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Comprehensive Aggregator Methodology for EVs in V2G Operations and Electricity Markets

FRANCESCO GIORDANO [1], CESAR DIAZ-LONDONO [2] (Member, IEEE),
AND GIAMBATTISTA GRUOSSO [2] (Senior Member, IEEE)

[1]Department of Energy, Politecnico di Torino, 10129 Torino, Italy
[2]Dipartimento di Elettronica Informazione e Bioingegneria, Politecnico di Milano, 20133 Milano, Italy

CORRESPONDING AUTHOR: CESAR DIAZ-LONDONO (e-mail: cesar.diaz@polimi.it)

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ABSTRACT Electric vehicles (EVs) are pivotal in the global shift towards sustainable energy systems. As EV adoption rises, effective integration into the power grid becomes vital. Vehicle-to-grid (V2G) operations, enabling bidirectional power flow between EVs and the grid, enhance grid resilience and leverage EVs as distributed energy resources. This article presents a comprehensive framework addressing gaps in EV integration. It combines EV travel energy forecasts and electricity market engagement, coordinating forecast-based optimization with real-time management. Our approach introduces a novel prioritization mechanism, optimizing power allocation based on forecasted state-of-charge for upcoming trips. The optimization follows a multi-objective function that aims to minimize the operational costs and maximize both the upward and downward flexibility to provide ancillary services. The study assesses EV participation in Replacement Reserve, Secondary Reserve, and energy arbitrage. Simulations compare scenarios, unveiling optimal performances. The framework showcases EVs' potential to bolster grid stability, yielding economic value for EV owners and the power system. This article pioneers a holistic approach to EV integration, bridging current limitations, and emphasizing economic and technical benefits.

INDEX TERMS Ancillary Services, electric vehicles, electricity markets, energy management, travel energy forecasts, vehicle-to-grid (V2G).

I. INTRODUCTION

Electric vehicles (EVs) are prepared to be a cornerstone in the energy transition towards a sustainable and low-carbon energy future. With the escalating adoption of EVs, their seamless integration into the power system takes center stage in both ensuring grid stability and optimizing the economic dividends of electric mobility [1]. The latent potential of EV batteries to serve as grid assets and enhance power grid operations' efficiency has ignited significant interest. This task, entrusted to an orchestrator known as the Aggregator, entails meticulous control and optimization of power interchange between EVs and the power system [2]. Simultaneously, the emergence of Vehicle-to-Grid (V2G) operations transformed the paradigm, enabling a two-way energy flow that positions EVs as distributed energy resources. This intricate interplay, encompassing not only EV-to-grid but also EV-to-EV power supply communication, necessitates robust and secure protocols [3].

While diverse strategies and techniques for EV charging management have been proposed [4], their predominant focus has been on optimizing charging schedules to minimize costs [5], enhancing grid stability, or mitigating grid overload during peak periods [6]. These strategies span a spectrum, ranging from multi-objective frameworks allocating EV charging stations in conjunction with renewable energy sources [7], to rule-based management of EV battery charging in tandem with residential photovoltaic systems [8]. Game-theoretic models have even been employed to decipher the dynamics between aggregators and EV owners [9]. The repercussions of uncertainties intertwined with the integration of EVs into the V2G operational mode have been studied [10]. Although these approaches encompass Grid-to-Vehicle (G2V) or V2G operations, they primarily address EV charging, falling short of exploring the full spectrum of energy service provisioning.

A noteworthy avenue in this trajectory is the delegation of flexibility services from EVs, orchestrated through energy communities [11], aggregators, or balancing responsible entities, participating in electricity markets [12]. The economic evaluation of V2G's role in ancillary services hinges on estimating available capacities through data-driven methodologies [13]. Delving deeper, a hierarchical framework has been proposed to tap into large-scale EVs for frequency regulation [14]. Similarly, cooperative and non-cooperative game-theoretic frameworks have been employed to incentivize EVs to contribute to these services [15]. Long-term effects of EV batteries engaging in primary frequency regulation have also been empirically tested [16]. Additionally, EV aggregators have ventured into Day-Ahead (DA) and Real-Time (RT) electricity markets via strategic approaches [17], entangling complexities arising from factors like arrival times, energy demands, and market outcomes [18].

An intriguing facet encompassing EV integration involves considering the EV's journey, wherein the time expended per trip holds a mathematical equivalence to its everyday utility [19]. Some strategies opt for cost minimization, maximizing revenue while adhering to travel time constraints [20]. Others seek to minimize travel costs by accounting for time-of-use energy prices, coupled with a model capturing EV energy consumption [21]. Balancing time-aware fairness and overall waiting time of EVs has also been explored to optimize individual waiting times [22]. Furthermore, the potential gains from coordinating commercial EV fleets' trips on a DA basis have been quantified [23].

Summing up the insights from the literature review, it is evident that a comprehensive framework is still lacking. For instance, certain strategies like those presented in [16] focus on non-smart control or non-V2G methods. On the other hand, charging strategies such as those proposed in [7], [8], [20], [21], [22], while considering V2G, often overlook the provision of energy services in the electricity market. Meanwhile, some smart charging strategies like those highlighted in [5], [6], [7], [18] not only consider aggregated EV models but also account for individual EVs. However, they fail to incorporate EV travel energy forecasts. Strategies such as those detailed in [9], [15], [23] propose control methodologies that may alter users' connection patterns. On a more comprehensive note, certain studies explore optimization approaches for EV aggregator systems, considering vital aspects like driver' patterns, capacity constraints, state of charge limitations, demand and offer regulations, as well as power-system security constraints [24]; nonetheless, these approaches primarily address the DA scenario and lack integration of EV travel forecasts.

This article aims to bridge this gap by introducing a comprehensive framework for EV integration into the power system. This framework is centered on maximizing economic returns via V2G operations. This framework considers EV energy trip and prices forecast, it operates on DA and RT markets, and provides different energy services to the electrical grid such as energy arbitrage, replacement reserve, and secondary reserve. Implemented on a fleet of EVs, this framework synchronizes forecast-based optimization with real-time management, effectuating a strategy that seamlessly harmonizes EV charging and discharging patterns. Importantly, the proposed approach not only accommodates aggregated EV models but also manages individual EVs while respecting their user preferences and considering travel forecasts. The EV usage future estimations are obtained through the DA EV forecast logic described in [25], thus in the form of vehicle-by-vehicle future behaviors. The versatility of the framework is underlined by its consideration of three distinct energy services: energy arbitrage in the DA market, and replacement reserve and secondary reserve in the RT market. Simulations, based on the provision of these services, dissect three distinct case studies, offering an understanding of the economic advantages and operational efficiencies to each scenario.

