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Intention-Aware Routing of Electric Vehicles

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***Abstract*—This paper introduces a novel intention-aware routing system (IARS) for electric vehicles. This system enables vehicles to compute a routing policy that minimizes their expected journey time while considering the policies, or *intentions*, of other vehicles. Considering such intentions is critical for electric vehicles, which may need to recharge en route and face potentially significant queueing times if other vehicles choose the same charging stations. To address this, the computed routing policy takes into consideration predicted queueing times at the stations, which are derived from the current intentions of other electric vehicles. The efficacy of IARS is demonstrated through simulations using realistic settings based on real data from The Netherlands, including charging station locations, road networks, historical travel times, and journey origin–destination pairs. In these settings, IARS is compared with a number of state-of-the-art benchmark routing algorithms and achieves significantly lower average journey times. In some cases, IARS leads to an over 80% improvement in waiting times at charging stations and a more than 50% reduction in overall journey times.**

***Index Terms*—Intelligent vehicles, vehicle routing, traffic control, electric vehicles, decision making, multi-agent systems.**

I. INTRODUCTION

THE expected increase in the number of electric vehicles (EVs) necessitates novel solutions for managing the infrastructure required to charge these vehicles [1]. While the increase in rapid charging stations is making en-route charging a viable option for enabling longer journeys (e.g., according to Tesla, its 120 kW supercharger can provide a 170 miles range in 30 minutes), even the fastest chargers to date take significantly longer compared to refueling, potentially resulting in significant congestion at charging stations [2], [3]. In addition, such charging stations are expensive to build and so it is important to use the existing infrastructure efficiently. To this end, we propose a novel navigation system that predicts congestion at charging stations based on dynamic information about current and future demand for charging. This system then suggests the most efficient route and station, in order to minimize both driving time and expected queueing time at stations.

For general (not necessarily electric) vehicles, optimal routing using real-time information about congestion is extensively studied within the area of dynamic route guidance and information systems (RGIS) [4, Ch.11]. RGIS nowadays have time-dependent estimates of driving times on road segments and work sufficiently well in practice for many routing problems. However, there can be a significant discrepancy between the estimated congestion, and the actual congestion when arriving at a particular point. This is partly because, if many people use the same system and follow the same advice, the bottleneck is just shifted elsewhere. In fact, it has been shown that simply providing real-time information can, in theory, *worsen* overall traffic conditions [5].

These problems are likely to become even more significant in the case of EV charging stations, since small discrepancies in the number of vehicles can have a significant impact on queueing time. For example, if a station has two charging points and charging takes 30 minutes, then every additional vehicle would add an average of 15 minutes to the overall journey of vehicles arriving there later. Even if the capacity of the stations were to increase, individual vehicles would still have a much higher impact on delays at charging stations compared to regular road networks.

To reduce congestion at the charging stations, we propose an Intention-Aware Routing System (IARS). In contrast to existing state-of-the-art two-way communication systems, where a driver's navigation system typically only communicates the vehicle's current position, our system communicates its *intentions*, i.e., relevant (probabilistic) information about its planned arrival times at charging stations, to a central system. Internally, each vehicle computes a routing policy, which takes into account uncertainty about road conditions, waiting times and which charging stations may be used. Intentions are then derived from this policy and constitute probabilistic information about *which* stations the EV could visit and *when*, thereby allowing the centralized component of the system to accurately predict congestion (and thus waiting times) at those stations. This information is then fed back to the EV driver's navigation system, which can automatically adjust its routing policy accordingly, and send updated intentions back to the central system.

This type of exchange of intentions is related to the dynamic traffic assignment (DTA) problem, where the goal is to compute

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dynamic user equilibria, e.g., using an iterative approach [6]. An equilibrium is reached when no user has an incentive to deviate to a different route (see, e.g., [7], [8] for an overview). Even though there are similarities, our approach and goals are fundamentally different. First, unlike in DTA equilibria, we do not assume full information about the intentions of all vehicles at any given time. Rather, only a fraction may participate in the system and, even of the vehicles that do participate, we may only receive information gradually over the course of a day. Thus, in order to predict congestion, we propose a new way to combine known intentions with historic information. Furthermore, we consider a time-dependent stochastic traffic flow model where pure-strategy Nash equilibria may not even exist [9], [10]. Instead of finding equilibria, we simply periodically update routing policies (e.g., once every minute), which may or may not converge to a steady state (typically not, since new vehicles enter the system all the time). In doing so, our goal is to see whether exchanging intentions increases overall efficiency, and whether participating in the system is in the best interest of the drivers.

Against this background, this paper makes the following contributions to the existing state of the art:

- We formalize the EV routing problem as a stochastic time-dependent problem. In doing so, we extend existing state-of-the-art methods in stochastic vehicle routing to include EV-specific parameters, such as the state of charge and waiting times at charging stations.
- We propose the concept of an intention-aware routing system (IARS), which combines three sources of information to derive probabilistic travel times (i.e., waiting times at charging stations): known intentions (i.e., arrival time distributions at specific charging stations), intentions from users who have participated in the past, and users whose intentions are not known to the system (but who charge at EV stations).
- Using experiments based on real data from road networks, traffic conditions, and charging station locations, we show that an IARS leads to significantly lower average journey times than state-of-the-art routing algorithms that rely only on historical information about driving and waiting times (as used by some modern navigation devices). In some cases, our approach leads to an over 80% improvement in waiting times at charging stations and a more than 50% reduction in overall journey times. Moreover, we demonstrate that even when only a small proportion of EV drivers use IARS (this can be as low as 10%), they achieve significantly lower journey times than those that do not.

The remainder of the paper is structured as follows. First, Section II provides a discussion of relevant related work. Next, Section III introduces the formal EV routing and charging station model, while Section IV presents the concept of an Intention-Aware Routing System applied to this model. Section V discusses the data and experiments performed to compare IARS against a set of benchmarks, while Section VI concludes with a discussion.

