Siting and Sizing Charging Infrastructure for Electric Vehicles with Coordinated Recharging

Sven Schoenberg, *Graduate Student Member, IEEE,* Dominik S. Buse, *Graduate Student Member, IEEE,*
Falko Dressler, *Fellow, IEEE*

***Abstract*—The popularity of electric vehicles is increasing, but the public charging infrastructure is still insufficient. To reduce extra time spent with charging on everyday trips, we introduce a new charging infrastructure siting and sizing approach. We analyze daily schedules of drivers to find suitable locations for slow and fast charging stations. In simulation, we test how many charge points to assign to each charging station. Vehicles can be charged with either en-route or destination charging using a realistic model for charging and energy consumption for five electric vehicle models of different car segments. To reduce waiting times at charging stations, we use a centralized charging station database (CSDB), that coordinates charging between vehicles. We found that a combination of a few centralized fast charging stations and many distributed slow charging stations is the best option to improve the average extra time spent with charging for all vehicle types. We also found that by using the CSDB to coordinate charging between vehicles, we were able to significantly reduce the necessary number of charge points to achieve an acceptable average extra time. In our scenario, to reach an average extra time of 15 min, we only had to add 53 charge points when using the CSDB, compared to 104 without.**

***Index Terms*—Charging stations, electric vehicles, intelligent vehicles, navigation, shortest path problem.**

I. Introduction

The popularity of electric cars is ever-increasing. Global sales of electric vehicles increased by 41 % in 2020 compared to 2019, despite a downturn of car sales due to the COVID-19 pandemic [1]. Most vehicles are still charged at home (or at work),[1] but not everyone has the option to do so. Especially in cities, many people do not have a garage or a designated parking space where they could install a private charger. As electric vehicles become more mainstream, many people will depend on using the public charging infrastructure instead. Using the public charging infrastructure for everyday charging requires extra time compared to charging at home or occasionally filling up the tank of a vehicle with an internal combustion engine. This extra time spent with charging is critical for the acceptance of electric mobility [2], but the existing charging infrastructure is often not yet sufficient to achieve acceptable extra times for the majority of drivers [3].

The problem can be tackled in different ways. One way is making vehicles smarter when using the charging infrastructure by, e.g., planning optimized routes and charge stops, integrating charge stops into the driver's schedule [4], or scheduling charge stops at charging stations [5]–[7]. Another way is improving the charging infrastructure itself by creating new charging stations or extending existing ones where they are most needed [8]–[10].

In this work, we combine both aspects in a new charging infrastructure planning approach. It is focused on the perspective of drivers that can not charge their vehicles at home or at work. The goal is to minimize the average extra time spent with charging on everyday trips. We assume that smart vehicles are able to plan routes and charge stops that are optimized for the driver's schedule. By combining such smart routes with charge stop coordination among vehicles and intelligent placement of charging infrastructure, we reduce the number of necessary charge points to achieve acceptable extra times.

Due to the big differences in charging time, fast and slow charging stations are used in a completely different manner [11]. We therefore distinguish two different kinds of charging that have different effects on the extra time spent with charging:

En-route charging: Stopping at a charging station while en route to another destination and waiting by the vehicle while it charges, similar to using a gas station. It is only suitable for fast charging, as slow charging would lead to unacceptable waiting times for the driver. For en-route charging, the extra time consists of the detour to the charging station, the waiting time for a free charge point and the charge time itself.

Destination charging: Charging the vehicle while it is parked at the intended destination. The driver visits the destination while the vehicle charges and does not have to wait by the vehicle. It is therefore suitable for slow charging, especially if the driver is staying for several hours. If the charging station is not next to the destination, the driver might have to walk from the charging station to the destination and back. Thus, the extra time additionally includes the walking time to and from the destination, but does not include the charge time, because the driver is staying at the destination while the vehicle charges.

Planning charge stops that take into account the driver's activities of the day can be used to minimize the extra time spent with charging. The daily mobility pattern of drivers are often modeled as activity plans [12]. An example of such an activity plan could be driving from home to work, staying there

Research reported in this paper was conducted in part in the context of the Hy-Nets4all project, supported by the European Regional Development Fund (EFRE-0801678).

Sven Schoenberg is with the Software Innovation Lab and the Department of Computer Science, Paderborn University, Germany. E-Mail: sven.schoenberg@c-lab.de

Dominik S. Buse is with the Software Innovation Lab and the Department of Computer Science, Paderborn University, Germany, and with the School of Electrical Engineering and Computer Science, TU Berlin, Germany. E-Mail: buse@ccs-labs.org

Falko Dressler is with the School of Electrical Engineering and Computer Science, TU Berlin, Germany. E-Mail: dressler@ccs-labs.org

[1]The Global Electric Vehicle Market Overview in 2021: Statistics & Forecasts https://www.virta.global/global-electric-vehicle-market (visited on 09/17/2021).

for a few hours, then driving to a mall to go shopping, and finally driving home again. Optimizing an activity plan for the driver of an electric vehicle does not only include the selection of the charging station, but also picking the optimal route to drive there. Taking the fastest route results in the shortest drive time, but it might require significantly more energy than a more energy efficient route and the additional energy increases the charge time. As the charge time also depends on the charging station, the optimal route should therefore be selected together with the charging station, from the set of multi-criteria paths for the criteria time and energy.

If all charge points are occupied when a vehicle arrives at a charging station, it has to wait for a free charge point. To minimize this waiting time, the vehicles could coordinate their charge plans with each other. In our previous work [3], we introduced this approach with our charge stop planner, which takes into account the driver's activities of the day. It can decide between en-route and destination charging and selects optimal routes to drive. We coordinated charging between electric vehicles with a central charging station database (CSDB), which substantially reduced waiting times and therefore extra times. However, it was revealed in our evaluation, that the existing charging infrastructure is not yet sufficient to achieve acceptable extra times for the majority of drivers.

In this work, we go beyond and present an approach to extend the existing charging infrastructure with the goal to optimize the average extra time spent with charging on everyday trips. Extending the charging infrastructure involves two problems: *siting* and *sizing*. Siting means finding new locations (sites) to install charging stations. As a baseline, we use locations of normal gas stations, which were historically placed quite optimal for refilling. Going beyond, we analyze daily schedules of drivers to find suitable locations for slow and fast charging stations. Sizing means finding the necessary number of charge points at the charging stations to prevent long waiting times. The overall concept is depicted in Figure 1. We use simulations to test at which charging stations additional charge points should be installed to reduce waiting times. In the simulations, vehicles use the charge stop planner to plan trips based on their driver's schedule and coordinate charging with the CSDB.

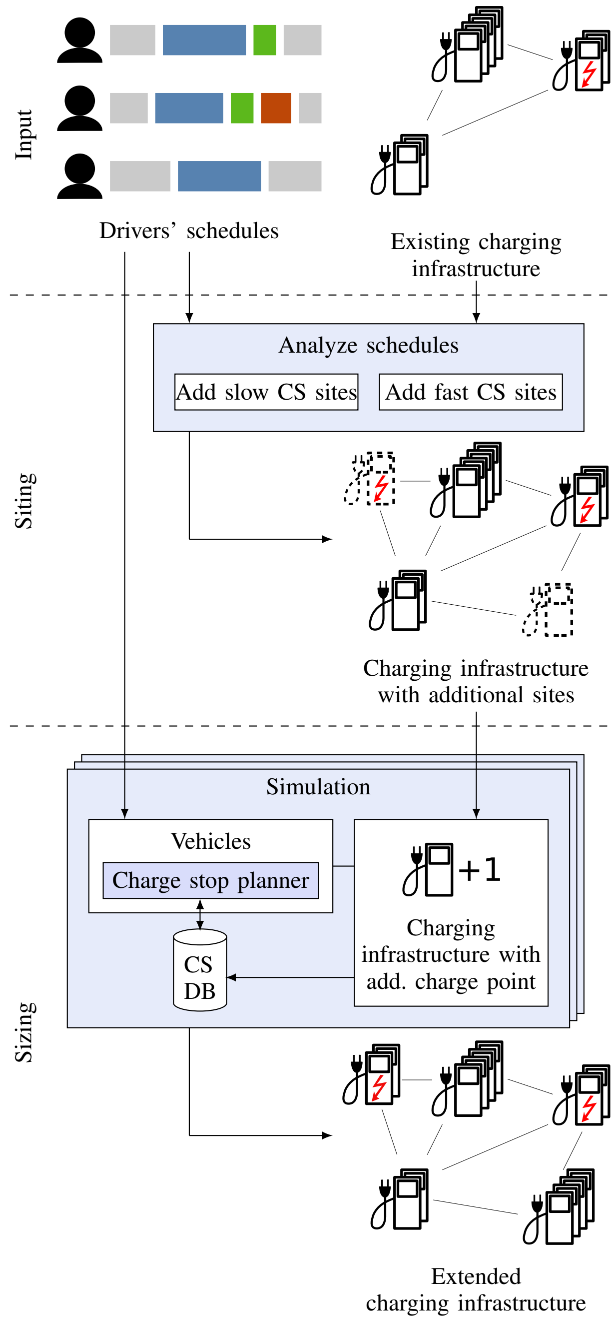


Figure 1. Charging infrastructure siting and sizing concept

Our main contributions can be summarized as follows:

- We present the charge stop planner, which uses en-route charging and destination charging to plan charge stops that fit the driver's schedule and minimize the extra time spent with charging. This includes coordinating charging between vehicles with the CSDB to reduce waiting times. The concept was introduced in our conference paper [3] and is presented here again to make the paper self-contained.
- We introduce a siting and sizing approach, which uses the drivers' schedules to site slow and fast charging stations. With our charge stop planner and the coordination of charging between vehicles, it can minimize the necessary number of charge points. It uses realistic charging and energy consumption models of five vehicle types from different car segments.
- We perform a simulation study to analyze the effect of our siting and sizing approach on en-route and destination charging for different car segments and compare our strategy to related approaches. We also show that by coordinating charging with the CSDB, we can significantly reduce the number of necessary charge points to reach an acceptable average extra time.

