Smart Charging Schedules for Highway Travel with Electric Vehicles

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***Abstract*—Electric vehicles (EVs) can contribute to reducing carbon emissions and facilitate renewable integration. However, EVs are not competitive with fuel-based vehicles, particularly for long distances, because of their limited range and long charging times. We propose a smart scheduling approach for EVs to plan charging stops on a highway with limited charging infrastructure. This approach aims to minimize the total travel time for each EV based on the A* algorithm with constraint verification and a peer-to-peer scheduling system. By considering the estimated state of the charging stations, we achieve indirect coordination between EVs. We introduce a simulation framework with trips generated using a data-driven approach and support for time-varying highway parameters. Furthermore, we apply our approach to a use-case for the German highway A9 from Munich to Berlin. The computation and communication requirements of the proposed solution remain moderate and privacy-preserving, contributing to its applicability. Results show that the smart scheduling approach significantly reduces the total travel times. Additionally, by dynamically adjusting the schedules, the proposed approach can account for changing highway conditions, for example, slow traffic on a given segment. Our approach can be generalized beyond fast-charging to different technologies such as hydrogen or battery swapping stations.**

***Index Terms*—Electric vehicles, Charging stations, Vehicle routing, Intelligent vehicles, Dynamic scheduling, Distributed information systems, Interconnected systems, Automated highways, Simulation**

I. Introduction

Climate change, carbon emission reduction, and independence from fossil-fuels have been important issues on the international agenda during the past few decades [1], [2]. The numerous efforts aimed at dealing with and realizing these topics have begun to show positive effects and the share of energy generated from renewable sources has significantly increased [3], [4]. At the same time, there has been an increased tendency towards electrification of products, services, and technology [5], electrification of transportation being perhaps the most representative example.

Transportation electrification offers two important advantages. First, it reduces local carbon emissions and fossil-fuel dependency [6]. Second, it shifts energy needs towards a power system that is increasingly able to leverage energy produced from renewable sources [7], [8]. Electric vehicles (EV), in particular, allow for emission reduction in urban areas [8] and, due to their use-patterns in urban environments, can potentially operate as flexible electric loads to support the operation of power systems and the integration of renewable energy [8]–[11].

The wide adoption of EVs, however, faces a number of challenges. First, the limitations on energy density of batteries and their effects on cost restrict the range or autonomy of EVs to way below that of their fuel-based siblings. Second, the requirements in terms of a new charging infrastructure, particularly if extended beyond places of residence or work, involve significant investments. For example,according to a recent study [12], investment in fast-charging infrastructure is unlikely to be profitable at low EV adoption rates, unless investment cost can be lowered. Last, the time required for charging an EV is substantial, with the additional disadvantage that, in general, increasing the charging power negatively influences the battery's lifetime [13]. A higher EV adoption rate can only be reached if sufficient infrastructure is made available.

These major challenges, particularly related to the use of EVs in urban environments, have been the subject of intense research in the last years [10], [11], [14]–[20]. We argue that range, infrastructure, and charging-time limitations are major factors in highway environments, an area not as densely researched as that of urban and sub-urban environments. The current range of most commercial EV models (generally below 150 km) is not extensive enough to cover long distances [21], [22]. This range decreases further as driving speed increases [21], [23], [24]. Basic infrastructure, such as electricity and services necessary for the charging infrastructure, are not available everywhere along a highway. Long charging times can potentially cause significant delays, not only because of the charging process itself, but also because of the potential waiting times resulting from busy charging stations (CS).

Although advances in chemistry, battery, and charging technology play a role in addressing these challenges, we believe that information and communication technologies (ICT) can make a major contribution in efficiently managing the available resources, reducing the required amount of infrastructure for a given service level, and assist in planning and dimensioning fast-charging infrastructure. Therefore, this work proposes a method for scheduling charging stops during highway travel such that the final destination is reached with the lowest possible cost, in our case total travel time. We put special focus on the applicability of this method from the ICT perspective and present our results within the context of a use-case for a 500 km long German highway accompanied by a methodology for generating EV trips based on real data.

As EVs enter the highway, they decide at which CSs to stop and generate a schedule accordingly. This schedule is then continuously updated during the EV's trip to account for

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changes in CSs and the highway. Unlike other approaches, we focus on total travel time, not only waiting time [25], [26] or infrastructure usage [27], apply a local decision-making approach at EV level with CS parameters (such as queue length and waiting times) as the coupling element instead of a global approach [25], [28], and use synthetic trips rather than probabilistic models [25]–[27]. The benefits of our scheduling approach are an efficient use of charging infrastructure, which potentially reduces costs, and the reduction of travel time, which contributes towards EV adoption.

Our contribution can be summarized as follows:

1) We introduce a scheduling method for planning charging stops on a highway trip, based on an extension of the A* search algorithm that accounts for problem constraints, including EV energy requirements and driving speeds, that enables the reduction of travel times and efficient use of available charging infrastructure.
2) We propose a trip generation method using data available from highway counters and travel surveys that enables the generation of synthetic highway trips that are closer to reality.
3) We develop a simulation framework for highway traffic that accounts for highway exits/entries, potential charging sites, variable highway speed limitations, and EV-specific characteristics, enabling us to test scheduling methods and account for changes such as traffic congestion.
4) We implement our approach in a use-case for a German highway connecting Berlin and Munich with the actual highway entries/exits, speed limits, and production EV models, while considering current fuel stations as potential charging sites.

The paper is organized as follows. Section II covers previous work on EV charging focusing on the highway environment. Section III introduces the charging scheduling algorithm for travel time minimization. Section IV describes the simulation framework including the method for data-driven traffic generation. Section V introduces the use-case for the highway A9 in Germany from Munich to Berlin and corresponding results. Finally, Sections VI and VII present a discussion and the conclusions of our work, respectively.

II. Related Work

Research on EV charging has focused on its relationship with the power systems infrastructure, mostly in urban or suburban environments [10], [11], [14]–[20]. Highway-related problems of EV charging have not been as densely studied.

EV highway-related work has focused on infrastructure planning and charging strategies. A number of studies have been focusing on placement of CS infrastructure along a highway. Some of these studies conclude that driving range is a major factor for defining CS infrastructure location, with facility cost and population coverage also playing an important role [29], [30]. Sathaye et al. [31] introduce a continuous optimization approach for locating charging stations on highway corridors with a case study for Texas. Furthermore, other studies take existing infrastructure into consideration and limit potential CS locations to existing rest areas or fuel stations [27], [32]. Different charging power rates are analyzed concluding that fast-charging is necessary to achieve a reasonable level of service and minimize the cost [33]. Bae et al. [34] aim at modeling charging demand using a fluid dynamic traffic model for arrival rates at different CS and a M/M/s queue model for the demand within the CS with focus on infrastructure planning and energy demand. In contrast, our work considers fast-charging infrastructure located on existing rest areas or fuel stations and uses data-driven synthetic highway trips for generating the charging demand.

In terms of modeling and charging strategies, Gong et al. [35] use a gas-kinetic model to optimize power management with dynamic programing. This work focuses on hybrid vehicles and fuel consumption. Rahman et al. [36] also focus on hybrid vehicles and fuel consumption where a method based on Satisfiability Modulo Theories (decision-problem techniques for logical formulas) and a price-based navigation technique for load balancing are presented. A dynamic allocation technique using a centralized control platform that focuses on maximizing infrastructure utilization has also been presented [27]. Our approach considers only battery-based EVs and focuses on travel time, not on consumption or infrastructure utilization.

Yang et al. [25] compare global vs. local information strategies for a highway in Taiwan with 6 CSs and an event-based model. They conclude that having global information about CS workload helps to reduce waiting times. Qin et al. [26] also aim at minimizing waiting time. They show that a theoretical lower-bound is achieved when the charging demand of all CSs is balanced and propose a distributed strategy based on CS reservation which follows certain success statistics. We also make use of a CS reservation system but account for changes via dynamic updates.

