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Forecasting the Grid Power Demand of Charging Stations from EV Drivers' Attitude

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***Abstract*—In recent years there has been a significant increase in the production of electric vehicles (EVs), in the global strive to reduce polluting gases produced by conventional fossil-fuel driven vehicles. Therefore, many optimization algorithms have been proposed for EV mobility and the charging of battery packs in the stations connected to power grids. However, there are situations in which experimental results are not sufficient, and simulations are needed.**

In this work, we address the effects of the charge demands of an EV fleet on the grid by considering the attitude of EV drivers, and especially their *range anxiety*. This influences their decision of when to recharge the battery pack. To this end, an agent-based model has been developed for the simulation of a power grid considering different scenarios based mainly on the state of charge (SOC) of battery packs at the time of the charging requests of EVs at service stations. The results indicate that in general a high battery SOC at the beginning of charging increases the probability of reaching higher power peaks on the grid.

***Index Terms*—Electric vehicles, smart grid, peak power, state of charge**

I. Introduction

The continuous increase of electric vehicles (EVs) and the consequent installation of new electric charging stations is attracting considerable attention from electricity suppliers and researchers. In fact, this new dynamic scenario poses challenges unknown previously. Therefore, optimization algorithms and methods have been developed, especially during the last decade, as regards both the power consumption in distribution networks and the electricity cost and charging time of EVs. The solution of the problems encountered in EV mobility, such as overstay in public stations and the fair distribution of charging requests over time, can be addressed using real data [1]. However, there are situations that can hardly be analyzed except through accurate simulations. For example, the analysis of all possible traffic conditions, the impact of some power failures on smart grids, and the planning of new stations to meet an excessive demand of charging services in a distribution network, require the use of prediction methods. Furthermore, the study of the general behavior of drivers also requires a virtual simulation environment. In this context, *range anxiety* is one of the most common driver attitudes towards EVs [2]. It concerns the driver's uncertainty of completing the expected journey using the battery as sole energy source. In fact, full-battery electric vehicles generally have a limited driving range compared to conventional vehicles with gasoline or diesel engines [3]. In addition, although the number and spatial distribution of charging stations are continuously being optimized in order to meet the ever-increasing demands for electricity supply for EVs, sometimes infrastructures are still below expectations. Figure 1 shows the current main locations for charging points, where most charging generally occurs in residential installations.

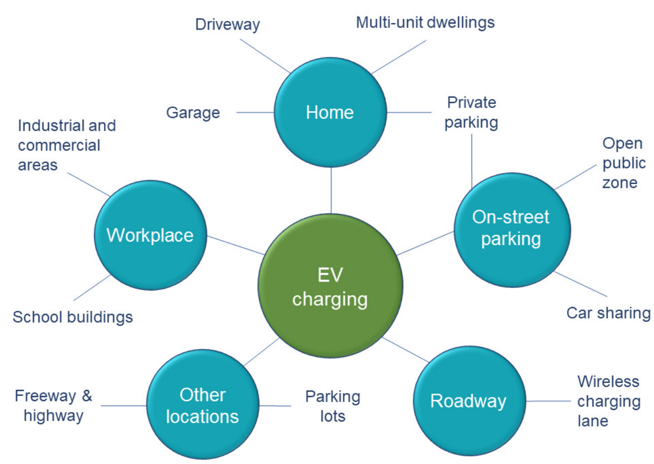

Fig. 1: Main locations for EV charging installations.

This work reports some results regarding the effect of the demand variation in EV charging on the instant power of a grid, in accordance with different behaviors of EV drivers based on *range anxiety*. Simulations have been carried out using an agent-based model (ABM). This model allows the characterization of different scenarios for the analysis of the impact of infrastructure and drivers' attitude on EV charging. The paper is organized as follows: Section II reports the background and related work on charging optimization for EVs, whereas Section III briefly describes the proposed agent-based model. Section IV reports results and an analysis on the data obtained from simulations, and Section V draws some conclusions.

