HEINZ NIXDORF INSTITUT
UNIVERSITÄT PADERBORN

Sven Schönberg

Trip Planning for Electric Vehicles

Dissertation

January 2023

Please cite as:
Sven Schönberg, “Trip Planning for Electric Vehicles,” Ph.D.Thesis (Dissertation), Heinz Nixdorf Institute, Paderborn University, Germany, January 2023.

Distributed Embedded Systems (CCS Labs)
Heinz Nixdorf Institute, Paderborn University, Germany

Fürstenallee 11 · 33102 Paderborn · Germany

http://www.ccs-labs.org/

Trip Planning for Electric Vehicles

Dissertation
zur Erlangung des Grades

DOKTOR DER NATURWISSENSCHAFTEN

vorgelegt von

Sven Schönberg

geb. am 25. Januar 1988
in Dortmund, Deutschland

angefertigt in der Fachgruppe

Distributed Embedded Systems
(CCS Labs)

Heinz Nixdorf Institut
Universität Paderborn

Betreuer:	**Prof. Dr.-Ing. habil. Falko Dressler**
Gutachter:	**Prof. Dr.-Ing. habil. Falko Dressler**
	Prof. Dr. Claudio Ettore Casetti
Tag der Abgabe:	**28. September 2022**
Tag der Promotion:	**20. Januar 2023**

Abstract

Electric vehicles are ever increasing in popularity and will likely supersede vehicles with internal combustion engines in the future. But short driving ranges and long charging times still make them less convenient for long-distance travel. Also, drivers that cannot charge at home have to rely on the public charging infrastructure for everyday charging, which often requires extra time compared to filling up an internal combustion engine vehicle or charging at home. Another potential issue is that long wait times could occur when too many vehicles want to charge at the same time at the same charging station. In this thesis, we present several approaches to address these issues.

First, by planning long-distance trips including charge stops, we can minimize the total travel time on long journeys. We select the best compromise between fast and energy-efficient routes by using a multicriteria shortest path search. We also take into account nonlinear charge curves and consider only partially charging the vehicle's battery at the charge stops. To achieve practical computation times, we exploit the fact that most route queries are between the known locations of the charging stations and precompute parts of the shortest path search for these locations. Simulation experiments confirmed that our routing and charging strategy results in reduced total travel times compared to alternative strategies.

Second, to minimize the extra time required for everyday charging, we plan urban trips including charge stops while taking the driver's schedule for the day into account. The vehicle is charged either en route while stopping at a fast charging station, similar to using a gas station, or at a charging station close to the destination. The latter has the advantage that the driver can visit the destination and does not have to wait with the vehicle, but it is only feasible if a charging station is available within walking distance of the destination. Simulation results indicate that having both options can significantly improve the extra time spent with charging compared to being limited to one option.

Third, we propose a central service that coordinates charging between vehicles to reduce the time people have to wait at charging stations. Vehicles can query wait time estimates for any charging station at any point in the future, if they agree to

announce their own planned charge stops to the service in exchange. The wait time estimates can be used by the vehicles when planning their trips to avoid long wait times. In simulations, we were able to achieve a reduction in wait times of up to 98 %.

Fourth, we introduce an approach to extend the public charging infrastructure. By analyzing typical driver schedules, we identify locations for new slow and fast charging stations and, using simulations, we determine a suitable number of charge points. With a combination of a few fast charging stations and many slow charging stations, we were able to significantly reduce the average extra time spent with charging.

Kurzfassung

Elektroautos werden immer beliebter und in Zukunft wahrscheinlich Fahrzeuge mit Verbrennungsmotoren verdrängen. Aufgrund der geringeren Reichweite und der langen Ladezeiten sind Langstreckenfahrten jedoch nach wie vor mit mehr Aufwand verbunden. Falls keine Lademöglichkeit zu Hause besteht, muss außerdem für das alltägliche Laden die öffentliche Ladeinfrastruktur genutzt werden. Dies nimmt oft zusätzliche Zeit in Anspruch, im Vergleich zum Tanken von Verbrennern oder dem Laden zu Hause. Ein weiteres potenzielles Problem sind lange Wartezeiten, wenn zu viele Fahrzeuge gleichzeitig an einer Ladestation laden wollen. In dieser Arbeit stellen wir mehrere Ansätze vor, um diese Probleme anzugehen.

Zum einen können wir durch eine Routenplanung inklusive Ladestopps die Gesamtreisedauer auf Langstrecken minimieren. Wir wählen den besten Kompromiss aus schnellen und energiesparenden Routen mithilfe einer multikriteriellen Routenplanung. Außerdem berücksichtigen wir nichtlineare Ladekurven und können bei Ladestopps Teilladungen der Fahrzeugbatterie planen. Damit die Rechenzeiten in einem akzeptablen Rahmen bleiben, führen wir Vorberechnungen der Routenplanung für bestimmte Standorte durch. Wir nutzen dabei die Tatsache aus, dass die meisten Routen zwischen den bekannten Standorten der Ladestationen berechnet werden müssen. Simulationsexperimente bestätigten, dass unsere Routenplanungs- und Ladestrategie bessere Gesamtreisedauern als alternative Strategien erzielt.

Im zweiten Ansatz minimieren wir die zusätzliche Zeit, die für das alltägliche Laden benötigt wird. Wir erreichen dies mit einer Routenplanung für den städtischen Raum die den Tagesplan des Fahrers berücksichtigt. Das Laden erfolgt entweder bei Zwischenstopps an Schnellladestationen, ähnlich der Nutzung einer Tankstelle, oder an Ladesäulen in der Nähe des Zielortes. Letzteres hat den Vorteil, dass der Fahrer während des Ladevorgangs nicht beim Fahrzeug warten muss, setzt aber eine Ladesäule in fußläufiger Entfernung zum Zielort voraus. Simulationsergebnisse zeigen, dass durch Verwendung beider Optionen deutlich bessere Zeiten erreicht werden können, als wenn nur eine der Optionen zur Verfügung steht.

Der dritte Ansatz ist ein zentraler Dienst, der durch Koordinierung der Fahrzeuge untereinander Wartezeiten an Ladestationen verringern kann. Fahrzeuge können

geschätzte Wartezeiten für beliebige Ladestation in der Zukunft abfragen, wenn sie dem Dienst im Gegenzug ihre eigenen geplanten Ladestopps mitteilen. Die geschätzten Wartezeiten können die Fahrzeuge bei ihrer Routenplanung berücksichtigen, um lange Wartezeiten zu vermeiden. In Simulationen konnten wir eine Reduzierung der Wartezeiten um bis zu 98 % erreichen.

Als Viertes präsentieren wir einen Ansatz zum Ausbau der öffentlichen Ladeinfrastruktur. Durch die Analyse typischer Tagespläne bestimmen wir geeignete Standorte für neue Langsam- und Schnellladestationen. Die passende Anzahl an Ladepunkten ermitteln wir mit Simulationen. Mit einer Kombination aus wenigen Schnell- und vielen Langsamladestationen konnten wir die zusätzliche Zeit, die für das alltägliche Laden benötigt wird, deutlich verringern.

Contents

Chapter 1

Introduction

Electric vehicles[1] are ever growing in popularity. Global sales of electric vehicles doubled in 2021 compared to 2020, and nearly 10 % of cars sold worldwide were electric [1]. Many countries have already announced to ban the sale of cars with internal combustion engines in the next few years. In June 2022, the European Parliament voted to effectively ban the sale of combustion engine cars by 2035 [2].

Nevertheless, electric vehicles still have some disadvantages compared to cars with internal combustion engines. The average driving range of an electric vehicle in 2021 was only 350 km [1]. Longer ranges are usually only available for large and expensive vehicles. Also, compared to refueling a combustion engine car, recharging still takes a lot more time, even at fast charging stations. In Germany, there are much fewer fast charging stations (about 2600 in 2022) than there are gas stations (14 458 in 2021 [3]). This means that long-distance trips require more travel time and planning, especially for vehicles with smaller driving ranges. Apart from driving long-distance trips, regular everyday charging can also be a problem. Not everyone has the option to install a charger at home or can charge at the workplace. These drivers have to rely on the public charging infrastructure instead. But slow charging can take many hours, and even fast charging often takes half an hour or more to recharge the vehicle's battery to 80 % state of charge (SOC). The long charge times, during which the charge points are occupied, can also lead to long wait times if multiple vehicles arrive at a charging station at the same time. Today, most electric vehicles are charged at home (or at work) [4], but as electric vehicles are becoming more common, this will likely change. Then, many more vehicles will rely on the public charging infrastructure, and this problem will become even more relevant.

[1]Although the term *electric vehicles* can refer to all kinds of vehicles, including bicycles, trains, buses, and aircraft with electric propulsion, in this work, we use the term exclusively for electric cars that only use energy stored in a rechargeable battery, also called battery electric vehicles (BEVs).

These issues can be tackled from multiple directions. Apart from technological advancements, such as larger batteries to improve the driving range and higher charging speeds, we can support drivers by planning trips that optimize the use of charging stations. We can also coordinate charging between vehicles to improve wait times and extend the charging infrastructure to provide more charging options.

1.1 Trip Planning

Planning trips for electric vehicles involves finding a route to drive and selecting charging stations to make charge stops when necessary. Finding the route is more challenging than for conventional vehicles because energy consumption plays a more important role. The fastest route (the one with the shortest drive time) might require a lot of energy that has to be recharged. Taking a slower, but more energy-efficient route might actually be faster overall, if it means the vehicle has to make fewer charge stops. To find the optimal route, a *multicriteria shortest path search* can be used for the criteria *drive time* and *energy consumption*. It will find all Pareto optimal routes from the fastest to the most energy-efficient route, but is a lot more computationally expensive than regular (single-criteria) route planning.

Optimizing the charge stops is also challenging. Charge speeds are highly nonlinear, especially for fast charging. Usually, the highest charge speed is only available when the battery's SOC is still low. It drops significantly as the battery is being charged, especially after reaching about 80 % SOC. Therefore, it might make sense to only charge the battery partially to keep the average charging speed high.

When planning long-distance trips, minimizing the total travel time, i.e., the sum of drive time and charge time, is usually the main goal. A routing and charging strategy is needed to find the optimal combination of routes and charge stops, including how much should be charged. On a realistically sized street network, thousands of routing and charging options have to be evaluated. The challenge is to find a routing and charging strategy that can do this and still achieves practical run times.

Urban trip planning has a different goal. The range of modern electric vehicles is typically long enough to cover all trips of the day in an urban scenario without recharging, assuming the vehicle has been fully charged overnight. But if the driver does not have the option to charge at home, the vehicle cannot simply be charged overnight. Instead, the driver has to rely on the public charging infrastructure to charge the vehicle throughout the day. The goal is then to minimize the extra time the driver spends with charging, compared to simply driving to each destination of the day. Two different types of charging can be considered for this purpose: *en-route charging* and *destination charging*. En-route charging means stopping to charge while en route to some other destination, while the driver waits with the vehicle, similar to using a gas station. Since the driver waits with the vehicle while it charges, it is only suitable for fast charging. Destination charging, on the other hand, means that the vehicle is charging at or near the destination that the driver is visiting. It is therefore also suitable for slow charging, especially if the driver is staying at the destination for several hours. To find the optimal combination of en-route charging and destination charging when planning trips, the driver's schedule for the day has to be taken into account. The challenge is to find a strategy that does this while also considering multicriteria route options and realistic nonlinear charge models.

Another issue is the optimization of wait times, i.e., vehicles having to wait at a charging station for a charge point to become free. The charge points are occupied by other vehicles that may have also planned their trips. If the trips of the vehicles are planned independently of each other, it is likely that some charging stations that are positioned in favorable locations will be selected by too many vehicles, which may result in queues and long wait times. This can be avoided by coordinating the charge stops of the vehicles in some way. Route planning for an individual vehicle is already computationally expensive and planning the trips of all vehicles simultaneously would be impractical for a realistic number of vehicles. The challenge is to coordinate charge stops between vehicles and effectively reduce the average wait time without adding computational complexity to the route planning.

1.2 Charging Infrastructure Planning

Extending the charging infrastructure and thereby creating additional charging options for electric vehicles is another way to improve the situation. Planning the extension involves finding suitable locations for new charging stations (siting) and determining the right number of charge points at each charging station (sizing). Since fast and slow charging stations are used in a completely different manner [5], they have to be considered separately in the siting process. Fast charging stations are mainly used for en-route charging and slow charging stations for destination charging. Or to put it simply, fast charging stations are needed where many cars drive and slow charging stations where many cars park. The challenge is to find a siting and sizing strategy that leverages a combination of slow and fast charging stations to effectively improve the situation of electric vehicles.

1.3 Contributions

The goal of this thesis is to tackle problems that still exist with charging electric vehicles. This includes supporting drivers to optimize charge stops on their trips, coordinating charging between vehicles, and extending the charging infrastructure.

The first major contribution of this thesis is our **long-distance trip planning** approach [6], which plans trips including charge stops that minimize the total travel time. It is based on a multicriteria shortest path search to find optimal routes from the fastest to the most energy-efficient route. It uses realistic energy consumption and nonlinear charging models and supports partial charging. The multicriteria shortest path search is very computationally expensive. To achieve acceptable run times, we introduce the acceleration technique **shortest-path-tree precomputing**, which exploits the fact that most path queries are between the known locations of the charging stations.

The next contribution is our **urban trip planning** approach [7]. It builds upon our long-distance trip planning approach, but instead of minimizing the total travel time to reach the destination, it minimizes the extra time spent with charging within the day's schedule of the driver. The most important addition is the option for destination charging, which uses the time the driver spends at an activity to charge the vehicle. The planner can decide between destination charging and en-route charging at fast charging stations. This way, it can utilize the available fast charging stations as well as slow charging stations.

Another major contribution is the **coordination of charging between vehicles** with our charging station database (CSDB) in order to reduce wait times [8]. The CSDB is a central service that electric vehicles can use when planning their trips to get wait time estimates in the future. In exchange for providing wait time estimates, the CSDB expects the vehicles to announce their own planned charge stops. The planned charge stops of all vehicles, along with the current utilization of the charging stations and historical data about past utilizations, form the basis for the calculation of the estimates. Both our long-distance trip planner and our urban trip planner can use them to effectively reduce wait times.

The final major contribution is our **charging infrastructure siting and sizing** approach [9], which has the goal of extending the public charging infrastructure to meet the future demand of electric vehicles. By analyzing typical driver schedules, it can find new locations for slow and fast charging stations in an urban scenario. Simulations are used to find a suitable number of charge points for the charging stations to reach acceptable wait times. By using our CSDB to coordinate charging between vehicles, we can reduce the number of necessary charge points.

1.4 Publications

This thesis is based on the following peer-reviewed publications:

- 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

  In this conference publication, I presented a long-distance trip planning approach that uses a multicriteria shortest path search. It can plan charge stops with partial charging using a nonlinear charge model. To accelerate the multicriteria shortest path search, I introduced *shortest-path-tree precomputing*, which takes advantage of the fact that most searches are between the known charging station locations and precomputes parts of the graph exploration.

- 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

  This journal article is an extension of the previous conference paper. I introduced the CSDB to coordinate charge stops between vehicles in order to reduce wait times at charging stations.

- 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

  In this conference publication, I created an urban trip planning approach that aims to charge vehicles of drivers that have no option to charge at home. It takes into account the drivers' schedules of the day when planning charge stops and can select between en-route charging and destination charging. The urban scenario including the drivers' schedules was contributed by Dominik S. Buse.

- S. Schoenberg, D. S. Buse, and F. Dressler, "Siting and Sizing Charging Infrastructure for Electric Vehicles with Coordinated Recharging," *IEEE Transactions on Intelligent Vehicles (T-IV)*, Apr. 2022

  This journal article is an extension of the previous conference paper. I introduced a siting and sizing approach to extend the existing charging infrastructure with slow and fast charging stations.

1.5 Structure

The remainder of this thesis is structured as follows: In Chapter 2, the fundamentals of route planning in general and for electric vehicles in particular are explained. Chapter 3 describes how we model electric vehicles in this work. We use five vehicle types from different car segments, each with individual battery capacities, realistic energy consumption models and charge curves.

Our long-distance trip planning approach is presented in Chapter 4. It also includes our acceleration technique, shortest-path-tree precomputing, which enables us to use multicriteria shortest path searches with acceptable run times. Following, in Chapter 5, we describe our urban trip planning approach. Chapter 6 is about the coordination of charging between vehicles with our CSDB to reduce wait times. In Chapter 7, we present our siting and sizing approach to extend the charging infrastructure with new charging stations and charge points. Finally, in Chapter 8, we conclude the findings of this thesis.

Chapter 2

Fundamentals and Related Work

In this chapter, we introduce the fundamentals and discuss related work that the rest of the work is built upon. We describe how the street network can be represented digitally, as well as how route planning works in general and specifically for electric vehicles.

2.1 Street Network

The street network is the system of interconnected streets and roads. Digitally, it is represented as a graph, with nodes forming the shape of the streets and directed edges signifying the permitted driving direction. The nodes have a position, which can be either two-dimensional (i.e., latitude and longitude) or three-dimensional (latitude, longitude, and elevation). They might also hold additional information about the junction type, traffic lights, etc. The edges can be annotated with information about the type of street and its speed limit.

The graph is a weighted graph, which means that each edge has a cost (or weight) associated with it, which represents how expensive it is to travel across it. The cost depends on the selected criterion. A simple criterion is driving distance, where the cost is the distance between the nodes of the edge. More practically useful criteria for path finding in a street network are travel time and energy consumption. They depend on the driving speed that is driven on the edge and can be vehicle specific.

A popular source of data for such a graph is OpenStreetMap (OSM), which is an open geospatial database that stores, among other things, information about the street network of the entire world and is freely available for anyone to use. We can extract information about the layout of the streets and roads, speed limits (either specified directly or inferred from the road classification), and traffic lights. However, the node positions in OSM are only two-dimensional. To create three-dimensional node positions, we have to include elevation data from an additional data source.

We can use the freely available data from NASA's Shuttle Radar Topography Mission (SRTM), which provides high-resolution elevation data for most of the Earth.

In this work, all graphs were created from OSM data combined with an improved version [10] of SRTM elevation data.

2.2 Shortest Path Problem

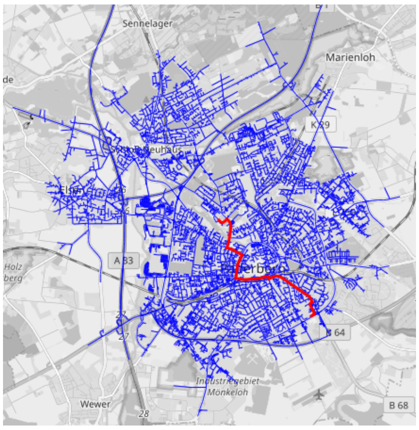
The shortest path problem is the problem of finding the path with the least cost in a graph between an origin node and a destination node. It is the fundamental problem that must be solved when planning routes in a street network. Depending on the criterion for the edge cost, the shortest path might be the shortest route (distance criterion), fastest route (travel time criterion), most energy-efficient route (energy consumption criterion), or some combination thereof.

There are several different algorithms that can solve the shortest path problem. In the following, we will discuss Dijkstra's algorithm, A*, and contraction hierarchies. All of them have to explore the graph when finding the shortest path, i.e., going through the nodes and edges to sum up the cost. Depending on the size of the graph and the distance between the origin and destination node, a large number of edges might have to be explored, which can make this a computationally expensive task. An example of how the edges are explored by these algorithms can be seen in Figure 2.1.

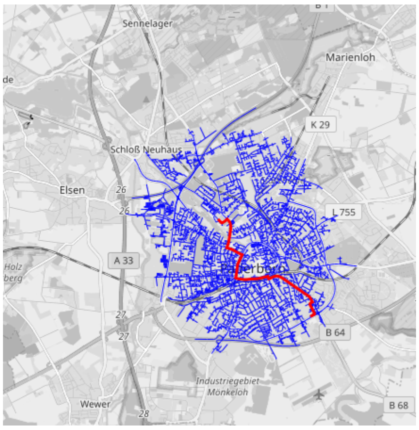
2.2.1 Dijkstra's Algorithm

Dijkstra's algorithm [11] is a well-known solution to solve the shortest path problem. The algorithm explores the graph node by node, starting with the origin node with a cost of zero and continuing with the node with the least summed up cost so far. For each node, it explores the edges to the neighbor nodes and sums up the cost to reach them. It continues to explore the graph until it reaches the destination node. Since the search is undirected, the exploration has a roughly circular shape, with the origin node in the center and the destination node at the edge of the circle (cf. Figure 2.1 (a)).

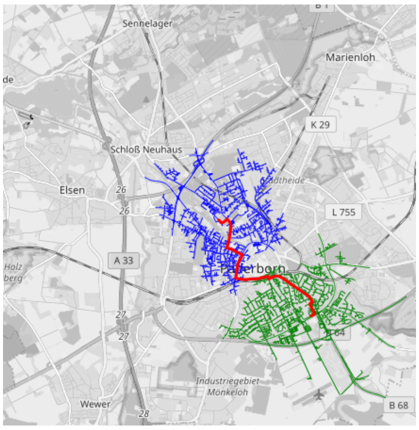
To reduce the number of nodes and edges that must be explored, we can also do a bidirectional search. In that case, the algorithm explores the graph simultaneously from the origin (forward search) and the destination (backward search) until both searches meet in the middle. This approximately halves the number of nodes and edges that have to be explored (cf. Figure 2.1 (c)).