A balanced CS demand is also considered the optimal strategy and a two-level approach is proposed by Gusrialdi et al. [28]. The higher-level distributed scheduling algorithm optimizes the operation of the charging network while the lower level cooperative control law allows individual EVs to decide whether or not to charge based on neighboring EVs. The approach requires communication between EVs to cooperate, is based on a stochastic model for CS arrivals, and is applied to an example with four CS. In our work, the objectives are local to each EV but EVs loosely interact with each other through estimates of CS occupancy levels as coupling variables.

Pourazarm et al. [37] address the scheduling problem as a path-finding problem within a graph of CS nodes. They use dynamic programming and, when dealing with multi-vehicle routing, apply a grouping technique based on flows. Similarly, Storandt et al. [38] uses a graph model and considers the problem as a constrained shortest path problem. The work concentrates more on urban environments where the number of paths can be very large and the number of CS visits is given as a constraint. The authors propose a pre-processing approach for saving computations. We also formulate the problem as a shortest path problem but use a modified A* algorithm focusing on total travel time.

Highway traffic modeling is a complex field with several approaches available depending on the level of detail provided and the information available [39], [40]. In our simulation framework, we do not apply complex inter-vehicular dependencies or gas kinetic-based flow simulations. However, we foresee the use of more robust and mature traffic simulation systems as an input for our framework in the form of time-varying highway speeds.

Our approach differs from previous work in several ways. First, we use a close-to-reality evaluation in a real highway scenario with data-driven traffic generation, full length highway, and a large number of CSs. Second, we consider the total travel time reduction as the objective function, accounting for driving and charging times in addition to waiting time. Last, we consider a local EV-centered approach with limited computation and communication requirements, which indirectly accounts for other EVs through a CS reservation system.

From the evaluation perspective, our work is based on data-driven generated trips whereas related work either allocates EVs randomly along the highway [27], or uses a stochastic (mostly Poisson-based) model [25], [26], [28]. Similar to Bodet et al. [27], we consider CS sites at rest and fuel stations along the highway and use a German highway as a use-case. In addition, we consider different types of EVs and variable speeds along the highway.

From the scheduling perspective, we focus on time reduction. However, our focus on total travel time reduction, not only waiting time, is advantageous under varying highway conditions. Similar to Pourazarm et al. [37], we adjust charging time to energy requirements. Time-varying driving speed, mostly limited by highway speeds, is also taken into account.

Finally, our work focuses on applicability. We do not use centralized control and focus on individual EV optimization. Communication only takes place between specific CSs and the EV without the need to provide all trip information. Although we do not aim at a global optimization (e.g., [25], [28]), we indirectly account for the behavior of other EVs by using the CS reservation information as a coupling variable. Similar to other studies [37], [38], our model is based on a graph abstraction and shortest-path search but we focus on algorithms with complexities achievable by existing in-car navigation technologies.

III. Active Scheduling of Fast-Charging Stops

In this section, we introduce our active scheduling approach. First, we describe the objective, model, and notation. Then, we introduce our modified A* shortest path algorithm for constrained searches. Next, we briefly discuss the specific graph abstraction used for the constrained A* algorithm. Last, we present the complete process for schedule calculation and maintenance. The units of measurement referred to in the following are seconds for time, km for distance, km/h for speed, kW for power, and kWh for energy, unless otherwise specified.

A. Driving, Charging, and Scheduling Model

The proposed model comprises three main components: EVs, a highway or highway path, and CSs. An EV enters the highway and, if its trip is longer than its range, will stop at least once at a CS. The choice of charging stops depends on the strategy an EV follows; for example, an EV could choose to charge at the last reachable CS.

The charging strategy we propose aims at an intelligent choice of charging stops to minimize overall travel time. This strategy requires real-time information. The strategy assumes there is a communication infrastructure that allows for CS and EVs to communicate with each other and for EVs to receive highway-related information. None of these assumptions are beyond the capacity of existing technologies. Vehicles can be connected via mobile communication technologies for vehicles and persons (e.g., 2G - 4G). Existing fuel stations already have access to communication services, for example, for processing credit card payments.

When an EV enters the highway, it first surveys the CSs available on its route and their current states. The EV then calculates a desired set of charging stops and charging times and makes a booking for the corresponding CSs including expected arrival time. The EV's charging schedule may be adapted if highway or CS conditions change.

Along a given highway of length HL, there is a set of entries/exits $\mathbb{EX}$ and charging stations $\mathbb{CS}$. Elements in $\mathbb{EX}$ are potential start and destination points for EVs, while elements in $\mathbb{CS}$ are potential charging stops. Exits and charging stations are characterized, among others, by their position on the highway. Additionally, a highway has a speed profile that defines the maximum driving speed as a function of time and position on the highway $V_{\mathrm{HW}}(s,k)$.

A position s on the highway can take values $[0, \mathrm{HL}]$ and can be given in two formats: absolute (highway kilometer) and relative to the driving direction (kilometer from origin point). That is, the absolute position increases in one direction and decreases in the opposite one, whereas the position relative to the driving direction always increases. In the following, we use s as a relative position unless denoted as s^{abs}.

A charging station $\mathrm{CS}_c \in \mathbb{CS}$ is characterized by the supported charger types and corresponding number of charging poles (CP) N_P^c. For each charger type, the CS has a queue $Q^c(k)$ representing those EVs in the CS waiting for a free CP, where $\mathrm{FP}^c(k)$ represents the number of free CPs. Each CS maintains its own booking system which includes estimated arrival and required charging time. Based on this booking system, a CP can estimate a queue length $\mathrm{Q}_{est}^c(k)$ for a given k in the future.

Individual characteristics of an EV are its trip, state, type, and schedule. The trip of the i^{th} EV is described by starting position S_{start}^i, starting time T_{start}^i, and destination position S_{end}^i. The EV's state at time k is characterized by the distance traveled $d_i(k)$, its position on the highway $s_i(k)$, the driving speed $v_i(k)$, a preferred speed $V_{pr}^i(k)$, the traveled, driven, waited, and charged times $t_{trav}^i(k)$, $t_{driv}^i(k)$, $t_{wait}^i(k)$, $t_{chrg}^i(k)$, respectively, and the state of charge (in percent) of the battery $SOC^i(k)$. The EV's state evolves in time steps of length Δt. The EV's type is characterized by maximum speed V^i_{max}, battery capacity E^i_{max}, minimum allowed battery level E^i_{min}, fast-charging power P^i_{FC}, a charging rate function in terms of time, charging power, and SOC $E^i_{chg}(\Delta t, P, SOC)$, and a consumption function in terms of speed and distance $E^i_{con}(\Delta d, v)$. Type parameters depend on the brand and model of the EV. The schedule $\mathbb{SD}^i$ is a set of tuples containing a planned CS to stop at, and the target SOC ($\text{CS}_c, SOC^{(i,c)}_{tar}$) to continue the trip.

The state of an EV is updated depending on its driving flag DF^i, where

$$DF^i = \begin{cases} idl & : \text{EV not on highway} \\ drv & : \text{EV moving along the highway} \\ wai & : \text{EV arriving/at a CS but not charging} \\ chg & : \text{EV at a CS and charging} \end{cases} \tag{1}$$

such that

$$idl \rightharpoonup drv, \text{ when current } k \text{ reaches } T^i_{start} \tag{2}$$
$$drv \rightharpoonup wai, \text{ when EV enters a CS} \tag{3}$$
$$wai \rightharpoonup chg, \text{ when } \text{FP}^c(k) > 0 \tag{4}$$
$$chg \rightharpoonup drv, \text{ when } SOC^i(k) \geq SOC^{(i,c)}_{tar} \tag{5}$$
$$drv \rightharpoonup idl, \text{ when } s^i(k) \text{ reaches } S^i_{end} \tag{6}$$

The state change in (3) occurs if the CS matching the EV's current position is included in the EV's schedule $\mathbb{SD}^i$. Equation (4) implies that a charging pole becomes available. Equation (5) indicates that the target SOC has been reached. Equation (6) implies that the EV has reached its final destination.

