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EV Charging Simulator for Public Infrastructure Considering Smart Charging and Price Policies

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***Abstract*—The popularization of electric vehicles (electric vehicles (EVs)) is becoming an unstoppable trend in modern society. Thus, efficient simulation tools that can predict the EV operation and deployment are significant assets for charging point operators (CPOs), electric mobility service providers (EMSPs), charging service providers (CSPs) and electricity companies. In this paper, an algorithm for simulating the utilization and availability of public EV charging stations (CSs) has been developed. Based on several EV user features, the proposed algorithm generates realistic scenarios of CS availability, utilization, and impact over the distribution network via AC power flows. Moreover, the impact of considering smart charging (i.e., remote CS power limit control) and price policies is also modeled by the proposed algorithm. With these enhancements, the proposed simulation tool is used to predict the aggregated behavior of a population of EV users within the vicinity of two real distribution feeders. Results show the capacity of the proposed algorithm to generate realistic CS utilization statistics subject to different smart charging and price policies.**

***Index Terms*—EV charging simulator, public charging infrastructure, price policies, smart charging.**

ACRONYMS

BESS	battery energy storage system.
CDF	cumulative distribution function.
CPO	charging point operator.
CS	charging station.
CSP	charging service provider.
DER	distributed energy resource.
EMSP	electric mobility service provider.
EV	electric vehicle.
PV	photovoltaic.
SoC	state of charge.

I. INTRODUCTION

SEVERAL countries are increasing their electrical vehicles (EV) fleets. Norway, for instance, is an outstanding country on the race for transport decarbonization [1]. Stimulus for EVs aim at reducing greenhouse emissions. Researchers in [2] show that the positive environmental impact is a more impacting factor than the economics when buying EVs.

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Determining the effects of large-scale EV charging, considering fast CSs, smart charging, and public charging infrastructure, is more important now than ever. EV players, such as charging point operators (CPOs), electric mobility service providers (EMSPs), charging service providers (CSPs) and electricity companies are in need for better EV and CS simulation tools. Several studies have focused on the impacts of high EV penetration in the electricity grid. In [3], a market analysis was carried out to explore the potential of public charging infrastructure to stimulate EV sales in the USA. An integration of photovoltaic (PV) panels in the EV charging system is demonstrated in [4], wherein EVs can function as bidirectional batteries through vehicle-to-grid (V2G) technology. Along with the effects of EV charging in the distribution network, many works have focused on predicting the behavior of EV users. Authors in [5] study several EV charging profiles considering demographic and social data. Similarly, [6] shows a study of 79 EV users over a period of six months. An agent-based behavior model was proposed in [7], comparing business models based on parking fees and energy sales.

In order to predict EV users' behavior, traffic simulation tools have been applied in several works. As an example, Simulation of Urban MObility (SUMO) [8], [9] is an open-source traffic simulator which has implemented EV models in the 0.24.0 version. On the other hand, MATSim [10] is an open-source framework for the implementation of large-scale agent-based traffic simulations. V2G-Sim [11] is a software for modeling the driving and charging behavior of individual plug-in EVs that generates time and space grid impact/opportunity predictions. The traffic simulators mentioned above can be used for several case studies, however, there are some shortcomings. Although SUMO has an EV model and it is able to model CSs in a region, the software alone does not take into account the impacts on the electricity grid, and the users reaction to price policies. V2G-sim has several functionalities, including impact on the grid. However, it is not open-source; it does not allow adjustments related to the grid operation, e.g., the inclusion of distributed energy resources (DERs), neither simulating the behavior of EV users considering smart charging and pricing policies.

Other works consider the impact of charging price variations and other aspects of EV user's behavior through travel simulation models [12]. The research conducted in [13] addresses the response of EV users to price dynamics, suggesting that EV users are averse to price uncertainty. Lastly, in [14], a stochastic model is proposed to describe the behavior of EV users. However, these works do not take into account smart charging policies, grid impact, and CS availability and utilization.