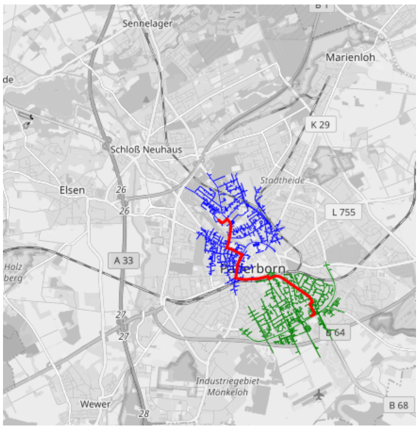
(a) Dijkstra's algorithm unidirectional
(27939 explored edges)



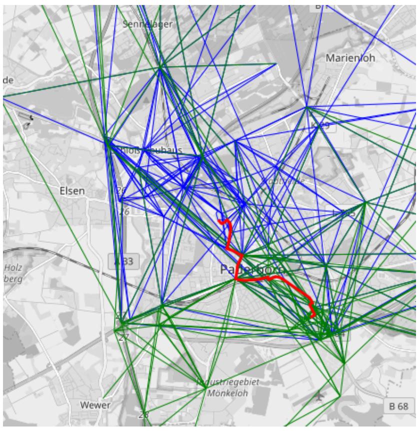
(b) A* algorithm unidirectional
(16350 explored edges)



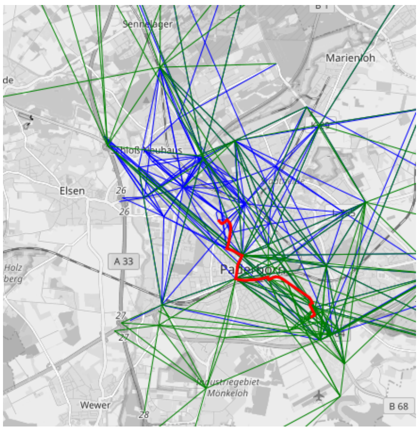
(c) Dijkstra's algorithm bidirectional
(9692 explored edges)



(d) A* algorithm bidirectional
(6183 explored edges)



(e) Contraction hierarchies
(490 explored edges)



(f) Contraction hierarchies with A* query
(404 explored edges)

Figure 2.1 – Graph exploration of different routing algorithms. Blue: Explored edges of forward search. Green: Explored edges of backward search. Red: Shortest path. (© OpenStreetMap contributors, CC-BY-SA)

2.2.2 A*

The A* algorithm [12] is a variant of Dijkstra's algorithm that uses a heuristic to do a directed search. The heuristic is an estimation of the minimal cost required to get from a node to the destination and is used in addition to the summed-up cost of the nodes to determine the order of node exploration. If the heuristic never overestimates the cost, the shortest path is guaranteed to be found. For the distance criterion, the heuristic could be the linear distance (beeline) between the node and the destination; for the travel time criterion, it could be the linear distance traveled at the maximum possible speed.

Depending on the heuristic, this can significantly reduce the number of nodes and edges that have to be explored. For a further reduction, a bidirectional search can also be used, analogous to Dijkstra's algorithm (cf. Figure 2.1 (b) and (d)).

2.2.3 Contraction Hierarchies

Contraction hierarchies, introduced by Geisberger et al. [13], are an approach to accelerate the shortest path search. Shortcuts are added to the graph in a preprocessing step to speed up query times. The preprocessing step is computationally expensive but only has to be performed once. Afterwards, queries for shortest paths can be computed significantly faster, compared to using Dijkstra's algorithm or A* on the original graph.

In the preprocessing step, the nodes of the graph are contracted one by one. When contracting a node, it is temporarily removed from the graph. As a replacement, new edges (called shortcuts) are added to the graph that directly connect the neighbor nodes with each other that were previously connected via the contracted node. The shortcuts are only added if the previous connection via the contracted node was the shortest path between the neighbor nodes. This ensures that the shortest paths are maintained after contracting a node without introducing unnecessary new edges. To find the shortest paths between the neighbor nodes, a shortest path search with Dijkstra's algorithm from each neighbor node to all other neighbor nodes has to be performed. The contracted node is also assigned a level, which is simply an ascending number (the first contracted node is level 1, the second node is level 2, and so on). A higher level indicates that the node was contracted later, and its shortcuts might have replaced shortcuts of lower level nodes.

The shortest path can be queried using a bidirectional search with a modified version of Dijkstra's algorithm. Both searches only traverse upwards, i.e., they only explore edges that lead to nodes with a higher level, which significantly limits the number of nodes and edges that are being explored. In contrast to the regular bidirectional version of Dijkstra's algorithm, the search is not finished as soon as both searches meet at a node. Instead, the searches will eventually overlap, i.e., explore several common nodes. Of these common nodes, the one with the lowest total cost determines the shortest path. The searches can be terminated when the next node to explore would have a higher summed up cost than the currently best shortest path determined by the common nodes.

The number of nodes and edges that must be explored is significantly reduced while also guaranteeing to find the optimal path. To further speed up the query, A* can be used instead of Dijkstra's algorithm for the bidirectional search [14]. An example of the exploration of such queries can be found in Figure 2.1 (e) and (f).

2.3 Route Planning for Electric Vehicles

There are special considerations to take into account when planning routes for electric vehicles, compared to simply finding the shortest path. When braking or driving downhill, the battery can recuperate energy, which means that there can be negative energy consumption. How to deal with the resulting negative edge costs is described in Section 2.4.

The battery of the electric vehicle creates additional constraints. The limited range must be taken into account, meaning the battery must not run empty, but also the battery cannot be charged to more than 100 % state of charge (SOC) when recuperating energy. Finding the shortest path that also considers the battery constraints is a Constrained Shortest Path (CSP) problem [15].

A common use case is to find the fastest route that is still reachable with the limited range of the vehicle. This can be done with a multicriteria shortest path search, using the criteria travel time and energy consumption. A multicriteria shortest path search returns all Pareto optimal paths for the selected criteria. From these paths, we can select the one with the best travel time that still fits the energy constraint. Having the option to select the best compromise between the fastest and most energy-efficient paths is also useful when taking recharging into account, as we will discuss later. How to do a multicriteria shortest path search is described in Section 2.5.

Apart from the path to be driven, the travel time and energy consumption can also be influenced by the driving speed. Driving at a high speed can shorten the travel time but also significantly increase energy consumption. Especially on roads with a high speed limit or no speed limit at all, such as the German Autobahn, driving below either the speed limit, or the maximum speed of the vehicle, can make sense to save energy. When using contraction hierarchies, this makes the preprocessing step more complicated as this would lead to variable edge costs. A trivial way to solve this problem would be to preprocess the graph separately for a number of discrete maximum driving speeds. The downside is the amount of computational effort required to preprocess and the amount of storage required to store all the graphs. Hartmann and Funke [16] presented a way to only preprocess the graph once for a set of discrete maximum driving speeds. It could then be queried for any speed within that set.

Baum et al. [14] define the Electric Vehicle Constrained Shortest Path (EVCSP) problem as finding the path that is feasible, i.e., the battery never runs empty on the way, and minimizes drive time. Their approach also considers variable driving speeds, but it is not limited to discrete values, instead allowing continuous adaptive speeds. They use a variant of contraction hierarchies and A*, modified for adaptive speeds, and can query optimal results in less than a second in a street network of Europe for realistic battery sizes.

In most practical use cases, getting the optimal solution is not as necessary as fast query times. When small inaccuracies are acceptable, heuristics can be used to significantly improve query times [14], [16].

2.4 Dealing with Negative Edge Costs

Electric vehicles can recuperate energy when braking or driving downhill, meaning we can have negative energy consumption and therefore negative edge costs. Dijkstra's algorithm, and, consequentially, contraction hierarchies, are limited to graphs with only non-negative edge costs. The alternative Bellman-Ford algorithm [17], [18], which does not have this constraint and can handle negative edge costs, is significantly slower in practice and too slow for graphs of realistic sizes.

As a solution, we can use Johnson's algorithm [19]. It is an additional preprocessing step, in which we use the Bellman-Ford algorithm to compute potential shift values for each node and reweight the edges such that there are no negative edge costs anymore. This preprocessing step only has to be performed once. For a graph of the street network of Germany, the preprocessing time is in the order of minutes. Afterwards, we can use Dijkstra's algorithm or contraction hierarchies on the reweighted graph to find the shortest path as usual. Since the edge costs have been modified, the cost (the sum of the edge costs or length of the path) returned by Dijkstra's algorithm, is shifted. We must reverse the potential shift by subtracting the potential shift value of the origin node and adding the potential shift value of the destination node.

In the case of multicriteria path finding with the criteria travel time and energy consumption, only the energy consumption values can become negative. We can ignore the travel time values when running Johnson's algorithm and only apply the potential shift on the energy consumption values.

2.5 Multicriteria Shortest Path Problem

The multicriteria shortest path problem is an extension of the shortest path problem, in which the edges have multiple edge cost values from different criteria. It is an optimization problem where the goal is to find all Pareto optimal paths for the selected criteria. In case of the criteria travel time and energy consumption, the solution is the set of Pareto optimal paths from the fastest to the most energy-efficient route. When two criteria are used, it is also called a bicriteria shortest path problem.

2.5.1 Dijkstra's Algorithm

Dijkstra's algorithm can be extended to solve the multicriteria shortest path problem [20]. Instead of having one label with the current best cost at each node, there is a Pareto set of labels at each node. And instead of exploring the graph from each settled node, it is explored from each label. As there can be multiple labels at each node, we might have to explore the same nodes and edges multiple times. Each label represents one Pareto optimal path alternative to the node, and the further away from the initial node we explore, the more path alternatives there will be. This makes the exploration much more computationally expensive, especially for longer distances.

2.5.2 Contraction Hierarchies

Contraction hierarchies can also be used to speed up multicriteria shortest path searches [21]. The preprocessing step has to be altered slightly. When a node is contracted, shortcuts are added to the graph to connect the neighbor nodes if the contracted node was part of any Pareto optimal path between them. This results in a lot more shortcuts being added, which in turn makes preprocessing a lot more computationally expensive.

Especially towards the end of the preprocessing, when the vast majority of nodes have already been contracted, the remaining few uncontracted nodes will be connected to many neighbor nodes via shortcuts. Because a multicriteria shortest path search has to be performed from every neighbor to find out which shortcuts have to be added, contracting the last few nodes might be prohibitively expensive for large graphs. In that case, it can make sense to leave the last few nodes uncontracted. Storandt [22] found that contracting only 99.5 % of the nodes resulted in reasonable preprocessing times. The uncontracted part of the graph is called the core graph [23]. Performing queries on a partially contracted graph is possible but affects query times. Figure 2.2 shows the effect of leaving parts of the graph uncontracted on the preprocessing time and the average query time. In this example of the street network of North Rhine-Westphalia, contracting all nodes takes more than 17 h, while contracting only 99.90 % takes less than five minutes. While saving preprocessing time, the average query time is several times higher. In this case, contracting 99.97 % seems to be a good compromise between preprocessing time and average query time.

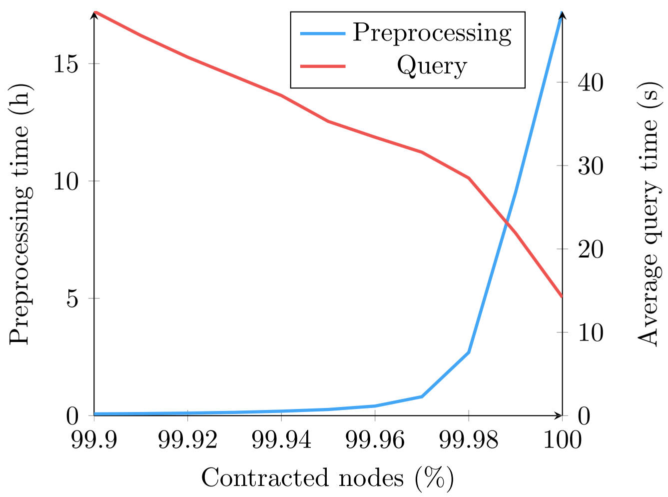


Figure 2.2 – Effect of number of contracted nodes on preprocessing time and average query time with the street network of North Rhine-Westphalia (based on [6] © 2019 IEEE)

Chapter 3

Electric Vehicle Modeling

Accurate models of electric vehicles are the basis for all routing and charging decisions made by our trip planning approaches. They compare routes with each other based on travel time and energy consumption and make charging decisions based on the time it takes to recharge the battery. There are many kinds of electric vehicles on the road today that have very different characteristics. We therefore cannot simply create one model that fits all.

In this chapter, we describe the vehicle types that we use in this work and present our travel time and energy consumption models, as well as our charge model.

3.1 Vehicle Types

Electric vehicles are available in various sizes that can differ significantly in terms of battery capacity, energy consumption, as well as charging performance. These differences have a great impact on trip planning and charge planning decisions. In this work, we use five vehicle types from different car segments, ranging from small city cars (A segment) to big SUVs (J segment). These vehicle types were introduced in [24], as part of an energy consumption model that we use in this work as well. Four vehicle types are based on real production vehicles, and one, the vehicle type for the J segment, is a generic model of an SUV. Of the electric vehicles sold in Germany in 2020, more than 90 % were from these five segments [25], which gives us a realistic coverage of vehicles on the road. The distribution of vehicle types that we use in our simulations is based on the market share of the segments [25]. An overview of the vehicle types and their battery capacities, energy consumption and charging speeds as well as their share in our simulations can be seen in Table 3.1.

Table 3.1 – Vehicle types and distribution within our simulations (based on market share of segments of electric vehicles sold in Germany in 2020 [25])

Segment	Share	Vehicle model	Battery capacity (kWh)	Average consumption (kWh/100km)	Max charge power (kW) AC / DC
A (city)	17 %	VW e-up!	32	14.8	7.2 / 40
B (small)	31 %	BMW i3	42	15.5	11 / 50
C (medium)	20 %	VW ID.3	58	15.9	11 / 100
D (large)	11 %	VW ID.4	77	18.6	11 / 125
J (SUV)	21 %	*generic*	70	23.7	11 / 150

3.2 Driving

In our trip planning approach, driving the vehicle means finding the multicriteria shortest paths for the criteria travel time and energy consumption. Therefore, our model needs to calculate accurate values for these criteria to be used as edge costs in our graph. Travel time and energy consumption both depend on how the vehicle interacts with traffic. We do not simulate traffic in our trip planning approach, but we do use results from the traffic simulator SUMO to calibrate our models of travel time and energy consumption to make them more accurate.

3.2.1 Travel Time

A trivial approach to calculate travel time would be to assume that vehicles simply drive at the posted speed limit for the length of the road. This would underestimate the travel time because vehicles have to slow down and wait from time to time. Assuming only light traffic, most vehicles drive close to the speed limit, but have to slow down and wait at traffic lights and other junctions.

Our model uses the trivial travel time, i.e., driving at the speed limit, as a basis and applies a constant factor to it. Additionally, a correction offset is added when encountering a junction. We distinguish between priority junctions, priority-to-the-right junctions, and traffic light junctions. We assume all vehicle types have the same travel time characteristics.

3.2.2 Energy Consumption

To calculate the energy consumption, we use the energy consumption model introduced in [24]. It is a physics-based model of individual powertrain components' characteristics that can be parametrized to accurately calculate the energy consumption of different electric vehicles. Five parameter sets for different electric vehicles were created, which match the vehicle types we use in this work. The energy consumption data of the four vehicles that are based on real production vehicles, was validated against manufacturer data and test bench measurements.

The model was developed for the traffic simulator SUMO to calculate the dynamic energy consumption of a vehicle with acceleration and deceleration in traffic. In this work, we only need static consumption values for the edge costs of our graph. To calculate the energy consumption, the model needs velocity, acceleration, and slope values as parameters. Because we do not consider it, we set the acceleration to zero and only set the velocity and the slope. Similar to the travel time, this would underestimate the energy consumption because we ignore traffic effects, especially deceleration and acceleration at junctions. Therefore, we also apply a factor and add correction offsets for different junction types.

3.2.3 Offset Calibration with SUMO

To calibrate the correction offsets of our travel time and energy consumption model, we used the traffic simulator SUMO. We simulated thousands of trips with each vehicle type, so we could compare the travel time and energy consumption results to our static calculation of the same trips. Then, we carefully adjusted the offsets until our static calculation matched the simulation results. The correction offsets for travel time can be seen in Table 3.2, and the vehicle-type specific energy consumption offsets in Table 3.3.

Figure 3.1 shows the correlation between our calibrated static calculations and the SUMO simulation results. The results of the static calculation can, of course, not always exactly match the results of the traffic simulation, because it does not consider dynamic traffic effects. However, for the majority of trips, the static values match the simulation results within ±10 %.

Table 3.2 – Travel time correction offsets

Factor	Priority junction (s)	Priority-to-the-right junction (s)	Traffic light junction (s)
1.02	0.5	2	10

3.3 Charging

There are two main ways to charge an electric vehicle, with alternating current (AC), and with direct current (DC). The electricity coming from the electrical grid is always AC, and the battery inside the vehicle is always charged with DC. Therefore, a conversion from AC to DC is necessary. The difference between AC and DC charging is that with AC charging, the conversion happens inside the vehicle with an onboard charger, and with DC charging, the charging station does the conversion.

The electrical grid transmits power with AC in three phases. Most public AC charging stations in Germany support three-phase AC charging, but not all electric vehicles do. All of our five vehicle types support three-phase charging, except the VW e-up!, which only supports two-phase charging. The available charge power with AC charging depends on the number of phases and the maximum current per phase that

Table 3.3 – 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

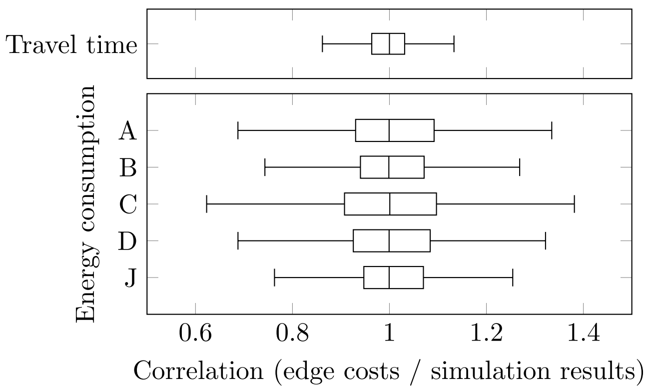


Figure 3.1 – Correlation of travel time and vehicle-type specific energy consumption of trips between our calibrated edge costs and the results of the SUMO simulation. (based on [9] © 2022 IEEE)

is supported by both the charging station and the vehicle's onboard AC charger. In this work, we make the simplifying assumption that all AC charging stations support three-phase charging, and only compare the supported charge power of the charging station and the vehicle.

Most AC charging stations support up to 22 kW, but many electric vehicles are only capable of charging at up to 11 kW or even less. Because it can take several hours to fully charge the battery, we define AC charging as slow charging. DC charging is much faster, with charging stations typically capable of charging at rates of between 50 kW and 350 kW. We therefore define DC charging as fast charging. The actual achievable charge power varies significantly between vehicles and can only be held for a part of the charge process. Not all electric vehicles are capable of DC charging; some manufacturers offer it as an optional extra.

Batteries in modern electric vehicles use lithium-ion cells, which must be charged with a charging protocol. The most commonly used charging protocols are CC-CV (constant current – constant voltage) and the very similar CP-CV (constant power – constant voltage), although there are also alternative charging protocols to improve fast charging [26]. The CC-CV charging protocol has two phases. In the first phase, the battery is charged with constant current. The cell voltage rises until it reaches its maximum voltage u_{high}. Then, it switches to the second phase, constant voltage. The charge current then steadily decreases, and when it is near zero, the charge process is complete. The alternative CP-CV uses constant power in the first phase. Figure 3.2 shows the battery's state of charge (SOC) and the charge current, power, and voltage for the CC-CV and CP-CV charging protocols.

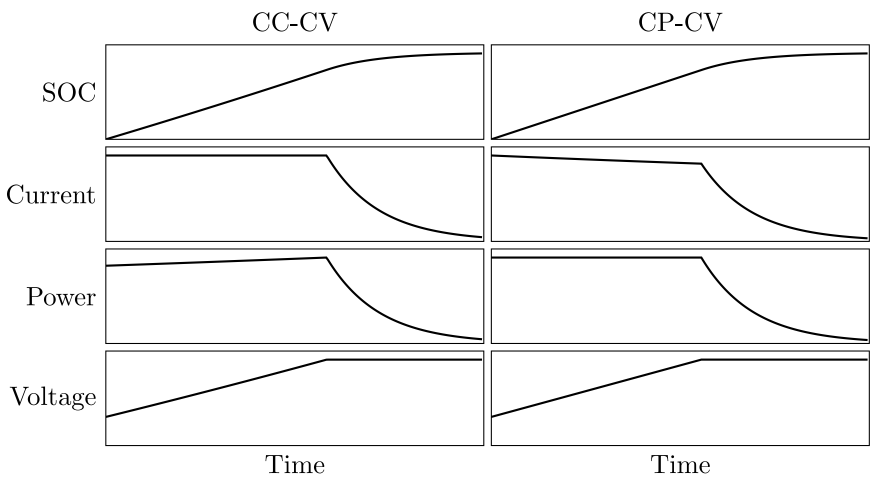


Figure 3.2 – CC-CV and CP-CV charging protocols

3.3.1 Slow Charging

The battery charging model we use in this work for slow charging supports both the CC-CV and the CP-CV protocols. We assume that the switch between the phases occurs at 80 % SOC and that the cell voltage increases linearly with the SOC [27]. The charge power p_{max} is determined by taking the lower value of charging station power and electric vehicle AC charging power. The SOC of the battery can be in the range $0 \leq soc \leq 1$. The cell voltage rises linearly with the SOC until 80 %, and then stays constant:

$$u(soc) = \begin{cases} u_{low} + \frac{soc}{0.8}(u_{high} - u_{low}) & \text{for } soc < 0.8 \\ u_{high} & \text{for } soc \geq 0.8 \end{cases} , \tag{3.1}$$

with the minimum cell voltage $u_{low} = 3.8\,\text{V}$ and the maximum voltage $u_{high} = 4.2\,\text{V}$. The charge current and power for the CC-CV protocol can be calculated as:

$$i_{cc\text{-}cv}(soc) = \begin{cases} i_{max} & \text{for } soc < 0.8 \\ \frac{1-soc}{0.2} \cdot i_{max} & \text{for } soc \geq 0.8 \end{cases} , \tag{3.2}$$

$$p_{cc\text{-}cv}(soc) = u(soc) \cdot i_{cc\text{-}cv}(soc) \; . \tag{3.3}$$

The calculation of current and power for the CP-CV protocol is very similar:

$$i_{cp\text{-}cv}(soc) = \begin{cases} \frac{p_{max}}{u(soc)} & \text{for } soc < 0.8 \\ \frac{1-soc}{0.2} \cdot i_{max} & \text{for } soc \geq 0.8 \end{cases} , \tag{3.4}$$

$$p_{cp\text{-}cv}(soc) = \begin{cases} p_{max} & \text{for } soc < 0.8 \\ u(soc) \cdot i_{cp\text{-}cv}(soc) & \text{for } soc \geq 0.8 \end{cases} . \tag{3.5}$$

The model calculates the power in one-second steps and iteratively adds the charged energy to the battery until $soc \geq 0.99$. To validate the model, we compared it to a measurement of the charging of an electric vehicle [28]. The source did not mention the charging protocol used, but we assume it was CP-CV. In Figure 3.3, we can see that our model matches the measurements within ±2 % when using the CP-CV protocol, but with CC-CV it has a relative error of about 10 % at the beginning.

