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Impact of Electrical Vehicle Private Charging Stations on the Quality of the Low Voltage Network Supply

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ABSTRACT The appearance of new single-phase intensive and often coincident loads, such as the electric vehicle private charging stations can affect the operation of low voltage (LV) distribution networks. Unbalances among the three-phase loading are extremely common, even if the end-users of a given LV network have similar behaviors. Due to the coincidence of such loads, excessive voltage drops may often appear, altering the quality of supply voltage provided to the LV end-users. This work evaluates the effects of residential and other charging stations in parking lots of shopping malls or workplaces on the quality of supply voltage of LV grids. Then, a decentralized approach is proposed, based on the multi-agent system, which allows the different flexibility resources available on the grid to act together to improve the network quality. The agents cooperate to regulate the network nodal voltage, taking into account the characteristics of the resources they are controlling and the needs of their owners. A case study derived from a portion of the Italian distribution system demonstrates the validity of the approach in solving the network operation criticalities.

INDEX TERMS Distribution networks, electric vehicles, energy management system, multi-agent system, voltage quality.

I. INTRODUCTION

THE increasing concerns on climate change and decarbonization have been pushing for a significant paradigm variation in almost all the fields related to electrical energy, i.e., not only for what pertains to production but also for its usages. This process is being translated, among other actions, into the introduction and consequent widespread installation of renewable energy sources (RESs) and a more aware and efficient use of electrical energy. In the wake of this revolution, the transportation sector is one field that has been affected the most, especially from the end-user viewpoint. Electric vehicles (EVs) are gaining an ever-increasing role in the energy transition. The transport sector is responsible for high shares of global CO_2 emissions. The EU is promoting several programs (e.g., the "Fit for 55" package) to reduce the use of internal combustion vehicles in favor of EVs. In EU 27, in 2030, it is expected that electricity demand for transport will increase by 11% from 2017 [1]. Charging infrastructures, spread on the distribution network both at MV (through fast charging infrastructures) and LV level (slow charging stations), will be fundamental for favoring EV deployment. Even though they have multiple beneficial effects [2], replacing traditional internal combustion vehicles with EVs comes at a cost, at least for what concerns their impact on the power distribution network.

In the UK, the British Regulator OFGEM estimated that by 2050 EVs could determine an increase of 35% of the peak demand if the charging process is not smart (i.e., without considering network and components constraints) [3]. Similarly, an increase of about 10% of the total electricity load is expected in California by 2030 [4]. Such an increase will be mostly due to residential charging since it will be the most widespread type of recharge, being the cheapest option for private EVs [5]. The impact of uncoordinated EVs is not solely associated with the growth in energy demand and peak power. Indeed, additional challenges arise because of the increasing variability of power withdrawal caused by the rising presence of distributed generation (e.g., rooftop solar panels) and new electric loads (e.g., heat pumps, electric stoves as greener replacements of traditional boilers and gas stoves) and consequent relevant impact on power quality [6], [7]. However, by adopting of proper coordination devices, the EVs charging could become an opportunity for the energy system [2], [8].

For these reasons, promoting a smart and cost-efficient charging process is pivotal to support the electrification of the private transportation sector, as foreseen by the most recent European environmental targets.

For residential charging stations, the Italian Regulatory Authority (ARERA) offered to EV owners the possibility to increase, with no additional costs, their available capacity during holidays and weekday night hours, as detailed in Section III [9]. However, publicly available charging infrastructures or charging stations at work are fundamental for EV drivers without a driveway or garage at home, thus encouraging EVs to take up.

Unfortunately, despite the effort made by Regulators to increase the spreading of residential EV charging, the low voltage (LV) distribution grid is often not ready to accommodate many EVs under charge. This condition can become critical also because the users often have similar habits, then will probably tend to charge their EVs at the same hours of the day (e.g., in the evening).

Such conditions may lead to exceeding the operational limits of the distribution grids, overcoming the maximum capacity of conductors and transformers, or worsening the voltage profiles along lines. In addition, since residential or small office charging is performed through single-phase charging stations, the three-phase voltage can be affected by unbalances. Also, in a shopping mall parking lot, the charging stations available to customers and workers could not be balanced among the three-phases due to their use that depends on the coincidence of the occupancy of the single station.

Regarding supply voltage unbalance, in particular, technical standard EN 50160 [10] prescribes that, under normal operating conditions, the 10 min mean of the r.m.s. value of the negative sequence component (fundamental) of the supply voltage shall be within the range of 0–2% of the positive sequence component. The general prescription of the technical standard imposes that such conditions must be complied with 95 % of the time. However, in some countries (e.g., Norway [11]), such limits are imposed 100% of the time at all supply terminals.

In this work, a methodology is proposed to evaluate the effects of private charging on the voltage quality of LV grids, specifically concerning voltage drops and unbalance of the grid phase voltages. Moreover, the possible countermeasures that the distribution system operator (DSO) could activate to limit grid criticalities (i.e., voltage regulation issues, line congestions, voltage unbalances, etc.) are identified.

The remainder of this paper is structured as follows. Section II proposes a brief review of the recent literature on the field. In Section III, the regulatory framework is analyzed. Then, Section IV presents the mathematical model adopted to represent EV residential charging and its impact on the LV network. Then, in Section V, the approach adopted, based on the multi-agent system (MAS), able to coordinate the different flexibility resources available on the distribution network, is depicted. The analyzed case study and the relevant numerical results obtained are reported in Section VI, and, according to them, conclusions are drawn in Section VII.

II. RELATED WORKS

The exploitation of distributed energy resource (DER) flexibility to supply services to the MV and LV distribution grid has recently shown increasing interest in the scientific community [12]. The modeled resources, the scheduler architecture, and the optimization strategies are topics widely debated.

In the literature, the scheduling architectures useful for managing DERs, are usually classified into two groups, according to the optimization models they are based on: *i)* centralized or *ii)* decentralized. In the former category, the Distributed Energy Resources Management System (DERMS) decides on the operating points of the controlled resources, for voltage regulation and power congestion relief. The DERMS collects all relevant information about the units and activates the regulating resources. On the other hand, in the decentralized approach, the resources define their strategies, considering internal and external limits. In such an approach, each resource is equipped with a control system, which dispatches the power exchanges to pursue a local individual goal (e.g., energy cost minimization) [13]. The timescale, type, number, and location of the involved resources influence the choice between the two strategies. In a centralized logic, better coordination of the resources is achieved since the architecture gathers all the system data. However, complex communication systems and privacy issues limit the application of this control logic in a framework characterized by different behaviors and needs like those in a residential framework. On the other hand, the decentralized system is characterized by reduced communication between the resource controllers, thus limiting privacy problems. Furthermore, this class of architectures is more suitable for a large aggregate of resources, characterized by different technical limits and behavior, since they offer great scalability, reliability, and resiliency [14], [15].