II. Related Work

In addition to RGIS and DTA mentioned above, our work is related to a range of other areas. Specifically, this paper builds on the state-of-the-art stochastic time-dependent network model introduced by Gao and Chabini [11], [12]. Similar to our work, they model the routing problem on a road network with vertices and edges where travel times over the edges are stochastic, and where their distributions depend on the time of day. The solution of the routing problem to a destination node is a so-called *policy*, which describes, for each vertex and at each time, the best next vertex to travel to. This model can also be seen as a Markov decision process [13]. We extend this model by introducing the battery's state of charge (SOC), and having charging stations where the SOC is reset. The SOC decreases when traversing regular roads, and so the routing policy automatically includes a charging station when needed. In addition, while we propose the communication of intentions as a way to coordinate EVs, others have discussed different types of coordination mechanisms. Many of these focus on scheduling of electricity charging at home or while parked away from home to reduce peak loads and/or satisfying constraints of the electricity network (e.g., [14]–[16]). However, this is different from our work, which coordinates vehicles for en-route charging. Here, the main aim is to avoid congestion at the charging stations (although knowing the intentions could also be used to improve the scheduling activities in other EV charging settings). Work that specifically considers coordination to reduce congestion includes [17], where vehicles can communicate observations about the congestion on different road segments to other nearby vehicles. Similarly, in [18], a system is proposed in which vehicles report their location, speed and driving times. More recently, the approach in [19] allows vehicles to negotiate with other nearby vehicles about which routes they are going to take. One key difference to our approach is that these systems do not model stochastic and time-dependent routing explicitly. More specifically, in [17]–[19], the delay on each edge is encoded by a single weight, whereas in our model the driving times on each edge are modeled by stochastic variables, whose distributions depend on the time of day. The advantage of our approach (and stochastic time-dependent models in general) is that it captures realistic situations where travel time is uncertain, and a delay on one part of the route can affect the travel time elsewhere, possibly making an alternative route more attractive. As a result, the optimal solution is not a single route but a *policy* which depends on the realizations of the travel times. In contrast, others have recognized the problem of congestion specifically for charging stations, but have studied conceptually different solutions to ours, such as centralized reservation-based approaches [2], [3], [20]. A largely unsolved challenge for reservation-based approaches is dealing with uncertain driving times, as delays could necessitate re-scheduling or even re-routing to a different charging station, invalidating the optimal schedule and existing reservations. Instead, other work considers more decentralized approaches. In [21], stations broadcast their ability to accept new vehicles, based on the length of the existing queues. In contrast, in our system it is the EVs themselves that broadcast

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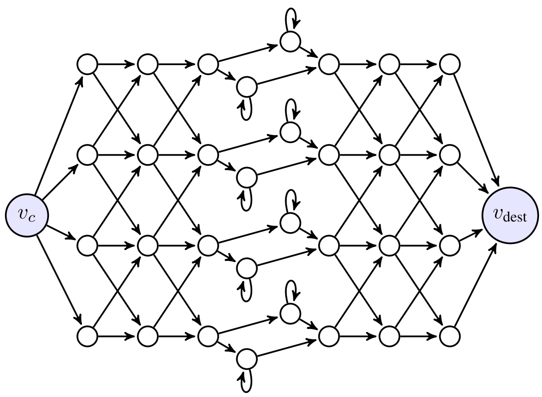

Fig. 1. Example road network from the perspective of a single EV with current position v_c and destination v_{dest}. Vertices indicate decision points, and edges are either roads or charging stations. Charging stations are indicated by self loops.

their driving intentions, which allows others to consider them before they even arrive at the stations. Yet other work, e.g., [22], [23], uses dynamic pricing or similar signaling to regulate congestion through demand response. IARS complements such approaches by planning further into the future. Price differences between stations and/or times could be easily integrated into such routing decisions. Finally, there are an increasing number of papers, e.g., [24]–[26], considering the problem of optimal deployment of the charging stations. While this problem is beyond the scope of our current work, our framework could be used as a model of EV decision-making to tackle such problems, assuming some form of coordination among EVs.

III. Model

In this section we first introduce our model of stochastic time-dependent routing for EVs, where roads and charging stations are abstractly represented by probability distributions of their waiting time. This is modeled as a Markov decision process (MDP). Given the stochastic nature of the problem, and that the aim is to find an optimal *policy*, MDPs are a natural framework to use in this setting. We then go on to present our queueing model of the charging stations, which will be used in Section IV to derive their waiting time probabilities, taking into account the intentions of other EVs.

A. The EV Routing Problem

We model an EV routing domain by $\langle V, E, T, P, S, C\rangle$, with directed edges $e = (v_i, v_j) \in E$ and vertices $v_i, v_j \in V$. Edges represent either roads or charging stations, denoted by $E_{\mathrm{stations}} \subset E$ and $E_{\mathrm{roads}} \subset E$ respectively, whereas vertices represent decision points. An example is given in Fig. 1. In our experiments, we represent stations as self loops to allow vehicles to easily avoid the station, but the framework is more general and allows any type of graph, e.g., to support even roadway-power vehicles (contactless charging while driving) [27].

Both roads and charging stations incur a probabilistic amount of travel or waiting time, described by a probability mass function P (more details below). These travel and waiting times vary depending on the time of the day, and $T = \{1, 2, \ldots, t_{\max}\}$ denotes a finite set of time points (e.g., within a day, or over a week). Roads furthermore incur a cost to EVs in terms of power usage, whereas charging stations reset the EV battery to its maximum capacity level (in order to somewhat reduce the number of parameters, in this paper we assume that a battery will always be fully charged at a station, but it is straightforward to include partial charges in our model). The power available to an EV is represented by a finite set of possible charging *states* $S = \{0, 1, \ldots, s_{\max}\}$, where a state represents the current state of charge of the battery, and $s_{\max}$ denotes a fully charged battery. Furthermore, we introduce function C, where $C(e) \in S$ are the (deterministic) charging costs for edge $e \in E_{\mathrm{roads}}$. Since we compute the route for each vehicle separately, C and $s_{\max}$ could, potentially, be different for each type of EV. This charging cost is deducted from the current state of charge when the edge is traversed.

