A Game-theory Analysis of Charging Stations Selection by EV Drivers

Francesco Malandrino, Claudio Casetti, Carla-Fabiana Chiasserini, and Massimo Reineri

***Abstract*—We address the problem of Electric Vehicle (EV) drivers' assistance through Intelligent Transportation System (ITS). Drivers of EVs that are low in battery may ask a navigation service for advice on which charging station to use and which route to take. A rational driver will follow the received advice, provided there is no better choice i.e., in game-theory terms, if such advice corresponds to a Nash-equilibrium strategy. Thus, we model the problem as a game: first we propose a congestion game, then a game with congestion-averse utilities, both admitting at least one pure-strategy Nash equilibrium. The former represents a practical scenario with a high level of realism, although at a high computational price. The latter neglects some features of the real-world scenario but it exhibits very low complexity, and is shown to provide results that, on average, differ by 16% from those obtained with the former approach. Furthermore, when drivers value the trip time most, the average per-EV performance yielded by the Nash equilibria and the one attained by solving a centralized optimization problem that minimizes the EV trip time differ by 15% at most. This is an important result, as minimizing this quantity implies reduced road traffic congestion and energy consumption, as well as higher user satisfaction.**

I. Introduction

Any technology touted as environmentally-friendly is likely to have its place secured on news media around the globe. Among green solutions, Electric Vehicles (EVs), viewed by all as emission-free, clean and noiseless, are rapidly rising in popularity and expectations, also thanks to the predictable shortage of fossil fuel in the not-so-distant future. Indeed, EV mass-production and widespread adoption seem all but likely if some early hurdles are overcome, such as short driving range, lack of recharging infrastructure and long charging time.

Arguably, any road scenario in ten years' time will likely feature some ratio of EVs taking over the streets [1]. Old-fashioned gas pumps might also be gradually phased out by public charging stations, with electric outlets popping up in places such as curbside parking, parking lots and cab stands.

Even in this rosy scenario, one wonders when worries about vehicle range and availability of charging stations will be lifted and whether drivers will not be forced to plan their entire trip or commute around such availability, at least early on in charging station development. Finally, it is not clear when the "time consuming" tag will be removed from the task of car recharging.

Given the above concerns, ICT and Intelligent Transportation System (ITS) can step in and provide solutions that alleviate such concerns. Indeed, traditional navigation services could be integrated with the information provided by roadside network infrastructure and on-board user terminals through wireless communication [2], [3]. A Central Controller (CC) could collect information on the vehicular traffic conditions and on the occupancy status of the charging stations through ITS facilities. Then, EV drivers with low battery level could send a request to the CC and ask for advice on the specific charging station to choose and the route to take.

The key point in this scenario, however, is that drivers that resort to such a navigation service will very likely behave as self-interested users, who aim at finding the best trade-off between the trip time (including the time they have to stop at the charging station) and the charge/change price they pay at the station. Thus, they will follow the advice provided by the CC only if they find it advantageous to themselves.

In this work, we show that the advice provided by the CC may not conform to the interests of EV drivers when it is obtained by solving a centralized optimization problem that maximizes the average per-EV utility. We demonstrate instead that the above requirement is satisfied when the problem is modeled as a non-cooperative game. Specifically, we resort to a congestion game [4] and a game with congestion-averse utilities [5], where the players are the EVs with low battery level. EVs behave differently from ordinary players of ordinary games, in that they do not compute their strategy themselves, but rather follow the CC's advice. However, as explained below, the advice EVs received by the CC corresponds to the choice they would make themselves, had they all the necessary information.

In both congestion games and congestion-averse games, the decision to be made concerns the charging station that an EV should use, along with the route to take passing through such a station. The two game models exhibit a different level of realism and complexity; however, for both of them, we show that, when the CC uses the game solution to provide advice to the EVs, the following facts hold.

(i) The navigation strategies suggested by the CC correspond to Nash Equilibrium (NE) strategy profiles[1], i.e., each EV finds the suggestion by the CC advantageous to itself and is willing to adhere to it.

(ii) When drivers value their trip time most, the advice provided by the CC leads to an average per-EV trip time that is very close to the minimum obtained by solving a centralized optimization problem, and much shorter than the one the drivers can obtain by adopting a greedy approach (e.g., always select the closest or the least congested charging

F. Malandrino, C. Casetti, C.-F. Chiasserini and M. Reineri are with Politecnico di Torino, Torino, Italy. C.-F. Chiasserini is also a Research Associate at IEIIT-CNR (Institute of Electronics, Telecommunications and Information Engineering of the National Research Council of Italy).

[1]Recall that an NE is a game solution, in which no player can gain anything by unilaterally changing his own strategy.

station). This is highly desirable since, shortening the average per-EV trip time, contributes to reducing road congestion and energy consumption due to EVs.

The remainder of the paper is organized as follows. In Sec. II, we discuss previous work highlighting the novelty of our contribution. The system scenario is introduced in Sec. III, along with the statement of the problem under study. We motivate our work in Sec. IV, by showing that centralized optimal solutions may lead to advice that may not be followed by the EV drivers. The game-theoretic approach that we adopt for the problem solution can be found in Sec. V. In Sec. VI, we introduce the simulation scenario that we use to derive the results presented in Sec. VII. There, we show the low complexity of the proposed method and its excellent performance. The latter results are derived through the Simulation for Urban MObility (SUMO) tool [6] and using a real-world road topology. We draw our conclusions in Sec. VIII.

II. Related Work

Recently, both the academic and industrial communities have devoted a great deal of interest to EVs and to the use of ITS services in support of EV drivers. As an example, in [7] Ferreira et al. consider the case where the behavior of EV drivers, i.e., whether they drive to the closest or the cheapest charging station, depends on their profile (age or gender). The authors design a system that, through various communication technologies, provides EV drivers with several pieces of information, among which, the locations of charging stations. The burden of selecting the charging station, however, is left to the drivers, as the study of the trip time associated to different alternatives is not within the scope of [7].

An analytical model for the study of the EVs trip time is presented in [8]. The road topology is modeled as a graph whose edges are associated with a fixed, i.e., non traffic-dependent, waiting time. Charging stations are likened to multi-server queues, and a theoretical lower bound to the charging time is derived. The model, however, does not include the availability of a central controller and, unlike our study, it does not consider that vehicles may deviate from their originally-planned route in order to reach a suitable charging station. Thus, the study in [8] does not account for the EV travel time to and from a charging station. The presence of a central controller is considered in [9], [10], where the route of an EV is minimized while accounting for stop-overs at charging stations. A multi-objective decision-making model is also presented in [11], where the gas station selection depends on drivers' personalized requirements and gasoline price, and it aims at minimizing travel distance and refuelling price. In these works, however, individual EV routing and charging are optimized through standard techniques, and the effect of such decisions on each other is not taken into account.

The works in [12]–[20] are mostly concerned with the EV consumption and its impact on the power grid. Indeed, what is a *charging* station from the viewpoint of EVs is at the same time an energy *storage* station from the viewpoint of the power grid – a place where surplus energy, produced during low-demand periods, can be stored for later usage. In particular, in [14] the authors envision a central controller that predicts the EVs mobility and advises each EV about which charging station to use and when, so as to smooth the power consumption peak. The work in [14], however, accounts neither for the time that EVs may have to wait in line at the charging station, nor for the fact that EVs may act strategically. A fully-distributed mechanism is proposed in [16], which lets EVs select fast charging stations along a highway. The mechanism is based on a multi-agent approach and requires EVs to continuously interact in order to adapt to each others' individual decisions. The work in [17] proposes a family of algorithms that, by regulating the voltage fed to EVs using different charging stations, aim at minimizing the load factor, the load variance or the power losses over the grid. Similarly, the goal of [18] is to ensure that EVs can obtain the energy they need to recharge their batteries, without impairing the stability of the power grid. The work in [18] takes into account the behavior of EV drivers, but it aims at influencing it by means of monetary incentives. The study in [19] jointly addresses the optimal power flow and the EV charging problems. The authors show that the optimal power flow problem is generally non-convex and non-smooth, but it can be solved optimally using its convex dual problem for most practical power networks. In [20], the rate at which EVs charge is controlled so as to lead to a better utilization of the power grid. A rather different approach is followed in [21], in which vehicles are assumed to negotiate day-ahead charging schedules. The overall objective is to shift the load due to EVs to fill the overnight electricity demand valley. On a similar note, the work [22] looks at charging stations from the viewpoint of the power grid, viewing them as energy storage stations. The authors envision generating more energy when the demand is low, and storing it – under the guise of charged EV batteries – for usage during subsequent, high-demand periods. We remark, however, that the study of the impact of EVs on the power grid, although interesting, is not within the scope of our work. Indeed, properly accounting for such aspects as the integration of distributed power sources in the power grid, would require a totally different study [23].