In [16], a distributed mixed integer linear programming model is proposed to manage the power exchanges of residential users. The proposed approach limits the private information shared among the participants. Despite the novelties of this work, the authors do not model either the presence of the electric vehicle or the possible criticalities on the distribution grid.

In [17], a transactive control method is proposed to schedule a fleet of private EV charging, limiting grid congestions and maintaining adequate voltage profiles. However, simplified assumptions are introduced to simulate EV usage and the corresponding charging requests. On the contrary, in this paper, EV usage and charging demand are modeled to accurately represent the availability of flexible resources and their impact on the network. In [18], a distributed control algorithm is proposed to optimally schedule EV charging requests to limit the grid reinforcement investments. The authors model two different charging modes: commercial and residential. However, the detailed evaluation of the distribution grid topology is not considered.

The study in [19] proposes a distributed optimization method to coordinate several demand response users to provide frequency control services without introducing congestions on the distribution grid. Although the analyzed case study involves residential users, EV charging requests are not simulated.

In [20], the authors propose a peer-to-peer energy trading scheme between different microgrids, in which renewable sources, conventional generation, and non-flexible loads are connected. The distribution network security is guaranteed by adopting an optimal ac power flow approach, while the energy trading process is formulated through a Stackelberg game model. Also, EV impacts on the grid are not examined.

A distributed optimization method, based on the alternating direction method of multipliers, is used in [21] to optimize EV charging while taking into account the maximum power constraints of the grid. The authors proposed a statistical approach to simulate EV charging requests. However, the presence of other DERs is neglected.

From the literature review, it emerges that most of the works do not accurately simulate EV usage (e.g., [16], [17], [19]). Moreover, only one type of EV charging mode is usually modeled. Finally, the impacts of the DERs on the distribution grid are evaluated by adopting a simplified approach based on a single-phase equivalent circuit (e.g., [17], [19], [20]).

On the contrary, in this work, a detailed statistical approach is adopted to simulate several charging modes and charging patterns of EV stations located in residential and private non-residential premises (e.g., offices, shopping mall parking lots) derived from measurement data. Driving habits for each of these categories and the technical characteristics of commercially available EV models are used for scheduling the charging patterns. Furthermore, to represent the unbalanced nature of the LV system, the distribution network feeding the charging stations is accurately modeled through an unbalanced three-phase four-wire system. The impact of EV charging on the network is then evaluated by assessing the voltage profiles and the voltage unbalances through unbalanced load flow calculations. Finally, since it clearly emerges that uncontrolled charging worsens the quality of supply, a decentralized multi-agent system for DER control proposed by the Authors in previous works [22] is used to schedule the charging patterns of EV stations with the aim of minimizing their negative impact on the grid operation. The validity of the proposed approach is tested on a three-phase four-wire distribution system derived from a portion of the Italian LV distribution system.

The main contributions of this article to the current state-of-the-art can be summarized as follows:

- The reproduction of a realistic current and future urban scenario of EV diffusion by modeling residential and non-residential charging stations.
- The analysis of the regulatory frameworks with particular referencce to the Italian scenario where the Regulator recently promoted an initiative that supports the electrification of the private transportation sector.
- The evaluation of the impact of the private, residential, and non-residential EV charging stations in a realistic LV network (four-wire system), also in the light of the Italian Regulatory initiative.
- Proving the need of LV network management systems to coordinate the flexibility of the DERs connected to the network to solve the upcoming network operation issues and improve the system supply voltage quality.

III. REGULATORY FRAMEWORK

The large diffusion foreseen for EVs and charging points underlines how this new sector is critical and requires a regulatory framework to cover mobility and electricity sector needs. The main problem in this context is caused by the many uncertainties about the sector and technology evolution (e.g., battery degradation, standards for charging equipment and communication protocols, users' participation, etc.). Thus, strategies, plans, and measures should be flexible enough to follow such uncertain development. From the mobility point of view, in order to foster the use of EVs also for those that cannot charge their vehicles at home, it is pivotal to the presence and availability of public charge points (e.g., installed at motorway stations and on streets), that should be evenly distributed across the territory. Also, using and paying for charging should be as simple as for traditional oil-based fuels. EV owners should be able to access easy and affordable charging services.

In the residential context, EV owners need to be supported during the phases of choosing and purchasing the most suitable home charging equipment and tariffs.

The experimental initiative promoted by ARERA is moving in this direction [9]. The increase of the available power capacity, without added costs during the night hours and on holidays, may represent an attractive solution for drivers that have to choose the EV model. Indeed, in Italy, the vast majority of residential electricity contracts have a maximum power demand which ranges from 3 to 4.5 kW, limiting the possibility of charging the EV at home. In this experimental phase, this limit is raised without extra charges to 6 kW during holidays and between 11:00 PM and 7:00 AM on working days, as shown in Fig. 1. This experimental phase is designed to make EV charging cheaper and more efficient for residential users. In addition, from the system point of view, shifting the charging loads to off-peak hours might help the dispatching problems that may arise during the night (e.g., RES power curtailment during windy nights) and do not further increase the ramp of the evening demand.

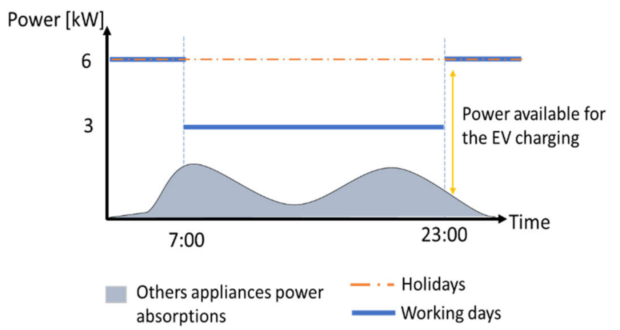

FIGURE 1. Example of the increase of the available peak power in the Italian context.

