IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 23 March 2024, accepted 10 April 2024, date of publication 17 April 2024, date of current version 24 April 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3389775

RESEARCH ARTICLE

Charging Electric Vehicles on Highways: Challenges and Opportunities

CLAUDIO SCARPELLI[1], MASSIMO CERAOLO[1], (Senior Member, IEEE), EMANUELE CRISOSTOMI[1], (Senior Member, IEEE), VALERIO APICELLA[2], AND GIULIA PELLEGRINI[2]

[1]Department of Energy, Systems, Territory and Construction Engineering, University of Pisa, 56122 Pisa, Italy
[2]Research & Development and Innovation, Movyon SpA—Gruppo Autostrade per l'Italia, 50123 Firenze, Italy

Corresponding author: Claudio Scarpelli (claudio.scarpelli@unipi.it)

This work was supported by MOST—Sustainable Mobility Center through European Union Next-GenerationEU (Piano Nazionale di Ripresa e Resilienza (PNRR)—MISSIONE 4, COMPONENTE 2, INVESTIMENTO 1.4—D.D.1033 17/06/2022) under Grant CN00000023.

ABSTRACT As new models of electric vehicles are put on the market, with larger batteries and higher charging rates, there are growing concerns about how the charging infrastructure should be upgraded and modernized to cope with the challenges they pose. Governmental directives and rules dictate minimal requirements for the future charging infrastructure, but would these be enough to handle massive numbers of electric vehicles? In this manuscript we describe an electric mobility simulator that can be used to mimic highway vehicular flows and evaluate the queues at charging stations under different penetration levels of electric vehicles. Based on actual vehicular flows from the most important Italian motorway, we find that non-homogeneous queues at charging stations can be predicted, and the infrastructure planned by the EU rules may not be able to accommodate a penetration level of more than 3% of electric vehicles in the highway without giving rise to unacceptably high waiting times at charging stations. Also, we note that smart assignments of electric vehicles at charging stations may significantly improve waiting times, opening the discussion on the need for allocation policies and guidelines. Extensive Monte Carlo simulations on an accurate reconstruction of the Italian case study support the discussion and our findings.

INDEX TERMS Electric vehicles, intelligent transportation systems, optimization methods, recharging, highway.

I. INTRODUCTION MOTIVATION

Growing environmental concerns are driving national and international governments to design rules and incentivize virtuous behaviors, in an attempt to mitigate polluting factors. For instance, the European Union's "Fit for 55" package contains rules that aim at facilitating the penetration level of EVs (Electric Vehicles) within the transportation sector, under the acronym AFIR (Alternative Fuels Infrastructure Regulation). Namely, new Charging Stations (CS's) need to be installed "every 60 km along TEN-T core network highways" (the Europe's continental highway system), delivering by end of 2025 a minimum of 400 kW of total charging capacity, and including at least one 150 kW+ charger, and by end of 2027 a minimum of 600 kW including at least two 150 kW+ chargers ([1], art. 3.4-a). Similar rules have been dictated for commercial vehicle charging, and plans for future years have been already outlined as well. For instance, the minimum total capacity must increase to 600 kW, with at least two 150 kW+ chargers by 2028. Clearly, comparable rules may be regarded as generic baselines to be adopted in all countries, but then they should be adapted to specific territories taking into account their peculiar characteristics, most notably, vehicular densities and flows.

In this manuscript, we evaluate what penetration level of EVs may be tolerated by the aforementioned rules in a specific case study, corresponding to the country of Italy, using realistic traffic flows and actual vehicular data. In addition,

The associate editor coordinating the review of this manuscript and approving it for publication was Tariq Umer.

we also compare two basic alternative decentralized strategies that drivers may choose to select a charging station along a highway and show that smart choices may significantly reduce waiting times at charging stations.

A. STATE OF THE ART

Electric vehicle traffic simulation stands at the forefront of transportation research, addressing the intricate challenges posed by the increasing penetration of electric vehicles. Many papers in the literature propose mobility simulators that leverage on dynamic modeling of EVs, realistic integration of existing charging infrastructure, urban and non-urban paths, and consideration of diverse vehicle types (e.g., passenger cars, electric buses or commercial vehicles). Subsequently, these tools aim to simulate various scenarios and conditions, including peak traffic hours, adverse weather conditions, and varying road topography. Additionally, these simulators implement optimization strategies aimed at minimizing specific performance indices, such as travel time, energy consumption, and congestion levels.

In [2] and [3], a planning methodology for the installation of highway charging stations has been proposed. This methodology is based on minimizing a combined cost function that considers both the construction and maintenance costs of the stations and the cost associated with user waiting times. The simulation involves a highway route with intersections covering a total length of approximately 300 km. The study determines the optimal number and spacing of charging stations along the highway to achieve the optimal solution.

In [4], a case study concerning a 530 km stretch of highway in Spain with 23 charging stations has been simulated using the agent-based simulation software AnyLogic. The simulation includes modeling electric vehicle consumptions, accounting for road slope, and weather conditions. Taking into account a maximum of 31 electric vehicles in transit, the authors demonstrate the optimization of the system by prioritizing user queue time as a critical index and enhancing the number of charging stations and their power capability.

In [5], [6], and [7], algorithms have been developed to simulate electric vehicle traffic integrating the transportation network and the power grid, encompassing user behaviors, the redistribution of charging facilities, congestion occurrences, and dynamic variations in user routes. These algorithms are applied to case studies involving multi-node networks and fleets of electric vehicles numbering in thousands of units. The same approach is followed by the authors in [8], where the focus is on refining the energy consumption of individual vehicles. This is achieved by introducing the impact of cabin thermal conditioning on energy consumption during different seasons. The authors analyze how the peak load of charging EVs changes in different seasons. Similarly, the authors in [9] have carried out a Monte Carlo analysis to examine the impact of EV charging and estimate the electric load growth on the Colombian grid, with particular interest in the overloading of transmission lines and transformers.

The authors in [10] have analyzed the localization of electric vehicle charging stations in the urban area of the city of Rome using the popular open-source traffic simulator SUMO in a geo-referenced environment.

