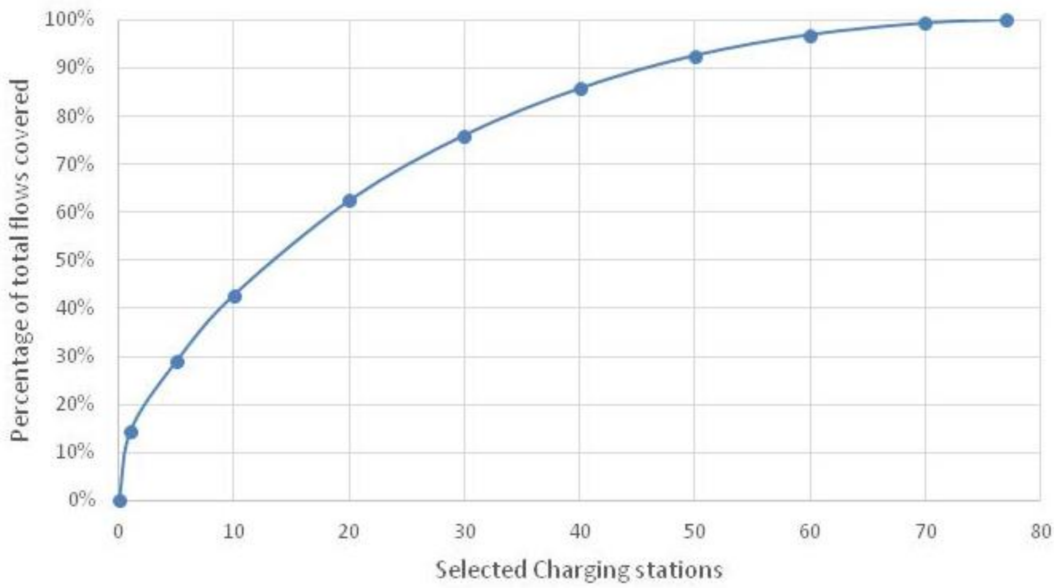


**Figure 3:** Number of placed fast charging stations in relation to the coverage of trips in % (for 100 km range)

**Table 4:** Results for all scenarios

| Objective | 70 km vehicle range | | 100 km vehicle range | | 150 km vehicle range | |
|---|---|---|---|---|---|---|
| | Covered Flow-volume [trips per year] | No. of Stations | Covered Flow-volume [trips per year] | No. of Stations | Covered Flow-volume [trips per year] | No. of Stations |
| 100 % coverage | 256,889,139 | 84 | 256,889,139 | 77 (scenario 4) | 256,889,139 | 50 |
| 80 % coverage | 205,521,931 | 55 | 206,462,301 | 34 (scenario 3) | 205,558,466 | 18 |
| 20 Stations | 119,786,700 | 20 (47 %)[1] | 160,341,499 | 20 (62 %)[1] (scenario 1) | 212,202,423 | 20 (83 %)[1] (scenario 2) |

[1] coverage of all trips.

workload, i.e., the electricity demand by BEV, which relies mainly on the number of BEV in the market, but also on the acceptance of fast charging (which might depend on the surcharge for fast charging and the assumed accelerated degradation of the battery). Due to this high uncertainty in many values, we can only present first estimates for the surcharge for fixed costs per charge for our scenario results and abstain from giving sophisticated financial ratios. Especially, the estimated costs (including the whole installation) for fast charging stations are still unclear and very individual for different locations due to the few installed stations and the heterogeneity of access to the electricity grid. We expect, however, learning curves in this field in the years to come. Nevertheless, we provided qualitative levels of uncertainty for all assumed variables given in the ‘‘Appendix’’.

Assuming a fleet of 500,000 BEV in Germany by 2020 (cf. Plötz et al. 2014c) and no changes in vehicles usage patterns, our flow data would result in about 14,819 fast charging processes per day along the highways in Baden-Württemberg and Bavaria at 34 fast charging stations (scenario 3 with 80 %coverage). In order to consider the unequal distribution of trips per daytime, which shows four times higher values during peak time compared to the daily average (Infas and DLR 2010), we multiplied the required number of charging point per station by the factor of four. This leads to an average number of 24 charging points per charging station which allows a parallel charging of 24 cars. Consequently, the number of charging processes per day and fast charging station equals to 436 and to 18 per charging point (i.e., an average occupancy rate of about 6 h per day).

The corresponding investment of a fast charging point are estimated to about 30,000 euros plus additional 30,000 euros for earthwork at each facility (Elektromobilität verbindet 2015). Assuming a linear depreciation over 6 years and an additional monthly maintenance cost of 1000 euros per facility, we derive average fixed costs per charging station of about 380 euros per day. These values are very vague—especially with respect to 2020. The resulting surcharge for fixed costs per charging process equals to about 1 euro.[3]

Compared to the price for electricity, this surcharge seems reasonable. The electricity costs for an average 80 % recharge of current BEV (18 kWh) assuming an average electricity price for German households of about 0.30 euros (Eurostat 2015) amount to about 5.40 euros. The final price might be even lower—at least if the fast charging station operator has an industrial electricity contract, which usually contains significantly lower electricity prices. Therefore, the surcharge to cover fixed costs (or even including marginal profits) of about 20 % seems reliable form a customer point of view. This confirms the results by Schroeder and Traber (2012) who also claimed a profitable operation of fast charging stations—at least under these assumptions. However, a postponed market penetration of BEV and a low acceptance of fast charging stations will significantly decrease the charging per day and therefore lead to significant higher costs per charging event. Furthermore, the results are based on rough estimates of costs which highly dependent on the location and the number of fast charging stations in the market.

