Coordinated Electric Vehicle Re-Charging to Reduce Impact on Daily Driving Schedule

Sven Schoenberg[1], Dominik S. Buse[1,2], and Falko Dressler[2]

***Abstract*— With improvements to ranges and a growing charging infrastructure, electric vehicles are becoming increasingly popular. However, many prospective owners can not charge their vehicle at home. They thus would have to use public charging infrastructure, which reduces the appeal of electric vehicles to them due to the extra effort and time spent during charging. Many previous works tried to enhance this situation by using intelligent charging station scheduling and/or route planning to reduce the time overhead. But most solutions are focused on long distance travel or single trips without considering the often regular schedule of drivers in urban areas. We propose a charge stop planner that takes into account the activities of a driver's daily schedule to minimize the additional time the driver has to spend charging the vehicle. The charging stops can either be en-route charging at fast charging stations between two activities or destination charging at slow charging stations. To reduce waiting times, we coordinate the charging station visits between the vehicles with a centralized service. In an extensive set of simulation experiments, we demonstrate that our approach reduces the additional time for charging by about 40 %, compared to only destination charging and only en-route charging. The charging station coordination further reduces the waiting time by about 50 %.**

I. Introduction

Electric vehicles are becoming increasingly popular. Until recently, due to short ranges and long charging times, they were often only feasible if a charger was available at home or at least nearby. Now that batteries are improving, the increased range and fast charging capabilities make them attractive also to people who cannot charge at home. However, fast charging stations are still not as fast as filling up at a gas station and they are usually a lot more expensive then slow charging stations [1].

In many cities, there are more slow charging stations available, because they are cheaper to build and less burden on the power grid. In Germany the public charging infrastructure consists of 33 811 slow charging stations and 5630 fast charging stations as of February 2021 [2]. Slow charging stations are typically used while the driver stays at his intended destination (also called destination charging). In comparison, fast charging stations are more likely used for en-route charging, i.e., the driver stops to charge and waits by his vehicle like at a gas station. Overall, the inconvenience caused by having to use the public charging infrastructure is a big barrier for buying electric vehicles if there is no possibility to charge at home.

In this context, quite some work has been done to improve the situation for electric cars. Recent work can be grouped into three lines of research. First, the identification of mobility and, thus, charging pattern, e.g., [3], [4]. Second, scheduling of charging attempts to reduce the waiting times at charging stations, e.g., [5]–[9]. Third, optimizing the route planning for electric cars to take energy constraints into account and, in some cases, plan recharging stops, e.g., [10]–[13].

Most of these works focused on only one of these aspects. Some works, e.g., our charging station database (CSDB) approach [14], tried to take all three aspects into consideration but only for long-distance rides.

In this paper, we bridge this research gap and study coordinated electric vehicle charging in urban environments based on the daily schedule of the drivers. We focus on an inner city scenario, where the distances are small enough, that most drivers would not need to charge the vehicle to reach all destinations of the day, if it were fully charged. We further assume the driver does not have a charging station at home or near his home and has to charge at the public charging infrastructure. In particular, we present an approach to minimize the additional time incurred by using the public charging infrastructure. By taking into account the drivers schedule when planning the trips for the day, we can select optimal routes and charging stops. The charging stops can either be en-route charging between two activities or destination charging near an activity of the schedule. In our scenario, we reduced the additional time for charging by about 40 %, compared to only en-route charging and only destination charging. By coordinating the charging station visits between the vehicles with our CSDB approach, we can further reduce the waiting time at charging stations by 50 %.

Our main contributions can be summarized as follows:

- We developed a novel charge stop planner algorithm that optimizes charging stops while minimizing the time spent during charging (III);
- we extended our previous CSDB solution to coordinate vehicles' routes and charging stops (IV); and
- we performed an extensive set of simulation experiments to demonstrate the advantages of our solution (V).

II. Related Work

There are many works in literature that are concerned with charging station scheduling and electric vehicle routing. Especially in the context of smart grid, where the objective is usually to limit the impact of electric vehicle charging on the

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).