In summary, the majority of studies propose simulators developed either independently or based on open-source or commercial software, capable of processing electric vehicle flows in urban and extra-urban environments, applied to realistic case studies. Most works use simulators as a support to take decisions about where to allocate and enhance the actual charging infrastructure; little attention is usually devoted about how to influence the habits and behavior of drivers to optimally utilize the existing infrastructure. Some works in the latter topic exist, usually referring to the problem of assigning EVs to charging stations, under the assumption that drivers will follow the received recommendation. See for instance [11] and [12] for similar assignment recommendations in an urban scenario.

In addition, most of the previous references only address simple scenarios with small numbers of vehicles and, as already mentioned, some of them focus on urban environments, while in the present paper we are explicitly interested to charging events in a motorway. Moreover, in this paper we explore what could happen in a future scenario, with a much greater penetration level of EVs than today, to assess how the 2028 EU planned charging infrastructure is expected to perform.

B. CONTRIBUTION

As per the previous section, our manuscript provides the following main contributions to the existing state of the art:

- we evaluate the latest rules dictated by the EU, in terms of their ability to accommodate for a large fleet of EVs, and we show that penetration rates larger than 3% may give rise to unacceptable waiting times at CS's;
- we present and discuss a tool that can be used to evaluate what CS's should be expanded, or where new CS's should be built;
- we evaluate the impact of different charging strategies and show that basic decentralized approaches may already provide significant improvements even without changing the charging infrastructure;
- while our results have been obtained for a specific case study, the same simulator may be adapted to evaluate different highways in different contexts.

Our manuscript is organized as follows: the next section is dedicated to present in detail the developed mobility simulator. Section III briefly describes the specific case study of interest, and Section IV describes our simulation results, highlighting the most interesting outcomes we have obtained. Finally, Section V summarizes the findings of the manuscript and outlines our current research interests on the topic.

II. ELECTRIC MOBILITY SIMULATOR

A. INPUT DATA

As classic mobility simulators, input data include the structure of the highway network, the Origin/Destination (OD) matrix, starting time of vehicles, and characteristics of the EV fleet (i.e., battery capacity, charging rates, energy consumption rates…). As per the characteristics of the CS's, we assume that all CS's are equipped with the charging infrastructure as per the AFIR rules according to the end-of- 2027 deadline: while this is not entirely true in Italy in this moment, yet the AFIR objectives will be met well before the deadline. Monte Carlo simulations are then performed to appreciate when queues start appearing at CS's under different penetration levels, and under different charging strategies. The specific components of the electric mobility simulator are now individually illustrated.

1) STRUCTURE OF THE HIGHWAY

We consider a single (two-way) linear segment of an Italian highway, namely, the longest linear segment – called Autostrada del Sole (A1) – depicted in Fig. 1a. This segment includes a sequence of motorway entrances and exits, in addition to charging stations (actual highway structure and data has been used). For the moment, for simplicity, we do not consider the intersections with other roadways.

In response to the AFIR rules, the charging stations on the A1 highway are equipped with pairs of High Power Chargers (HPCs), that can each deliver up to 300 kW, but the sum of the two cannot exceed the same amount as well. This charging infrastructure is by large compliant with the previously mentioned prescriptions of [1], according to the latest deadline (end of 2027). In addition to this, stations are also equipped with a fast charger with 64 kW max power.

In our simulations, we slightly simplify this architecture assuming that each charging station is equipped with five independent chargers with maximum power equal to 150 kW. The effects of this simplification are however negligible because the charging rates of the considered vehicles (taken as average charging power between 10-80% of State of Charge) cannot exceed 150 kW, which is consistent with current EV specifications. This assumption is consistent also with the vast majority of electric vehicles that are currently in circulation, which, as specified later in the text, have average charging powers lower than 150 kW. For the purposes of this study, the presence of charging power peaks higher then the CS's limit will not be considered, as it is reasonable to assume that the occurrence of two vehicles simultaneously charging with synchronous peaks exceeding the station's limit is extremely unlikely.

2) OD MATRIX

The OD matrix corresponding to an average working day has been considered as our baseline to identify the trips taken by single vehicles. This matrix was obtained by considering the average toll information at entrances/exits of the motorway during weekdays; only vehicles starting and ending their journey on the same A1 segment have been considered for our purposes. Interestingly, the same OD matrix may be also used to represent peak days (e.g., those occurring at the beginning or at the end of summer holidays in Italy), after appropriate scaling to consider the increased volume of traffic. Toll data show that the total number of vehicles increases during peak days, but their distribution does not change significantly if a single piece of the whole highway network is considered, as in our case.

The (i,j) entry of the OD matrix contains the number of vehicles that during the considered day start their trip from the i'th entry of the motorway and leave the highway at the j'th exit. The OD matrix is then normalized so that the sum of all its terms is 1. The so obtained elements of the OD matrix are called *baseline* values, and then they are slightly perturbed according to a pre-defined probabilistic distribution, to evaluate the sensitivity of our traffic analysis under different conditions. The baseline OD matrix is depicted in Fig. 1c and Fig. 1d, in a 2D and in a 3D view to appreciate the most common trips.

3) STARTING TIME

For simplicity, we assume that all trips from the OD matrix have the same starting time, which is drawn from the probability function depicted in Fig. 1b. Roughly speaking, this implies that most trips start during the morning and during the afternoon, while fewer trips take place during lunch time or during the night.

4) ELECTRIC VEHICLE FLEET COMPOSITION

We assume that each EV travelling in the road network is randomly drawn from a "class" of vehicles, which is required to determine its battery size and its charging rate. For simplicity, we assume that the charge rate is constant, corresponding to the average value of the typical recharging curves for EV fast charges between 10 to 80% SOC. It is well known that such an approximation actually provides accurate estimates of charging times [12]. The composition of the fleet of EVs is summarized in Table 1, in addition to other input information related to our case study. According to the table, we assume that small cars, with small capacities and low charging rates, are less likely to take long trips along the highway network (i.e., we assume that they are mainly used for urban trips). Furthermore, to simulate more realistic conditions, the State of Health (SOH) of each vehicle's battery is also taken into account. This is done by multiplying the value of the individual batteries' nominal energy by the SOH coefficient randomly sampled from a uniform distribution between 0.7 and 1. In this way, we are tacitly assuming that the 70% threshold corresponds to the end-of-life value for the battery, which is consistent with what is recommended by most EV manufacturers.