The rest of this paper is organized as follows. After discussing related work (Section II), we briefly introduce our charge stop planner (Section III) and our approach to coordinate vehicles (Section IV). We present our charging infrastructure siting and sizing approach in Section V. Then, we discuss our energy consumption and charging model for different vehicle types in Section VI. We evaluate our approach in Section VII. Finally, we draw some conclusions in Section VIII.

II. Related Work

A. Electric Vehicle Route Planning

Electric vehicle route planning is a topic that has been discussed in many works. In an urban city scenario, where vehicles are often charged with destination charging, taking into account mobility patterns and user behavior is important [13]. Mobility patterns are considered by some works that are focused on smart grid, e.g., [14], [15], to forecast energy demand and schedule the use of charging stations accordingly. For destination charging, some works also consider that charging stations may not be at the same location as the destination, but close by, so the driver has to walk from the charging station to the destination and back [16], [17]. Gerding et al. [17] call this *park 'n charge*, and use it as a real-world scenario to evaluate their system. They also separately considered an *en-route charging* scenario, but did not combine both approaches. Yang et al. [18] combine both in their route selection and charging navigation strategy. It can use destination charging, and, if necessary to reach the destination, en-route charging at fast charging stations. However, to the best of our knowledge, considering the driver's schedule when making charging decisions and selecting between en-route charging and destination charging has not been presented yet.

Recharging the battery of an electric vehicle takes time, even with fast charging. Each charging station only has a limited number of charge points, and if many vehicles want to charge there at the same time, this can lead to long queues and waiting times. One way to prevent waiting times is a reservation system, where drivers can reserve a time slot to charge at the charging station. They can plan their trip around available time slots and are guaranteed to be able to charge at the reserved time. A reservation system is described in many publications [19]–[24], sometimes with the option to update the reservation, if needed [20]. The reservations are usually assigned on a first-come-first-serve basis, but some works also consider prioritized reservations [22]. Another approach is to use a central server that makes charge stop recommendations to drivers, by taking into account the current utilization of charging stations [25]. In addition, the vehicles could announce their intended charge stops to the server, so that it can predict the utilization in the future. De Weerdt et al. [7] call this intention-aware routing. Combined with historical data on charge stops, they were able to reduce waiting times in some cases by about 80 %.

Some more recent works on route planning and charging station selection are using deep reinforcement learning [5], [24], [26]. By learning optimal policies they can make complex decisions in stochastic environments with varying conditions, e.g., traffic, weather, and dynamic charge prices. However, these works also do not consider the driver's schedule or compare en-route charging with destination charging.

Route planning is more difficult for electric vehicles than for conventional vehicles. The limited range has to be taken into account, as well as the option to recharge the battery by regenerative braking when slowing down or driving downhill, also called recuperation. A shortest-path problem that includes these additional constraints is a constrained shortest path (CSP) problem [27]. Finding the fastest route that is still feasible with the limited range can be done with a multi-criteria shortest-path search. We can use the criteria travel time and energy consumption to compute all Pareto optimal paths for these criteria. Then, we exclude paths which violate the energy constraint and, from the rest, select the path with the best travel time. A multi-criteria shortest-path search can be performed with a modified version of Dijkstra's algorithm [28]. However, it is much more computationally expensive, and not practical for graphs of realistic sizes [29]. Geisberger et al. [30] introduced contraction hierarchies, which can be used to speed up the search. Originally developed for conventional shortest-path searches, it can also be used to accelerate multi-criteria shortest-path searches to solve the CSP [29]. The approach utilizes a preprocessing step, where shortcuts are added to the graph. These shortcuts can later significantly speed-up the search, by reducing the number of edges that have to be traversed.

Even with contraction hierarchies, a multi-criteria shortest-path search can be too slow in practice on realistically sized graphs. To further accelerate the search, in our previous work [31] we introduced shortest-path tree precomputing in combination with contraction hierarchies. We perform an additional preprocessing step, in which we explore the graph from those nodes that are likely origins or destinations of queries, and save the resulting shortest-path trees. We exploit the fact, that most queries are between the known locations of charging stations. This can reduce the query times by about two orders of magnitude.

In this work, we go one step further by considering the driver's schedule of the day when making charging decisions. We can select between en-route charging between two activities and destination charging near an activity to minimize the time the driver has to spend with charging the vehicle. Additionally, we use our shortest-path tree precomputing approach to select optimal routes and coordinate charging between the vehicles to minimize waiting times. We already published an initial version of this approach in [3].

B. Charging Infrastructure Siting and Sizing

So far, we assume that there is an existing charging infrastructure available that the vehicles can use. When extending the charging infrastructure, we are faced with two problems. Finding suitable locations for new charging stations (siting) and determining how many charge points to install (sizing).

Some approaches use a list of criteria to evaluate potential location candidates. Erbaş et al. [8] take 15 criteria from the dimensions environmental/geographical, economic and urbanity into account and map them with a GIS software to identify location candidates. Król and Sierpiński [32] use existing parking lots as initial location candidates and evaluate them with criteria that only require easily accessible data as input. They distinguish between different types of charging stations, e.g., fast charging stations should be easily accessible from major roads.

Distinguishing between slow and fast charging stations is important, because they are used in a completely different manner [11]. Due to the long charging times, slow charging is mainly used for destination charging. For en-route charging, where the driver waits by the vehicle, fast charging is more suitable. Basically, slow charging stations need to be where cars park and fast charging stations where cars drive. Locations for fast charging stations are selected to maximize the capture of traffic flow [9]. Gas station locations have a similar objective and some works use them as candidates for fast charging stations [10], [33], [34]. For slow charging stations, there are several strategies to site locations. One is to deploy them near potential customers, either minimizing the number of charging stations required so that all customers can reach a station within a specified distance, or deploying a fixed number of charging stations in a way that minimizes the average or median distance to the customers [9].

Another way is to use an agent-based simulation with electric vehicles driving around and recharging their batteries at the charging stations. The driver behavior can be modeled in different ways. A simple behavior is to drive until the battery state of charge (SOC) drops below a threshold and then start driving to the nearest charging station [34], [35]. An alternative is to plan the charge stops at the beginning of the trip [33], [36]. The trips are sometimes simply random origin-destination (OD) pairs [34]. Other works use activity chains with multiple stops [4], [33], [35], [36], but only few of them simulate a driver behavior that can select between en-route charging and destination charging.

One such approach has been presented by He et al. [36]. They assume that drivers will simultaneously plan their tour path and recharging plans to minimize their total travel time, including charging. This allows them to deploy slow and fast charging stations in a way that minimizes average travel times. However, they do not consider the possibility that all charge points are occupied at a charging station and a vehicle having to wait.

Most works in the field of siting and sizing charging infrastructure make simple assumptions about charge curves and the energy consumption of the electric vehicles. The charge power is often assumed to be constant ([4], [33]–[36]) and the energy consumption is often a fixed amount of energy per distance driven ([4], [34]–[36]).

This paper is an extension of our conference paper [3], where we introduced the charge stop planner, to coordinate charging between vehicles in order to minimize waiting time. It can plan trips ahead of time, including charge stops with en-route charging and destination charging, by taking into account the drivers' schedules of the day. Building upon this, we present a new charging infrastructure siting and sizing approach, that uses the charge stop planner as a basis for an agent-based simulation. It uses realistic energy consumption and charging models of five electric vehicles from different vehicle segments. This enables us to site locations for new slow and fast charging stations and extend existing ones in a way that minimizes the extra time spent with charging, including waiting time. By coordinating charge stops between vehicles, we can reduce the necessary number of charge points significantly. To the best of our knowledge, this is the first work that considers how siting and sizing can be influenced by vehicles coordinating their charge plans of the day with each other to reduce waiting times.

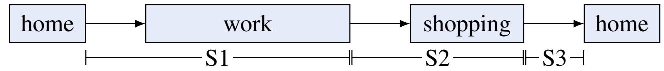


Figure 2. Day's schedule divided into segments

III. Charge Stop Planner

Our charge stop planner is an approach to select charge stops for the driver of an electric vehicle that fit into the driver's schedule, with the goal to minimize the extra time spent with charging. The driver's schedule is an activity chain, containing the times and locations the driver visits throughout the day, e.g., work, shopping, leisure activity. It is assumed to be known, which is of course a simplification. In a real-world scenario, either the on-board navigation system of the vehicle or a smartphone app could create the schedules based on a prediction from historical data, maybe combined with analyzing the user's calendar, or simply by user input. The charge stop planner tries to find the optimal times and places within the schedule to charge the vehicle to the desired level. This could also mean to sequentially charge the vehicle at multiple stops. We introduced this concept in [3] and present it in this section to make the paper self-contained.

The day's schedule has an initial start point and a final destination, which might be the same, e.g., home. As we are focusing on drivers that have no option to charge their vehicle at home, charging has to happen during an activity or while driving to one. To make charging decisions easier, we divide the schedule into segments, each consisting of an activity and the trip to it. The last trip to the final destination is an additional segment. An example of a schedule divided into segments can be seen in Figure 2.