3.3.2 Fast Charging

Our simple charging model works well for slow charging, but fast charging is more complicated. The switch between phases can happen a lot earlier than at 80 % SOC,

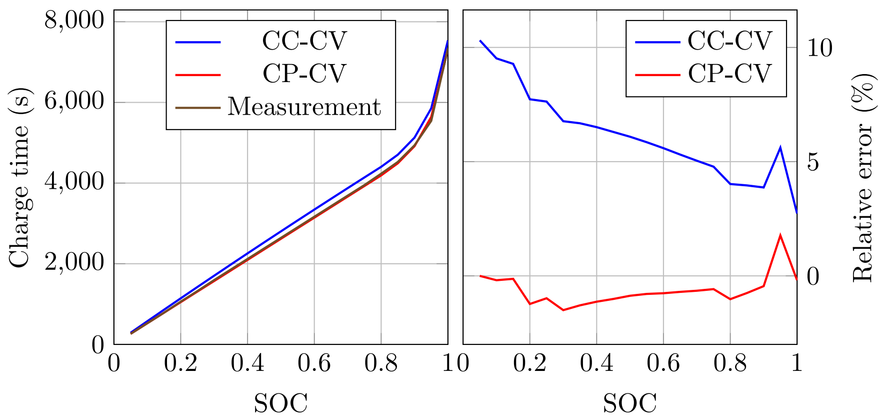


Figure 3.3 – Comparison of CC-CV and CP-CV charging protocols with measurement data [28]. Absolute charge time (left) and relative error compared to measurement data (right). (based on [6] © 2019 IEEE)

and some vehicles might use an alternative charging protocol. To make realistic calculations for fast charging, we used publicly available fast charging curves from the charging station operator Fastned [29], which were available for the four vehicles of our vehicle types that are based on real electric vehicles. For our generic SUV vehicle type in the J segment, we created a fast-charging curve similar to the others. As can be seen in Figure 3.4, the maximum charge power can only be held for a short time and then drops significantly for most vehicles. And, while the highest maximum charge power is more than three times greater than the lowest, the charge times are much closer together. This can be attributed to the fact that the vehicles with high fast charging speeds also have larger batteries.

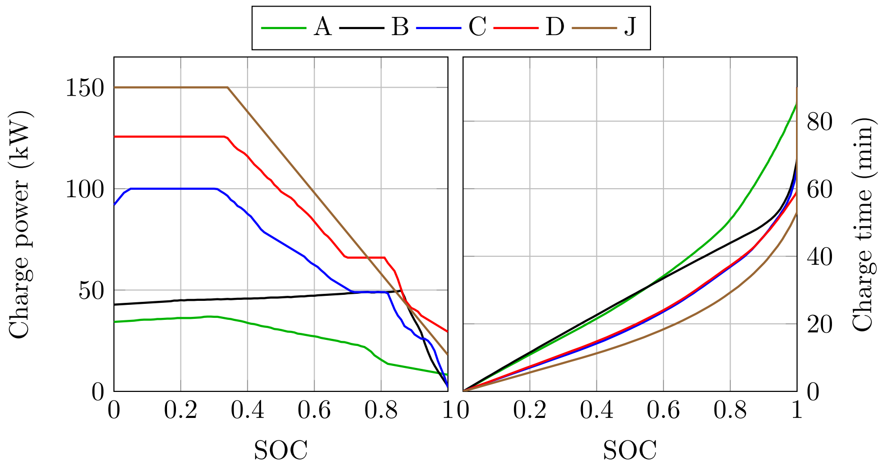


Figure 3.4 – Fast charging curves of vehicle types at a fast charging station with at least 150 kW charge power (based on [9] © 2022 IEEE; data from [29])

Chapter 4

Long-Distance Trip Planning

In this chapter, we describe our long-distance trip planning approach. By long-distance trips, we mean trips that cannot be driven non-stop without recharging the battery on the way. The goal of our trip planner is to find the route, including charge stops, that minimizes the total travel time. We define the total travel time as the sum of drive time and charge time. The trip planner also has to find the optimal charge amount at each charge stop. Since charging curves are highly nonlinear, especially for fast charging, and charge power generally decreases as the state of charge (SOC) of the battery rises, it makes sense to only partially charge the battery at each charging station to avoid charging at low speeds towards the end.

The problem with minimizing the total travel time is that while driving a faster route decreases the drive time, it also increases the energy consumption and therefore the charge time. It might be faster overall to choose an energy-efficient route over a fast route, if it saves time at the charging station. Our trip planner uses an adaptive routing and charging strategy that selects the optimal route from all Pareto optimal routes from fastest to most energy efficient, together with the optimal charge amount at each charging station. But this multicriteria shortest path search is very computationally expensive, and we have to repeat it many times to find routes between the charging stations and the origin and destination. To speed this up, we take advantage of the fact that we already know where the charging stations are and calculate parts of the shortest path search ahead of time.

4.1 Related Work

Related work regarding route planning for electric vehicles in general was already discussed in Section 2.3. In this section, we describe works that also consider charge stops to recharge on long-distance trips.

Storandt and Funke [30] presented an approach to find routes for electric vehicles that include charge stops. They create an auxiliary graph of charging stations (or battery swapping stations), where each charging station is connected to those charging stations that are within the vehicle's range. They can efficiently query for routes that minimize the number of necessary charge stops to reach the destination. In a subsequent work, Storandt [21] also took travel times and driving distances into account to find routes that are a practical compromise between quick and energy efficient. This includes, among other things, finding the most energy-efficient route, which is at most 5 % longer than the shortest one, or finding the fastest route with a limited number of charge stops. To accelerate the query, contraction hierarchies are used with an uncontracted core graph that includes all charging station nodes.

Baum et al. [31] can compute energy-optimal shortest paths in polynomial time, which allows for very low query times. This also applies to *profile* queries, which find energy-optimal routes for different initial SOC values that respect battery constraints. Using these profiles, they can find optimal amounts of energy to recharge at charge stops to minimize the energy consumption. In [32], they take into account the total travel time, i.e., the drive time and charge time, which is much more computationally expensive. To accelerate queries, they use contraction hierarchies with an uncontracted core graph that includes the charging stations, similar to [21]. They combine this with using an A* search, restricted to the core graph, when making queries that include charge stops.

Morlock et al. [33] use a very different approach. In a first step, they query a set of route alternatives between the origin and destination from a commercial routing service. These routes are then used as a very simple street network graph. In the second step, they make multicriteria shortest path queries on the graph to find routes including charge stops. Because the graph is so heavily reduced, compared to a full country-sized graph, they can use the Bellman-Ford algorithm, which would be too slow in practice for ordinary sized street network graphs. This enables them to achieve good query times in practice, but the reduced graph might lead to suboptimal routes.

Similarly, Hecht et al. [34] also describe an electric vehicle route planner based on routes from a commercial routing service. They use precise charging curves for five electric vehicles to accurately calculate charging speeds. In their work, they discuss more general questions, such as how much extra travel time an electric vehicle causes on long-distance trips due to recharging, compared to a vehicle with an internal combustion engine, and the influence of different parameters such as battery capacity and charging station power. The results, which are specific to the real-world charging infrastructure of Germany, show that the travel time is about 8 % longer compared to non-stop driving and depends on the travel distance and the battery size. Increasing the charging station power has only a negligible effect, as there are already many charging stations in Germany with higher charging power than vehicles can utilize.

Many modern electric vehicles are capable of fast charging with more than 100 kW, but they can usually only hold the top charging power for a short period of time (cf. Section 3.3.2). With the exception of [34], the aforementioned works use simple charging models, either ignoring charge time altogether [30], [31], using a fixed time penalty [21], assuming that charge power is constant [33], or that it drops only after about 80 % SOC [32]. Consequently, some works [21], [30], [35] always assume to fully recharge the battery.

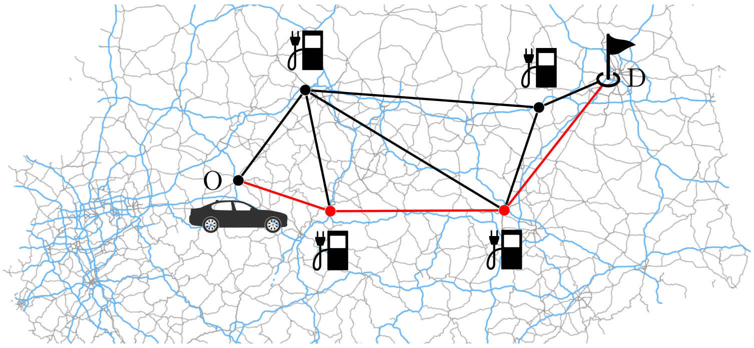
The long-distance trip planner presented in this chapter extends the state of the art in the following way: It minimizes the total travel time, including charge stops, by considering partial charging with an adaptive charging strategy that uses realistic fast-charging curves and energy consumption models for five different vehicle types (cf. Chapter 3). Optimal routes are selected with a multicriteria shortest path search. To achieve practical query times, we present a way to use precomputed shortest-path trees for the known locations of the charging stations.

4.2 Concept

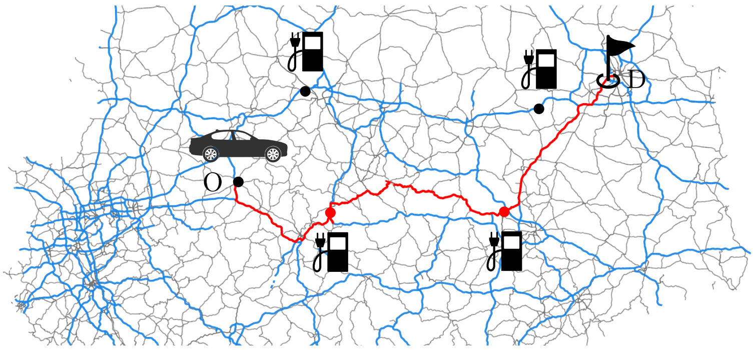
To plan long-distance trips including charge stops, we create a separate graph with the origin, destination, and all charging stations as nodes. We call this the charging station graph. While the graph is being explored, edges are dynamically added to connect the nodes that are within the driving range of the vehicle.

The goal of our trip planner is to minimize the total travel time. Traversing an edge on the charging station graph represents driving to a charging station and charging there. The edge cost therefore consists of the travel time and the charge time. The charge time depends on the energy that was consumed while driving, i.e., driving a more energy-efficient route might increase travel time, but will decrease the charge time. To select the optimal route, for each edge on the charging station graph, we perform a multicriteria shortest path search on the street network graph for the criteria travel time and energy consumption. From the resulting set of Pareto-optimal paths, we select the one that results in the least combined travel time and charge time.

A complication arises from the fact that we consider partial charging, i.e., not always charging to 100 % SOC. The target SOC depends on which edge will be traveled next, i.e., we need to charge less if the next charging station or the destination is close. The target SOC is therefore unknown when we explore an edge, which means we cannot calculate the exact charge time. To solve this issue, we temporarily assume to charge to 100 % SOC and subtract the excess charge time from the edge



(a) Charging station graph with selected route (red)



(b) Street network graph with selected route (red)

Figure 4.1 – Long-distance trip planning example with multiple charge stops

cost of the following edge[2]. Additionally, we add a time penalty of $t_{pen} = 5\,\text{min}$ for each charge stop, to account for the time needed to park and plug in the vehicle. This also prevents the algorithm from making an excessive number of short charge stops, which would be inconvenient to the driver. The edge cost for an edge between charging stations a and b is therefore calculated as follows:

$$\text{edgecost} = \min_{r \in R}(-t^a_{chr}(soc_{start}) + t_r + t_{pen} + t^b_{chr}(soc_{start} - \frac{e_r}{C}))\,, \tag{4.1}$$

where t_r and e_r denote the travel time and energy consumption of route $r \in R$ respectively, and C is the battery capacity. $t^c_{chr}(soc)$ calculates the charge time at charging station c from soc to 100 %. soc_{start} denotes the target SOC to which the previous charging station should charge the vehicle. Calculating this value is part of the charging strategy discussed in Section 4.2.1.

We use a slightly modified version of Dijkstra's algorithm (or A*) to find the shortest path on the charging station graph. The modifications being that we dynam-

[2]The apparent alternative to only consider the charge time of the previous charging station when calculating the edge cost is not feasible, because then, we could not take into account the time required to recharge the consumed energy when we select a route from the route alternatives on the street network graph.

ically generate the graph and the edge costs while traversing it and keeping track of the battery's SOC. The resulting shortest path contains the optimal charge stops including partial charge amounts to minimize the total travel time. The selected routes of the drives between charging stations can be joined to form the complete route on the street network graph. An example can be seen in Figure 4.1.

4.2.1 Charging Strategy

Many trip planning approaches assume that the vehicle is being fully charged at every stop. But charging speeds are highly nonlinear, especially for fast charging. The speed is generally high at the beginning, and then decreases significantly with increasing SOC. It can therefore make sense to only partially charge the vehicle to prevent wasting time with slow charging speeds at high SOCs. We call selecting the partial charge amount the *charging strategy*. Trivial charging strategies are to always fully recharge or to always charge to 80 % SOC. Another charging strategy would be to charge just enough to reach the next charging station.

Our adaptive charging strategy selects the charge amount based on the charge curve of the vehicle and the maximum charge powers of the current charging station and the following one. For the charge curves, we use our charging model from Section 3.3. We charge at least enough energy to reach the following charging station or the destination. We continue charging as long as the charge power, according to the charge curve, is above the maximum charge power of the following charging station. See Figure 4.2 for an example.

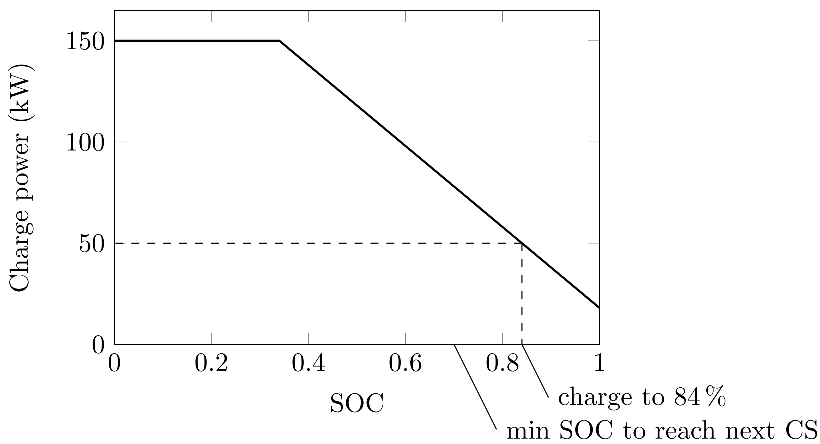


Figure 4.2 – Adaptive charging strategy example. Minimum SOC to reach next charging station: 70 %. Next charging station max charge power: 50 kW. We charge until the power drops below the following charging stations maximum charge power (84 %).

4.3 Acceleration Techniques

The long-distance trip planner makes frequent multicriteria shortest path searches on the street network graph to calculate edge costs for the charging station graph between the origin, destination, and charging stations. These multicriteria shortest path searches are very computationally expensive and would lead to unacceptable run times if we were simply using contraction hierarchies to query routes. We make use of several acceleration techniques to achieve acceptable performance.

4.3.1 Shortest-Path-Tree Precomputing

When making multicriteria shortest path searches, the most computationally expensive part is exploring the graph and creating Pareto sets of labels at each visited node. By using contraction hierarchies, we can greatly reduce the number of nodes that have to be visited, which significantly improves run time, but even then, it is still expensive. For long distances of >200 km on a complex graph, the query times might still be in the order of seconds or even minutes. Because the long-distance trip planner makes many such queries, the overall computation time would become unacceptably long.

All these queries are between the origin, the destination, and the charging stations. We can exploit the fact that we know the locations of the charging stations in advance and can explore the graph and create Pareto sets of labels for all of them in a preprocessing step. The result of this exploration is a shortest-path tree, which is why we call this approach shortest-path-tree precomputing. The trip planner only has to explore the graph once from the origin and the destination. After that, queries between the origin, the destination, and all charging stations are about two orders of magnitude faster, compared to exploring the graph for every query again. An example of this concept can be seen in Figure 4.3.

It should be noted that this is only feasible in combination with contraction hierarchies. Otherwise, the number of nodes being explored, and consequently the Pareto sets being created, would be too large to be practically stored.

4.3.1.1 Precomputing

Precomputing the shortest-path trees is an additional preprocessing step, in which we explore the graph around each charging station and store the result to be used in queries later. The exploration can be limited to an energy cost equal to the battery capacity of the vehicle.

The queries for contraction hierarchies use a bidirectional search. Because the street network graph is directed, to represent the allowed driving direction, the exploration for the forward and backward search is different. While the forward

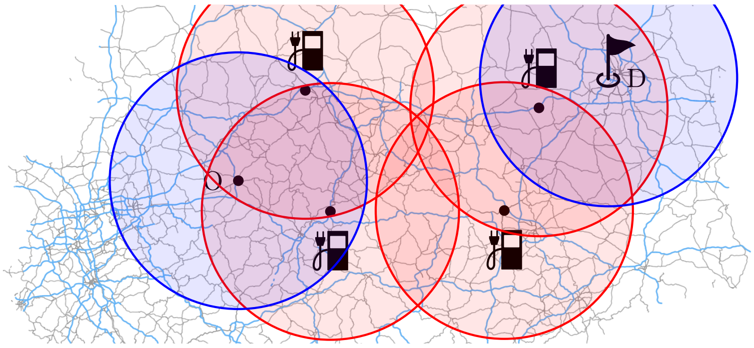


Figure 4.3 – Shortest-path-tree precomputing concept. Red circles: shortest-path trees that can be precomputed by exploring the graph around the charging stations. Blue circles: Exploration around origin and destination necessary for a query.

search (origin to destination) explores the graph in the direction of the edges, the backward search (destination to origin) explores it in the opposite direction. Since the charging stations can be both the origin and the destination in a query, we have to explore the graph in both directions. Therefore, for each charging station, we create a forward shortest-path tree, and a backward shortest-path tree.

4.3.1.2 Query

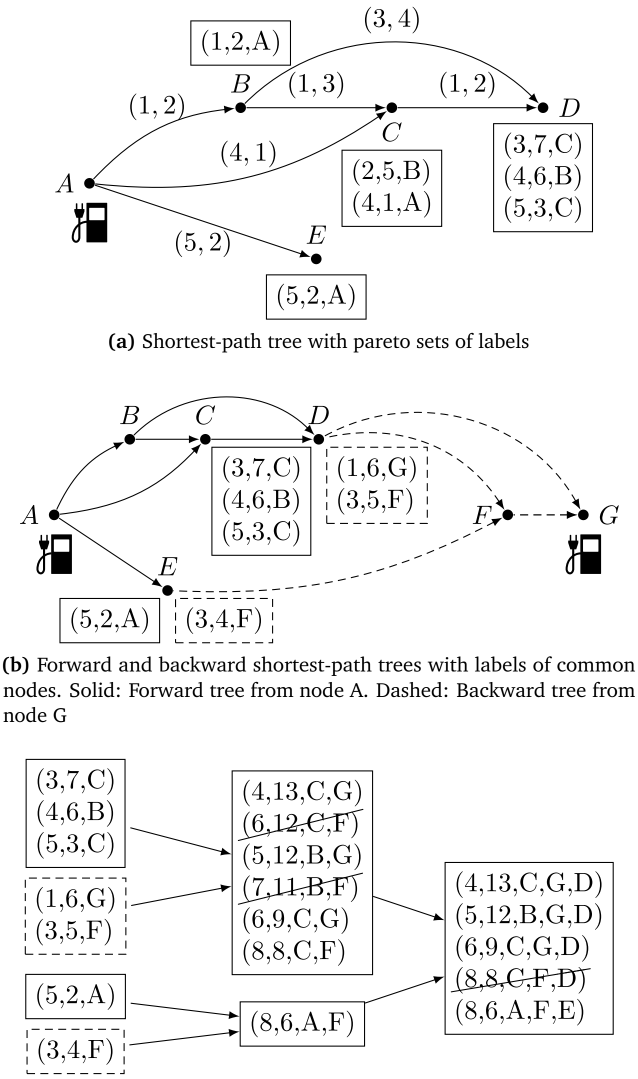
A query is bidirectional, we therefore need the forward shortest-path tree of the origin node and the backward shortest-path tree of the destination node. First, we find the common nodes, i.e., the nodes that are covered by both trees. Second, for each common node, we create the sumset of the Pareto sets of labels for that node from both trees and remove non Pareto optimal entries. Each of these Pareto sets contains the costs of the Pareto optimal shortest paths from origin to destination, but only for those paths that contain the respective node. Finally, we combine all the Pareto sets into one, which gives us the costs of all Pareto optimal shortest paths. An example query with shortest-path trees for two criteria is depicted in Figure 4.4.

