Stochastic Assignment of Electric Vehicles at Charging Stations Based on Personalized Utility Functions

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Abstract—In this paper we propose a stochastic decentralized algorithm to recommend the most convenient Charging Station (CS) to Plug-in Electric Vehicles (PEVs) that need charging. In particular, we use different utility functions to describe the possibly different priorities of PEV drivers, such as the preference to minimize charging costs or to minimize charging times, or both of them. For this purpose we generalize the notion of a simple CS to include the possibility of supplying other loads in addition to PEVs, and exploit locally generated energy from renewable sources. Extensive simulations based on the mobility simulator SUMO in realistic city-wide networks have been provided to illustrate how the proposed PEV assignment procedure works in practice and to validate its performance.

Index Terms—SUMO, electric vehicles, optimization problems, distribution control.

I. INTRODUCTION

A. Motivations

The sale of electric vehicles (EVs) in the world is rapidly increasing every year. While the original main driver towards the adoption of EVs was the decreasing of harmful emissions in city centers, there is now a growing interest of power Distributed System Operators (DSOs) in utilizing EVs as mobile storage units, in the case of Plug-in EVs (PEVs), to improve the robustness and the resilience of the power grid. In addition, PEVs may be successfully used to facilitate the penetration of Renewable Energy (RE), to both mitigate their fluctuating energy generation, and to fully exploit energy generated at peak times. It is thus clear that a smart management of the charging process of PEVs is required to fully exploit their potential, while avoiding possible inefficiencies for the distribution grid, e.g., in terms of voltage limits of the buses or thermal inefficiencies of electrical feeders and substations. In this regard, a deep analysis was conducted in [11], where authors showed that an uncontrolled power consumption of PEVs can lead to grid problems in terms of power losses and voltage deviations.

Accordingly, smart management and charging of PEVs has attracted the interest of many researchers, as illustrated in greater detail in the following section.

B. State of the Art

The impact of PEVs on the power grid has been widely investigated in a number of papers, see for instance [2], where a comprehensive survey of artificial-intelligence based solutions is provided, and [3] for deterministic methodologies like Model Predictive Control (MPC). In this context, the availability of measured data is extremely valuable to realistically model actual real drivers’ charging patterns (e.g., [4], [5]) and design well-coordinated charging strategies [6]. Some works have rather focused on the minimization of the impact on the power grid [7], while other works prioritized the waiting time at CS’s [8] or the minimization of polluting emissions and charging costs [9].

Specifically, in this paper we are interested in the assignment problem, which consists in recommending the most convenient CS to any vehicle requesting to be charged. Usually this problem is formulated as an optimization problem, where the best assignment is the one that optimizes a utility function of interest. For instance, in [9] the optimal scheduling aimed at minimizing the waiting time of PEVs at each CS; in [10] a Lyapunov optimization approach was used to improve the utilization of RE and reduce charging costs. A combined utility function was used in [11] to take into account traffic congestion, waiting time at CS’s, battery constraints and also the energy price.

Most of the aforementioned approaches (e.g., [7], [11] and [12]) may arguably have a limited effectiveness in practice. For instance, optimal solutions are static: as a Nash Equilibrium represents the optimal solution of a static system, a new element (that could be a CS or a PEV) entering or leaving the system may in general require to recompute the optimal solution. Also, such methodologies implicitly assume that the actors (here the PEVs) will follow the received optimal recommendations, as declining to follow the received recommendation has an impact on the optimality of the global solution. In addition, another important aspect that is often neglected in most of the literature is the behavior of the drivers, as not all drivers have the same priorities, and may take different decisions (e.g., the choice of a CS where charging) based on their own perception and interests. For instance, this aspect is investigated in [11] and [13], where prospect theory (14) and cumulative prospect theory respectively are used to model real-life human choices, and in [15], where the interaction of drivers with utilities and retailers is modeled as a function of their social classes (e.g., to predict the reaction

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of PEVs to discount charging fees).

As from the above discussion, this paper proposes a decentralized algorithm, that can be easily implemented in a dynamic scenario, where the different priorities of different drivers are explicitly taken into account. In addition, the algorithm is validated in a realistic city-wide simulated scenario, using the popular mobility simulator SUMO (Simulation of Urban MObility [16]).

C. Paper contributions

In this paper, we propose a novel algorithm for the assignment problem described before. The main features of this algorithm are that, differently from most models previously mentioned, it is implemented in a decentralized way, and at the same time priorities of different drivers are taken into account.