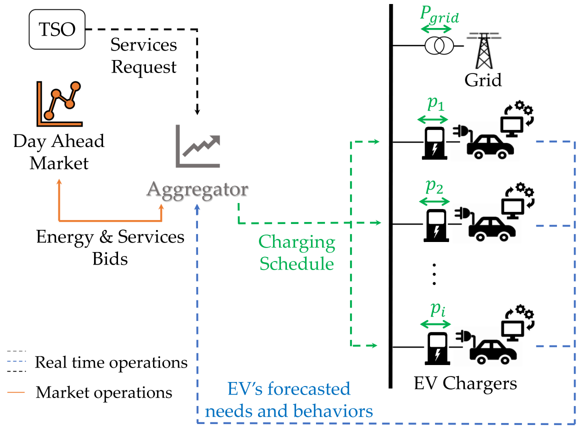


FIGURE 1. Scheme of the EVs-grid integration model.

In the following, Section II elucidates the physical model, while Section III unravels the intricacies of electricity market participation models. Section IV meticulously unpacks the proposed hybrid methodology, seamlessly integrating EV fleet management with electricity market participation. In Section V, the stage is set for extensive simulations, illuminating diverse scenarios. Ultimately, in Section VI, the curtain falls, concluding this chapter and projecting pathways for future enhancements to this pioneering methodology.

II. PHISICAL MODEL FORMULATION

The model presented in this research is based on a centralized architecture, as shown in Fig. 1. The aggregator serves as a central entity responsible for coordinating the power of all the EVs within its region. It facilitates the participation of EVs in the DA electricity market, which comprises an energy market and a reserve market.

In the energy market, the aggregator offers energy in order to determine the power profile for the next day. This profile specifies the expected energy consumption or generation of the EVs. On the other hand, in the reserve market, the aggregator provides offers to indicate its availability to provide

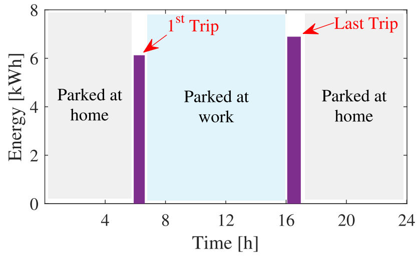


FIGURE 2. EV-to-charger connections: battery availability.

ancillary services. Thus, the aggregator assumes the role of a Balancing Service Provider (BSP). The specific balancing services considered in this research are the Replacement Reserve [26] and Secondary Regulation [27].

Furthermore, in the RT market, the Transmission System Operator (TSO) has the authority to request the activation of these ancillary services. The TSO may need additional balancing services to ensure the stability and reliability of the power system in RT operation. The principal hypotheses of the proposed model are as follows:

1) The aggregator possesses control over all the chargers to which the EVs are connected. This enables effective coordination and management of EVs.
2) EVs remain connected to the chargers when parked.
3) EVs are equipped with data collection capabilities that capture information about their usage patterns. The aggregator or an onboard logic utilizes this data to forecast the behavior of EVs for the following day.

A. EVS REPRESENTATION AND CHARGERS OCCUPANCY MODEL

This subsection elucidates the interaction between EVs, their travels, and the chargers. Firstly, we discuss the representation of EVs and chargers, along with the corresponding hypotheses. Secondly, we explain the allocation of EVs to specific chargers. Finally, we define the principal quantities of the model, encompassing both individual and aggregated powers and State of Charges (SOCs).

The behaviors of EVs throughout the day are modeled using vehicle usage profiles derived from a real database [28]. We assume that at the end of the day, each EV remains connected to the same charger it was connected to at the beginning of the day, typically assumed to be the EV user's home.

To illustrate, Fig. 2 presents the travel patterns of an EV over the course of a day. At midnight, the EV is parked near the user's home. Around 6:00, the first trip commences, lasting 45 minutes. Subsequently, at 6:45, the EV arrives at a different location, such as the workplace, where it can be connected to a bidirectional charger. Another trip takes place around 16:00, representing the final trip of the day, assumed to be headed back home. This last trip lasts 1 h, and at 17:00, the EV is once again parked near the user's home.

In this research, we model N chargers, also known as Electric Vehicle Supply Equipment (EVSE), by considering the occupancy of the i-th EVSE, denoted as Ch_i. The occupancy status is defined as follows:

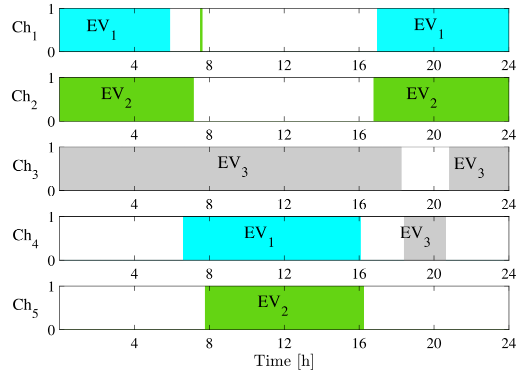


FIGURE 3. Allocation of EVs in chargers.

$$Ch_i = \begin{cases} 1 & \text{if charger } i \text{ has an EV connected} \\ 0 & \text{if charger } i \text{ has not an EV connected} \end{cases} \tag{1}$$

Therefore, referring to Fig. 2, the EVSE is occupied by the EV from midnight to 6:00 and from 17:00 to midnight, indicating that Ch is equal to 1 during this period. In contrast, the charger at the workplace is occupied from 6:45 to 16:00, while being available for other vehicles during the early morning and evening.

To assign the EVs to the EVSEs, we develop a Charger Scheduling Algorithm (CSA), it applies the following criteria:

- Initially, all EVs are allocated to their nearest chargers. For instance, EV_1 is associated with Ch_1, EV_2 with Ch_2, and so on, during the morning and evening periods.
- At the end of their first trip, EVs search for a charger to occupy for a specified period.
- The CSA checks the availability of chargers for the occupation period. Generally, the CSA starts its search from Ch_1 and onward, excluding the charger from which the trip originated. It selects the first charger that meets the availability condition.
- EVs are allocated to other chargers, transitioning their state from available to occupied.
- The algorithm repeats this process until all EVs are allocated throughout the simulated day.

Fig. 3 illustrates the allocation of the first three vehicles from the dataset to five chargers. The allocation is based on the EV usage profiles presented in [25]. EV_1 leaves Ch_1 and after its first trip, it moves to Ch_4, then returns to Ch_1. EV_2 departs from Ch_2 and after its first trip, briefly stops at Ch_1 before heading to Ch_5. Finally, EV_2 returns to Ch_2. EV_3 remains parked at Ch_3 for most of the day, with its first trip occurring at 18:16 and its second trip at 20:38, which represents the trip and the trip back to and from Ch_4. It should be noted that due to the relatively short trip durations, especially in the case of EV_3, distinguishing the departure and arrival times on the graph's scale is not always straightforward.