The distance traveled, position, and corresponding initial values of an EV are expressed as

$$d_i(k + \Delta t) = d_i(k) + \Delta d^i(k), \tag{7}$$
$$\text{with } \; d_i(0, \cdots, T^i_{start}) = 0$$
$$s_i(k + \Delta t) = s_i(k) + \Delta d^i(k), \tag{8}$$
$$\text{with } \; s_i(0, \cdots, T^i_{start}) = S^i_{start},$$

where

$$\Delta d^i(k) = v_i(k) \cdot \Delta t_{(hr)} \tag{9}$$
$$v_i(k) = \begin{cases} \max\left(V^i_{pr}(k), V_{\text{HW}}(s_i(k), k)\right), & \text{if } \text{DF}^i = drv \\ 0, & \text{otherwise.} \end{cases} \tag{10}$$

$V^i_{pr}(k)$ is given and $\Delta t_{(hr)}$ stands for the value converted into hours. Equation (10) implies that EVs will travel at their preferred speed unless the highway speed limit is lower.

Updates to the different time measurements are expressed as

$$\Delta t^i_{trav}(k) = \begin{cases} \Delta t, & \text{if } \text{DF}^i \neq idl \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

$$\Delta t^i_{driv}(k) = \begin{cases} \Delta t, & \text{if } \text{DF}^i = drv \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

$$\Delta t^i_{wait}(k) = \begin{cases} \Delta t, & \text{if } \text{DF}^i = wai \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

$$\Delta t^i_{chrg}(k) = \begin{cases} \Delta t, & \text{if } \text{DF}^i = chg \\ 0, & \text{otherwise.} \end{cases} \tag{14}$$

Finally, updates to the SOC of an EV is expressed as

$$SOC^i(k + \Delta t) = \begin{cases} SOC^i(k) - \Delta SOC^-_{(i,k)}, & \text{if } \text{DF}^i = drv \\ SOC^i(k) + \Delta SOC^+_{(i,k)}, & \text{if } \text{DF}^i = chg \\ SOC^i(k), & \text{otherwise,} \end{cases} \tag{15}$$

where

$$\Delta SOC^-_{(i,k)} = \frac{E^i_{con}(\Delta d^i(k), v^i(k))}{E^i_{max}} \tag{16}$$
$$\Delta SOC^+_{(i,k)} = E^i_{chg}\left(\Delta t, P^i_{FC}, SOC^i(k)\right). \tag{17}$$

Equations (15 - 17) imply that EVs consume energy while driving, depending on the driving distance and speed, and gain energy depending on charging power and current SOC. $E^i_{con}(\cdot)$ and $E^i_{chg}(\cdot)$ are EV-specific functions. $E^i_{con}(\cdot)$ indicates the consumption of a given EV as a function of traveled distance and speed while $E^i_{chg}(\cdot)$ indicates the energy gain as a function of time, charging power, and current SOC. Although our evaluation does not cover battery aging or driving style (e.g., [41]), one could update the definition of $E^i_{con}(\cdot)$ and $E^i_{chg}(\cdot)$ to account for these factors.

The objective of our scheduling strategy is to find a schedule $\mathbb{SD}^i$ such that the total travel time, including driving, waiting, and charging time, is minimized. The strategy has to fulfill the constraints of the individual EV and the highway.

$$\min_{\mathbb{SD}^i} \sum^{\hat{k}} \left(\Delta t^i_{driv}(\hat{k}) + \Delta t^i_{wait}(\hat{k}) + \Delta t^i_{chrg}(\hat{k})\right),$$
$$\left\{\hat{k} \mid S^i_{start} \leq s^i(\hat{k}) \leq S^i_{end}\right\} \tag{18}$$

s.t.

$$E^i_{min} \leq SOC^i(k) \cdot E^i_{max} \leq E^i_{max}, \forall\, k$$

The interpretation of (18) is as follows: for a given EV, choose a schedule such that the sum of driving, waiting and charging times along the duration of the trip are minimized, subject to the energy limitations of the EV. Although the problem formulation (18) may appear simple, its solution is not as simple. All quantities are time-dependent and are influenced by external factors. Equations (11 - 15) indicate that SOC and times depend on the vehicle state. The vehicle's state depends on position and time. Position depends on speed while driving, which depends on highway conditions. The portion of t^i_{wait} for a stop on a given CS depends on the length of the queue at that CS which correspondingly depends not only on the arrival time of the given EV, but also on when other EVs arrive.

One alternative for solving this problem is to use existing shortest path algorithms considering travel time as the weight or cost. However, existing shortest path algorithms, such as Dijkstra and A* search, normally do not account for constraints. Therefore, we introduce an enhanced A* shortest path search algorithm that accounts for the constraints in this problem.

B. Constrained A Path Search for Fast-Charging Schedules*

The A* algorithm is widely used for shortest path searches and is based on a directed graph data-structure abstraction [42], [43]. Similar to Dijkstra's algorithm, it incrementally explores neighbors and accumulated weights to choose a path with the lowest weight. The A* algorithm includes a heuristic function to estimate the minimum remaining cost or distance at every node which can be used to accelerate the computation.

The main reasons for choosing A* as our base algorithm are threefold. First, neighbor exploration allows us to test for constraint fulfillment at every step and exclude non-feasible alternatives at an early stage. Second, the use of a heuristic function to calculate the minimum remaining cost is convenient because the earliest an EV can arrive at its destination is limited by distance and speed. Third, A* is a widely used algorithm with efficient implementation for a variety of systems [44], [45] which is relevant for the applicability of the proposed solution.

The conventional A* algorithm keeps track of the variable it aims to minimize along the entire search. In our case, that would be the traveled time $\hat{t}^i_{trav}$. We introduce a modification where we maintain a second variable, the available energy in the EV $\hat{E}^i$. Each time a neighboring node is explored, we test that the resulting value of $\hat{E}^i$ remains within $[E^i_{min}, E^i_{max}]$. If this is not the case, the corresponding potential path is avoided. This can be done, as in our case, by not queuing the neighbor into the queue of potential nodes, or alternatively assigning an extremely high cost to the corresponding path.

The constrained A* shortest path algorithm receives as input a graph describing all possible paths, the source and destination nodes, and the EV_i, including state and type. The specific implementation of the A* algorithm is based on [44]. The algorithm is described in the following.

Algorithm: Constrained A* Shortest Path

```
function constrained_search(graph, src, dst, ev) returns path:

PriorityQueue queue,
Dict enqueued, explored

queue.push((0, src, 0, graph[src]['current_energy'], None))

while queue:
    o, this_node, time, cum_energy, parent ← queue.pop

    # If target reached, traverse path:
    if this_node == target:
        path ← build_path(explored)
        return path

    if this_node in explored: continue
    explored[curnode] ← parent

    for neighbors in graph[this_node]:
        if neighbor in explored: continue
        e_cons, t_cost, feasible ← graph.get_costs(this_node,
                                    neighbor, cum_energy, ev)
        if not feasible: continue

        # Update accumulated values:
        e_ncost ← cum_energy - e_cons
        t_ncost ← time + t_cost

        # Compare with so-far-best:
        if neighbor in enqueued
            t_qcost, h_time ← enqueued[neighbor]
            if t_qcost ≤ t_ncost: continue
        else:
            h_time ← graph.get_h_time(neighbor, dst, ev)

        # Enqueue new so-far-best values:
        enqueued[neighbor] ← t_ncost, h_time
        queue.push((t_ncost + h_time, neighbor, t_ncost, e_ncost,
                    this_node))
```

The function **get_h_time**(·) is the heuristic function describing the minimum remaining time from a given node to the destination. In our case, it is a function of distance and speed. For an always underestimating heuristic, and resulting certainty that the found path is the shortest, one can use the EV's preferred speed V^i_{pr}. Less strict heuristic functions can be used to accelerate the algorithm.