5) CHARGING STRATEGY

In this manuscript, we only consider so-called *decentralized* charging strategies, i.e., where each driver autonomously

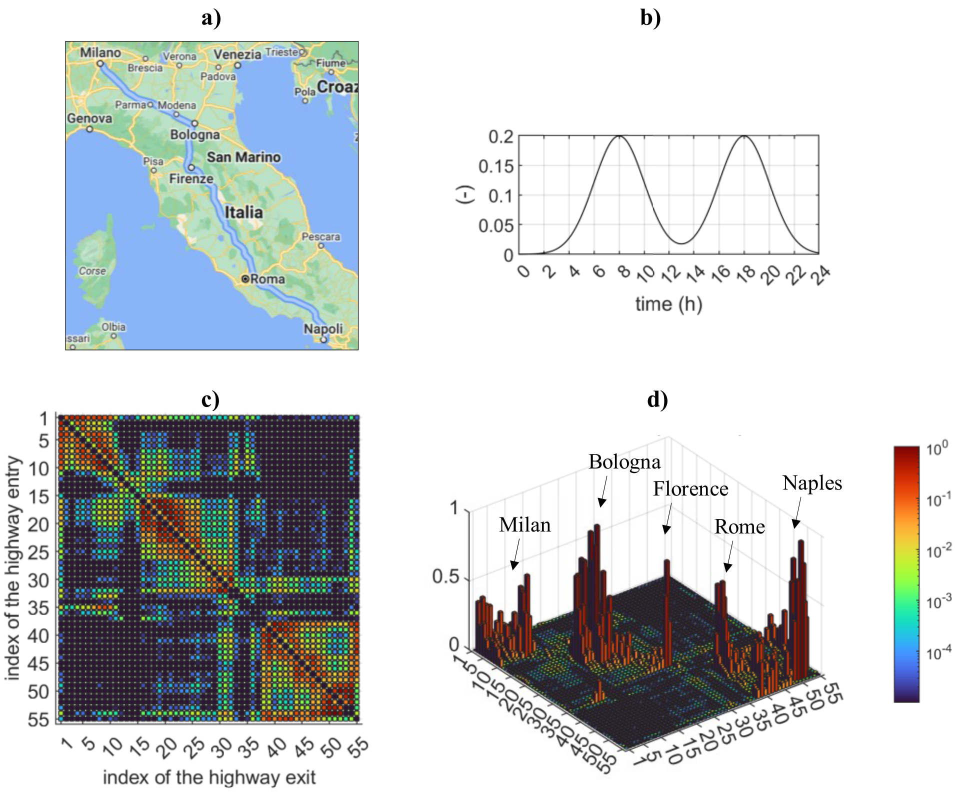

FIGURE 1. a) Case study: Italian highway "Autostrada del sole (A1)"; b) Probability function of the starting time probability of the EVs; c) 2D visualization of the baseline OD matrix; c) 3D visualization of the baseline OD matrix.

TABLE 1. Case study input information.

Structure of the highway			
Length (km)			760
Number of entries/exits N_b			55
Number of charging stations N_s			48
Average distance between toll booths (km)			14
Average distance between charging stations (km)			31
Number of charging posts per charging stations N_{posts}			5
Maximum charging power per charging posts (kW)			150
Electric vehicle fleet composition			
Class	Battery size (kWh)	Charging power (kW)	Percentage (%)
Small	50	35	10
Medium	60	80	30
Big	80	120	50
Prime	100	140	10
Other information needed for the simulator			
Simulation time horizon T (h)			24
Total number of time steps Z_{tot}			288
SOC_{start} range (%)			50-100
v range (km/h)			100-130
SOC_{min1} (%)			30
SOC_{min2} (%)			15
SOC_{max} (%)			80
Total number of vehicles (electric and non-electric) N_{tot}			$500 \cdot 10^3$

decides when and where charging the vehicle, based on only local information (e.g., SOC, distance to the final destination). In particular, we consider two alternative strategies: in the first one, an EV is charged in order to prevent its SOC from going below a prespecified threshold, that we shall denote by SOC_{min1}. Accordingly, when an EV gets in proximity of a CS, it will estimate the value that its SOC may reach if it does not stop for charging now, and will wait until the next CS (or its destination). If the estimated SOC is below SOC_{min1}, then it will stop for charging now. If the estimated SOC is above SOC_{min1} then it will proceed until the next CS, where the same decision process is repeated.As a second alternative strategy, we assume that if an EV is informed that the next CS is currently full, then it accepts to go below the threshold SOC_{min1} and wait until the next CS, in the hope that the following one will not be full. This second option is acceptable provided that the estimated SOC will not anyway go below a second threshold SOC_{min2} (where $SOC_{min2} < SOC_{min1}$). In our simulations, we set $SOC_{min2} = 15\%$ and $SOC_{min1} = 30\%$, so that according to the first strategy no vehicles will ever have a battery with a SOC below 30%, while with the second strategy some vehicles accept to have a SOC below 30% (but never below 15%) with the hope to decrease waiting times at CS's. Such choices of SOC_{min1} and SOC_{min2} have been tuned according to known preferences of drivers, to mitigate *range anxiety* [13].

B. SIMULATOR ALGORITHM

The electric mobility simulator consists of two main phases, as illustrated in Fig. 2. In the first phase, denoted as

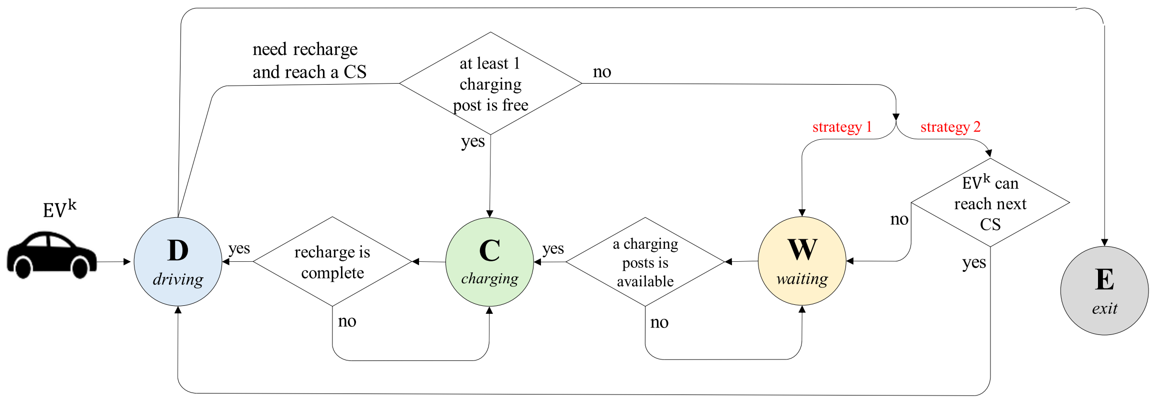

FIGURE 2. Diagram of the possible states of EVs, as implemented in the simulator.