The study in [24] focuses on estimating the battery discharge time. The trips of the EVs are modeled using real data and traffic statistics, and vehicles are assumed to use the closest available charging station. Again, the waiting time at the charging station and the fact that EV drivers may significantly deviate from their planned route to reach a station are neglected.

A game-theoretic approach is adopted in [25], whose main contribution is to provide an analytical framework that is suitable for capturing the interactions between charging stations and EVs. The latter are assumed to act in groups, and need to decide on their charging profiles. The problem is modeled as a generalized non-cooperative Stackelberg game, in which the charging stations act as leaders and the EV groups are the followers. With respect to this work, we account for the fact that EVs pursue a *trade-off* between charge price and trip time, and that such a trade-off can be vehicle-specific.

At last, we mention that in [26], we presented a preliminary work that investigates *which* information is important that

EV drivers receive through ITS. In particular, we showed the benefit of transmitting specific suggestions to EV drivers on which charging station to use with respect to the case where only mere updates on traffic conditions and charging station occupancy are provided. The evident advantages brought by specific advice motivated our present work, which is concerned about *how* such advice should be determined. A sketch of this work with a few preliminary results has been included in [27].

III. System Scenario and Problem Statement

We consider a road topology including a set of *road segments* $\mathcal{L}$ and a set of *charging stations* $\mathcal{C}$. Any ordered sequence of adjacent segments $l \in \mathcal{L}$ is said to form a *route*. Among all vehicles that travel across the topology, we identify the following three categories:

(i) non-EVs or EVs with medium-high battery level, which are not interested in using a charging station;
(ii) EVs whose battery is low, but that will not resort to the navigation service to identify the charging station;
(iii) EVs with low battery that use the navigation service to select a charging station.

Note that the vehicles in the first category just contribute to the traffic intensity over the roads, while those in the last two categories contribute both to the intensity of vehicular traffic and to the occupancy of the charging stations. Furthermore, the fact that vehicles start looking for a charging station when their battery level becomes low, implies that they will all have (approximately) the same battery level. We account for all these types of vehicles and their influence on the effectiveness of our solution in Sec. VII.

Upon stopping at a charging station, the battery of the vehicle will be *replaced* with a fully-charged one. This is due to the comparatively long charge times in both current and (conceivably) future technologies [28]. In this case, the charging station also represents an energy storage station as defined in Sec. II. Our model also accounts for the fact that there may not be fully-charged batteries at a station. In this case, the battery is recharged, in a time which is assumed to be constant and equal to half an hour [28]. Assuming a constant recharge time does not account for the fact that different vehicles may have different battery capacity and arrive at the station with different battery levels. However, since batteries are replaced in virtually all cases, the impact of this assumption on our results is negligible. Charging stations have a number of replacing stalls (hereinafter servers), possibly varying from one station to another. Clearly, upon reaching a charging station, an EV incurs a waiting time that depends on the occupancy of the station, the service time, the number of fully-charged batteries available and the number of servers.

Next, we focus on EV drivers that belong to the last category, i.e., they have got a low battery level and resort to the navigation service. As mentioned, such EVs can be considered as self-interested (or, rational) users. Specifically, we assume that *their goal is to pursue a (possibly, user-specific) trade-off between the trip time and the charge price.* This translates into assuming that drivers consistently act in order to pursue such an objective – as opposed to, e.g., driving to the charging station they like better, or to the one where they can collect bonus points or miles.

In the most general case, such EV drivers may be able to reach a number of possible charging stations and, for each of them, they may choose among multiple, different routes. Therefore, they will ask the advice of the CC to make a decision on the charging station to use and the route to take, including their current position and final destination in the request. It is fair to assume that the CC has knowledge of the road topology, the traffic conditions, as well as the locations of the charging stations, their current occupancy and availability of fully-charged batteries. Also, the CC can collect information on the position, speed and heading of cars through a real-time traffic monitoring system, such as those currently implemented by recent navigation solutions [2], [29]. How the CC gathers the information is an orthogonal problem with respect to ours; in general, secure positioning schemes [30] could be employed to make sure that vehicles do not lie about their positions. Based on the collected information, the CC indicates to the EVs which station to use and the route to take. Upon receiving a response from the CC, all rational EVs that made a request will be willing to follow the suggestion of the CC if they find it advantageous, even if they have to deviate from their original route to reach the charging station suggested by the CC. Note that EV drivers that are not rational, and eventually decide not to adhere to the received advice, fall into the second of the categories mentioned at the beginning of this section.

IV. Why a Game Model?

A natural choice to solve the problem of selecting the charging station for each EV, and the corresponding route, would be to let the CC formulate an optimization problem that maximizes the EV utility, defined as a function of its trip time and the charge price[2] the driver has to pay. However, it is easy to show that in general such an approach yields solutions that EV drivers may find not advantageous to themselves, hence to which they will not adhere. The same observation holds in the case where the CC tries to maximize the minimum EV utility.

As an example, consider the EV utility to be represented by its expected trip time only, and let us focus on the toy scenario depicted in Fig. 1, where there are two charging stations, c_a and c_b, both with one idle server and service time equal to 2 time units. Assume that, at the same time, two EVs, v_1 and v_2, have low battery and ask for the help of the navigation service to select the charging station to use. EV v_1 can reach either c_a or c_b, but its travel time toward the two stations is 2 and 1 time units, respectively, while from both stations to its final destination, d_1, the travel time is equal to 1 time unit. EV v_2 instead can only[3] head toward c_b, with travel time equal to 1.5 time units, and from there it can reach its destination d_2 in 1 time unit.

It is easy to verify that, if the CC provides its advice to the EVs so as to minimize either the average per-EV trip time or

[2]In the following, we indicate by *charge* place the price that drivers have to pay to obtain a fully charged battery, whether by replacing or recharging their one.

[3]Indeed, v_2 could travel to c_b, then to the location of v_1, and from there to c_a, but such an option is clearly dominated by choosing c_b (see Tab. I).

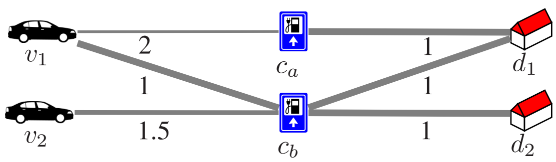

Fig. 1. A toy scenario.

the maximum EV expected trip time, then the solution is: v_1 heads to c_a while v_2 uses c_b. This would indeed lead to an average per-EV trip time and a maximum EV expected trip time equal to 4.75 and 5 time units, respectively[4]. However, v_1 will not find the advice of the CC advantageous since, by heading to c_b, it would incur a total trip time of 4 time units, against the trip time of 5 time units it would experience by following the suggestion of the CC. Thus, v_1 will ignore it.

Based on the above observation, we propose a different approach. We model the problem of selecting the charging station, and the corresponding route, as a non-cooperative game, which the CC solves considering as players the EVs that use the navigation system for advice. Then, we look for a strategy profile that is an NE and is advantageous from the viewpoint of the system performance, and we take this as a solution to the problem. Since in this case the advice by the CC corresponds to an NE, there is no alternative choice for an EV that leads to a shorter time to destination, hence self-interested drivers will adhere to it. For instance, in the example above, the CC will suggest to both v_1 and v_2 to use c_b, and no one will deviate from the advice of the CC. It is clear, however, that a game-theoretic approach does not ensure that the average per-EV trip time is minimized (e.g., in the above toy scenario it increases from 4.75 to 5 time units)[5]. Nevertheless, in Sec. VII we show that, even in real-word scenarios, the average per-EV trip time obtained through our game-theoretic approach is remarkably close to the optimum.