## 5 Discussion

Our results for the German highway network show that vehicle range and the number of charging stations have a significant impact on the coverage of flows (cf. Fig. 5; Table 4). Overall, for an average vehicle range of 100 km, 34 charging stations already cover 80 % of flows within this highway network of 3569 km. This is comparatively few compared to Japan, where already more than 5000 fast charging stations are installed at about 60,000 km long highway network (CHAdeMO 2015; Road Bureau 2015).

[3] We applied a sensitivity analysis with alternative values for EV market penetration (e.g. 400,000) and fixed costs per charging station (e.g. 100,000 euros) and derived average costs within the same range (e.g. 0.99 euros).

Capar et al. (2013) show numbers in the same magnitude for their optimization model. They indicate that Florida's (Orlando's) highway network with 74 nodes (102 nodes) require 4 (12) fast charging stations for covering 60 % of the flows assuming a range of 200 km. Even though these numbers depend strongly on network architecture, length of links, trip length, etc., Capar et al. (2013) validated these correlations for similar artificial networks. A comparison with other empirical networks is however associated with high uncertainties.

This uncertainty in transferability is even stronger when we consider other sources of uncertainty: the future pathway of market penetration of BEV, the costs for charging stations and the change in user behavior. E.g., a further increase in the acceptance of car sharing systems will have a strong impact on the traffic volumes of BEV on the highway. Users will prefer to take conventional vehicles or PHEV from the car sharing fleet for long distance trips. Furthermore, the market success of fuel cell electric vehicles (or even other battery improvements) with longer ranges, will have a strong impact on the profitability of fast charging stations, too. In countries with longer distances BEV might be unsuitable for average trips, as charging stops increase and waiting time becomes more and more severe.

Even though the above applied range of 70 km seems short during cold and congested winter days, this scenario might come true due to a higher electricity demand for heating and lower battery efficiency at low temperatures (Tourani et al. 2014). Additionally, this scenario might reflect the range anxiety of BEV users (Naubauer and Wood 2014) or should be considered for long climbing roads.

Furthermore, we should point out here that our assumption of allocating fast charging stations at nodes with an exit and driveway is currently under discussion. While conventional fuel stations might serve as a preferred location because of their higher user acceptability and developed surrounding infrastructure for driver's recovery, they do usually have no turning point to the opposite lane (which leads to at least two charging stations per location) and the electricity grid might not be sufficient on these sites for several charging points. Our assumption here to locate fast charging stations at highway nodes with an exit and driveway is more flexible with the electricity grid connection (i.e., the location might be a few meters away from highway) and the access from both directions is assured. However, the access might be more complicated for vehicle users and the environment for recreation might be lacking. We leave this point open for discussion and recommend to analyze each optimal allocation with regard to the local circumstances and to adapt the concrete allocation accordingly by a few kilometers if necessary.

## 6 Conclusions

The market penetration of battery electric vehicles (BEV) seems irresistible. So far BEV are mainly used for short distance trips while long distance travel is accomplished by conventional internal combustion engine vehicles or plug-in hybrid electric vehicles. Currently, three technologies for fast charging stations (i.e.,combined charging system, CHAdeMO and super charger) are introduced in the German market. The installation of each fast charging station is costly. Hence, an efficient allocation of fast charging stations along the highway might have a strong impact on the future market penetration of BEV and is influencing the allocation of further fast charging stations. Therefore, the right allocation of the fast charging stations does not only influence the profitability of these stations, but also all following charging stations. This is considerably a severe investment for the futuremobility system.

We applied and extended the flow-refueling location model (FRLM) developed by Capar et al. (2013) to the German autobahn with a focus on the states Baden-Württemberg and Bavaria. Our extension comprehends mainly the inclusion of the access distance from each district to its closest network node. Therefore, our underlying origin–destination data does not only contain the trips between highway nodes, but rather the bidirectional trips between all 140 rural districts in Baden-Württemberg and Bavaria. In order to analyze the impact of different vehicle ranges and the desired coverage of flows we defined four scenarios. Two of them are calculated by the set-covering formulation of the FRLM. They calculate the maximum coverage of trips by allocating 20 fast charging stations for electric vehicles with a range of 100 (scenario 1) and 150 km (scenario 2). The other two scenarios use the maximum-covering formulation of the FRLM. They minimize the number of charging stations for a given desired coverage of 80 % of all trips (scenario 3) and 100 % of all trips (scenario 4), respectively.