"*Initialization phase*", all the input data are prepared and given to the simulator. This includes the time horizon and the time step (e.g., 1 day and 5 minutes in our case study respectively) that give rise to the total number of time steps to be simulated Z_{tot}. Given N_{EV}, the total number of EVs traveling on the highway within the simulated time horizon (measured from data), EVs are allocated into classes according to the stochastic behavior as described in Section II-A4), their trips are randomly decided according to the OD matrix described in Section II-A2), and their starting time is randomly selected as explained in Section II-A3). At the end of this phase, each EV, denoted by index k, knows its initial position (p^k_{start}), its destination (p^k_{end}), and the time step at which it enters the highway (z^k_{start}). In addition, each EV, depending on its class, is associated with further information, such as its initial state of charge (SOC^k_{start}), where the initial SOC is defined as the ratio between the initial battery energy and the battery size; the vehicle average speed (v^k), considered constant throughout the journey, finally, both SOC^k_{start} and v^k, for each vehicle $k \in [1, N_{EV}]$ are randomly extracted between their respectively allowed minimum and maximum values, according to a uniform distribution. Once the speed is known, the algorithm computes the vehicle consumption, necessary to determine how much the battery discharges as the vehicle proceeds along the road. For high speeds, such as those expected on the highway, the consumption can be considered dependent solely on the vehicle speed, since acceleration and braking actions are much rarer than in urban or rural environments, and the resistance to movement due to friction and air resistance is very large and dominates on other factors (cf. Equation (2) in [14]).

Finally, the "*state flag*" identifies the mode in which a vehicle can be found during the simulation, chosen among 4 possible conditions: "*D*" (driving), where the vehicle is moving along its route, or still has to start its trip; "*W*" (waiting), where the vehicle is stopped in a queue at a charging station, waiting for a charging post to become available; "*C*" (charging), where the vehicle is connected to a charging post and the battery is charging; "*E*" (exit), meaning the vehicle has completed its route and has exited the highway.

The second phase of the algorithm, named "*Elaboration phase*", is where the mobility simulator processes the evolution of the vehicular flow throughout the entire established time horizon. In this phase, at each time step all vehicles' states are updated, especially for what regards their position along the highway, and their SOC. In particular, if a vehicle is on the highway at a certain time step, it is processed based on the value of its state flag:

- if the vehicle is driving (state flag = "D", represented with a blue background in Fig. 2) its position and SOC values are updated (respectively pos^k_{z+1} and SOC^k_{z+1}), based on the constant speed model. If the EV reaches its exit destination at the very next time step (*if* $p^k_{z+1} = p^k_{end}$), its state flag is updated to "E". If the vehicle reaches a charging station, then it decides whether to stop for charging or not, according to the selected charging strategy (as per Section II-A5) and its actual SOC. If the EV decides to stop, if it finds an available charging post, it starts charging and the state flag is updated to "C" (charging), otherwise, its state flag is updated to "W" (waiting) and the vehicle is added to the CS queue.
- If the vehicle is queuing (state flag = "W", represented with a yellow background in Fig. 2) the position and SOC values are not updated, and the vehicle waits for its turn for charging, according to a classic first-in-first-out (FIFO) logic. When the vehicle is the first of the queue, as soon as a plug becomes available, the vehicle goes from the "W" state to the "C" state flag.
- If the vehicle is charging (state flag = "C", represented with a green background in Fig. 2), the position does not change, but the SOC is updated based on the maximum charging power allowed by its vehicle class. The level of the battery energy (i.e., the variation of its SOC) during the charging time step is computed as the product between the interval duration and the charging power. The vehicle remains in the "C" state flag until it reaches a predefined maximum SOC threshold for the end of charging (SOC_{max}). Once this threshold is reached, the EV completes the charging phase, frees the

charging post, and resumes driving, setting its state back to "D".

- Finally, if the vehicle has the "E" state flag (represented with a gray background in Fig. 2), it must have concluded its journey, and it is not updated anymore.

C. KEY PERFORMANCE INDICATORS

In this section we list some significant key performance indicators (KPIs) that will be used to evaluate the ability of the charging infrastructure to accommodate fleets of EVs for different values of penetration levels, and to compare the impact of different charging strategies. In addition to KPIs dedicated to evaluate mobility parameters (e.g., queuing times at CS's), it is also critical to evaluate the electrical power absorbed by CS's. While this aspect is only marginally addressed in this manuscript, power and energy requirements need to be taken into careful consideration when planning and sizing new CS's, or upgrades of existing ones.