This algorithm builds on previous work of some of the authors [8]. In [8], a completely decentralized stochastic assignment algorithm had been proposed to assign a vehicle to the CS with the shortest queue. Accordingly, such an algorithm managed to fairly balance vehicles in a network of CS’s. In this short paper, we show how that algorithm can be modified to handle personalized utility functions that take into account the (possibly different) priorities of vehicles’ owners. The new utility functions combine three different components (distance, time for charging, and charging costs) in a single utility function to reflect personal preferences (e.g., one driver may wish to charge its vehicle as quick as possible, another one may prefer to just spend as little as possible). Accordingly, while the algorithm described in [8] ended up balancing vehicles at CS’s, that fully cooperated to achieve this goal, the algorithm proposed here aims at optimizing the utility function of single drivers. This new formulation appears to be more suitable as it may be utopian to expect that different CS’s, owned by different entities, would be actually willing to cooperate to achieve a common goal (e.g., fairly balancing vehicles at CS’s) while it is more realistic to assume that they will offer different charging prices to compete to attract consumers, as it is considered in this paper.

Furthermore, we generalize the notion of a CS that in addition to charging PEVs, may also supply other loads, exploit locally generated RE, and provide ancillary services to the outer grid. Note that such a generalized notion of CS allows one to consider in the same model fast CS’s, CS’s at shopping malls, research centers, or other facilities. While, as we have mentioned, other authors have considered the presence of REs in conjunction with CS’s ([10], [17]), the novel aspects of our work consist in handling the presence of REs in a short time-scale to assign vehicles to available CS’s, and in retaining the convenient plug-and-play philosophy of the original algorithm in [8].

Finally, our results are obtained and validated by using MATLAB in combination with the popular mobility simulator SUMO (Simulation of Urban MObility), an open-source, microscopic road traffic simulation package ([15]) for realistic city-wide road networks.

II. ASSIGNMENT ALGORITHM FOR CHARGING

We consider an urban network, where a PEV requiring charging has several options of where to go. In particular, now we make the following assumptions, that are common in most PEV-CS assignment problems:

- We use a Poisson process to model a new PEV requiring charging (as in [8] and [18]);
- We assume that the time between the PEV charging request and the recommendation of the optimal CS is short enough so that the optimal solution is computed upon updated information (this implies that the assignment optimization problem is solved in a very short time, e.g., 1 s);
- We assume that the time required for charging is proportional to the required energy (as in [8], and similar to [7] and [12] with constant charge step);
- Finally, we assume that once a vehicle accepts to get charged to the recommended CS, it will in fact drive towards the CS. This information is used to update the total time for charging that will be required by other vehicles that intend to drive to the same CS. This assumption may be relaxed by considering possible penalties for vehicles that do not respect the negotiated recommendation, as is typically done in the case of non respected social contracts (see for instance [19]).

We now present in Section II-A the proposed assignment algorithm based on personalized utility functions. In Section II-B it is shown how it can be solved in a centralized ideal framework where all CS’s are willing to exchange the relevant information. In section II-C we show how it can be solved in practice in a decentralized way.

A. Optimization problem

We consider utility functions that are a weighted sum of three aspects: the charging time, which includes the travel time to the CS, the possible time spent queuing and the effective time for charging; the charging price, where we use the amount of energy generated from renewable sources as a proxy for the discount in the price of charging; and finally, the distance from the CS, used as a proxy for battery discharge (i.e., if the battery level is very low, one may just want to choose the nearest CS). Based on their own priorities, users can choose the values of the weights in the vector \( \alpha \) (\( \alpha = (\alpha_1, \alpha_2, \alpha_3) \)), where the three positive weights sum up to 1. Then, given \( I \) the set of the available CS’s, at every time step \( t \) when a PEV asks for charging its battery of \( m \) kWh, the following optimization problem is solved:

\[
\begin{align*}
\hat{i}^* &= \arg \min_{i \in I} F_t(i),
\end{align*}
\]

where the outcome \( \hat{i}^* \) is the most convenient CS to be recommended to the PEV, and the utility function \( F_t(i) \) combines the three social aspects already mentioned. More precisely,

\[
F_t(i) = \alpha_1 T_t(i) + \alpha_2 P_t(i) + \alpha_3 D_t(i),
\]

where \( T_t \) represents the overall time required for charging, \( P_t \) is the price of energy, and finally \( D_t \) corresponds to the
distance between the PEV and the CS’s. In particular, the three terms are computed and normalized as follows:

- \( T_i(i) = (E_i(i)/e_r + T_{rel}(i))/M_{\text{max}} \) is the total time required for charging. This consists of the time \( T_{rel}(i) \) required to reach the \( i \)-th CS, plus the time required for charging all vehicles in the queue (included the vehicle itself), computed as \( E_i(i)/e_r \), where \( E_i(i) \) is the sum of all the queued energy at CS \( i \) and \( e_r \) is the energy received in 1 second, in kWh. The term \( M_{\text{max}} \) is included for normalization purposes, so that on average this term of the utility function has a similar weight of the other two terms;

- \( P_i(i) \) represents the normalized price of charging at CS \( i \). In this work the charging price is computed as a function of the RE local generation, assuming that the energy locally generated from renewable sources, if available, is free. To simplify the computation of this factor, inspired by [10], we compute the not-normalized price \( S_i(i) \) as the following:

\[
S_i(i) = e \cdot \max(m - RES_t(i), 0), \tag{3}
\]

where \( e \) is the energy tariff per kWh (\( \text{€}/\text{kWh} \)), assumed to be the same for all CS’s) for conventional energy, \( m \) is the energy requested by the user, and \( RES_t(i) \) is the forecast of power generation from local RE (at CS \( i \)) during the future charging time interval. Since \( e \) in Equation (3) is the same for all CS’s, we consider as normalized price the following term

\[
P_i(i) = \max(m - RES_t(i), 0)/m,
\]

where we remind that \( m \) is the energy requested by the user, used for normalization purpose.

- \( D_i(i) = \text{dist}(x_{CS}(i), x_{PEV}(t))/d_{\text{max}} \), where \( x_{CS}(i) \) is the position of the CS \( i \), \( x_{PEV}(t) \) is the spatial location at step \( t \) of the PEV, and \( d_{\text{max}} \) is the maximum considered distance between the vehicle and a CS.

The role of the \( \alpha \) parameters in Equation (2) is crucial because they represent the preferences of the drivers, and consequently drivers that choose different values of \( \alpha \) ’s will in principle receive different assignment recommendations. The normalization factors are required to make the different objectives comparable, so that when one driver gives the same importance to all three the components (i.e., equal weights), the three components have a similar impact on the recommended CS.

**Remark:** While any other more sophisticated equation may be used to compute the charging price, Equation (3) simply reflects the fact that power generated from RE is cheaper than the power generated from other sources.

### B. Centralized solution

The problem (1-2) is a discrete optimization problem that can be easily solved in a centralized way by checking what value of \( i \) (i.e., what CS) gives rise to the lowest value of the utility function. PEVs looking for charging broadcast their position, personal preferences and energy requests, and the algorithm computes the optimal CS solution for them; however, this requires that different CS’s exchange some personal relevant data (e.g., to determine the length of the queue at each CS, and the expected future availability of energy generated from renewable sources at each CS). In practice, CS’s may be reluctant to reveal and communicate this kind of information. For this reason, in the next section we show how the same problem can be solved in a decentralized way, exploiting the same strategy developed in [8], and in Section II we shall use the solution obtained in the centralized framework as a benchmark for comparison.

### C. Decentralized solution

A decentralized stochastic implementation of the previous algorithm usually has a number of advantages, as mentioned in [8]. In particular, if the centralized-deterministic approaches require a large amount of communication between all participants, in the stochastic algorithm these kinds of requirements are usually lower; CS’s do not need to exchange information among themselves (which may be convenient in terms of privacy preservation of some relevant data). Finally, decentralized solutions are known to be more robust than centralized solutions in general.

We now briefly recall how a centralized algorithm had been implemented in a decentralized fashion in [9]. In practice, we assume that when a PEV needs charging, it broadcasts its position, its personal preferences (i.e., vector \( \alpha \) in Equation (2)), and its energy request. Then, the CS’s start to broadcast a green signal with a frequency that is proportional to the value of the utility function. Mathematically, the green signal’s frequency is modeled by a decreasing function of the objective function \( F_t(i) \) defined in (2). In this way, the CS’s more convenient signal their availability more frequently. In particular, we assume that the \( i \)-th CS communicates its availability at time step \( t \) with probability \( p_{\text{CS}}^{(i)}(t) \), that similarly to [9] is computed as

\[
p_{\text{CS}}^{(i)}(t) = 10^{-F_t(i)}, \tag{4}
\]

where \( F_t(i) \) is the objective function (as in Equation (2)), computed with the data of the PEV. Once a vehicle receives a green signal by a CS and accepts the recommendation, then it travel towards the recommended CS, and its required energy is added to the queue of the chosen CS. Fig. 1 illustrates the process of the decentralized approach just explained.