[1]Software Innovation Lab and the Department of Computer Science, Paderborn University, Germany sven.schoenberg@c-lab.de, buse@ccs-labs.org

[2]School of Electrical Engineering and Computer Science, TU Berlin, Germany dressler@ccs-labs.org

power grid. This is usually achieved by setting charging price incentives to shift the load from peak to off-peak hours [4], [15]–[17]. In some cases, a service assigns charging stations to the electric vehicles to minimize charging cost and/or waiting time [9], [11], [12], [17]–[20].

Especially in an urban scenario with destination charging, taking user behavior or mobility patterns into account is important [3]. Some smart grid focused works consider mobility patterns to forecast energy demand and schedule charging stations accordingly [4], [16]. Other works, e.g., [17], [21], consider that the driver could charge while they park near and then walk to the final destination (destination charging). Gerding et al. [21] describe a *park 'n charge* scenario, where the driver parks near and then walks to the final destination, as a real-work scenario for their system. In a different scenario, they also considered *en-route charging*, but they did not combine the scenarios, so that there would be a choice between them. Yang et al. [12] present a route selection and charging navigation strategy that can take into account destination charging as well as fast charging en-route if necessary to reach the destination. However, none of these works consider the day's schedule of the driver to make charging decision or compare en-route charging with destination charging.

Charging an electric vehicle even at a fast charging station is still not as fast as filling up a conventional vehicle. The number of charge points at charging stations is limited and if there is no coordination between the vehicles, this will lead to queues and long waiting times. A possible solution to this problem is a reservation system, where the vehicles can reserve a time slot at a charging station in the future and can therefore plan their trip accordingly to avoid waiting times. Many publications make use of such a reservation system [6]–[9], [22], [23], sometimes with the possibility to update the reservation, if needed [23]. Most of these systems have a first-come-first-serve policy, but some can also prioritize reservations, leading to cases where high priority vehicles can charge before others even if they arrive later at the charging station [7]. Hou et al. [8] use a scheduler that allocates reservations based on user given information about their time preferences. Due to the assumption that users are selfish and do not want to reveal their true time preferences to avoid unfavorable time slots, they propose an iterative auction which, by progressively eliciting the users' preferences as necessary, preserves their privacy. A different approach is a centralized service that knows about the current charging station utilization and can give vehicles advice on where to charge [24]. The vehicles could also announce their charging intentions to this service, so that it can predict the waiting time in the future. De Weerdt et al. [5] call this intention-aware routing. They combined the information about charging intentions with historical data and were able to reduce waiting times in some cases by about 80 %.

Recently, some approaches for charging station and route selection have been using deep reinforcement learning. It enables them to make complex decisions in a stochastic environment with changing conditions like traffic, weather, dynamic charge prices etc. by learning an optimal policy. Qian et al. [19] present a charging navigation solution which aims to minimize the total travel time and charging cost. It can take into account waiting times at charging stations, traffic conditions and charge prices, thereby coordinating smart grid and intelligent transportation systems. However, they do not consider direct coordination between vehicles, but simply assume that charging stations know how long the waiting times will be. Lee et al. [9] propose a similar system where there is coordination between vehicles with a reservation system and charging decisions are made by a central service. However, both solutions suffer from poor scalability. They evaluated very small instances with graphs of only 39 nodes and three charging stations. Zhang et al. [20] use deep reinforcement learning for planning charging scheduling at a larger scale. They evaluated instances of a big city with more than 1000 charging stations. However, these works also do not consider the day's schedule of the driver or compare en-route charging with destination charging.

Finding an optimal route for an electric vehicle is more difficult than for a conventional vehicle. The constraints of the battery, especially the limited range, have to be accounted for. This can further include recuperation, also called regenerative braking, i.e., charging the battery when slowing down or driving downhill. Finding the shortest path that also considers such battery constraints is a Constrained Shortest Path (CSP) problem [25]. To find the fastest route that is reachable with a limited range, a multi-criteria shortest path search can be performed using the criteria travel time and energy consumption. This results in all Pareto optimal paths for these criteria and we can, for example, choose the one with the best travel time that still fulfills the energy constraints. A multi-criteria shortest path search is very computationally expensive. It is possible to use a modified version of Dijkstra's algorithm [26], but it is not practical for graphs of realistic sizes [13]. To accelerate the search we can use contraction hierarchies introduced by Geisberger et al. [27]. In a preprocessing step, shortcuts are added to the graph that can later speed-up the path finding query significantly, by reducing the number or nodes that need to be visited when exploring the graph. Contraction hierarchies were originally intended for conventional shortest path searches, but can also be used to speed-up multi-criteria path finding to solve the CSP [13].

