Policies for Efficient Usage of an EV Charging Infrastructure Deployed in City Parking Facilities

M. Gharbaoui‡, B. Martini†, R. Bruno†, L. Valcarenghi‡, M. Conti‡, and P. Castoldi*  
*Scuola Superiore Sant’Anna - email: {m.gharbaoui, luca.valcarenghi, castoldi}@sssup.it  
†IIT, CNR - email: {rafaele.bruno, marco.conti}@iit.cnr.it  
‡ CNIT - email: {barbara.martini}@cnit.it

Abstract—Transportation sustainability is largely being evaluated considering the effectiveness and the efficiency of public and private transportation systems and their impact on the environment. In this context, Electric Vehicles (EVs) play a key role in the reduction of greenhouse gas (GHG) emissions. The major issues of the large-scale adoption of EVs are related to their limited range and the lack of accessible charging infrastructures. An approach based on an intelligent dimensioning and management of the charging infrastructure might be a solution. In this work, practical strategies for providing efficient recharging services and improving user satisfaction (e.g., by maximizing battery charges) are compared.

I. INTRODUCTION

A widespread use of EVs would be desirable for making private and public transportation more environmentally sustainable through the reduction of GHG emissions. However, electric vehicle utilization is only at its dawn. The Electric Vehicle Initiative (EVI) reports that the current number of electric vehicles in its fifteen member countries is more than 180000 and that the number of non-residential “slow” and “fast” charging points is slightly less than 5000. On the other hand, the number of EVs sold in 2012 doubled with respect to the sales in 2011 [1]. Therefore, although these numbers are still low, if the EV sales keep increasing at this pace, a variety of management issues will rapidly arise for EV charging.

On the one hand, the need to recharge the batteries of EVs generates additional load on the power grid, and the simultaneous charging of several EVs located in the same area can lead to local problems in the distribution grid such as peaks or instabilities [2]. Thus, power system operators will have to deploy new automated control mechanisms to regulate the charging process of EVs in order to flatten peak demands or to shift EV charging to off-peak periods [3], [4]. On the other hand, from the user perspective, one of the major barriers to the extensive adoption of EVs is the “range anxiety”, i.e., the drivers’ concern that EVs have too limited ranges and that re-charging stations are not easily accessible. To address such concerns it will be necessary to deploy a widely diffused network of charging stations, also supporting faster charging than standard residential sockets. Currently, in most cases, charging stations are provided by electric utility companies and they are spread out in the city where there is on-street parking [5]. Another option is to assume that charging infrastructure layouts will closely resemble the ones of today networks of gas stations since conventional filling stations could be easily expanded to incorporate EV charging capabilities [6]. Recently, many studies have also proposed to co-locate multiple charging stations in large parking facilities, such as public garages, parking decks and large parking lots [7], [8], [9]. However, the indefinite increase of charging stations is not a viable solution due to high operating costs that it entails. Instead, solutions to efficiently and effectively manage charging stations would be preferable [10].

In this study we aim at exploring the design of policies for the efficient usage of an EV charging infrastructure that leverages activity-based models of drivers’ behaviors to derive charging needs. Specifically, the activity-based scheme takes into account the travel demands derived from the daily activity of workers, students or households, to model trips. In such context, the trip is deduced from the movements taken by the driver and is subject to a set of constraints such as the order of starting/destination points (trip sequences), stops duration, interaction with other persons, and time consumed to reach the activity [11]. In this case we might assume that charging can occur during intermediate stops at parking lots nearby the activities. However, this can make charging management quite challenging because the vehicles stop for a time that is independent of charging times but it is mainly related to the activity. Thus, depending on the activity model charging stations could be underutilized or occupied by vehicles that have completed their re-charge. One option to resolve these issues is to develop a smart system to monitor parking availability and to facilitate charging station reservation in order to help operators to maximize their revenues. However, such approach would require a sophisticated information system providing remote access to real-time availability data and relaying on an accurate knowledge of users’ behaviors and activities, which is difficult to obtain in real world. Hence, in this study we explore an alternative approach that relies on simple admission control techniques to prioritize service requests from vehicles with lower residual energy. Specifically, we present an approach leveraging threshold-based admission control techniques to reduce range anxiety of EV drivers, which aims at prioritizing service requests from vehicles with lower residual energy. Moreover, we provide results of a simulation-based study of synthetic vehicular mobility traces on a real city map, i.e., the city map of Pisa, and show that reserving a subset of the available charging stations to the EVs that have a critical battery level is effective to improve user satisfaction and efficiently use the charging infrastructure.
II. STATE OF THE ART

The design of control strategies for EV charging has gathered significant interests in the past recent years.