In addition to the cost, each entry in a Pareto set of labels contains the predecessor node within the shortest-path tree. The node is necessary to reconstruct the path on the street network graph. When we create the sumsets of Pareto sets for the common nodes, the labels have to contain the predecessor nodes of both trees. The labels in the combined Pareto set additionally have to store the common node from which the label is from. Together, this information can be used to reconstruct each shortest path of the query result.

Reconstructing a path involves resolving all shortcuts to their underlying edges in both shortest-path trees. Doing this for all shortest paths in the Pareto set is computationally expensive. To save computation time, the long-distance trip planner does not reconstruct every path. It makes decisions based on the costs alone and only reconstructs the final path.

4.3.2 Charging Station Lookup Table

We can also simply calculate the Pareto sets of costs between all charging stations in another preprocessing step. A simple lookup table can be used to get the resulting



(a) Shortest-path tree with pareto sets of labels

(b) Forward and backward shortest-path trees with labels of common nodes. Solid: Forward tree from node A. Dashed: Backward tree from node G

(c) Create sumsets from node labels and combining them to get resulting Pareto set

Figure 4.4 – Example query with precomputed shortest-path trees (based on [8] © 2022 IEEE)

Pareto set for each combination of charging stations, which is significantly faster than doing a query even with shortest-path-tree precomputing.

This is, of course, only feasible if the number of charging stations is somewhat limited. For long-distance trip planning in Germany, it is sufficient to consider the fast charging station locations in Germany, of which there are 2667 in our scenario. This creates $n \cdot (n-1) = 7112889$ possible combinations. To be able to precompute these entries in a reasonable amount of time, we use shortest-path-tree precomputing.

4.3.3 Preliminary Edge Costs

In a realistic scenario with a dense network of charging stations and an electric vehicle with a long range, there are many charging stations to choose from. Even with shortest-path-tree precomputing, the trip planner has to minimize the number of queries. Finding a single-criteria shortest path is orders of magnitude faster than finding all multicriteria shortest paths. Thus, when we explore a node in the charging station graph and have to calculate the edge costs to all neighbor nodes, we do not perform multicriteria shortest path searches for all edges. Instead, we calculate a preliminary heuristic edge cost, based on two single-criteria shortest path searches for the fastest and the most energy-efficient route. With this, we create a best-case cost for this edge, assuming the travel time of the fastest route and the energy consumption of the most energy-efficient route. Only if this edge is selected to be explored next, do we perform the multicriteria shortest path search and replace the cost with the accurate value.

Note that this only affects the costs between the origin or destination with the charging stations. The costs between the charging stations themselves are queried with the charging station lookup table.

4.4 Performance Evaluation

4.4.1 Experimental Setup

The algorithms were implemented in C and compiled with GCC 10.3.0 with the highest optimization setting (-03). All experiments were run on a 64-core AMD Ryzen Threadripper 3990X with 256 GB of RAM.

The street network graph was created from OpenStreetMap (OSM) data, combined with an improved version [10] of SRTM elevation data. It contains the entire street network of Germany, with the exception of very small streets[3]. The graph is

[3] Downloaded from `http://download.geofabrik.de` on 2022-01-01. All OSM ways with highway tag except for path, steps, elevator, corridor, platform, bridleway, footway, cycleway, pedestrian, proposed, construction, raceway, emergency_bay, rest_area, track, unclassified, residential, living_street, service, tertiary, or tertiary_link.

made up of 4 599 852 nodes. The majority of these nodes only define the shape of the street or road. Only 163 697 have more than two edges.

For our experiments, we also need a list of charging stations. To get a realistic coverage of the German charging infrastructure, we use the extensive list of public charging stations provided by the German Bundesnetzagentur[4]. For the experiments in this chapter, which regard long-distance trip planning, we only consider fast charging stations. We merged very close (distance < 500 m) locations together, which resulted in 2611 fast charging station locations.

4.4.2 Shortest-Path-Tree Precomputing

Our long-distance trip planner makes many multicriteria shortest path queries between the charging stations and the origin and destination. As described in Section 4.3.1, to achieve practical run times, we precompute all shortest-path trees for the known locations of the charging stations. This potentially saves us a lot of query time at the cost of some additional preprocessing time and disk space.

In our first experiment, we test how much preprocessing time and disk space is required for different battery capacities. Because the exploration of the shortest-path trees is limited by the battery capacity, it has a big influence on the precomputing effort. Not only are more nodes and edges explored, but the further away the nodes are, the more potential route alternatives exist and therefore the size of the Pareto sets is greater. The results can be found in Table 4.1. As can be seen, precomputing the shortest-path trees for all 2611 charging stations takes only a few seconds for a 25 kWh battery, and the size of each shortest-path tree is less than one MB. Increasing the battery capacity causes significantly higher precomputing time and disk space requirements. For the 100 kWh battery, it takes nearly half an hour and almost 50 GB for all shortest-path trees.

We then tested how the precomputed shortest-path trees compare against plain contraction hierarchies in terms of query times. We queried multicriteria shortest paths for origin-destination (OD) pairs of different distances, from 100 km to 500 km in 100 km steps (all distances $\pm$ 10 %). Both the origin and the destination nodes

[4] `https://www.bundesnetzagentur.de/DE/Fachthemen/ElektrizitaetundGas/E-Mobilitaet/Ladesaeulenkarte/start.html` (visited on 27th Apr. 2022)

Table 4.1 – Shortest-path-tree precomputing times and sizes

Battery capacity (kWh)	Time	Size (GB)	Size per CS (MB)
25	00:00:13	1.2	0.5
50	00:02:24	9.0	3.3
75	00:12:21	27.3	10.0
100	00:28:33	49.4	18.0

were charging stations, therefore precomputed shortest-path trees existed for them. Reconstructing the paths of all route alternatives is computationally expensive and not necessary for our trip planner. We measured query times with and without reconstructing all paths. For each distance step, we measured the query times of 100 OD pairs and averaged the results. As can be seen in Table 4.2, the query times for precomputed shortest-path trees with path reconstruction are about one order of magnitude smaller than for plain contraction hierarchies. Not reconstructing the paths improves the query times by another one or two orders of magnitude. Reconstructing the paths is especially expensive for longer distances, because there are likely more route alternatives and each path consists of more edges.

4.4.3 Trip Planner

In our next experiment, we test how our long-distance trip planning approach with its adaptive charging and routing strategy compares to related strategies. We have generated 100 random OD pairs with distances of more than 500 km, ensuring that the vehicles have to recharge on the way, often multiple times. For each strategy, we plan the trips for all OD pairs with our trip planner and average the results. We do this for each of our five vehicle types (cf. Section 3.1). Since the vehicle types have different energy consumption models, we have to preprocess the shortest-path trees and the charging station lookup tables for each vehicle type separately. As an additional comparison, we have also calculated the drive times for all OD pairs when driving the fastest route non-stop. This way, we can easily see how much extra time is spent with charging, i.e., making detours to charging stations and taking more energy-efficient (but slower) routes. The average non-stop drive time for all OD pairs is 06:25 h.

We have plotted the results of these tests in Figure 4.5. In Figure 4.5 (a), we compare the trip results of our five vehicle types. It is clear to see that the vehicles vary greatly in their suitability for long-distance travel. The A segment vehicle's total travel time is more than 4 h or 70 % longer than the non-stop drive time. The vehicle has a comparatively small battery and poor fast-charging capabilities. Even

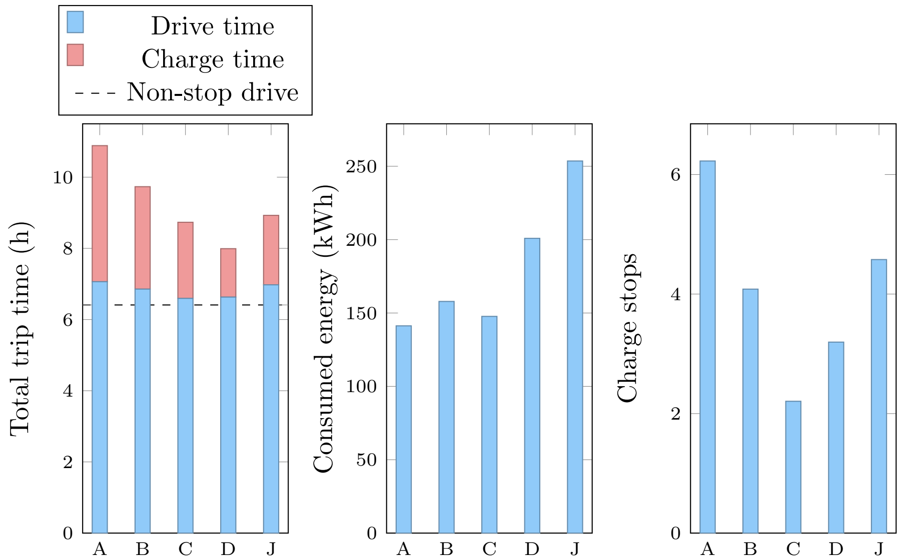
Table 4.2 – Query time comparison between plain contraction hierarchies (CH), precomputed shortest-path trees (SPT) with (R) and without reconstructing all paths.

Type	Average query times (s)				
	100 km	200 km	300 km	400 km	500 km
Plain CH	0.202	2.672	13.903	37.822	88.522
SPT (R)	0.043	0.370	1.551	4.188	9.911
SPT	0.010	0.010	0.024	0.058	0.114

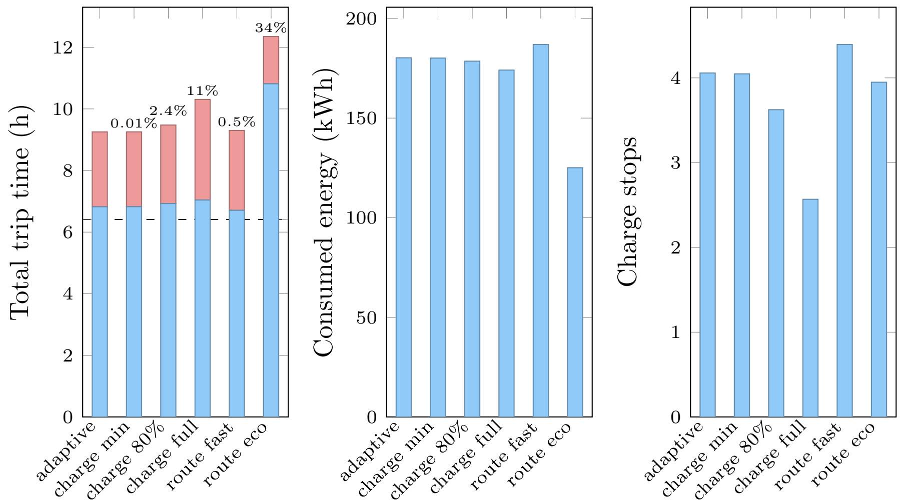
though it has the lowest energy consumption, it makes more than 6 charge stops on average and has the highest charge time of all vehicles. Higher charging speeds significantly shorten the extra time. The D segment vehicle has a large battery and good fast-charging speeds. It has the lowest extra time with 1.5 h or 25 % and only needs two charge stops on average, which could be considered tolerable breaks on a trip that takes more than 6 h. The J segment vehicle's fast-charging speed is even higher compared to the D segment vehicle, but its total travel time is worse, which can be attributed to the higher energy consumption and smaller battery capacity.

The comparison of our adaptive charging and routing strategy with other related strategies can be found in Figure 4.5 (b). The differences between the strategies were very similar for all vehicle types. To make the charts easier to read, we have therefore averaged the trip results of all vehicle types. We compare our adaptive charging strategy to three different strategies: Only charging the minimum amount required to reach the next charging station (*charge min*), always charging 80 % (*charge 80%*) and always making a full charge (*charge full*). Our adaptive charging strategy has a significant advantage over *charge 80%* (2.4 % slower) and especially *charge full* (11 % slower). These strategies cause a lot more charge time, because the charge power drops significantly as the SOC increases, especially after about 80 %. Our strategy only has a negligible advantage over the *charge min* strategy. In fact, in many cases, the selected routes and charge amounts are identical. Our strategy only has an advantage in cases where a charging station on the trip has a higher usable charging power than the following one. As there are many fast charging stations available in Germany that are more than powerful enough for the charging capabilities of the vehicles, slower fast charging stations are only rarely ever selected. However, our strategy can be advantageous in cases where more factors are involved when selecting charging stations, such as wait time.

We also compare our adaptive routing strategy with alternative strategies, namely always taking the fastest route (*route fast*) and always taking the most energy-efficient route (*route eco*). Especially the latter strategy is commonly used in literature [16], [30], [31]. It is therefore an interesting observation that this strategy causes the highest total travel time with 34 % more than our strategy. The most energy-efficient routes often take small, slow roads, far from major highways. It saves significant amounts of energy and therefore has the best charge time, but this does not make-up the lost time on the road. Always taking the fastest route is much closer to the optimum. Even though the energy consumption and the average number of charge stops are a bit higher, the total trip time is only slightly worse (0.5 %) than our adaptive routing strategy. This can be attributed to a sufficient number of fast charging stations that can quickly recharge the vehicles along the way.



(a) Results of different vehicle types with adaptive charging and routing strategy



(b) Results of different strategies averaged over all vehicle types

Figure 4.5 – Long-distance trip planner results

Chapter 5

Urban Trip Planning

In this chapter, we describe our urban trip planning approach. In contrast to long-distance trip planning, reaching the destination, with recharging, if necessary, is not the main objective. The range of modern electric vehicles is long enough to cover a typical day in an urban scenario without recharging, assuming the vehicle has been fully charged at home. But what if it is not possible to charge the vehicle at home, because, e.g., the driver lives in an apartment without a dedicated parking spot? As vehicles with internal combustion engines are slowly being phased out, more and more people are driving electric vehicles with no option to charge at home. These drivers rely on the public charging infrastructure to recharge their vehicles.

The problem is that charging an electric vehicle takes a lot of time, even at fast charging stations. But if we charge the vehicle while it is parked anyway, e.g., at work or during other long stays, the charge time does not matter as much. Our urban trip planner plans charge stops that fit into the driver's schedule and minimizes the extra time spent with charging. It can select between *en-route charging*, where the driver stops en route to some other activity at a fast charging station and waits with the vehicle until the charge process has finished, and *destination charging*, where the driver parks the car at a charging station near the activity (the destination) and visits the activity while the vehicle charges. In the latter case, if the charging station is not directly adjacent to the activity, the driver has to walk to the activity and back.

5.1 Related Work

Urban trip planning is used by many works in various ways. In contrast to long-distance trip planning, reaching the destination is usually not the main objective. Many works consider the effect of electric vehicle charging on the power grid and select when and where vehicles should charge to flatten the load on the grid (peak shaving) [36]–[41]. From the driver's perspective, the algorithms minimize the charge cost. In some cases, the vehicles can also sell energy back to the grid (vehicle-to-grid (V2G)) [36], [40], [41].

Some works [36], [37], [39], [41] only consider charging the vehicle at times when it is parked anyway (destination charging). For destination charging, it is essential to take user behavior and mobility patterns into account [42]. Sortomme and El-Sharkawi [36] use *driving profiles* that include morning and evening commutes on weekdays and different random trips on weekends. An algorithm decides when parked vehicles are charged or discharged using V2G, with the goal of minimizing the charge costs for drivers and reducing the peak load on the power grid. Similarly, Sun et al. [41] consider commuting electric vehicles that travel between home and the workplace at certain time slots. The vehicles can form homogeneous fleets that share the same activities, including charging/discharging and routing decisions and can participate in day-ahead electric power scheduling. While the individual vehicles minimize their travel time, the fleets optimize charge costs and discharge revenue. They assume that charging and V2G is possible at home and at the workplace.

In cases where there is no charging station directly at the destination, we could also consider walking to and from a charging station that is nearby. Rigas et al. [39] consider the time it takes to walk from the charging station to the destination when selecting charging stations. They minimize the drive time, charge time, and walk time and also the charge costs. Gerding et al. [43] describe a similar *park 'n charge* scenario, where the vehicle is charged at a charging station while the driver walks to the nearby destination. They also consider en-route charging in a different scenario, but do not combine both approaches, such that there would be a choice between them. The approach presented by Yang et al. [38] does this to some degree. Their route selection and charging navigation strategy considers destination charging when the car is parked and en-route fast charging if necessary to reach the destination. Gambuti et al. [44] also consider something similar in their multimodal trip planning approach. Vehicles can be charged en-route at fast charging stations to reach their destination, but also at slow charging stations while the driver is changing to another mode of transportation, such as public transit. However, none of these works consider the driver's schedule to make charging decisions or select between en-route charging and destination charging.

All of the works mentioned above employ simple energy consumption models with a fixed energy consumption value per km. They also do not use charge curves but assume constant charge power or fixed charge times.

We extend the state of the art with an approach to plan charge stops within the day's schedule of the driver that minimize the extra time spent with charging. It can select between en-route charging and destination charging, including the option to walk to and from the charging station to the destination. We also use the realistic energy consumption and charging models of our five vehicle types (see Chapter 3).

5.2 Concept

Our urban trip planner plans charge stops for drivers of electric vehicles that rely on the public charging infrastructure because they do not have the option to charge their vehicle at home. The goal is to minimize the extra time the driver has to spent with charging the vehicle throughout the day.

5.2.1 Driver Schedules

To minimize the extra time spent with charging, the trip planner has to know the driver's schedule. The schedule is an activity chain of times and locations the driver plans to visit throughout the day, e.g., going to work, shopping, or leisure activities. The initial starting point, and the final destination might be the same, e.g., home. It could be created by the vehicle's on-board navigation system or a smartphone app based on a prediction from historical data, maybe combined with analyzing the user's calendar, or simply by user input. Within this work, the schedule is simply assumed to be known.

The schedule is divided into segments, each consisting of an activity and the trip to it. An additional segment is the trip to the final destination. For each of these segments, the trip planner can make separate charging decisions. Figure 5.1 shows an example of a driver's schedule, divided into three segments.

5.2.2 Charging Alternatives

The trip planner can make a charging decision for each segment of the schedule. For each segment, it selects one of the following three alternatives (cf. Figure 5.2): The first (trivial) alternative is to drive directly to the activity without charging the vehicle and simply parking it there. The second alternative is *en-route charging*. While en route to the activity, the driver makes a stop at a fast charging station, lets the vehicle charge and afterwards continues to drive to the activity, similar to using a gas station. Since the driver has to wait with the vehicle, this is only really suitable for fast charging. The battery is also only charged to 80 % state of charge (SOC), because the charging speed typically drops significantly after that point. In the third alternative, *destination charging*, the vehicle is charged near the activity (the destination) while the driver visits the activity. If there is no charging station

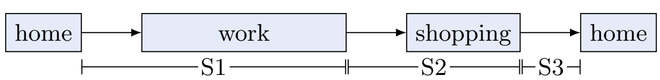


Figure 5.1 – Driver's schedule divided into segments (based on [7] © 2021 IEEE)

directly adjacent to the activity, the driver has to walk from the charging station to the activity and back. This may take some time, but the driver also saves time by not having to wait with the vehicle while it charges. Depending on the duration of the activity, this makes it suitable for slow charging, especially if the driver stays at the activity for several hours. The vehicle is charging as long as the driver is away, which means it could charge to any SOC up to 100 %. We assume that the driver will not interrupt the activity to unplug and repark the vehicle after it has reached 100 % SOC. Doing so would only cost extra time without any benefit to the driver.

5.2.3 Route and Charging Station Selection

When evaluating the charging alternatives, the urban trip planner also has to select the route to take when driving to an activity or a charging station. Similarly to our long-distance trip planner in Chapter 4, we do not simply take the fastest route to minimize drive time, because a slower, more energy-efficient route that saves us charge time, might take less time overall. The route must, of course, also respect the battery constraints, i.e., the battery must not run empty on the way. The trip planner selects the route from the set of Pareto-optimal routes from fastest to most energy efficient. To efficiently find these routes, we use shortest-path-tree precomputing (see Section 4.3.1).

There are usually multiple charging stations to choose from. The alternatives thus include the charging stations and the route alternatives to (and from) these charging stations as well. For each segment, the planner iterates over all alternatives and calculates the SOC and the time at the end of the segment. The time depends on the charge time and the drive time to and from the charging stations, in case of en-route charging, and on the walk time between the charging station and the activity, in case of destination charging. After calculating these values for all alternatives, the planner can dismiss those alternatives that are dominated by others, i.e., those that have lower time and a higher SOC at the end of the segment. The remaining alternatives

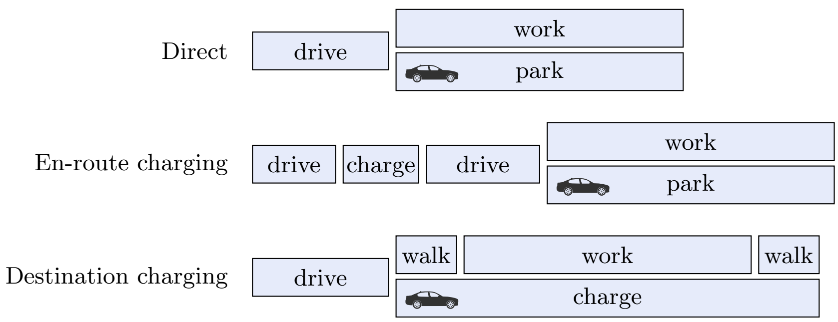


Figure 5.2 – Charging alternatives for each segment (based on [7] © 2021 IEEE)

are used as possible result candidates and are the basis for the calculation of the next segment. The planner evaluates a segment for each candidate of the previous segment separately, thereby creating a result tree.

Once the candidates for the final segment have been calculated, we can select one of them as our end result. Each candidate has a predecessor candidate in the result tree. This way, we can recreate the selected charging alternative, charging station, and route for each segment that led to the end result. 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.

5.3 Performance Evaluation

5.3.1 Scenario

We evaluate our urban trip planner by planning a large number of trips for drivers in an urban environment that all have individual schedules.