The CSA successfully allocates all 214 EVs from the dataset. With this allocation methodology, assuming that EVs are always parked and connected when not in travel, the required number of chargers N is 225.

B. AGGREGATED SOC AND POWER DEFINITIONS

The SoC of an EV j at time step t is denoted as $SoC_{j,t}$ and is defined as follows:

$$SoC_{j,t} = \begin{cases} SoC_{j,t-1} + 100\left(\frac{p_{i,t}\Delta t - E_{EV,t}}{E_{C,j}}\right) & \text{if } p_{i,t} \geq 0 \\ SoC_{j,t-1} + 100\left(\frac{\eta_{rt}\, p_{i,t}\Delta t - E_{EV,t}}{E_{C,j}}\right) & \text{if } p_{i,t} < 0 \end{cases} \quad (2)$$

In the equation, $p_{i,t}$ represents the power delivered or absorbed by Ch_i at time step t, $E_{C,j}$ is the battery capacity of the EV j, η_{rt} is the round-trip efficiency indicating the fraction of energy put into storage that can be retrieved, and $E_{EV,t}$ is the energy associated with EV trips at time t. If no trips occur, $E_{EV,t}$ is assumed to be 0.

During vehicle travel, the battery capacity cannot contribute to the aggregated capacity. To address this, we introduce the SoC of the charger, denoted as $SoCh_{i,t}$. This variable indicates the SoC that charger i can read throughout the day and depends on EV j. It is defined as follows:

$$SoCh_{i,t} = \begin{cases} SoC_{j,t} & \text{if } EV_j \text{ is connected to } Ch_i \text{ at } t \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

The aggregated SoC, denoted as $SoC_{BSP,t}$, represents the sum of the $SoCh_{i,t}$ values for the chargers under the control of the Aggregator (or BSP, Balancing Service Provider), divided by the total number of connected vehicles J. It represents the amount of energy stored in the EVs relative to the aggregated battery capacity. Assuming a total battery capacity of 40 kWh for each vehicle and the 214 vehicles of the database, the aggregated battery capacity is 8.5 MWh.

$$SoC_{BSP,t} = \sum_{i=1}^{N} \frac{SoCh_{i,t}}{J} \quad (4)$$

Furthermore, the aggregated power $P_{BSP,t}$ is defined as the sum of the powers $p_{i,t}$ delivered or absorbed by the chargers:

$$P_{BSP,t} = \sum_{i=1}^{N} p_{i,t} \quad (5)$$

III. ELECTRICITY MARKET PARTICIPATION FORMULATION

This section discusses the objectives and considerations of EV aggregator participation in the electricity market, focusing on the DA energy market and reserve market, particularly on replacement reserve and secondary reserve.

In this research, the information on April 6^{th}, 2020, is used as an exemplary RT day, chosen due to its alignment with the low national electricity load resulting from the COVID-19 pandemic in Italy. The observed scenario of reduced electricity absorption and increased renewables integration offers valuable insights into future electricity grid configurations. Analysis of this day's data sheds light on the impact of low electricity demand on prices and informs grid planning and management strategies.

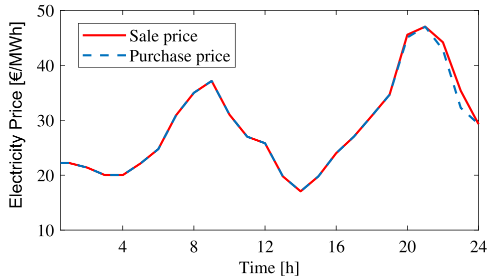


FIGURE 4. Electricity prices for purchases π_E^+ and sales π_E^-.

A. DAY AHEAD ENERGY MARKET: ENERGY ARBITRAGE CRITERION

In the DA energy market, the EV aggregator must determine the power profile for the upcoming day to ensure the energy requirements of the EV fleet are met. However, as an aggregator, it can also participate in bidirectional power exchanges, allowing it to offer energy to the market. To maximize profits, the aggregator employs an energy arbitrage strategy by purchasing energy when prices are low and selling energy when prices are high. This strategy relies on the price difference between energy sales and charging costs, including additional energy due to losses [29].

The power profile is divided into two parts of the day: one with low electricity prices for purchasing energy and another with higher prices for selling energy. By capitalizing on this criterion, the aggregator can enhance its revenue. The electricity energy price π_E considers the cost profile for charging (π_E^+) and the price received for discharging (π_E^-), adjusting based on the direction of power flow. Fig. 4 shows the actual electricity prices for energy purchases (π_E^+) and sales (π_E^-) during the evaluated day.

The power profile (P_{base}) cannot be defined solely based on the energy arbitrage strategy. It must also consider the energy-reserved part of the aggregated capacity to satisfy grid services, as discussed in the following subsections.

B. RESERVE MARKET: REPLACEMENT RESERVE AVAILABILITY

This study focuses on the participation of aggregators in the reserve market, particularly on the availability of replacement reserve service in Italy, as per the regulatory developments outlined in [30]. Since 2017 (directive 300/2017), not only relevant production units but also aggregators have been enabled to participate. However, specific conditions are required for Aggregators' involvement, as detailed below.

- The Aggregator must have the capability to modify its power profile by reducing its power absorption (or discharging) by at least 1 MW.
- The Aggregator must be able to adjust its power profile within 15 min of receiving the command.

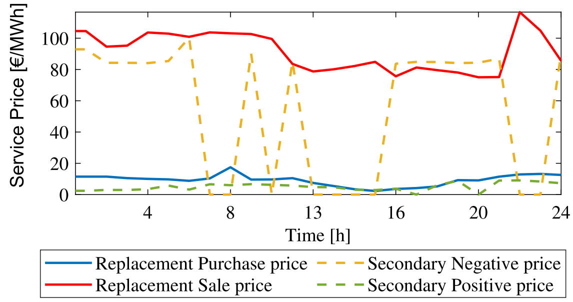


FIGURE 5. **Replacement service energy purchases π_R^+ and sales π_R^-; and Secondary regulation energy price: positive π_S^+ and negative π_S^-.**

- The Aggregator must ensure the power profile variation for at least two consecutive hours, guaranteeing a minimum of 2 MWh of available energy. Specifically, this availability must be maintained between 14:00 and 20:00 each day.