The charge stop planner makes a charging decision for each segment, for which there are three alternatives (cf. Figure 3). The first (trivial) alternative is not to charge, in which case the vehicle is driven directly to the activity and is parked there for the duration of the activity. The second alternative is en-route charging, in which case the driver stops en route to the activity at a charging station, waits for the charge process to be complete, and then continues to drive to the activity, similar to using a gas station. To limit the time the driver has to wait by the vehicle, only fast charging stations are considered, and the battery is only charged to 80 % SOC, because the charging speed typically decreases significantly after that point. The third alternative is destination charging, in which case the vehicle is charged near the activity (the intended destination). The driver might have to walk from the charging station to the destination and back, but will save time by not having to wait at the vehicle while it charges. This makes it suitable for slow charging, especially when the driver stays at the activity for several hours. The vehicle might be charged to more than 80 % SOC, if the driver stays long enough. We do not assume that the driver will interrupt the activity to unplug and repark the vehicle, so it will block the charge point even after it has reached 100 % SOC. This is because the option to unplug and repark the vehicle would only cost extra time and therefore

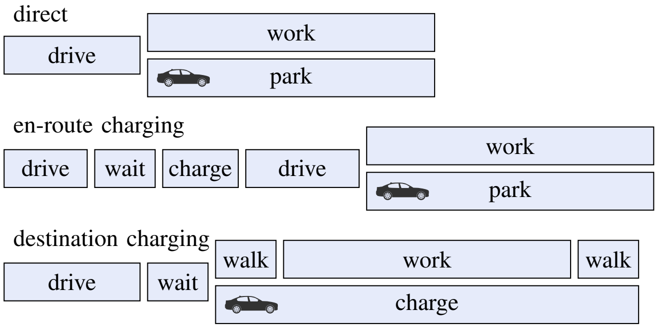


Figure 3. Charging alternatives for each segment

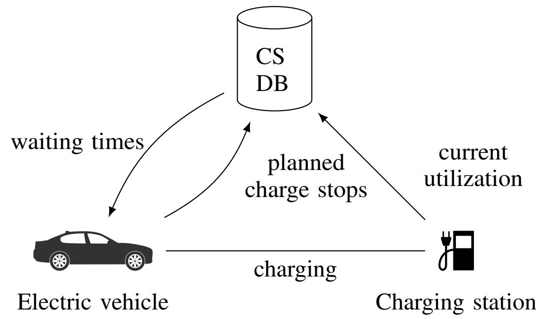


Figure 4. Charging station database concept

would never be selected by the charge stop planner, as it tries to minimize the extra time spent with charging.

For each alternative, the planner also has to consider which route to take when driving to an activity or a charging station. Simply calculating the fastest route (or shortest path) minimizes driving time, but the additional energy consumption, compared to a more energy efficient route, might cause additional charging time. The route must also respect the energy constraints of the vehicle, i.e., keeping the battery SOC positive. To efficiently calculate the shortest paths from fastest to most energy efficient, we use shortest-path tree preprocessing [31]. The energy consumption model can return negative energy consumption values, e.g., when recuperating energy by driving downhill. To deal with the negative edge weights, we use Johnson's algorithm [37].

For each segment, the planner iterates over all alternatives, including charging stations and possible routes, and calculates the time and SOC at the end of the segment. The SOC results from the energy consumption of the selected route and the charged energy at the charging station. The time is influenced by the drive time of the route and the estimated waiting time and charge time of the selected charging station. To estimate waiting times, we use our CSDB (cf. Section IV). For the third alternative, destination charging, the charge time is the sum of the stay time at the activity and walking time to and from the activity.

The planner keeps all alternatives as possible candidates, that are not dominated by other alternatives with a lower time and higher SOC. The candidates' time and SOC values are then used as a basis for the calculation of the next segment. Charging times depend on the vehicle's SOC, and waiting time estimates depend on the arrival time. Because a segment can have several candidates, we have to calculate the next segment for each candidate, thereby creating a result tree.

When the candidates for the final segment have been calculated, we can select one of them as our end result. Because each candidate has a predecessor candidate in the result tree, this includes the selected alternatives for each segment that lead to the end result, including routing and charging decisions. We can select the result based on some criterion, such as having a minimum battery SOC of 70 % at the destination or having charged at least once.

In a real world scenario, the charge stop planner would have to include a safety buffer, e.g. 5% or 10% of the battery state of charge, to account for unexpected events such as traffic jams.

IV. Coordination of Vehicles

We coordinate the charging station visits of electric vehicles with our CSDB approach that we introduced in [38]. We present the concepts in this section to make this paper self-contained.

The concept of the CSDB can be seen in Figure 4. It is a centralized service, that can estimate waiting times at any charging station in the future, so they can be taken into account by the charge stop planner of the vehicle when making charging decisions. The vehicles that want to use it, have to announce their planned charge stops to the service in advance. It also receives information about the current utilization of charging stations and stores historical data about charging station utilization internally. The CSDB does not need any information about vehicles' trip histories or drivers' schedules. The drivers' schedules are only used internally by the charge stop planner and could be stored locally on a user's device, such as a smartphone or the vehicle's on-board navigation system.

Compared to a reservation system, it does not require cooperation with charging station providers. Only information about the current utilization of the charging stations is needed, which many providers already provide as a service to potential customers. The system also does not require every vehicle to take part in it to be useful.

The estimation of waiting times is accomplished by combining three data sources. The current utilization of a charging station is known to the database in the form of occupied charge points and the time when the vehicles occupying the charge points will depart. The announced planned charge stops of the vehicles include an estimated arrival time and charge time at the charging station. To fill in gaps of vehicles that do not announce their planned charge stops, we use historical data of the utilization of the charging station. The historical data is gathered by the CSDB itself and contains the statistical average utilization of the charging station for each hour of the day. When we combine this data, we can forecast the utilization of the charging station in the future and use it to estimate waiting times.

The data in the CSDB can quickly change as additional vehicles announce their planned charge stops. This means that estimated waiting times, which were queried by the charge stop planner at the beginning of the day, might have significantly changed by the time the vehicle arrives at the charging stations. Therefore, to keep the plan optimal, we update it at the beginning of each trip segment.

V. Charging Infrastructure Siting and Sizing

Our main contribution in this paper is the introduction of a siting and sizing approach for slow and fast charging stations. We take into account en-route charging as well as destination charging. Our approach directly builds on our charge stop planner to minimize the average extra time with a minimal number of charging stations and charge points.

In our approach, we strictly separate charging infrastructure siting and sizing. The concept is depicted in Figure 1. In the siting phase, we find locations for new charging stations, to extend the existing charging infrastructure. We analyze typical daily schedules of drivers to find locations that would best improve the average extra time spent with charging. At the new locations, we add charging stations to our existing charging infrastructure, initially with only one charge point. In the sizing phase, we use simulations to test which charging stations we should extend with additional charge points, to best improve the average extra time spent with charging. The charging stations can either be the ones that were added in the siting phase, or be part of the existing charging infrastructure.

A. Siting

Our siting algorithm tries to find suitable locations for new charging stations within the graph of the road network. Each node of the graph is a potential location for a charging station. We analyze the drivers' schedules and assign each node a score, based on how much a new charging station at that location would potentially improve the average extra time, compared to the existing charging infrastructure. The node with the highest score is selected as a site for a new charging station. To find multiple sites, we have to iteratively calculate the node scores, add a charging station to the node with the highest score, and repeat. This is necessary, because each new charging station influences the score of the nodes around it by satisfying the charging demand in its vicinity.

Because slow and fast charging stations are used in a completely different manner, we process them separately and use two different ways to calculate the node scores.

1) Slow Charging Score Calculation: The score for slow charging stations is calculated by using the stops at activities of the drivers' schedules. The idea is to assess locations based on how many vehicles park nearby for long enough to charge a considerable amount with slow charging, and how much walking time the drivers could save compared to existing charging stations.

Let V be the node set of our graph and S the set of stops. The function $d(v_1, v_2)$ returns the linear distance between the nodes $v_1, v_2 \in V$. Each stop $s \in S$ is located at a node $v_s \in V$. The distance from a stop to the closest existing charging station is defined as

$$d_{\min,s} = \min_{c \in C} d(v_c, v_s) \ , \tag{1}$$

where C is the set of charging stations and v_c is the node where the charging station $c \in C$ is located.

Potential locations for new charging stations must be closer than already existing charging stations. We also assume that the driver is not willing to walk very long distances from the charging station to the activity. We therefore define the search radius around the stop s as

$$d_{\text{search},s} = \min(d_{\min,s}, d_{\text{maxwalk}}) \ , \tag{2}$$

where d_{maxwalk} is the maximum walking distance.

For each node $v \in V$, we can calculate a score, based on all stops for which this node is in their search radius, as

$$x_{\text{slow},v} = \sum_{s \in S | d(v, v_s) < d_{\text{search},s}} x_t(t_s) \cdot x_d(d(v_s, v)) \ , \tag{3}$$

where $x_t()$ is a time score based on the stop duration time t_s and $x_d()$ is a distance score based on how close the stop location is to the node. The time score is defined as

$$x_t(t_s) = \begin{cases} \frac{t_s}{t_{\text{charge80}}} & \text{if } t_s < t_{\text{charge80}} \\ 1 & \text{else} \end{cases} \ , \tag{4}$$

where $t_{charge80}$ is the time it takes to charge to 80 % SOC with slow charging. The distance score is defined as

$$x_d(d) = d_{\text{search},s} - d \ . \tag{5}$$

It can be thought of as the walking distance that could be saved if a charging station would be installed at that node.

In Figure 5, we show an example of the score calculation for a node. The score of node v is influenced by the stops s_2 and s_3. Stop s_1 is not used, because the distance to the node is greater than the stop's search radius $d(v_{s_1}, v) > d_{\text{search},s_1}$ (cf. Equation (3)). The time score for stop s_2 is 0.5, because the stop duration is only half the time needed to charge to 80 % SOC (t_{charge80}), and 1.0 for stop s_3, because the stop duration is greater than t_{charge80} (cf. Equation (4)). The distance score represents how much walking distance could be saved compared to the existing charging infrastructure. The distance of stop s_3 to the nearest charging station is 450 m, the distance to the node is 250 m, which results in a distance score of 200. There is no charging station within the maximum walking radius of 600 m around stop s_2, and the distance to the node is 500 m therefore the distance score for s_2 is 100 (cf. Equations (2) and (5)). The total score of the example node is $x_{\text{slow},v} = 0.5 \cdot 100 + 1.0 \cdot 200 = 250$.

2) Fast Charging Score Calculation: The score for fast charging stations is calculated by using the trips to activities of the drivers' schedules. The idea is to assess locations based on how much time vehicles would save in detours compared to existing fast charging stations.