- $perc^{recharge}$: percentage of EVs that recharge at least once during their trip;
- $perc^{waiting}$: percentage of EVs that, before charging, need to wait because all plugs are busy;
- $N_{tot}^{recharge}$: total number of recharging events;
- $t_{avg}^{recharge}$: average time for a single charging event;
- $t_{tot}^{recharge}$: total time required for all charging events;
- $t_{avg}^{waiting}$: average waiting time before starting the charging process (computed among EVs that charge at CS's);
- $t_{max}^{waiting}$: maximum waiting time before charging (for all vehicles during one day of simulation);
- P_{max}^{s} and P_{avg}^{s} : maximum and average charging power of the s'th charging station;
- $perc_{use}^{s}(z)$: percentage of utilization of the s'th CS at time step z, as per Equation (1) below, where $N_{EV}^{s}(z)$ represents the number of EV charging at the s'th CS at time step z;
- $perc_{use,avg}^{s}$: average value of $perc_{use}^{s}$ for the s'th station, as defined in Equation (2);
- $var_{use}^{stations}$: variance of $perc_{use,avg}^{s}$ among all the stations, as defined in Equation (3), to evaluate if the charging EVs are well balanced amongst the available CS's.

$$perc_{use}^{s}(z) = 100 \cdot \frac{N_{EV}^{s}(z)}{N_{posts}^{s}} \tag{1}$$

$$perc_{use,avg}^{s} = \frac{1}{Z_{tot}} \sum_{z=1}^{Z_{tot}} perc_{use}^{s}(z) \tag{2}$$

$$var_{use}^{stations} = \frac{\sum_{s=1}^{N_s} \left[perc_{use,avg}^{s} - \left(\frac{1}{N_s} \sum_{s=1}^{N_s} perc_{use,avg}^{s} \right) \right]^2}{N_s} \tag{3}$$

III. CASE STUDY

As already mentioned, the proposed mobility simulator is used for a case study consisting of the A1 highway in Italy. This two-way road is 760 km long from Milan to Naples, passing through the cities of Bologna, Florence and Rome. Overall, we consider 55 entries/exits and 48 CS's. Charging stations are placed in a symmetric way on both sides of the road (i.e., 24 per each direction), and each one of them is equipped with 5 charging posts (according to the EU directive). All details are summarized in Table 1 and in Fig. 1. The OD matrix illustrated in Fig. 1 shows that the majority of trips along the highway consists of short trips of a few kilometers, corresponding to large values along the diagonal of the matrix.

In the following simulations we evaluate what happens if the percentage of EVs varies from 0.5% to 5%. The percentage of EVs in Italy is currently around 0.4%, but the percentage of EVs in the highway is even lower. This is due to the fact that in some cases EVs have been purchased for local urban usage, and are rarely used for longer trips. This is especially true for small EVs with small batteries and low charge rates. In the following, we do not consider commercial vehicles. Energy consumption is estimated according to a second-order polynomial function dependent on the cruising speed, in order to have 177 Wh/km at 100 km/h and 245 Wh/km at 130 km/h.

IV. SIMULATION RESULTS

A. MONTE CARLO SIMULATIONS

All results are provided as the outcome of 50 Monte Carlo simulations, to average the stochastic effects of each simulation (i.e., in terms of OD matrix, starting time of trips, actual composition of the EV fleet, cruising speeds, ...). In addition to average values, we also provide the standard deviation of the results, to appreciate their statistical spread and evaluate possible critical situations.

Finally, all results are provided for six different penetration levels (namely, 0.5, 1, 2, 3, 4 and 5%), and for the two different charging strategies explained in Section II-A5, so that, overall, 12 different scenarios have been evaluated, and each one is simulated 50 times.

B. QUEUES AT CHARGING STATIONS

Fig. 3 summarizes the results of the simulation. In the boxplots, the central line indicates the median value of the Monte Carlo simulations, while the top and bottom edges of the boxes denote the 75th and the 25th percentiles, respectively. Circles refer to what have been automatically identified as outliers. In particular, Fig. 3a shows that the number of charging events obviously increases with the penetration level of EVs, and Fig. 3b shows that the average duration of a charging event is constant (i.e., it only slightly varies depending on the stochastic composition of the EV fleet). The other figures (Fig. 3c-Fig 3f) provide interesting insights regarding the queues at the charging stations. In particular, it can be noticed that queues start appearing when the penetration level is at least 2%. In this case about 10-20% of the charging vehicles need to wait some time at the CS before starting their charging process, and while the average waiting time is negligible (i.e., less than 10 minutes – see Fig. 3e), on average, during