**Remark:** While both the centralized and the decentralized solution solve the same problem (1-2), the centralized solution is guaranteed to recommend the most convenient CS. On the other hand, in the decentralized solution the most convenient CS’s advertise their availability more often than the least convenient CS’s, so it is more likely, but definitely not guaranteed, that the PEV will first sense the availability of the most convenient CS.

### III. Analysis and Results

We now analyze and present the main results that are obtained by applying the proposed algorithms to assign PEVs
to CS’s. To better clarify how the algorithm works, we first present results that are obtained in an idealized scenario where CS’s are points in a unit square and vehicles can directly drive within the square towards the CS’s. All distances are thus measured using the Euclidean metrics, disregarding of whether there exists a direct road that connects the PEV with a CS. In the second set of simulations, we relax this assumption, and distances are the true distances in a realistic urban network.

In our simulations, we assume that vehicles are charged with a charge rate of 22 kW (i.e., $e_{r} = 0.0061$ kWh in the definition of $T_{v}$ in Eq. (2)) at each simulation step (1 sec), that is consistent with the power rate of most public charging poles (see [20]). In [21] it had been shown that the average charged energy at urban CS’s is around 5 kWh, and consistently we have assumed that the energy required by PEVs is sampled from a Gaussian distribution centered in 5 kWh with a standard deviation of 1.2 kWh. This implies that the maximum charging time is about 1300s (i.e., about 22 min), corresponding to a request of 8 kWh. Finally, we assume that CS’s may either be equipped with PV panels of 10 kW of nominal power, or with a wind turbine of 5 kW, or may not have renewable sources at their disposal.

A. Characteristics of the optimal solution of the optimization problem

In our paper we consider personalized utility functions. This implies that two drivers with different priorities may have two different recommended CS’s.

In order to clarify the exposition, we now introduce three different performance indicators to quantify the impact of the single components of the utility function (2):

1) $i_{dt}$, the performance index for the charging time. It is the average waiting time for charging (i.e., it includes travel time to the CS, the possible time spent queuing and the effective time for charging), averaged over the set of charged vehicles during the simulations;

2) $i_{ep}$, the average energy price per kWh. It is computed following the idea of Equation (3), that is by considering $e \cdot (E_{\text{charged}} - E_{RE})/E_{\text{charged}}$, where $E_{\text{charged}}$ is the energy charged in the simulation, $E_{RE}$ is the amount of RE used, and the tariff $e$ is chosen as 0.45 €/kWh, which is consistent with the price in Italy. Consequently, in the absence of energy generated from REs, the average energy price per kWh will be exactly 0.45 €/kWh, whereas if the CS’s have their own REs, they may sell energy at a lower price.

3) $i_{d}$, the average distance between a PEV and the assigned optimal CS (here, in the unit square).

For the next analysis, we considered results related to 75 simulations run with different cars positions and different charging requests; the performance indicators are computed and averaged over the 75 different simulations, in order to get a more robust statistical index. Each simulation is related to a period of 7 hours, during which about 500 PEVs get charged. Assuming that all the drivers have exactly the same weighting coefficients in Equation (2). Fig. 2 illustrates the 3D plot when the weights vary between 0 and 1, with a step size of 0.1. Since only combinations of weights that sum up to 1 are considered, then 66 overall cases appear in the figure. In particular, diamonds are used to show the extreme cases when all users decide to optimize a single component of the utility function. Among other things, it is possible to observe that charging times rise to about 110 minutes when all vehicles aim at minimizing charging costs as all PEVs go to the cheapest CS, while charging times reduce to about 16 minutes when all vehicles minimize the time required for charging. In this case, there are practically no queues at CS’s and a very short travel time to the station, since the average time for only charging is about 13.5 minutes. This result further emphasizes the important of smart charging, intended as a smart assignment of PEVs to CS’s.

(1) https://www.enelix.com/it/it/mobilita-elettrica/prodotti/privati/servizi-x-recharge
This short paper proposes a novel procedure to assign PEVs to the most convenient CS. Assignments are personalized, as they take into account specific, possibly different, interests and priorities of different drivers, leveraging on the availability of real-time data on electricity prices and queue lengths. The proposed procedure has been illustrated through extensive simulations, and validated using the mobility simulator SUMO.