We consider time-dependent stochastic travel and waiting times and treat them as stochastically independent. That is, conditional on the time of day, the distributions at edges are uncorrelated, and we do not take into account the fact that these distributions may be updated over time. This is common in the stochastic routing literature [28], but in principle recent work on predicting driving times based on current observations could be straightforwardly implemented in our model. Formally, $P(t_b - t_a | e, t_a)$ denotes the probability mass function of the travel/waiting time at edge $e = \langle v_a, v_b\rangle \in E$, where $t_a \in T$ denotes the arrival time at vertex v_a, and $t_b \in T, t_b \geq t_a$ the arrival time at vertex v_b. Thus, when e is a road, then $t_b - t_a$ is the driving time, and when e is a charging station, $t_b - t_a$ is the combined waiting and charging time. Given this, the problem for a single vehicle is to find an optimal *routing policy* π^* which maximizes the driver's expected utility without running out of charge at any point during the journey. Formally, a routing policy is a function $\pi : V \times T \times S \to V$, which gives the next vertex (and the corresponding edge to follow, which is the one that connects the current and the next vertex) for each possible state. Here, a vehicle's current state is given by the current position or vertex $v_c \in V$, the current time at the vertex (i.e., the arrival time) $t_c \in T$, and the current state of charge $s_c \in S$. Then, given a policy π and the current state (v_c, t_c, s_c), the next edge to follow is given by $e_c = (v_c, \pi(v_c, t_c, s_c))$ and the expected utility for the policy π from the current state can be computed using the following recursive formulation:

$$
\begin{aligned}
&\mathrm{EU}\left(e_c = (v_c, w), t_c, s_c | \pi\right)\\
&= \begin{cases} -\infty & \text{if } s_c \leq 0\\ \sum_{\Delta t \in T} P(\Delta t | e_c, t_c) \cdot U(t_c + \Delta t, s') & \text{if } w = v_{\mathrm{dest}}\\ \sum_{\Delta t \in T} P(\Delta t | e_c, t_c) & \\ \quad \cdot \mathrm{EU}\left((w, \pi(w, t_c + \Delta t, s')), t_c + \Delta t, s' | \pi\right) & \text{otherwise} \end{cases}
\end{aligned}
$$

where $s' = \mathrm{SOC}(e_c, s_c)$ determines the new state of charge when traversing edge e_c, i.e.,

$$
\mathrm{SOC}(e_c, s_c) = \begin{cases} s_c - C(e_c) & \text{if } e_c \in E_{\mathrm{roads}}\\ s_{\max} & \text{if } e_c \in E_{\mathrm{stations}}. \end{cases} \tag{1}
$$

In this model we assume that the state of charge is not influenced by the time it takes to traverse an edge. We argue that this is reasonable given that batteries are charged when braking, although the formulation above can be easily extended to make this time-dependent or even stochastic. Furthermore, $U(t_c, s_c)$ is the vehicle's utility function for a given arrival time t_c and a state of charge s_c on arrival such that $U(t_c, s_c) = -\infty$ if $s_c \leq 0$. Consequently, a policy will always be chosen ensuring the vehicle will not run out of charge (if such a policy exists). Otherwise, we use $U(t_c, s_c) = -t_c$; then maximizing the expected utility means minimizing the expected time of arrival. However, other functions describing the driver's preferences could be easily used instead.

B. Charging Stations Model

In addition to the general routing problem, we explicitly model the queues at charging stations to compute the probabilistic waiting times (discussed in detail in Section IV). We focus on the charging stations, since individual vehicles can have a significant effect on waiting times. Hence there is a greater potential benefit in knowing the intentions compared to roads.

The station's queueing model is as follows. We assume that each station $e \in E_{\text{stations}}$ has a fixed capacity, cap_e, due to space or electricity network constraints. This capacity is the maximum number of vehicles that can charge simultaneously. Furthermore, for simplicity, we assume that the time to (fully) charge a vehicle, denoted by $t^{\text{charge}} \in T$, is fixed (although it is straightforward to extend the model to stochastic or charge-dependent times). We assume a first-come-first-served queueing model when the station is at full capacity and that there is no queue before time $t = 1$. Finally, if several EVs arrive at the same time, we assume they arrive in the order of a randomly assigned unique identifier.

IV. Intention-Aware Routing System

In this section we provide an overview of an IARS to reduce congestion at charging stations, and we explain how waiting times are computed. The section is organised as follows. We start in Section IV-A by discussing the system as a whole and how the individual drivers' navigation devices interact via a central system. We then detail the steps to compute the probabilistic waiting times of the charging stations. First, in Section IV-B, we discuss how the optimal routing policy can be computed. Then, in Section IV-C, we derive the arrival probabilities (i.e., intentions) from a routing policy. In Section IV-D, we discuss the computation of arrival probabilities from historical data. Finally, we combine this information in Section IV-E to compute the probability distributions of the waiting times.

A. IARS Architecture

Fig. 2 presents an overview of the system. As can be seen, the system consists of two types of components: several navigation devices, henceforth called *agents*, who autonomously exchange information with a central system, henceforth called the *centre*. Note that the agents do not exchange intention information directly with other agents. Instead, each agent periodically

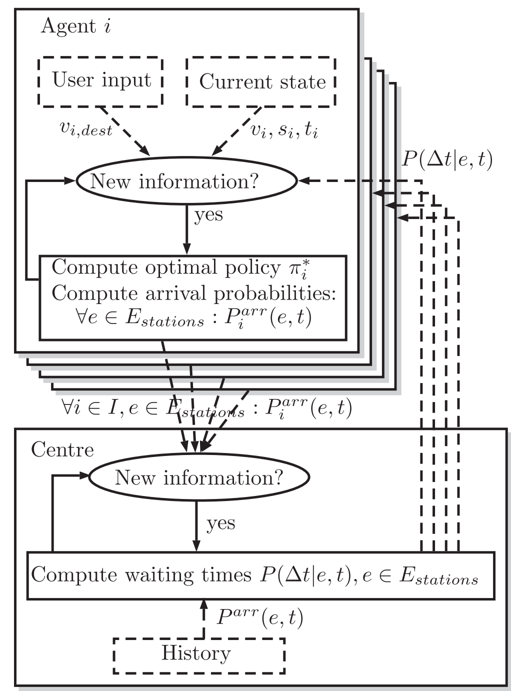

Fig. 2. Intention-aware routing system architecture.

receives updated probabilistic waiting times from the centre, denoted by $P(\Delta t|e, t)$ (see also Section III-A).[1] Furthermore, using this architecture, the agents only need to communicate their arrival probabilities for the charging stations to the centre, and not the entire routing policy, thereby reducing communication overhead and increasing privacy.[2] Given the user input, $v_{i,dest}$, the state of the vehicle (the current position, v_i, state of charge, e_i, and time t_i), and the information received from the centre, each agent first computes its optimal routing policy (as described in Section IV-B). From this policy, the agent derives the arrival probabilities for relevant stations (see Section IV-C below), which are periodically sent to the centre. Note that the set of participating agents, denoted by I in the figure, constantly changes over time. This is because, even if IARS is used, the user may not yet have entered the destination. Therefore, the centre needs to combine both currently known arrival probabilities (intentions) of individual agents, with more generic historic information about arrivals about agents whose intentions are not (yet) known (which also accounts for users not using the system at all) to compute the probabilistic waiting times (as detailed below). This information is then fed back to the agents, completing the cycle. In our simulations we repeat such a best-response cycle for all agents a fixed number of times (20), but usually there are no significant changes already after two or three iterations. The policies converge in 85% of the cases.