The scenario we are using is based on the Paderborn traffic simulation scenario [45]. It was developed for the traffic simulator SUMO [46] and takes place in the City of Paderborn, a mid-sized German city with a population of around 150 000. Each simulated inhabitant has an individual schedule over a 24 h period that was

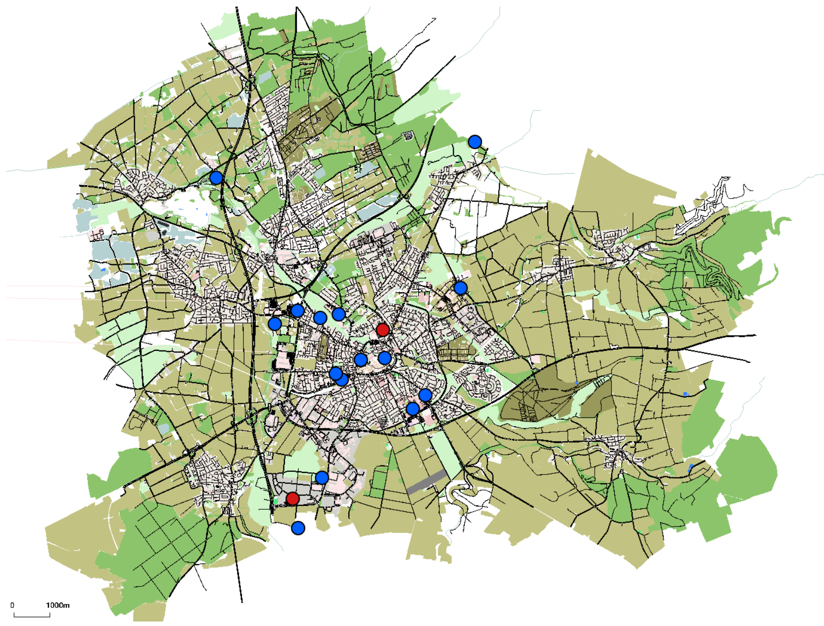


Figure 5.3 – Overview of the Paderborn traffic simulation scenario with slow charging stations (blue) and fast charging stations (red) (based on [7] © 2021 IEEE)

created using SUMO's ACTIVITYGEN tool. The schedules consist of activities such as driving to work or University, going shopping, etc. The resulting traffic demand consists of more than 200 000 trips and resembles real-world measurements. The street network was generated from OpenStreetMap (OSM) data, enriched with elevation data from SRTM and contains some SUMO specific details, e.g., lanes, internal edges at intersections, traffic lights, etc.

For our experiments, we have extracted the street network and removed the SUMO-specific details. To model the public charging infrastructure of Paderborn, we added 15 slow charging stations with a power of 22 kW and two fast charging stations with a power of 150 kW. An overview can be seen in Figure 5.3.

We assume that the vehicles have no option to charge at home and charge every few days using the public charging infrastructure. To simulate such a day, we set the initial SOC of the vehicles' batteries to 20 %. The goal is to reach the final destination with an SOC of 70 %. This way, the vehicle can be charged to 80 % at a fast charging station and still has enough energy for the rest of the trip.

5.3.2 En-Route Charging and Destination Charging

In our first experiment, we compare our strategy of selecting between en-route charging and destination charging with being limited to just one of these options. We examine how much extra time the driver has to spend with charging the vehicle, compared to just driving the fastest route to each activity of the schedule without charging. For each trip, we measure the composition of drive time, walk time, and charge time from en-route charging. We do not count the charge time from destination charging, because the driver is spending the time at the scheduled activity. But if the driver has to delay his stay at the activity because the vehicle would otherwise not be sufficiently charged to reach the 70 % goal, we report this as *stay delay* time. The trip planner plans around 30 000 trips with random schedules from the scenario for each vehicle type and averages the results.

As can be seen in Figure 5.4, our strategy causes significantly less extra time than the alternative strategies across all vehicle types. The only en-route charging strategy is especially disadvantageous to the smaller vehicle types. These vehicle types have poor fast-charging capabilities and therefore high charge times. This strategy also causes higher drive times for all vehicle types, because the scenario only contains two fast charging stations and many vehicles have to drive significant detours to reach them.

The only destination charging strategy, on the other hand, is unfavorable to the larger vehicle types. Destination charging is mainly used with slow charging stations, and the high battery capacities of the larger vehicle types cause very long charge times. They are often longer than the planned stay durations at the activities of the schedules, which in turn results in long stay delay times. Additionally, at many locations of the activities, there are simply no charging stations within a comfortable walking distance. This causes average walk times of around 20 min, which makes the strategy impractical for our scenario, because we cannot assume drivers would be willing to walk that far.

Averaged over all vehicle types, only en-route charging causes an extra time of 39.0 min, and only destination charging 39.3 min. Our strategy clearly improves the situation with an average extra time of only 20.0 min. It selects the optimal charging type for each schedule and vehicle type, which is also reflected by the significantly higher share of destination charging for smaller vehicles. However, the average walk times of the trips generated by our trip planner are between 9 min . . . 14 min, which might also be too long to be practical for some drivers.

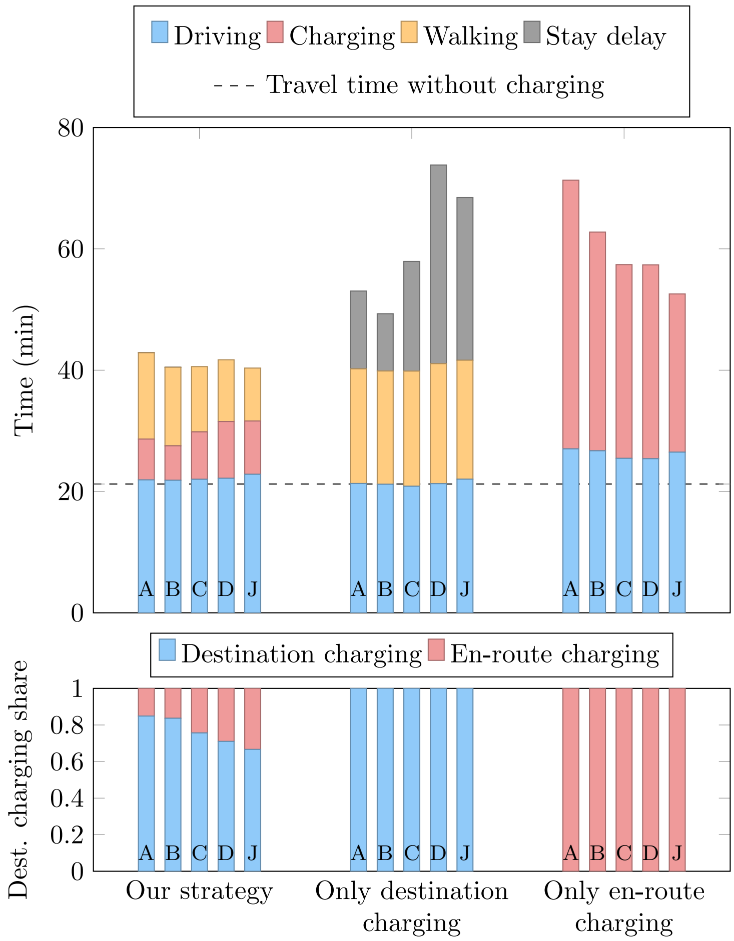


Figure 5.4 – Comparison of our strategy, only destination charging, and only en-route charging for all vehicle types. Travel time composition (top) and destination charging share (bottom) (based on [9] © 2022 IEEE)

5.3.3 Walk Time Limit

Some drivers may not accept long walk times for destination charging. We can set a walk time limit for the trip planner, so that only charging stations within that limit are considered for destination charging. This could make destination charging infeasible in some places and might increase the extra time spent with charging, as vehicles now have to drive detours to fast charging stations for en-route charging. To see how different walk time limits affect the extra time, we tested 3 different walk time limits: 5 min, 10 min and 15 min.

The results can be seen in Figure 5.5. Limiting the walk time to 5 min reduces the share of destination charging from 67 % . . . 85 % to 32 % . . . 36 %. This significantly increases the extra time spent with charging, especially for the smaller vehicles. While the extra time for the J segment vehicle increases by 22 % from 19.1 min to 23.3 min, for the A segment vehicle it increases by 61 % from 21.7 min to 35.0 min.

These results are, of course, highly dependent on the available charging infrastructure. In our scenario, there are simply not enough charging stations available to allow the majority of drivers to comfortably charge their vehicles within their daily schedules. Drivers either have to be willing to walk long distances or endure waiting with their vehicles at fast charging stations. In Chapter 7, we will look at how to extend the charging infrastructure to improve the situation.

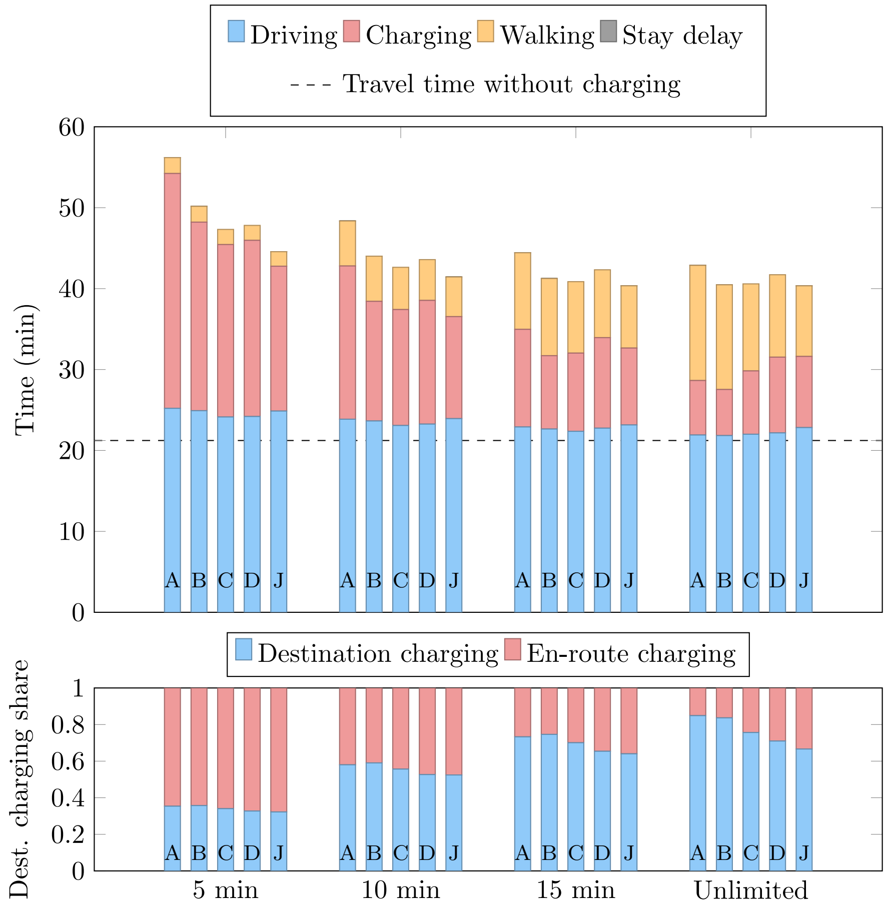


Figure 5.5 – Comparison of different walk time limits for all vehicle types. Travel time composition (top) and destination charging share (bottom)

Chapter 6

Coordination of Charging Between Vehicles

In this chapter, we describe our approach to coordinate charging between electric vehicles in order to reduce wait times. Charging can take a lot of time, and charging stations only have a limited number of charge points. Without coordination between vehicles, there will be queues and long wait times. We propose a central charging station database (CSDB) that assists vehicles with planning their trips. The vehicles can query wait time estimates for any charging station and for any point in time in the future. In exchange, the vehicles have to announce their own planned charge stops to the CSDB.

The wait time information can easily be used by our long-distance trip planner (Chapter 4) and our urban trip planner (Chapter 5) as an additional time cost at the beginning of each charge stop. The adaptive charging and routing strategy will take advantage of this information when planning trips. It might, for instance, select a slower but more energy-efficient route if the vehicle has to wait at the next charging station anyway. It might also select a different charging station if the additional drive time for the detour is less than the saved wait time.

6.1 Related Work

There are several ways to coordinate electric vehicle charging in order to reduce charging station wait times. A popular approach is to use a reservation system [47]–[53]. Vehicles can reserve a time slot at a charging station in advance to avoid waiting when they arrive. The time slot is either selected by the vehicle [48], [49] or assigned by a central scheduler [47], [50], [52], [53]. In some systems [48], [53], the vehicles can update their reservations if needed. While most systems operate on a first-come, first-served basis, Cao et al. [50] describe a system with prioritized reservations, where vehicles with a high priority charge before vehicles with a low priority. To minimize the average wait time, a central scheduler needs to know the time preferences of its users. Hou, Wang, and Yan [51] assume that users are selfish and would not reveal their true preferences to avoid unfavorable time slots. They propose a bidding process which, by progressively eliciting the users' preferences in an iterative auction, preserves the users' privacy.

Some approaches use deep reinforcement learning to schedule charging stations. Qian et al. [54] present a charging navigation approach that tries to minimize the charging cost as well as the total travel time. By considering wait times at charging stations, traffic conditions, and charge prices, it can coordinate smart grid and intelligent transportation systems. However, there is no direct coordination between vehicles. They simply assume that the charging stations know how long the wait times will be. Lee et al. [52] propose a similar system that coordinates charge stops between vehicles with a reservation system and makes charging decisions with a central service. However, both approaches suffer from poor scalability. The street network graph used for evaluation consists of only 39 nodes and three charging stations. Zhang et al. [55] demonstrate deep reinforcement learning for scheduling charging stations on a larger scale. Their evaluation uses a graph of a big city with more than 1000 charging stations. However, they assume that the energy consumption simply depends on the driven distance, and only select the routes with the shortest distance. While this may be sufficient for inner-city navigation, more sophisticated models are needed for long-distance navigation.

Another approach is a central service that keeps track of the charging stations' state and assists vehicles with their trip planning. It can provide vehicles with information about the charging stations, such as the current queue length [56] or average wait times [57]. De Weerdt et al. [58] also take into account the vehicles' future charging intentions. The vehicles announce their intentions to the service, which in return predicts wait times in the future. By combining the charging intentions with historical data, they were able to reduce average wait times in some cases by about 80 %. Tian et al. [59] present a similar system to recommend charging stations to electric vehicle taxis. The system uses real-time GPS data and historical data to understand the drivers' recharging behavior patterns and identify their charging intentions. In real-world experiments, they were able to reduce the wait times of electric vehicle taxis by 50 %.

We go one step further and combine information about the current utilization, announced planned charge stops of other vehicles, and historical data to estimate wait times at charging stations in the future. We use realistic energy consumption and charging models and show that this system works well with long-distance and urban trip planning to reduce average wait times.

6.2 Charging Station Database (CSDB)

The CSDB is a central service that can be used by electric vehicles to coordinate charging station visits. Its main function is to estimate wait times at charging stations in the future. Electric vehicles may query wait time estimates for any charging station and for any future point in time. They can use these estimates to plan their trips and take them into account when selecting charging stations. To use this service, the vehicles agree to announce their own planned charge stops to the database. In addition to the planned charge stops it gets from the vehicles, the database also knows the current utilization of the charging stations and maintains statistical data about past utilization. The CSDB combines this data for the wait time estimation. The concept is depicted in Figure 6.1.

The CSDB is not a reservation system, it only estimates wait times for vehicles based on information from other vehicles and charging stations. This has several advantages. One is that it is independent from the charging station operators. It only needs to know the current utilization of the charging stations, and many charging station operators publish this information as a service to potential customers. Therefore, it is not limited to charging stations of operators that specifically support the system. Another advantage is that deviations from the planned charge stops do not cause any significant issues. Charge stops might be planned hours in advance, and deviations from the planned arrival time at the charging stations due to, e.g., traffic jams, could cause issues with a reservation system. Depending on the implementation of the reservation system, a reserved charge point for a vehicle that is late might be blocked for other vehicles even though it is unused. When the late vehicle finally arrives, there might not be enough time left to complete the charge process before the next reservation. This could potentially be a frustrating experience for the drivers.

In our system, we assume vehicles charge on a first-come, first-served basis. Aside from making it more flexible to deviations from plans, it also means that vehicles not participating in the system are not placed at a disadvantage.

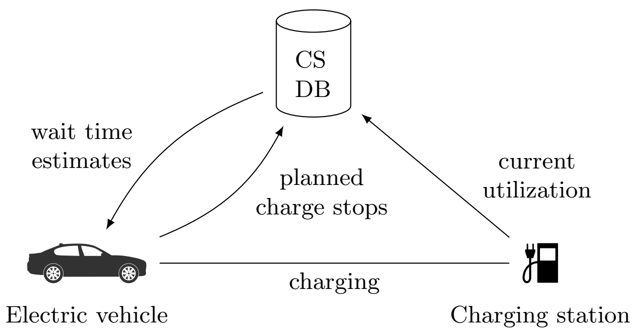


Figure 6.1 – Charging station database concept (based on [8] © 2022 IEEE)

The CSDB was designed to work with our long-distance trip planner and our urban trip planner to reduce wait times. The trip planner itself could be run locally on a user's device, such as a smartphone or on the vehicle's on-board navigation system. The only user data received by the CSDB would be requests for wait time estimates and the planned charge stops. It would not need to know about the trip destinations or the drivers' schedules.

6.2.1 Wait Time Estimation

The CSDB estimates wait times by combining three data sources. The current utilization of charging stations, announced planned charge stops of vehicles, and statistics about historical utilization. To ease the reading of the following part, we provide a table of the used symbols in Table 6.1.

For the charging stations' current utilization, the database maintains the state of each charge point. This includes whether the charge point is occupied and when an occupying vehicle will depart. For each charge point $c \in C_s$ of a charging station $s \in S$, we denote the departure time of the occupying vehicle as t^c_{dep}. In case the charge point is vacant, we define $t^c_{dep} = t_0$, with t_0 being the query time (the current time when the query is made). The set of announced planned charge stops by electric vehicles is denoted as P. Each planned charge stop $p \in P$ has an arrival time t^p_{arr} and a charge time t^p_{chr}. As we assume vehicles are charged on a first-come, first-served

Table 6.1 – Description of symbols

Symbol	Description
S	Set of charging stations
C_s	Set of charge points of charging station s
t_0	Query time
t^q_{arr}	Arrival time of the query
t^q_{start}	Charge start time of the query
t^q_{wait}	Resulting wait time of the query
P_s	Set of planned charge stops of charging station s
t^p_{arr}	Arrival time of planned charge stop p
t^p_{start}	Charge start time of planned charge stop p
t^p_{chr}	Charge time (duration) of planned charge stop p
t^p_{dep}	Departure time of planned charge stop p
c_p	Charge point assigned to planned charge stop p
T	Period of charge stops for statistical utilization
t_{chr}	Charge time of charge stops for statistical utilization
u	Statistical utilization of charging station
n	Number of charge points of charging station

basis, the time when the charge process will start t^p_{start}, depends on the arrival time at the charging station and implicitly on the vehicles that will arrive earlier (cf. Equation (6.6)). The charge start time and departure time t^p_{dep} are defined as:

$$t^p_{start} = t_{start}(t^p_{arr}) \,, \tag{6.1}$$

$$t^p_{dep} = t^p_{start} + t^p_{chr} \,. \tag{6.2}$$

We assign each planned charge stop to one of the charge points $c \in C_s$ of the charging station. Which charge point is selected, depends on the arrival time of the planned charge stop:

$$c_p = \arg\min_{c \in C_s}(t^c_{free}(t^p_{arr})) \,. \tag{6.3}$$

The function $t^c_{free}(t^p_{arr})$ (cf. Equation (6.5)) returns the time when the charge point c would become free for a vehicle arriving at the given arrival time. This, of course, depends on other planned charge stops assigned to that charge point with earlier arrival times, which are denoted as:

$$P_c(t_{arr}) = p \in P_s, c_p = c, t_0 < t^p_{arr} < t_{arr} \,. \tag{6.4}$$

To calculate when a charge point becomes free for an arrival time t_{arr}, we take the last departure time of these planned charge stops. If there are none, we instead return the departure time of the vehicle currently occupying the charge point t^c_{dep}. As mentioned before, if the charge point is vacant, this value is simply the query time t_0, i.e., the charge point is free immediately.

$$t^c_{free}(t_{arr}) = \begin{cases} \max_{p \in P_c(t_{arr})} t^p_{dep} & \text{if} P_c(t_{arr}) \neq \emptyset \\ t^c_{dep} & \text{else} \end{cases} \,. \tag{6.5}$$

With this, we can calculate the charge start time. It is the soonest time any charge point of the charging station becomes free, but cannot be before the arrival time:

$$t_{start}(t_{arr}) = \max(t_{arr}, \min_{c \in C_s}(t^c_{free}(t_{arr}))) \,. \tag{6.6}$$

We can use this function to calculate the charge start time for the query. The estimated wait time is then simply the difference between the start charge time and the arrival time:

$$t^q_{start} = t_{start}(t^q_{arr}) \,, \tag{6.7}$$

$$t^q_{wait} = t^q_{start} - t^q_{arr} \,. \tag{6.8}$$

6.2.2 Statistical Utilization

We assume that not all vehicles will participate in using the CSDB, and that, therefore, not all charge stops will be announced to it. This could potentially lead to significant errors in the wait time estimation. To also take charge stops into account that were not announced, the CSDB maintains statistical data about the charging station utilization, based on historical data. It is stored in the form of average utilization per hour for a 24 h period. In our wait time estimation, we account for it by adding short virtual charge stops that repeat periodically. The period depends on the duration t_{chr} of the virtual charge stops, the utilization u, and the number of charge points of the charging station n:

$$T = \frac{t_{chr}}{u \cdot n} \,. \tag{6.9}$$

In our experiments, we set t_{chr} to 1 min. For a charging station with two charge points and a 25 % utilization rate, we would add a virtual charge stop every two minutes. Figure 6.2 depicts an example of a wait time estimation including virtual charge stops.