Furthermore, the charging equipment should communicate with another third party to enable the implementation of innovative solutions, such as smart charging. Smart charging may be useful both for the network (e.g., for avoiding criticalities) and for the customers (e.g., for saving money). This aspect is fundamental since EV charging if properly managed, could represent the largest source of flexibility demand by 2050 due to the possibility of modulating (or postponing) the power drawn from the network. EVs can be considered small capacity service providers [23]. Thus, their aggregation is compulsory in order to overcome the minimum bid size limit, particularly at TSO-level markets, and reduce the verification process compared to one asset of a larger size. The aggregation of different vehicles with different charging patterns could provide local and global ancillary services.

Whatever the charging type is, the standardization of smart interfaces and advanced smart metering infrastructures capable of supporting network operation must drive to accessible and interoperable systems (e.g., usable by different drivers and cars). In this context, ARERA mandated the national standardization body to devise a technical standard ensuring interoperability at interfaces. In [24], the role of the charging station controller (CSC) is defined based on second generation smart meters. The CSC is requested to:

- Collect data (i.e., the power drawn from the charging infrastructure and exchanged with the grid) in real time.
- Optimize the capacity needed for charging EVs, depending on the absorption of other loads.
- Exploit on-site power production.
- Exchange data with a remote subject, namely the balancing service provider (BSP), for offering services through the flexibility service market.
- Provide grid services for electric system security based on the availability of local measurement of the grid frequency.

IV. MODELING OF THE EV USAGE

To accurately compute the impacts of EV charging requests on the LV grid and the advantages of exploiting their flexibility, it is essential to realistically simulate the vehicle usage.

In this work, a statistical model based on real data is proposed. The schematic representation of the approach is shown in Fig. 2. It is designed to accurately simulate three categories of trips and the corresponding charging requests [25]. In particular, the most common charging modes are modeled: i) residential, ii) workplace/offices, and iii) shopping mall charging [26]. Distance traveled and arrival and departure hours are associated with these three charging modes and the corresponding trip category.

As reported in Fig. 2, firstly, the procedure imports raw data on driving habits for these three categories and the technical characteristics of commercially available EV models. Then, an iterative process is executed (see the blue box in Fig. 2) to simulate the behavior of each vehicle in the EV fleet ($\forall ev \in \boldsymbol{N_{Fleet}}$,). The charging mode (i.e., residential, workplace, or shopping mall charging) and the EV model are selected for each vehicle. In particular, the best-selling EVs currently available in the Italian market and the corresponding technical characteristics are considered.

The simulated time horizon is subdivided into working days and holidays so to capture the variability of the vehicle's usage on different days. The probability that a specific charging mode occurs also depends on the day simulated. For example, during holidays, workplace charging requests are neglected, and only residential and shopping mall charges are considered.

Once the vehicle charging mode is selected, the departure time (t_{dep}^{ev}), the arrival time (t_{arr}^{ev}) and the distance covered during the travel (d_{dist}^{ev}) are extracted from a probability density function (PDF) associated with the corresponding travel category.

Since these parameters (i.e., t_{dep}^{ev}, t_{arr}^{rv} and d_{dist}^{ev}) are obtained from independent PDFs, it is necessary to check the coherence of these values (see green box in Fig. 2). The algorithm verifies if $t_{dep}^{ev} > t_{arr}^{ev}$ and then checks if the average speed during the travel (v^{ev}) is feasible. Incoherent behaviors are discarded.

Finally, assuming a constant vehicle consumption per kilometer (e_{cns}^{ev}), specific for each EV model, it is possible to evaluate the SoC when the vehicle is connected (SoC_{arr}^{ev}):

$$SoC_{arr}^{ev} = SoC_{dep}^{ev} - \frac{d_{dist}^{ev} e_{cns}^{ev}}{E_{cap}^{ev}} \tag{1}$$

where, $SoC_{dep}^{ev,day}$ is the EV SoC at the departure from the previous charging stop, while E_{cap}^{ev} is the battery capacity on the ev-th vehicle.

Therefore, the proposed approach models the charging requests by simulating the actual EV usage. This approach is

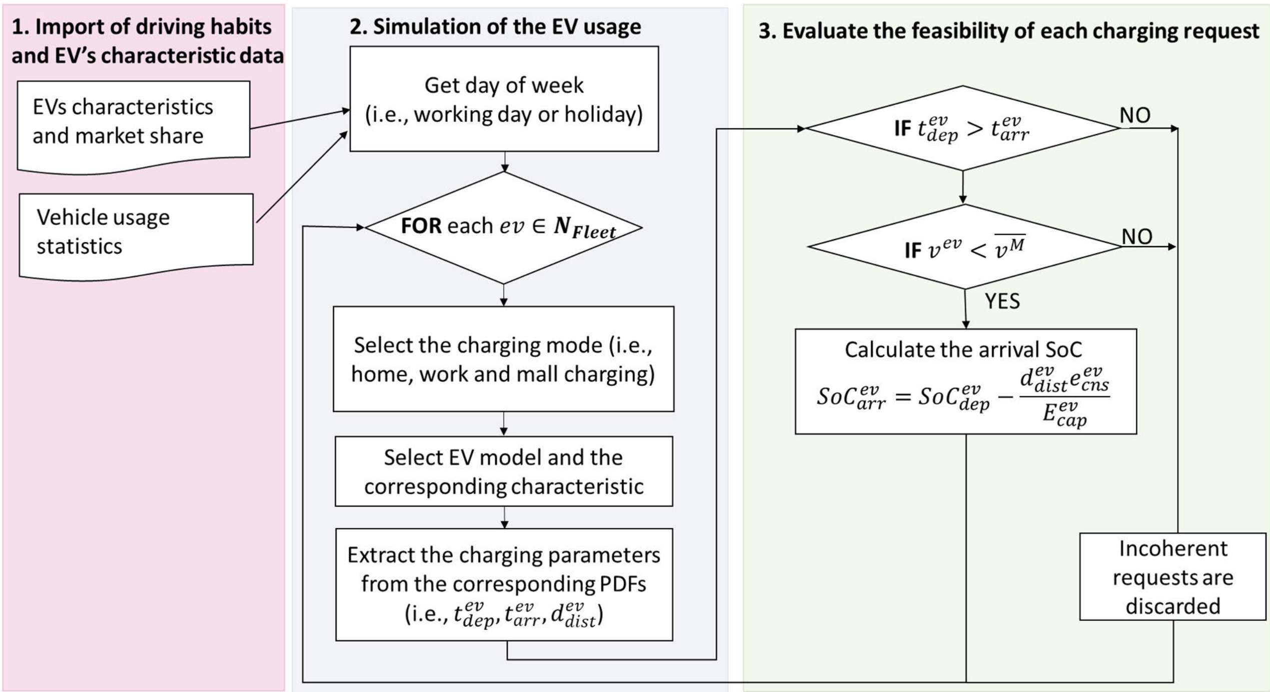

FIGURE 2. **Schematic representation of the approach adopted to simulate EV charging requests.**

used as input of the model described in the following Section to estimate the impact of e-mobility on LV grid operation and to quantify the flexibility that residential EV charging could provide to solve the issues on the grid.

