Designing and Evaluating Activity-Based Electric Vehicle Charging in Urban Areas

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***Abstract*—The design of an effective charging management system plays a key role in the widespread deployment of Electric Vehicles (EVs). However, such design must consider a number of issues, especially in case of public charging stations, such as the impact of the EV charging on the power grid, the predictability of user mobility, the charging station utilization level, and, last but not least, user satisfaction. In this work, we focus on activity-based drivers' behaviors and we derive charging needs the EV management system shall deal with and evaluate the impact on user satisfaction of some implemented EV charging strategies. To this end, we have extended SUMO, a popular open-source generator of vehicular mobility traces to support activity-based mobility modes, EV charging and discharging models and EV charging planning and control. To validate the functionalities of this simulation environment we have carried a simulation-based study on a real city map by considering simple EV charging strategies that do not allow charging station reservation. Our preliminary results show that in this case public charging stations can be underutilized and more sophisticated strategies are needed to reduce range anxiety issues.**

I. Introduction

Electric vehicles (EVs) play a key role in the quest to make private and public transportation more environmentally sustainable through the reduction of GHG emissions. However, EV utilization is only at its dawn and the design of effective charging management systems is becoming crucial.

First of all, 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 [1]. Thus, new management mechanisms to regulate the charging process of EVs in order to flatten peak demands or to shift EV charging to off-peak periods must be developed [2], [3]. On the other hand, by considering a more user-centric perspective one of the major barriers to large scale adoption of EVs is the "*range anxiety*", i.e., the drivers' concern that electric vehicles have too limited ranges and that re-charging stations are not easily accessible or available. To address such concerns it will be necessary to deploy a widely distributed network of publicly accessible charging stations, some of which may support faster charging than standard residential sockets. In most cases, charging stations will be found where there is on-street parking, but we may also envisage that conventional filling stations will incorporate charging stations [4]. However, a solution based on simply increasing the number of charging stations to maximize user satisfaction is neither practical nor effective. Therefore efficient and effective solutions to dimension and manage such charging infrastructure must be provided [5].

The design of a smart management system for public charging stations will significantly depend on the recharging patterns, which are determined by the trips and activities of each individual. Thus, the design EV charging strategies leveraging mobility information has gathered significant interests recently. For instance, in [6] a charging scheduling system is designed for EVs traveling on highways to minimize the average charging waiting time during their trips. In [7] 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 is analyzed in [8]. In [9] a scheduling algorithm is presented for managing EV charging when renewable sources are complementing traditional electricity sources.

In this work we explore an *activity-based* scenario for EV charging. Thus an activity-based model is utilized to derive charging needs and evaluate charging strategy impact on user satisfaction. Specifically, the activity-based model takes into account the travel demands derived from people daily activities. A trip is modeled based on the destinations drivers must reach and it is subject to a set of constraints such as the order of starting/destination points (trip sequences), stop duration, interaction with other persons, and time consumed to reach the activity [10]. In this scenario, we assume that charging occurs during intermediate stops at parking lots nearby the activity place while minimizing the impact on the scheduled activity plans. In this scenario charging management results quite challenging because EVs stop for a time that is independent of charging times but it is mainly related to the activity. Thus, depending on the activity-based model, charging stations could be underutilized or occupied by EVs that have completed their re-charge. A possible solution to such issues is to develop a sophisticated system that monitors parking availability, allows charging station reservation and keeps EVs plugged only for the time necessary for their recharge rather than for their entire parking time. Such a system would maximize charging station utilization and operator revenues. However, such approach is quite unrealistic at present because it would require a sophisticated information system providing remote access to real-time charging station availability, an accurate knowledge of users' behaviors and activities, and on site management of EV recharge.

This study analyses the performance of a simple charging system in which EVs are not allowed to reserve charging stations and they occupy the charging station during the entire driver activity. Synthetic vehicular mobility traces on a real city map are considered. The performance evaluation is conducted by means of a flexible and extensible simulation environment, developed during the project, that integrates SUMO, a well-known vehicular

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traffic generator, with activity-based models of EV drivers' behaviors, EV charging and discharging models, and a Java-based tool for EV charging planning and control. Performance evaluation shows that depending on EV mobility patterns, charging stations deployed in public parking areas can be underutilized.