[1] In this paper, we focus on the information related to charging stations (i.e., the waiting time probabilities for remaining edges remain fixed), but in practice both roads and charging stations would be updated.

[2] In practice, the routing policy may have to be computed by the central servers anyway, as is the case with Waze and Google Maps.

1 $P_i^{arr}(v,t,s) \leftarrow 0$ for all v, t, s, but $P_i^{arr}(v_i, t_i, s_i) \leftarrow 1$
2 $P_i^{arr}(e,t) \leftarrow 0$ for all $t \in T$, $e \in E_{\text{stations}}$
3 $Q \leftarrow \{(v_i, t_i, s_i)\}$ `// priority queue on time`
4 **while** $Q \neq \emptyset$ **do**
5 $\quad (v,t,s) \leftarrow \mathbf{pop}(Q)$ `// remove from queue`
6 $\quad (v,w) \leftarrow \pi(v,t,s)$
7 $\quad$ **if** $(v,w) \in E_{stations}$ **then**
8 $\qquad P_i^{arr}((v,w),t)$ += $P_i^{arr}(v,t,s)$
9 $\quad$ **if** $w \neq v_{dest}$ **then**
10 $\qquad$ **for** $\Delta t \in T$ **do**
11 $\qquad\quad P_i^{arr}(w, \Delta t + t, \text{SOC}((v,w),s))$ +=
12 $\qquad\qquad P(\Delta t|(v,w),t) \cdot P_i^{arr}(v,t,s)$
13 $\qquad\quad$ **if** $P_i^{arr}(w, \Delta t + t, \text{SOC}((v,w),s)) > 0$ ***and*** $(w, \Delta t + t, \text{SOC}((v,w),s)) \notin Q$ **then**
14 $\qquad\qquad$ **add** $(w, \Delta t + t, \text{SOC}((v,w),s))$ **to** Q

Fig. 3. An agent's arrival probability P_i^{arr} at each station s is derived from its policy π by considering all possible delays on the route towards s.

B. Computing the Optimal Policy

The *optimal* policy from a state (v_c, t_c, s_c) is given by:

$$\pi^* = \arg\max_{\pi \in \Pi} \text{EU}\left((w, \pi(v_c, t_c, s_c)), t_c, s_c | \pi\right)$$

where Π is the set of all valid policies. Since for every computation of EU the policy π_i is required only for times strictly later than t_i (we assume $\Delta t > 0$), the optimal policy can be computed using dynamic programming in line with work on Markov decision processes [13] based on the following recursive definition: if $v_i = v_{\text{dest}}$ or $s_i \leq 0$, then there is no good decision, and otherwise:

$$\pi^*(v_i, t_i, s_i) = \arg\max_{\{e|(v_i,w) \in E\}} \text{EU}(e, t_i, s_i | \pi^*).$$

All computations described above can be done in running time bounded by $\mathcal{O}(|T|^2 \cdot |V| \cdot |S| \cdot |E|)$. Note that the optimal routing problem can still become computationally expensive for large road networks. However, the routing problem is solved for individual agents for which we only need to consider a subset of the entire graph since not all charging stations can be reached. In our experiments (see Section V) we have different road networks for each agent and, for any individual agents, we only consider routes to and from a limited number of alternative charging stations.

C. Computing Arrival Probabilities (Intentions)

The algorithm for deriving the arrival probabilities of an EV at stations at particular times is given in Fig. 3.

Formally, the probability $P_i^{arr}(e,t)$ that EV i arrives at station $e \in E_{\text{stations}}$ at time $t \in T$ depends on i's current policy π_i^* and current state (v_i, t_i, s_i). Besides the probability for each arrival time at each station, the algorithm also needs to maintain a probability of the arrival time at all other states, denoted by $P_i^{arr}(v,t,s)$. The initialization sets all these probabilities to 0, except for the probability of arriving in the current state, which is 1. All reachable states are then considered in turn by using a priority queue Q where states are sorted on time. Initially, this queue contains only the current state (see line 3). From any state taken from this queue (i.e., with location v, time t, and state of charge s), the policy for this state defines the next location w. If (v,w) is a station (i.e., $(v,w) = e$ with $e \in E_{\text{stations}}$), the computed arrival probability is added to $P_i^{arr}(e,t)$. Then, for each possible delay Δt on (v,w) (see line 10), we add the respective arrival probability $P(\Delta t|(v,w),t) \cdot P_i^{arr}(v,t,s)$ to the new state (i.e., updating the state of charge, to $(w, \Delta t + t, \text{SOC}((v,w),s))$). Any state reached with non-zero probability is treated in the same way by inserting it into the queue, until the policy reaches the destination. The algorithm computes all possible futures and their probabilities given the policy π, and from that extracts the arrival time distribution for each charging station.

D. Historical Arrival Probabilities

As already mentioned, not all intentions of the agents are known by the system, either because the drivers have not yet entered their route in the system, or they are not using the system at all. However, to compute future waiting times, agents with unknown intentions still need to be taken into account. We do so by using arrival probabilities based on historical information for agents whose intentions are not known. This facilitates the integration of known and unknown intentions (discussed in the next part). Specifically, the system keeps track of *when* and *where* (i.e., at what station) vehicles arrive for charging.[3] These historical arrivals are then aggregated to compute the probabilities $P^{arr}(e,t)$ which gives, *for an average EV*, the probability that it arrives at station $e \in E_{\text{stations}}$ at time $t \in T$. Note that this approach is anonymous in that it does not compute different probabilities for different vehicles.