This paper presents a new simulation tool to predict the utilization of public charging infrastructure, considering a flexible set of EV user profiles, which are reactive to smart charging strategies (i.e., remote CS power limit control) and charging price policies. Furthermore, the proposed algorithm calculates the impact of the CS utilization in the electrical distribution system, considering the presence of renewable generation sources, such as PVs. With these enhancements, the proposed simulation tool is used to predict the aggregated behavior of a population of EV users within the vicinity of two real distribution feeders. Results show the capacity of the proposed algorithm to generate realistic CS usage statistics subject to different smart charging and price policies.

II. Methodology

A. Input Data

The input data required by the proposed simulator consists of the initial simulation date-time, the number of time-steps, the population of EV users, the distribution network topology, and the demand/renewable generation data sets. In particular, the EV user population is a data structure created from a class whose attributes describe each EV users' behavior. The attributes are shown in Fig. 1: `Preferences` is the attribute used to define (on a scale of 0 to 1) the user's preference for a given CS. `Status` determines the state of charge (SoC) and, if the battery is fully charged, the user leaves the CS. `Idle` is the mandatory time that the user stays without charging. `Occupied` determines the CS the user is currently using (empty otherwise). `Battery` corresponds to the battery capacity of the EV. `Economical` and `Hurried` are Boolean features that indicate whether the EV user is sensitive to price signals, or not. In particular, the `Intention` feature is a vector that describes the user's intention of charging the EV at a given time of the day. `Intention` can be customized or, as in this paper's case, it can be described by a Gaussian distribution function, as shown in Fig 2. For simplicity, the intention of charging at any given time within the algorithm's time-step duration is constant.

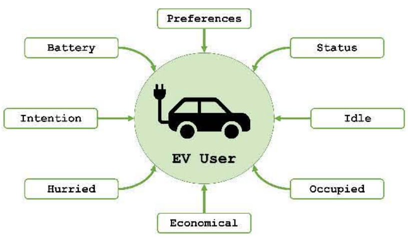

Fig. 1. EV user class and attributes.

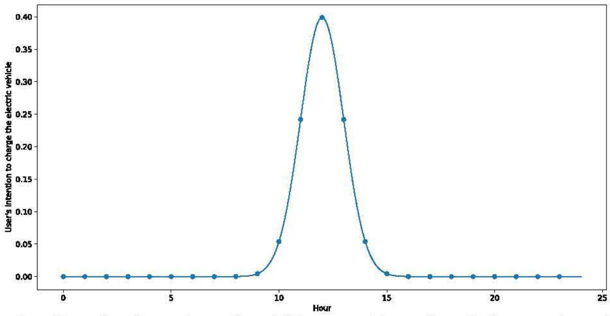

Fig. 2. Charging intention of an EV user with preferred time at the middle of the day.

B. Main Algorithm

The main structure of the simulator is shown in Fig. 3. The algorithm starts by reading the input data, discussed in the previous subsection. After that, utilization and availability profiles are created, as shown in block A. Output data consists of a data structure that contains the simulation results for each time-step. Block A of the algorithm is detailed in Fig. 4.

As soon as the utilization and availability profiles are generated, the iteration counter starts and the AC power flow, expressed by block B, is executed at each time-step until the counter reaches the total simulation time. Results contain the time-series operation of the charging infrastructure and the grid status (i.e., voltages, currents, and power flows). In this case, block B identifies all CSs that are in operation and it uses the OpenDSS/Python library [15] to solve the AC power flow. In block B, if the CS has smart charging capabilities, the power limit policy will be applied, diminishing the amount of power that the CS is able to provide.

C. Utilization and Availability Profiles

The utilization and availability profiles for each CS are deployed in block A of Fig. 3, whose process is detailed in Fig. 4. In this case, the algorithm starts by reading the input data and it initializes the time-steps at 0. After loading the smart charging and price policies for the current month, the CS availability is calculated in block C.