In summary, it is worth stressing that vehicles do not compute any Nash equilibrium themselves. It is the task of the CC to issue suggestions that correspond to the most rational action of each vehicle– even if this comes at some cost in terms of global optimality, as in the above example. Also, we remark stress that the game could be solved by the EVs themselves, provided that they have the required information. In our case, however, we take a practical perspective and consider that it is the CC that collects all the information, processes it and solves the game so as to provide the EV drivers with the strategy to adopt (i.e., the charging station to use and the route to take). This implies that the proposed mechanism neither significantly increases the system overhead due to communication protocols, nor requires EV drivers to exchange sensitive information about themselves, or make any computation to make a decision.

TABLE I
TRAVEL PLUS WAITING TIMES IN THE TOY EXAMPLE

v_1 \ v_2	c_a	c_b
c_a	$(5, 9.5)$	$(5, 4.5)$
c_b	$(4, 9.5)$	$(4, 6)$

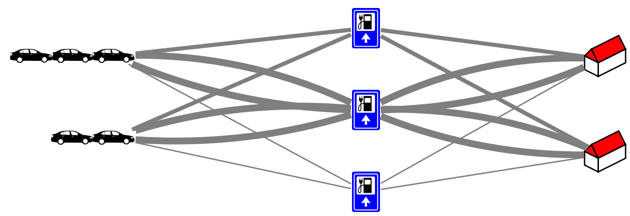

Fig. 2. Abstract representation of the vehicular scenario where each EV may take several different routes to a given charging station and from there to its intended destination.

V. THE RECHARGING GAME

We now detail the game models we use to solve the recharging problem in the system scenario described in Sec. III. Assume that the CC processes the requests received from EVs with low battery every T seconds. We denote the set of EVs that ask for advice during a T-second time period by $\mathcal{N}$, and its cardinality by N. The vehicles that resorted to the advice of the CC in the previous time periods are not considered as players (e.g., because they do not change their choice), but their impact on charging times is taken into account by the CC. Consider the most general case in which each of the N EVs may reach several charging stations and take different routes to arrive at a given station, as well as to go from there to its final destination. For clarity, we depict an abstract representation of such a scenario in Fig. 2; we will deal with a real-world road topology and realistic vehicular mobility while deriving the performance results in Sec. VII.

In the figure, lines connecting vehicles with charging stations, and the latter with final destinations, represent the possible road segments that EVs can take to or from the charging station. The different thickness of the lines denotes the fact that road segments may be characterized by various levels of traffic intensity, hence they may imply different travel times. Clearly, in a more general setting, road segments may end at any intersection on the map, other than a charging station or an entry/destination point.

We then consider the N EVs to be the players of a congestion game [4] (solved by the CC), i.e., a non-cooperative game, in which players strategically choose from a set of facilities and derive utilities that depend (in an arbitrary way) on the congestion level of each facility, i.e., on the number of players using it. Congestion games are of particular interest to us since they have been proved [4] to admit at least one pure-strategy[6] NE. Thus, if the CC derives its advice by modeling

[4]If v_1 uses c_a, its trip time is 2+2+1=5 time units, while the trip time of v_2 is 1.5+2+1=4.5 units. This results in an average per-EV trip time of 4.75 and a maximum EV expected trip time of 5. If instead v_1 heads toward c_b, it arrives there first and its trip time becomes 1+2+1=4 units, while v_2 finds the station server occupied by v_1, thus its trip time increases to 1.5+1.5+2+1=6. It follows that the average per-EV trip time and the maximum EV expected trip time become 5 and 6 time units, respectively.

[5]In game theory, this concept is related to the price of anarchy (PoA), which is defined as the ratio of the average per-EV trip time at the equilibrium to the optimal one.

[6]A pure-strategy NE is a deterministic solution, as opposed to a probabilistic one (e.g., go to charging station c_x, rather than go to c_x with probability 0.5).

$$\eta_c(n_c) = \begin{cases} \sigma & \text{if } \overline{w}_c < \min\{S_c, B_c\} \\ \rho & \text{if } B_c \leq \overline{w}_c < S_c \\ (1-\overline{\phi})\sigma + \left\lfloor \frac{\overline{w}_c - S_c}{S_c} \right\rfloor \sigma + \sigma & \text{if } S_c \leq \overline{w}_c < B_c \\ (1-\overline{\phi})\sigma + \left\lfloor \frac{B_c - S_c}{S_c} \right\rfloor \sigma + \left\lfloor \frac{\overline{w}_c - B_c}{S_c} \right\rfloor \rho + \rho & \text{if } S_c \leq B_c < \overline{w}_c \\ \frac{B_c}{S_c}\sigma + \frac{S_c - B_c}{S_c}(1-\overline{\psi})\rho + \left\lfloor \frac{B_c - S_c}{S_c} \right\rfloor \sigma + \left\lfloor \frac{\overline{w}_c - B_c}{S_c} \right\rfloor \rho + \rho & \text{if } \overline{w}_c \geq B_c \wedge B_c < S_c \end{cases} \quad (2)$$

the system as a congestion game and finding a solution that is an NE, then all rational, self-interested EVs will follow the advice.

A. The Congestion Game

Congestion games [4] are games where the utility of a player depends on (i) the resources she chooses to utilize, and (ii) how many other players choose to utilize those resources. For these games, we are guaranteed [4] that at least one pure-strategy Nash equilibrium exists.

A congestion game is defined by the 4-tuple

$$\Gamma = (\mathcal{N}, \mathcal{F}, \{\mathcal{S}_i\}, \{\tau_l(n_l), \eta_c(n_c)\}) \ , \quad (1)$$

whose elements in our case are as follows.

(a) The set of players, $\mathcal{N} = \{v_1, \ldots, v_N\}$, which, as mentioned, correspond to the EVs using the navigation service and that have asked for the advice of the CC during the past T seconds.

(b) The set of facilities, $\mathcal{F}$, which is composed of all possible charging stations and road segments included in the road topology, i.e.,

$$\mathcal{F} = \mathcal{C} \cup \mathcal{L} = \{c_a, c_b, \ldots l_1, \ldots\}.$$

Given $\mathcal{F}$, for each player $i \in \mathcal{N}$, a subset $\mathcal{F}_i \subseteq \mathcal{F}$ can be identified, including all facilities that EV i can reach and use on its way to the destination. Clearly, if the road topology is fully connected, then $\mathcal{F}_i = \mathcal{F}$, $\forall i \in \mathcal{N}$. Note that considering the road segments l_i allows us to account for driver-spcific travel times.

(c) Denoting by $\mathcal{P}(\mathcal{F}_i)$ the set of all possible partitions of $\mathcal{F}_i$, $\mathcal{S}_i \subseteq \mathcal{P}(\mathcal{F}_i)$ is the set of viable strategies for EV i, i.e, all groups of facilities that can be used by i. In our context, each strategy in $\mathcal{S}_i = \{\{c_a, l_{ia}, l_{ai}\}, \{c_b, l_{ib}, l_{bi}\}, \ldots\}$ is composed of:

- (i) one of the charging stations that EV i can reach, along with
- (ii) the road segments forming a route that allows i to go from its current position to the selected charging station (for brevity, indicated as $l_{ia}, l_{ib}, \ldots$), and from there to its final destination (for brevity, indicated as $l_{ai}, l_{bi}, \ldots$).