The function **get_costs**(·) returns an estimation of both time cost and the energy consumption between two nodes (or the graph's edge) and a feasibility statement. The edge is feasible only if the cumulated energy minus the consumption for that edge is within $[E^i_{min}, E^i_{max}]$. The time costs result from driving, waiting, and charging. Driving time is calculated based on the expected speeds along the route between nodes. Charging and waiting times depend on the predicted demand of a specific charging station. Energy consumption is positive during driving and negative while charging.

In the following, we describe the graph abstraction and calculation methods used in our approach.

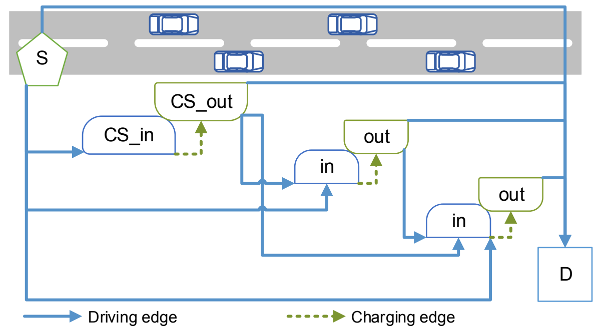


Fig. 1. Graph abstraction

C. Graph Abstraction for EV Charging Stops

Fig. 1 illustrates the graphs abstraction of our approach. We have four type of nodes: one source node, one destination node, and a number of **CS_in** and **CS_out** node pairs (each of these node pairs represents a CS). By defining CSs as pairs of in/out nodes, we are able to differentiate between two types of edges: driving edges and charging edges.

A driving edge connects either the source node or a **CS_out** node to either a **CS_in** or the destination node. A driving edge cannot connect the **CS_out** node to the **CS_in** node of the same CS. If a driving edge ends on a **CS_in** node, the EV

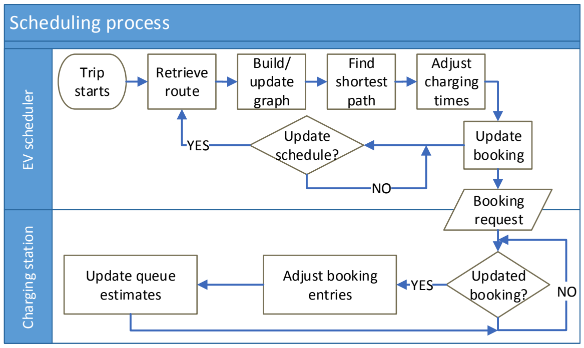


Fig. 2. Scheduling process

stops to charge. The costs of a driving node are the driving time and positive energy consumption. Both values depend on the driving speed which may be time-dependent and estimated based on current available data.

A charging edge connects a **CS_in** node to the **CS_out** node of the same CS. The time cost is a combination of waiting and charging time and is estimated by the corresponding CS on request. The waiting time depends on the expected length at the time of arrival which is calculated based on the existing bookings at the time of the request. The charging time depends on the estimated cumulated energy, charging power, and target SOC. Charging power is EV specific but a constant from the EV perspective. The target SOC is fixed to an ideal level, likely to be EV specific, but currently at 80% for existing commercial vehicles. A second process described in Section III-D adjusts this target SOC to the requirements of the chosen route.

To build the graph, an EV scheduler defines the source node as its current position and initializes the estimated cumulated energy to its actual energy level. Then, the scheduler submits a request for a list of available CSs between the current position and the destination and connects the nodes with edges, according to the logic described above.

D. Schedule Generation Algorithm

Fig. 2 summarizes the scheduling process for each EV. Upon initiating a trip or entering a highway, the EV retrieves its route. Next, it produces a graph abstraction and uses it to find the shortest path as described in Sections III-B and III-C. Then, the charging times at each chosen stop are adjusted and the corresponding booking request is sent to the CS. The EV then continues the trip as planned unless an update schedule event is received, in which case, the process above is repeated. Upon receipt of a booking request, a CS will update its booking entries and process its corresponding queue estimates.

The route contains the destination, a list of CSs available on the way, and the highway information including speeds and traffic notifications. This information can come, for example, from the map or navigation system used by the EV.

Once the target charging stops are defined by the shortest path algorithm, the EV computes the target SOC ($SOC_{tar}^{(i,c)}$) for each stop. In the previous step, the path is calculated assuming a fixed target SOC, usually 80%. However, the distance between two planned stops might require less energy. Therefore, for each stop, the target SOC is calculated based on the energy required to reach the next planned stop, or the destination if it is the last stop. This calculation uses the EV's consumption function $E_{con}^{i}(\cdot)$ and desired driving speed V_{pr}^{i}, i.e., the worst case, and adds a certain margin on top.

Once the charging times have been adjusted, the EV has defined its schedule with a set of planned stops containing expected arrival time and target SOC. This information is then shared with each of the involved CSs in the form of booking requests.

Upon receipt of a booking request, each CS updates its planned bookings and recomputes its expected queues. A CS recomputes its expected queues by emulating the planned bookings and producing queue lengths for time windows of pre-defined length. The queue length at a given time window depends on the queue length at the previous time window, the arrivals at the current time window, the number of charging poles, and an average charging time.

The CSs become the coupling element on the system as they indirectly reflect the plans of other EVs. In other words, an EV planning to stop at a given CS bases its decision on the expected queue length, which correspondingly depends on the decision of other EVs. Individual EV decisions, therefore, depend on decisions made by other EVs.

Since an EV is constantly updating its schedules, it is also indirectly adapting to what other EVs are doing. Although there is no guarantee that an equilibrium can be achieved, two statements hold true for our approach. First, an EV will only modify its path if there is a better path available. Second, any computed path remains feasible, independent of the actions of other EVs. In other words, an EV will follow a path that was, in the worst case, the shortest path possible the last time it checked, and, even if there may be a better path available, the chosen path is compliant with the particular EV's constraints.

In terms of complexity, the determination of a the schedule benefits from its distributed computation and the underlying A* algorithm. Since the schedule is generated at EV level, its computation time does not directly depend on the number of EVs and remains constant as the number of EVs increases. The most computationally intensive task from the EV perspective is the modified A* shortest path search which only adds a constant time operation to the original A* algorithm. Computations performed by the CS do increase in complexity as the number of EVs increase. However, this complexity is proportional to the number of EVs served by each station and not the total number of EVs. In Section V-B, we provide experimental evidence for the performance and scalability of the approach.

IV. Highway EV Traffic Simulation Framework

In this section, we introduce the highway EV traffic simulation framework used for our experiments. This traffic simulation network does not pretend to compete with comprehensive simulation tools like [46], [47]. However, it offers a simplified, modular, and adaptive alternative for studying

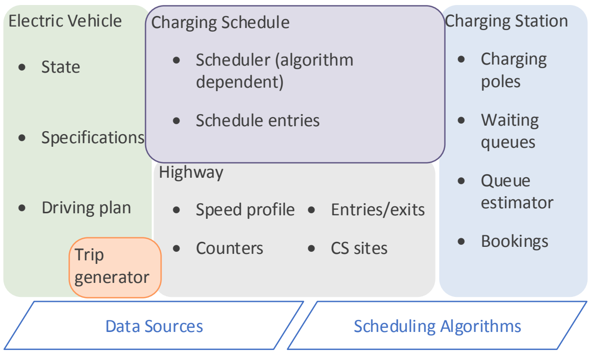


Fig. 3. Simulation tool architecture

different charging strategies for EVs along a highway. First, it produces highway trips based on highway-specific data and trip length statistics, producing trips that are closer to reality using publicly available data. Second, the EV traffic simulation framework allows for the insertion of highway specific parameters, such as exits, position of CS, and speed limits. Third, the framework can process time- and segment-specific speeds from external data sources to reproduce the current state of the highway like heavy traffic. Last, it enables the comparison of different scheduling strategies, accepting virtually any algorithm with a very simple interface.