In order to generate the availability profile, the probabilities of having a long or a temporary outage are defined for each CSs on an hourly basis, and the cumulative distribution function (CDF) of these events are calculated. Using the CDF,

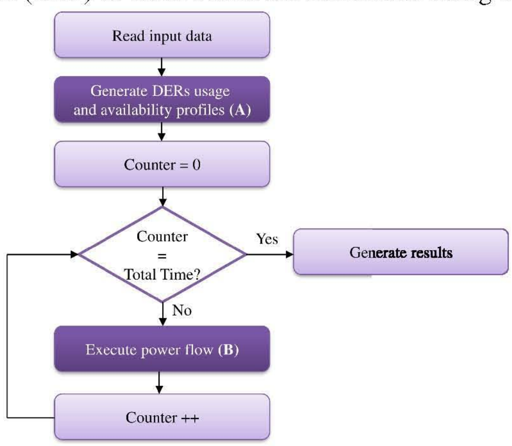

Fig. 3. Flowchart of the proposed algorithm.

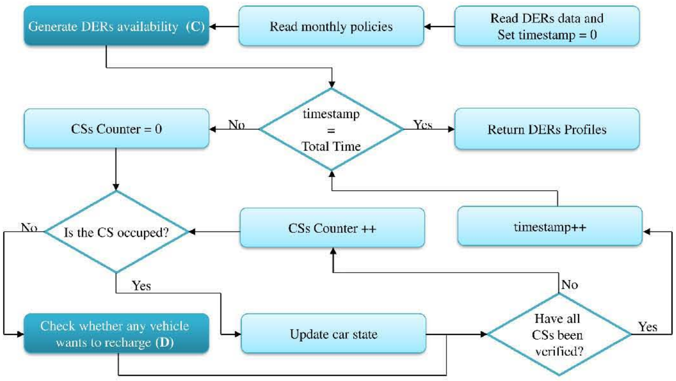

Fig. 4. Flowchart of the proposed CSs utilization and availability profiles.

the random event of having an outage is established at each iteration. After the execution of block C, a conditional loop is used to check whether the timestamp is equal to the total simulation time. If this is the case, the algorithm returns the availability and utilization profiles of the CSs. Otherwise, the list of CSs is used to verified which CSs are vacancy, and if there are EV users wanting to use them.

The process of user arrival at CSs is given by block D and the decision to charge the EV is given by the user's intent level. The EV user's intention at each point in time is affected by its reaction to the given price and power policies (i.e., smart charging). In this scenario, users that are reactive to price are considered aware of the charging cost of all preferred CSs. Thus, they can decide between charging at public fast-charging CSs or charging at home, in which energy price is generally constant. For users reactive to CS power reduction, it is assumed that they know the CSs that use renewable energy as their main power supply source, and that their EVs may take longer to charge than expected. The user's intention to charge the EV is given by equation (1).

$$i^r_{u,n,c} = \max\left\{p_{u,n} \cdot \left(1 - \frac{\Delta^{\text{price}}_{n,c}}{f_{\text{price}}} - \frac{\Delta^{\text{power}}_{n,c}}{f_{\text{power}}}\right) \alpha_c \beta, 0\right\}$$
$$\forall u \in \mathcal{U}, c \in \mathcal{C}, n \in \mathcal{N} \quad (1)$$

Given the user's intention from equation (1), roulette wheel selection is used to define whether at time instant n the user will charge the EV. Where $p_{u,n}$ is the user's default intention for charging the EV, as in Fig. 2. The parameters $\Delta^{\text{price}}_{n,c}$ and $\Delta^{\text{power}}_{n,c}$ are the price and power policies at time-step n and CS c. α_c is the user preference towards a given CS c, obtained from the `preferences` attribute. β is a correction coefficient for weekends and holiday. f_{power} and f_{price} are coefficients used to map the price and power policies into realistic probability modifiers. $\mathcal{U}$, $\mathcal{C}$ and $\mathcal{N}$ represent the sets of users, CSs, and samples. The initial EV charge, a value that impacts the user's status, is based on [16], wherein the use of public CSs with a characteristic SoC probability density curve for EVs was analyzed. Finally, whenever the CS is occupied, the SoC is updated with the power provided by the CS. After the battery is fully charged, the CS will be vacancy for a random period of time. This time guarantees that there will not be an EV user charging at the same time.