II. Activity-based EV Charging

Urban vehicular traffic can be represented by random trips between pairs of random starting/destination points. On the contrary, in an *activity-based traffic model* a set of random points must be defined, which correspond to point of interests (e.g., home, workplaces, schools, shopping malls, train stations) where a driver stops. Moreover, vehicles may be forced to visit these points in a specific sequence depending on the driver activities (e.g., home-school-work-school-home). In a more general case, a probability can be associated to each activity, and each driver will select the next activity based on the activity probabilistic model. Once the next destination/activity is selected, the path used to reach the destination depends 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).

In this study we considered a simplified scenario where a set of EV drivers move from one parking lot to another one as part of their daily activities and a variable number of charging stations are deployed at each of those parking lots. EV drivers do not change their route/trip whenever a charging is needed. While parked, EVs recharge their batteries if needed and if possible. In this way, the activity-based model is converted in an EV mobility model in which we assume that EVs move from one charging station to another one. 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 the user activity. Thus, after completing the charging of the battery, an EV remains in the parking connected to the charging station for all the time required by the activity. Similarly, we assume that preemption is not possible. Depending on charging speed, this may lead to many charging stations that are occupied but unutilized. As observed in Section I, we might envisage that the owners (e.g., municipalities) of the public charging infrastructure deploy a sophisticated information systems to allow EV drivers to book the use of a charging station in advance. However, there are several compelling challenges in deploying such information system, ranging from the monitoring of the charging infrastructure, the development of mobile applications to remotely access the system, to the design of suitable reservation and payment policies. In addition, as per the motivations explained in section I, in this work, we consider a simple system that does not allow EV drivers to reserve charging stations (i.e., service requests cannot be scheduled a priori)

In this scenario, our goal is to investigate which is the quality of the charging service that a customer experience and which is the minimum size of the charging infrastructure that could guarantee an acceptable charging service. Thus, we consider a traditional First Come First Serve (FCFS) service strategy, 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 and thus it is also low the probability that a charging request is rejected due to the lack of free charging stations. More sophisticated strategies are discussed in SectionV.

III. Simulation Environment

For the performance evaluation, a Java-based custom-built simulator has been developed. To reproduce an urban traffic environment, the simulator has been integrated with an extended version of the open-source and widely used vehicular traffic simulator, namely SUMO (Simulation of Urban MObility) [11], developed at the Institute of Transportation Research at the German Aerospace Centre [12]. SUMO simulates the movement of each vehicle in a city, thus contributing to the overall travel demand in an urban area depending on a selected traffic model, e.g., random. However, SUMO does not consider the mobility of an heterogenous set of vehicles, for example including both 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. The resulting building blocks of the overall simulation environment are shown in Fig. 1.

The *Road Network Importer* elaborates a graphic map into a OpenStreetMaps [13] format while the *Road Network Converter* is responsible for converting a variety of map formats, including OpenStreetMaps, into a SUMO-specific XML format describing the overall road network (i.e., `pisa.net.xml`). The *Traffic Model* specifies the traffic pattern of vehicles across the road network, e.g., the random movement of vehicles. The Road Network components along with the Traffic Model provide the main inputs for the *Simulation Exporter* to generate road traffic within SUMO simulator [14]. In the Simulation Exporter, the *Road Network Exporter* is responsible for generating and updating SUMO internal data structures related to the road map by exploiting the Road Network information provided by the Road Network components, while the *Traffic Generator* generates the vehicular traffic based on the specified Traffic Model, e.g., random, activity-based model, and based on the detailed vehicle positions along each route of the map provided by the *DuaRouter* component. As result, a data structure is generated and updated detailing all the routes followed by vehicles during simulations (i.e., `pisa.rou.xml`).

The SUMO components, have been modified to take into account the activity-based EV behavior. Firstly, the Road Network Exporter has been modified for extending the existing data structures and including the description of the parking areas (i.e., pisa.add.xml). Secondly, the Traffic Model has 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 a result, additional information is introduced in SUMO simulator for the inclusion of EV characteristics and charging models (i.e., `pisa.add.xml`). This information includes the set of parking areas and the status of charging stations as shown in Fig. 2, the battery level and the set of assigned parking areas for each EV such as presented in Fig. 3, the possible routes from a parking to another parking, and, finally, the specific routes followed by each EV including the stops at the charging stations.