(d) For each strategy, there is a cost to pay for each facility that is used (either a charging station or a road segment). Such a cost is defined as a function mapping the number n_f of players selecting the facility f onto a time value in $\mathbb{R}$. Note, however, that congestion games are characterized by the so-called anonymity property, i.e., the facility cost cannot on depend the players identity. In our context, we therefore define the cost of a strategy as the sum of 1) the waiting time and the service time at the corresponding charging station incurred by the generic player, 2) the expected travel time on the associated route, from current road segment to destination, via the charging station, and 3) the charge price π_c at the selected station, multiplied by the equivalence factor K (expressed in hour/\$) representing how much EV drivers value their time with respect to money. We denote the first contribution by $\eta_c(n_c)$, with $c \in \mathcal{C}$ and n_c being the number of players selecting station c, while we denote the second contribution by $\sum_l \tau_l(n_l)$, with the l's being the road segments in the chosen route and n_l the number of players taking segment l. Thus, the total cost for the strategy, corresponding to the selection of charging station c, can be written as:

$$\eta_c(n_c) + \sum_l \tau_l(n_l) + K\pi_c,$$

and each player will aim at minimizing such a cost. In accordance with the scenario detailed in Sec. III, we write $\eta_c(n_c)$ so as to account for (a) the number of servers at station c, S_c, (b) the service time, (c) the number of fully-charged batteries currently available at c, B_c, and (d) the waiting time before an EV can be served. The quantity $\overline{w}_c$ that appears in the last three lines of (2), however, deserves a more detailed explanation.

Before we can write the expression of $\eta_c(n_c)$, we need to study the expected number of EVs that the generic player finds at the charging station upon its arrival. This is because the anonymity property of congestion games forbids player-specific utilities and payoffs. Such a value is given by

$$\overline{w}_c = \overline{m}_c + \overline{q}_c + n_c \quad (3)$$

where:

$\overline{m}_c$ is the expected number of *non-player* EVs that the CC estimates to be already at the station upon the arrival of the generic player;

$\overline{q}_c$ is the expected number of EVs that took part in the previous rounds of the game and that the CC estimates to be at the station upon the arrival of the generic player (this includes the players that selected c in one of the previous rounds but have not reached it yet);

n_c is the number of player EVs selecting station c at the present round.

The first two terms are overlined because they represent the *expected* number of EVs that a generic player will find before her in line[7]. Also, we remark that, since none of the

[7] The fact that the payoffs of our games include expected values is consistent with the fact that deterministic utility functions can include probabilities and expected values [31, Ch. 1].

above quantities depends on the player identity, our definition complies with the anonymity property of congestion games.

The price that we pay, in terms of realism, to comply with such a property is twofold:

- the number of waiting player vehicles $\overline{q}_c$ does not include the ones of the current round, and
- utility functions cannot account for the fact that different players may value their time differently.

As will be shown in Sec. V-B, we will be able to remove both assumptions by switching to a CAG model.

Finally, note that the term $\overline{q}_c$ represents the link between subsequent rounds of the game, and that the $\overline{w}_c$ and $\overline{q}_c$ can be acquired by the CC through the ITS, by exploiting services similar to those currently implemented by recent navigation solutions [2], [29]. We study the impact of errors in such an estimation in Sec. VII.

We are now able to write $\eta_c(n_c)$ as shown in (2). In (2), we assume all players to select the server with the shortest queue. The parameters σ and ρ are the time necessary for battery replacement and battery charging, respectively; for simplicity, we assume them to be constant[8]. Also, $\overline{\phi}$ and $\overline{\psi}$ represent the (estimated) remaining fraction of, respectively, replace and recharge time for the vehicle now being served at the selected station.

The first and second line of (2) correspond to the case where the generic player finds an idle server, hence its stopping time at c coincides with the time necessary for battery replacement, σ, if there is any fully-charged battery available, or with the battery charge time, ρ, otherwise. The third line, instead, represents the case where all servers are busy and the tagged player is able to replace her battery with a fully-charged one. The last two lines apply when the fully-charged batteries are not enough for the vehicles waiting at the station, hence the batteries of the vehicles arriving after the B_c-th are not replaced but charged, in a time ρ. In particular, the different expressions reported in the two lines account for the cases where the available fully–charged batteries are, respectively, more and less than the servers at the charging station.

To summarize, we report the game elements in Tab. II. As mentioned, it has been shown in [4] that congestion games admit at least one pure-strategy that is an NE. However, finding the NE for one-shot games[9], such as ours, is NP-hard [32]. In order to lower the level of complexity, below we introduce a new game, namely, a game with congestion-averse utilities.

[8]Considering ρ to be a constant is a fair assumption as it is conceivable that EVs resort to the CC advice only when their battery is low; hence, differences in the EVs battery level can be neglected.

[9]Equilibria for congestion games in which players subsequently make their moves can instead be found in polynomial time [33].

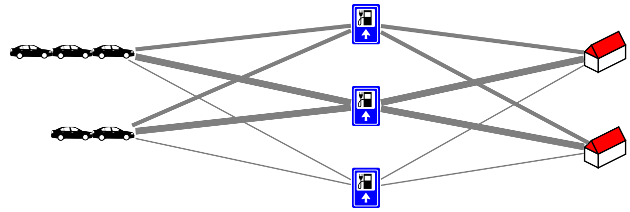

Fig. 3. Abstract representation of the vehicular scenario where for each EV there is only one possible route toward a given charging station, and from there to its intended destination.

B. Game Model with Congestion-averse Utilities

Games with congestion-averse utilities [5] are a variant of congestion games, where utility functions can depend upon the identity of the player – and not only upon their decisions, as in congestion games. As shown in [5], these games (i) admit at least one pure-strategy Nash equilibrium, and (ii) such equilibrium can be found in polynomial time.

Let us now consider the same scenario as above, but assume that, for every EV-charging station pair, there exists only one possible route to take, as depicted in Fig. 3. We stress that, although simpler, such a model is still realistic if, for the current strategy, the CC associates to each EV-charging station pair the route deemed to be the fastest one, based on its recent estimates. Indeed, such a route, dynamically selected depending on the current road traffic status, is likely to be the most advantageous to the EV, hence neglecting the others will not lead to significantly worse performance. This is also confirmed by our results derived in real-world scenarios, shown in Sec. VII.

Under the above assumption, the system can be modeled as a game with congestion-averse utilities (CAG), for which NEs are pure-strategies and can be found in polynomial time [5]. The game is defined as a 4-uple similar to Γ, as in (1), however, two main differences exist between CAGs and congestion games:

- in CAGs, it must hold that $\mathcal{S}_i = \mathcal{P}(\mathcal{F}_i), \forall i \in \mathcal{N}$, i.e., all partitions of $\mathcal{F}_i$ are possible strategies, and
- the costs of the facilities can depend on player identities.

The first difference implies that, for each player i, the CC has to consider as viable strategies not a subset but all possible partitions of $\mathcal{F}_i$. A set $\mathcal{F}$ defined as in the case of the congestion game would force the CC to consider non-meaningful strategies where an EV stops at more than one charging station, located either on the same route or on different routes. In order to overcome this issue, as a first step we redefine the set of facilities as $\mathcal{F} = \mathcal{C}$, i.e., we remove the road segments and consider only the charging stations. It

TABLE II
COMPARING CONGESTION GAMES VS. CAGS

	Players	Facilities	Strategies	Strategy Cost
Congestion game	$\mathcal{N}$	$\mathcal{F} = \mathcal{C} \cup \mathcal{L}$	$\forall i \in \mathcal{N} : \mathcal{S}_i = \{\{c_x, l_1, \ldots, l_m\}_x\}$ s.t. $c_x \in \mathcal{C}$ is reachable by i, and $\{l_i\}_{i=1\ldots m} \in \mathcal{L}$ form a route from current i's segment to dest., through c_x	$\eta_c(n_c) + \sum_l \tau_l(n_l)$ (sum over l's $\in$ route)
CAG	$\mathcal{N}$	$\mathcal{F} = \mathcal{C}$	$\forall i \in \mathcal{N} : \mathcal{S}_i = \{\{c_x\}_x, \{c_x, c_y\}_{x,y}, \{c_x, c_y, c_z\}_{x,y,z}\}$ s.t. $c_x, c_y, c_z \in \mathcal{C}$ and reachable by i; $\overline{\mathcal{S}}_i = \{\{c_x\}, \{c_y\}, \{c_z\}\}$	$\eta_c(n_c^{(i)}) + \tau_{i,c}$ (depends on player id)

follows that the set of facilities that the generic player i can use, $\mathcal{F}_i$, is now given by just the charging stations that the EV can reach. This is a viable choice since, per the initial assumption in this subsection, each EV-charging station pairs is implicitly, and univocally, associated to one route only. As a second step, we prove the lemma below.