TABLE I
SIMULATED POPULATION PROFILE

User	Battery	preferred time	User	Battery	preferred time
1	30 kWh	6 a.m	6	30 kWh	3 p.m
2	24 kWh	8 a.m	7	24 kWh	4 p.m
3	15 kWh	10 a.m	8	15 kWh	4 p.m
4	24 kWh	12 p.m	9	24 kWh	6 p.m
5	24 kWh	3 p.m	10	24 kWh	7 p.m

TABLE II
NOMINAL SPECIFICATIONS OF DERS

	DER1	DER2	DER3	DER4
Type	CS	CS+PV+BESS	CS	PV
CS power [kW]	2 × 14	22	10.5	–
PV Power [kW]	–	50	–	336.8
BESS power [kW]	–	10	–	–
BESS Energy [kWh]	–	25	–	–
feeder	BGE06	BGE10	BGE10	BGE06

III. CASE STUDY AND RESULTS

A real distribution network located in a university region of Campinas was used to simulate the behavior of a given EV users population. A set of four DERs was considered and the user's behavior subject to the price and power policies was analyzed under different scenarios.

Policies consist of signals for variations in magnitudes to encourage or discourage the utilization of a particular CS. The policies considered are price (i.e., variation of the current price) and power (i.e., reduction of the maximum power provided by the CS).

Those policies are applied aiming to promote a uniform utilization of the CSs along the day, avoiding high energy demand in specific hours. For this purpose, a particular EV users population that allows the power reduction has been chosen, assuming that the users are aware of charging delays due to the usage of renewable energy as the main power supply source of the CSs.

Details of the EV population including battery capacities and preferred charging hours of 10 different users are shown in table I; the battery capacities are within the common range in current EV models [17]. Moreover, it is considered that all users are reactive to price and power policies. Additionally, the simulations are executed every minute during one month.

The simulated region comprises two networks with their own feeders as shown in Figs. 5 and 6; the specifications of the simulated DERs in the region are described in Table II. The network shown in Fig. 5 is called BGE06 and posses two DERs. The first DER is a PV power plant with nominal


Fig. 5. BGE06 network topology.

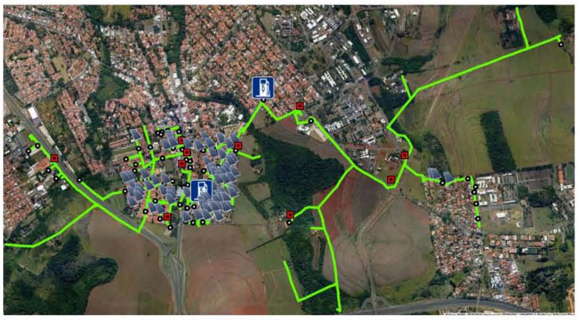

Fig. 6. BGE10 network topology.

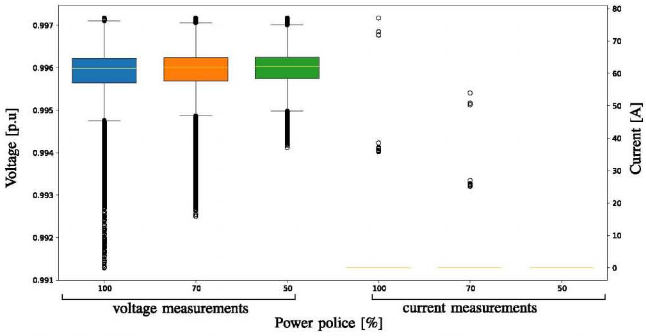

Fig. 7. Voltages and currents in CS1 after applying power policies.

power equal to 336.8 kW. The second one is a CS (CS1) with two connectors of 14kW each. Fig. 6 shows the second real network called BGE10 with two DERs: The first DER is the conjoint CS (CS2 with one connector) + PV + BESS. The second DER is a single glscs (CS3).

The values considered for f_{price} and f_{power} were 50U\$ and 50kW, respectively. Those values may be higher or lower in studies of more or less policy-sensitive populations.