In large graphs, multi-criteria path finding can be too slow in practice even with contraction hierarchies. In our previous work [28] we introduced shortest-path tree precomputing in combination with contraction hierarchies as a way to accelerate queries even further. The most computationally expensive part of the query is the creation of a Pareto set of labels at each visited node while exploring the graph. In a preprocessing step, we explore the graph for nodes that will likely be the origin or destination of queries, and save the resulting shortest-path trees. This is only feasible because the number of nodes that need to be visited is significantly reduced by the contraction hierarchies. By exploiting the fact that most routes are queried between the known locations of the charging stations, we were able to accelerate these queries by about two orders of magnitude.

In this paper, we go one step further by considering the drivers day's schedule 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.

III. Charge Stop Planner

Our charge stop planner tries to find optimal charging stops for electric vehicles that minimize the time spent with the charge process by the driver within his day's schedule. We assume to know the schedule of the driver, which consists of activities, i.e. times and locations the driver visits with his vehicle throughout the day, like going to work, shopping, leisure activity, etc. It could be extracted from previous behavior or may be supplied by the driver himself.

We divide the schedule into segments, for which we can make separate charging decisions. Each segment consists of one activity including the drive to that activity. Figure 1 shows an example of a day's schedule, divided into three segments. The day's schedule ends at the final destination, therefore the last segment only consists of a drive.

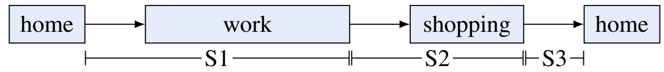


Fig. 1. Day's schedule divided into segments

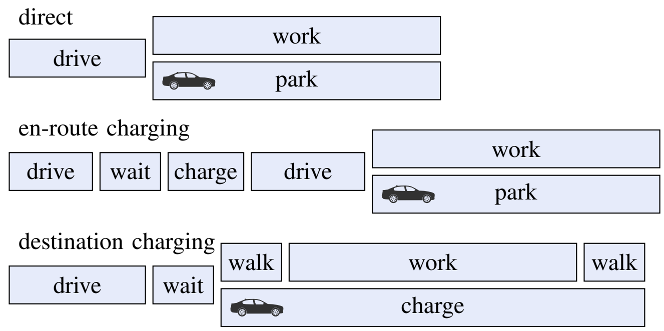


Fig. 2. Charging alternatives for each segment

For each segment, we can select from a number of alternatives. There are three charging alternatives, as can be seen in Figure 2. The first alternative is to drive directly to the activity and parking the vehicle there without charging. The second alternative, en-route charging, is to drive to a charging station, charge there and continue to drive to the activity. The driver may have to wait until the charging station is free if it is occupied on arrival and stays with the vehicle while it is charging. When evaluating the alternative, we estimate the waiting time with our CSDB (cf. Section IV). Because of the time the driver has to be with his vehicle, this is usually only feasible with fast charging. We only plan to charge to 80 % State of Charge (SOC), because the charging speed decreases significantly after that point. The third alternative, destination charging, is to drive to a charging station near the activity, parking there and walking to the activity while the vehicle charges. The driver saves time by not having to be with his vehicle while it charges, but may have additional walking time to and from his intended activity. We can limit the walking time, to account for the fact, that many people would be unwilling to walk very far, even if it saves them time overall. This is suitable for slow charging stations, especially if the driver stays a long time at the activity. We assume to charge the vehicle as long as the driver is staying at the activity, which could result in less than 80 % SOC, if the driver only stays for a short time. If he stays longer than necessary for a full charge, the charge point will be blocked by the vehicle, because we assume the driver will not interrupt his activity to unplug and park the vehicle somewhere else.