A first category of schemes (called home-based charging models) assume that EVs can be charged either at workplaces or homes. Typically, in this case the average time an EV is connected to the charging station can be assumed large enough to fully charge EV batteries without noticeable inconvenience to the users due to a slower charging. Hence, the goal of the majority of charging algorithms in this class is to schedule a number of EV charging processes such that the operation of the power grid is optimized and all EV batteries are charged by the end of a period $T$. For instance, in [3], [12] decentralized control strategies are proposed to establish charging schedules that are able to flatten the aggregate EV charging loads (known as valley filling). Authors in [13] focus on a residential use case and they propose control mechanisms for Home Energy Management systems that minimize peak loads. Alternative optimization objectives have also been considered, such as the minimization of the power generation and charging costs [14], the minimization of distribution system losses due to load variance [4], or improved frequency regulation [15].

The optimal charging of a large number of EVs in a public parking deck has been considered in [16] with a heuristic optimization approach. Finally, other studies have focused on V2G use cases in which EVs are allowed to pump energy back to the grid in addition to draw energy from the grid with the object to provide ancillary services to the grid [17], [18].

A second category of charging algorithms assume that EVs must charge their batteries while traveling (mobility-based charging models). For instance, in [19] a charging scheduling system is designed for EVs traveling on a highway road system to minimize the average time period that each vehicle has to wait for charge during its trip. In [20] a method is presented to plan the individual charging schedules of a large EV fleet such that each vehicle is guaranteed to have sufficient energy for next-day trips while minimizing the total electricity cost and avoiding distribution grid congestion. The impact of renewable energy for EV charging in terms of EV charging waiting times in analyzed in [21]. In [22] a scheduling algorithm is presented for managing EV charging when renewable sources are used to complement electricity by conventional grid resources.

Different from the above works, our study focuses on an activity-based charging model and we investigate the trade-offs between the efficiency in the use of a public charging infrastructure and the quality of the charging service provided to the users.

III. ACTIVITY-BASED EV CHARGING

The purpose of this section is twofold. First, we describe in details the features of an activity-based model for EV drivers’ behaviors. Then, for the sake of discussing the typical problems of managing a public charging infrastructure in this application scenario we present two exemplifying strategies for handling EV service requests.

Urban vehicular traffic might be represented by random trips from random starting points to random destination points. On the contrary, when using activity-based trip modeling a set of start and stop points are explicitly chosen, which correspond to points of interest (e.g., home, workplaces, schools, shopping malls, train stations). Then, vehicles may be forced to follow a sequence of destinations depending on a predetermined scenario (e.g., home-school-work-school-home). In a more general case, an individual probability can be associated to each activity, and each driver will select the next activity based on the activity probabilistic model [23]. Once the next destination/activity is selected, the path used to reach each destination will depend on the road network topology, the traffic congestion levels, and the drivers’ preferences (in the simplest case a shortest path to the destination can be chosen). As a simplified scenario, we model the behavior of a set of EV drivers that move from one parking lot to another as part of their daily activities and a variable number of charging stations are deployed at each of those parking lots. Thus, EV drivers can take advantage of these stops to recharge their batteries if needed. In other words, the activity-based model can be converted in an EV mobility model in which we assume that EVs move from one charging station to another, still as part of their daily activities. Specifically, once arrived to the parking, an EV driver checks if there is an available charging station to recharge its battery. It is important to point out that each EV stops for a pre-determined period of time that is independent from the charging time and it is mainly related to the type of activity. However, if no available slot is found the EV stops in the parking anyway. Otherwise, after completing the charging of the battery, the vehicle remains in the parking connected to the charging station for all the scheduled time. In other words, an EV leaves a charging station only when its activity is finished and not when charging is complete. Similarly, we assume that preemption is not possible in our system. Depending on charging speed, this may lead to many charging stations that are occupied but not utilized. For the sake of simplicity, we assume that an EV does not change its route/trip whenever a charging is needed.