II. Background and Related Work

Nowadays, the two major limitations in adopting electric vehicles, especially electric cars, are still (i) the maximum distance that an EV can travel with the energy of the battery pack alone and (ii) the recharging time which is generally in the order of a few hours. Although great progress is being made in fast charging, an efficient charging of battery packs in only a few minutes remains one of the primary objectives in the automotive sector. These long electric recharges over time can easily involve an overlap of requests for the use of public recharging columns and, consequently, the possibility of instantaneous electrical power peaks provided by the grid [4]. In general, there are mainly two different goals in this scenario: (i) optimal power distribution in a smart grid and (ii) optimal EV charging from a cost of ownership perspective.

A. Optimal Power Distribution

Firstly, policies are required that favor the flexibility and distribution of the power demand from charging stations, which should be as uniform as possible over time [5], [6]. To this end, possible scenarios in the integration of EVs in power grids can be simulated and analyzed preliminarly using models. These can help in the choice of strategies for the load prediction based on charge behavior [7] and then optimization [8]. They are generally based on mathematical methods [9], [10] and computational methods [11]. Among the latter, agent-based models are of great use for the study and simulation of complex systems with an *emergent* property, which appears when the characteristics of the interaction between several elements differ from those of a single basic element. For instance, this is the case of the mobility of an EV fleet [12]–[14] and its related impact on a power grid [15]. In this context, an ABM developed with NetLogo [16], an open-source tool by Northwestern University, was recently proposed [17]. It focuses on the implementation of an optimal infrastructure through only to predict the charging demand of a 24-hour EV mobility. Our work differs from this study in the long-term analysis, that is, a 300-day simulation of mobility for each adopted scenario where each EV is generally independent from another in energy consumption and daily mileage. Furthermore, our work focuses on the optimization of the power demand of an existing charging infrastructure connected to a grid instead of optimizing the location of new stations.

Another multi-agent model including customer behavior was also recently proposed [18]. It simulates a time interval of one year, including weather conditions and the degree of customer satisfaction with the charging service over time. Although a threshold for battery SOC is defined in the model (i.e., SOC_{Limit}, a constraint on the decision to charge the battery), there is not a description of the possible choices for different values of this variable and the consequent results.

In the literature, there are therefore many algorithms and methods for optimizing the use of electricity in grids with charging stations. They consider different situations according to various constraints [10], [19] especially battery capacity and charging rates [20], [21], and also the location of new planned stations [1]. In general, these techniques are based on the analysis of real data collected by charging stations and/or those of each specific EV. These last source of data seems more suitable for a faster forecast, but presents the disadvantage of less privacy regarding the habits of the users of charging services [22]. Other techniques also analyze EV mobility and parking patterns as optimization keys to flattening the load profile of a grid [6], [13], also using auxiliary energy storages to compensate demand flexibility [23].

B. Optimal EV Charging

Methods for optimal charging, from the point of view of the cost of EV ownership, usually consider the state of charge (SOC) of battery packs, time-of-use (TOU) price [24], charging current [20], the minimization of battery aging [25], and the quality of service [26] as crucial factors. In general, predictive models and decision-making methods for these optimizations are based on well-known techniques such as dynamic programming [9], Markov chain [21], fuzzy theory [8] and neural networks [27], whereas ABMs are useful for an exploratory analysis of scenarios involving *emergent* behaviors.

III. Agent-Based Model

The model was developed in NetLogo [16], a tool that allows the simulation of multi-agent systems through the development of program code in an agile way. In fact, it includes specific libraries for the description of the behavior of individual agents and their interactions, and the definition of a graphical user interface. Figure 2 shows the interface of the proposed ABM.

It includes four sliders for setting the following variables: the number of charging stations, charge power, the number of EVs, and the maximum SOC of an EV battery at initial charging. The latter is the threshold that defines the maximum level of the state of charge of the pack of an EV before it is parked in a charging station that refills the battery cells. In other terms, this variable is a constraint that binds an EV to access the recharge service only if the SOC of its battery is lower than or equal to this threshold.

The interface also includes nine data monitors, especially for the real-time display of the most significant simulation values such as the maximum instantaneous power of the grid, the number of occupied stations and the number of stations supplying electricity to any EV. In fact, a station may be occupied with a vehicle that is no longer actually being charged (i.e., overstay) as its battery pack already reached 100% SOC. In this case, the station is busy but without providing energy. At the bottom of the interface, a window for two different plots is included. These plots concern the instant power of the EV grid under simulation test and the average SOC of all the EVs not parked in a charging station, so that a comparison of the trend of these two quantities is made possible.