In the DA market, the aggregator must define a power profile, considering the possibility of modification during a 2-hour window between 14:00 and 20:00. As EVs can engage in bidirectional power exchanges, receiving a reduction command when the power profile is less than 1 MW results in an injection of power into the grid. For example, if the absorption is 0.5 MW at the moment of the reduction command reception, a 1 MW reduction will lead to a 0.5 MW injection.

During the RT operation, the TSO can activate or deactivate the reserved availability from the aggregator for replacement reserve service. If the reserve is activated, the aggregator receives payment for the service rendered.

In this research, it is assumed that the replacement reserve service is paid at the average price of the offers, denoted as π_R. For reductions in absorbed power (relative to P_{base}), the price is denoted as π_R^-, whereas for increases in absorbed power, it is indicated as π_R^+. The case of power reduction is akin to energy sale, and thus the price represents revenue (upward regulation from the TSO's perspective).

Fig. 5 displays the replacement service prices for the RT day. The graph illustrates the electricity price paid in the case of power reduction (energy sale - upward regulation) as well as the cost of energy when the TSO requires an increase in consumption (energy purchase - downward regulation). However, this study solely considers availability in power reduction; hence, only the sales profile is examined further.

At the end of the day, the aggregator generates revenue through energy arbitrage and ancillary service provision. This revenue can be partially redistributed among EV users as a reward for their battery usage.

C. RESERVE MARKET: SECONDARY RESERVE AVAILABILITY

The Aggregator actively participates in the secondary reserve, where the TSO provides a regulation signal indicating the instantaneous deviation from the power profile. This deviation can be either a reduction in power absorption (upward deviation) or an increase in power adoption (downward deviation). To quantify this regulation signal, a percentage level with respect to a pre-contracted maximum power deviation is used, representing a variable between -100% and 100%.

The price of the secondary reserve service π_S depends on the market's demand and offer trends. It takes different values depending on the direction of the power deviation. In the case of power reduction, it is considered as an energy sale, and thus the price π_S^- is interpreted as revenue. Conversely, for power increases, it involves an energy purchase, and therefore, the price π_S^+ is considered a cost. However, since the purchase is required from the TSO, this cost is substantially lower than the revenue from negative deviations, resulting in the potential for a net gain. Fig. 5 displays the secondary reserve prices considered for the RT operation.

The revenue generated from the activation of the secondary reserve can be partially redistributed among the EV users. However, this study examines revenues as the net economic benefit that can be obtained from an individual vehicle or the aggregator as a whole.

D. AGGREGATED COST AND ECONOMIC BENEFIT MEASUREMENTS

In the DA market, the BSP defines the power profile P_{base}, representing the profile for the following day without any replacement or secondary reserve activations. However, on the RT market, the aggregated power accounts for the powers due to the activation of the replacement P_R and secondary P_S reserves. The RT aggregated power is expressed as:

$$P_{BSP_{RT}} = P_{base} + P_R + P_S. \tag{6}$$

Notably, P_R takes non-zero values only for the hours in which the replacement service is activated (2 hours), while P_S, if activated, represents the power deviation from P_{base} throughout the RT operation.

The Aggregated economic cost/revenue C_{TOT} can be expressed as,

$$C_{TOT} = P_{base}\pi_E + P_R\pi_R + P_S\pi_S, \tag{7}$$

where the prices are positive while the power can assume negative values, i.e., selling energy to the market. Moreover, since the aggregated cost/gain is obtained by exploiting the power of each vehicle, it can also be expressed as the sum of the cost/revenue c_j of each j vehicle.

$$C_{TOT} = \sum_{j}^{J} c_j \tag{8}$$

For clarity, in the following, the case with negative values of C_{TOT} will be distinguished and referred to as the gain G_{TOT}.

Despite providing grid services, the aggregator incurs net energy consumption daily due to the EV fleet's energy requirements for travel. Additionally, depending on the final occurred power profile P_{BSP}, the aggregator may have stored more or less energy in the Aggregated Battery (AB) compared to the beginning of the day. Hence, the Net Energy Purchased (NEP) is defined as follows:

$$NEP = E_{\text{fleet}} + \left(SoC_{BSP,0} - SoC_{BSP,T}\right) \frac{E^{AB}_{C,Tot}}{100}, \tag{9}$$

where E_{fleet} represents the fleet energy required for travel during the day, $SoC_{BSP,0}$ and $SoC_{BSP,T}$ represent the SoC at the beginning and end of the day, respectively, and $E^{AB}_{C,Tot}$ is the total capacity of the aggregated battery, which is assumed to be 8.5 MWh in this research.

The Cost of the Net Energy Purchased (CNEP) allows for a comparison between the aggregated cost/gain and the value of the net energy acquired from the aggregator. Essentially, CNEP can be considered as the cost that the aggregator would have incurred if no V2G operations were allowed. CNEP is the product of NEP and the average electricity price throughout the day, denoted as $\overline{\pi_E}$.

$$CNEP = NEP\ \overline{\pi_E} \tag{10}$$

IV. AGGREGATOR MANAGEMENT AND CONTROL METHODOLOGY

This section presents a methodology for the aggregator to effectively manage the EV fleet while maximizing economic benefits and satisfying the mobility needs of EV users. The proposed automatic methodology aims to provide grid services while considering the users' travel requirements. However, it is acknowledged that EV users may be reluctant to make their cars available for V2G operations if they are constantly required to provide information about their upcoming travels. Furthermore, the information provided may not always align with their actual behavior.

Therefore, the control algorithm here proposed takes automatically EV usage historical data and daily profiles of electricity prices as inputs. Based on these inputs, the algorithm is divided into the following three phases.

A. PHASE 1: *FORECAST OF INDIVIDUAL EV USAGE PROFILES AND ELECTRICITY PRICES*

To estimate the behavior of the EV fleet for the next day, a DA forecast routine is employed. This routine utilizes historical data of each vehicle to identify systematic usage patterns and predict the most probable EV behavior for the upcoming day. In order to capture various systematic behaviors, the forecast routine differentiates between weekdays, treating each day separately. The EV usage forecast methodology is fully discussed in [8].

For the specific example in this research, which focuses on the RT operation day of Monday, April 6^{th}, 2020, the routine calculates the most probable usage profiles for all EVs in the dataset. To assess the accuracy of the forecast and have a measure of the capacity of an EV to be forecasted, the average error is computed by comparing the forecasted profiles with the historical data of each vehicle for all previous Mondays.