A. Data-based EV Traffic Generation

The proposed method for generating EV highway trips is based on a combination of diverse data sources. In the following we describe the method and its application to German highways.

Traffic on highways varies by time of day, position, day of the week, season, and a long list of other factors. In many countries, counters at specific points on the highway provide insight on these variations. German highways are highly instrumented and hourly counts for each counter are accessible either as a statistical summary or as detailed entries upon request [48].

Lengths of trips also play an important role and this information cannot be inferred from the counter data. Therefore, a second source that provides this information is needed. For the German case, a mobility survey includes a specific section regarding long distance trips [49]. This information allows us to classify trips by the size (population) of the place of origin.

Finally, the type of personal vehicle (e.g., size, energy consumption, category) may be of interest. Although the mobility survey [49] also surveys information on vehicle type, the relationship between type of vehicle and long distance trips is not addressed. Information on vehicle type is commonly available from data for car registrations, for example in Germany [50].

The first step for generating a trip is defining a potential counter where the EV in question was counted and the time this happened. This information is retrieved from the counter data in form of spatial and temporal distributions. The spatial distribution comprises the number of counts on a given station with respect to the total counts. Each counter has its own temporal distribution consisting of counts on a given hour with respect to the daily counts.

Once a potential counter and hour of the day have been defined, the method offers two alternatives for generating trips: vehicle was counted at the beginning of its trip, or vehicle was counted at a random point during its trip.

After start position, end positions, and starting time for a given trip have been defined, we choose an EV type based on the vehicle-type distribution. This process is repeated for all EVs in the simulation.

B. Simulation Tool

The architecture of the simulation tool is illustrated in Fig. 3. The three main components are the EVs, the highway, and the CS. There is, in general, a many-to-one relationship between EVs and a highway as well as between CSs and a highway. The simulation tool is discrete-time-based, whereby the time steps can be set in seconds.

A CS component consists of a number of charging poles grouped into pole types (e.g., Tesla super charger and standard fast-charging poles) and a waiting queue per pole type. Each queue has a queue estimator that, based on the bookings of a given CS, updates estimated queue lengths along a given period (e.g., a day) for pre-defined intervals (e.g., 30 min). The results of this queue estimator are used by the charging schedule to evaluate potential waiting time at a given arrival time. CS are located on the highway at specific CS sites.

In addition to a number of CS sites, the highway consists of a speed profile, entires or exits, and counting stations. Counting stations are only used to maintain traffic statistics. Entries and exits are assumed to be a single point on the highway and always bidirectional, i.e., EVs can enter or leave the highway at this point. Similar to CS sites, entries and exits are characterized by their position on the highway and the driving direction in which they are located (although they are mostly located in both driving directions).

The speed profile of a highway consists of two sub-components: a static speed profile and a traffic notice profile. The static speed profile is a set of entries describing fixed speed limits along the highway and is position-dependent. The traffic notice profile is a set of entries describing temporal speed limits that can be updated during runtime. This type of entry is used to describe a time-dependent restriction (such as evening speed limits for noise reduction), externally set speed limits (such as those on variable speed limit boards managed by a transportation authority), and traffic congestion. The speed profile is used by EVs to set their driving speeds along the highway and by the charging schedule to estimate driving times and energy consumption along the planned route.

An EV consists of state, specifications, and a driving plan. The state component takes care of updating the simulation-dependent parameters of the EV such as time, position, and current SOC. The specifications are used to calculate vehicle-specific allowed speeds, charging rate, and speed-dependent energy consumption while driving. The driving plan executes the charging stops following the charging schedule.

TABLE I
EV PARAMETERS FOR EVALUATION

Parameter	Tesla S	BMW i3	Nissan Leaf	Generic
Battery capacity (kWh)	85	18	24	16
Maximum speed (km/h)	223	160	135	130
Charging power (kW)	120	50	50	50
Time (min) to $SOC_{tar} = 80\%$	40	30	30	30

TABLE II
A9 FAST CHARGING SCENARIOS

Experiment		Description
1.	LiR vs. AS	We compare the two strategies under the same experimental conditions assuming that the speed profile remains constant along the entire simulation.
2.	AS under varying traffic conditions	We run the AS strategy in two modalities: i. schedule generation only on initiation of the trip, and ii. continuous schedule update. We then insert a traffic notice with 50 km/h speed limit for the segment between km 250 and km 350, between 15:00 and 16:00, inserted during runtime at 15:00. This experiment evaluates the adaptive capacity of the AS.
3.	Uniform trip generation	We compare LiR and AS for trips starting in Munich and ending in Berlin with a uniform random starting time within 24 hours. This experiment gives us some insights about the global benefit of local EV decision making.
4.	Potential as planning methodology	We compare LiR and AS but with an infinite number of charging poles on this station. This experiment gives some insight on the number and location of required charging poles if we were to achieve zero waiting times.

A charging schedule component is responsible for planning and managing the charging stops for an EV. It resides in the EV but interacts with the highway and CS components. The scheduler applies an algorithm to define a charging strategy and uses the EV's current state and specifications to estimate future states along the highway. As explained above, the scheduler influences the EV's driving plan and makes use of the highway speed profile and the CS queue estimations. The scheduler produces schedule entries which are also shared with the corresponding CS to update its bookings. This component is flexible and can be used to realize virtually any scheduling strategy with two constraints: the scheduler should implement the **generate_schedule** and **update_schedule** functions, and the resulting schedule entries must follow a specific format. The strategy presented in Section III is implemented with the charging schedule component.

The trip generator applies the data-driven traffic generation described in Section IV-A. Other data sources include highway details (such as exits and speed limits), geographical information (cities and population), and CS details (position, number of poles, and pole types).

V. EVALUATION

We apply our scheduling method and simulation framework to a use-case based on the German highway A9 from Munich to Berlin. First, we describe the use-case and the experimental setup. Then, we present the corresponding results.

A. Use Case

The A9 connects Berlin and Munich. Our study is concerned with the driving direction Munich to Berlin. The highway has 36 traffic counters [48], 79 exits/entries, and 45 CS locations. The exact position of exits, counters, CS locations, and the driving speed limits are based on [51] and manual inspection in Google Maps. The 45 CS locations reflect existing fuel stations along and near the highway plus existing or planned Tesla Super Charger locations [52]. The number of charging poles on each Tesla CS location follows the information in [52]. For the remaining CS, we consider four 50kW fast-charging ports per location. Some of these CS locations are only accessible in one driving direction.

To model the time it takes to reach a CS location from the highway, a penalty time is associated to each CS location. In our case, we select one time-step (5 min) for CSs located directly on the highway and 2 time-steps (10 min) for those located nearby but not directly on the highway.

We consider four types of EVs. Three are based on commercial specifications: Nissan Leaf, BMW i3, and Tesla S, and one is defined as a generic model. The generic model consumes 0.15 kWh per km. For the other three EV types, the consumption curves are produced by fitting curves to data available from [21]–[24]. The EV types are uniformly distributed and we define a preferred driving speed of 120 km/h for all EVs. The EV-specific parameters are described in Table I. The consumption curves are defined by the following functions.

$$E_{con}^{Tesla}(d,v) = \tag{19}$$
$$\frac{7.41v^5 - 266v^4 + 51,590v^3 + 679v^2 + 29.83v - 0.061}{v^4 + 458.1v^3 - 1647v^2 - 758.8v + 490.3} \cdot d$$
$$E_{con}^{BMW}(d,v) = (0.00625v^2 + 0.725v + 50) \cdot d \tag{20}$$
$$E_{con}^{Leaf}(d,v) = (0.008837v^2 + 0.1393v + 63.26) \cdot d \tag{21}$$

In [53], a more detailed description of these functions is provided.