The results indicate the significance of vehicle range and the desired coverage of vehicle flows. Even though, a first allocation of 20 charging stations influences the optimality of all further charging stations, 20 charging stations seem to be a good compromise for Baden-Württemberg and Bavaria. 20 optimally allocated fast charging stations along the highways lead already to a coverage of about 62 % (100 km vehicle range) or even 83 % (150 km vehicle range) of all trips. A more pessimistic assumption of 70 km vehicle range enables, however, only less than half of all trips. A complete coverage of trips requires at least 50 (150 km vehicle range), 77 (100 km vehicle range) or even 84 (70 km vehicle range) fast charging stations. The last 30 % coverage leads to a tripling of charging stations.

A first estimation of the corresponding surcharge for fixed costs per charging process amounts to about 1 euro, which equals to about 20 % of the total costs for a charging process. This indicates that an economical rollout of fast charging stations is conceivable—at least if the market diffusion of fast charging compliant vehicles succeeds in the coming years.

Our model still neglects structural and construction specific characteristics of the highway. A concrete analysis of our results with respect to available grid connections and other highway specific limitations has to complete this work. This is crucial because a parallel charging of 24 electric vehicles with an average charging power of 80 kW at a single charging station would lead to an additional grid load of about 2 MW. Furthermore, neglecting vehicle flows from other federal states and countries should be considered within the model. The improved algorithm should also consider that users of BEV avoid long distance trips (i.e., the number of trips above 80 km should be lower for electric compared to conventional vehicles). Real GPS based trip data might even improve our results and might serve as a cornerstone for a more sophisticated and BEV specific OD flow simulation. Additionally, the acceptance of increased idle time for vehicle users during charging as well as the individual preferences for locations (i.e., from investors, user acceptance, etc.) should be considered in further research. Overall, the methodological approach is however unaffected.

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## Appendix

Assumptions for the costs calculation in Sect. 4.4.

| | Explanation | Sources and Calculations | Value | Unit | Uncertainty level |
|---|---|---|---|---|---|
| 1. | Total number of electric vehicles (EV) in 2020 | Plötz 2014c | 500,000 | No. of EV | Very high |
| 2. | Total number of passenger cars in Germany 2014 | Kraftfahrtbundesamt | 44,000,000 | No. of passenger cars | Almost sure |
| 3. | Total vehicle trips per day with a distance > 80 km in Baden-Württemberg and Bavaria (BWB) | OD-Data with the assumption that the total amount of cars in 2020 will be the same as in 2014 | 767,123 | No of vehicle trips per day | Moderate |
| 4. | EV trips per day with a distance > 80 km in BWB in 2020 | L1/L2*L3 | 8,717 | No. of EV trips per day | Moderate (result) |
| 5. | Assumption on the share of main fast charging technology (e.g. CCS) used by EV in 2020 | Assumption | 85% | percentage | Moderate |
| 6. | EV trips per day with a distance > 80 km in BWB with CCS in 2020 | L4*L5 | 7,410 | No. EV trips/day | Moderate (result) |
| 7. | Average distance of roundtrips > 80 km in BWB | OD-Data | 300 | km | Moderate |
| 8. | Average number of charges needed for an average 300 km trip | Assumption | 2.5 | No. of charges/trip | Moderate |
| 9. | Average number of charges per day in BWB | L6*L8 | 18,524 | No. of charges/day | Moderate (result) |
| 10. | Percentage of flows covered | Assumption from paper | 80% | percantage | Moderate |
| 11. | Average number of charges per day in BWB with a coverage of 80% (demand) | L9*L10 | 14,819 | No. of charges/day | Moderate (result) |
| 12. | Required No. of charging stations to cover 80% of all EV flows in BWB | Result from model | 34 | No. of charging stations | High (result) |
| 13. | Average number of charges per charging station per day in BWB (demand) | L11/L12 | 436 | No. of charges/charging station | Moderate (result) |

| | Explanation | Sources and Calculations | Value | Unit | Uncertainty level |
|---|---|---|---|---|---|
| 14. | Maximum possible charges per charging point per day | (60min/h)/(20min/charge) *24h/day | 72 | No. of charges/charging point | High |
| 15. | Optimistic charges per charging point per day (25 % workload) | Assumption | 18 | No. of charges/charging point | High |
| 16. | Required number of charging points per charging station | L13/L15 | 24 | No. of charging points/ charging station | High (result) |
| 17. | Average cost for one charging point | ABB/Elektromobilität verbindet | 30,000 | € per charging point | Moderate |
| 18. | Fix cost for one charging station | Elektromobilität verbindet | 30,000 | € per charging station | Moderate |
| 19. | Cost estimation for 80% coverage | (L16*L17+L18)*L12 | 25,719,045 | € | High (result) |
| 20. | Linear depreciation for 6 years for one station | L19/(L12*6) | 126,074 | € per year and charging station | High (result) |
| 21. | Maintenance costs per month | Assumption | 1,000 | € per month and charging station | Moderate |
| 22. | Cost per day | (L20/365)+(L21/30) | 379 | € per day and charging station | High (result) |
| 23. | Fix Cost percentage per charging process | L22/L13 | 0.87 | € per charging process | High (result) |

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