Lemma 1: Consider the game with congestion-averse utilities introduced above, in which each facility has a cost greater than 0. Then, in order to identify a pure-strategy NE, for any player $i \in \mathcal{N}$ it is sufficient to examine the subset of viable strategies $\overline{\mathcal{S}}_i \subseteq \mathcal{S}_i$, such that each strategy in $\overline{\mathcal{S}}_i$ includes one facility only.

Proof: Players are self-interested and aim at finding an optimal trade-off between trip time and charge price. Recall that costs are positive, thus selecting more than one facility (i.e., charging station) leads to an increased overall cost. A player will therefore always deviate from a strategy profile that makes her use more than one facility. Thus, in order to find an NE, it is enough to consider as viable strategies the ones that imply the use of one facility only. ∎

Based on the above result, we can limit our attention to the set of strategies $\overline{\mathcal{S}}_i$, which includes only partitions of $\mathcal{F}_i$ with cardinality equal to 1, and each of them corresponding to only one of the charging stations that EV i can reach.

Next, we leverage the second difference between CAGs and congestion games, i.e., the fact that in CAGs utilities can depend on the player identity. In particular, we define the cost of a charging station c, which can be used by player i, as the total trip time i would incur, and we write it as:

$$\eta_{i,c}(n_c^{(i)}) + \tau_{i,c} + K_i \pi_c \,. \tag{4}$$

In (4), the first term is the sum of the delay due to the estimated waiting time and the charging time at station c, while the second term is the travel time through the route associated to the EV-charging station pair (i, c). Note that all the terms in (4) depend on the player identity i, including K_i. It follows that, unlike the congestion game described above, the CAG formulation can account for *player-specific* trade-offs between trip time and charge price, i.e., for the fact that players may value time differently with respect to money. Furthermore, the following remarks hold.

(a) $\eta_{i,c}(n_c^{(i)})$ can be obtained from (2) by replacing ρ with ρ_i, and $\overline{w}_c$ with

$$w_c^{(i)} = m_c^{(i)} + q_c + n_c^{(i)} \,. \tag{5}$$

Indeed, the recharging time ρ_i may be different from one player to another, and depend on the remaining battery charge of the EV. Also, the terms in (5) are not averaged over the players $i \in \mathcal{N}$, but estimated with reference to the position and route of i, as now the CC can account for the number $m_c^{(i)}$ of non-player EVs that it estimates to be at the station upon the arrival of player i. Similarly, $q_c^{(i)} + n_c^{(i)}$ is the number of players, respectively, of the previous rounds and of the current one, that the CC estimates to arrive at c before player i does.

(b) The travel time $\tau_{i,c}$, associated to the EV-charging station pair (i, c), does not depend on $n_c^{(i)}$, as it now accounts for the vehicular traffic intensity due to all non-player vehicles only. The impact of such an approximation is very limited since typically the number of players, i.e., the number of EVs with low battery that ask for advice in a time period T, is much smaller than the number of all other vehicles traveling over the road topology (see also the results in Sec. VII). This approximation represents the price we have to pay for the lower complexity of the CAG model with respect to the CG one.

The elements of the CAG are summarized in Tab. II. By comparing the elements above to the ones of the congestion game (Sec. V-A), we observe three important aspects. First, the facilities $\mathcal{F}$ in the CAG correspond to the charging stations, as road segments are not taken into account. Second, in the CAG, the sets $\mathcal{S}_i$ of possible strategies correspond to the possible subsets $\mathcal{P}(\mathcal{F}_i)$ of reachable facilities, including the non-viable ones like $\{c_a, c_b\}$. Third, such dominated strategies are discarded by moving to the sets of non-dominated solutions $\overline{\mathcal{S}}_i$ which, by Lemma 1, only includes subsets of $\mathcal{F}_i$ with cardinality one.

As mentioned, in the case of CAGs, pure-strategy NEs can be found in polynomial time [5], thus the CC can solve the game with low complexity. Below, we evaluate the number of strategies that the CC has to process before an NE is found and the social utility corresponding to such an NE, i.e., how good the NE is from the system performance viewpoint. We also show that, in spite of its low complexity, the CAG model approximates very well the previous scenario where multiple routes may exist for any EV-charging station pair.

VI. Simulation Scenario

In order to show the benefits that can be obtained through our game-theoretic approach, we use a real-world road topology representing a 3×2 km^2 section of the urban area of Ingolstadt, Germany [34], depicted in Fig. 4. The vehicle mobility has been synthetically generated using the SUMO simulator [6], with a time granularity of 0.1 s. The mobility trace is representative of 60-minute-long road traffic and of average traffic intensity in the area. We stress that we preferred a synthetic trace over real-world ones, e.g., taxi or bus traces, since these only include a small portion of car traffic and the represented vehicles have predetermined routes that cannot be changed. Arguably, using synthetic mobility over a real topology allows us to fine-tune such parameters as the number of vehicles and players. The number of vehicles simultaneously present in our road topology is a varying parameter of the system, and the average vehicle trip time clearly depends on such a value.

The scenario includes 6 charging stations, which are placed on the main arteries of the road topology, as portrayed by the red dots in Fig. 4. The number of servers at each station may vary; namely, two stations have 2 servers, other two have 6 servers and the remaining ones have 4 and 10 servers each. We assume that the time to replace a battery with a fully-charged one is equal to 3 minutes, while the battery recharging time is 20 minutes. Unless otherwise specified, we assume that the fully-charged batteries available are enough to serve all EVs resorting to the navigation service in a time period

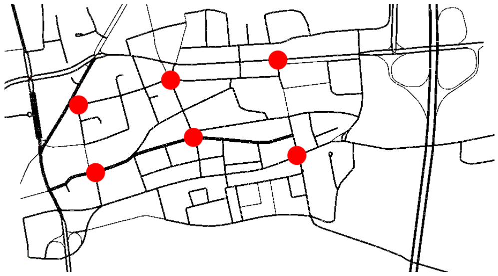

Fig. 4. Road topology: red dots highlight the six charging stations.

T. Also, unless otherwise specified, we keep charge prices constant at $\pi_c = 10$ \$ per charge, and $1/K_i = 15$ \$$/hour$. The latter figure roughly corresponds to the minimum wage in the U.S., which could represent a lower bound for the value an EV driver may give to her time (at least in popular culture [35]).

Without loss of generality, all vehicles are assumed to be electric. The average number of EVs that resort to the navigation service is a varying parameter in our simulations. The time instant at which an EV finds itself in need of a charged battery and asks the CC for advice is uniformly distributed over its trip time, i.e., the time interval since the EV enters the road topology till it leaves. Notice that in practice this time corresponds to the moment when the battery level is medium, rather than low, as suggested by manufacturers in order to improve battery life.

The navigation service is provided via the cellular network, through which an EV may issue a query to and receive a response from the CC without significant delay. However, alternative solutions exploiting 802.11p-based roadside units could be considered as well. As for the CC, we consider that information on the number of EVs currently waiting at a charging station to be served, as well as on the traffic conditions, is acquired and processed every 10 seconds. The requests for the navigation service sent by the EVs are instead processed by the CC every $T = 60$ s. Such an interval is sufficiently short, so that, even if impatient, vehicles will wait for the suggestions of the CC. Also, even if in general low values of T imply a high correlation between game rounds, we properly account for such a correlation in (3) and (5).

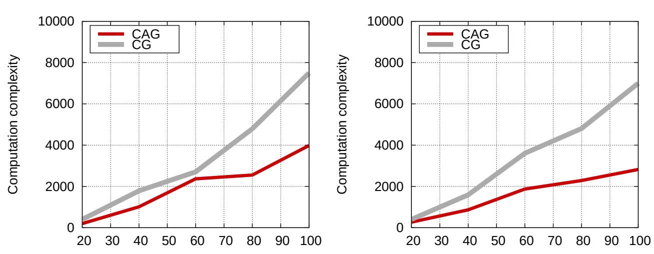

Fig. 5. Average computational complexity vs. number of players, when they are 20% (left) and 60% (right) of all vehicles. CAG and congestion game (CG) are compared.