Let R be the set of trips of all schedules, we define the driving time of the shortest path of a trip $r \in R$ with a detour via node v as $t_{r,v}$. The minimum time required to drive the trip with a detour to an existing fast charging station is determined as

$$t_{\min,r} = \min_{c \in C_{\text{fast}}} t_{r,v_c} \ , \tag{6}$$

where $C_{\text{fast}} \subseteq C$ is the set of fast charging stations. We assign a score to each node based on the time a potential new charging

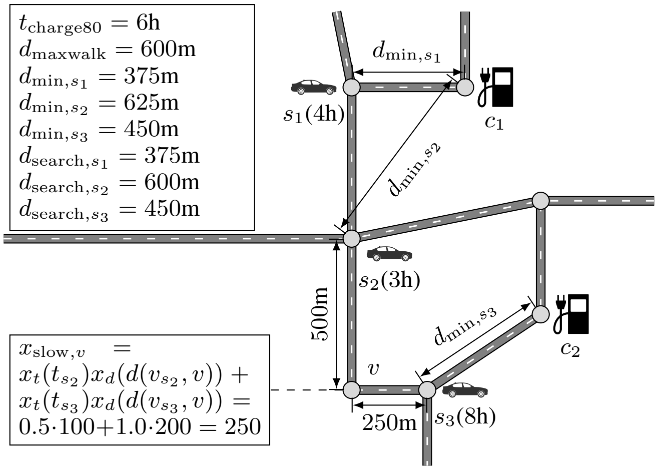


Figure 5. Slow charging infrastructure siting. Example calculation of a node score based on stops s_2 and s_3. Stop s_1 is not used because the node is not within the stop's search radius.

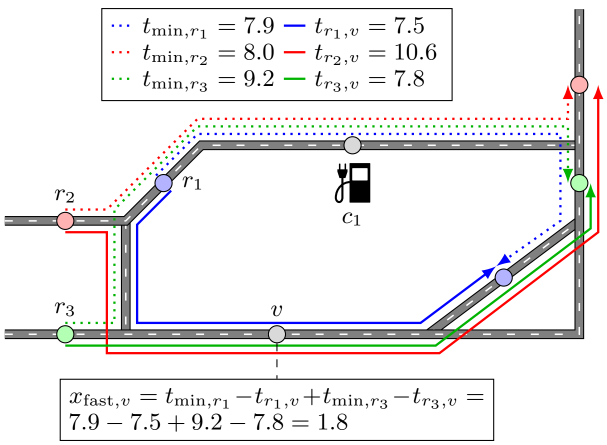


Figure 6. Fast charging infrastructure siting. Example calculation of a node score based on trips r_1 and r_3. Trip r_2 is not used because the condition $t_{r_2,v} < t_{\text{min},r_2}$ is not met.

station would save compared to existing fast charging stations as

$$x_{\text{fast},v} = \sum_{r \in R | t_{r,v} < t_{\text{min},r}} t_{\text{min},r} - t_{r,v} \ . \tag{7}$$

In Figure 6, we outline an example of the score calculation for a node. The score of node v is influenced by the trips r_1 and r_3. Trip r_2 is not used, because the condition $t_{r_2,v} < t_{\text{min},r_2}$ is not met (cf. Equation (7)), which means driving by the node would result in a bigger detour than driving by one of the existing fast charging stations. For trip r_1, driving by the node would result in a shorter detour of $7.9 - 7.5 = 0.4$ minutes compared to the existing fast charging stations and for trip r_3 it would save $9.2 - 7.8 = 1.4$ minutes. The total score of the example node is therefore 1.8.

To calculate the node score, we have to calculate the detour time for each trip. This involves finding the shortest path from the trip's origin to the node and from the node to the destination of the trip. It would be computationally expensive to calculate this for every node in a typical graph of a street network. To limit the computation time, we preselect a small number of

Table I
VEHICLE TYPES

Segment	Vehicle model	Battery capacity (kWh)	Average consumption (kWh/100km)	Max charge power (kW) AC / DC
A (city)	VW e-up!	32	14.8	7.2 / 40
B (small)	BMW i3	42	15.5	11 / 50
C (medium)	VW ID.3	58	15.9	11 / 100
D (large)	VW ID.4	77	18.6	11 / 125
J (SUV)	*generic*	70	23.7	11 / 150

nodes as candidates, based on how many vehicles would drive by the node in one of their trips without detours. This can be easily counted by once finding the shortest paths of all trips. In our experiments, we preselected 2500 of the 100 790 nodes of our graph.

B. Sizing

In the first phase, the siting algorithm has found sites for new slow and fast charging stations, but it did not define the number of charge points for these charging stations. The number of charge points, that a charging station has, influences the waiting time of arriving vehicles for a free charge point. The waiting time cannot simply be calculated with the static analysis of the drivers' schedules by the siting algorithm, because it depends on complex charging decisions made by the drivers and their vehicles, that can also influence each other. To account for this, we have to run simulations in a separate sizing phase. The vehicles in the simulations use the charge stop planner for their charging decisions, and they can coordinate charging between each other using the CSDB. This allows us to evaluate how changes in the number of charge points affect the waiting time and the average extra time spent with charging.

At the beginning, we initialize the new charging stations with one charge point. We then iteratively extend the charging stations with additional charge points to improve the average extra time spent with charging. To select the most suitable charging station to extend, we run $|C|$ parallel simulations, each temporarily adding a charge point to one of the charging stations. We compare the results of all simulations, to see which charging station extension caused the best improvement of extra time and permanently add a charge point to that charging station. We repeat this process until a fixed number of charge points has been added, or the average extra time is below some threshold.

VI. Electric Vehicle Modeling

The charge stop planner and our charging infrastructure siting and sizing approach need precise energy consumption and charging models of the electric vehicles. But, as there are many different types of vehicles on the road today, we cannot simply create one model that fits all. To get a realistic coverage, we use five vehicle types from different car segments ranging from city cars (A segment) to SUVs (J segment), as first introduced in [39]. Table I shows an overview of theses vehicle types.

Table II
ENERGY CONSUMPTION CORRECTION OFFSETS

Segment	Factor	priority junction (Wh)	priority-to-the-right junction (Wh)	traffic light junction (Wh)
A	1.057	4.6	3.4	0.0
B	1.038	6.3	3.9	16.7
C	1.000	11.3	0.0	0.0
D	1.074	12.5	10.0	0.0
J	1.082	9.0	6.0	10.0

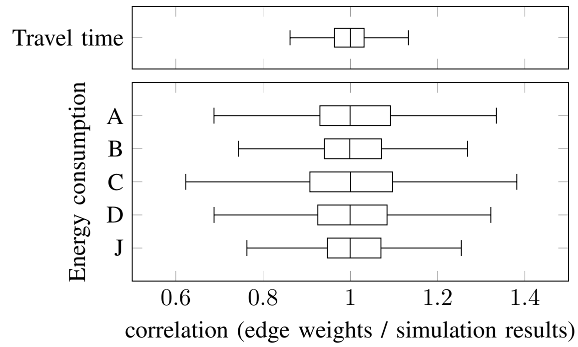


Figure 7. Correlation of travel time and vehicle type specific energy consumption of trips between our calibrated edge weights and the results of the SUMO simulation.

A. Energy Consumption Model

The energy consumption varies significantly between vehicle types. To get accurate vehicle type specific consumption values, we use the energy consumption model introduced in [39]. It was developed for the traffic simulator SUMO and contains a precise physics-based model of individual powertrain components' characteristics. Consumption models for five different vehicle types from different car segments were created. Four are based on real vehicles and were validated against manufacturer data and test bench measurements, and one (J segment) is a generic consumption model for SUVs. We selected our five vehicle types to match those in the publication, to be able to use the same consumption models.

Although the model was developed to calculate the dynamic energy consumption of a vehicle with acceleration and deceleration in traffic, we only use it to get static consumption values for the edges of the road network, because that is all we need for our route planning approach. Apart from vehicle specific characteristics, the energy consumption model takes speed, acceleration, and slope as input parameters to calculate the energy consumption at a given time. To calculate the static energy consumption of an edge, we set the speed and slope to the speed limit and slope of the edge and set the acceleration to zero. This would, of course, underestimate the travel time and energy consumption, because we are omitting traffic effects, especially slowing down and waiting at junctions. To compensate for this, we add a correction offset and factor to the energy consumption and travel time at different types of junctions. We distinguish between priority junctions, priority-to-the-right junctions, and traffic light junctions.

To calibrate the correction offsets for the vehicle types, we have simulated several thousand trips with each vehicle type in the traffic simulator SUMO. We have then adjusted the offsets in such a way, that the travel time and energy consumption of our static edge weights match the corresponding values of the simulated trips. As a result, for the travel time, we apply a factor of 1.02 and an offset of 0.5 s for priority junctions, 2 s for priority-to-the-right junctions and 10 s for traffic light junctions. The energy consumption offsets are vehicle type specific and can be seen in Table II. We are still omitting dynamic traffic effects, and therefore, the static edge weights can not always exactly match the result of the traffic simulation. But, as we can see in Figure 7, in the majority of cases the static edge weights match the results of the traffic simulation within ±10 %.

B. Charging Model

Many authors in the field of electric vehicle route planning and charging infrastructure siting and sizing assume that electric vehicles charge with constant power [4], [6], [15], [33]–[36], [40]. In reality, however, the charge rate is very nonlinear and depends on the type of charging station and the vehicle's charging capabilities. Electric vehicles are charged with either alternating current (AC) or direct current (DC). Charging with AC is limited by most charging stations to 22 kW and many vehicles are only capable of charging with up to 11 kW or even less. For our purposes, we define AC charging as slow charging, because it can take several hours to completely charge the battery. DC charging stations are capable of much faster charging, usually ranging from 50 kW to 350 kW. We define DC charging as fast charging, although it should be noted that not every vehicle is capable of DC charging and that the actual charge power can vary significantly between vehicles. Also, the maximum charge power can only be held up to a certain battery SOC, after which it decreases considerably.

Modern electric vehicles use lithium-ion batteries, which are most commonly charged with a CC-CV (constant current – constant voltage) charging protocol, although alternative charging protocols exist to increase fast charging speeds [41]. The CC-CV protocol begins to charge with constant current, during which the cell voltage continuously rises until it reaches its maximum voltage u_{high}. After that, it switches to constant voltage, during which the current steadily decreases until it falls to near zero. A common alternative is the CP-CV (constant power - constant voltage) protocol, where the first phase charges with constant power instead of constant current, but is otherwise very similar.