V. MODELING OF THE EV MANAGEMENT SYSTEM

MAS represents a suitable technology for the management of a multitude of resources dispersed in an environment with different operating modes that have to act together to achieve a global goal thanks to agents' reactivity, proactiveness, and social ability, i.e., their capacity to react to environmental changes [27]. For this reason, this paper adopts a MAS approach for the optimal coordination of charging stations. The agents cooperate for the regulation of the network nodal voltage, taking into account the characteristics of the resources they are controlling and the needs of DER owners. MAS hierarchy is characterized by a master agent (MA) in charge of supervising the actions of DER agents, which, in turn, control the resources by modifying their expected active power profile (i.e., consumption, production, charging/discharging) and, in some cases, also their expected reactive power profile.

A. MASTER AGENT

The MA acts as an aggregator that connects the agents to the DSO and vice versa. The MA broadcasts the data necessary to perform the local optimizations (i.e., electrical quantities, the energy price, etc.), gathers the results, and requires new optimizations until an optimal stable solution is reached, without imposing any setpoint.

B. DER AGENTS

DER agents control the active power exchange of different types of DERs: Demand Response (DR), distributed generation (DG), EV, and distributed energy storage (DES). DG and DES agents can also control the reactive power exchange, contributing to the volt/var regulation, according to the European technical rules for DG connection in LV networks [28].

DER agent strategy consists of the minimization of the objective function (OF), described in (2), subject to technical constraints and DER owners' needs [22]:

$$\min J_i\left(P_i, P_{-i}\right) = \sum_{t=0}^{T-1} \{p\left(t, P_t\right) \cdot \boldsymbol{P_i}\left(\boldsymbol{t}\right) + \delta \cdot [\boldsymbol{P_i}\left(\boldsymbol{t}\right) - avg\left(P_t\right)]^2\}, \qquad (2)$$

where $p\left(t, P_t\right) = f\left(\frac{D(t)+\sum_{i=1}^{N} P_i(t)}{P_{tr}}\right)$ is a virtual cost function; $P_t(t) = \sum_{i=1}^{N} P_i(t)$is the sum of the power contributions $P_i(t)$ of the i-th ($i = 1, \ldots, N$) agent; N is the number of the local agents; $D\left(t\right)$ is the contribution to the forecasted demand at the MV/LV transformer of the customers not participating in the network operation at time t; $P_{tr}$is the nominal power of the MV/LV transformer; $avg(P_t)$ is the average power controlled by the agents, and δ is a tracking parameter with non-negative constant value crucial for Nash's equilibrium, which links the individual behavior of the agent to the social behavior.

The first term of the OF is the virtual cost of purchasing energy from the system. This cost increases during peak hours. The goal of the second term in (2) is to avoid the risk that by moving far from the peak, all agents will create a new undesired peak in another hour. Indeed, each agent tries to maximize its benefit, but the deviation from the mean behavior is a cost that guides the global optimization to the global (system) optimum.

The local minimization is subject to network technical constraints on nodal voltage, cable thermal limit, and DERs technical limits (e.g., battery capacity, PV capacity, inverter capability curve). DER owners' needs (e.g., amount of curtailable power, final SoC of the battery, end of charging session) are additional constraints to the problem. When elaborating the optimal charging strategy, the EV agent takes into account the technical constraints of the charging station (maximum deliverable power, charging and discharging efficiency, etc.) and the characteristics of the vehicle battery (e.g., power and energy). The user needs (initial and desired charging state at the end of charging, time of the end of charging), as shown in equations (3)–(7) are also inputs of the optimization:

$$SOC_i(T-1) = \alpha \cdot \mathrm{SOC}_{max} \tag{3}$$

$$\Delta t \cdot P_i(t) \cdot \eta_{ch} \leq \mathrm{SOC}_{max} - \mathrm{SOC}_i(\mathrm{t}-1) \tag{4}$$

$$\mathrm{SOC}_i(\mathrm{t}) = \mathrm{SOC}_0 + \sum_{t'=0}^{t} P_i(t') \cdot \Delta t \tag{5}$$

$$0 \leq P_i(t) \leq P_{plug} \tag{6}$$

$$SOC_i(t) \leq SOC_{i,max} = \gamma_{max,i} \cdot C_{bat} \tag{7}$$

$P_i(t)$ is the EV battery charging capacity in the time interval Δt, $\mathrm{SOC}_i(t)$ is the state of charge at instant t, T is the number of intervals in the considered period (e.g., one day), η_{ch} is the charging efficiency of the battery, $SOC_{i,max}$ is the allowable charging limit (can be written as a function of the battery capacity C_{bat} [kWh], as in (7)), α is a coefficient between 0 and 1 that reflects the user needs as it indicates the desired state of charge at the end of the considered period ($t = T-1$), and P_{plug} is the maximum power of the charging system.

Eq. (7) represents the technical constraints for preventing charging beyond the allowed technical limits and avoiding the deterioration of the battery (through the correction coefficient $\gamma_{max,i}$). In addition, the EV agent can also work in vehicle-to-grid mode, in which the EV behaves as a distributed storage system, charging itself, for example, during the hours of maximum production from renewable energy sources and then discharging, thus providing services for grid regulation [29].