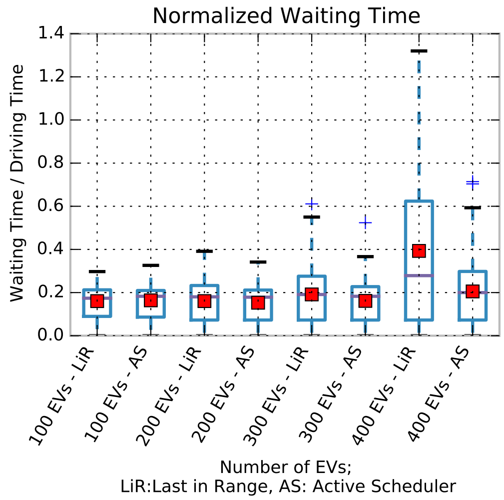
We generate trips for a period of 24 hrs but continue to run the simulation for another 24 hrs to allow all EVs to reach their destination. The time step is 5 minutes and the queue estimator for the CS generates estimates for 15 minute windows.

We use the same generated set of trips and EVs to run the simulation for two strategies: last in range (LiR) and active scheduling (AS). In the LiR strategy, EVs will charge at the last CS they are able to reach. The AS strategy implements the method proposed in Section III

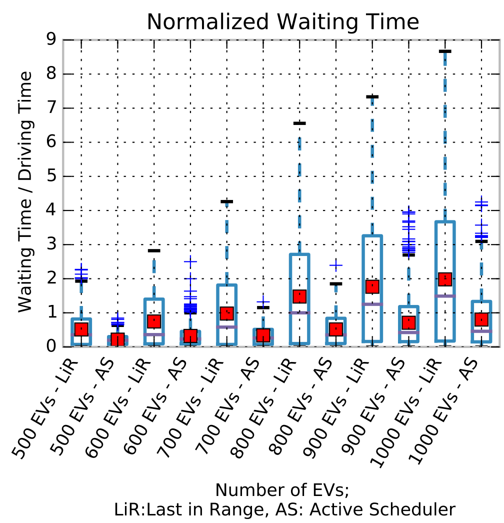
We run experiments as described in Table II.

B. Results

1) LiR vs. AS: We first evaluate the waiting time. For results to be comparable between EVs and different traffic volumes, we normalize the waiting time over the driving time. That is, the time spent waiting at CSs as a fraction of the driving time.



(a)



(b)

Fig. 4. Normalized waiting time for different daily number of EVs

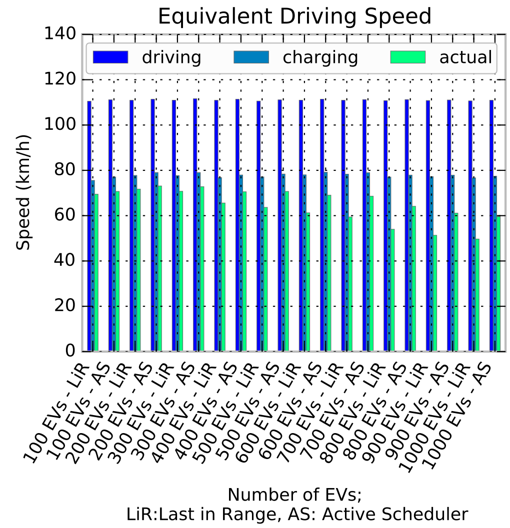


Fig. 5. Mean equivalent driving speeds for different daily number of EVs

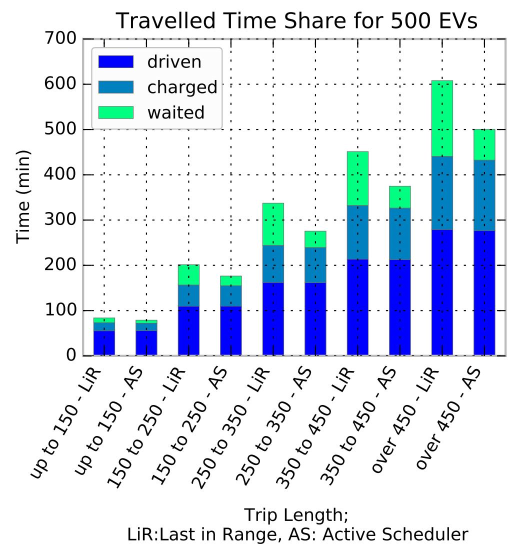


Fig. 6. Proportion of traveled time (mean) for 500 EVs by trip distance

Fig. 4 shows the statistics in form of a boxplot of the normalized waiting time for different values of daily EV traffic volume. The results show that the waiting time is significantly reduced when using the AS approach. All descriptive statistics indicate a significant improvement in waiting time when applying our method.

The normalized waiting time provides a comparable measurement between EVs and traffic volumes, and a ratio between waiting time and driving time. A more intuitive measurement is presented in Fig. 5. Here, we see the average equivalent driving speeds when the charging time and, cumulatively, the waiting time are taken into account. As depicted in this figure, for an average driving speed of 110 km/h, if we take into consideration the time needed only to charge, the equivalent speed would be 80 km/h. From this reference, the waiting time reduces the speed further. Using our approach increases the equivalent driving speed significantly, although the resulting speed is still low with respect to the driving speed due to the charging time.

The benefits of applying the proposed scheduling strategy become more evident as the traffic volume increases since the amount of available resources become proportionally scarcer. The benefits also become more evident as the length of trips increase. In Fig. 6 we see the proportion of the traveled time which is used for driving, charging, and waiting for trips of different lengths. Here we see that the scheduling algorithm succeeds in reducing the waiting time but also, due to the charging-time adjustment, we are able to reduce the time EVs spent charging.

We also compare the individual performance of every EV. In Fig. 7 we see that most of the 500 EVs reduced their waiting time by several minutes. Few EVs ended up with a longer waiting time which was never longer than 30 minutes (the charging time for a single EV). This result suggests that

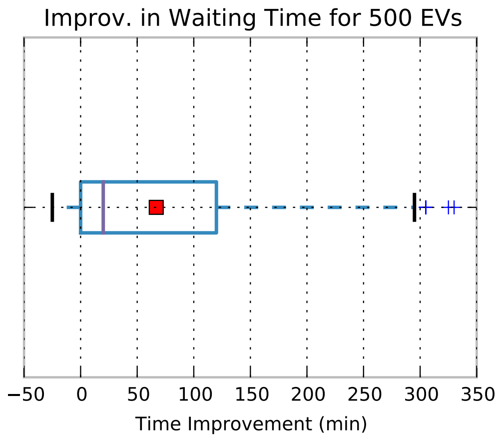


Fig. 7. Vehicle-specific waiting time improvement for 500 EVs

although EVs optimize for their own benefit only, given the coupling effect of CSs, a collective benefit is also achieved.

Finally, we look into the queue lengths of the different CS vs. time of the day. Fig. 8 shows the queue lengths for a daily traffic volume of 500 EVs. When the AS strategy is used, EVs tend to distribute themselves more uniformly among the available CSs. This is consistent with findings from previous work [26], [28] where a uniform use of CS is the objective for optimal utilization.

Energy consumption at the CS is also positively influenced by the active schedules. Although the daily peak energy consumption cannot be entirely avoided due to the charging demand, the energy consumption along the day is better distributed among the CSs. Fig. 9 shows this effect for a daily traffic volume of 500 EVs.