In this work, we use the following battery charging model for slow charging, which supports both the CC-CV and the CP-CV approach. We already introduced this model in our previous work, where we also validated it against real world measurements [31]. We assume that the voltage increase is linear in the first phase and, for simplicity, the current decrease is also linear in the second phase, which is consistent with the literature [42]. For our model, we use the following variables: The maximum charging power of the charging station is defined as p_{max}. The SOC of the battery is defined as soc in the range $0 \leq soc \leq 1$. In the first phase (constant current/power), the charging voltage increases from $u_{low} = 3.8\,\mathrm{V}$ to $u_{high} = 4.2\,\mathrm{V}$. The phase switch happens exactly at $soc = 0.8$. The maximum current can be calculated as $i_{max} = \frac{p_{max}}{u_{high}}$. Now, the current $i(soc)$ and voltage $u(soc)$ for the CC-CV charging approach can be calculated based on the SOC of the battery as

$$i(soc) = \begin{cases} i_{max} & \text{for } soc < 0.8 \\ \frac{1-soc}{0.2} \cdot i_{max} & \text{for } soc \geq 0.8 \end{cases}, \tag{8}$$

$$u(soc) = \begin{cases} u_{low} + \frac{soc}{0.8}(u_{high} - u_{low}) & \text{for } soc < 0.8 \\ u_{high} & \text{for } soc \geq 0.8 \end{cases}, \tag{9}$$

$$p_{cc\text{-}cv}(soc) = u(soc) \cdot i(soc)\ . \tag{10}$$

Similarly, the power $p_{cp\text{-}cv}(soc)$ can be calculates as

$$p_{cp\text{-}cv}(soc) = \begin{cases} p_{max} & \text{for } soc < 0.8 \\ u(soc) \cdot i(soc) & \text{for } soc \geq 0.8 \end{cases}. \tag{11}$$

In our model, we estimate the power every second and terminate the charging process when SOC reaches $soc = 0.99$.

The model works well for slow charging, but for fast charging, we cannot make the same assumptions. Some vehicles might use a different charging protocol for fast charging, or if they use CC-CV or CP-CV, the switch between phases may happen a lot earlier than at 80 % SOC. To get realistic fast charging curves, we used data from the charging infrastructure operator Fastned, who published fast charging curves for four of our vehicle types.[2] For our generic SUV vehicle type (J segment), we created a generic charging curve similar to the others. As can be seen in Figure 8, most vehicles can only keep up the fast charging speed for a short range of the battery SOC. It can also be seen that even though the maximum charge speed varies by more than a factor of three between the vehicle types, the difference between charge times is significantly lower. This is due to the fact, that the vehicles with slow charge speeds also have smaller batteries.

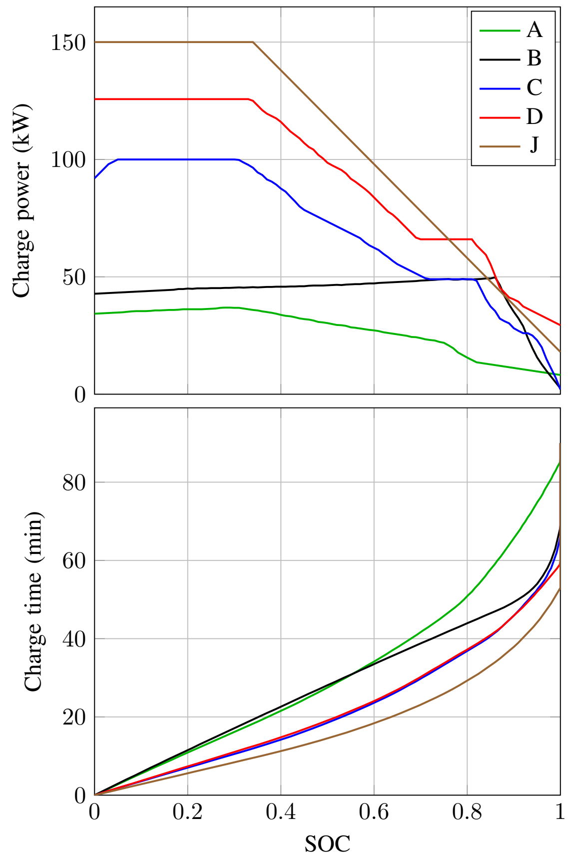


Figure 8. Fast charging curves of vehicle types at a fast charging station with at least 150 kW charge power

VII. Performance Evaluation

A. Experiment Setup

In our experiments, we simulate one day (24 h) of drivers driving to various activities of their day's schedule and wanting to charge their electric vehicle at some point using the public charging infrastructure. We assume the electric vehicle has a 60 kWh battery and an initial SOC of 20 %. The goal is to minimize the extra time spent with charging and to reach the final destination with an SOC of at least 70 %. This allows the vehicle to charge to 80 % at a fast charging station and then still drive to the destination. For simplicity, we assume there is no limit on the maximum walking distance.

B. Paderborn Scenario

The schedules of the drivers in this work are based on the Paderborn traffic simulation scenario [43]. It is a road traffic simulation scenario for SUMO [44] and models the City of Paderborn, a typical mid-sized European city of around

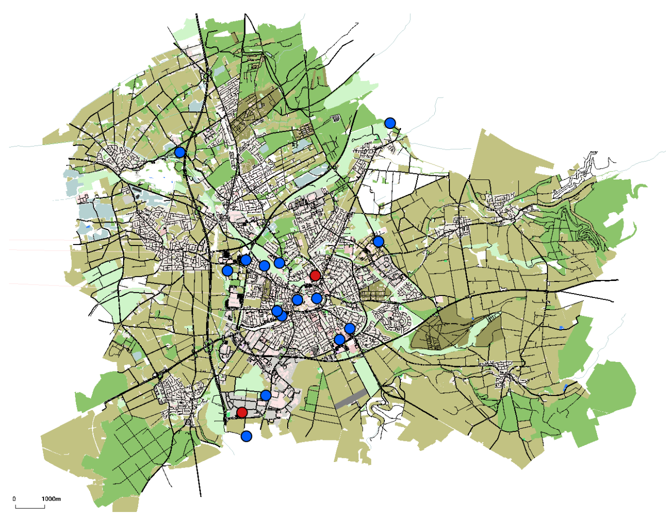


Figure 9. Overview of the Paderborn traffic scenario with slow charging stations (blue) and fast charging stations (red)

[2]https://support.fastned.nl/hc/en-gb/sections/115000180588-Vehicles-charging-tips (visited on 07/27/2021)

Table III
DISTRIBUTION OF VEHICLE TYPES

Segment	Proportion
A	17.0 %
B	30.7 %
C	20.4 %
D	11.2 %
J	20.7 %

150 000 inhabitants. The scenario contains the core of the city as well as outskirts (cf. Figure 9). It includes both major highways (e.g., the Autobahn A33 and Bundesstrassen B1, B64, and B64) as well as urban roads and residential areas. The traffic demand of the scenario consists of more than 200 000 trips over a 24-hour period, with up to 3000 simultaneously active vehicles. It is derived from the daily activities of a population simulated with SUMO's ACTIVITYGEN tool. Each trip models an individual activity, e.g., going to work or University, taking kids to school, driving into the city for shopping, etc. Individuals of the simulated population then each have a day plan of these activities. Statistics such as car ownership, age distributions and typical work hours were fed into the model to make these daily activity plans realistic. Furthermore, specifics like parking spaces, school locations, and distributions of local housing and workplace density were incorporated. The resulting daily traffic demand curve resembles real-world measurements and exhibits phenomena like early-morning rush hours and increased traffic — with some temporary jams — on afternoon commutes.

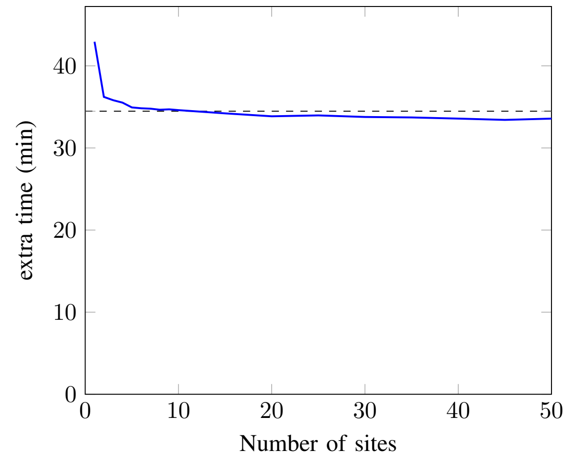
In our experiments, we randomly select a small number of vehicles from the total population to be electric vehicles that have to be charged that day. The vehicle type is assigned according to the distribution in Table III which is based on the actual proportion in Germany in 2020. The majority of vehicles are assumed to not have to charge that day using the public charging infrastructure, because they either charge at home, or because they are vehicles with internal combustion engines. As these vehicles do not affect the public charging infrastructure, they are not considered in our simulation.

We have extended the Paderborn scenario with the existing charging infrastructure of Paderborn.[3] This includes 15 slow charging stations with a power of 22 kW and two charge points each, and two fast charging stations with a power of 150 kW and four charge points each.

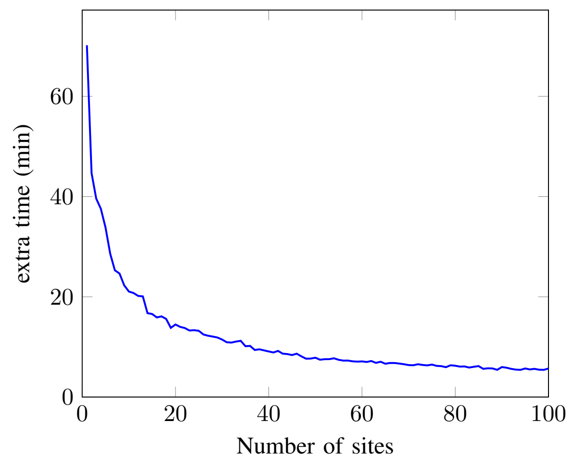
C. Experiments

1) Impact of the number of slow and fast charging station sites: In our experiments, we want to evaluate how well our charging infrastructure siting and sizing approach works. In the first experiment, we analyze the effect of the number of slow and fast charging station sites on the extra time spent with charging. This will later enable us to select a suitable number of slow and fast charging station sites to extend the existing charging infrastructure of the Paderborn scenario.