C. OPTIMIZATION PROCEDURE

As stated before, the MAS procedure is an iterative optimization process for the coordination of DERs to obtain a global optimum. The procedure starts when the MA (green blocks in Fig. 3) that receives from the DSO the scheduled power and voltage profile curves asks the agents to optimize their energy profile on the basis of a virtual price. Each agent (blue blocks in Fig. 3) performs the mono-dimensional optimization process in (2), subject to the given constraints. The agent's optimal pattern is returned to the MA, which updates the requests after all agents have completed the local optimization. If the

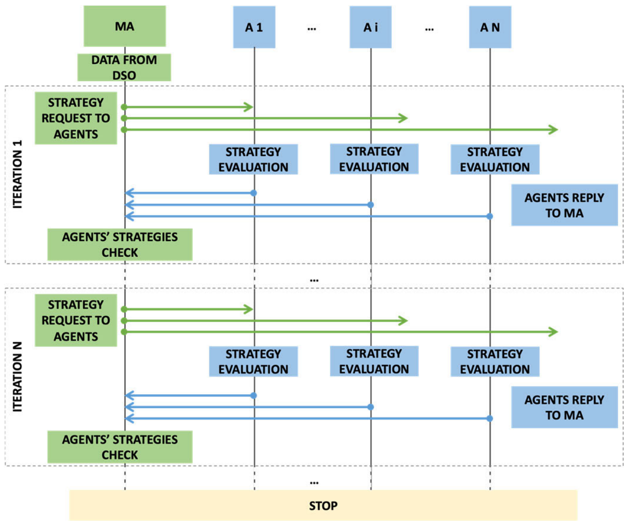

FIGURE 3. **Iteration between MA and agents.**

voltage limits are violated or if the convergence criterium is not met, the MA sends again to the agents the relevant voltage and the necessary data to start a new optimization. The convergence of the procedure is reached if (i) a preset maximum number of iterations reached ($k = k_{\max}$), or (ii) the difference between the results of subsequent iterations is smaller than a predefined threshold ψ, under (8).

$$max|P_i^k - P_i^{k-1}| \leq \psi \tag{8}$$

VI. CASE STUDY AND NUMERICAL RESULTS

A. THE EV MODEL

The approach described in Section IV is designed to simulate the charging requests of a fleet of EVs. Thanks to the decentralized scheduler proposed in Section V, it is used to evaluate the impacts on the LV network and the flexibility these resources can provide.

The technical characteristics and the market share of each model are defined considering the best-selling EV models in Italy in winter 2021–2022 [30]. For each model, the corresponding market share is assumed to be equal to the probability that the model is present in the simulated fleet. Data adopted for this purpose are shown in Table 1.

To accurately model the residential charging requests, the statistics collected from a large survey conducted in Italy have been considered [31]. The raw data have been gathered and preprocessed, obtaining the two PDFs displayed in Fig. 4. As it can be seen, almost 60% of the simulated EVs leave the residential charging stations (CSs) by 7 AM. For what concerns the connection time (blue bars in Fig. 4), data show a higher dispersion around the average value, which is 4:30 PM, and 90% of the EVs are connected before 8 PM. As a consequence, on average, the EVs are connected to the residential CS for 15 hours. During this period, the proposed optimal scheduler can exploit EV charging flexibility to solve grid criticalities.

TABLE 1. EV characteristics and corresponding market share.

Vehicle model	Energy Consumption [kWh/km]	Battery Capacity [kWh]	Market share [%]
Fiat 500e 3+1	0.152	37.3	22
Smart EQ forfour	0.176	16.7	13
Renault Twingo	0.164	21.3	12
Volkswagen ID.3	0.182	58	11
Tesla Model 3	0.155	70	11
Renault Zoe	0.168	52	8
Dacia Spring	0.152	27.4	7
Peugeot 208	0.156	50	6
Peugeot 2008	0.161	50	5
Volkswagen e-Up!	0.158	32.3	5

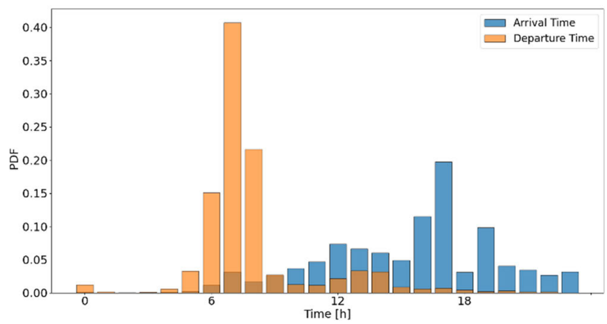

FIGURE 4. Discrete PDFs of the arrival (in blue) and departure (in orange) times at the residential charging stations.

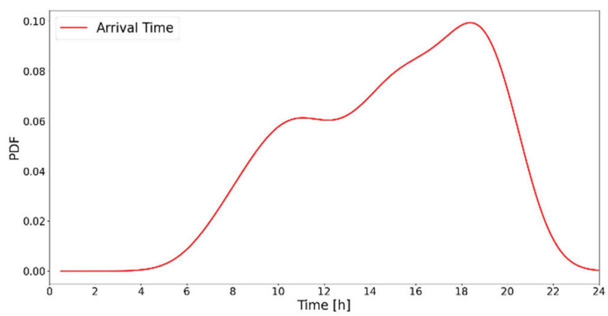

FIGURE 5. PDF of the arrival time at the shopping mall parking.

The simulation commercial and workplace charging request is based on data gathered through Google Maps. The collected data refer to the number of vehicles observed in two parking lots in Milan (Italy) near a shopping mall and a workplace. The arrival and departure time statistics are derived from the collected data.

Fig. 5 shows the PDF of the arrival time at the shopping mall parking, while the duration of the stop is described by a normal distribution function having $\mu = 1$ h and $\sigma = 0.5$.

Fig. 6 shows the PDFs of arrival (in blue) and departure (in orange) times from the workplace parking. In this case, almost 50% of the EVs are connected to the charging stations between 7:30 AM and 9:00 AM, introducing a steep variation in the power absorption. This load coincidence could introduce further operation network criticalities.

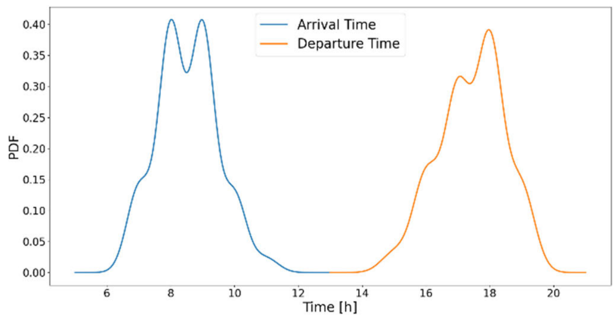

FIGURE 6. PDFs of arrival (in blue) and departure (in orange) times at the workplace parking.