The other main component of the simulation environment is the smart management system for electric vehicle recharge (SMS-EV) simulator, that, based on the movements of the EVs generated by SUMO, evaluates the performance of different policies for EV recharging in an activity-based traffic model scenario and for the generation and collection of correspondent

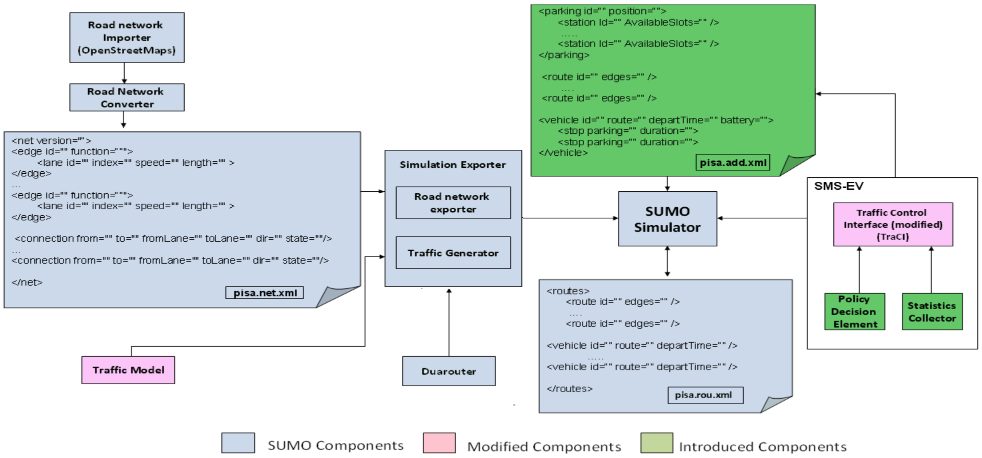

Fig. 1. Building blocks of the simulation environment.

```
<?xml version="1.0" encoding="UTF-8" standalone="no"?><
    additional xmlns:xsi="http://www.w3.org/2001/XMLSchema-
    instance" xsi:noNamespaceSchemaLocation="http://sumo.sf
    .net/xsd/additional_file.xsd">

<vType accel="2.6" color="0,1,0" decel="4.5" id="EV" length=
    "2" maxSpeed="40" minGap="3" sigma="0.5"/>

<parking endPos="180" id="parking1" lane="5532530#1_0" name=
    "SantaCaterina" startPos="1">
        <station availableSlots="1" Id="station1"/>
        <station availableSlots="1" Id="station2"/></parking
            >
<parking endPos="400" id="parking" lane="20177043#0_0" name=
    "Carrefour" startPos="10">
                <station availableSlots="1" Id="station1"/>
        <station availableSlots="1" Id="station2"/></parking
            >
<parking endPos="420" id="parking" lane="22986452#1_0" name=
    "Ospedale" startPos="1">
                <station availableSlots="1" Id="station1"/>
        <station availableSlots="1" Id="station2"/></parking
            >
<parking endPos="110" id="parking4" lane="-22576119#0_0"
    name="Pietrasentina" startPos="1">
                <station availableSlots="1" Id="station1"/>
        <station availableSlots="1" Id="station2"/></parking
            >
  <parking endPos="400" id="parking5" lane="-25643295_0"
      name="Stazione" startPos="1">
            <station availableSlots="1" Id="station1"/>
        <station availableSlots="1" Id="station2"/></parking
            >
</additional>
```

Fig. 2. Description of the Parking areas

performance statistics. The SMS-EV consists of the following modules: the *Policy Decision Element* which implements the charging strategies (e.g., FCFS) while enforcing the decision to the charging system, and the *Statistic Collector* for generating and elaborating statistics related to the charging station utilization, battery consumption and user satisfaction. SMS-EV leverages the *Traffic Control Interface (TraCI)* [15] for interfacing with SUMO and exploiting real-time information about vehicle mobility, e.g., number of vehicles, position of vehicles across the road network. In this work, TraCI has been extended to include additional EV status information regarding the initial 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.