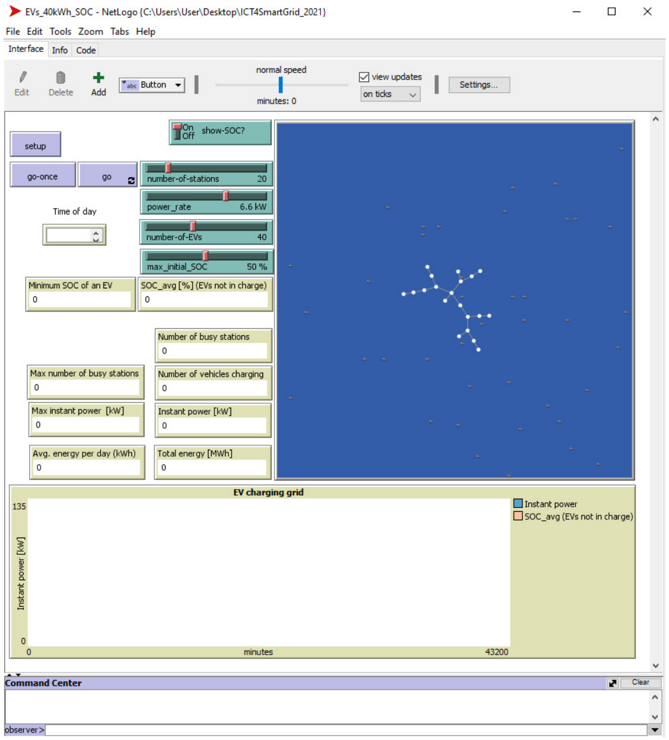

Fig. 2: The NetLogo interface developed for the proposed model.

The 24-hour period is divided into two time slots: daytime, from 7.00 a.m. to 7.00 p.m., and nighttime from 7.00 p.m. to 7.00 a.m. the following day. If an EV is parked in a charging station during the night, it overstays after its battery has been fully charged, until the following morning. Moreover, mobility during the night is very limited compared to the day, but not absent. Thus, all the constraints adopted have the sole purpose of creating the typical conditions of the use of EVs.

IV. Results

We developed an ABM with NetLogo 6.1.1, which allows user-defined variables for the configuration of different simulation scenarios. Table I reports the main settings of the model. In this case the number of charging stations and EVs are 20 and 40, respectively. These values were defined to guarantee a mostly comprehensive coverage of possible scenarios and avoid easy saturation conditions during simluation. The total energy of the battery pack of each EV is a pre-set variable that was defined in the program code; it is 40 kWh. In this work, the charging power depends on the 6.6 kW on-board charger of each EV. Nonetheless, the actual charging power is lower than this value because of the efficiency, so that a full charge (from 0 to 100% SOC) of a 40-kWh battery pack takes about 7.5 hours.

Possible scenarios are indentified by the maximum SOC threshold value, from 10% to 60% with an increment step equal to 10%. For each scenario we carried out 10 simulations

TABLE I: Model parameter setting.

Parameter	Value
Charging stations	20
Electric vehicles	40
Battery pack	40 kWh
On board charger	6.6 kW
SOC threshold	from 10% to 60% (step 10%)

of 30 days each. For each simulation, the initial setting of the battery SOC of each EV and the battery depletion over time are mostly random. In this way, the behavior of any vehicle is independent from another so that this model can generate, through a stochastic approach, all the situations required for a comprehensive analysis.

A. Peak power

Figure 3 summarizes the results regarding the range of the maximum peak power during all the simulations for each scenario. It is worth noting that, in general, a greater value of battery SOC at the beginning of a charging phase leads to a higher maximum power that can be reached. In addition, the range (see the vertical segments) and the mean value (see the horizontal line markers) of the maximum peak power also increase. Nevertheless, the mean value is almost constant at two different levels, when considering the low and high values of SOC threshold (i.e., $\leq$ 30% and $\geq$ 40%, respectively). In any case, an attitude of EV drivers to charge their vehicles when battery packs have a medium or high SOC entails a larger number of service requests, albeit for a shorter time for each of them in comparison with the recharge time of batteries at low SOC level. This situation leads to a greater instability, and therefore uncertainty, in a power grid.