In addition to the three charging alternatives, we have to select a route when driving to the activity or to and from the charging stations. To minimize time, we could always take the fastest route, but in some cases it might actually take less time if we take a slower, but more energy efficient route, if it saves us charging time later. The route must also respect the energy constraints of the vehicle, i.e. keeping the battery SOC positive. We efficiently calculate all Pareto-optimal shortest path from the fastest to the most energy efficient by using shortest-path tree preprocessing [28].

Of course, for the second and third charging alternative, we also have to select the charging station. For each segment, we iterate over all alternatives, routes and charging stations and calculate the time and SOC at the end of the segment. We discard all results for which we have a better alternative which requires less time and has a higher SOC. The remaining results should have at least one direct drive and one charge alternative. The result time and SOC is used as a basis for the next segment. Charging times depend on the vehicles SOC, and waiting time estimates depend on the arrival time. Because a segment can have several result alternatives, we have to calculate the next segment results for each alternative, thereby creating a result tree.

After all segments have been calculated, we can select one of the result alternatives from the final segment as our end result. Because each result has a predecessor result in the result tree, we thereby also select the alternative for each segment that lead to this 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.

IV. Coordination of Vehicles

We coordinate the charging station visits of electric vehicles with our CSDB approach that we introduced in [14]. The concept of the CSDB can be seen in Figure 3. 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

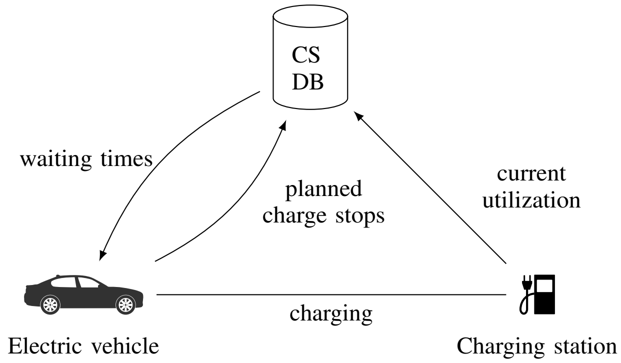


Fig. 3. Charging station database concept

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.

Compared to a reservation system, where the vehicles reserve time slots in the future, we believe this approach is far more practical. There cannot be a situation, where a vehicle with a reservation is late and one charge point has to remain vacant even though there are other vehicles waiting to charge. This could lead to reduced average utilization and bad experience from drivers not using the system The CSDB does not require cooperation with the charging station providers, apart from providing information about the current utilization, 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.

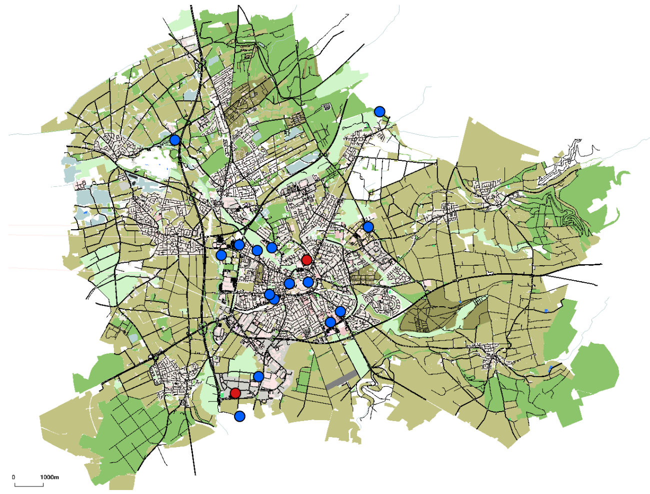


Fig. 4. Overview of the Paderborn traffic scenario with slow charging stations (blue) and fast charging stations (red)

V. 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 time spent with charging the vehicle 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 reach the destination.

B. Paderborn Scenario

The schedules of the drivers in this work are based on the Paderborn traffic simulation scenario [29]. It is a road traffic simulation scenario for SUMO [30] and models the City of Paderborn, a typical mid-sized European city of around 150 000 inhabitants. The scenario contains the core of the city as well as outskirts (cf. Figure 4). 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. The resulting daily traffic demand curve resembles real-world measurements. 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.