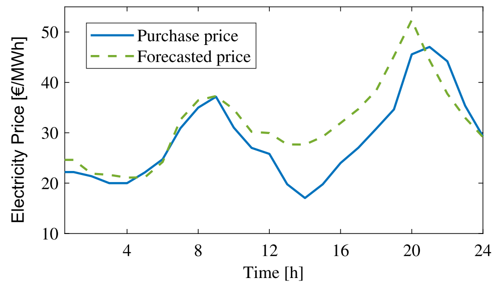


FIGURE 6. Forecasted $\tilde{\pi}_E$ and actual electricity π^+_E prices.

This average error is denoted as TE^{all}_j. Additionally, the expected occupancy of a bidirectional charger is considered and represented by the variable $\widetilde{Ch}_i$.

In order to estimate the electricity price for the RT day, an Autoregressive Moving Average-based approach is employed. The price is calculated as the hour-by-hour average of the previous four Monday's prices. As the charging cost π^+_E and the discharging price π^-_E exhibit similarity, the electricity price forecast is based solely on the charging cost data. Fig. 6 depicts the estimated electricity price $\widetilde{\pi} E$ in green, alongside the actual electricity price πE^+ in blue.

B. PHASE 2: *OPTIMIZATION OF THE POWER PROFILE BASED ON FORECASTS*

The objective of this phase is to determine the power profile for the next day that satisfies the mobility needs of EV users while minimizing costs. The Energy Arbitrage Strategy is employed to achieve this goal. However, considering the possibility of activating grid services on the RT operation day, the power profile must also ensure a certain availability in both charge and discharge. Consequently, a multi-objective optimization problem is formulated.

The multi-objective function of the optimization problem encompasses three distinct objectives:

1) Minimize operational costs through the implementation of the Energy Arbitrage Strategy.
2) Maximize availability in power reduction, representing energy sales and upward reserve. The variable AED_t denotes the Available Energy for Discharging at time t, while π_{AED} represents the price at which this energy is sold. π_{AED} takes into account both the ancillary service prices for discharge, namely π^-_R and π^-_S. Based on historical data, π_{AED} is assumed to be 105 €/MWh. This objective aims to keep the aggregated SoC close to 100%, ensuring a certain availability in discharge.
3) Maximize availability in power adsorption increase, corresponding to energy purchases and downward reserve. The variable AEC_t denotes the Available Energy for Charging at time t, and π_{AEC} represents the price at which energy is purchased for grid services. Based on historical data, π_{AEC} is assumed to be 8 €/MWh. Unlike the second objective, this third objective aims to keep the Aggregated SoC close to the minimum boundary, ensuring a certain availability in charge.

The formulation of the optimization problem seeks a compromise among these objectives, resulting in the power profile that best satisfies the requirements. Therefore, the cost function is defined as follows:

$$f(*) = \Delta t \sum_{t}^{T} \left(P_{base,t} \widetilde{\pi}_{E,t} - AED_t \pi_{AED} - AEC_t \pi_{AEC} \right). \tag{11}$$

The optimization problem is subject to the following constraints:

- The power of the charger, denoted as $p_{i,t}$, is always positive (indicating the charging process) when the forecasted SoC of the charger $\widetilde{SoChi}, t$ is below the minimum boundary $\widetilde{SoChi}, t^{\min}$:

$$0 \leq p_{i,t} \leq \widetilde{Ch}_{i,t} p_{i,\max} \text{ if } \widetilde{SoCh}_{i,t} \leq \widetilde{SoCh}_{i,t}^{\min} \tag{12}$$

  The decision variable $p_{i,t}$ represents the power of charger i and is limited by the maximum power $p_{i,\max}$ that the charger can provide or the EV can receive, depending on the estimated occupancy $\widetilde{Ch}_{i,t}$. Based on the available data, the maximum power level is set at 13.3 kW.
- The power limits of the charger, either in charge or discharge, are defined by $\pm p_{i,\max}$:

$$-\widetilde{Ch}_{i,t} p_{i,\max} \leq p_{i,t} \leq \widetilde{Ch}_{i,t} p_{i,\max} \text{ if } \widetilde{SoCh}_{i,t} > \widetilde{SoCh}_{i,t}^{\min} \tag{13}$$

  It should be noted that the charger can only inject power when $\widetilde{SoCh}_{i,t}$ exceeds the minimum boundary.
- The forecasted boundaries of the charger's SoC:

$$0 \leq \widetilde{SoCh}_{i,t} \leq 100 \tag{14}$$

- The availability of discharging for ancillary services is considered within the time window from 14:00 to 20:00. This constraint is reflected in the estimated aggregated SoC, denoted as $\widetilde{SoC}_{BSP,t}$, which is limited by the estimated aggregated SoC boundary $\widetilde{SoCh}_{BPS,t}^{\min}$ and the SoC level corresponding to the minimum required discharge availability, which is 2 MWh. Given the aggregated battery capacity of 8.5 MWh, the SoC_{2MWh} corresponds to 23%:

$$\widetilde{SoC}_{BSP,t} \geq \widetilde{SoCh}_{BPS,t}^{\min} + SoC_{2MWh} \tag{15}$$

Moreover, the boundary $\widetilde{SoCh}_{i,t}^{\min}$ is defined as:

$$\widetilde{SoCh}_{i,t}^{\min} = SoC_{\min} + \widetilde{E}_{EV_{j,next},t} + SoC_{\gamma,j}, \tag{16}$$

where $SoC_{\min}$ represents a minimum value set to prevent excessive stress on the EV battery chemistry, which is assumed to be 30%. $\widetilde{E}EV j, next, t$ is the estimated energy consumption for the next trip of EV j, and $SoC_{\gamma,j}$ is an additional value intended to mitigate EV forecast errors.

In more detail, $SoC_{\gamma,j}$ is determined based on the error TE_j^{all} and the average trip energy consumption $\bar{E}EV j$ of EV j:

$$SoC_{\gamma,j} = TE_j^{all} \bar{E}_{EV_j} \tag{17}$$

Since TE_j^{all} falls within the range of 0 to 100%, the tolerance value $SoC_{\gamma,j}$ is defined as a fraction of the average trip energy.

The estimated aggregated boundary $\widetilde{SoCh}_{BPS,t}^{\min}$ is computed by considering all the minimum boundaries of the chargers:

$$\widetilde{SoCh}_{BPS,t}^{\min} = \sum_{i=1}^{N} \frac{\widetilde{SoCh}_{i,t}^{\min}}{J} \tag{18}$$

C. PHASE 3: *RULE-BASED MANAGEMENT FOR RT DISPATCHING*

During the RT operation day, the Rule-based logic is employed with a sampling time of one minute. The logic is responsible for applying the power profile P_{base} (defined in *Phase 2*) to the EV fleet, considering potential deviations from the forecasted EV behavior. Additionally, the Rule-based logic facilitates the activation of grid services.