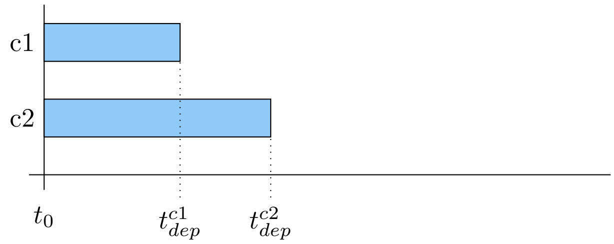
6.2.3 Long-Distance Trip Planning

The long-distance trip planner plans the full trip before the departure of the vehicle. It queries wait time estimates from the CSDB for charging stations that are potential charge stops. Because the drive can take hours, by the time the vehicle arrives at a charging station, the wait time may differ significantly from the original estimate. Additional vehicles may have planned charge stops at the charging station but announced them only after our vehicle planned the trip, or more vehicles than expected arrived unannounced. We therefore might want to update the wait time estimates from time to time and alter the plan if necessary. This requires additional communication with the CSDB and additional computation time by the trip planner. We have defined three levels of when trip plan updates take place:

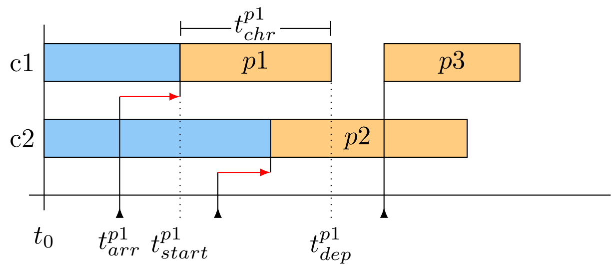
Level 1 The trip is planned at the beginning and never updated. The vehicle communicates with the CSDB once to query wait time estimates and to announce its planned charge stops.

Level 2 The trip is updated when arriving at a charging station. In addition to the communication for the initial planning, the vehicle communicates with the CSDB at every charge stop to query wait time estimates. If any estimate changes, the trip planner replans the trip and updates the planned charge stops at the CSDB.

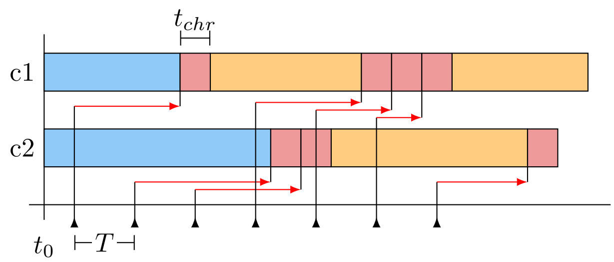
Level 3 The trip can also be updated while driving. The vehicle is in constant communication with the CSDB. Unlike levels 1 and 2, the CSDB actively monitors the wait time estimates and automatically notifies the vehicle of any changes. The vehicle can then immediately replan the trip from the current position on the road.



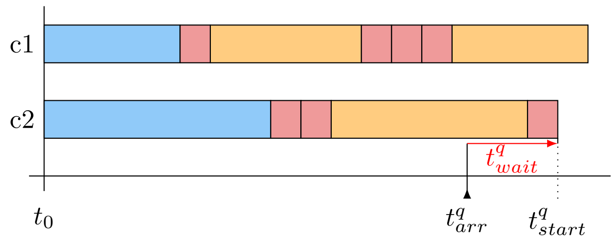
(a) Current utilization of charge points (blue) including departure times of the occupying vehicles



(b) Planned charge stops (orange) added to the next free charge point after their arrival (triangle). Wait times (red arrow) may occur if no charge point is free on arrival



(c) Statistical utilization added as short virtual charge stops (red)



(d) Wait time of the query t_{wait}^{q} is the difference between the arrival time t_{arr}^{q} and the charge start time t_{start}^{q}

Figure 6.2 – Wait time estimation example (based on [8] © 2022 IEEE)

6.2.4 Urban Trip Planning

We can also use the CSDB to coordinate charging with our urban trip planner. Similarly to long-distance trip planning, the trips of the day are planned before the first departure of the vehicle. But unlike long-distance trip planning, the trips have rather short drive segments (minutes instead of hours) and can have long stay durations at activities. Updating the plan when arriving at a charging station or while on the road provides little benefit, because the wait time estimates will not change significantly after only a few minutes. They may, however, change significantly after the vehicle has been parked at an activity for several hours. For urban trip planning, we therefore only update the trip plan when departing from an activity.

6.3 Performance Evaluation

6.3.1 Experimental Setup

We evaluate the CSDB in combination with long-distance trip planning and urban trip planning. For the experiments in this section, we use the same experimental setups as we did in Chapter 4 and Chapter 5 respectively. In the previous chapters, we simply calculated plans with the trip planners and analyzed the results. The vehicles had no interaction with each other. In the experiments in this chapter, the vehicles do interact and affect each other. We therefore now perform a discrete-event simulation (DES) of the vehicles and charging stations. Each charging station has a limited number of charge points. When all charge points are occupied, arriving vehicles must wait in a queue for a free charge point before they can be charged.

6.3.2 Long-Distance Trip Planning

To evaluate the CSDB with long-distance trip planning, we simulate one day with 2000 vehicles making long-distance trips. Each vehicle is assigned a random origin-destination (OD)-pair with a distance of 500 km, which ensures that the vehicle has to recharge on the way. Departure times are selected randomly based on the distribution of trips on a weekday (Mon–Fri) in Germany [60] (see Figure 6.3). The charging infrastructure, which was taken from the scenario in Chapter 4, consists of 2611 fast charging stations with a total of 8356 charge points. We ran the simulations 10 times for each vehicle type and averaged the results.

In our first experiment, we examine how the total travel time of our vehicle types is affected by the penetration rate of the CSDB, i.e., how many vehicles take part in the system. We ran tests with penetration rates from 0 % . . . 100 % in 10 % steps. Of the vehicles using the CSDB, one-third uses CSDB level 1, one-third level 2, and

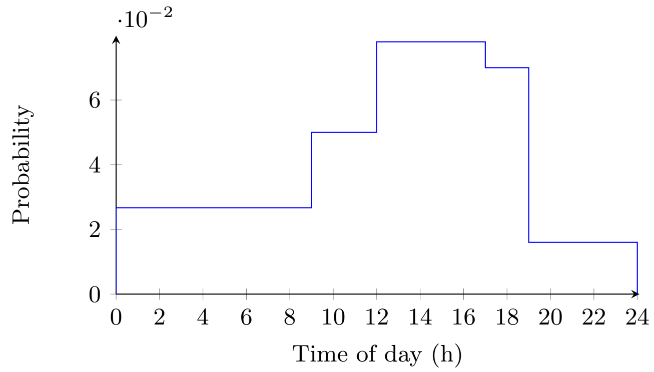


Figure 6.3 – Departure time distribution (based on distribution of trips on a weekday (Mon–Fri) [60])

one-third level 3. We denote not using the CSDB as level 0. The division of CSDB levels among vehicles for the penetration rate steps can be seen in Figure 6.4.

As can be seen in Figure 6.5, using the CSDB reduces the total travel time of all vehicle types significantly. Higher penetration rates of the CSDB lead to significantly lower wait times without affecting the drive or charge times in a major way. The A segment vehicles have the smallest batteries and the worst fast-charging capabilities, which results in long charge times and, in turn, long wait times at the charging stations. At a 0 % penetration rate, the average wait time is about 4 h. When all vehicles use the CSDB, it is reduced to 4 min, which is an improvement of about 98 %. The D segment vehicles need to recharge a lot less as their batteries are larger and their fast-charging capabilities better, which leads to lower wait times. Nevertheless, we see a significant improvement here as well. The average wait time for 0 % and 100 % penetration rates is 17 min and 37 s respectively, which is an improvement of 96 %.

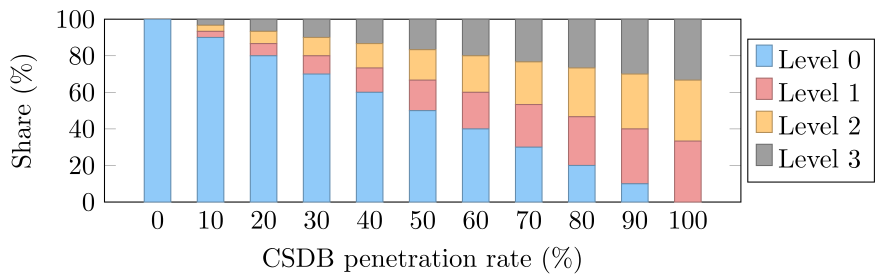


Figure 6.4 – Division of vehicles into CSDB levels for the penetration rate steps in our experiments

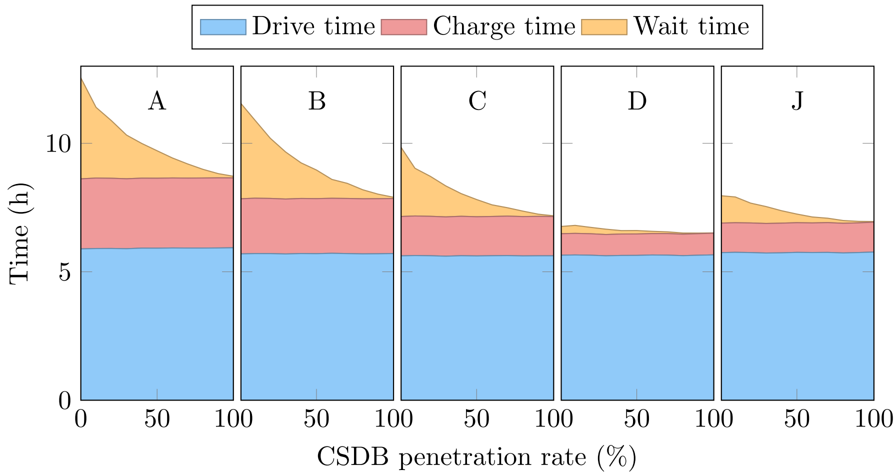


Figure 6.5 – Travel time composition of all vehicle types for different CSDB penetration rates

In Figure 6.6, we look at how the different CSDB levels affect the average wait times of our vehicle types. A higher CSDB penetration rate improves the wait times of all vehicles, even the ones not using the CSDB (level 0). They benefit from more evenly utilized charging stations, which results in shorter queues and wait times. For the vehicles using the CSDB, there is a significant difference between levels. The average wait time has improved for all levels, but levels 2 and 3 see a much larger improvement than level 1. Vehicles with CSDB level 1 only plan their trip once at the beginning with the then current wait time estimates. These wait time estimates become outdated after a while as more and more vehicles announce their planned charge stops. By updating the trip plan at every charge stop, vehicles with CSDB level 2 achieve significantly better average wait times. Vehicles with CSDB level 3 can update their plan while driving. This is an advantage, especially for vehicles with large batteries that can drive for a long time between charge stops. For vehicles with small batteries, e.g., the A segment, the difference between levels 2 and 3 is smaller.

It should be noted that CSDB level 2 only has an advantage over level 1 when the vehicle has to make multiple charge stops. Updating the trip plan at a charge stop mostly improves the situation for the following charge stops. We therefore designed the tests so that most vehicles have to make multiple charge stops.

The main cause of long wait times is the uneven utilization of charging stations, with a few hot spots where many vehicles want to charge at the same time, while the majority of charging stations have low utilization. Using the CSDB shifts the load from the hot spots to other charging stations and leads to a more evenly utilized charging infrastructure. The effect can be seen in Figure 6.7. It shows the utilization

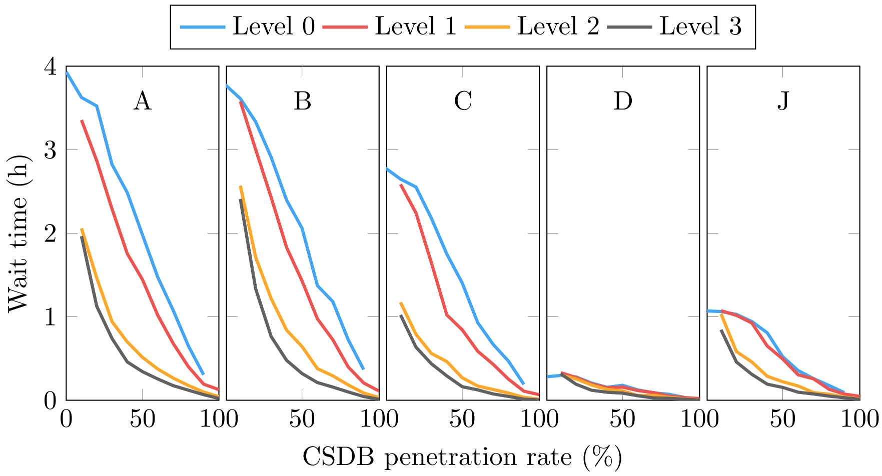


Figure 6.6 – Wait times of all vehicle types for different CSDB levels and CSDB penetration rates

of charging stations during peak hours (15 h . . . 18 h) with A segment vehicles, which generally have the highest wait times in our experiments. We can see that with a CSDB penetration rate of 100 %, there are no hot spot charging stations with a utilization of 100 % anymore. In turn, the utilization of most other charging stations has increased slightly. The charging stations are still far from being evenly utilized; the majority are not used at all. This can be attributed to the design of our tests. We consider all fast charging stations in Germany, but only test long-distance trips. Many charging stations are not close to major highways, which makes them unsuitable for long-distance travel.

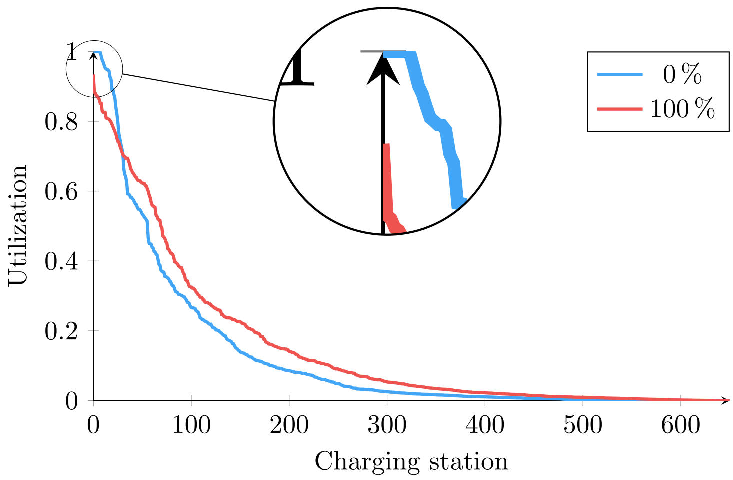


Figure 6.7 – Average utilization of charging stations in peak hours (15 h . . . 18 h) for CSDB penetration rate of 0 % and 100 %, sorted by utilization

In our next experiment, we evaluate using statistical data about the charging station utilization to improve the wait time estimation. We generated the statistical data from the average charging station utilization of our previous experiment. In the experiment, we compare the average wait time of A segment vehicles using CSDB level 3, with and without using statistics. The results are plotted in Figure 6.8. As can be seen, the average wait time when using the statistics is approximately halved, compared to not using the statistics. We can also observe that the statistics not only improve average wait times at low penetration rates, where only few vehicles announce their planned charge stops to the CSDB, but also at high penetration rates, including 100 %, when all charge stops are announced to the database. This can be explained by the fact that the vehicles do not announce their planned charge stops until the time of departure. Wait time estimates might become outdated when other vehicles announce their planned charge stops later. And even though they can update their route while driving, by the time they know they are on a suboptimal path, it might already be too late to change it. It is therefore beneficial to account for vehicles departing in the future by using statistical data.

6.3.3 Urban Trip Planning

In this experiment, we evaluate the effectiveness of using our CSDB for urban trip planning. When evaluating urban trip planning, our main metric is the extra time spent with charging. We do not use the wait time directly, because choosing a different charging station to reduce wait time could significantly increase the walk

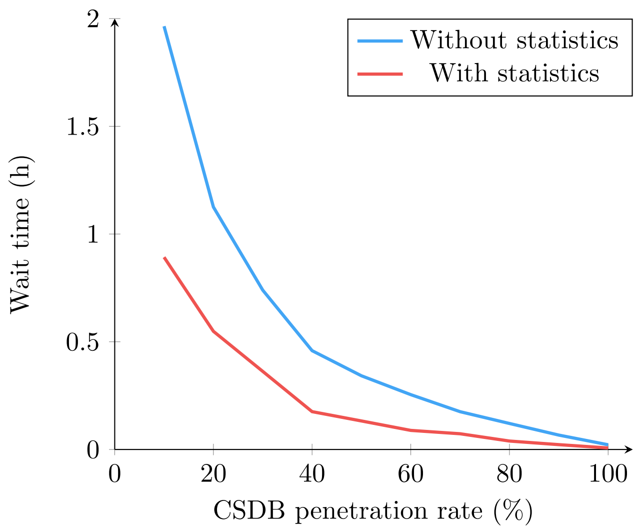


Figure 6.8 – Wait times compared with and without using statistics on CSDB level 3

time for destination charging or, in the case of en-route charging, lead to additional charge time. For simplicity, we assume that all vehicles either use the CSDB or do not use it. We simulated scenarios with varying numbers of electric vehicles that want to charge that day using the public charging infrastructure from 0.1 %…0.2 %.

We can make a simple rule of thumb calculation to see that this range is a realistic assumption. Even though the market share of electric vehicles in Germany was 13.6 % in 2021 [61], the share of electric vehicles among the vehicle population was only 1.3 % in January 2022 [62]. According to surveys, the vast majority of charging in Germany happens at home (59 %), or at work (14 %), and only about 26 % by using the public charging infrastructure [63]. In 2020, German cars traveled an average of 13 323 km [64]. If we assume an average range of an electric vehicle of 350 km and that the vehicle is charged from 20 %…80 % state of charge (SOC), this corresponds to approximately one charge every 5.8 days. Therefore, on a given day, we can expect that of all existing vehicles, about $\frac{0.013 \cdot 0.27}{5.8} = 0.0006$ or 0.06 % want to charge their vehicle using the public charging infrastructure. And with the increasing popularity of electric vehicles, that number will likely rise quickly in the near future.

In Figure 6.9, we can see that using the CSDB reduces the average extra time spent with charging by 80 %…90 %. However, due to the limited number of charging stations and charge points, it is still unacceptably high. In the next chapter, we will see how we could extend the charging infrastructure to achieve acceptable extra times and how the CSDB can help with that.

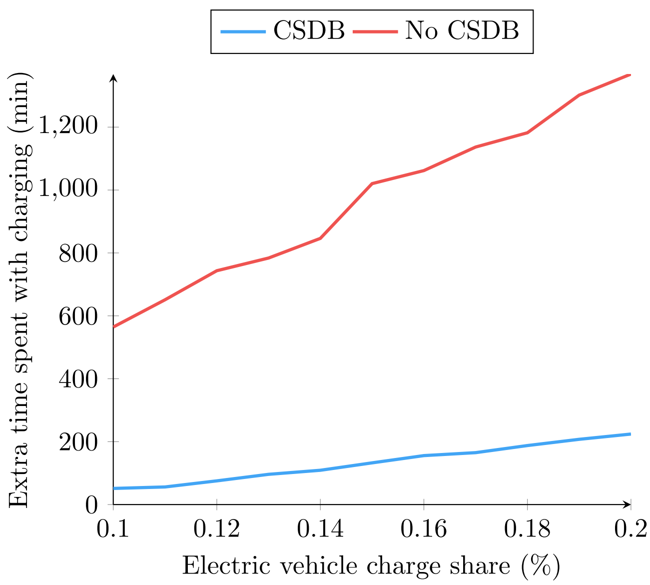


Figure 6.9 – Average extra time spent with charging depending on electric vehicle rate with and without using the CSDB

Chapter 7

Charging Infrastructure Siting and Sizing

In this chapter, we describe our charging infrastructure siting and sizing approach. While today most electric vehicles are charged at home (or at work), we assume that in the future, many electric vehicles will be owned by drivers who do not have the option to charge at home. They have to rely on the public charging infrastructure to recharge their vehicle in everyday life. As we have seen in Chapter 5 and Chapter 6, the existing public charging infrastructure is not yet sufficient to provide convenient charging for the majority of drivers. The public charging infrastructure therefore needs to be extended, especially for drivers who cannot charge at home.

Extending the charging infrastructure consists of two problems. Siting suitable locations for new charging stations and sizing the charging stations, i.e., determining the number of charge points to deploy. It is also important to distinguish between slow and fast charging stations, because they are used in a completely different manner [5]. We assume that slow charging stations are predominantly used for destination charging due to the long charge times. Fast charging stations, on the other hand, are more suitable for en-route charging where the driver waits with the vehicle.

Our siting and sizing approach is designed to extend the charging infrastructure for everyday charging in an urban scenario. The goal is to improve the average extra time spent with charging by identifying locations for new slow and fast charging stations, and to reduce the average wait time by finding an appropriate number of charge points. We use the same scenario as in Section 5.3.1. Charging infrastructure for long-distance travel would be sited in a different way, with most fast charging stations set up along major highway corridors.

7.1 Related Work

Extending the public charging infrastructure to meet the needs of electric vehicles (in the future) is a popular research area. The public charging infrastructure is used in different kinds of scenarios. It plays a crucial role in enabling electric vehicles to travel long distances. Fast charging stations are usually placed along major highways to allow vehicles to reach destinations beyond their normal range. Jochem, Szimba, and Reuter-Oppermann [65] examined how many fast charging stations are needed along European highways to cover all flows of electric vehicles. A similar study [66] was conducted to find optimal locations for fast charging stations on interstate highways in the United States. In addition to fast charging stations along highways, slow charging stations may be placed at destinations where the vehicles stay for a longer time. A well-known example of this concept in practice is Tesla's network of fast charging stations along major highways (*Superchargers*) and slow charging stations at hotels, resorts, and restaurants (*Destination Charging*) [67]. The chargers are intended to enable long-distance travel, with the assumption that everyday charging takes place at home.