We have extended the Paderborn scenario with the existing charging infrastructure of Paderborn [2]. 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. Energy Consumption and Driving Times from SUMO

Our charge stop planner makes routing decisions based on the required energy and time to drive the route. Therefore, to make useful decisions, we need to accurately model these criteria. Especially in an urban setting, like the Paderborn scenario, factors such as traffic density can play an important role. To create an accurate model, that is not prohibitively time expensive to run, we start off with simple models for energy consumption and driving times. We then use the microscopic traffic simulator SUMO to increase the accuracy of these models.

Our simple driving time model is based on the assumption that vehicles always drive at the speed limit, i.e., the driving time t can be expressed as

$$t = \sum_{r \in R} \frac{l_r}{v_r^{max}} \ , \tag{1}$$

where $r \in R$ are the route segments, l_r is the length, and v_r^{max} is the speed limit of a route segment.

Our energy consumption model for electric vehicles is based on the driving speed. The driving speed impacts the energy consumption due to friction and air drag, which are a function of the speed. In addition, other energy consuming components of the vehicle need to be considered, e.g., entertainment system, air conditioning, and the head and tail lights. These components are speed-independent and therefore dominate the energy consumption per km at lower speeds. The used energy B is calculated as a function of the speed v as

$$B = 0.05 + \frac{v^2}{90000} + \frac{2}{v} \ . \tag{2}$$

By simulating each individual vehicle with a car-following model, SUMO takes factors like traffic density into account and can provide accurate driving times, assuming a realistic traffic scenario is used. It also has an accurate energy consumption model for electric vehicles [31].

To improve the accuracy of our models, we ran the Paderborn scenario in SUMO with slight modifications, such as defining all vehicles as electric vehicles and removing non passenger vehicles like busses. The electric vehicles were configured as generic electric vehicles with the default settings from SUMO. We exported edge based measurement data, i.e., plain edge data and emissions edge data, which contains aggregated electric vehicle energy consumption, from SUMO and extracted average driving time and energy consumption values for each edge. We then compared these values with the values of our simple models and assigned a correction offset to each edge. This way, our models can estimate driving speeds and energy consumption a lot more accurately, for all edges used in the simulation run. For the other edges, our simple models act as a fallback. The adjusted models are used by our charge stop planner and for the evaluation.

D. Charging Model

Traditionally, many authors in the field of charging station scheduling and electric vehicle routing assumed that the charging speed of electric vehicle batteries is constant [11], [15], [16]. However, in reality, this speed is very nonlinear after reaching about 80 % of the battery's SOC. It actually decreases considerably at that point [32].

Modern lithium-ion batteries are charged with the CC-CV (constant current – constant voltage) charging protocol [32]. The charging process follows a two-phase approach. In the first phase, a constant current approach is used for charging the battery. During this time, the charge voltages continuously rises. This process continues until the charge voltage reaches 4.2 V and the SOC is at about 80 %. Now the second phase starts using a constant voltage approach to prevent overcharging. In this phase, the current steadily decreases. The charging process is assumed to be complete when the current falls below a predefined threshold. Alternatively, a CP-CV (constant power - constant voltage) protocol can be used. Here, the charge power is constant in the first phase. Otherwise, it is very similar to the CC-CV approach.

For our purposes, we use the following battery charging model, which supports both the CC-CV and the CP-CV approach. 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 [32]. 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 $u_{low} = 3.8\,\text{V}$ to $u_{high} = 4.2\,\text{V}$. 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

$$i(soc) = \begin{cases} i_{max} & \text{for } soc < 0.8 \\ \frac{1-soc}{0.2} \cdot i_{max} & \text{for } soc \geq 0.8 \end{cases} \ , \tag{3}$$

$$u(soc) = \begin{cases} u_{low} + \frac{soc}{0.8}(u_{high} - u_{low}) & \text{for } soc < 0.8 \\ u_{high} & \text{for } soc \geq 0.8 \end{cases} \ , \tag{4}$$

$$p_{cc\text{-}cv}(soc) = u(soc) \cdot i(soc) \ . \tag{5}$$

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

$$p_{cp\text{-}cv}(soc) = \begin{cases} p_{max} & \text{for } soc < 0.8 \\ u(soc) \cdot i(soc) & \text{for } soc \geq 0.8 \end{cases} \ . \tag{6}$$