To evaluate the effectiveness of the public charging infrastructure within the activity-based scenario, we employ to exemplifying strategies that are applied to assign a charging station to an EV arriving at the parking lot. The first strategy is a traditional First Come First Serve (FCFS), which simply admits all charging requests that arrive until there is an available charging station. We expect that FCFS can perform reasonably well when the overall charging load is low such that it is also low the probability that a charging request is rejected due to the lack of free charging stations. However, when many charging requests arrive in a short time (e.g., during rush hours) it is necessary to evaluate how critical is a charging request. Thus, we propose a second strategy, called Low Residual Charge First (LRCF), which gives precedence to EVs with low battery levels by implementing a threshold-based admission control. More precisely, we assume that one subset of deployed charging stations is managed by using FCFS, while a second subset, $k$, is reserved to EVs that have a battery level lower than a predetermined threshold. As a consequence, with LRCF it is possible that a charging request is rejected although there are unutilized charging stations. It is important to point out that both FCFS and LRCF imply that charging requests cannot be
scheduled. One reason is that we envisage a system has no knowledge on the distribution of battery charging requests. In addition, charging needs do not affect the drivers’ behaviors, which are dominated by the activity model.

IV. SIMULATION ENVIRONMENT

To evaluate the effectiveness of the recharging policies of the proposed EV charging system, a Java-based event-driven simulator has been developed. For the purpose of reproducing an urban traffic environment, this simulator leverages an open-source and widely used vehicular traffic simulator, namely SUMO (Simulation of Urban MOBility) [24]. SUMO is a space-continuous, time-discrete, microscopic traffic simulator developed at the Institute of Transportation Research at the German Aerospace Centre [25]. SUMO simulates the movement of each vehicle that participates in the road traffic, thus contributing to the overall travel demand in an urban area depending on the selected traffic model, e.g., random. However, SUMO does not consider the mobility of an heterogeneous set of vehicles as we need in this study comprising electric and conventional vehicles selecting their trips according to an activity-based model. For this reason, we extended SUMO to include parameters and behaviors that are essential to model EV mobility, as well as information related to the public charging infrastructure. Specifically, data structures related to the road network have been extended to include the description of the parking areas. Moreover, the traffic patterns of vehicles across the road network have been extended to include the activity-based model used in this work for modeling EVs movement from one parking to another in a cyclic way. As result, additional information can be elaborated by SUMO simulator that includes the set of parking areas and the status of charging units, the possible routes from a parking to another parking, and, finally, the specific routes followed by each EV including the stops at the charging units. Moreover, we integrated SUMO with a custom-built full-fledged Java simulator (SMS-EV) which includes a policy decision element implementing EV recharging policies in an activity-based traffic model scenario, a statistics collector for the generation and collection of correspondent performance statistics and a control facility that interfaces with SUMO to exploit real-time information about vehicle mobility, e.g., number of vehicles, position of vehicles across the road network, including additional EV status information regarding the battery capacity and EV departure time during the simulation. The battery capacity is also updated during simulations based on the actual movement of EVs according to specific charging and consumption models [26].

For the sake of simplicity a linear charging model has been considered (level 2 and level 3 charging [27]), although more sophisticated models can be easily included:

\[ C_2 = C_1 + (t_2 - t_1) \times V \]  

where \( C_2 \) and \( C_1 \) are the capacities in percentage of the battery after and before recharging, \( (t_2 - t_1) \) is the charging duration, and \( V \) is the charging speed in % per minute (level-3 sockets fully recharge a battery in 30m while from 4 to 8 hours are needed for level-2 sockets).

A linear model is also used for the electricity consumption during the movement of the EVs, which is function of the traveled distance and the battery efficiency:

\[ C_2 = C_1 - D \times R \]  

where \( D \) is the traveled distance, and \( R \) is the average battery use given in % per km. A thorough description of the simulation environment is given in [26].

A. Case study and simulation settings

As a case study we consider the city of Pisa. As shown in Fig. 1, the road map has been extracted from OpenStreetMap [28] with an overall extension of 375 km\(^2\) (19.78 km \times 18.94 km). Within this map, a different number of charging stations have been deployed in a limited set of parking areas. Five parking lots were located on the map next to workplaces, shopping malls, municipal offices while being uniformly distributed across the city.