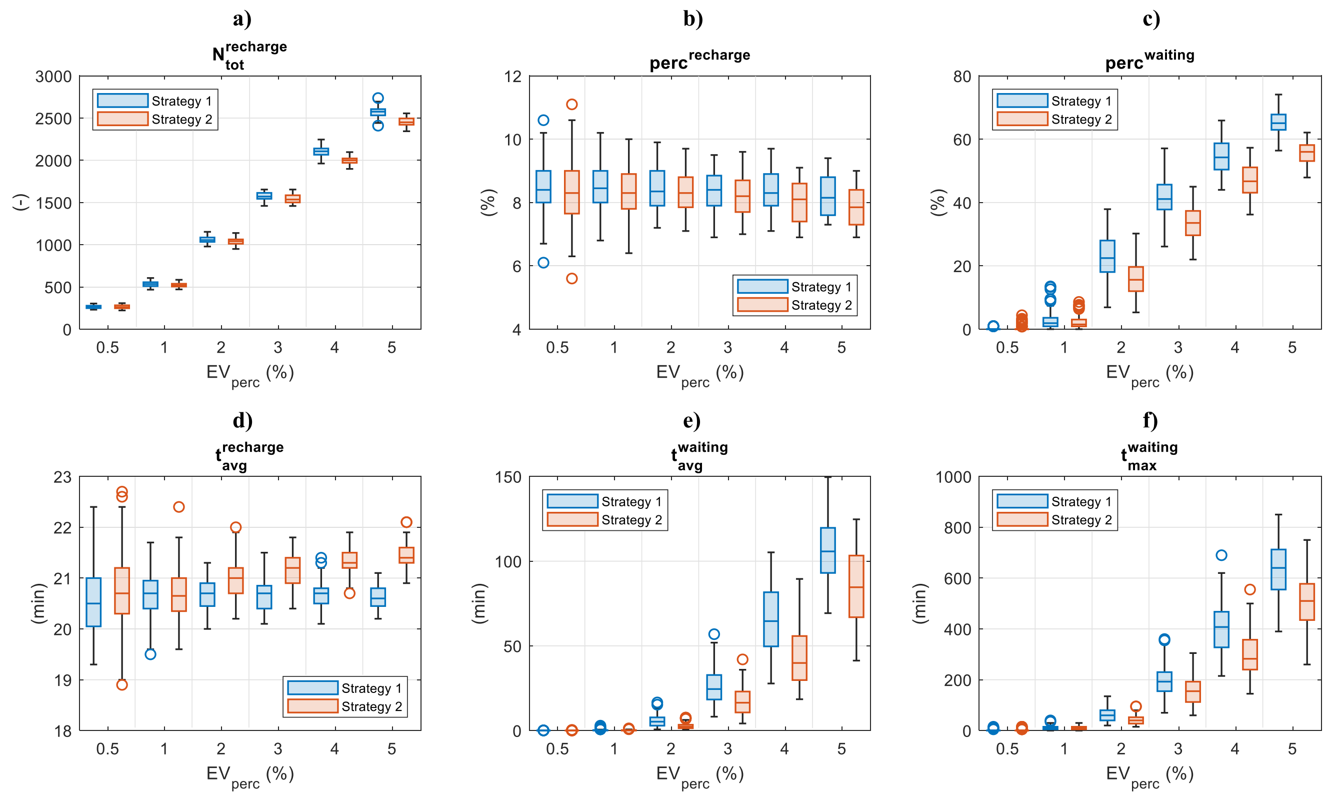

FIGURE 3. KPIs from the simulation results.

the day, there is always at least one vehicle that experiences a waiting time greater than 1 hour (see Fig. 3f).

It can be also noted from Fig. 3 that different charging strategies have a significant impact on the waiting time at the CS's. A first difference between the two strategies is that the second strategy gives rise to a smaller amount of charging events (see Fig. 3a), although the time for charging is on average longer (see Fig. 3d). The reason is that the second strategy allows for a deeper depletion of the batteries of the EVs (down to 15%) under specific conditions (i.e., if the upcoming CS is fully occupied). Accordingly, it takes a longer time to charge the battery starting from a SOC equal to 15% (strategy 2) than it takes from a SOC equal to 30%, and likewise fewer charging events may be required. However, the most relevant difference between the two strategies is that the second strategy gives rise to significantly shorter queues: for instance, with a penetration level equal to 3%, the percentage of vehicles having to wait at a CS decreases from 40 to 30% if the second strategy is adopted. Or similarly, the average waiting time decreases from 20 to 10 minutes. This observation is particularly interesting, because the second strategy does not require any upgrade of the existing charging infrastructure, and only assumes that drivers may be able to know if the next CS is full or not.

From Fig. 3 we can conclude that with the assumed vehicle data and charging strategies 3% is the maximum penetration level that can be supported by this motorway without incurring excessively long waiting times at CS's, which is in agreement with [14]. Indeed, already with the penetration level of 3% there are vehicles that have to wait for more than 100 minutes before they can start the charging process.

Remark 1: Regarding our simulator predictions, we want to clarify that they are based on realistic traffic data (derived, after some obfuscation, from actual measures from the company handling the motorway of the case study), and some assumptions on the EV characteristics and behaviour (summarised in Table 1). A proper validation of the results is not feasible in the Italian context, as the current penetration of EVs is still too low (around 0.4%).

Remark 2: we note again that in this context, we refer to penetration levels of EVs within vehicles travelling on the highway, and not penetration levels of EVs in the car market. Indeed, a penetration level of 3% in the highway is supposed to correspond to a much greater penetration level of EVs in the market, since many EVs are often purchased only for local urban traffic.

A final consideration is that even if we conservatively assume that EVs adopt the less convenient first charging strategy (which uses a SOC range of 50%, between 30 and 80%), assuming a battery size around 75 kWh, and an average consumption of about 210 Wh/km (corresponding to a speed of 115 km/h), then our simulator suggests that the average charging speed of an EV is around 428 km/h (which means that after 1 hour of charging, the EV can travel for about 428 km). This result is consistent with the expected average performance of the electric vehicles fleet composition in the upcoming years, as displayed by EV manufacturers and global trends [15], [16].

Fig. 4 shows the percentage of utilization of the different CS's in the two directions (i.e., from Milan to Naples, and from Naples to Milan), providing information on which geographical areas require greater attention for potential enhancement of the charging infrastructure. It can be noticed that the most frequently used CS's are those located in the proximity of the city of Naples: this is both due to the high traffic density in the region, and most importantly to the fact that there are fewer CS's in the last segment of the roadway. In particular those indexed by number 22 in both directions of travel, for which, in the scenario with a 3% EV penetration, utilization rates exceeding 50% are reached (meaning that on average all charging posts are occupied for 12 out of 24 hours). Even the CS's located near other major urban centers exhibit peaks of demand, with values up to 20% in the Milan area (stations number 3-5).

The obvious discrepancy between over-utilized and under-utilized CS's is the main limitation of the current uniform allocation of the stations. This is compliant with the requirement of [1], and ensures a minimum level of charging capability to users entering from any place in the motorway. It indicates, however, that future enforcements of charging stations should be targeted at the mostly congested areas, which in the case study are near Naples and Milan.

Alternatively, incentives should be designed to push drivers to choose alternative charging strategies (i.e., even when the SOC is not below 30%) to prevent most EVs from stopping at the same CS's, and rather exploit the available infrastructure in a more balanced fashion. At this regard, Fig. 5 shows the variance of utilization of the different charging stations, where a smaller value of the variance corresponds to a more balanced utilization of the infrastructure. As one could expect, the second charging strategy outperforms the first one, because it allows for a more balanced exploitation of the available infrastructure (a lower variance).

The strategies used in the paper are derived from choices made by drivers based only on:

1. SOC;
2. the position of charging stations along the route;
3. whether the next charging station is full or not.

The first two items are already available on all cars, the third one can be easily provided through digital panels, similarly to what is currently done for available parking spots at parking lots. Nevertheless, we strongly believe that the charging potential of a motorway can be further significantly improved if driver's decisions are centrally orchestrated and supported. For instance, the motorway manager is aware of the whole real-time EV charging load across all CS, of actual traffic flows in the highway network, and can determine a

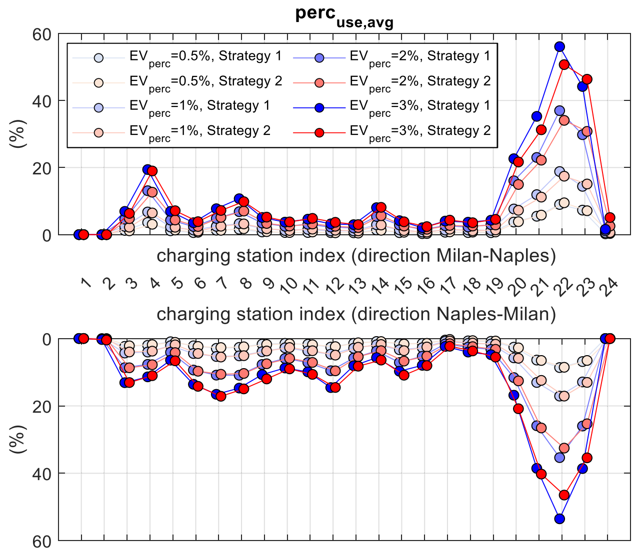

FIGURE 4. Percentage of utilization of the different CS in the two directions (average values for scenarios up to 3% of EV_{perc} are shown).