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

In a first validation step, we compared our battery charging model with published measurements of an electric vehicle [33]. The results are shown in Figure 5. Even though the charging protocol is not mentioned for the measurement data, we can see that the CP-CV approach in our model very closely matches the measurement results. Actually, the CP-CV approach has a relative error of ±2 %, whereas the CC-CV protocol has a relative error of more than 10 % at the beginning of the charging process. We conclude that the vehicle was charged using the CP-CV approach.

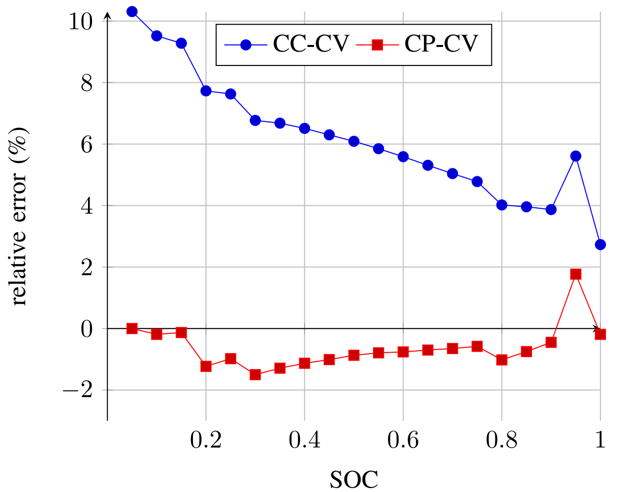


Fig. 5. Comparison of CC-CV and CP-CV charging protocols with measurement data.

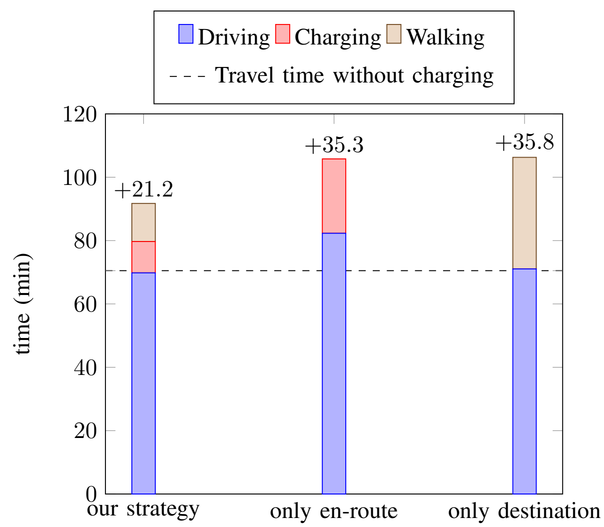
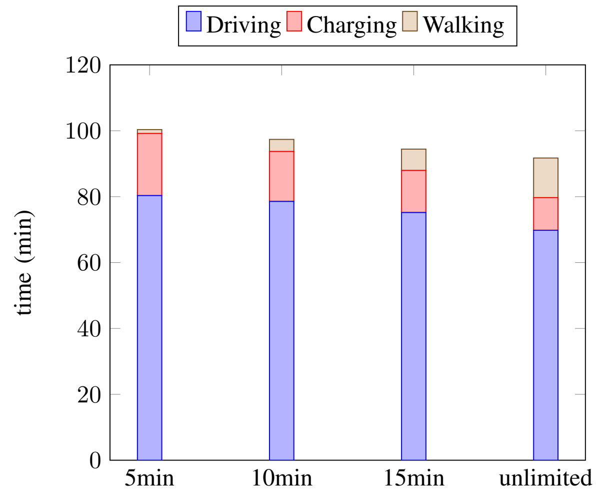
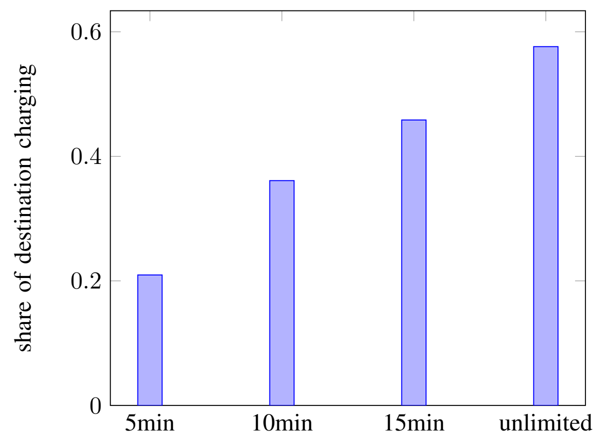