2) AS under varying traffic conditions: Since the scheduling algorithm considers the total travel time, one would expect it to readjust when a notice of a change in traffic conditions is added. In Fig. 10, we see the utilization of CS (busy poles plus queues) and times of the inserted traffic notice for static and continuously updated schedules. One can see a more intense use of CS when updating the schedules which indicates that charging at the time of slow moving traffic was convenient for some of the vehicles.

3) Uniform trip generation: Fig. 11 presents the results for the uniform-trip experiment. Since all EVs start from the same location, LiR is expected to perform poorly as many EVs will tend to stop at the same locations. However, a consistent trip length together with a uniform time distribution allows us to experimentally evaluate the performance of our approach in terms of the global optima. The authors in [26], [28] define a balanced distribution of EVs to CS as the objective for global optimization. In Fig. 11, we see that, despite the high correlation between trips, the AS strategy results in balanced waiting queues.

4) Potential as planning methodology: The proposed framework can potentially be used for planning activities. Provided that the simulated trips are representative of the highway traffic, the simulation tool can be used to estimate the demand at the different CSs for a given charging strategy. In other words, this experiment provides insights on how to dimension the different target CS locations.

For this purpose, we run the simulation with an unlimited number of charging poles at each CS and evaluate their maximum and average demand. The results are shown in Fig. 12. The demand at each CS varies depending on the chosen strategy, i.e., LiR or AS, however, one can already identify key CSs where demand is high for both strategies.

One can iteratively use such an approach to plan and dimension CS sites. For example, one could choose to remove CS sites with the lowest demand and repeat the experiments iteratively. Alternatively, one could assign a given amount of resources to each CS proportionally to the result of this experiment.

5) Complexity: Fig. 13 and 14 illustrate the mean, 75-percentile and maximum computation times of EV and CS operations, respectively, as the number of EVs increases.

The computation time of EV operations remains constant as the number of EVs increases. The worst case does increase slightly. This is not due to an increase of complexity itself. As the number of EVs increases and CSs become busy, certain EVs will in some cases need to search further for different CSs to find the shortest path.

The computation time of CS operations increases proportionally to the number of EVs but at a moderate rate. The worst case increases faster but this is mostly limited to peak demand times at the busiest CSs.

VI. Discussion

A. Applicability

The proposed strategy for scheduling fast-charging stops in a highway environment considers a number of factors from the applicability perspective. First, the required information, such as CS location, estimated arrival times, and traffic situation, is already provided by commercial navigation products and is a target of further improvements with oncoming trends in inter-vehicular communication and GPS tracking. Second, the complexity of the algorithms that are to be executed in the EV is moderate and comparable to current capabilities of navigation products such as route planning. Third, the information exchange is limited since only the planned stop is communicated externally, meaning that data, such as EV-state, start, destination, speed, etc., remain private. Fourth, the communication requirements are also moderate and achievable with existing technology. Last, the solution is scalable due to its distributed nature.

As part of the EV's equipment or as a mobile device, communication technology is readily available for vehicles. Since CS infrastructure is relatively new, i.e., there is no significant legacy equipment in the field, one would expect CSs to be equipped with some kind of communication technology which, in addition to smart applications such as the one presented in this work, would be required at least for electronic payment purposes.

The proposed approach benefits from scalability since most of the computation is performed at the EV and some at the CS. Although the computational requirements of the CS are

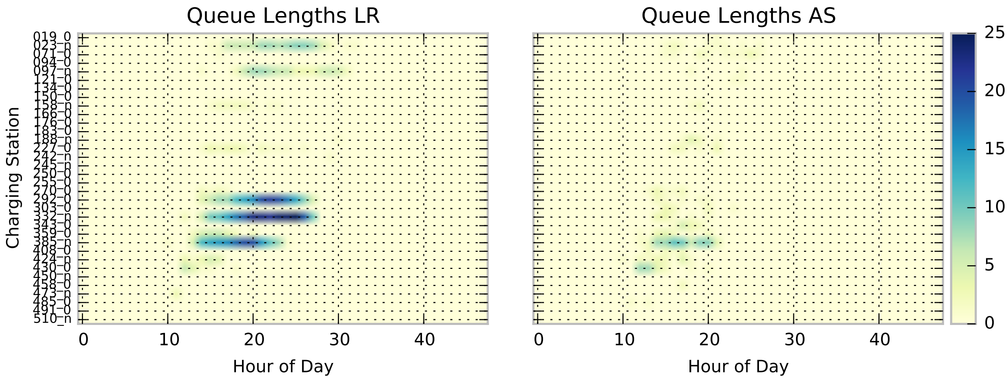


Fig. 8. Queue lengths per CS and time for 500 EVs

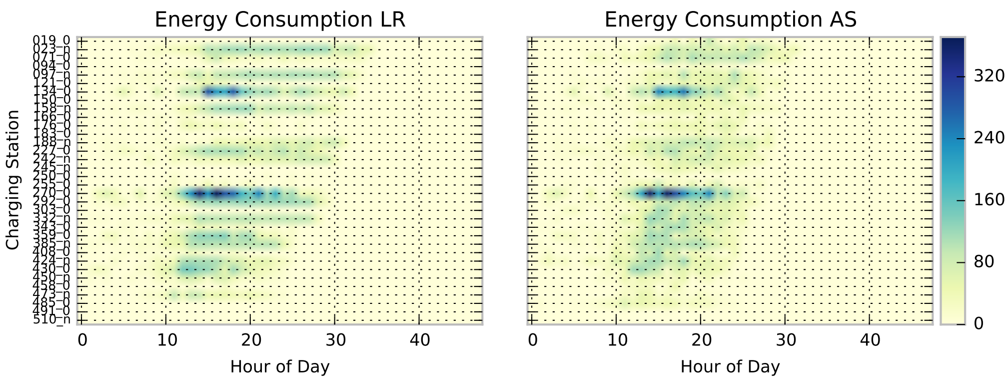


Fig. 9. Energy consumption per CS and time for 500 EVs

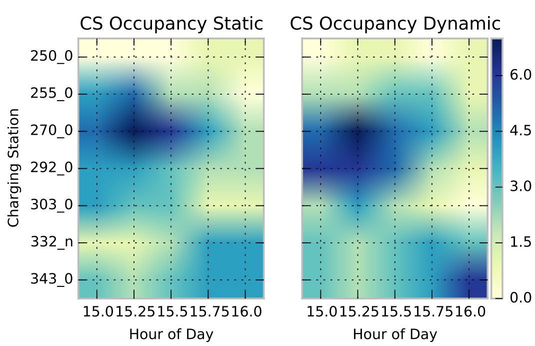


Fig. 10. CS utilization on slow traffic

proportional to the number of EVs, this is only true for those EVs planning to stop at a particular CS and not the total number of EVs on the road.

B. Distribution vs. Global Optimum

Our approach is based on local decision making and execution for each EV without the direct influence of the actions of other EVs. However, the estimated queue lengths of each CS work as coupling variables. These estimates reflect the decision of other EVs and are constantly updated. Our results suggest that this coupling achieves a global benefit although