Finally, the statistics on the daily distance covered by users are collected from [32]. As it is possible to observe from Fig. 7, during holidays, the probability of covering longer trips is higher [33]. For example, 75% of EVs travel for less than 35 km during working days, while the percentage decreases to 65% during holidays. It is worth noting that the proposed tool models trips completed on the same day (i.e., the number of EVs in the fleet remains constant during the simulated period). For this reason, the maximum daily distance is assumed equal 150 km/day.

B. DISTRIBUTION NETWORK MODEL

The proposed model of charging requests from the EV drivers has been included in a test network derived from a portion of the Italian LV distribution system, shown in Fig. 8. It is a typical suburban network supplied by a secondary substation equipped with a 400 kVA MV/LV transformer. Four feeders deliver energy to different kinds of customers of the network, residential and non-residential, with three-phases and single-phase connections. Real daily profiles of consumption derived from a measurement campaign are used for simulating the end users' behavior for one month [34]. The length of the feeders varies from a few meters (feeder F_3) to approximately 1 km (feeder F_2). Some PV generators are included in the test LV network.

In the simulated current scenario, all the 17 residential customers (mainly households) of the test network have one EV each, and consequently, a residential charging station appears in the corresponding node of connection. In a future year (i.e., 2030), doubling the number of residential charging stations and a few charging columns for each non-residential building, private but publicly available (i.e., offices or shopping malls) have been supposed, as represented in Fig. 8. Furthermore, the loads other than EVs increase their consumption with variable growth rates (i.e., 0.9 %/year and 0.6 %/year for residential and non-residential customers, respectively), according to the forecast proposed in [1].

In the model, it is supposed that the recharging stations are included in the same point of delivery for the existing customer with no extra meter installed either in the commercial center office or in the household facilities. This assumption limits the maximum number of recharging columns that

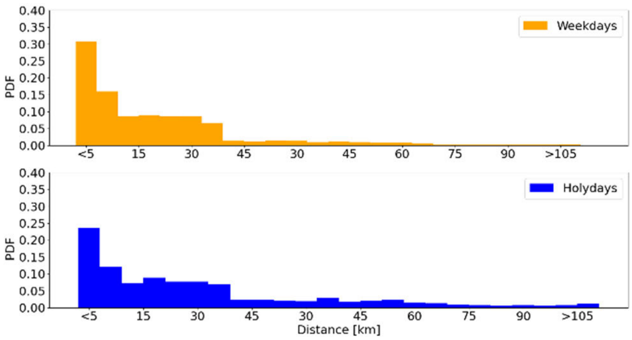

FIGURE 7. **Distance covered by the vehicle during weekdays (above) and holidays (below).**

TABLE 2. **Simulation parameters.**

Year	EV charging station premises	Growth rate	EV penetration
Current	residential customers	—	1 EV/customer
Future	residential customers	0.6 %	2 EV/customer
	non-residential customers	0.9%	variable

can be hypothesized for each customer and the maximum available power for charging that depends on the hourly consumption of the loads other than EVs. In particular, the nominal power of the charging station, assumed in the paper, is equal to 6 kW, and the number of charging stations for each customer is detailed in Fig. 8.

In the proposed case study, the flexibility of the workplace and shopping mall charging stations is not exploited by the MAS. Therefore, the charging requests of these two modes are considered non-flexible load, and the corresponding power absorptions are calculated by assuming that all vehicles start charging at full power as soon as they are connected to the charging station.

C. RESULTS AND DISCUSSION

Regarding the EV charging request model, for each considered year four scenarios, plus one variant of one of them, with different characteristics have been simulated through unbalanced load flow calculations by using OpenDSS for three-phase four-wire distribution systems to highlight the relevant effect on the network operation and the benefits of MAS architecture. Table 2 reports the parameter used for the simulations.

In particular, the studied cases for both the considered current and the future year are:

- *Case 1*: the EVs start to recharge right after they arrive home. The charging stations use the maximum available power allowed by their contract, calculated hour by hour, as the difference between the peak power (i.e., 110 % of the rating power) and the hourly consumption (i.e., the power requested by household appliances). The maximum power is constant over time.
- *Case* 2: the MAS coordinates the agents for solving the possible operation issues and, at the same time, guarantees the EV recharging by considering the arrival and departure hours used in Case 1.
- *Case* 3: as in Case 1 but with variable maximum power for some users. It is, thus, supposed that the customers with 3 or 4.5 kW contracts exploit the increase of their peak power, as regulated by ARERA, in the evening and night hours of working days and during holidays.
- *Case 3b:* as in Case 3, but differently than Case 3, the customers with the increase of their peak power start the EV charging at 11:00 PM.
- *Case* 4: the MAS coordinates the agents by exploiting the power peak increase of Case 3.

The voltage drop limit is assumed to be –10% of the nominal value V_n for the MV and LV distribution systems. Nevertheless, if the DSO decides to equally share the allowable voltage reduction between LV and MV networks (i.e., –5% V_n for each voltage level), undervoltages (UVs) below 0.95 p.u. are excessive for the LV grid. Table 3 reports the resulting number of violations in the network in non-optimized cases. As expected, UVs that exceed –5% V_n and unbalances with V_{rms_n}/V_{rms_p} ratio, i.e., the ratio between the negative sequence component of the supply r.m.s. voltage and the positive sequence component of the supply r.m.s. voltage, greater than a 2% increase in future year cases. But the most interesting result is that by shifting the charge starting hour of the small residential customers to 11:00 PM, the number of violations increases by 25% in the current year (i.e., 215 vs. 172) and about 40% in the future year (i.e., 1170 vs. 836). The artificially created coincident peak at 11:00 PM causes network operation issues during hours that are normally non-critical in distribution systems.