E. Computing Waiting Times Probabilities

We now discuss the main part of the system and show how to compute the waiting times probability mass function, $P(\Delta t|e,t)$, by combining the historical information, P^{arr}, with known arrivals so far, and with the intentions-derived probabilities, P_i^{arr}, $i \in I$, where I is the set of EVs who have (so far) reported their intentions to the system. We let n denote the total number of unique vehicles that have charged in the past (across stations), including both ones that use the system, and ones that do not. For simplicity, we assume that each EV charges en-route at most once per journey, although having a single vehicle charge multiple times can be approximated by considering these are different vehicles. Furthermore, let m denote the number of vehicles which have already charged today, and $I' \subseteq I$ those vehicles with known intentions which still need to charge (i.e., they are visiting a station with non-zero probability). Given this, there are $n - m$ EVs that may still choose to charge, of which we know the intentions of $|I'|$.

We then approximate the probability mass function by drawing a number of samples from the respective probability distributions on arrival time and simulating the resulting queue.

[3]For an accurate account of historic information, this includes keeping track of vehicles not using IARS but which are still using the charging stations. This can be achieved, for example, through sensors and/or credit card payment information at the stations.

For each sample, we independently draw for $n - m - |I'|$ vehicles a pair $\langle e, t\rangle \in (E_{\text{stations}} \times T) \cup \{\perp\}$ according to the probabilities $P^{arr}(e, t|\text{not charged})$, i.e., the arrival conditional on not having charged before (where the probability of charging before the current time is zero). Here, $P^{arr}(\perp) = 1 - \sum_{e\in E_{\text{stations}}, t\in T} P^{arr}(e, t|\text{not charged})$ is the probability that the EV does not charge at all. Similarly, we draw a single pair $\langle e, t\rangle$ from each distribution P_i^{arr} (note that we do not need to compute the conditional distribution, since it has already been updated). Finally, we add the EVs that have already arrived today with probability 1. Then, starting from $t = 1$, we simulate the queues at each station based on the model described in Section III-B until the end of the day, and measure the waiting times for each future time point. This process is repeated for a number of times and $P(\Delta t|e, t)$ is estimated by averaging the waiting times at each station and time slot. Such an approach using a combination of sampling and simulation is used quite often and is called a *Monte-Carlo simulation*. In the experiments in Section V we use 5000 samples, which altogether take, on average, around 0.2 seconds on a single core of a 2.93 GHz Core i7 iMac with 16 GB RAM.

```
initialise history P^arr
for each day do
    initialise agents; and set currentTime ← 0
    while (currentTime < endOfDay) do
        currentTime ← moveToNextState()
        converged ← FALSE; and set iter ← 0
        while (!converged &
        iter < maxNumIterations) do
            converged ← TRUE
            for agents with known intentions i ∈ I do
                compute π_i^*
                compute P_i^arr(e, t)
                compute P(Δt|e, t)
                if π_i^* has changed then
                    converged = FALSE
            iter++
    update history P^arr;
```

Fig. 4. Pseudocode of the main simulation loop.

V. Experiments

In this section, we experimentally evaluate our intention-aware routing system in a wide range of settings. The purpose of this is to establish and quantify the potential benefits of 1) modeling station waiting times and 2) incorporating other agents' intentions into routing decisions. For ease of presentation, we assume that all agents wish to minimize their arrival time at the destination, and therefore our primary measure of performance is the average journey time of individual agents. In the following, we first describe the benchmarks we test against. We then discuss the simulation used for the evaluation and provide details of the specific scenario. Finally, we present the results.

A. Benchmarks

In order to provide a thorough experimental evaluation of our approach, we implemented and evaluated a range of RGIS strategies:

- **Min**: A strategy that always minimizes the expected journey time. As such, it simulates existing state-of-the-art navigation systems.
- **Logit**(λ): A randomized variant of Min.
- **IARS**: Our proposed intention-aware routing system, which is the main contribution of this paper.
- **Infinite Capacity**: A lower bound on the social optimum.

All strategies use the time-dependent stochastic model of road travel times and include the state of charge, as discussed in Section III. We include Logit, because agents employing Min on similar source and destination pairs will often follow the same routes, exacerbating congestion at charging stations. While this is an inherent problem with current routing systems, we are interested in whether occasional randomization may alleviate this. The Logit algorithm is a good benchmark, as it is often used to model the sub-optimal behavior of people [29]. As we expect this randomization to benefit the average journey time, in our experiments we consider a best-case scenario where this randomization has maximal benefit (by optimizing the λ parameter).

To achieve this, we use an approach where the probability of selecting an alternative is directly related to the expected utility of that same alternative. This is in line with work on the logit *agent* quantal response equilibrium [30] and is defined as follows. Given a parameter $\lambda \in [0, \infty]$, the probability of selecting an edge e is defined as:

$$P(e|v_c, t_c, s_c) = \frac{e^{\lambda\cdot \mathrm{EU}(e,t_c,s_c|\pi')}}{\sum_{\{e'|(v_c,w)\in E\}} e^{\lambda\cdot \mathrm{EU}(e',t_c,s_c|\pi')}}. \quad (2)$$

The policy $\pi'(v_c, t_c, s_c)$ is then drawn from this distribution, and the expected utilities are computed knowing that this distribution is used in future time steps: $\mathrm{EU}((u, v_c), t_c, s_c|\pi') = \sum_{\{e'|(v_c,w)\in E\}} P(e'|v_c, t_c, s_c) \cdot \mathrm{EU}(e', t_c, s_c|\pi')$.

Both Logit and Min assume zero waiting time at charging stations. We also implemented enhanced versions of these strategies, denoted by the "Learning" label, to describe that the system models (and hence "learns") waiting times at charging stations using *historical data*. Therefore, Min and Logit model situations where current standard GPS routing systems are used that do not model queues, while Min-Learning and Logit-Learning use historical arrivals to estimate queueing times. Finally, we compute a lower bound on the social optimum by including a benchmark with unlimited capacity at the charging stations, allowing every vehicle to take the shortest path (in expectation) without any queueing time. This is always guaranteed to be *better* than the social optimum.

B. Simulation

The IARS architecture explained in Section IV is entirely decentralized and asynchronous. That is, in practice, each agent can recompute their route and submit updated arrival probabilities to the system independently and at different time intervals.

However, to allow for reproducible results, for the purpose of our evaluation we use a discrete event simulation.

Specifically, the main simulation loop is given in Fig. 4. To explain, a run of the simulation starts with no history (each station/time combination is equally likely). Then, at the start of each simulated day a set of agents is initialized with their journey consisting of starting time, their origin and their destination (as detailed in Section V-C), and an initial optimal policy given the current history. Depending on the setting, a proportion of these agents will use IARS whereas others will use one of the benchmark strategies from Section V-A.