To achieve these objectives, the Rule-based logic operates based on a priority criterion. In the absence of grid services activation, the logic assigns the optimized power profile by distributing the power $P_{base,t}$ minute by minute among the various EV chargers. This operation is made possible by defining different priority indices specific to each vehicle and varying them throughout the day based on the EV's energy requirements. The priority index ranges from 0 to 1, representing the portion of $P_{base,t}$ that should be allocated to charger i based on the forecasted charging urgency or discharge availability of the connected EVs.

Thus, in the absence of grid services activation, the charging/discharging power of each charger is determined according to the following formulation:

$$p_{i,t} = \begin{cases} P_{Base,t} PC_{i,t} & \text{if } P_{Base,t} > 0 \\ P_{Base,t} PD_{i,t} & \text{if } P_{Base,t} > 0 \end{cases} \tag{19}$$

where,

$$\sum_{i=1}^{N} PC_{i,t} = 1 \text{ and } \sum_{i=1}^{N} PD_{i,t} = 1. \tag{20}$$

Here, $PC_{i,t}$ represents the priority for charging the EV connected to charger i at time t, while $PD_{i,t}$ represents the priority for discharging. Naturally, the sum of all priority indices across all chargers equals unity. In the absence of grid services activation, the real-time aggregated power $P_{BSP,t}$ is equal to $P_{Base,t}$, while each EV supports a portion of the aggregated power.

The charging and discharging priorities, i.e., $PC_{i,t}$ and $PD_{i,t}$, are defined as follows:

$$PC_{i,t} = \frac{SoCh_{i,t}}{\widetilde{SoCh}_{i,t}^{\min}} \sum_{i=1}^{N} \frac{\widetilde{SoCh}_{i,t}^{\min}}{SoCh_{i,t}} \text{ if } SoCh_{i,t} < 100\% \tag{21}$$

$$PD_{i,t} = \frac{\widetilde{SoCh}_{i,t}^{\min}}{SoCh_{i,t}} \sum_{i=1}^{N} \frac{SoCh_{i,t}}{\widetilde{SoCh}_{i,t}^{\min}} \text{ if } SoCh_{i,t} \geq SoC_{\min} \tag{22}$$

These definitions are based on the estimated EV usage. As mentioned earlier, $\widetilde{SoChi}, t^{\min}$ represents the estimated amount of energy required by an EV for its next trip, accounting for an appropriate level of tolerance. Thus, it represents the minimum SoC needed by the EV before leaving the charger. However, during the RT operation, the SOC of the charger may be lower. In such cases, the rule-based logic restores $\widetilde{SoChi}, t^{\min}$ before the next trip occurs. The charging priority is defined as the ratio between the current state $SoCh_{i,t}$ and the forecasted $\widetilde{SoCh}_{i,t}^{\min}$. This ratio is then normalized with respect to the sum of the ratios for all other chargers. Consequently, chargers (and their corresponding EVs) with lower SOC values will be allocated higher charging power.

On the other hand, the discharging priority is obtained as the ratio between the forecasted SOC required for the next trip $\widetilde{SoChi}, t^{\min}$ and the current $SoChi, t$ (inverse of the preceding ratio). If the SOC of a charger is close to full charge, it will be assigned a higher discharge power. Finally, the $PD_{i,t}$ value remains defined as long as the SOC of the charger exceeds $SoC_{\min}$, a threshold set to avoid excessive stress on the battery chemistry. Once this threshold is crossed, the EV is disabled for discharge, and other vehicles will utilize its power allocation.

V. SIMULATION RESULTS

The proposed methodology is tested based on 214 EVs. The cost analysis refers to the real prices that occurred in Italy on April 6th, 2020. The initial SoC is assumed as the sum of a minimum value $SoC_{\min} = 30\%$, and a tolerance part different for each vehicle $SoC_{\gamma,j}$. The aggregated battery capacity is 8.56 MWh, with each single EV having a battery capacity of 40 kWh. The maximum charge/discharge power for each vehicle is 13.3 kW. The proposed logic uses the definitions of priority $PC_{i,t}$ and $PD_{i,t}$. A comparison with an alternative scenario without priorities is also presented.

In the following, the results for three cases are reported. The first case presents the output of the RT management in *Phase 3* and the relative cost analysis with no grid service activation on the RT operation day. The other two cases report the results for Replacement Service activation and Secondary Reserve activation. The model is formulated in the Matlab environment, and the optimizations are performed through the Yalmip tool.

A. CASE WITH NO GRID SERVICES ACTIVATION

Fig. 7(a) shows the SoC evolution during the simulated day of the first three EVs for the case without grid services activation. The EVs are allocated to five chargers as discussed in Section II. It is worth noting that the SoC of an EV is correctly updated at the trip starting time, i.e., once EV 1 arrives at charger 4 after the first trip, its SoC is appropriately reduced according to the trip energy consumption.

The dashed red lines represent the $SoCh_{i,t}^{\min}$ that the EV needs in order to approach the next real trip safety. This SoC is calculated as the sum of $SoC_{\min} = 30\%$ and the real consumption of the next real trip. It follows that the EV SoC should be higher than this boundary when a trip starts. In the figure, it is possible to observe that for all the trip starting times, the SoC of each EV is always higher than the corresponding boundary.

Fig. 7(d) shows the aggregated power profile P_{BSP} on the RT operation day, and the relative aggregated SoC SoC_{BSP}. In this case, with no grid services activation, the power profile perfectly overlaps with the base power profile P_{base}, which is defined as the output of the optimization.

When P_{BSP} is negative, it means that the aggregator is injecting power into the grid. When it is positive, the aggregator is purchasing power, thus charging the aggregated battery. This is also evident from the aggregated SoC profile, which increases when the power is positive. The aggregated power profile follows the Energy Arbitrage Strategy.