VII. Results

We now show the performance that is attained through our approach, and compare it to the results obtained when a centralized optimization problem is solved at the CC as well as when a greedy selection of charging station and route is adopted. In order to derive the results in the cases where the CC generates its advice from the solution of the CAG or of the congestion game (labelled as CG in the plots), we proceed as follows. Every time interval T, the CC solves the game considering as players the EVs from which it has received a request. To do so, the CC starts from a random strategy profile, i.e., a random assignment of the facilities to the players. In the case of the congestion game, it assigns both the charging station and the corresponding route, while in the CAG, it assigns only the charging station and associates to each player-charging station pair the fastest route that takes the EV from its current road segment to the station, and from there to its destination. Player payoffs (i.e., trip times) are then computed through SUMO in the scenario described in Sec. VI. To derive the trip times, we assume that every non-player vehicle takes its originally-planned route, while players will conform to the advice of the CC, hence they will follow the suggested route.

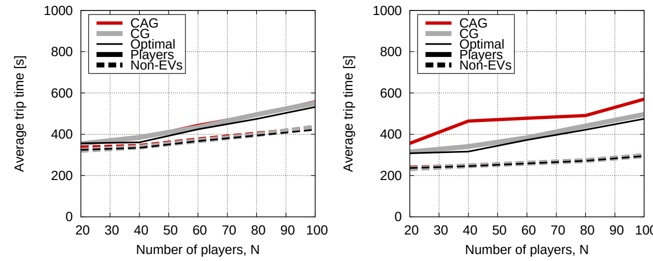

Fig. 6. Average per-EV trip time as a function of the number of players, when they represent 20% (left) and 60% (right) of all vehicles. CAG and congestion game (CG) are compared against the optimal, for both player and non-electric vehicles.

Given the current strategy profile and player payoffs, the CC examines other strategies according to the solution algorithm in [5] for the CAG, and to the one in [31, Ch.7] for the congestion game. For every strategy, player payoffs are computed via SUMO as before. If a more profitable strategy is found for any of the players (i.e., if any of the players could deviate from the previous strategy), then the new strategy is adopted and the whole procedure is repeated until an NE is reached.

Unless otherwise specified, we consider that the CC takes the first NE it finds as the solution of the game. While subsequent equilibria could in principle be better, we found that in practical cases all the equilibria found for the CG yielded virtually the same payoffs. Using different starting solutions, e.g., assigning to each player the closest station or a station at random, did not influence the quality of the solution but only the convergence time, i.e., the number of iterations needed to find it.

For both the CAG and the congestion game, we evaluate the computational complexity, i.e., the number of strategies that the CC has to examine before reaching the game solution, which also corresponds to the number of SUMO runs. Then, we calculate the per-player trip time associated to such a solution. All results are averaged over 10 runs. We compare such values with the trip time obtained through the techniques described below.

Optimal: the solution that the CC can obtain by minimizing the trip time averaged over all EVs that ask for advice. This solution in general is not an NE, thus it may not be followed by rational drivers.

Greedy: the CC only disseminates information on the road travel time, and on the occupancy and the charging time at stations. Based on this knowledge, each EV independently makes its own decision by selecting the charging station and the route that are deemed to minimize its own trip time. Note that, in this case, the CC just informs the EVs without providing any advice, and the EV decision is taken disregarding the presence of other vehicles looking for a charging station.

Now, let us initially neglect the presence of non-rational drivers and of EVs with low battery whose drivers do not use the navigation service. Fig. 5 depicts the number of strategies that the CC has to examine before the solution to the game is found, for both the CAG and the congestion game (CG). We stress that the CC returns its advice to EV drivers only once the game solution (which is a pure-strategy NE) has been reached, thus the computational burden is solely carried by the CC. The two plots in the figure refer to the cases where the average number of EVs that are low in battery and ask for advice (i.e., players) is, respectively, 20% and 60% of the average total number of vehicles simultaneously present in the road topology.

As expected, the complexity of the congestion game is always higher than that of the CAG and, in both cases, it increases as the number of players grows. In particular, for our range of player numbers, the CC always examines less than 4000 strategies before finding the solution in the case of the CAG, and less than 8000 in the case of the congestion game. We remark that one SUMO run only takes a few seconds, hence simulation time is manageable.

The plots also provide a striking comparison between the CAG and the congestion game. While the complexity of the former remains remarkably low, the complexity of the latter increases severely as the number of players grows beyond 60. On the contrary, the total number of EVs in the road topology has just a marginal impact on both the CAG and the congestion game solution time. These results indicate that the CAG model is highly scalable, hence it can be successfully applied even to very large, crowded system scenarios.

Next, one may wonder whether the solution obtained through the CAG is as good as the one of the congestion game, or if the gain in complexity we have with the CAG takes a high toll in terms of system performance. To answer this question, in Fig. 6 we show the average vehicle trip time, for both player and non-electric vehicles, again as the number of players is 20% and 60% of the total number of vehicles. The performance corresponding to the solutions of the two games are also compared to that of the optimal solution.

The figure shows that the average trip times of player and non-electric vehicles have the same qualitative behavior, with the former clearly being higher than the latter since players stop at a charging station during their trip. Also, comparing the two plots, it can be seen that the smaller the total number of vehicles simultaneously present in the road topology, the lower the traffic intensity and the shorter the average per-EV trip time. As for the comparison among the CAG, the congestion game and the optimal, the difference in performance can be barely noticed when the players are 20% of the total number of EVs (left plot of Fig. 6). When the percentage of players is large (right plot), the difference with respect to the optimal is limited in the case of the CAG, and it is again unnoticeable for the congestion game. This indicates that neglecting the contribution of player EVs to the travel time makes the CAG model less precise only when players represent the majority of vehicles on the road topology.

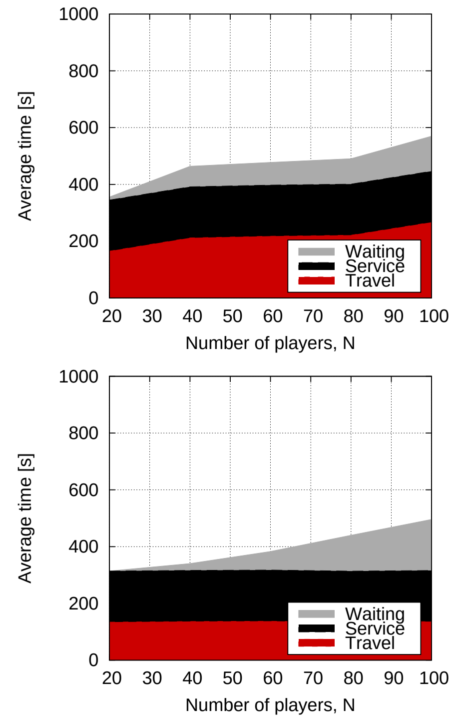

Fig. 7. Trip time breakdown for the CAG (top) and congestion game (bottom), when players are 60% of the total number of vehicles.

Fig. 7 confirms such an observation. The figure highlights the different contributions to the average per-player trip time, due to the waiting time at the charging station, the service time (which is constant) and the travel time. The results refer to the CAG (top plot) and to the congestion game (bottom plot), when the players are 60% of all vehicles. It can be seen that the difference between the two game models mainly resides in the travel time, which is higher when the CAG solution is adopted.