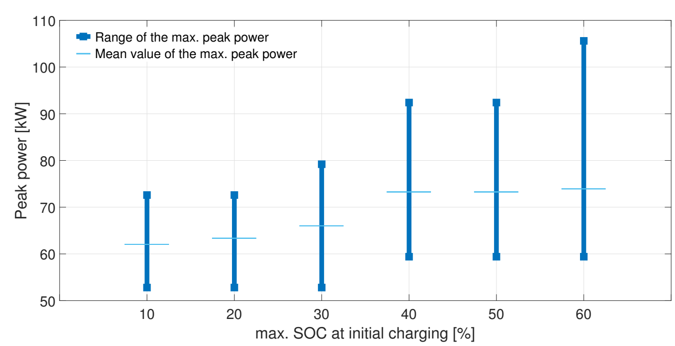

Fig. 3: The peak power for different thresholds of battery SOC.

For a sake of clarity, Fig. 4 reports all the results regarding the maximum peak power for each simulation run. In fact, it is also important to analyze the probability of high power peaks from the number of events during the simulations. Although relatively low power peaks are possible in any scenario, this map shows that the probability to have the largest values of peak power increases as the SOC threshold value increases.

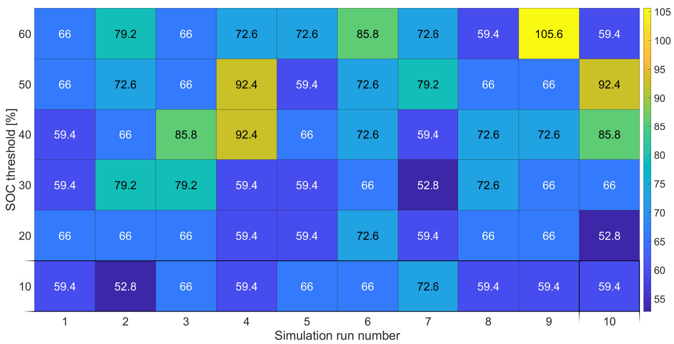

Fig. 4: The maximum peak power [kW] during each simulation run.

B. Charging stations

As for the effects deriving from the attitude of EV drivers on charging, Fig. 5 shows (i) the mean value of the maximum number of stations that simultaneously charge EVs and (ii) the mean value of the maximum number of busy stations, which include the stations with EVs being charged and those with EVs parked after the end of charging. In the first case, the trend is similar to that of the mean value of maximum peak power. In fact, these results (blue dots) are mostly grouped into two different levels of values, when considering low and high values, respectively, of SOC threshold.

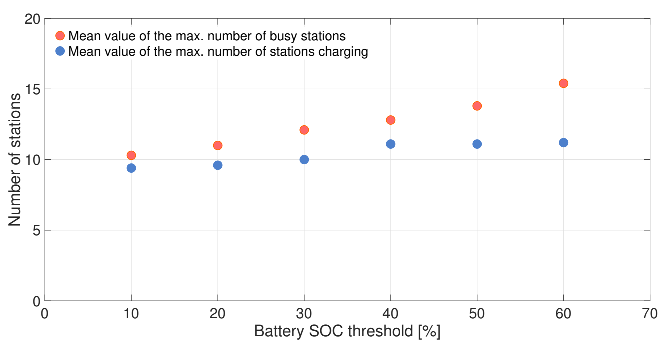

Fig. 5: The mean maximum number of stations for different SOC thresholds.