One thousand conventional vehicles (non-EVs) move in the area in a random way, thus contributing as “background traffic”. Moreover, one hundred EVs have been considered moving from one parking to the other according to the activity-based model. All the vehicles move following the Krauss-based car-following model [29], which makes the driver stay at a safe distance from the other vehicles and at safe speed allowing him to adapt his driving behavior with respect to the leader’s deceleration. The reaction time of the driver is assumed to be equal to one second.

Both EVs and non-EVs are inserted at the beginning of the simulation at different random points on the map. Non-EVs follow pre-determined trips that start from a random location on the map and finish at a random destination. Once arrived to the destination, the vehicles restart the same trip in a circular way, in order to keep a constant traffic density of vehicles during all the duration of the simulation. The EVs, on the other hand, move continuously from one parking to the other, following a random, but pre-selected, order. At the departure time, an initial battery level is assigned to each electric vehicle. This level is kept within the interval [10%, 40%] of the total battery.
capacity. As EVs we have considered the Nissan Leaf electric car, manufactured by Nissan and introduced in Japan and the United States in December 2010 [30] which is characterized by a 24 kWh lithium ion battery. For the non-EVs, we have considered a maximum speed of 50 km/h.

During each run, the simulation time is equal to 10 hours. We consider a range of 76 km corresponding to a heavy inter-city stop-and-go traffic. This range allows a minimum percentage of battery capacity equal to 26 to ensure an average of 20 km for each trip. We adopt the level 2 charging which necessitates from 4 to 8 hours to fully recharge a battery. When an EV arrives to the parking, the duration of each stop is uniformly distributed between 20 and 40 minutes. In such a scenario, we can still have the risk to run out of battery and then have a set of vehicles that can not reach the parking.

V. PERFORMANCE EVALUATION

In this section the simulation results are presented using the case study and the simulation setting described in Sec IV-A. A comparison between the FCFS and LRCF strategies is drawn. In the LRCF policy, we define k as the number of dedicated charging stations in a parking lot over the N available ones and we fix the value of the threshold used to reject a charging request for high-priority charging stations to 15%.

A. Comparison between FCFS and LRCF with k=1

Fig. 2 shows the percentage of the charging requests that are rejected because no charging stations were available when the EV arrives to the parking, considering the policies FCFS and LRCF. From the shown results we can observe that in the FCFS case, as expected, the rejection probability decreases with the number of deployed charging stations. The same trend is expected to occur with the LRCF policy. However, the rejection percentage is higher and decreases less rapidly. In fact, the more charging stations are present and the more vehicles get recharged, which also increases the probability that a vehicle that reaches the parking has a sufficiently high charge to be not allowed to use the high-priority charging stations.

This trend is also confirmed by the results presented in Fig. 3 where the percentage of EVs that reach the charging station with a battery level higher than the fixed threshold (i.e., 15%) is plotted as a function of the number of available charging stations per parking. Moreover, dedicating only one charging station to the EVs with critical battery levels slightly improves the performance of LRCF policy with respect to the FCFS policy. In fact, increasing the number of dedicated charging stations increases the rejection percentage but raises the residual charging level.

Fig. 4 plots the distribution of the battery level of individual EVs computed at the beginning and at the end of the simulation. Results show that when only 2 charging stations are available, the percentage of vehicles with a battery level lower than 10% increases, whereas the number of vehicles with a battery level between 20% and 40% decreases. This is mainly due to the fact that vehicles initially start with a battery level uniformly distributed between 10% and 40% and then keep moving from one parking to the other, without being able to charge the vehicle because of the low number of vacant charging units. In such conditions, many vehicles risk to run out of battery and not be able to reach the destination (i.e., next parking lot). This is confirmed by the high percentage (almost 80%) of vehicles with a residual charge less than 5%.

By increasing the number of available charging stations, a significant decrease in the percentage of vehicles with critical residual charge (under 15%) is noticed, and on the other hand, the number of vehicles with a battery level between 15% and 35% raises which corresponds to more vehicles being accepted for the recharge. A small percentage of EVs has a residual battery level around 55%. Those EVs correspond to the one’s that come out of the parking lot shortly before the end of the simulation. However, the battery capacity mainly remains below 60% since all charging stations employ a level-2 socket, which necessitates between 4 and 8 hours to fully charge the battery capacity. Since the duration of the stop by each parking for every vehicle is uniformly distributed between 20 and 40 minutes, in practice a vehicle can recharge less than 10% during
Fig. 5 plots the battery residual charging level while applying the LRCF policy. The number of vehicles with a battery level between 10% and 20% is slightly higher than in the FCFS case which is adequate with the threshold fixed to 15%. However, the trend is similar to the results obtained with the FCFS policy. We can conclude that dedicating only one charging station is not sufficient to significantly increase the residual charge.