The day then proceeds as follows. The function *moveToNextState*() in line 5 finds the next event, where an event is triggered by either a new agent entering the system, or an existing agent reaching a new vertex (i.e., decision point). At such an event, if the agent is using IARS, it may update its policy given the new information available, which could trigger a cascade of changes for other agents using IARS. Therefore, for each such event, the system proceeds with a *best-response loop* (lines 7–15). Specifically, each agent with known intentions (i.e., that has started its journey and is using IARS) in turn updates its policy and arrival probabilities if needed, and the resulting waiting probabilities are then updated which could trigger changes in other agents. This procedure is repeated until the policies converge (i.e., there are no more changes), or a maximum number of iterations is reached. In the experiments we set *maxNumIterations* to 20. Finally, at the end of each day the historic arrival probabilities are updated as described in Section IV-D.

We first performed an evaluation on two completely different time-independent synthetic scenarios as described in the conference paper [31]. This showed that IARS can realize a significant reduction in travel time if capacity is tight. To gain more insight whether this effect also holds in more realistic settings, we repeat a study of this effect for 100 different realistic time-dependent scenarios, as described in the next section.

C. Realistic Scenario

Using the simulation we consider a realistic scenario to evaluate the performance of IARS compared to the other solutions. Specifically, we consider the coordination of electric vehicle charging around the city of Utrecht in the Netherlands. Utrecht, situated in the center of the country, is the main transit hub in the Netherlands, and hence the location where congestion at EV charging stations is most likely to occur. To generate realistic traffic data, we took origin—destination pairs with departure times from a Dutch National Survey [32]. This survey describes over 127000 moves, from which we selected those that were more than 50 km and passed, but did not start or end near Utrecht. To make this selection, we used a local copy of the Open Source Routing Machine (OSRM) using data from OpenStreetMap to create routes. This resulted in a set of 118 moves with driving times (without delays) ranging from 45 minutes to 3 hours, as displayed in Fig. 5.

In our experiments we fix the number of EVs to 50 (which gives reasonable waiting times at stations for the road network we consider), and we vary the congestion at the charging stations by changing their capacity (i.e., the number of EVs that can be charged simultaneously). We force each EV to visit exactly one charging station for a full charge by initializing the state of charge by 1 and requiring a charge of 3 (which is the maximum level in this simulation) for all edges incident to the final destination, and 0 for all other edges. For each run of the experiment we sample the 50 agents by selecting a random journey (with replacement) out of the above set of moves for each agent. For the sequence of weekdays[4] in a single experimental run, these agents depart with some Gaussian noise ($\sigma = 10$ minutes) around the respective departure time from the survey. This simulates the same people making the same journeys on weekdays, but at slightly different times.

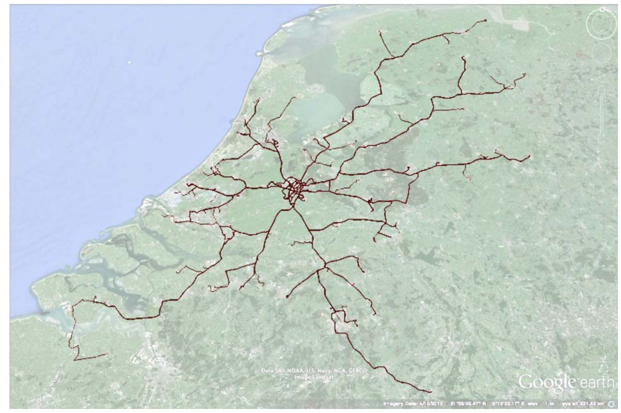

Fig. 5. All 118 selected routes longer than 50 km passing Utrecht (satellite image by Google Earth and Data SIO, NOAA, U.S. Navy, NGA, GEBCO).

For each of the selected moves we find the 6 charging stations out of the set of 906 as of June 2014 from Open Charge Map with the smallest detour (again using OSRM), resulting in a total of 36 relevant charging stations in or around Utrecht. At the moment five of which are fast charging stations (about 40 kW). We set the capacities to be the same for all stations, and we vary these from 1 to 5 per station.

We obtained speed measurement data along these routes (including going via the charging stations) for the morning rush hour. For this we collected the average speed for every 5 minute interval from 2800 measurement points along the selected routes on weekdays from 5:00 to 11:00 from 3rd February 2014 to 7th June 2014 (ignoring two days and 100 measurement points that had missing data). The speed measurements were obtained from the Nationale Databank Wegverkeersgegevens (NDW), a cooperation of several governmental organizations, who together aim to collect all traffic measurements in the Netherlands. First, for each day and for each 5 minute interval on every day, these speed measurements are used to derive driving times for longer road segments by assuming the observed speeds are maintained until the next measurement point. Then, for each time of day the derived driving times from all 88 weekdays are combined into a time-dependent road driving

[4]Most experiments are run over 20 weekdays, to allow the agents to collect and use historical data. Those involving IARS agents are run over 5 weekdays, due to the more computationally expensive best-response mechanism. However, the performance of all strategies typically converges within 3–4 days, and we only record journey times on the last simulated day.

time distribution, which has five driving times and associated probabilities (as evenly distributed as possible) such that it has the same mean as the driving times of the 88 days.

Each route connecting an origin or destination to a charging station initially consists of about 2000 edges. Whenever prefixes of these routes coincide, they are combined. Each sequence of edges and nodes with degree 2 is then compressed into a single edge with the respective aggregated time-dependent stochastic travel time distribution. This results in a graph for each of the agents with 13 nodes and 17 such edges. The charging station queues at their respective nodes are shared among these agents. The experiments are then run with a time step size of 30 seconds and charging times are fixed to 30 minutes.

D. Hypotheses

Our experiments are guided by the following hypotheses. The first (H1) examines the overall benefit of modeling historical station queueing times, the next two (H2 and H3) describe expected differences in average journey time between the different routing strategies, and H4 describes the uncertainty regarding these journey times. Then, hypothesis H5 sets our expectation on the effect of capacity and thus congestion at charging stations. Finally, hypotheses H6 and H7 describe our expectations regarding vehicles that decide to deviate from the advised routing strategy.