To enable everyday charging for drivers without the option to charge at home, one approach is to place slow chargers distributed throughout the city. To find locations for the chargers, Erbaş et al. [68] use GIS software to evaluate location candidates with 15 criteria from the dimensions environmental/geographical, economic, and urbanity. Król and Sierpiński [69] try to evaluate locations with easily accessible data, such as proximity to major roads or densely populated areas. They use existing parking lots as location candidates and have different criteria for slow and fast charging stations. Fast charging stations can also be used for everyday charging. Wolbertus and Van den Hoed [5] investigated the need for fast charging stations in cities. They concluded that fast charging stations are used in a completely different manner than slow charging stations and must be treated separately in the planning of charging infrastructure. And that while slow charging is better suited for everyday charging at home or at work, if there are no charging stations in the vicinity of these locations, fast charging can be a substitute if the charging speed is fast enough.

Because slow and fast charging stations are used in a completely different manner, it is important to distinguish between them. Simply put, fast charging stations are needed where many cars drive, and slow charging stations are needed where many cars park. Therefore, fast charging station siting approaches try to maximize the capture of traffic flow [65], [66], [70]. Gas stations are used in a similar manner to fast charging stations, and their locations are selected with similar objectives. Some works [71]–[73] use existing gas stations as location candidates for new fast charging stations. Slow charging stations, on the other hand, are generally placed close to where potential customers live or park. One strategy is to minimize the number of charging stations while still providing all potential customers with a station within a certain distance. Another is to deploy a fixed number of charging stations and minimizing the median distance to the customers [70].

Another aspect that can be considered is the impact of electric vehicle charging on the power grid. Ma and Zhang [74] present an approach to find locations for slow charging stations in a city that satisfy power grid constraints. Especially fast charging stations can place a considerable load on the power grid. Sun, Chen, and Yin [75] describe an approach to plan charging infrastructure for long-distance travel that takes the interaction between transportation and power networks into account. In addition to fast charging stations for en-route charging, wireless charging lanes and destination charging are also considered.

A different approach is an agent-based simulation where electric vehicles make trips and recharge their batteries when necessary, in order to infer the demand for charging infrastructure. The driver behavior with regard to recharging significantly affects the results. It can be modeled in different ways. Simple models assume that the drivers drive their trips until the battery's state of charge (SOC) drops below a certain threshold and only then begin looking for a charging station [73], [76]. In other models, charge stops are planned at the beginning of the trip [72], [77]. Some works generate the trips from random origin-destination (OD) pairs [73]. Other works [72], [76]–[78] use activity chains (driver schedules), but they usually do not differentiate between destination charging and en-route charging. One exception is an approach by He, Yin, and Zhou [77]. They assume that drivers plan their trips together with charge stops in order to minimize the total travel time. They distinguish between slow and fast charging and can deploy charging stations in a way that minimizes average travel times. However, they do not take wait times into account, it is a pure siting approach without sizing.

Most works in the field of siting and sizing charging infrastructure use simple models for charging and energy consumption of electric vehicles. The charge power is often assumed to be constant ([72], [73], [76]–[78]) and the energy consumption is often a fixed amount of energy per distance driven ([73], [76]–[78]).

The siting and sizing approach we present in this chapter intends to extend the charging infrastructure for everyday charging. We use an agent-based simulation with a sophisticated driver behavior model based on our urban trip planner (cf. Chapter 5) to plan trips including charge stops with destination charging and en-route charging. This includes using our five vehicle types from different vehicle segments with realistic energy consumption and charging models. This way, we can site locations for new slow and fast charging stations and extend existing ones to minimize the extra time spent with charging, including wait time. By coordinating charging with our charging station database (CSDB) (cf. Chapter 6), we can significantly reduce the necessary number of charge points to reach acceptable extra times.

7.2 Concept

Our approach to charging infrastructure siting and sizing builds upon our urban trip planner (cf. Chapter 5). The goal is to improve the average extra time spent with charging by extending the charging infrastructure with additional charging stations and charge points. We consider both slow and fast charging stations and distinguish between en-route charging and destination charging.

In our approach, siting and sizing are two separate phases. In the siting phase, typical driver schedules are analyzed to find locations for new charging stations. The new charging stations are added to the existing charging infrastructure, initially with only one charge point. In the sizing phase, we identify which charging stations should be extended with additional charge points. We run multiple parallel simulations to test how each possible charging station extension would improve the average extra time spent with charging, including wait time. The vehicles in the simulations plan their trips with the urban trip planner and coordinate their charge stops with our CSDB. An illustration of the concept can be found in Figure 7.1.

7.3 Siting

The siting algorithm tries to identify good locations for new charging stations. Potential candidates for these locations are the nodes of our street network graph. We assign a score to each node that reflects how much a charging station at that node would potentially improve the average extra time for the vehicles. To calculate the scores, we analyze the drivers' schedules and also take into account the existing charging infrastructure.

The charging station sites are selected iteratively, one by one. The node with the highest score is selected as a new charging station site and added to the charging infrastructure. After a new site has been added, the node scores are recalculated because the new charging station affects the scores of the surrounding nodes by satisfying the charging demand in its vicinity.

Slow and fast charging stations are used in an entirely different manner [5]. We therefore use two different scoring algorithms.

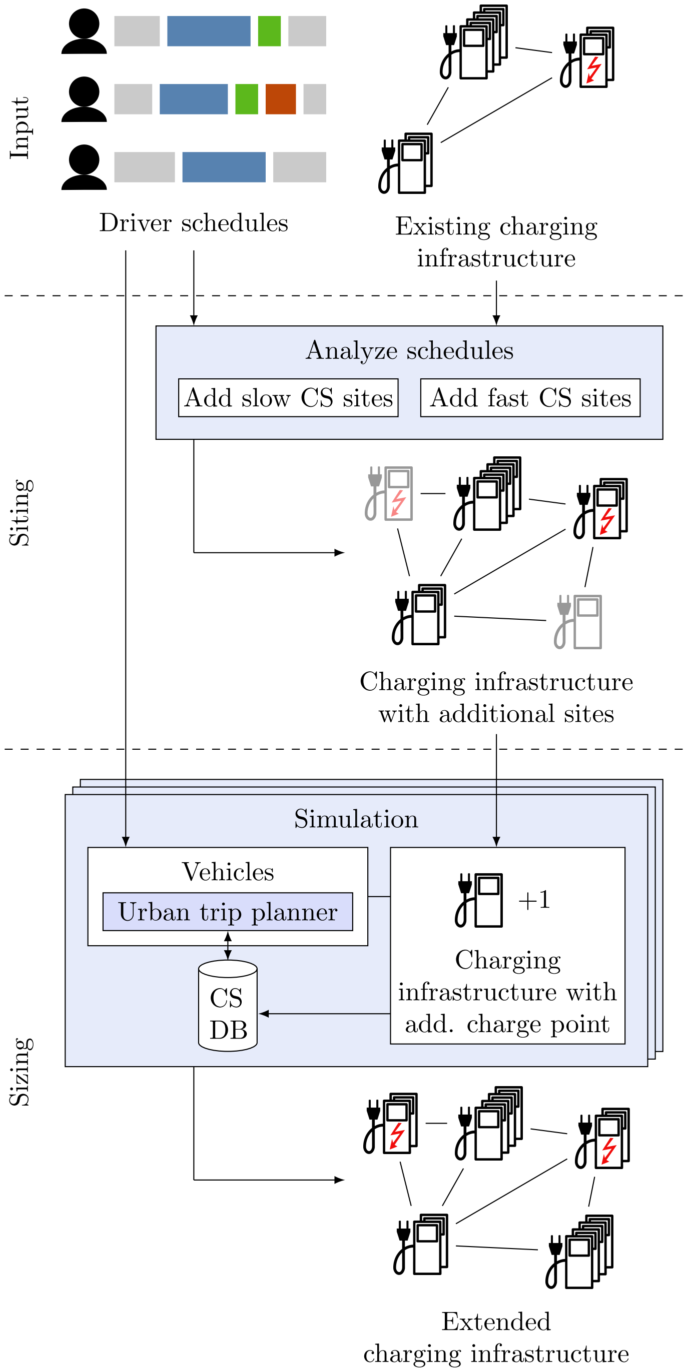


Figure 7.1 – Charging infrastructure siting and sizing concept (based on [9] © 2022 IEEE)

7.3.1 Slow Charging Score Calculation

We assume that slow charging is mainly used for destination charging. To find suitable locations for slow charging stations, it is therefore important to know where vehicles park and for how long. We analyze the stops of typical driver schedules to calculate the scores of the nodes. The scores reflect how much walk time a new charging station at a node would save, compared to existing charging stations in the area. We also take into account how long the vehicles are parked, i.e., a stop long enough to completely charge the vehicle weighs more than a quick stop that only takes a few minutes.

Let S be the stops of our typical driver schedules, V the nodes of the street network graph, and C the existing charging stations. Each stop $s \in S$ and each charging station $c \in C$ is assigned to a node $v_s \in V$ and $v_c \in V$ respectively. The linear distance between two nodes $v_1, v_2 \in V$ is defined as $d(v_1, v_2)$. With this, the distance from a stop s to the closest charging station is:

$$d_{\text{min},s} = \min_{c \in C} d(v_s, v_c) \ . \tag{7.1}$$

Stops only affect the scores of nodes within a certain search radius. To improve the potential walk time, only nodes that are closer than already existing charging stations are considered. We also assume that drivers are not willing to walk very long distances from the charging station to the activity. The maximum walking distance is d_{maxwalk}. The search radius around a stop s is therefore defined as:

$$d_{\text{search},s} = \min(d_{\text{min},s}, d_{\text{maxwalk}}) \ . \tag{7.2}$$

The stops contribute to the scores of all nodes within their search radius. The score of each node is the sum of these contributions:

$$x_{\text{slow},v} = \sum_{s \in S | d(v,v_s) < d_{\text{search},s}} x_t(t_s) \cdot x_d(d(v_s, v)) \ , \tag{7.3}$$

where t_s is the stop duration time, and $x_t()$ and $x_d()$ are functions to calculate the time score and distance score for the stop. The time score reduces the impact of the stop on the score if the duration of the stop is too short to charge the vehicle to 80 % SOC:

$$x_t(t_s) = \begin{cases} \frac{t_s}{t_{\text{charge80}}} & \text{if } t_s < t_{\text{charge80}} \\ 1 & \text{else} \end{cases} \ , \tag{7.4}$$

where $t_{charge80}$ is the time it takes to charge the battery to 80 % SOC with slow charging. The distance score represents the walking distance that could potentially be saved by installing a charging station at that node:

$$x_d(d) = d_{\text{search},s} - d \ . \tag{7.5}$$

An example of the score calculation for a node v can be seen in Figure 7.2. As can be seen, the node's score is only affected by the stops s_2 and s_3. The stop s_1 does not contribute to the score, because the node is outside of the stop's search radius $d(v_{s_1}, v) > d_{\text{search},s_1}$ (cf. Equation (7.3)). Because the stop duration at stop s_2 is only half the time necessary to charge to 80 % SOC (t_{charge80}), its time score is 0.5. The stop duration of s_3 is more than enough, therefore its time score is 1.0 (cf. Equation (7.4)). Stop s_3 has a distance to the node of 250 m, which is 200 m less than the distance to the nearest charging station (450 m). Its distance score is therefore 200. The distance from the node to stop s_2 is 500 m, which results in a distance score of 100. Because there is no charging station within the maximum walking distance of 600 m around stop s_2, the search radius equals the maximum walking distance. In this example, the total score of node v is $x_{\text{slow},v} = 0.5 \cdot 100 + 1.0 \cdot 200 = 250$.

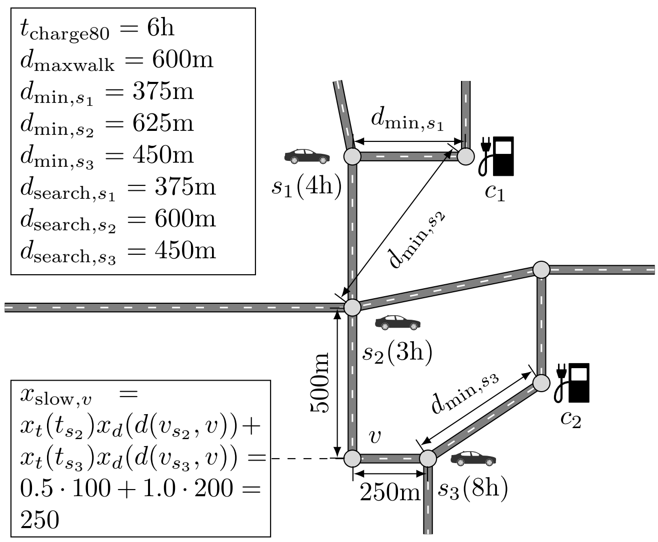


Figure 7.2 – Slow charging station siting. Example calculation of a node score based on stops s_2 and s_3. Stop s_1 is not used because the node is not within the stop's search radius. (based on [9] © 2022 IEEE)

7.3.2 Fast Charging Score Calculation

In contrast to slow charging, we assume that fast charging is predominantly used for en-route charging, which means the driver stops at a fast charging station while en route to another destination. It does not matter where the destination is, but whether the driver has to make a significant detour to stop at the charging station on the way. We therefore evaluate fast charging station sites by how much time vehicles would save on detours compared to existing fast charging stations. Similar to the slow charging score calculation, we use typical driver schedules, but instead of the stops, we look at the trips between activities.

Let R be the set of trips of all schedules. The drive time of a trip $r \in R$ with a detour via node v is defined as $t_{r,v}$, assuming the shortest path between the origin, node v, and the destination. The minimum drive time for a trip with a detour to an existing fast charging station is then:

$$t_{\min,r} = \min_{c \in C_{\text{fast}}} t_{r,v_c} \ , \tag{7.6}$$

where $C_{\text{fast}} \subseteq C$ is the set of fast charging stations. To calculate the score of a node v, we sum up how much detour time could be saved over all trips as

$$x_{\text{fast},v} = \sum_{r \in R | t_{r,v} < t_{\min,r}} t_{\min,r} - t_{r,v} \ . \tag{7.7}$$

In Figure 7.3, you will find an example of the score calculation for a node v. The node score is only affected by the trips r_1 and r_3. Trip r_2 does not contribute to the score, because driving by the node would be a bigger detour than driving by an existing fast charging station: $t_{r_2,v} > t_{\min,r_2}$ (cf. Equation (7.7)). A fast charging station at our example node would save $7.9 - 7.5 = 0.4$ minutes for trip r_1 and $9.2 - 7.8 = 1.4$ minutes for trip r_3 compared to using existing fast charging stations. The score of node v is therefore 1.8.

As we have just seen, calculating a node score involves finding the shortest path for every trip with a detour using that node. Doing this for every node in a typical street network graph would be very computationally expensive. We therefore preselect a small number of nodes that see a lot of traffic. To do this, we find the shortest paths of the trips once without detours and count the number of vehicles per node. The graph in our example consists of 100 790 nodes, of which we preselected the 2500 nodes with the highest vehicle count.

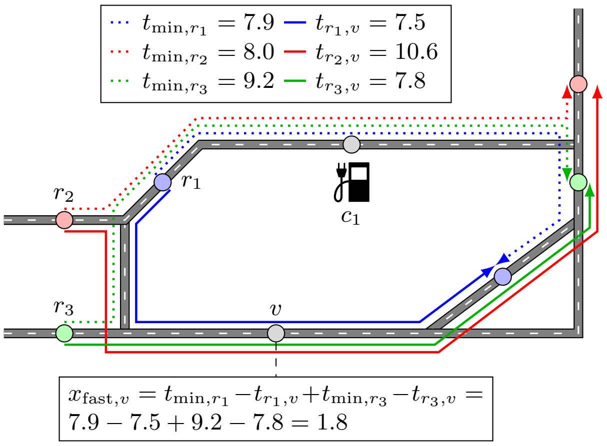


Figure 7.3 – Fast charging station siting. Example calculation of a node score based on trips r_1 and r_3. Trip r_2 is not used because the condition $t_{r_2,v} < t_{\min,r_2}$ is not met. (based on [9] © 2022 IEEE)

7.4 Sizing

The siting algorithm only identifies locations for new charging stations, but it does not determine how many charge points the charging stations should have. If multiple vehicles want to charge at the same charging station at the same time, if and how long they have to wait until they can charge, depends on the number of charge points. The wait time cannot simply be calculated with a static analysis of the drivers' schedules. It depends on the charging decisions made by the drivers or their vehicles, which can also influence each other. To calculate it, we use the same discrete-event simulation (DES) that we used to evaluate the CSDB in Chapter 6. The vehicles' charging decisions are made by our urban trip planner. To coordinate charging between the vehicles, they can use the CSDB.

The sizing algorithm works as follows: Initially, the charging infrastructure consists of the existing charging stations and the new charging stations with one charge point each at the sites identified by the siting algorithm. We then iteratively add charge points to the charging stations. In each step, we select one charging station to extend. To select the charging station, we temporarily add one charge point to each charging station in separate parallel simulations to determine the average extra time spent with charging. The charging station whose extension resulted in the best improvement of extra time permanently keeps the additional charge point. The steps are repeated until a set number of charge points have been added, or the average extra time has dropped below some threshold.

7.5 Performance Evaluation

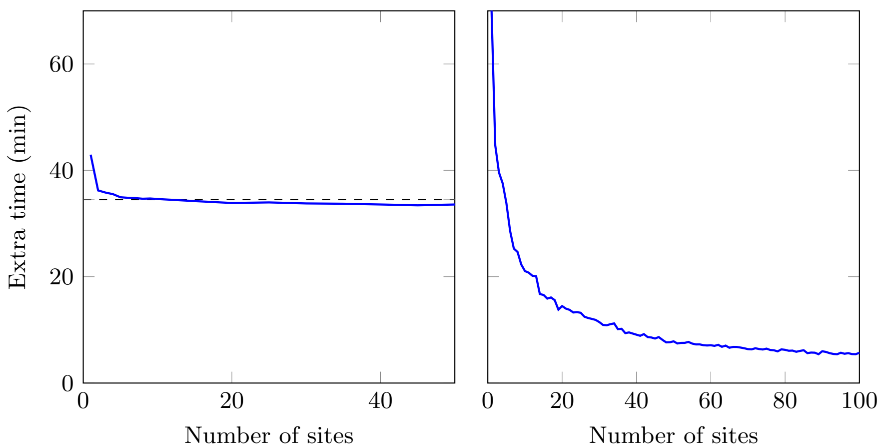
7.5.1 Experimental Setup

To evaluate our siting and sizing approach, we use the same experimental setup as in Section 6.3.1 for the urban trip planner. This includes using the Paderborn traffic simulation scenario (Section 5.3.1).

7.5.2 Impact of the Number of Charging Station Sites

In our first experiment, we evaluate the impact of the number of slow and fast charging station sites on the extra time spent with charging. This allows us to determine the number of sites that are needed to achieve practical extra times for the majority of drivers in our scenario. We ignore wait times for now, because they mainly depend on the number of charge points at the charging stations, which is a separate problem that we solve in the sizing phase. We run simulations to determine the extra time spent with charging for a varying number of slow and fast charging station sites. For slow charging, we test with 1 to 100 sites, and for fast charging, we test with 1 to 50 sites. To find the sites, we use our siting algorithms.

The extra time spent with charging for different numbers of charging station sites is plotted in Figure 7.4 for slow and fast charging stations. Because fast charging stations are used somewhat similarly to gas stations, we also compare the extra time of the fast charging station sites found by our siting algorithm with the existing 24



(a) Fast charging station sites

(b) Slow charging station sites

Figure 7.4 – Comparison of extra time for numbers of fast and slow charging station sites. The dashed line in (a) represents the extra time, if we were using the 24 gas stations as fast charging station sites. (based on [9] © 2022 IEEE)

gas station sites in our scenario. As can be seen, 10 fast charging station sites found by our siting algorithm achieve roughly the same extra time as the 24 gas station sites. But we also see that the benefit of installing more than 5 fast charging stations is marginal. Fast charging stations are predominantly used for en-route charging, where the drivers wait with the vehicle until charging is complete. The locations of fast charging stations affect the extra time only through the detours that vehicles must take for a charge stop. In our scenario, five well-placed fast charging stations are sufficient to allow most vehicles to reach one with only a small detour.

In contrast to this, slow charging stations are used for destination charging, where the driver visits the destination (activity) while the vehicle charges. The extra time is primarily affected by the walk time from the charging station to the destination and back. To improve the average walk time, the charging station sites need to be close to popular destinations. Since there are many possible destinations, we need a lot of charging stations. In our scenario, after about 50 slow charging station sites, additional sites improve the extra time only marginally.

As a result, we have added 5 fast charging stations and 50 slow charging stations to the existing charging infrastructure in our scenario. The extended charging infrastructure will be used in the following experiments. The scenario with the extended charging station sites can be seen in Figure 7.5 (see Figure 5.3 for the original charging infrastructure).