On the other hand, a monotone increasing function is more evident when analyzing all the busy stations (orange dots). In this case the trend is almost quadratic according to the following relation:

$$N_b = 0.7321e^{-3} \cdot x^2 + 0.4761e^{-1} \cdot x + 9.79 \tag{1}$$

In (1), N_b is the mean value of the maximum number of busy stations at the same time for each scenario, and x is the maximum SOC of EV batteries at initial charging. This function concerns the analysis of busy stations only for the battery SOC range from 10% to 60%. In fact, we considered that it is generally rare to charge an EV with an initial battery SOC outside this range, especially considering that range anxiety in drivers may rise to a more stressful level as a battery pack is close to depletion, and that the life degradation of batteries generally increases at high SOC values [25]. Furthermore, the gap between the two plots of Fig. 5 tends to increase as the SOC threshold increases. This means that, in general, a greater value of the initial SOC in EV charging leads to a greater probability of non-availability of a station, so that more stations are needed to efficiently meet the energy demand of the same fleet from a quality of service perspective. This drawback should be addressed by better analyzing the causes for which EVs remain parked beyond charging times [1]. However, this is outside the scope of this work.

In this context, we define η as the efficiency in the use of stations, as follows:

$$\eta = \frac{\max(S_p)}{\max(S_b)} \tag{2}$$

In (2), S_p is the number of stations supplying power to EVs at the same time, whereas S_b is the number of busy stations. These parameters were evaluated during all the simulations of each considered scenario, with a sample time of 1 minute. Accordingly, η=1 when each occupied station is charging a vehicle. Otherwise, it is less than 1 in the case of overstay of any EV. Figure 6 reports the values of η for each of the ten simulation runs considered in each scenario, and using different shades of blue for a quick visual analysis. Table II reports, in a summarized way, only the minimum and maximum value of η for each scenario. It is worth noting that both values tend to decrease with an increase of the SOC value at initial charging. In this case, 40% is the maximum threshold value of the SOC to achieve, with a good probability, an efficiency equal or close to 1. Conversely, η could be less than 0.7 for SOC threshold values of 50% and 60%. This effect can be explained by the fact that the larger is the SOC value of an EV battery at the beginning of each recharge, the higher is the frequency of service requests to charging stations. Therefore, in this context the SOC threshold value may also represent the level of range anxiety.

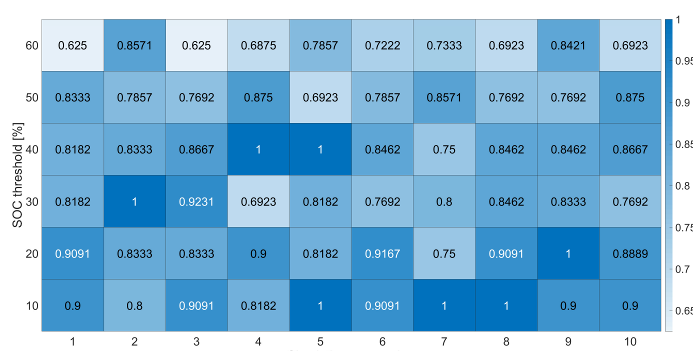

Fig. 6: The efficiency η obtained from each simulation run.