The following charging and the electricity consumption models

```
<?xml version="1.0" encoding="UTF-8" standalone="no"?><
    additional xmlns:xsi="http://www.w3.org/2001/XMLSchema-
    instance" xsi:noNamespaceSchemaLocation="http://sumo.sf
    .net/xsd/additional_file.xsd">

<vType accel="2.6" color="0,1,0" decel="4.5" id="EV" length=
    "2" maxSpeed="40" minGap="3" sigma="0.5"/>

<vehicle id="ev1" type="EV" depart="0.0" route="elecRoute0"
    battery="12.0">
        <stop parking="parking1" duration="1547" parking="
            true"/>
        <stop parking="parking2" duration="1247" parking="
            true"/></vehicle>
<vehicle id="ev2" type="EV" depart="0.0" route="elecRoute1"
    battery="23.0">
        <stop parking="parking3" duration="2067" parking="
            true"/>
        <stop parking="parking5" duration="1837" parking="
            true"/></vehicle>

</additional>
```

Fig. 3. Description of EV characteristics

have been considered to set the actual level of battery electric charge:

a) Charging model: For the sake of simplicity a linear charging model has been considered, for both level 2 and level 3 charging [16]), although more sophisticated models can be easily included:

$$C_2 = C_1 + (t_2 - t_1) \times V \tag{1}$$

where C_2 and C_1 are the capacities 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).

b) Consumption model: 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:

$$C_2 = C_1 - D \times R \tag{2}$$

where C_2 and C_1 are the capacities of the battery after and before recharging, D is the traveled distance, and R is the average battery use given in % per Km.

Fig. 4. Parkings Locations on the map.

IV. Performance Evaluation

A. Case study and simulation settings

In this work, the city of Pisa is the considered case study. The road map of the city of Pisa has been extracted from OpenStreetMap [13] with an overall extension of 375 km^2 (19.78 km $\times$ 18.94 km). Within this map, a variable number of charging stations is deployed in a limited set of parking areas. As shown in Fig. 4 five parking areas are located on the map next to workplaces, shopping malls, municipal offices while being uniformly distributed across the city.

One thousand conventional vehicles (i.e., non-EVs) move in the area in a random way, thus contributing as "background traffic". Moreover, one hundred EVs move from one parking to the other according to activity-based model. All the vehicles move following the Krauss-based car-following model [17], which makes the driver stay at a safe distance from the other vehicles and at safe speed allowing him to adapt his driving behaviour 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 cyclic way, in order to keep a constant traffic density of vehicles during the whole simulation. The EVs, on the other hand, move continuously from one parking to the other in a cyclic way, following a pre-selected order. At the departure time, an initial battery level is assigned to each electric vehicle. This level is within the interval [10%, 40%] of the total battery capacity. When the EV arrives to the parking, the duration of each stop is uniformly distributed between 20 and 40 minutes. The considered EV is the Nissan Leaf electric car, manufactured by Nissan and introduced in Japan and the United States in December 2010 [18]. The Leaf is characterized by a 24kW·h lithium ion battery which lasts around 160km on the city driving cycle at 40km/h and with air conditioning off. For the non-EVs, we have considered a maximum speed of 50km/h.

During each run, the simulated time is 10 hours. We consider a range of 76km corresponding to a heavy inter-city stop-and-go traffic which is equivalent to the maximum distance that can be traveled by an EV with a battery capacity level of 100%, without charging and without running out of energy. This range allows a minimum percentage of battery capacity equal to 26% to ensure an average of 20km for each trip. Since in our scenario the initial battery level can be below 26% and the road map has an overall extension of 375 km^2, some EVs might still run out of battery and cannot be capable to reach the parking area. Those EVs are then seen as background traffic and are not anymore considered in the statistics.

B. Simulation Results

In this section the simulation results are presented using the case study and the simulation setting described in Sec IV-A. The effectiveness of the proposed policies are evaluated in terms of user satisfaction (i.e., rejection rate of EV charging requests, residual charge of EVs and charging station utilization rate).

Fig. 5(a) shows the rejection percentage of the charging requests since no charging stations were available as the EV arrives at the parking area, considering the FCFS policy. As expected, we can observe the rejection probability decreases with the number of deployed charging stations. In fact, the more charging stations are available, the more vehicles get recharged.

Fig. 5(b) plots the residual charge of EVs computed at beginning and at the end of the simulation as a function of the number of charging stations for the FCFS policy. Results show that when only 2 charging stations are available, the percentage of vehicles with a battery level lower than 25% increases with respect to the initial charge, whereas the number of vehicles with a battery level between 25% 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 recharge because of the low number of free charging stations. However, since the considered area is relatively restrained, even with a few number of accepted charging requests, the vehicle does not risk to run out of battery and not be able to reach the destination (i.e., next parking area). This is confirmed by the absence of vehicles with a residual battery charge less than or equal to zero. However, the battery capacity remains always below 50% 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 at each parking for every vehicle is uniformly distributed between 20 and 40 minutes, in practice a vehicle can recharge less then 10% during each stop.