Fig. 7 shows the results related to the impact of applying power policies on the distribution network. The voltage and currents were obtained for each power policy applied to CS1 after simulating the system for one month. The values shown in the box diagrams were determined from the load flow execution at each minute. Note that as voltages and currents dropped by reducing the charging powers at CS1 for 100%, 70% and 50% of the maximum supplied power, fewer discrepant points are obtained. In general, the distribution network in the region is robust and the amount of installed CSs is low, for which their impact in the grid is not significant.

On the other hand, a statistical analysis related to the utilization rate and energy supplied by the CSs was carried simulating the system for one year. Each point in Figs. 8 and 9, corresponds to an average value calculated with all measurements obtained through the year with the application of different policies at all times of day. Fig. 8 shows the effects of pricing policies (Δ_{price}) in different scenarios. The first scenario considers the price variation only in CS1. In this case, the graph shows the migration of users to the other CSs due to the increase of the charging price in CS1. Similarly, when the prices increase for CS1 and CS2, users switch their charging to CS3. The third scenario shows the behavior when policies are applied across all CSs showing users' aversion to high prices.

The effects of varying power policies on user behavior are shown in Fig. 9. The first scenario shows the reduction of power only in CS1. In this case, the graph shows the transfer of users to the other CSs, as well as the reduction of power supplied by CS1. The second case shows the reduction of power in CS1 and CS2. With the application of the policies, the users show a tendency to use CS3. When the policies are applied to all CSs, some users persist to charge between 70% and 90% and the utilization rate slightly increases. In general, Fig. 9 shows that users decide to stop using the CSs due to the charging delay provoked by the power decrease.

IV. Conclusions

In this paper, a charging simulator for electric vehicles (EVs) in public charging stations (CSs) was proposed. It consists of an algorithm that, based on several features of an EV population, generates realistic scenarios of CS availability, utilization, and impact over the distribution network via AC power flows. The proposed simulator also considers the impact of smart charging (i.e., remote CS power limit control) and price policies on EV users charging behaviour through time. Two real distribution feeders located in a university region of Campinas were used to verify the ability of the proposed simulation tool to predict the aggregated behavior of a population of EV users within the vicinity.

Results showed that through the application of simple rules for price and power policies it is possible to decrease the impact of EV charging in the distribution system, and also to persuade the behavior of EV users. For instance, the increase of the charging prices in some CSs makes that EV users switch their charging to other CSs with lower prices. Similarly, the reduction of the charging power in some CSs increases the utilization rate of others; moreover, when there is a strong power reduction in the CSs, EV users stop using them.

The proposed simulator can be used to describe specific behaviors given a customized intention distribution for each EV user in scenarios with and without policies. Additionally, the simulator is useful for studies in which it is desired to verify the network's operating status for a specific population of EV users (public fleet planning, etc.), as well as to verify public policy algorithms under different scenarios.

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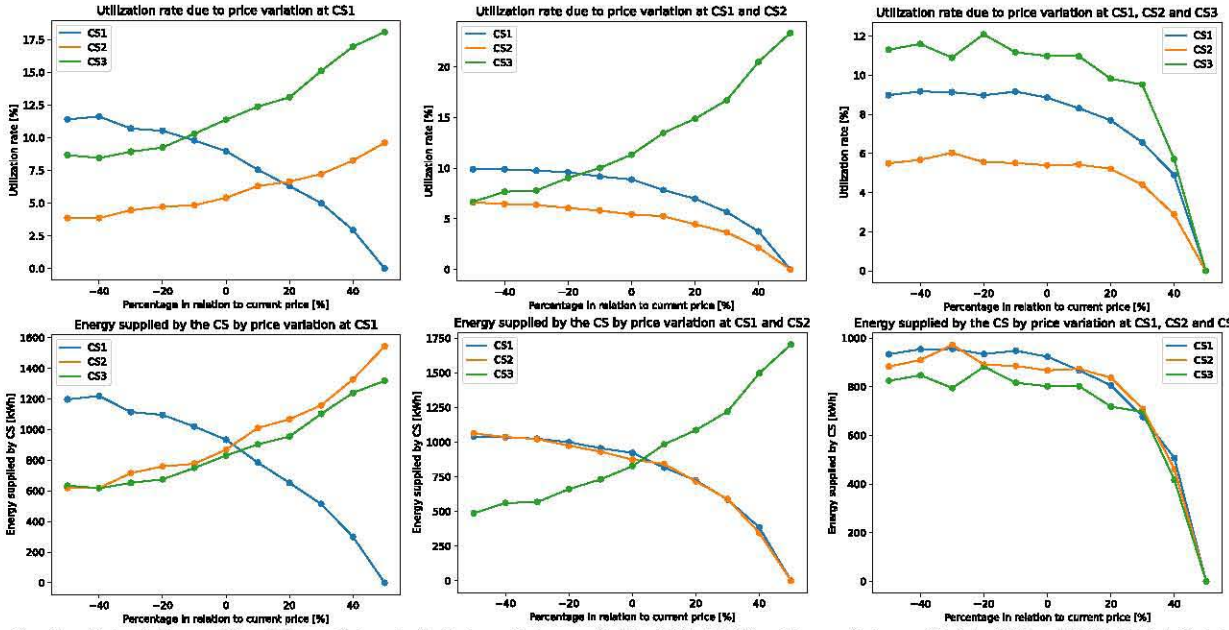