Fig. 6. Travel time comparison of our strategy with only en-route charging and only destination charging



(a) Travel times for walking time limits



(b) Share of destination charging for walking time limits

Fig. 7. Travel times and destination charging share for different walking times limits (per way)

E. Experiments

In our first experiment, we evaluate how much extra time the driver has to spend with charging the vehicle. With extra time, we mean the time the driver has to spend compared to just driving to the activities of the day's schedule without charging at all. We compare our strategy with only en-route charging and only destination charging. We calculated the trips for 1038 vehicles of the Paderborn scenario and averaged the results.

As can be seen in Figure 6, our strategy takes far less extra time than the alternative strategies. It takes on average 21.2 min extra time to charge the vehicle with our strategy, which is an improvement of about 40 %, compared to only en-route charging and only destination charging, which take 35.3 min and 35.8 min extra time respectively. En-route charging requires the driver to wait by the vehicle to finish charging, which is why it is mostly feasible for fast charging. To reach fast charging stations, the drivers have to drive detours which leads to additional driving time. With destination charging, the vehicle charges while the driver is at an activity of his day's schedule, but the driver might have to walk to the activity from the charging station and back. In our scenario, there are many activities at locations where there is simply no charging station nearby, which leads to very long average walking times. It is, of course, unrealistic to assume that drivers would be willing to walk that far, which means that only destination charging is not a feasible strategy for our scenario.

We can limit the walking time for destination charging to make it more realistic, but the limited choice of charging stations will lead to more time spent with charging overall. In Figure 7, we can see that limiting the walking time to 5 minutes per way reduces the share of destination charging from nearly 60 % to about 20 %. The drivers that have no charging station within 5 minutes of an activity of their day's schedule have to drive detours to fast charging stations which increases the time spent with charging significantly.