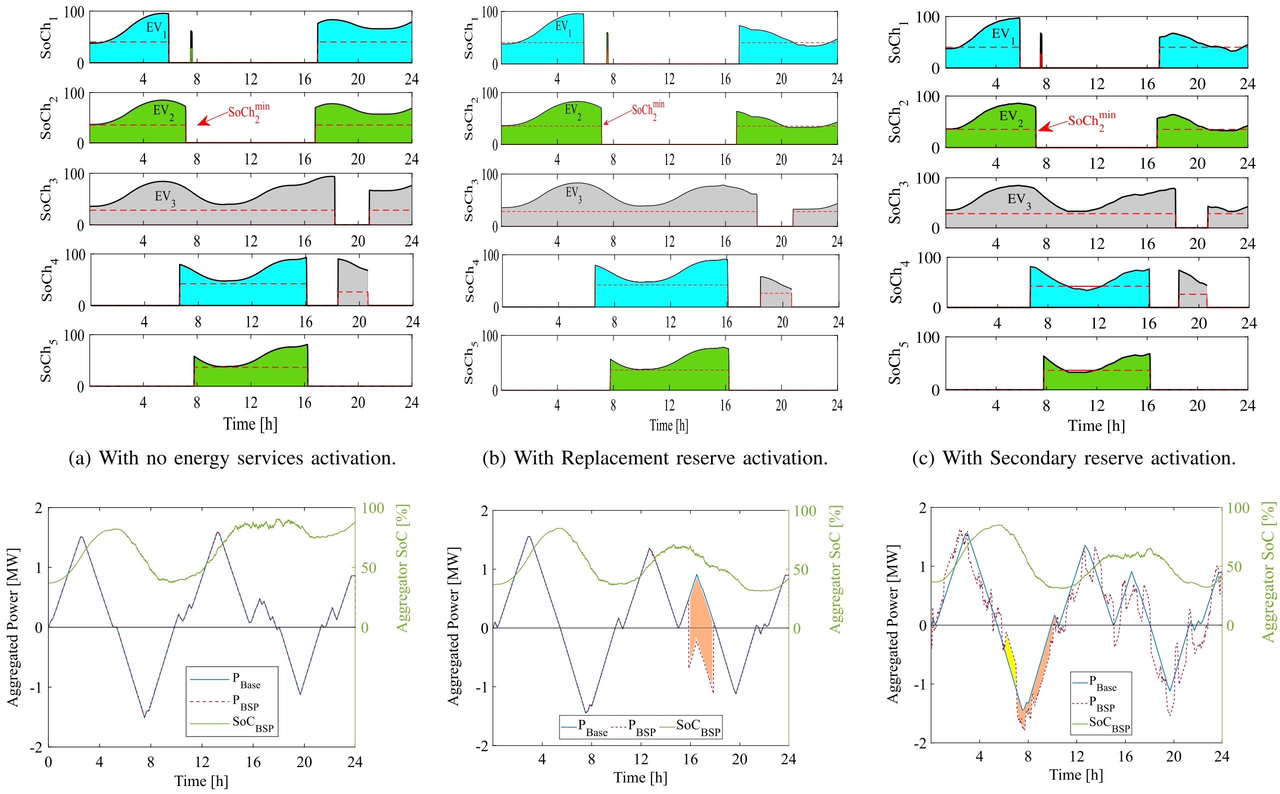
Table 1 lists the cost analysis of the case under study. The total cost C_{TOT} of fleet management at the end of the simulated day results in 77€ (0.36€ per EV per day). The value of the CNET from the fleet amounts to 124€. This means that in the absence of the Energy Arbitrage Strategy, in order to acquire the same amount of energy, the expense would have been 124€. Thus, an economic saving of 38% is achieved. The table also provides information on the cases in which the EV SoC falls below the boundary $SoCh_{i,t}^{\min}$ before a trip. This condition occurs 29 times during the day. However, the total number of trips made by the 214 EVs during the simulated day is 895. Therefore, the boundary is exceeded in only 3% of the cases.

Table 2 presents the results in terms of boundary "exceedances" for two other cases: when priorities are not considered and when exact priorities are considered. If priorities are not considered, the rule-based logic imposes the power profile by equally sharing the power among the 214 EVs. Meanwhile, if exact priorities are considered, $PC_{i,t}$ and $PD_{i,t}$ are calculated not based on the forecasted boundary $\widetilde{SoChi}, t^{\min}$ but with the actual boundary $SoChi, t^{\min}$.

The results show that without priorities, the number of boundary exceedances is 36. Thus, the proposed logic shows a relative improvement of 19%. With exact priorities, the exceedances decrease to 18, with a relative improvement of 50% compared to the case without priorities. The reason why exceedances are still present in this latest case is that some EVs do not stay parked long enough to be charged at the maximum power considered, or they connect while the power profile is not in charging operation.

B. CASE WITH REPLACEMENT RESERVE ACTIVATION

Fig. 7(b) shows the SoC evolution during the simulated day for the case with Replacement Service activation. Also, in this case, the SoC of the EVs is always higher than the boundary at the trip starting times. However, it is visible that for EV_1 and EV_2, around 22:00, the SoC goes below the boundary for a short time while connected. This is part of the normal functioning of the logic. In fact, by the end of the day (before



(a) With no energy services activation. (b) With Replacement reserve activation. (c) With Secondary reserve activation.

(d) With no energy services activation. (e) With Replacement reserve activation. (f) With Secondary reserve activation.

FIGURE 7. EV chargers SOCs evolution.

TABLE 1. Technical-Economic Performance

Case	C_{TOT} [€]	G_{TOT} [€]	$CNEP$ [€]	Economic Savings [%]	Average Cost per EV per day [€]	Average Gain per EV per day [€]	Boundary Exceedances [#]
No service	77	-	124	38	0.36	-	29 (3%)
Replacement reserve	-	109	48	327	-	0,51	45 (5%)
Secondary reserve		243	53	558	-	1,15	56 (6%)

TABLE 2. Different Priorities Adoptions Comparison

Case	Boundary Exceedances With No Priorities	With Priority Index	With Exact Priority
No services	36	29 (-19%)	18 (-50%)
Replacement reserve	67	45 (-33%)	35 (-48%)
Secondary reserve	77	56 (-27%)	47 (-39%)

midnight), the missing energy is fully recovered, and the EVs can approach the next trip safely.

Fig. 7(e) shows the aggregated power profile P_{BSP} on the simulation day and the relative aggregated SoC SOC_{BSP}. In this case, with the Replacement Reserve activation, the power profile is the same as P_{Base} until 15:51 when the ancillary service is activated. This ancillary service remains active for two hours until 17:51, after which the power profile again follows P_{Base}.

During these 2 hours, a reduction of power absorption of 1.1 MW is achieved, resulting in total energy for the replacement service of about 2.2 MWh (27% of the aggregated battery capacity). This amount of variation is the maximum the fleet under analysis can operate as a Replacement Service. With higher energy variations, the SoC of some EVs reaches the boundary $SoC_{\min} = 30\%$, and these vehicles are disabled for discharging operations. As a result, they no longer participate in the Aggregated Power Profile dispatching, and the other vehicles take charge of this gap. Moreover, this figure also shows the SoC increasing when the power is positive and decreasing when the power is negative The energy for the replacement service is paid through the sales price π_R^-. Table 1 provides the cost analysis. Due to both the Energy Arbitrage Strategy and the grid service provided, a net gain of 109€ is achieved. The value of the CNEP from the fleet amounts to 48€. This means that in the absence of the Energy Arbitrage and Ancillary Service, in order to acquire the same amount of energy, an expense of 48€ would have occurred. Thus, an economic benefit of 327% is achieved. In this case, on average, every car has gained 0.51€. While 45 boundary exceedances have been recorded, with an effect of 5% on the total.