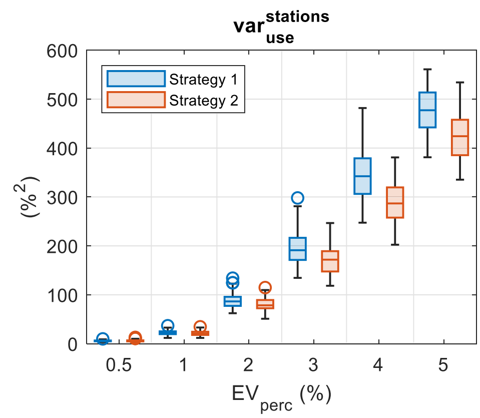

FIGURE 5. Variance of utilization of the different charging stations.

more convenient allocation of future EVs than individual drivers with only local information. The interesting research aspect then becomes how to incentivize drivers to accept the central recommendations of where to charge.

As example, it may appear convenient to design dynamic pricing schemes, to force drivers to adhere to centralized recommendations regarding the choice of the charging station. Dynamic pricing may be highly effective in urban contexts (see examples in [11] and [17]), less on highways because there would be fewer opportunities for charging (i.e., a driver cannot change its route to find an alternative charging station), and tighter constraints (i.e., the final destination cannot change either). Nevertheless, significant improvements are expected also on motorways.

Such a central management architectures is the natural completion of this study and will be addressed in greater detail in a following paper. In addition to more sophisticated assignment algorithms, our work can be expanded also in other directions. First of all, the full national motorway network should be considered, and not just the A1 stretch, and maybe even the whole TEN-T network, to fully appreciate all European traffic flows, and obtain more accurate traffic data, and better identify critical highway links. Also, the power peaks at CS's, and the overall energy requirements, should be better correlated with the actual properties of distribution networks to identify what are the margins of upgrading of existing CS's, or where new ones could be built, taking into account appropriate integration with renewable energy sources and battery storage systems. If so, then the mobility simulator could be also deployed as a proactive tool to plan and size new infrastructure.

V. CONCLUSION

In this paper we presented an electric mobility simulator that allows us to evaluate the charging load at the charging stations of a motorway. The simulator has been used in a realistic case-study (the most important Italian motorway), and has shown that, using realistic vehicle data and charging strategies based on currently available information (or what may be simply available in the near future) the maximum reasonable penetration of EVs running on motorways would be around 3%. Beyond this value, the charging infrastructure recommended by the AFIR directive may give rise to unacceptable queues at the CS's. This result casts shadows regarding the future horizon of the directive, although it is obviously intertwined with the actual penetration level of EVs, which is currently significantly far from the 3% threshold in most Southern Europe countries.

The paper has also shown that in the considered motorway, having a uniform distribution of charging stations, the largest queues are generated just around two urban areas. Therefore, future empowerment of the charging station capability should address these areas, rather than keep following a uniform approach.

In addition to the physical empowering of the charging capability, also a managerial improvement can mitigate the situation. This paper shows that moving from a first basic strategy to a second one, significant improvements can be already obtained.

In conclusion, even larger improvements can be foreseen using a centralized allocation strategy of charging vehicles, which has been sketched in this paper, but not implemented yet. Such last an observation may serve as a starting point to discuss who should better be in charge of orchestrating the charging process of EVs at CS's.

ACKNOWLEDGMENT

The authors would like to thank the (anonymous) reviewers whose remarks contributed to improve the quality and the clarity of the final version of this article. They also like to thank Dr. Ekaterina Dudkina for her helpful suggestions. This manuscript reflects only the authors' views and opinions; neither the European Union nor the European Commission can be considered responsible for them.

REFERENCES

[1] (2014). *Regulation of the European Parliament and of the Council on the Deployment of Alternative Fuels Infrastructure, and Repealing Directive 2014/94/EU*. [Online]. Available: http://data.consilium.europa.eu/doc/document/PE-25-2023-INIT/en/pdf

[2] J. Zhang, H. Zhou, S. Liu, C. Liu, S. Zeng, L. Jiang, B. Li, and H. Liu, "Highway charging station plan based on dynamic traffic flow simulation," *IOP Conf. Ser., Earth Environ. Sci.*, vol. 170, Jul. 2018, Art. no. 032014, doi: 10.1088/1755-1315/170/3/032014.

[3] H. Jinglin, L. Yunpeng, Y. Jun, Z. Yang, H. Tianhua, F. Shengtao, Z. Haizhou, and C. Liang, "Planning of electric vehicle charging station on highway considering existing service areas and dynamic traffic simulations," in *Proc. China Int. Conf. Electr. Distrib. (CICED)*, Tianjin, China, Sep. 2018, pp. 2645–2649.

[4] A. Saldarini, S. M. Miraftabzadeh, M. Brenna, and M. Longo, "Strategic approach for electric vehicle charging infrastructure for efficient mobility along highways: A real case study in Spain," *Vehicles*, vol. 5, no. 3, pp. 761–779, Jul. 2023.

[5] X. Zhang, P. Li, J. Hu, M. Liu, G. Wang, J. Qiu, and K. W. Chan, "Yen's algorithm-based charging facility planning considering congestion in coupled transportation and power systems," *IEEE Trans. Transport. Electrific.*, vol. 5, no. 4, pp. 1134–1144, Dec. 2019.