Fig. 6 plots a comparison between the FCFS and LRCF policies regarding the charging stations utilization, where we show the time during which n stations (n=0,1,2, ..., N) are occupied, over the total duration of the simulation. When only two charging stations are available, for almost 35% of the time the charging units are vacant which is due to the burst arrival of the electric vehicles to the charging lots (workers arrive almost at the same time to the workplace parking, users go essentially after work to the shopping centers during the week, etc.). Increasing the number of available charging stations increases the acceptance percentage of charging requests and consequently the utilization of the charging units. However, keeping only one dedicated charging station for the critical battery levels does not improve the results while adopting LRCF. In fact, the charging station utilization rate remains almost the same in the two policies and the only advantage is a slightly less probability to have all the charging stations occupied.

B. Impact of the k parameter on LRCF

In this subsection we study the impact of increasing the number of dedicated charging stations (i.e., k) on the performance of the EVs and the charging infrastructure.

Fig. 7 shows the rejection percentage when the number of charging stations is fixed to 10 and the number of dedicated stations varies between 1 and 10. As expected, the rejection percentage increases when the number of dedicated stations increases. However, on the other hand, the percentage of stopped vehicles (i.e., vehicles that stop before reaching the parking lot because of the complete consumption of the battery) decreases, which means that more vehicles have a battery level higher than the critical level, making them able to reach their next destination without any risk.

Fig. 8 plots the residual charge of the batteries when 1, 5, and 10 stations are dedicated to the EVs with critical battery levels, with respect to their initial charge. Results show that by increasing the number of dedicated stations we decrease the percentage of vehicles with very low battery level (under 5%) and get more vehicles with a battery level around the fixed threshold (15%). However, adopting such strategy does not allow to have high residual charges mainly because, as we previously explained, we employ a level-2 socket, which necessitates much more time to fully charge the battery capacity with respect to the stopping time in the parking lot. A faster charging level associated to more sophisticated management strategies might be the solution to the tradeoff between the efficient use of the charging structure and the charging requests acceptance rate.

Fig. 9 finally shows the overall utilization of the charging stations at all the parking lots, as a function of the number of dedicated charging stations k. When k is between 1 and 5, all the available charging stations are almost occupied at the same rate. This means that replacing one charging station by a dedicated one improves the user satisfaction (less stopped vehicles) without having an impact on the efficiency in the exploitation of each stop.
the charging infrastructure. However, the number of dedicated charging stations cannot be increased indefinitely. In fact, when k is equal to 10, the charging stations are unoccupied for almost 60% of the simulation duration, with respect to a limited gain equal to 10% for the number of non stopped vehicles.

VI. CONCLUSIONS
In this work we have integrated SUMO, a vehicular traffic generator, with a custom-built Java-based simulator that carries out EV charging planning and control within activity-based trip modeling scenarios. Two strategies for the efficient usage of the EV charging infrastructure, namely FCFS and LRCEF policies have been considered and compared to assess the efficiency of the recharging services and the impact of the charging policies on the user satisfaction. Results show that there is a tradeoff between the size of the charging infrastructure and the necessity to guarantee an acceptable residual charging level. To this end, we confirm that admission control policies that take into account critical battery levels are more effective. Future work is under investigation on more sophisticated policies that foster a fair and profitable management of the charging infrastructure.

ACKNOWLEDGMENT
This study has been sponsored in part by the KIC EIT-ICT Labs Smart Energy Systems “EV2Grid Expert Activity 2013”, by the “Intelligent Management of Electric Vehicles and Microgrid for Sustainable Mobility (GEMMA)” project, co-financed by the Region of Tuscany within the framework “POR CRO FSE 2007-2013 Asse IV-Capitale Umano” and partly funded by the FP7 NoE EINS (grant number 288021) and CNR-MIUR project “Renewable Energy Resources and ICT for Sustainability”.

REFERENCES