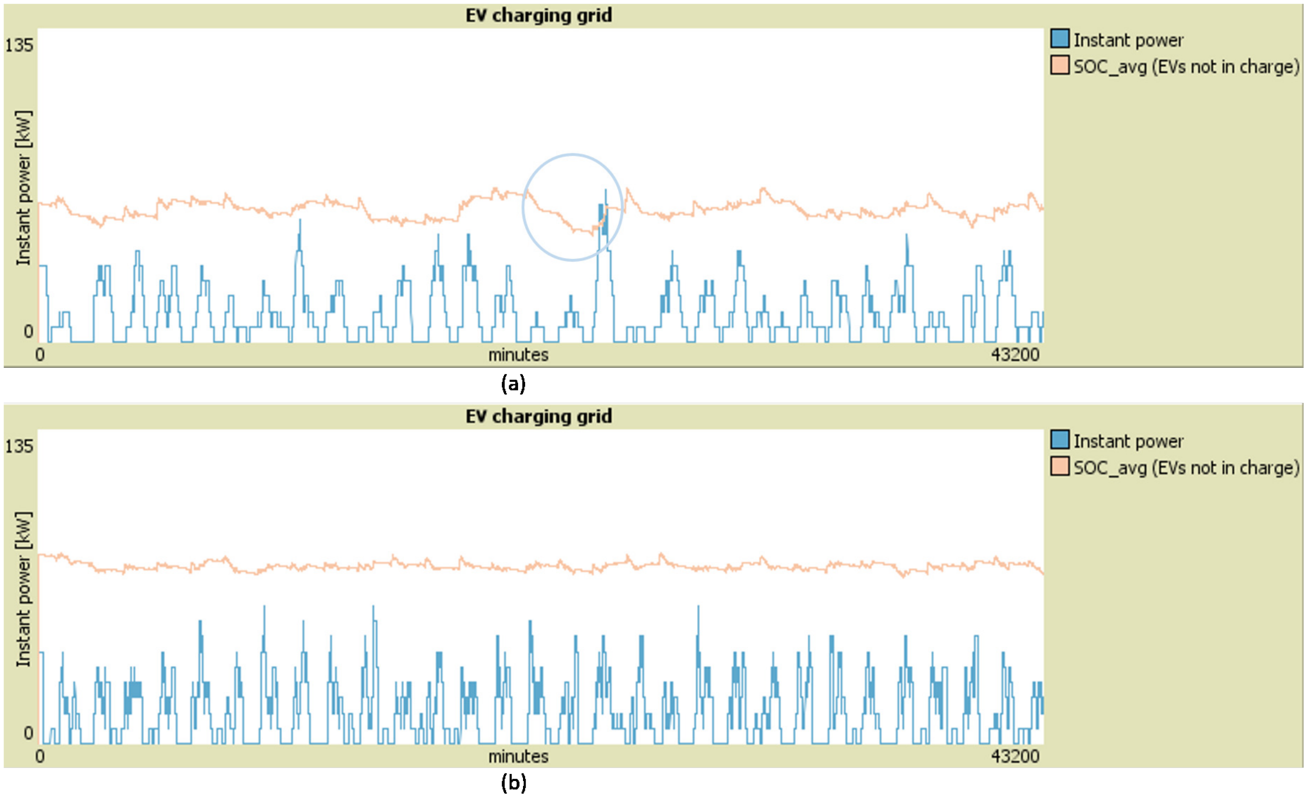

Fig. 7: The grid instant power and SOC$_{avg}$ of the EV fleet in two 30-day simulations: max. SOC threshold at 20% (a) and 60% (b).

TABLE II: Efficiency in the use of stations.

SOC threshold [%]	η	
	min.	**max.**
10	0.8000	1.000
20	0.7500	1.000
30	0.6923	1.000
40	0.7500	1.000
50	0.6923	0.8750
60	0.6250	0.8571

C. Discussion

Firstly, the results suggest that the attitude of EV drivers to charging their vehicles with an initial SOC value of battery pack greater than 30% leads to a greater uncertainty for the forecast of power demand, and that a value greater than 40% could drastically worsen the optimized use of the infrastructure. This result reveals that the impact is generally different when considering the probability of a high peak power and that of station utilization, although the trend is generally very similar.

Figure 7 reports two snapshots of two simulations at different SOC thresholds: one at 20% of the other at 60%. They show the plots of the instant power of the EV grid and the average SOC of all the vehicles that are not parked at any charging station. An observation is that high power peaks generally follow the prolonged declining phase of the mean SOC value of the fleet, as in the example pointed out in the circled area of Fig. 7(a). Furthermore, a greater fluctuation of the average SOC over time leads to a greater probability of having very different peak power values. On the other hand, a stable or flat trend of SOC, such as the example reported in Fig. 7(b), considerably improves grid power peak stability. From these results, it can be inferred that the analysis of the battery SOC and position of every vehicle in a certain area can effectively help in managing the energy distribution in a smart grid by better predicting possible demand peaks.

V. Conclusion

This work reported the impact of the attitude of EV drivers in charging their plug-in vehicles, based on the state of charge of battery packs, on a power grid. The results from the simulation of the agent-based model we developed for this analysis indicate that driver's behavior based on *range anxiety* impacts on the uncertainty of power peaks in an EV charging grid and on the efficient use of stations. In fact, it can lead to an increase of the maximum peak power of about 45% and reduce the efficiency by about 40%, for a range of the maximum battery SOC at initial charging from 10% to 60%. In this context, these latter values can also reflect the levels of driver anxiety.

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