Fig. 5(c) evaluates the utilization percentage of all the available charging station in a parking area. We notice that for almost 50% of the time the charging stations are vacant which is due to the burst arrival of the electric vehicles to the charging lots (e.g., workers arrive almost at the same time to the workplace parking, users go essentially after work to the shopping centers during the week). The remaining 50% of the time is equally distributed between the available charging stations.

V. Discussion on Ongoing Work

The simulation results for the FCFS policy have shown that there is a tradeoff between the number of stations per parking area and the need of guaranteeing that all EV drivers are able to recharge their batteries above the threshold that triggers the range anxiety (i.e., 26% of the battery level). To this end, we argue that admission control policies could be effective in ensuring the EVs with low battery levels could have a preferential access to the charging stations. Another important research direction concerns the integration of renewable energy resources in the public charging infrastructure. For instance, we might envisage

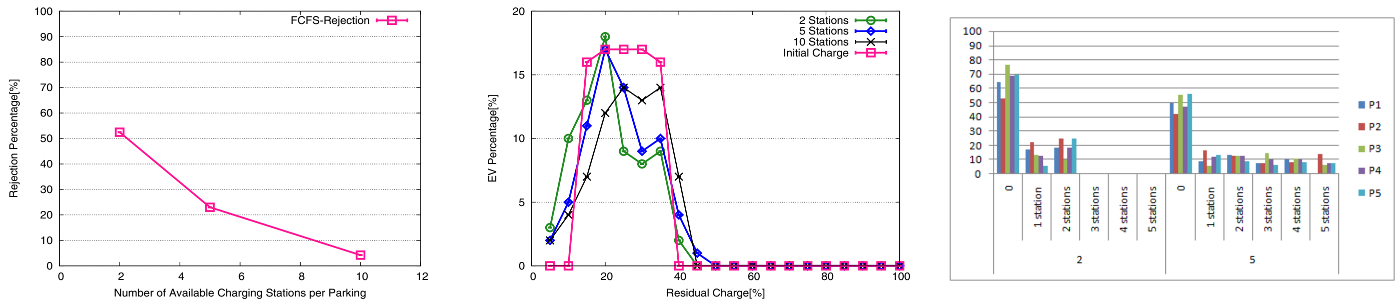

Fig. 5. Rejection Percentage (a), Battery Residual Charge (b), Charging Station Utilization (c).

that power generators using renewable energy resources could be deployed at the charging stations sites, so as to integrate or even substitute electricity from conventional power generators located in the grid. In this case the admission control policy should be adapted to also take into account the variable charging capacities. This is particularly critical for system operators that want to guarantee a minimum recharge to admitted users. Finally, a key issue to address in the design of a public charging infrastructure is the optimal deployment of charging stations. In our context, charging stations must be deployed at public charging areas, but how to select the subset of available charging areas to optimize system performance (e.g., by guaranteeing that the state of charge of EV drivers is maximized)? Alternatively, given a limited number of deployable charging stations, which is the distribution of the charging stations over the selected parking areas that optimizes the system performance? Clearly the deployment of charging stations must depend on the activity-based mobility of EVs, which is not yet clear due to the lack of large-scale traces from real urban areas. Given the uncertainty of the environment, we are exploring the use of stochastic optimization methods to deal with the complexity of the problem.

VI. Conclusions

In this work we have introduced a new application scenario for EV charging in urban area leveraging on activity-based mobility models. In this case, we can assume that drivers's mobility is not influenced by the charging needs. Thus, the EV charging process get superimposed over the sequence of parking times due to the daily activities of the EV driver. Then, in this work we addressed the design guidelines for a public charging infrastructure that is capable of supporting such EV charging scenario. Our main contribution is the development of a simulation tool that integrates SUMO, a well-known vehicular traffic generator, with activity-based models of EV drivers' behaviors, and a Java-based module for EV charging planning and control. We have also carried out a simulation-based study using synthetic vehicular mobility traces on a real city map showing that suitable charging strategies are needed to increase the utilization of the charging infrastructure while reducing range anxiety issues.

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