Table 2 lists the results of the comparison with no priorities and with exact priorities. With no priorities, the number of exceedances goes up to 67. Thus, the proposed logic shows a relative improvement of 33%. With exact priorities, the exceedances decrease to 35, with a relative improvement of 48% compared to the case without priorities.

C. CASE WITH SECONDARY RESERVE ACTIVATION

Fig. 7(c) shows the SoC evolution during the simulated day of the first three EVs for the case with the Secondary Reserve activation. The EV SoCs in the figure are always higher than the boundary at the trip starting times. For EV_1 and EV_2, around 11:00 and 22:00, the SoC goes below the boundary for a short time, but the missing energy is fully recovered by the next trip starts.

Fig. 7(f) shows the Aggregated Power Profile P_{BSP} on the RT operation day and the relative Aggregated SoC SOC_{BSP}. In this case, with the Secondary Reserve activation, the Power Profile orbits around P_{Base} with a maximum deviation chosen equal to 13% of the maximum power (thus 370 kW). This deviation is the maximum that the fleet under analysis can operate as Secondary Reserve while being able to always follow the profile defined in the DA market. The regulation signal used for the analysis is provided by the Italian TSO (Terna S.p.A.) and refers to the real signal that occurred on the RT operation day. Finally, the SoC increases when the power is positive (charge) and decreases if the power is negative (discharge).

When the Power Profile is below P_{Base} (negative deviation), the corresponding energy is considered a sale and is paid with the negative deviation price π_S^-. When the deviation is positive, it is considered a purchase and is bought at the positive deviation price π_S^+ (see Fig. 5). However, since purchase is required from the TSO, this cost is much lower than the negative deviation revenue, resulting in a net gain.

The case with Secondary Reserve activation achieves the highest economic gain. Table 1 lists the cost analysis of the case under study. Due to both the Energy Arbitrage Strategy and the Secondary Reserve activation, a net gain of 243€ is achieved by the end of the day. The value of the CNEP from the fleet amounts to 53€. This means that in the absence of Energy Arbitrage and Secondary Reserve activation, an expense of 53€ would have been incurred to acquire the same amount of energy. Thus, an economic benefit of 558% is achieved. In this case, on average, every EV has gained 1.15€. Meanwhile, 56 boundary exceedances have been recorded, with an effect of 6% of the total.

Table 2 lists the results of the comparison with no priorities and with exact priorities. With no priorities, the number of exceedances goes up to 77. Thus, the proposed logic shows a relative improvement of 27%. With exact priorities, the exceedances decrease to 47, with a relative improvement of 39% compared to the case without priorities.

VI. CONCLUSION

This study introduces a comprehensive framework for seamlessly integrating electric vehicles (EVs) into the power grid, focusing on maximizing economic benefits through vehicle-to-grid (V2G) operations and active participation in electricity markets. As EV adoption rises, this integration becomes pivotal for a sustainable energy landscape. Leveraging bidirectional power flow in V2G operations, EVs enhance grid stability and serve as distributed energy resources.

Our methodology bridges the gap between EV travel forecasts and electricity market engagement. Merging forecast-based optimization with real-time management, it ensures seamless coordination of EV charging and discharging. An innovative prioritization mechanism, considering state-of-charge forecasts for upcoming trips, optimizes power allocation among EVs, enhancing reliability and V2G efficiency.

Through simulations covering energy arbitrage and ancillary services, our framework evaluates economic viability and efficiency. Comparing Replacement Reserve, Secondary Reserve, and energy arbitrage scenarios, we identify configurations with maximum benefits. This underscores EVs' potential to stabilize grids, contribute to ancillary services, and generate economic value.

Our approach addresses limitations in EV integration, fostering holistic EV participation in V2G operations and markets. Incorporating travel forecasts, streamlined charging, and strategic power allocation, this optimizes EV grid integration, strengthens grid stability, and bolsters returns. Insights guide EV-grid interactions toward an economically viable energy landscape.

Future work should expand vehicle samples, refine power dispatch priorities, explore vehicle-to-vehicle exchanges, and enhance EV models with the battery degradation. This study advances efficient EV integration, fostering intelligent electric mobility management and realizing V2G's economic and grid-stabilizing potential.

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FRANCESCO GIORDANO received the M.Sc. degree in electrical engineering and the Ph.D. degree in electrical, electronics, and communication engineering from Politecnico di Torino, Turin, Italy, in 2016 and 2021, respectively. His Ph.D. was focused on electric vehicle-grid integration, smart charging, and reserve availability enabling. In the subsequent years he was also with the automotive sector for an electric vehicle manufacturer. He is currently an Expert Researcher with LINKS Foundation, Italy, focusing on smart grids and electrical vehicles related fields.

CESAR DIAZ-LONDONO (Member, IEEE) was born in Bogota, Colombia. He received the B.Sc. and M.Sc. degrees in electronics engineering from Pontificia Universidad Javeriana, Bogota, Colombia, in 2014 and 2016, respectively, and a double doctoral degree, the Ph.D. degree in engineering from Javeriana, and the Ph.D. degree in electrical, electronics, and communications engineering from the Politecnico di Torino, Turin, Italy, in 2020. From 2018 to 2021, he was a Research Fellow with the Department of Energy, Politecnico di Torino. He is currently an Assistant Professor with Politecnico di Milano within the Dipartimento di Elettronica Informazione e Bioingegneria. His research interests include a broad spectrum, focusing on smart grids, demand response, integration of electric vehicles into the electrical grid, optimal control techniques, and electrical networks analysis in real-time simulators.

GIAMBATTISTA GRUOSSO (Senior Member, IEEE) was born in 1973. He received the B.S. and M.S. degrees in electrical engineering and the Ph.D. degree in electrical engineering from the Politecnico di Torino, Turin, Italy, in 1999 and 2003, respectively. From 2002 to 2011, he was an Assistant Professor with the Department of Electronics and Informatics, Politecnico di Milano, Milan, Italy, where he has been an Associate Professor, since 2011. He is the author of more than 80 papers on Journals and conferences on the topics. His research interests include electrical engineering, electronic engineering, and industrial engineering. His main research interests include electrical vehicles transportation electrification, electrical power systems optimization, simulation of electrical systems, digital twins for smart mobility, factory and city, and how they can be obtained from data. He is the Head of Simlab40 group at Politecnico di Milano.

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