This result is, of course, highly dependent on the available

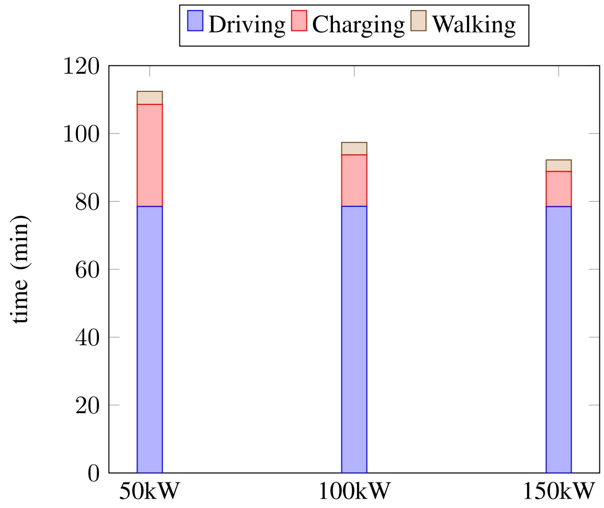


Fig. 8. Travel times for different maximum charge power settings

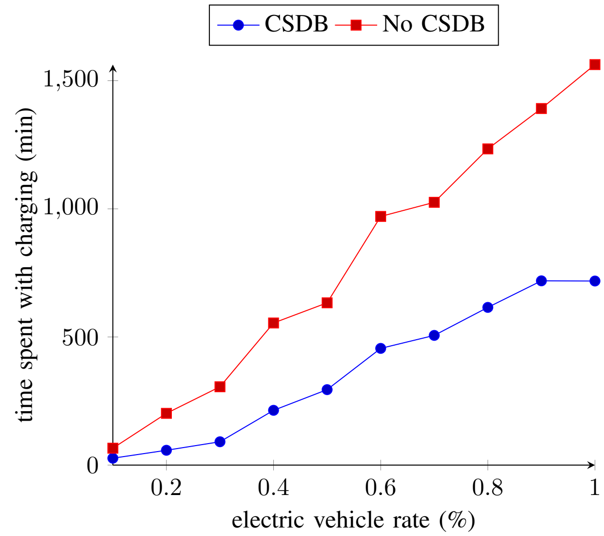


Fig. 9. Average time spent with charging depending on electric vehicle rate with and without using the CSDB

charging infrastructure. For our Paderborn scenario, we can conclude that the density of charging infrastructure is not sufficient for the majority of drivers to conveniently charge their vehicle with destination charging. In our further experiments, we have limited the walking time to 10 minutes per way.

In our next experiment, we evaluate the effect of different maximum charge powers on the travel times. Our Paderborn scenario contains two fast charging stations with a charge power of 150 kW. But most vehicles today are not capable of charging that fast, especially not continuously [34]. We compare three maximum charging speeds, 50 kW, 100 kW and 150 kW. For charging at slow charging stations, this makes no difference.

In Figure 8, we can see that slower maximum charging speeds significantly increase the travel time due to additional charging time. The share of destination charging increases slightly from 34.8 % for 150 kW, to 36.1 % and 37.0 % for 100 kW and 50 kW respectively. The share of destination charging is already limited by the 10 minute walking time limit which eliminates this option for many drivers.

In our last experiment, we evaluate the effectiveness of our CSDB approach to coordinate charging between vehicles to reduce the extra time spent with charging. We varied the number of vehicles that need to charge at the same day from 0.1–1.0 % of all vehicles. This percentage is not to be confused with the share of electric vehicles in the city. It is much lower because the majority of electric vehicles are charged at home and the ones that have to use the public charging infrastructure do not charge everyday.

In Figure 9, it can be seen that coordinating the vehicles with our CSDB reduces the time spent with charging by about half. Due to the limited number of charging stations and long charging times, waiting times still significantly increase the extra time spent with charging.

VI. Conclusion and Future Work

We presented an approach to coordinate electric vehicle charging with the goal to minimize the extra time drivers have to spent with charging their vehicle. The driver's schedule is taken into account when planning a trip for the day including charge stops either en-route between two activities or near an activity of the schedule. To prevent long waiting times at the charging stations, we use our centralized CSDB, which knows about the utilization of charging stations and to which vehicles can announce their planned charge stops. Based on this data, it can estimate waiting times in the future, which other vehicles can take into account when planning their trips.

To evaluate our approach, we used the Paderborn traffic simulation scenario which gives us realistic traffic and schedules of drivers for one day. We showed that our approach reduces the required extra time for charging by about 40 %, compared to only destination charging and only en-route charging. In some cases, destination charging was the most time efficient option even if the charging station was not close to the activity and the driver had to walk for a long time. Because we assume drivers are not willing to walk very far, we tried limiting the walking time to different values. We found that limiting the walking time to 5 minutes reduces the share of destination charging from nearly 60 % to about 20 % and increases the extra time for charging from 21 min to 30 min, because many drivers then have to charge en-route and wait with their vehicle while it is charging.

Of course, this result is highly dependent on the scenario and the available charging infrastructure. It also reveals that the density of charging stations in our scenario is not high enough to conveniently charge the majority of electric vehicles with destination charging. As the number of electric vehicles that depend on the public charging infrastructure grows, the need for coordination between these vehicles does as well. Especially slow charging stations can lead to long waiting times. By using our CSDB in combination with our charging strategy we could reduce the waiting by about 50 %.

We showed that it makes sense to not only focus on destination charging at slow charging stations or en-route charging at fast charging stations, but a combination of both. In future work, we want to tackle the question on how we could extend the charging infrastructure in an urban scenario to make charging more convenient for drivers that have no way to charge at home, with the focus on finding a good balance between slow and fast charging stations.

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