In Case 1, in the current year, despite V_{rms_n} does not exceed 2% of V_{rms_p} during the simulated period at all terminals, the EV charging profiles cause voltage drops in some nodes in several critical hours. Fig. 9 shows the phase voltage profiles of feeder F_2 on a Sunday of the considered period: some customers connected to phase 1 suffer excessive voltage drops, being 1.43 % of the maximum value of V_{rms_n}/V_{rms_p} on this day. The MAS solves the operation issues by rescheduling the EV charging requests (Case 2). The voltage profiles comply with the technical constraints without resorting to any other flexibility services from the other network resources. In Fig. 10, the improved phase voltage profiles resulting from the optimization also shows that the unbalancing is reduced (i.e., the maximum value of V_{rms_n}/V_{rms_p} is 0.27 % on the same day of Fig. 9).

The increase of peak power allowed by the Italian Regulator in the evening and holidays in Case 3 produces more severe voltage drops. Indeed, the maximum ratio between the negative and the positive phase sequences of the r.m.s. voltage overcomes the limit of 2 % in some time intervals. Fig. 11 shows the phase voltage profiles of the feeder F_2 of the test network by considering the EV charging schedules of Case 3.

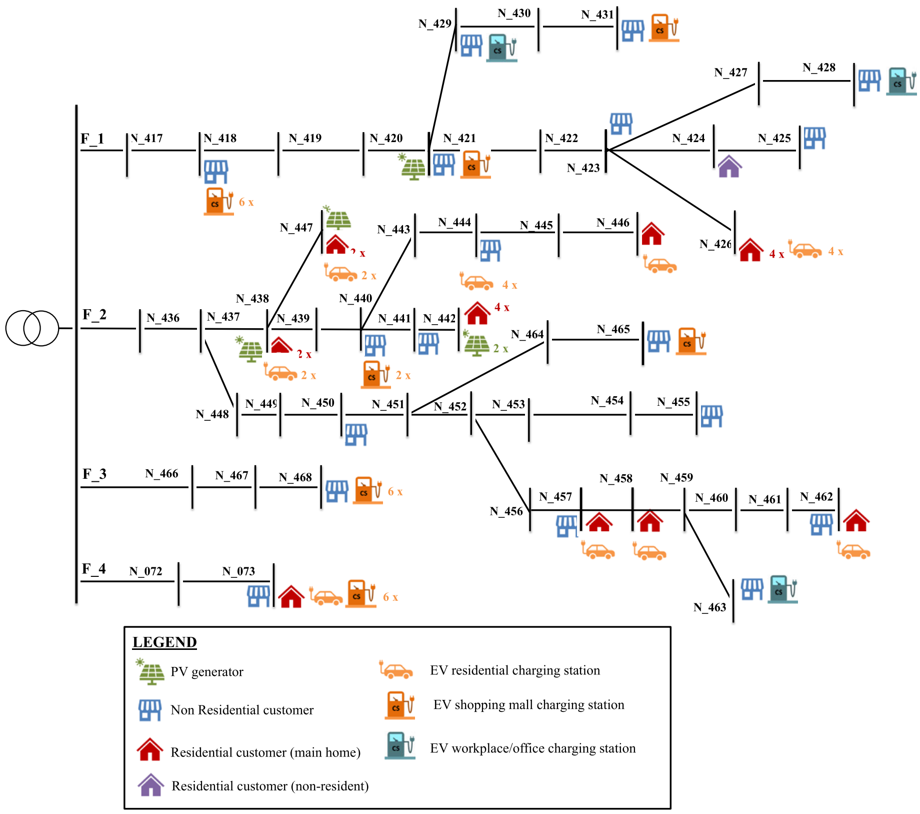

FIGURE 8. **The LV test network.**

TABLE 3. **Voltage violations.**

	Case	Number of (Uvs) [hours·nodes/period]	Number of days with Uvs	Number of unbalances	Number of days with unbalances
Current year	Case 1	127	19	0	0
	Case 3	172	23	7	1
	Case 3b	215	26	69	9
Future year	Case 1	675	30	0	0
	Case 3	836	30	118	9
	Case 3b	1170	30	474	30

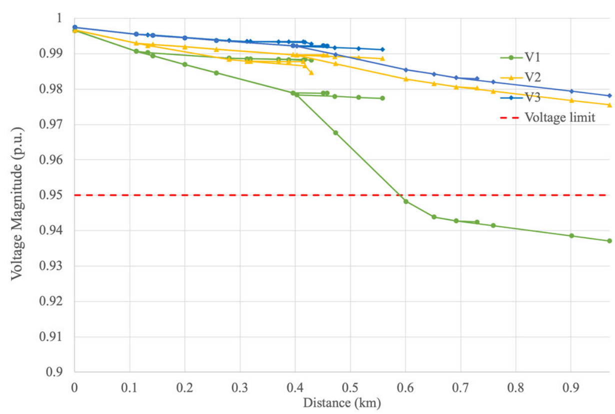

FIGURE 9. **Case 1: voltage profile of the three phases of the feeder F_2 in one critical hour (5:00 PM on one Sunday of the considered month) – current year.**

It is worth noticing that on Sunday, the peak power increase is allowable all the time, and the most critical hour is the one at which most EV drivers get home and start charging their EVs. The unbalancing also worsens, being 2.40 % of the maximum ratio V_{rms_n}/V_{rms_p}.

Case 3b worsens the network condition but shifts the critical hour to 11:00 PM. Fig. 12 shows the phase voltage profiles of the feeder F_2 on the same day. The maximum voltage drop is more significant (i.e., 0.898 p.u.) and overcomes the total allowable limit for the whole MV and LV distribution system (i.e., –10% V_n).

Again, the MAS used in Case 4 solves the technical constraint violations and significantly improves the unbalancing, ensuring compliance with the limit at all terminals 100% of the time (max ratio $V_{rms\_n}/V_{rms\_p} = 0.27\%$). Despite the agents of the MAS having a greater degree of freedom, due to the increase of available power for recharging, the resulting voltage profile of feeder F_2 in Case 4 is the same as in Case 2.

Fig. 13 shows the comparison of the recharging profiles of the EV of the 3 kW-customer connected to phase 1 of the node N_457 of the test network, placed approximately 0.6 km from the secondary substation, on the same day. The EV arrives home at 5:00 PM and departs at 8:00 AM the following day. In Case 1 and Case 3, the recharging starts immediately when the EV arrives home. In Case 3, the allowed peak increase reduces the recharge duration to three hours only. Such uncontrolled charging profiles provoke the excessive voltage drop at the node of connection (Fig. 9 and Fig. 11).