Fig. 8 depicts the 10th (dashed line) and the 90th (solid line) percentiles of the per-player trip time, when players are 20% (top) and 60% (bottom) of all vehicles. In the case of the 10th percentile, the difference, among the solution of the CAG, that of the congestion game and the optimal, can be barely detected. As for the 90th percentile, it can be observed that, when the optimal solution is adopted, a fraction of player EVs may experience a significantly longer trip time than under the congestion game or the CAG. This suggests that applying the optimal solution may lead to higher unfairness in the user

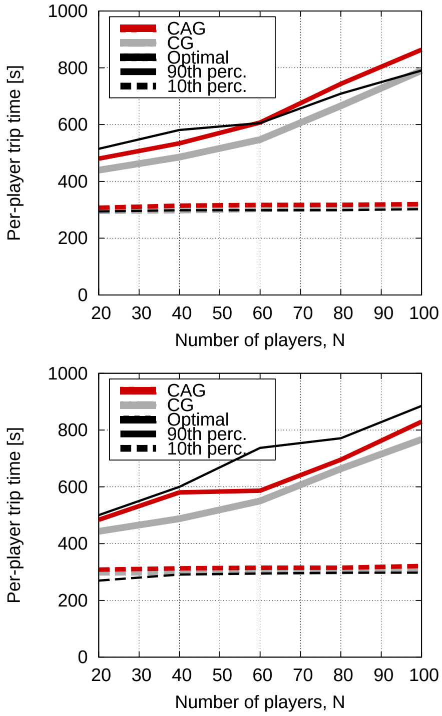

Fig. 8. CAG, congestion game and optimal: 10th and 90th percentile of the per-player trip time, vs. number of players, when they are 20% (top) and 60% (bottom) of all vehicles.

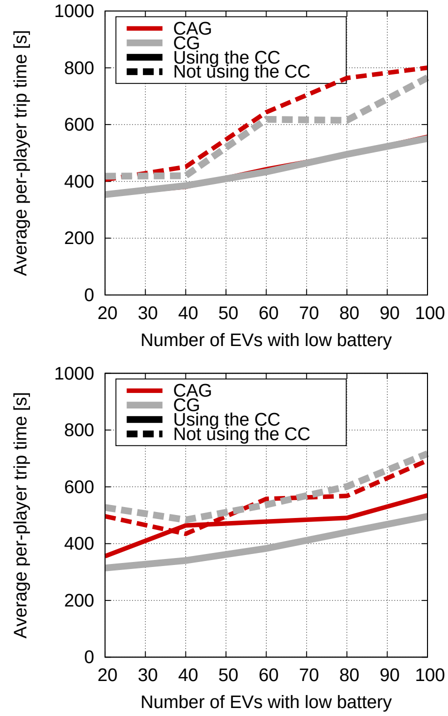

Fig. 10. Average trip time vs. number of EVs with low battery, when they are 20% (top) and 60% (bottom) of all vehicles. Comparison between EVs that resort and those that do not resort to the advice of the CC.

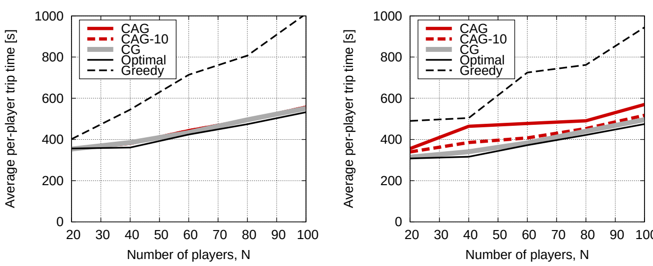

Fig. 9. Average per-player trip time vs. number of players, when they represent 20% (left) and 60% (right) of all vehicles. Comparison among CAG, congestion game, optimal, and greedy. CAG-10 indicates that the CC takes as a solution of the game the best among the first 10 NEs it finds.

performance. Intuitively, this lack of fairness is connected to the fact that some users will deviate from the optimal solution, which is therefore not an equilibrium.

We now investigate the benefit of our approach with respect to the aforementioned greedy scheme. Recall that the greedy technique assumes the EVs to have periodically updated information about road traffic and status of the charging stations. In spite of this, Fig. 9 clearly shows that a greedy approach cannot cope with the other techniques in terms of performance: the degradation that is observed is indeed severe and becomes exceedingly high as the number of players increases. Intuitively, this is due to many users selecting the (currently) least crowded station, which suddenly becomes overloaded (as in the well-known route-flapping effect). Fig. 9 also depicts the performance of the CAG when the CC does not solve the game using the first NE that is reached, but the NE that minimizes the average per-player trip time among the first 10 it finds. In the plots, we label this curve by CAG-10. Interestingly, such a simple enhancement to the solution procedure makes the CAG approach as effective as the congestion game and the optimal, without impairing its scalability.

In conclusion, not only modeling the system through a CAG is a feasible, practical approach to the problem, but its solution also leads to a performance that is remarkably close to the optimum and much better than that attained with a greedy scheme.

We now consider the case where not all EVs with low battery resort to the navigation service, rather they act according to the greedy scheme. Recall that this case also represents the behavior of non-rational EVs, i.e., EV drivers that ask the CC for advice but they do not follow its suggestion. The results portrayed in Fig. 10 refer to the case where there is an equal number of rational EVs (i.e., player EVs) that ask for advice and of EVs that instead do not resort to the CC. The plot shows that EVs that do not exploit the navigation service, on average, experience a higher trip time than those that use it. Such a difference in performance is particularly evident as the number of EVs with low battery increases. This further confirms that our game-theoretic approach always leads to solutions (i.e., advice from CC) that are advantageous to the EVs, thus increasing the user satisfaction.

Next, we assume that the information the CC can acquire through the ITS is not fully accurate. Specifically, Fig. 11 shows the effect of such inaccuracy when the waiting time at the charging stations is affected by a random jitter, uniformly distributed between 0 and 300 s. From the plots, we can see that the average per-EV trip time increases, and that a longer

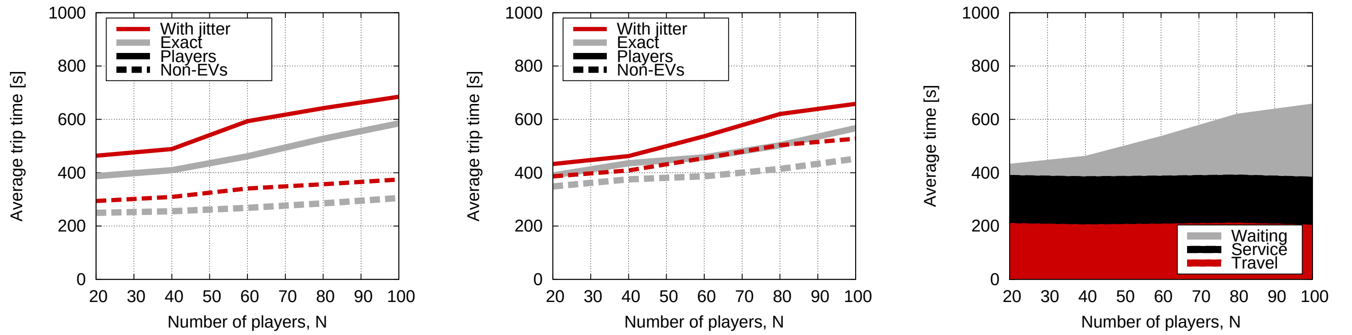

Fig. 11. Inaccurate information at the CC: average per-EV trip time as a function of the number of players, when they represent 20% (left), 60% (middle) of all vehicles and CAG is used; time breakdown for the latter case (right).

time is spent waiting at the stations. Indeed, stations that were free might have been advertized as busy and vice versa. As a consequence, EVs avoid free stations that are advertized as busy, while they flock to busy stations advertized as free.

In Fig. 12, we consider that the number of charged batteries available at the charging stations is limited, i.e., EVs may have to wait until their own battery is charged. Fig. 12 refers to the case where at every time period T, the number of charged batteries available at each station is equal to twice the number of servers at the station. We observe a sharp increase in the average per-EV trip time as the number of player EVs increases. More interestingly, the right plot in Fig. 12 shows that only a fraction of such an increase is due to vehicles waiting for their battery to be charged. Rather, vehicles find it advantageous to travel very far away to find a station with charged batteries available – hence the longer travel times – and possibly waiting in line at such stations – hence the longer waiting times.