- H1: Explicitly modeling historic information on station queues leads to a higher utility for individual agents as well as to a lower average journey time.
- H2: The average journey time for IARS is lower than for any of the other approaches.
- H3: The average journey time for LOGIT is lower than the average journey time for MIN.
- H4: The uncertainty regarding the journey time is lower for IARS than for any of the other approaches.
- H5: With increasing congestion (less charging capacity at the stations), the effect of coordination through IARS and randomization through LOGIT becomes more pronounced.
- H6: When all agents use LOGIT, a single agent can increase its utility by switching to MIN.
- H7: When all agents use IARS, a single agent cannot increase its utility by switching to MIN or LOGIT.

The next section describes the results of our experiments and relates them to these hypotheses.

E. Results

In order to obtain a fair comparison for the LOGIT strategy, we first establish the value for the randomization parameter λ that gives the best results. Given that the expected utilities (EU) for the different routes are the negation of the journey time, and that journey times are in the region of 100 to 300 minutes, rather small values for λ in Equation (2) give the most sensible values for $e^{\lambda \cdot \mathrm{EU}}$. We run an experiment for $\lambda \in \{0, 0.001, 0.01, 0.1, 1\}$ on a set of representative problem

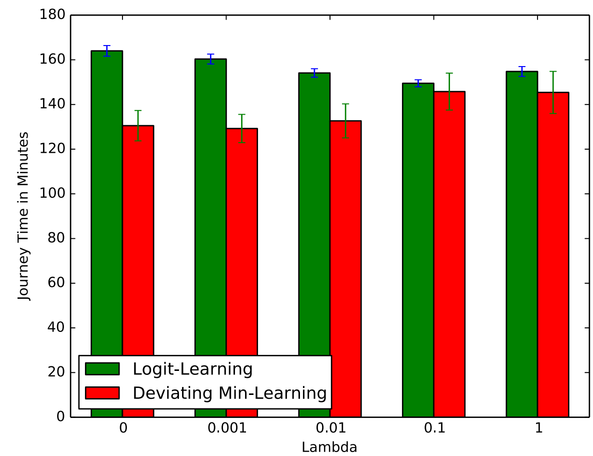

Fig. 6. All (except for one) agents use LOGIT(λ) in a scenario with station capacity of two.

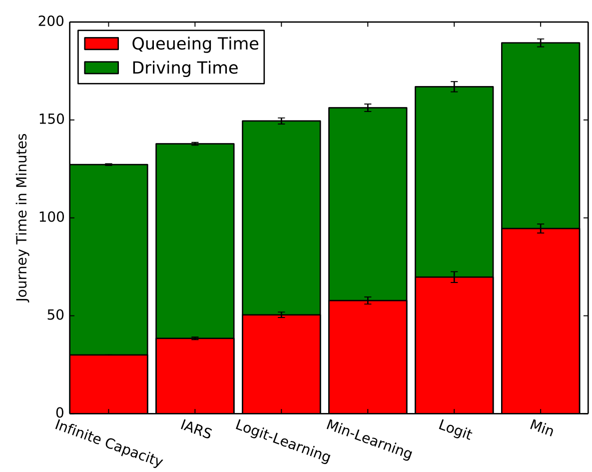

Fig. 7. IARS results in the lowest overall journey time and performs quite close to the lower bound with unlimited capacity at the charging stations. LOGIT performs better than MIN.

instances where stations have a capacity of 2, and measure the average journey time of all 50 vehicles using LOGIT(λ)-Learning (we focus on the Learning variant here, but the trends for LOGIT(λ) are similar). The results of this experiment can be found in Fig. 6, where the green bars show the average journey time of LOGIT(λ)-Learning and the red bars show the average journey time of a single deviating agent that adopts the MIN-Learning strategy (which we will discuss later). In all results, a 95% confidence interval over 100 different runs with 50 vehicles each is shown by the (vertical) length of an error bar around the mean. We observe that LOGIT-Learning performs best with the randomization parameter value around $\lambda = 0.1$. In further experiments, we thus show only results for this value.

Having established a good value for λ, we are set to compare all strategies on a series of instances. To this end, Fig. 7 shows the average journey times for all RGIS strategies tested in the same setting as before. Here, all approaches that use historic information about station queues clearly outperform those that do not, confirming H1. IARS outperforms all other strategies by significantly reducing queueing times, confirming H2 and both

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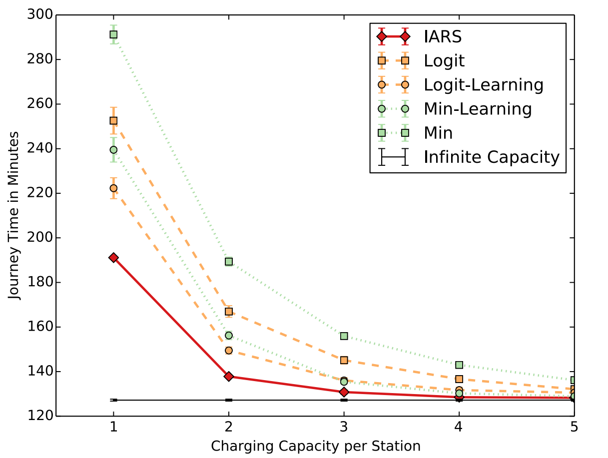

Fig. 8. For high congestion and thus little capacity at charging stations, IARS significantly reduces the average journey time (by almost 50% in some occasions), but when there is an overcapacity (e.g. for capacity 3, there are 108 places to charge around Utrecht for only 50 vehicles), the gain is relatively small (≈10%).

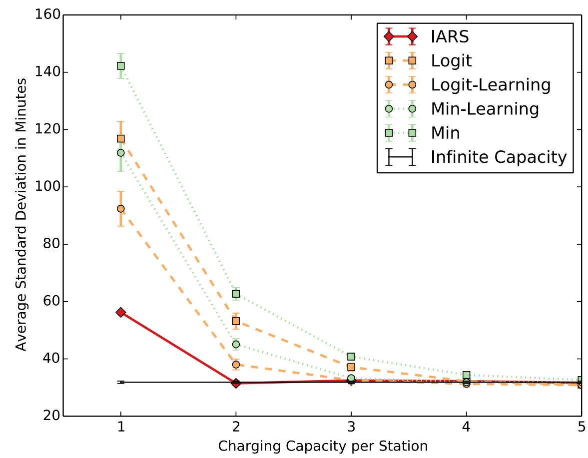

Fig. 9. The standard deviation is significantly lower for IARS than for any of the other approaches.