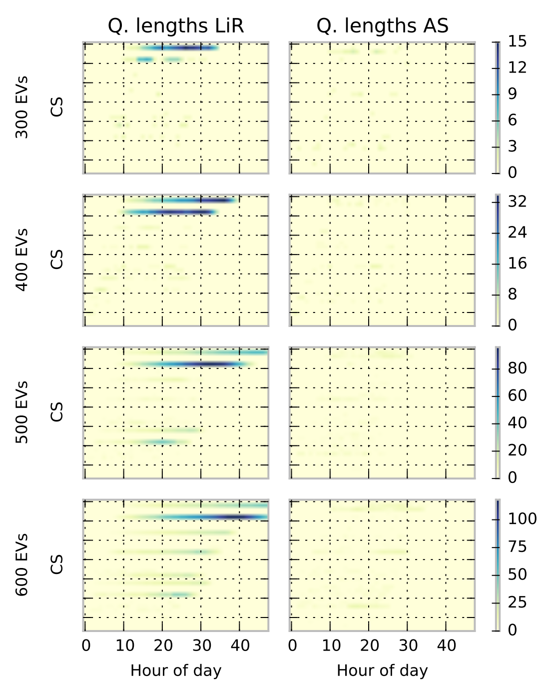


Fig. 11. Queue lengths for uniform trip generation

we cannot qualify the result as a global optimum or social

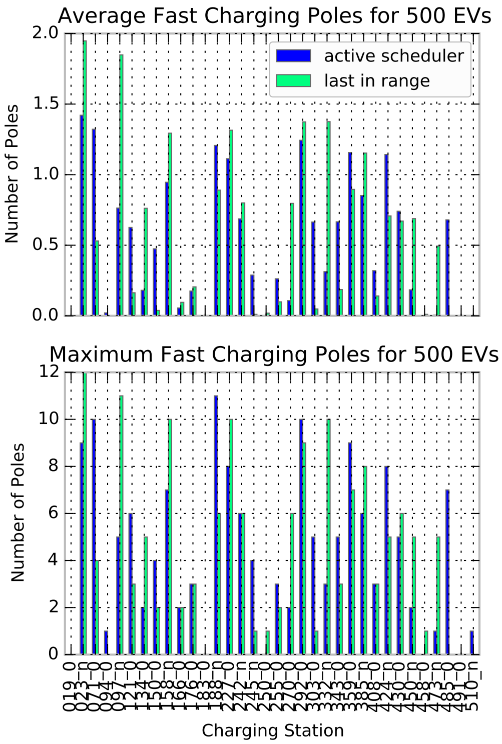


Fig. 12. Average and maximum number of busy poles

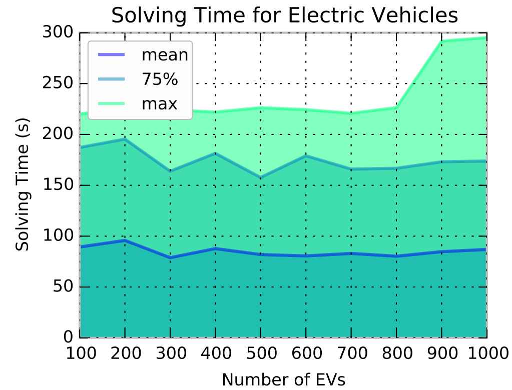


Fig. 13. Computation times for EVs

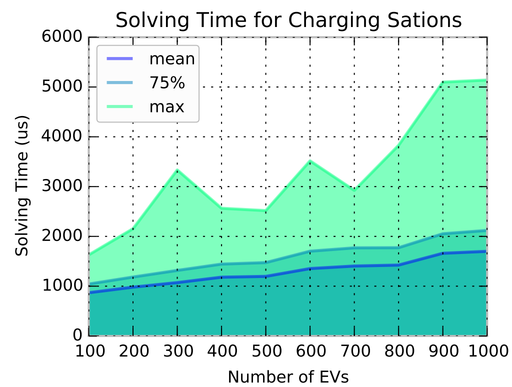


Fig. 14. Computation times for CSs

equilibrium.

A global approach could potentially improve the results. There are, however, a number of disadvantages, particularly from the applicability perspective. A centralized approach faces scalability challenges as the number of EVs and CSs increase. A distributed global approach would likely require more communication than the amount proposed here. Finally, a global approach would probably require more information from EVs to assign resources which could be undesirable from a privacy perspective.

C. Relevance

We believe this work is relevant towards increasing EV penetration. Due to their limited range and long charging times, EVs are not the best choice for highway trips and their price does not justify them as a second “city-only” car. That said, even if we succeed in reducing the travel time, success can only be achieved if charging technology and battery prices and density continue to evolve. Nevertheless, the proposed approach can be generalized to other candidate technologies such as hydrogen or battery swap since they all require new infrastructures and significant investments.

Since charging time is a major factor on highway trips, we do not consider ancillary or support services, such as frequency regulation, to the power grid. In our opinion, these services are provided by EVs which stay idle or parked generally longer than the time they need to charge; for example, at home or at work. By reducing the disadvantages of EVs for long trips, we hope that more EVs become available to provide these kind of services in urban and suburban environments. Alternatively, one could explore the use of CSs on highways (i.e., not EVs directly) for supporting the power grid, provided that they are equipped with local energy storage and generation capabilities; for example, batteries and photovoltaic panels.

A direct benefit of our approach for the power grid is the predictability of power requirements for the different CSs for a given day. Since CSs are booked and estimated arrival times are constantly updated, both medium and short term estimates of power consumption can be derived, facilitating the energy supply and balance tasks of the operator or utility.

D. Improvements, Extensibility, and Future Work

From the simulation framework perspective, the data-driven trip generation is an important contribution but is also subject to further improvement. We concentrate on publicly available data sources which in some cases are built from statistical studies. In particular, we are unable to separate commuting from long-distance traffic based only on counter data. Richer data sources, for example GPS traces or highway specific studies and surveys, could contribute to more realistic solutions.

In terms of accuracy of traffic models, our simulation network uses the highway speed value for simulating vehicle flows. Therefore, it can potentially be integrated with more evolved traffic simulation tools that provide the vehicle’s speed as output. Furthermore, speed would also be the input in the real-life scenario where EVs drive to a given desired speed bounded either by speed limits or traffic conditions.

From the security perspective, our work assumes that EVs are honest and fair-players. However, security concerns should be studied further. A reliable authentication and monitoring mechanism is required to prevent EVs or intruders from intentionally overbooking CSs, for example. Although we partially protect privacy through distributed computation and limited information exchange, security best practices should be applied in both communication and data storage.

Another benefit of the proposed approach is that it can be extended to networked environments, that is, when more than one highway is used. EVs use their route as the planning starting point and the relevant information is the location and state of a CS along the route, independent of the highway on which they are located. Similarly, bookings depend on planned stops on a given CS and do not depend on the EV's origin, destination or specific route. This flexibility, however, does not apply to our simulation framework as, to date, only single highway simulation is supported. From the simulation framework perspective, one could look into an extension to networked environments and potential integration with specialized traffic simulation tools or open source projects such as OpenTraffic [54].

Potential future work includes the following. From the scheduling perspective, one could explore the benefits of considering driving speed as one of the decision variables. Also, a secondary load management between CS could be studied. Finally, a market-style scheduling with dynamic pricing based on CS state and EV preferences could be considered. In this case, energy prices could vary from CS to CS, where prices could be influenced by the charging demand from EVs and even power grid factors, such as higher than predicted solar power generation.

From the battery perspective, one could explore the influence of driving styles (e.g., [41]) and battery aging. On the one hand, a more sportive driving style may influence the range significantly. On the other hand, since fast charging influences battery aging, one could explore how this could be considered in the decision variables.

VII. Conclusion

In this work, we propose a scheduling approach, based on a modified A* algorithm with constraint verification, for EVs to plan charging stops in a highway environment and minimize the total travel time. The computation and communication requirements of the proposed solution remain moderate, which contributes to applicability. We also introduce a simulation framework that includes the generation of EV trips using a data-driven approach and support for time-dependent highway parameters. We apply our approach to a use-case for the German highway A9 from Munich to Berlin.

Using the proposed approach, waiting times and overall travel times can be significantly reduced, leading to the more efficient use of resources. By considering the estimated state of the CSs as input for the algorithm, we achieve indirect coordination between EVs. Additionally, by dynamically adjusting the schedules, the proposed approach accounts for changes on the highway, such as slow traffic on a given segment.

We believe that this work has the potential to improve driving experience and EV adoption rates with a limited cost, both economical and computational. With ongoing projects for fast-charging infrastructures [52], [55], the use of this type of approach can have a positive impact in terms of investment and success of these projects and the overall EV adoption.

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