Finally, we focus on the CAG and look at the case in which stations have significantly different charge prices. More specifically, such prices are uniformly distributed in $[10, 50]$ and $K_i = K$. In Fig. 13, we study the effect of the "value of time", $1/K$, on the average trip time of player EVs. Recall that the higher $1/K$, the more EV drivers value time with respect to money. As expected, we observe that if vehicles give more importance to the charge price rather than to the trip time, the latter tends to increase. Indeed, vehicles will be more willing to wait in line at the cheapest stations, as well as to make longer trips to reach them.

Tab. III highlights another interesting aspect: giving a higher importance to money rather than to time significantly decreases the computational complexity of finding an equilibrium. This effect has the following intuitive explanation: trip times depend on other players' choices, while charge price only depend on the station selected by each player. Therefore, the more important price is for a player, the less likely it is that her choice will be affected by the decisions of other players, which only influence trip times. Fig. 14 shows the average per-charge prices paid by the vehicles. When vehicles only consider time ($1/K = \infty$), prices are very close to the average. If price is also accounted for, we observe that (i) prices are lower, and (ii) fewer players (hence shorter trips) are associated to cheaper prices.

TABLE III
COMPUTATIONAL COMPLEXITY AS A FUNCTION OF K, WHEN PLAYERS REPRESENT 60% OF VEHICLES AND CAG IS USED

	$1/K = \infty$	$1/K = 30\$/h$	$1/K = 15\$/h$
20	350	284	124
60	3854	1425	960
100	7112	3487	2301

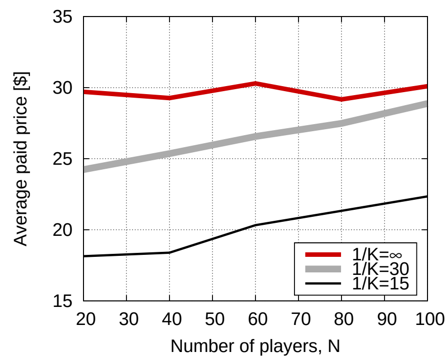

Fig. 14. Average price paid by players for different values of K and as a function of the number of players, when they represent 60% of vehicles and CAG is used.

VIII. CONCLUSIONS

Leveraging the use of ITS, we envisioned the availability of a navigation service that provides electric vehicles (EVs) that are low in battery with advice on the charging station to use and the route to take. We focused on how to determine such advice so that EV drivers find it advantageous to themselves and they are willing to follow it.

After showing that traditional optimization approaches fail to achieve the above goal, we considered a realistic scenario and modeled the problem as a congestion game, for which at least one pure-strategy Nash equilibrium exists (i.e., a solution that all EVs find satisfactory). Then, in order to lower the complexity, we introduced a game with congestion-averse utilities (CAG) that applies to a slightly simpler scenario but for which an NE can be found in polynomial time. We assessed the performance of our approach through SUMO and under a real-world vehicular environment. The results show that using CAGs, not only is a viable, scalable technique, but it also leads to an average per-EV trip time that is remarkably close the

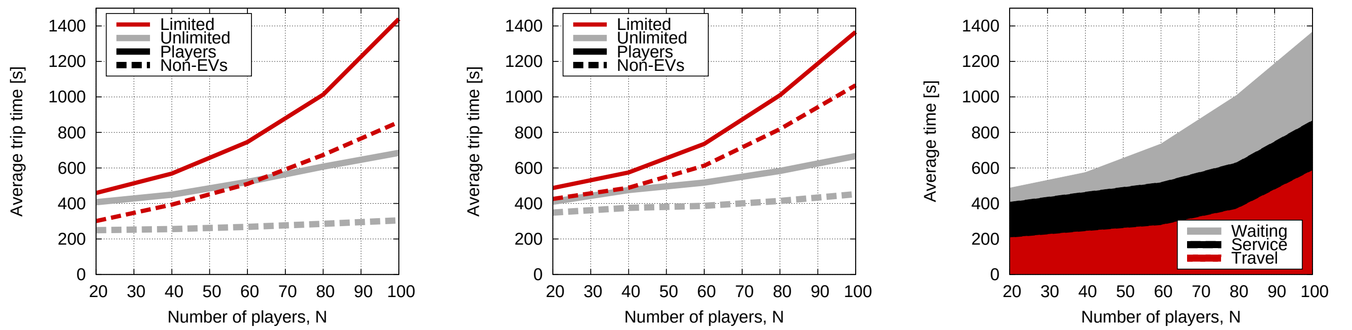

Fig. 12. Limited number of fully-charged batteries: average per-EV trip time as a function of the number of players, when they represent 20% (left), 60% (middle) of all vehicles and CAG is used; time breakdown for the latter case (right).

minimum that can be found through a traditional optimization approach.

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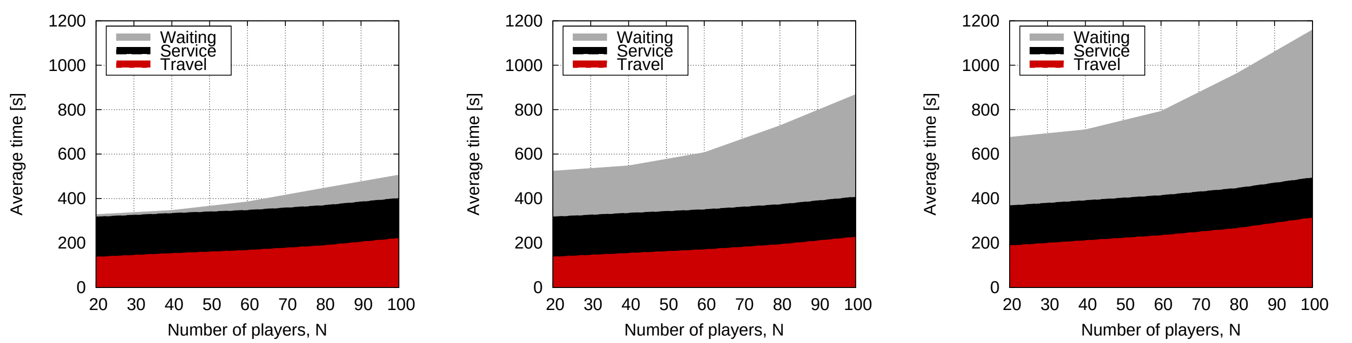

Fig. 13. Price-aware objective: breakdown of average per-EV trip times as a function of the number of players, when they represent 60 % of all vehicles and CAG is used, for $1/K = \infty$ (left), $1/K = 30\$/h$ (middle), $1/K = 15\$/h$ (right).

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Francesco Malandrino (S'10) graduated (summa cum laude) in Computer Engineering from Politecnico di Torino in 2008. He received his PhD from Politecnico di Torino in 2011. From 2010 till 2011, he has been a visiting researcher at the University of California at Irvine. His interests focus on wireless and vehicular networks and infrastructure management.

Claudio Casetti (M'05) graduated in Electrical Engineering from Politecnico di Torino in 1992 and received his PhD in Electronic Engineering from the same institution in 1997. He is an Assistant Professor at the Dipartimento di Elettronica of Politecnico di Torino. He has coauthored more than 130 journal and conference papers in the fields of networking and holds three patents. His interests focus on ad hoc wireless networks and vehicular networks.

Carla-Fabiana Chiasserini (M'98, SM'09) received her Ph.D. from Politecnico di Torino in 2000. She has worked as a visiting researcher at UCSD in 1998–2003, and she is currently an Associate Professor at Politecnico di Torino. Her research interests include architectures, protocols, and performance analysis of wireless networks. Dr. Chiasserini has published over 190 papers in prestigious journals and leading international conferences, and she serves as Associated Editor of several journals.

Massimo Reineri graduated from Politecnico di Torino (Italy) with summa cum laude degree in Computer Science and Communication Networks, in January 2009. From February to December 2009, he worked as a research assistant with the Dipartimento di Elettronica of Politecnico di Torino. In January 2010, he joined the Telecommunication Networks Group at the Dipartimento di Elettronica of Politecnico di Torino as a Ph.D student. His research activities are focused on testbed, content downloading, routing and channel assignment in Wireless Mesh and Vehicular Networks. He is the recipient of a Fulbright grant.