[3]Ladesaeulenkarte, https://www.bundesnetzagentur.de/DE/Sachgebiete/ElektrizitaetundGas/Unternehmen_Institutionen/E-Mobilitaet/start.html (visited on 02/14/2021)



(a) Fast charging station sites



(b) Slow charging station sites

Figure 10. Comparison of extra time for numbers of fast and slow charging station sites. The dashed line in (a) is our baseline for siting fast charging stations. It represents the extra time, if we were using the 24 gas stations of Paderborn as fast charging station sites.

We use our siting algorithms to find new locations for fast and slow charging stations and simulate one day with a varying number of sites. We run simulations with 1 to 50 fast charging station sites and 1 to 100 slow charging station sites. In this first step, we assume an infinite number of charge points at each charging station, so there will never be any waiting time, because we are only interested in the number of sites and not in sizing the charging stations themselves, which is a separate step.

In Figure 10, we show the number of charging station sites and the average extra time for slow and fast charging stations. Fast charging stations are primarily used with en-route charging, i.e. the vehicle stops en-route on one of its trips and the driver waits by the vehicle until it has finished charging, similar to how gas stations are used. Because the driver waits by the vehicle, the extra time is made up mainly from the charging time in addition to the detour to drive to the charging station. Additional fast charging station sites in the city only influence the detour time, but have no effect on the charging time. We can see that after about 5 fast charging sites, the extra time only decreases marginally. As a baseline, we also simulated

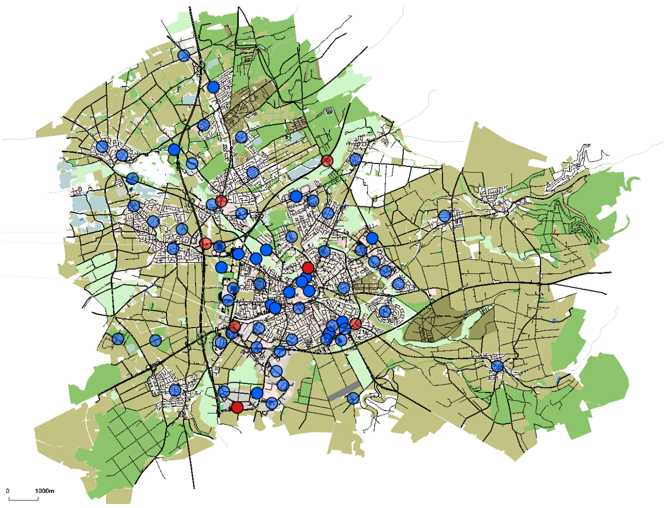


Figure 11. New charging station locations for fast and slow charging stations from our charging station siting algorithm. Slow charging stations are shown as blue and fast charging stations as red, existing charging stations opaque and new locations half transparent.

the same scenario with the 24 gas stations in Paderborn as fast charging station sites. Because fast charging stations are used somewhat similarly to gas stations, they are considered as locations for fast charging stations by several works [10], [33], [34]. We can see that our siting algorithm achieves roughly the same outcome with 10 fast charging station sites.

Slow charging stations on the other hand are primarily used with destination charging, i.e., the vehicle is parked at a charging station near the destination of an activity and the driver visits the destination while the vehicle charges. The extra time in this case is made up mainly of walking time from the charging station to the destination and back. Each additional slow charging station site can reduce the average walking time. We can see that after about 50 slow charging sites, the extra time only decreases marginally.

Based on these results, for the following experiments, we extended the existing charging infrastructure of our Paderborn scenario with 50 slow charging stations and 5 fast charging stations. The new charging station locations can be seen in Figure 11.

2) Impact of the new charging stations: In our second experiment, we analyze the effect of the new charging stations on the travel times of our vehicle types and also compare our strategy of selecting between destination charging and en-route charging with only allowing one of these options. The results can be seen in Figure 12.

For the existing charging stations, only allowing destination charging leads to significant average walking times of about 20 min. This can be attributed to the fact, that only so few charging stations exist, that in most cases there are not any suitable ones nearby. For our extended charging stations, this value is lowered to about 5 min. In both cases, we see a large stay delay time. This is the time, the drivers have to extend their stay at the destination in order for the vehicle to charge enough to fulfill the goal to reach the final destination with 70 % SOC. It varies considerably between vehicle types, and we can see that the vehicles with smaller batteries tend to also have a lower stay delay time, because the time required to charge the battery is lower. Except for the B segment vehicle (BMW i3), which has a lower stay delay than the A segment vehicle (VW e-up!) even though it has a larger battery. This can be attributed to the fact, that the A segment vehicle's slow-charging speed is lower. Overall, this shows that only destination charging with slow charging stations is not suitable for all schedules, as many drivers simply do not stay long enough at their activities. Only allowing en-route charging has a different problem. With the existing charging stations, the vehicles have to drive detours of about 5 min, and with the extended charging stations this is reduced to about 1 min. But the biggest contributor to the travel time is the charging time, which is not significantly influenced by the location of the charging station. Especially vehicles from the smaller segments have only limited fast charging capabilities and suffer from long charging times.

Our strategy can select between destination charging and en-route charging. To limit charging time, we preferably use destination charging and only use en-route charging to avoid stay delay at the slow charging stations or if there is no charging station close to the destinations. In Figure 13 we can see that for the existing charging infrastructure we use destination charging in 67–85 % of all cases. By adding many new slow charging opportunities, with the extended charging infrastructure we use destination charging in 83–91 % of all cases. Overall, we can see that our strategy leads to significantly lower travel times for all vehicle types and that the extended charging infrastructure reduces the average extra time from about 20 min to under 10 min.

3) Impact of sizing approach: In the first two experiments, we evaluated our siting approach and assumed infinite charge points at each charging station and therefore no waiting time. Now, we want to test our sizing approach, which mainly means figuring out how many charge points are needed at each charging station to prevent long waiting times. We can reduce waiting times at the charging stations by coordinating charge stops between vehicles with our CSDB. In our third experiment, we evaluate our sizing approach and compare its results with and without using the CSDB. As an additional comparison, we also tested a spontaneous selection approach that does not use the charge stop planner. Instead of planning their charge stops for the entire day in advance, the drivers select a (random) time within their schedule to charge, and then spontaneously select the charging station with the least expected waiting time, based only on the current occupancy of the charging stations. This way we avoid long waiting times without any coordination between the vehicles. All new charging stations are initialized with one charge point, and then charge points are added to the charging stations by our sizing algorithm one by one to reduce the extra time spent with charging.

The sizing algorithm runs simulations to test extending each charging station. For the simulations, we assume that 250 of the 121 176 vehicles, about 0.2 %, of our scenario are electric vehicles without an option to charge at home that have to charge that day using the public charging infrastructure. We

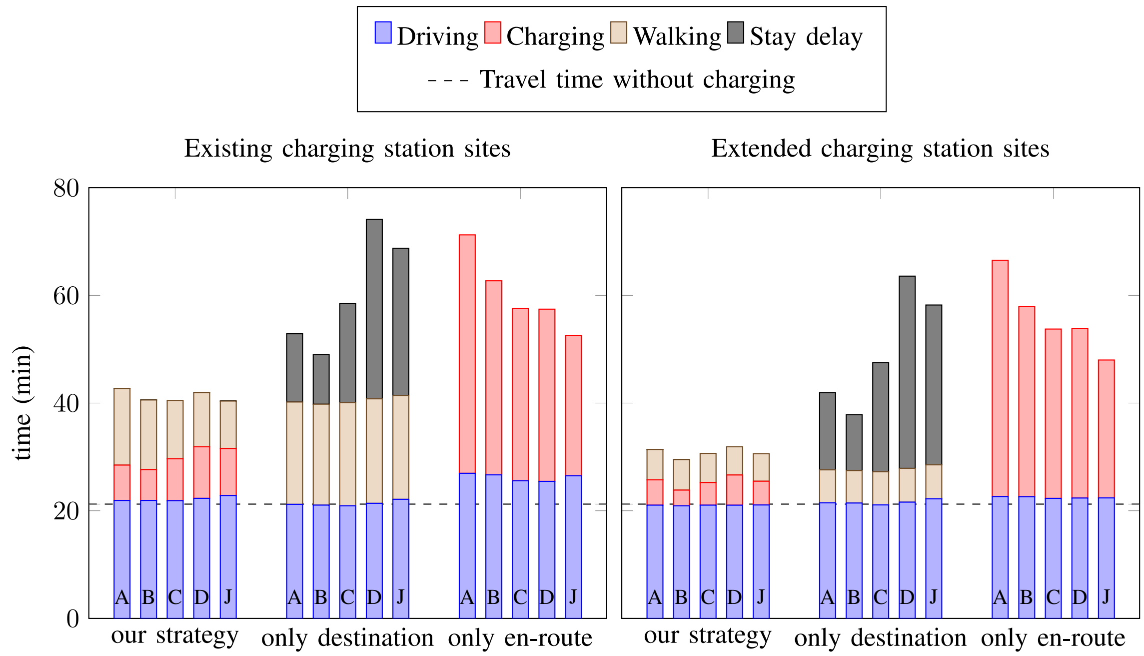


Figure 12. Travel time composition of the vehicle types for our strategy, only destination charging and only en-route charging. Comparison between the existing charging station sites and the extended charging station sites.