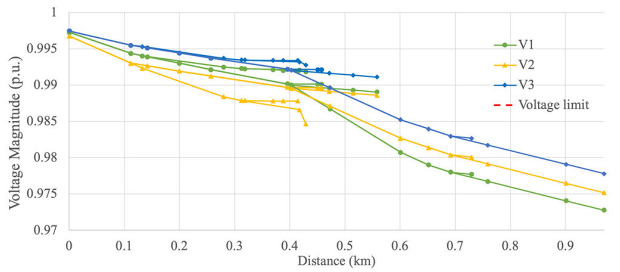

FIGURE 10. **Case 2: improved voltage profile of the three phases of the feeder F_2 in one critical hour (5:00 PM on one Sunday of the considered month) - current year.**

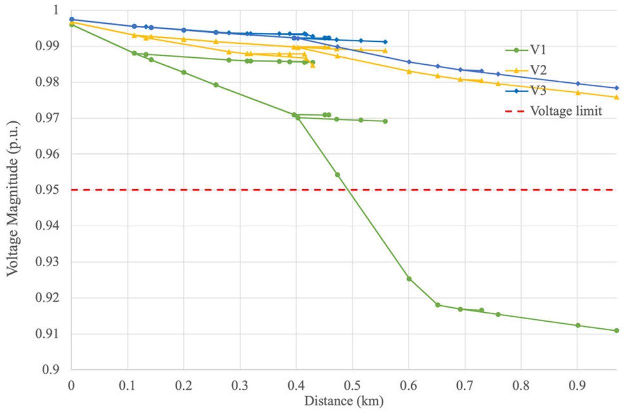

FIGURE 11. **Case 3: voltage profile of the three phases of the feeder F_2 in one critical hour (5:00 PM on one Sunday of the considered month) - current year.**

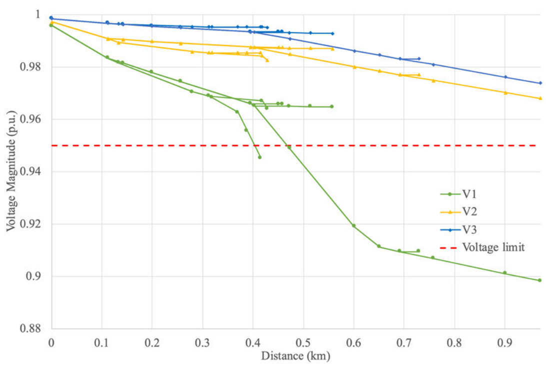

FIGURE 12. **Case 3b: voltage profile of the three phases of the feeder F_2 in the new starting charging hour (11:00 PM on one Sunday of the considered month) - current year.**

MAS (Case 2 and Case 4) delays the recharging profile to less critical hours and solves the voltage constraint violations (Fig. 13). It is important to observe that the recharging power in the same hours of the optimized cases and the Case 3b are very different. Less exploitation of the available capacity by the MAS improves the voltage profiles.

In the future year, when the residential EVs have doubled, the operation of the grid is expected to be more critical. In Fig. 14 the comparison of the EV recharging profile is made for a working day of the considered future year. The represented charging profile refers to the same residential customer in Fig. 13. The arrival time of the EVs is 6:00 PM, and the total energy absorbed in the day for the future year is about

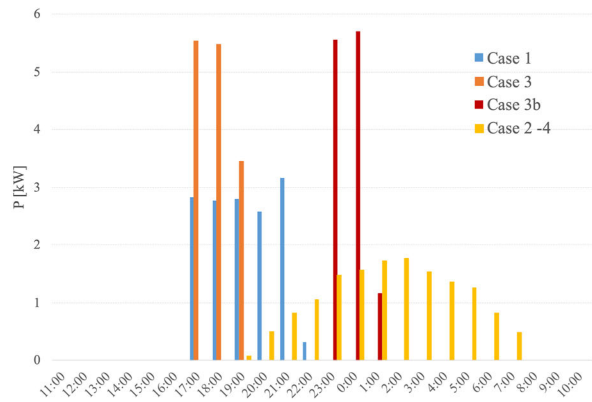

FIGURE 13. **EV recharging profile comparison – holiday, current year.**

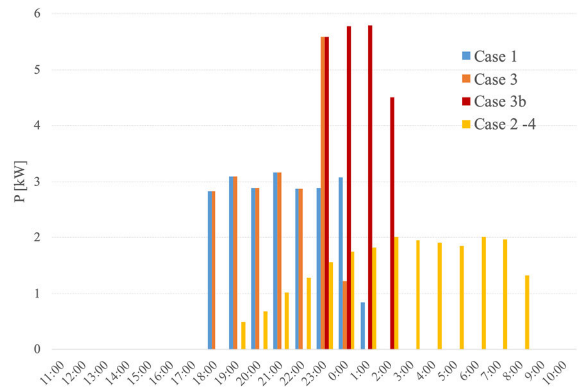

FIGURE 14. **EV recharging profile comparison – working day, future year.**

21.6 kWh. The change of peak power at 11:00 PM quickens the charging duration in Case 3 and Case 3b (i.e., Case 1 charging lasts 8 hours, Case 3 charging lasts 7 hours, and Case 3b charging lasts only 4 hours). Nevertheless, such an exploitation of the increased peak power raises critical issues in the grid operation (Table 3). MAS delays the start of charging by one hour (i.e., 7:00 PM) and maintains lower absorption than the non-optimized cases. With optimal scheduling, the network operation issues disappear.

VII. CONCLUSION

The electrification of the final energy uses, including the transport sector is a necessity and a significant challenge for the future of electrical distribution networks. The analyses carried out in the paper highlighted how the increasing adoption of residential charging, if not properly coordinated, could significantly affect the quality of supply voltage on LV networks, worsening both voltage drops and voltage unbalance. Such a condition is even exacerbated in future scenarios. Furthermore, the shifting of coincident loads in off-peak hours, as promoted for supporting the residential EV diffusion, causes critical operation issues that can be solved only with intelligent scheduling of the EV charging. Energy management system architectures, such as the proposed one, based on a multi-agent system technology, can effectively solve such critical network operation issues. In addition, new tools able to coordinate EV charging with the other flexibility resources available on distribution networks could be even more beneficial in opening the ancillary services market to aggregators. In this scenario, by using the regulation capabilities of residential charging stations, transmission and distribution system operators could collect new control services aimed at improving power system reliability and efficiency with little incremental costs.

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