Fig. 8. Results of simulations with pricing policies. Left: Price policies applied to CS1. Middle: Price policies applied to CS1 and CS2. Right: Pricing policies applied to all CSs.

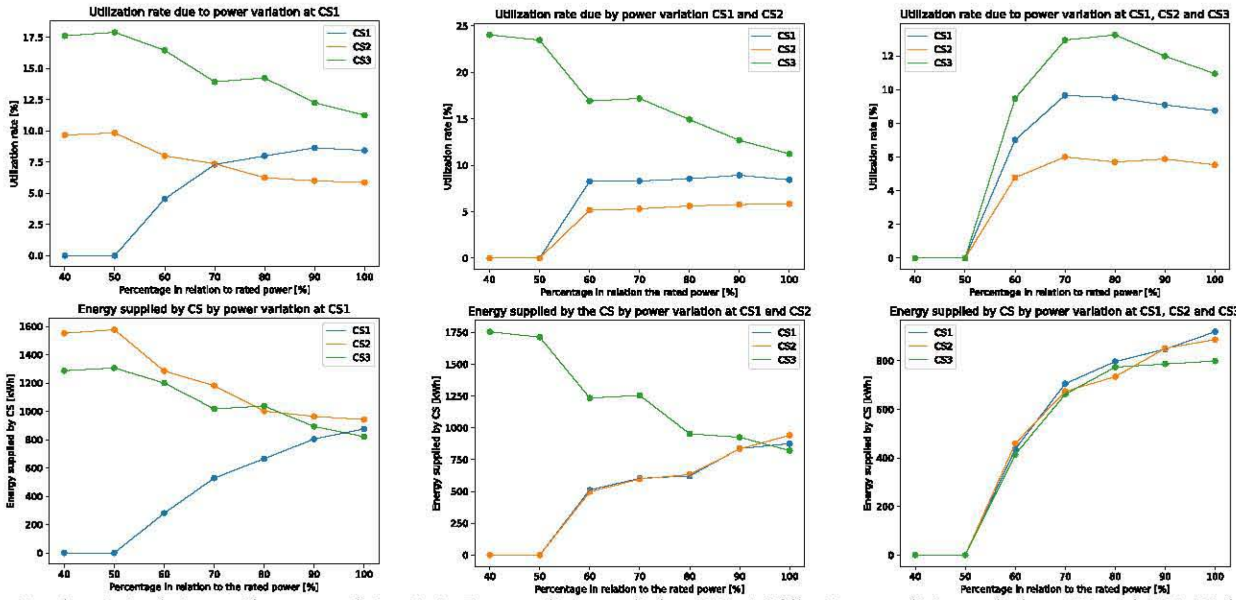

Fig. 9. Results of simulations with power policies. Left: Power policies applied to CS1. Middle: Power policies applied to CS1 and CS2. Right: Power policies applied to all CSs.

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