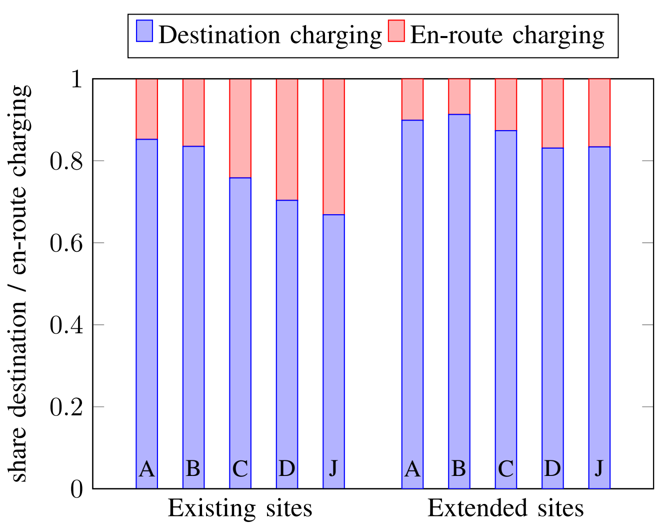


Figure 13. Share of destination charging and en-route charging when using our strategy with the existing charging station sites and the extended charging station sites.

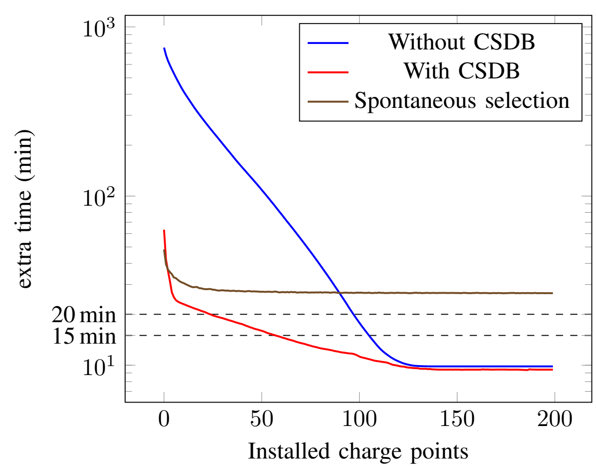


Figure 14. Sizing charging stations with and without using CSDB and with spontaneous selection. Dashed lines at 15 min and 20 min extra times for easier comparison.

repeat the algorithm until we have added 200 charge points. In total, we run 20 iterations with different vehicles and average the results.

The results can be seen in Figure 14. We can observe, that with our CSDB approach, we can reduce the average extra time spent with charging considerably, especially with only few installed charge points. This means, that we would need to install significantly fewer charge points to serve the same amount of vehicles with acceptable extra times. For example, to reach an average extra time of 20 min, we would need to add 97 charge points without using the CSDB, but only 22 charge points when using the CSDB. To reach an average extra time of 15 min, we would only have to add 53 charge points when using the CSDB, instead of 104 without. Eventually, after adding about 125 charge points, the average extra time stays just under 10 min in both cases. At this point, there are enough charge points available, so that there are no significant waiting times anymore, even without any coordination. When using spontaneous selection, we can observe much lower waiting times compared to the charge stop planner without using the CSDB. This is because when using the charge stop planner, some charging stations at bottlenecks will be selected by many vehicles. Without coordination, this leads to queues and long waiting times. By spontaneously checking the occupancy of charging stations, long queues and waiting times can be avoided. At the same time, this does not allow the optimization of charge stops for the driver's schedule. The charge stop planner taking into account the drivers' schedules, therefore outperforms spontaneous selection in the coordinated case, and also in the uncoordinated case if enough charge points are available.

VIII. Conclusion

We introduced a new charging infrastructure siting and sizing approach with the goal to optimize the average extra time spent with charging electric vehicles. We can find locations for slow and fast charging stations by analyzing typical daily schedules of drivers. To determine the number of charge points necessary to prevent long waiting times at charging stations, we test extending charging stations in simulations and compare the average extra time. In the simulations, we planned charge stops with either en-route or destination charging using a realistic model for charging and energy consumption for five electric vehicle types of different car segments. To reduce waiting times at charging stations, we can use our CSDB, which coordinates charging between vehicles.

We evaluated our approach with the Paderborn scenario, which gives us 24 h of realistic traffic with daily trips for individual vehicles in a mid-sized city. We found that smaller vehicles, which have small batteries and only limited fast charging capabilities, are not well suited for en-route charging at fast charging stations and are better off using destination charging. The opposite is true for larger vehicles. They are less suitable for destination charging, because charging large batteries takes a long time with slow charging, but their better fast charging capabilities make en-route charging a viable option. Having the choice between en-route and destination charging significantly improves the extra time spent with charging for all vehicle types, which makes a combination of slow and fast charging stations the best option. We also found that while we only need a few centralized fast charging stations, we need a large number of slow chargers to significantly improve the average extra time, but that the possible improvement in that case is better than with only fast charging stations. By extending the existing charging infrastructure of our scenario with 5 fast charging and 50 slow charging sites, we were able to reduce the average potential extra time for all vehicle types by about 50 %, from 20 min to 10 min. When evaluating our sizing approach, we found that by using our CSDB to coordinate charging between vehicles, we were able to significantly reduce the necessary number of charge points to achieve an acceptable average extra time spent with charging. For example, to reach an average extra time of 15 min, we only had to add 53 charge points when using the CSDB, instead of 104 without.

Overall, our solution can help make electric mobility a viable choice even for drivers that have no option to charge at home. By extending the existing charging infrastructure with a combination of slow and fast charging stations that can be used by drivers on their daily trips and by coordinating charging between vehicles, we can reduce the extra time spent with charging to an acceptable level. For future work, we want to address monetary constraints as well. The cost of installing and operating charging stations and charge points can vary significantly among different locations and charging station types. To incentivize drivers to charge their vehicle at low demand charging stations or off-peak hours, dynamic pricing can be used. We also plan to include a fee for blocking the charging station after the charge is complete to motivate drivers to unplug and repark the car.

In a real-life scenario, drivers' schedules will likely not be exactly accurate, especially if they are generated from historical data. We want to analyze the effects inaccuracies have on the performance of the system.

References

[1] IEA, "Global EV Outlook 2021," IEA, Paris, Tech. Rep., 2021.

[2] R. Philipsen, T. Schmidt, and M. Ziefle, "A Charging Place to Be - Users' Evaluation Criteria for the Positioning of Fast-charging Infrastructure for Electro Mobility," *Elsevier Procedia Manufacturing*, vol. 3, pp. 2792–2799, 2015.

[3] S. Schoenberg, D. S. Buse, and F. Dressler, "Coordinated Electric Vehicle Re-Charging to Reduce Impact on Daily Driving Schedule," in *32nd IEEE Intelligent Vehicles Symposium (IV 2021)*, Nagoya, Japan: IEEE, Jul. 2021.

[4] J. Dong, C. Liu, and Z. Lin, "Charging infrastructure planning for promoting battery electric vehicles: An activity-based approach using multiday travel data," *Elsevier Transportation Research Part C: Emerging Technologies*, vol. 38, pp. 44–55, Jan. 2014.

[5] C. Zhang, Y. Liu, F. Wu, B. Tang, and W. Fan, "Effective Charging Planning Based on Deep Reinforcement Learning for Electric Vehicles," *IEEE Transactions on Intelligent Transportation Systems (TITS)*, vol. 22, no. 1, pp. 542–554, Jan. 2021.

[6] W. Wu, Y. Lin, R. Liu, Y. Li, Y. Zhang, and C. Ma, "Online EV Charge Scheduling Based on Time-of-Use Pricing and Peak Load Minimization: Properties and Efficient Algorithms," *IEEE Transactions on Intelligent Transportation Systems (TITS)*, pp. 1–15, Sep. 2020.

[7] M. M. De Weerdt, S. Stein, E. H. Gerding, V. Robu, and N. R. Jennings, "Intention-Aware Routing of Electric Vehicles," *IEEE Transactions on Intelligent Transportation Systems (TITS)*, vol. 17, no. 5, pp. 1472–1482, May 2016.

[8] M. Erbaş, M. Kabak, E. Özceylan, and C. Çetinkaya, "Optimal siting of electric vehicle charging stations: A GIS-based fuzzy Multi-Criteria Decision Analysis," *Elsevier Energy*, vol. 163, pp. 1017–1031, Nov. 2018.

[9] I. S. Bayram and S. Bayhan, "Location Analysis of Electric Vehicle Charging Stations for Maximum Capacity and Coverage," in *14th IEEE International Conference on Compatibility, Power Electronics and Power Engineering (CPE-POWERENG 2020)*, Setúbal, Portugal: IEEE, Jul. 2020, pp. 409–414.

[10] U. Zafar, I. S. Bayram, and S. Bayhan, "A GIS-based optimal facility location framework for fast electric vehicle charging stations," in *The 30th International Symposium on Industrial Electronics (ISIE 2021)*, Virtual Conference: IEEE, Jun. 2021.

[11] R. Wolbertus and R. Van den Hoed, "Electric Vehicle Fast Charging Needs in Cities and along Corridors," *World Electric Vehicle Journal*, vol. 10, no. 2, pp. 1–13, Jun. 2019.

[12] S. Uppoor, O. Trullols-Cruces, M. Fiore, and J. M. Barcelo-Ordinas, "Generation and Analysis of a Large-Scale Urban Vehicular Mobility Dataset," *IEEE Transactions on Mobile Computing (TMC)*, vol. 13, no. 5, pp. 1061–1075, May 2014.

[13] M. Schmidt, P. Staudt, and C. Weinhardt, "Evaluating the importance and impact of user behavior on public destination charging of electric vehicles," *Applied Energy*, vol. 258, p. 114 061, Jan. 2020.

[14] E. Sortomme and M. A. El-Sharkawi, "Optimal Scheduling of Vehicle-to-Grid Energy and Ancillary Services," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 351–359, Mar. 2012.

[15] D. Wang, H. Wang, J. Wu, X. Guan, P. Li, and L. Fu, "Optimal Aggregated Charging Analysis for PEVs Based on Driving Pattern Model," in *IEEE Power & Energy Society General Meeting*, Vancouver, Canada: IEEE, Jul. 2013.