[6] C. Marmaras, E. Xydas, and L. Cipcigan, "Simulation of electric vehicle driver behaviour in road transport and electric power networks," *Transp. Res. C, Emerg. Technol.*, vol. 80, pp. 239–256, Jul. 2017.

[7] L. Z. Terada, J. C. López, N. B. Arias, M. J. Rider, L. C. P. da Silva, and E. P. L. Junior, "EV charging simulator for public infrastructure considering smart charging and price policies," in *Proc. IEEE PES Innov. Smart Grid Technol. Conf.-Latin Amer.*, Lima, Peru, Sep. 2021, pp. 1–5.

[8] J. Yan, J. Zhang, Y. Liu, G. Lv, S. Han, and I. E. G. Alfonzo, "EV charging load simulation and forecasting considering traffic jam and weather to support the integration of renewables and EVs," *Renew. Energy*, vol. 159, pp. 623–641, Oct. 2020.

[9] D. Betancur, L. F. Duarte, J. Revollo, C. Restrepo, A. E. Díez, I. A. Isaac, G. J. López, and J. W. González, "Methodology to evaluate the impact of electric vehicles on electrical networks using Monte Carlo," *Energies*, vol. 14, no. 5, p. 1300, Feb. 2021.

[10] J. Morán and E. Inga, "Characterization of load centers for electric vehicles based on simulation of urban vehicular traffic using geo-referenced environments," *Sustainability*, vol. 14, no. 6, p. 3669, Mar. 2022.

[11] M. Moschella, P. Ferraro, E. Crisostomi, and R. Shorten, "Decentralized assignment of electric vehicles at charging stations based on personalized cost functions and distributed ledger technologies," *IEEE Internet Things J.*, vol. 8, no. 14, pp. 11112–11122, Jul. 2021.

[12] E. Crisostomi, *Electric and Plug-in Hybrid Vehicle Networks*. Boca Raton, FL, USA: CRC Press, 2018.

[13] T. Rajasekar, P. Mohanraj, and K. Hemmasri, "Reducing driver's range anxiety for electric vehicle using machine learning," in *Proc. 8th Int. Conf. Commun. Electron. Syst. (ICCES)*, Coimbatore, India, Jun. 2023, pp. 1251–1257.

[14] E. Bertucci, F. Bucchi, M. Ceraolo, F. Frendo, and G. Lutzemberger, "Battery electric vehicles: How many gears? A technical–economic analysis," *Vehicles*, vol. 6, no. 1, pp. 71–92, Dec. 2023.

[15] *EV Database Official Site*. Accessed: Mar. 20, 2024. [Online]. Available: http://www.ev-database.org

[16] (2023). *Global EV Outlook 2023*. [Online]. Available: https://www.iea.org/reports/global-ev-outlook-2023

[17] Y. Cao, J. Cui, S. Liu, X. Li, Q. Zhou, C. Hu, Y. Zhuang, and Z. Liu, "A holistic review on e-mobility service optimization: Challenges, recent progress and future directions," *IEEE Trans. Transport. Electrific.*, pp. 1–31, 2024, doi: 10.1109/TTE.2023.3311410.

CLAUDIO SCARPELLI received the M.S. degree in electrical engineering, in 2018, and the Ph.D. degree from the Department of Energy, Systems, Territory and Construction Engineering (DESTEC), University of Pisa, in 2022, with a thesis entitled "Modeling and Experimental Validation of Battery Energy Storage Systems." In 2023, he become a Junior Assistant Professor of electric power system area with DESTEC, University of Pisa. In 2021, he won a Research grant at DESTEC, University of Pisa, regarding the "study on electro-thermal models for the characterization of lithium cell and battery packs."

MASSIMO CERAOLO (Senior Member, IEEE) received the M.S. degree (Hons.) in electrical engineering from the University of Pisa, in 1985. He has been a Full Professor of electric power systems, since 2002, and teaches electric and hybrid vehicles and electric power systems with the University of Pisa, Italy, and naval electric systems with the Naval Academy (Accademia Navale) of Livorno, Italy. He is the author or coauthor of around 180 scientific articles the large part of which are either international conference or international journal papers. In 2014, he authored the book ''*Fundamentals of Electric Power Engineering–From Electromagnetics to Power Systems*'' (IEEE/Wiley). He is the author of plotting/post-plotting program PlotXY, which is still used by many researchers worldwide. He has been involved in electric power systems analysis and simulations for many years. His current research interests include electrochemical storage systems, electric and hybrid vehicles, and guided electrified transportation systems.

EMANUELE CRISOSTOMI (Senior Member, IEEE) received the bachelor's degree in computer science engineering, the master's degree in automatic control, and the Ph.D. degree in automatics, robotics, and bioengineering from the University of Pisa, Pisa, Italy, in 2002, 2005, and 2009, respectively. He is currently an Associate Professor of electrotechnics with the Department of Energy, Systems, Territory and Construction Engineering, University of Pisa. He has coauthored the recently published book *Electric and Plug-in Hybrid Vehicle Networks: Optimization and Control Series: Automation and Control Engineering* (Crisostomi, Shorten, Stüdli, Wirth, CRC Press, 2017), and a Co-Editor of the book on *Analytics for the Sharing Economy: Mathematics, Engineering and Business Perspectives* (Springer Nature). His research interests include control and optimization of large-scale systems, with applications to smart grids and green mobility networks.

VALERIO APICELLA received the B.Sc. and M.Sc. degrees in energy engineering from the University of Sannio, Benevento, in December 2013 and May 2016, respectively, and the Ph.D. degree in electrical engineering from the University of Sannio, in April 2020, with a thesis on magnetostrictive materials for sensing and energy harvesting applications. He is currently the Research and Development Stream Leader of Movyon SpA, a company of Autostrade per l'Italia Group. His activity is focused on renewable energy sources, electrical mobility, and energy harvesting for highway applications.

GIULIA PELLEGRINI received the bachelor's and master's degrees in computer engineering from the University of Florence, in 2017 and 2021, respectively. From 2022 to 2024, she was an AI and Data Science Specialist with the Research and Development Group, Movyon SpA. She is currently responsible of innovation projects based on AI with Autostrade per l'Italia Group. Her main activity is focused on predictive analysis and systems optimization.

Open Access funding provided by 'Università di Pisa' within the CRUI CARE Agreement