LOGIT approaches lead to consistently lower journey times than their MIN counterparts, confirming H3.

In terms of run-time, IARS is significantly more expensive than the other strategies, taking about 3.5 minutes of computation time per vehicle per day on a 2.6 GHz Intel Sandybridge running on a single core with 4 GB of RAM.[5] All other strategies take a few seconds or less.

Next, Fig. 8 displays the average journey times of the 50 vehicles for each of the strategies for different charging station capacities: ranging from 1 to 5 charging bays at a station. From this figure we can make several observations. First, the strategies using historic information (i.e., MIN-Learning, and LOGIT-Learning) perform significantly better than their non-learning counterparts, again confirming hypothesis H1. Second, IARS performs better than LOGIT, which in its turn is better than MIN. This is significant until a capacity of four (confirming H2 and H3). Third, this experiment simulates increasing congestion by decreasing capacity at the charging stations. Here we see that average journey times significantly increase for increasing congestion (smaller capacities) and that this makes the differences between the different strategies more pronounced, confirming H5. The figure also shows that IARS is very close to the lower bound for capacities above two, proving that IARS is very close to optimal.

Next, to investigate H4, for each run of the simulation we record the standard deviation of the journey times for all 50 agents. This indicates how much the journey times vary between agents and, when comparing between different strategies, a higher standard deviation indicates higher uncertainty about the journey time of a randomly chosen agent. The average standard deviation is shown in Fig. 9 with 95% confidence intervals. Here, we see that this is significantly lower for IARS than for the other approaches. This means that the uncertainty for drivers regarding the journey time is typically smaller, confirming H4.

[5]Note that this includes all best-response iterations whenever new information becomes available. In practice, these could be performed less frequently to save computation time.

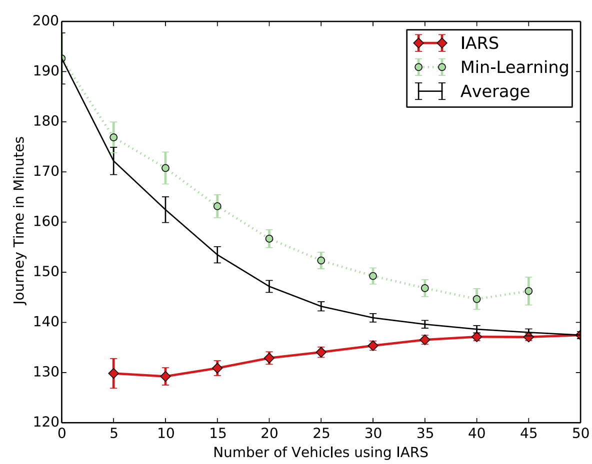

Fig. 10. In a scenario with station capacity of two, the more agents use IARS, the lower the average journey time (if other agents use MIN).

An important issue when introducing a new strategy for navigation systems is that there must be an incentive for drivers to use it. We therefore compare average journey times also when only a part of the drivers use a particular system. In our experiments we study IARS versus MIN (results in Fig. 10), IARS versus LOGIT (results in Fig. 11), and we have already seen some results on LOGIT versus MIN (in Fig. 6). Figs. 10 and 11 clearly show that no matter what strategy the current population of drivers use, any driver is better off using IARS, and such a switch further reduces the average journey time, confirming hypothesis H7. However, the opposite is the case for LOGIT: Fig. 6 shows that any individual driver is better off *not* using LOGIT (confirming H6).

VI. CONCLUSION AND FUTURE WORK

The main contribution of this paper is the concept of an intention-aware routing system (IARS) to coordinate the en-route charging of electric vehicles, together with a realistic evaluation of this system. The evaluation considers actual charging

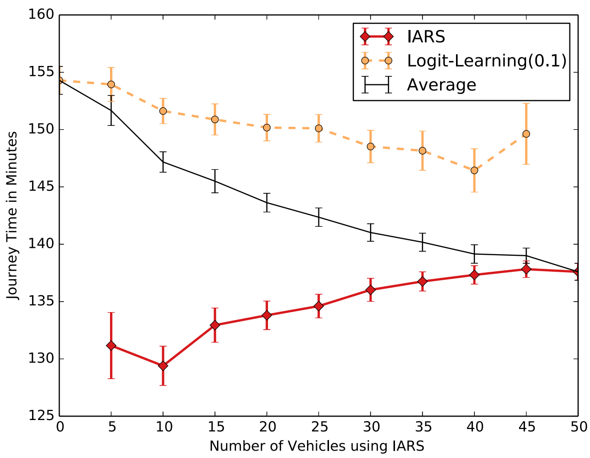

Fig. 11. In a scenario with station capacity of two, the more agents use IARS, the lower the overall journey time (if other agents use LOGIT).

station locations, time-dependent road travel time distributions based on historic traffic information, and an origin-destination pair distribution for the vehicles created from a country-wide survey. The experiments show that individual drivers are better off using the navigation advice from IARS than with classic route guidance systems, even when these learn time-dependent waiting times at charging stations, and even when an optimal perturbation is mixed in according to the Logit model. Overall, IARS leads to significantly shorter journey times (up to 50% with high congestion), and also has significantly less uncertainty than existing benchmarks, which is a highly desirable property. The observed trends are in line with the results of our previous experiments on artificially constructed road networks where all vehicles depart simultaneously (reported in a conference paper [31]). However, given the extensive experiments in this paper based on real data, we are now able to show the effect of an intention-aware routing system in practice.

There are several directions for future work. First, while the focus of this paper is on the use of an IARS to reduce congestion at charging stations, it would be interesting to investigate whether the approach could be extended to coordinate general road usage. Second, while we have compared IARS to adaptive route guidance systems that use historic information, these benchmarks could be extended to additionally use real-time queueing information. Third, it is interesting to investigate whether there are (significant) incentives to misreport intentions, and study potential ways to discourage such behavior. Fourth, future work could consider a principled comparison between IARS and reservation-based systems. Our hypothesis is that, in settings where driving time (and therefore arrival time at the station) is uncertain, reservation systems are less efficient than IARS due to the frequently required changes and/or cancellations of reservations.

Another possible extension of this work is to consider the dynamics and efficiency of settings with multiple competing IARS providers, and where agents can choose to participate in one or more of such systems. Finally, as the uptake of electric vehicles increases, we would like to explore a real deployment of IARS.

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