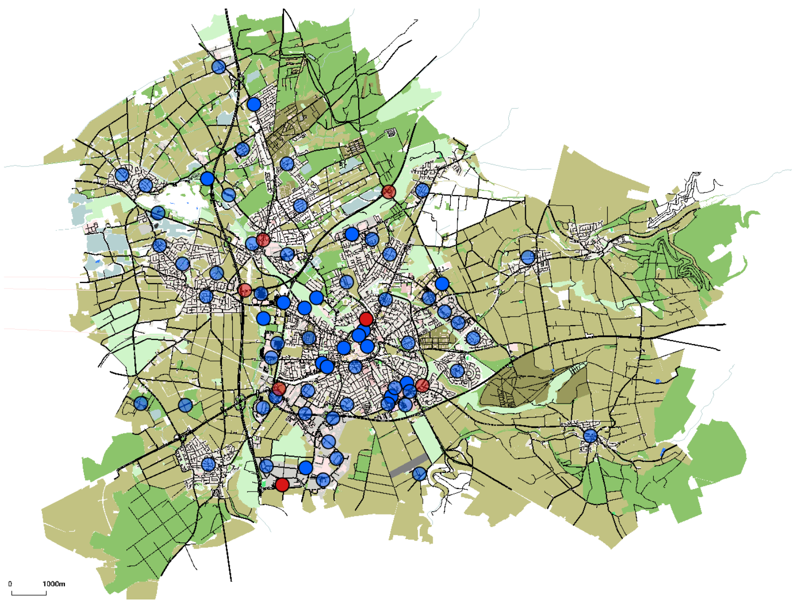


Figure 7.5 – New charging station locations for fast and slow charging stations from our charging station siting algorithm. Slow charging stations are shown as blue and fast charging stations as red, existing charging stations opaque and new locations half transparent. (based on [9] © 2022 IEEE)

7.5.3 Impact of the New Charging Stations

In our next experiment, we analyze the impact of the new charging stations on the travel times of our vehicle types. To compare it with the existing charging infrastructure, we repeat the experiment from Section 5.3.2 with the extended charging infrastructure. In the experiment, we compare our strategy of selecting between destination charging and en-route charging with being limited to one of these options. The original results for the existing charging infrastructure and the new results for the extended charging infrastructure are depicted in Figure 7.6. The original results are identical to the ones presented in Section 5.3.2. We present them here again to make it easier to compare them with the new results.

In the following, we will discuss the differences in the results between the existing and the extended charging infrastructure. For a detailed description of the original results, please refer to Section 5.3.2.

We can see that the extended charging infrastructure significantly improves the situation for both alternative strategies. Using only destination charging led to average walk times of about 20 min for the existing charging infrastructure. With the new charging stations, we have reduced this value to about 5 min. The stay delay values have not improved however, because they are the result of driver schedules with too short stays. Therefore, the strategy of only doing destination charging is still impractical for many drivers. For the strategy of using only en-route charging, the new fast charging stations significantly reduce the necessary detours, from about 5 min to about 1 min on average. However, due to long charge times, especially for smaller vehicles with limited fast charging capabilities, this strategy is also still impractical.

Our strategy of selecting between destination charging and en-route charging benefits most from the additional charging stations. We use en-route charging to avoid stay delays at slow charging stations or in cases when there are no charging stations close to the destination. The additional fast charging stations improve the drive time by reducing detours. More importantly, though, the additional slow charging stations offer new opportunities for destination charging, which is preferable to en-route charging due to the long charge times. With the existing charging infrastructure, we had a destination charging share of 67 %. . . 85 %. This value increases to 83 %. . . 91 % with the additional charging stations. Overall, the extended charging infrastructure reduces the average extra time spent with charging across all vehicle types from about 20 min to under 10 min.

Figure 7.6 – Travel time composition and destination charging share 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. (based on [9] © 2022 IEEE)

7.5.4 Impact of Sizing Approach

After ignoring the wait time in the first two experiments to evaluate our siting approach, we now focus on the sizing approach, where we try to minimize the wait time. The wait time at a charging station mainly depends on the number of arriving vehicles and the number of charge points. To improve wait times, our sizing approach adds charge points to the charging stations. Additionally, by using the CSDB, we can coordinate charging between vehicles to reduce the number of vehicles that want to be charged at the same charging station at the same time.

In this experiment, we evaluate how adding charge points affects the extra time spent with charging with and without using the CSDB. New charging stations that were found by our siting algorithm are initialized with one charge point. In this experiment, we assume that 250, or about 0.2 %, of the 121 176 vehicles are electric vehicles that want to charge that day using the public charging infrastructure. The sizing algorithm iteratively adds charge points to the charging stations one by one until 200 charge points have been added. We ran the algorithm 20 times with random vehicles and schedules and averaged the results.

In Figure 7.7, we can see that using the CSDB reduces the average extra time significantly, especially when only few charge points have been added. As a result, we need to install considerably fewer charge points to achieve acceptable extra times. For example, to reach an average extra time of 15 min, we would only have to add 53 charge points when using the CSDB, but 104 without. When there are so many charge points available that every vehicle can take the optimal trip without waiting anywhere, using the CSDB does not make any difference anymore. In our scenario, this starts at about 125 charge points. The average extra time then stays just under 10 min.

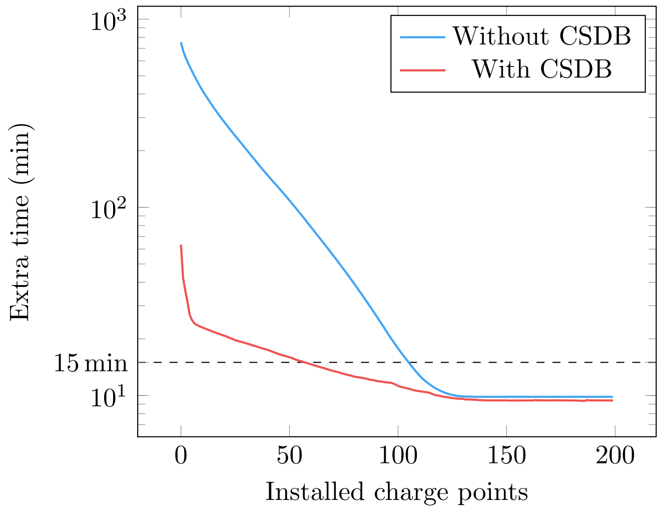


Figure 7.7 – Sizing charging stations with and without using the CSDB. Dashed line at 15 min extra time for easier comparison. (based on [9] © 2022 IEEE)

Chapter 8

Conclusion

In this thesis, we presented several approaches to improve the situation of electric vehicles, including trip planning for long-distance and urban scenarios, coordinating charging between vehicles, and extending the charging infrastructure with additional charging stations and charge points. All of them utilized realistic energy consumption and charging models for five vehicle types in different car segments.

First, we created a long-distance trip planner that can plan trips including charge stops with minimal total travel time. An adaptive charging strategy selects the optimal amount of energy to charge at each charge stop, depending on the power of the current and the following charging station. An adaptive routing strategy selects the best compromise between fast and energy-efficient routes by using a multicriteria shortest path search. To achieve acceptable query times for these searches, we introduced shortest-path-tree precomputing, which exploits the fact that most queries are between the known locations of the charging stations. Our results show that when precomputed shortest-path trees are used for both origin and destination, query times are reduced by about 2 to 3 orders of magnitude. The results also show that our adaptive charging and routing strategies outperform other similar strategies. The greatest advantage was achieved over the strategy of always taking the most energy-efficient route, which, on average, took 34 % more total travel time. This is noteworthy because many publications in the field of electric vehicle routing have the goal of minimizing the energy consumption. On the other hand, always choosing the fastest route and only charging the minimum amount to reach the next charging station only led to marginally higher total travel times. Driving a slower, more energy-efficient route to save time at the charging station later does not seem to pay off when enough fast charging stations with high charge power ($\geq$ 150 kW) are available. Another observation is that larger vehicle types require significantly less total travel time than smaller types, even though they have a higher energy consumption. This can be attributed to their larger batteries and better fast-charging capabilities, which is advantageous for long-distance travel.

Second, we created an urban trip planner that was specifically designed for drivers that have no option to charge at home and have to rely on the public charging infrastructure for everyday charging. It plans trips by taking into account the driver's schedule for the day and minimizing the extra time spent with charging. The vehicle can either be charged en route, with the driver waiting with the vehicle while it is being charged, similar to using a gas station. Or it can be charged at the destination, with the driver visiting the destination while the vehicle is being charged nearby. This can save time and it makes slow charging stations a suitable option, but the driver may have to walk from the charging station to the destination and back. Our results clearly show that selecting between en-route charging and destination charging results in significantly lower extra times, compared to being limited to one of these options. Large vehicle types suffer especially from being limited to destination charging, while small vehicle types suffer more from being limited to en-route charging. Even though our strategy performs better than the alternatives, the extra time was still high, with about 20 min on average. The average walk time might also be unacceptably long with over 10 min for some drivers, but limiting it would increase the extra time even further. This shows that the charging infrastructure in our scenario was insufficient to provide acceptable extra times for the majority of drivers.

Third, we created a central service, called charging station database (CSDB), that coordinates charging between vehicles in order to reduce wait times. It can be used by vehicles to query wait time estimates for any charging station in the future. In exchange, the vehicles are expected to announce their own planned charge stops to the service. The CSDB uses these announced charge stops, information about the current utilization of the charging station, and statistical data about past utilizations to calculate the wait time estimates. We evaluated the approach in combination with our long-distance trip planner and our urban trip planner. The results with the long-distance trip planner show that if all vehicles use the CSDB, the average wait time can be reduced by up to 98 %. The wait time can also be significantly reduced if only a subset of vehicles use it. When 10 % use it, the wait time is reduced by about 75 % for these vehicles, assuming the CSDB uses statistical data of past utilization and that these vehicles update their route immediately when wait time estimates change. The experiments with the urban trip planner demonstrate a similar effectiveness of the CSDB in that scenario. Using the CSDB significantly reduces the average extra time spent with charging and would allow a larger number of electric vehicles to use the public charging infrastructure.

Finally, we presented an approach to extend the charging infrastructure in an urban scenario for everyday charging. It can analyze typical driver schedules to find new sites for slow and fast charging stations. Simply put, slow charging stations are placed where many vehicles park, and fast charging stations are placed where many vehicles drive. To determine the number of charge points for each charging station, it uses simulations with the urban trip planner. The results show that adding 5 fast charging stations and 50 slow charging stations to our urban scenario reduces the average extra time spent with charging for all vehicle types from about 20 min to under 10 min (without wait time). The average extra time was significantly improved for en-route charging and for destination charging, and all vehicle types saw a higher rate of destination charging. Additionally, we were able to significantly reduce the necessary number of charge points to achieve an acceptable average extra time (including wait time) by using the CSDB. To achieve an average extra time of 15 min, we only had to add 53 charge points instead of 104 when not using the CSDB.

In conclusion, the approaches presented in this thesis can provide a step forward in the advancement of electric vehicles. We have shown how smart trip planning and coordination of charging between vehicles can help minimize the inconveniences of long-distance travel and everyday charging. By extending the public charging infrastructure with a combination of slow and fast charging stations, we can make electric vehicles an attractive option even for drivers that cannot charge at home.

A potential direction for further research could be to also consider monetary aspects. Optimizing charging costs when planning trips could increase the benefit to the drivers. Also, potentially saving money could be an incentive to coordinate charge stops with others. Furthermore, building new charging infrastructure is very expensive. Taking the costs into account and planning new charging stations and charge points on a limited budget would be an interesting problem. It would also be interesting to see how the approaches perform in the real world. So far, all the results have come from simulation experiments, where many simplifying assumptions have to be made. Real-world experiments could provide valuable insights to further improve the approaches and make them useful in practice.

List of Abbreviations

AC	alternating current
BEV	battery electric vehicle
CC-CV	constant current – constant voltage
CP-CV	constant power – constant voltage
CSDB	charging station database
CSP	Constrained Shortest Path
DC	direct current
DES	discrete-event simulation
EVCSP	Electric Vehicle Constrained Shortest Path
OD	origin-destination
OSM	OpenStreetMap
SOC	state of charge
SRTM	Shuttle Radar Topography Mission
V2G	vehicle-to-grid

List of Figures

List of Tables

Bibliography

[1] IEA, “Global EV Outlook 2022,” IEA, Paris, Tech. Rep., 2022.

[2] J. Posaner. (2022). European Parliament votes to ban combustion engine cars from 2035, [Online]. Available: `https://www.politico.eu/article/european-parliament-votes-to-ban-combustion-engine-cars-from-2035` (visited on 07/07/2022).

[3] bft. (2021). Entwicklung der Tankstellenanzahl in Deutschland, [Online]. Available: `https://www.bft.de/daten-und-fakten/entwicklung-tankstellenanzahl` (visited on 07/07/2022).

[4] Virta. (2022). The Global Electric Vehicle Market Overview in 2022: Statistics & Forecasts, [Online]. Available: `https://www.virta.global/global-electric-vehicle-market` (visited on 07/09/2022).

[5] 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.

[6] 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.

[7] 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.

[8] 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.

[9] S. Schoenberg, D. S. Buse, and F. Dressler, “Siting and Sizing Charging Infrastructure for Electric Vehicles with Coordinated Recharging,” *IEEE Transactions on Intelligent Vehicles (T-IV)*, Apr. 2022.

[10] A. Jarvis, H. Reuter, A. Nelson, and E. Guevara, Hole-filled seamless SRTM data V4, International Centre for Tropical Agriculture (CIAT), available from https://srtm.csi.cgiar.org, 2008.

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

[12] P. E. Hart, N. J. Nilsson, and B. Raphael, “A Formal Basis for the Heuristic Determination of Minimum Cost Paths,” *IEEE Transactions on Systems Science and Cybernetics*, vol. 4, no. 2, pp. 100–107, Apr. 1968.

[13] 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.

[14] M. Baum, J. Dibbelt, D. Wagner, and T. Zündorf, “Modeling and Engineering Constrained Shortest Path Algorithms for Battery Electric Vehicles,” *Transportation Science*, vol. 54, no. 6, pp. 1571–1600, 2020.

[15] 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.

[16] F. Hartmann and S. Funke, “Energy-Efficient Routing: Taking Speed into Account,” in *KI 2014: Advances in Artificial Intelligence (KI 2014)*, Stuttgart, Germany: Springer, Sep. 2014, pp. 86–97.

[17] R. Bellman, “On a routing problem,” *Quarterly of Applied Mathematics*, vol. 16, no. 1, pp. 87–90, 1958.

[18] L. R. Ford, “Network Flow Theory,” RAND Corporation, Tech. Rep. Paper P-923, 1956.

[19] 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.

[20] E. Q. V. Martins, “On a multicriteria shortest path problem,” *European Journal of Operational Research*, vol. 16, no. 2, pp. 236–245, May 1984.

[21] 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.

[22] S. Storandt, “Route Planning for Bicycles - Exact Constrained Shortest Paths Made Practical Via Contraction Hierarchy,” in *22nd International Conference on Automated Planning and Scheduling (ICAPS 2012)*, Atibaia, Brazil: AAAI Press, Jun. 2012, pp. 234–242.

[23] J. Dibbelt, T. Pajor, and D. Wagner, “User-Constrained Multi-Modal Route Planning,” in *Meeting on Algorithm Engineering & Experiments (ALENEX 2012)*, Kyoto, Japan: Society for Industrial and Applied Mathematics, Jan. 2012, pp. 118–129.

[24] L. Koch, D. S. Buse, M. Wegener, S. Schoenberg, K. Badalian, F. Dressler, and J. Andert, “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.

[25] Kraftfahrt-Bundesamt, Pressemitteilung Nr. 01/2021 - Elektromobilität in Deutschland auf der Überholspur, [Press Release], Jan. 2021.

[26] A. Tomaszewska, Z. Chu, X. Feng, S. O’Kane, X. Liu, J. Chen, C. Ji, E. Endler, R. Li, L. Liu, et al., “Lithium-ion battery fast charging: A review,” *eTransportation*, vol. 1, p. 100 011, Aug. 2019.

[27] 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.

[28] T. Zündorf, “Electric Vehicle Routing with Realistic Recharging Models,” Master’s Thesis, Department of Informatics, Karlsruhe, Germany, Nov. 2014.

[29] Fastned. (2021). Vehicles and charging tips, [Online]. Available: `https://support.fastned.nl/hc/en-gb/sections/115000180588-Vehicles-charging-tips` (visited on 07/27/2021).

[30] S. Storandt and S. Funke, “Cruising with a Battery-Powered Vehicle and Not Getting Stranded,” in *26th AAAI Conference on Artificial Intelligence (AAAI 2012)*, Toronto, Canada: AAAI Press, Jul. 2012, pp. 1628–1634.

[31] M. Baum, J. Dibbelt, T. Pajor, J. Sauer, D. Wagner, and T. Zündorf, “Energy-Optimal Routes for Battery Electric Vehicles,” *Algorithmica*, vol. 82, no. 5, pp. 1490–1546, May 2020.

[32] M. Baum, J. Dibbelt, A. Gemsa, D. Wagner, and T. Zündorf, “Shortest Feasible Paths with Charging Stops for Battery Electric Vehicles,” *Transportation Science*, vol. 53, no. 6, pp. 1627–1655, 2019.

[33] F. Morlock, B. Rolle, M. Bauer, and O. Sawodny, "Time Optimal Routing of Electric Vehicles Under Consideration of Available Charging Infrastructure and a Detailed Consumption Model," *IEEE Transactions on Intelligent Transportation Systems (TITS)*, vol. 21, no. 12, pp. 5123–5135, Dec. 2020.

[34] C. Hecht, K. Victor, S. Zurmühlen, and D. U. Sauer, "Electric Vehicle Route Planning Using Real-World Charging Infrastructure in Germany," *eTransportation*, vol. 10, p. 100 143, Nov. 2021.

[35] M. T. Goodrich and P. Pszona, "Two-Phase Bicriterion Search for Finding Fast and Efficient Electric Vehicle Routes," in *22nd ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (SIGSPATIAL 2014)*, Dallas, TX: ACM, Nov. 2014, pp. 193–202.

[36] 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.

[37] 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.

[38] 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.

[39] 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 (SmartGridComm)*, Vancouver, Canada: IEEE, Oct. 2013.

[40] X. Tang, S. Bi, and Y.-J. A. Zhang, "Distributed Routing and Charging Scheduling Optimization for Internet of Electric Vehicles," *IEEE Internet of Things Journal*, vol. 6, no. 1, pp. 136–148, Feb. 2019.

[41] Y. Sun, Z. Chen, Z. Li, W. Tian, and M. Shahidehpour, "EV Charging Schedule in Coupled Constrained Networks of Transportation and Power System," *IEEE Transactions on Smart Grid*, vol. 10, no. 5, pp. 4706–4716, Sep. 2019.

[42] 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.

[43] 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.

[44] R. Gambuti, S. Canale, F. Facchinei, A. Lanna, and A. Di Giorgio, "Electric Vehicle Trip Planning Integrating Range Constraints and Charging Facilities," in *23rd Mediterranean Conference on Control and Automation (MED 2015)*, Torremolinos, Spain: IEEE, Jun. 2015.

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

[46] P. Alvarez Lopez, M. Behrisch, L. Bieker-Walz, J. Erdmann, Y.-P. Flötteröd, R. Hilbrich, L. Lücken, J. Rummel, P. Wagner, and E. Wießner, "Microscopic Traffic Simulation using SUMO," in *21st IEEE International Conference on Intelligent Transportation Systems (ITSC 2018)*, Maui, HI: IEEE, Nov. 2018, pp. 2575–2582.

[47] 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.

[48] 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.

[49] 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.

[50] 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.

[51] 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.

[52] 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.

[53] Y. Cao, T. Wang, O. Kaiwartya, G. Min, N. Ahmad, and A. H. Abdullah, “An EV Charging Management System Concerning Drivers’ Trip Duration and Mobility Uncertainty,” *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 48, no. 4, pp. 596–607, Apr. 2018.

[54] 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.

[55] 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.

[56] 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.

[57] B. T. Lokesh and J. T. Hui Min, “A Framework for Electric Vehicle (EV) Charging in Singapore,” *Energy Procedia*, vol. 143, pp. 15–20, Dec. 2017.

[58] 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.

[59] Z. Tian, T. Jung, Y. Wang, F. Zhang, L. Tu, C. Xu, C. Tian, and X.-Y. Li, “Real-Time Charging Station Recommendation System for Electric-Vehicle Taxis,” *IEEE Transactions on Intelligent Transportation Systems (TITS)*, vol. 17, no. 11, pp. 3098–3109, Nov. 2016.

[60] G. Pasaoglu, D. Fiorello, A. Martino, G. Scarcella, A. Alemanno, A. Zubaryeva, and C. Thiel, “Driving and parking patterns of European car drivers - A mobility survey,” Institute for Energy and Transport (Joint Research Centre), European Commission, Scientific and Technical Research Reports, Nov. 2012.

[61] Kraftfahrt-Bundesamt, “Fahrzeugzulassungen (FZ) Neuzulassungen von Kraftfahrzeugen nach Umwelt-Merkmalen Jahr 2021 - FZ14,” Tech. Rep., May 2022.

[62] Kraftfahrt-Bundesamt, “Fahrzeugzulassungen (FZ) Bestand an Kraftfahrzeugen nach Umwelt-Merkmalen 1. Januar 2022 - FZ13,” Tech. Rep., May 2022.

[63] M. Wietschel, S. Preuß, R. Kunze, and M. Keller, “Laden von Elektrofahrzeugen in Deutschland mit Ökostromverträgen,” Fraunhofer ISI, Karlsruhe, Working Paper Sustainability and Innovation, Feb. 2022.

[64] Kraftfahrt-Bundesamt, “Inländerfahrleistung,” Tech. Rep., Jun. 2021.

[65] P. Jochem, E. Szimba, and M. Reuter-Oppermann, “How many fast-charging stations do we need along European highways?” *Elsevier Transportation Research Part D: Transport and Environment*, vol. 73, pp. 120–129, Aug. 2019.

[66] Y. He, K. M. Kockelman, and K. A. Perrine, “Optimal locations of U.S. fast charging stations for long-distance trip completion by battery electric vehicles,” *Elsevier Journal of Cleaner Production*, vol. 214, pp. 452–461, Mar. 2019.

[67] Tesla. (2017). Charging Is Our Priority, [Online]. Available: `https://www.tesla.com/blog/charging-our-priority` (visited on 06/26/2022).

[68] 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.

[69] 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.

[70] 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.

[71] 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.

[72] 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.

[73] 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.

[74] J. Ma and L. Zhang, “A Deploying Method for Predicting the Size and Optimizing the Location of an Electric Vehicle Charging Stations,” *Information*, vol. 9, no. 7, pp. 1–19, Jul. 2018.

[75] X. Sun, Z. Chen, and Y. Yin, “Integrated planning of static and dynamic charging infrastructure for electric vehicles,” *Elsevier Transportation Research Part D: Transport and Environment*, vol. 83, p. 102 331, Jun. 2020.

[76] 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.

[77] 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.

[78] 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.