**B. Centralized versus Decentralized**

This second section of results compares our stochastic decentralized algorithm with the deterministic centralized one. Recall that, in the stochastic approach it is probable, but not guaranteed, that a vehicle is assigned to the optimal CS. Thus, in this simulation we wish to identify how suboptimal is the stochastic decentralized solution with respect to the deterministic centralized solution, that represents the benchmark.

In order to simplify the interpretation of this analysis, we compare the two methodologies in one setting, which is the one referring to the parameters configuration $\alpha = (1, 0, 0)$; similar results are obtained also for the remaining 3-uple of $\alpha$’s.

**Configuration: $\alpha = (1, 0, 0)$:** in this case the only goal is to minimize the charging time. Similar results to the ones of paper [8] are obtained, since we just add the travel time to the waiting time factor of the previous model. In Fig. 5 is shown the charging time of the whole system, as a function of the time, hence it is a mean value, including possibly empty CS’s. As can be seen from the graph, the behaviour of the decentralized stochastic approach (dashed line) is very close to the optimal one (solid line): the RMSE (Root Mean Squared error) is about $0.5087$ minutes, while on average the charging time of the decentralized solution is about $5\%$ more of that of the centralized case (8 minutes instead of 7.6 minutes).

**C. Simulations with SUMO**

In this section we investigate the proposed approach using the mobility simulator SUMO in a realistic urban network. For this purpose, we consider the road network of the city-center of Pisa, with 12 CS’s, as shown in Fig. 6(a). In a first simulation, we mimic what could happen if our proposed assignment procedure is not used. In this case, it is realistic to assume that drivers quickly learn average electricity prices, and decide to get charged to a cheap CS along (or near) their typical driving patterns, as currently occurs for fuel vehicles. In the second simulation, our proposed assignment procedure is fully used, assuming that all drivers have the same weights for all components of their utility function (a similar result would be obtained if the driving population were divided into equal groups of people aiming at minimizing charging times, or charging distances, or charging prices). In this case, driving quantities such as the travel time and the driving distance are computed by using available commands in SUMO, while in practical applications of our algorithm, they can be easily recovered by using popular tools and apps (e.g., Google maps, Azure maps, etc.).

Final results are summarized in the two heat maps (Fig. 4 and Fig. 5). It can be clearly seen that in the first case most vehicles decide to get charged at the cheapest CS’s, while more uniform utilization factors are achieved when the proposed procedure is used. In the second case, it happens that cheaper (or nearer) CS’s are initially taken, but when queues start forming then more expensive CS’s may become more attractive as queues are shorter.

The same result can be also visualized through the bar plots shown in Fig. 6(b). In particular, it can be noticed that in the first case (drivers minimizing charging prices) all drivers choose the CS’s where the prices are lower (because a greater amount of energy is generated from renewable sources, as shown in Fig. 6(b)). On the other hand, in the second case drivers take advantage of the queuing information and by using the proposed algorithm a balancing effect is achieved among the CS’s.

**IV. Conclusion**

In this section we investigate the proposed approach using the mobility simulator SUMO in a realistic urban network. For this purpose, we consider the road network of the city-center of Pisa, with 12 CS’s, placed as shown in Fig. 4(a). In a first simulation, we mimic what could happen if our proposed assignment procedure is not used. In this case, it is realistic to assume that drivers quickly learn average electricity prices, and decide to get charged to a cheap CS along (or near) their typical driving patterns, as currently occurs for fuel vehicles. In the second simulation, our proposed assignment procedure is fully used, assuming that all drivers have the same weights for all components of their utility function (a similar result would be obtained if the driving population were divided into equal groups of people aiming at minimizing charging times, or charging distances, or charging prices). In this case, driving quantities such as the travel time and the driving distance are computed by using available commands in SUMO, while in practical applications of our algorithm, they can be easily recovered by using popular tools and apps (e.g., Google maps, Azure maps, etc.).
for the realistic case study of the city of Pisa in Italy. The next step of this work foresees the practical implementation of the proposed algorithm. As a first step, we shall implement a centralized version of the algorithm, exploiting publicly available data (e.g., position and price) to have the algorithm working in a smartphone app that can be used by PEV drivers. However, our plan is to involve CS’s to advertise themselves their availability using private information as well (e.g., queue lengths).

In addition, we are interested in adding some features in the assignment mechanism that have been tacitly overlooked so far. This includes considering social contracts between PEVs and CS’s for enforcing reservation mechanisms [19] (here we assume that PEVs that accept an assignment will in fact drive towards the charging station). Also, PEVs may further provide ancillary services, as for instance providing a storage capability in a Vehicle-to-Grid (V2G) fashion, or voltage regulation via reactive power exchange.

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