[16] E. S. Rigas, S. D. Ramchurn, N. Bassiliades, and G. Koutitas, "Congestion Management for Urban EV Charging Systems," in *IEEE International Conference on Smart Grid Communications (SmartGrid-Comm)*, Vancouver, Canada: IEEE, Oct. 2013.

[17] E. H. Gerding, S. Stein, V. Robu, D. Zhao, and N. R. Jennings, "Two-Sided Online Markets for Electric Vehicle Charging," in *12th International Conference on Autonomous Agents and Multi-Agent Systems (AAMAS 2013)*, Saint Paul, MN: International Foundation for Autonomous Agents and Multiagent Systems, May 2013.

[18] H. Yang, Y. Deng, J. Qiu, M. Li, M. Lai, and Z. Y. Dong, "Electric Vehicle Route Selection and Charging Navigation Strategy Based on Crowd Sensing," *IEEE Transactions on Industrial Informatics*, vol. 13, no. 5, pp. 2214–2226, Oct. 2017.

[19] H.-J. Kim, J. Lee, G.-L. Park, M.-J. Kang, and M. Kang, "An Efficient Scheduling Scheme on Charging Stations for Smart Transportation," in *1st International Conference on Security-Enriched Urban Computing and Smart Grid (SUComS 2010)*, Daejeon, South Korea, Sep. 2010, pp. 274–278.

[20] H. Qin and W. Zhang, "Charging Scheduling with Minimal Waiting in A Network of Electric Vehicles and Charging Stations," in *8th ACM International Workshop on Vehicular Internetworking (VANET 2011)*, Las Vegas, NV: ACM, Sep. 2011.

[21] L. Bedogni, L. Bononi, M. Di Felice, A. D'Elia, and T. S. Cinotti, "A Route Planner Service with Recharging Reservation: Electric Itinerary with a Click," *IEEE Intelligent Transportation Systems Magazine*, vol. 8, no. 3, pp. 75–84, 2016.

[22] Y. Cao, S. Liu, Z. He, X. Xie, R. Wang, and S. Yu, "Electric Vehicle Charging Reservation Under Preemptive Service," in *1st International Conference on Industrial Artificial Intelligence (IAI 2019)*, Shenyang, China, Jul. 2019.

[23] L. Hou, C. Wang, and J. Yan, "Bidding for Preferred Timing: An Auction Design for Electric Vehicle Charging Station Scheduling," *IEEE Transactions on Intelligent Transportation Systems (TITS)*, vol. 21, no. 8, pp. 3332–3343, Aug. 2020.

[24] K.-B. Lee, M. A. Ahmed, D.-K. Kang, and Y.-C. Kim, "Deep Reinforcement Learning Based Optimal Route and Charging Station Selection," *Energies*, vol. 13, no. 23, p. 6255, Nov. 2020.

[25] S.-N. Yang, W.-S. Cheng, Y.-C. Hsu, C.-H. Gan, and Y.-B. Lin, "Charge scheduling of electric vehicles in highways," *Mathematical and Computer Modelling*, vol. 57, no. 11, pp. 2873–2882, Jun. 2013.

[26] T. Qian, C. Shao, X. Wang, and M. Shahidehpour, "Deep Reinforcement Learning for EV Charging Navigation by Coordinating Smart Grid and Intelligent Transportation System," *IEEE Transactions on Smart Grid*, vol. 11, no. 2, pp. 1714–1723, Mar. 2020.

[27] A. Artmeier, J. Haselmayr, M. Leucker, and M. Sachenbacher, "The Shortest Path Problem Revisited: Optimal Routing for Electric Vehicles," in *Advances in Artificial Intelligence (KI 2010)*, Karlsruhe, Germany: Springer, Sep. 2010, pp. 309–316.

[28] E. W. Dijkstra, "A Note on Two Problems in Connexion with Graphs," *Numerische Mathematik*, vol. 1, no. 1, pp. 269–271, Dec. 1959.

[29] S. Storandt, "Quick and Energy-Efficient Routes - Computing Constrained Shortest Paths for Electric Vehicles," in *5th ACM SIGSPATIAL International Workshop on Computational Transportation Science (IWCTS 2012)*, Redondo Beach, CA: ACM, Nov. 2012, pp. 20–25.

[30] R. Geisberger, P. Sanders, D. Schultes, and D. Delling, "Contraction Hierarchies: Faster and Simpler Hierarchical Routing in Road Networks," in *7th International Workshop on Experimental Algorithms (WEA 2008)*, Provincetown, MA: Springer, May 2008, pp. 319–333.

[31] S. Schoenberg and F. Dressler, "Planning Ahead for EV: Total Travel Time Optimization for Electric Vehicles," in *22nd IEEE International Conference on Intelligent Transportation Systems (ITSC 2019)*, Auckland, New Zealand: IEEE, Oct. 2019.

[32] A. Król and G. Sierpiński, "Application of a Genetic Algorithm With a Fuzzy Objective Function for Optimized Siting of Electric Vehicle Charging Devices in Urban Road Networks," *IEEE Transactions on Intelligent Transportation Systems (TITS)*, pp. 1–12, Jun. 2021.

[33] R. Bi, J. Xiao, V. Viswanathan, and A. Knoll, "Influence of Charging Behaviour Given Charging Station Placement at Existing Petrol Stations and Residential Car Park Locations in Singapore," *Procedia Computer Science*, vol. 80, pp. 335–344, 2016.

[34] A. Hess, F. Malandrino, M. B. Reinhardt, C. Casetti, K. A. Hummel, and J. M. Barceló-Ordinas, "Optimal Deployment of Charging Stations for Electric Vehicular Networks," in *1st Workshop on Urban Networking (UrbaNe 2012)*, Nice, France: ACM, Dec. 2012.

[35] P. Tadayon-Roody, M. Ramezani, and H. Falaghi, "Multi-objective locating of electric vehicle charging stations considering travel comfort in urban transportation system," *IET Generation, Transmission & Distribution*, vol. 15, no. 5, pp. 960–971, Mar. 2021.

[36] F. He, Y. Yin, and J. Zhou, "Deploying public charging stations for electric vehicles on urban road networks," *Elsevier Transportation Research Part C: Emerging Technologies*, vol. 60, pp. 227–240, Nov. 2015.

[37] D. B. Johnson, "Efficient Algorithms for Shortest Paths in Sparse Networks," *Journal of the ACM (JACM)*, vol. 24, no. 1, pp. 1–13, Jan. 1977.

[38] S. Schoenberg and F. Dressler, "Reducing Waiting Times at Charging Stations with Adaptive Electric Vehicle Route Planning," *IEEE Transactions on Intelligent Vehicles (T-IV)*, Jan. 2022.

[39] L. Koch, D. S. Buse, M. Wegener, et al., "Accurate physics-based modeling of electric vehicle energy consumption in the SUMO traffic microsimulator," in *24th IEEE International Conference on Intelligent Transportation Systems (ITSC 2021)*, Indianapolis, IN: IEEE, Sep. 2021.

[40] C. Liu, M. Zhou, J. Wu, C. Long, and Y. Wang, "Electric Vehicles En-Route Charging Navigation Systems: Joint Charging and Routing Optimization," *IEEE Transactions on Control Systems Technology (TCST)*, vol. 27, no. 2, pp. 906–914, Mar. 2019.

[41] A. Tomaszewska, Z. Chu, X. Feng, et al., "Lithium-ion battery fast charging: A review," *eTransportation*, vol. 1, p. 100 011, Aug. 2019.

[42] K. S. Ng, C.-S. Moo, Y.-P. Chen, and Y.-C. Hsieh, "Enhanced coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries," *Applied Energy*, vol. 86, no. 9, pp. 1506–1511, Sep. 2009.

[43] D. S. Buse, "Paderborn Traffic Scenario," Zenodo, Traffic Simulation Scenario version 0.1, Feb. 2021.

[44] P. Alvarez Lopez, M. Behrisch, L. Bieker-Walz, et al., "Microscopic Traffic Simulation using SUMO," in *21st IEEE International Conference on Intelligent Transportation Systems (ITSC 2018)*, Maui, HI: IEEE, Nov. 2018, pp. 2575–2582.

Sven Schoenberg (Graduate Student Member, IEEE) received the double B.Sc. degree from the Dortmund University of Applied Sciences and Arts, Dortmund, Germany, and from Staffordshire University, Stoke-on-Trent, U.K., in 2011. He received the M.Sc. degree from Paderborn University, Paderborn, Germany, in 2014. He is currently working toward the Ph.D. degree with the Data Communications and Networking Group of Falko Dressler, Technical University of Berlin, Berlin, Germany. He is currently working with Software Innovation Lab, Paderborn University. His research focuses on algorithms for electric vehicle route planning.

Dominik S. Buse (Graduate Student Member, IEEE) received the B.Sc. and M.Sc degrees from Paderborn University, Paderborn, Germany, in 2013 and 2016, respectively He is currently working toward the Ph.D. degree with the Data Communications and Networking Group of Falko Dressler, Technical University of Berlin, Berlin, Germany. He is currently working with Software Innovation Lab, Paderborn University. His research interests include real-time simulation of vehicular networks and intelligent transportation systems.

Falko Dressler (Fellow, IEEE) received the M.Sc. and Ph.D. degrees from the Department of Computer Science, University of Erlangen, Erlangen, Germany, in 1998 and 2003, respectively. He is a Full Professor and Chair for Telecommunication Networks at the School of Electrical Engineering and Computer Science, TU Berlin, Germany. Dr. Dressler is an IEEE Fellow as well as an ACM Distinguished Member. He is a member of the German National Academy of Science and Engineering (acatech). He has been serving on the IEEE COMSOC Conference Council and the ACM SIGMOBILE Executive Committee. His research objectives include adaptive wireless networking (radio, visible light, molecular communications) and embedded system design (from microcontroller to Linux kernel) with applications in ad hoc and sensor networks, the Internet of Things, and cooperative autonomous driving systems.