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Integrated operation of electric vehicles and renewable generation in a smart distribution system

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ABSTRACT

Distribution system complexity is increasing mainly due to technological innovation, renewable Distributed Generation (DG) and responsive loads. This complexity makes difficult the monitoring, control and operation of distribution networks for Distribution System Operators (DSOs). In order to cope with this complexity, a novel method for the integrated operational planning of a distribution system is presented in this paper. The method introduces the figure of the aggregator, conceived as an intermediate agent between end-users and DSOs. In the proposed method, energy and reserve scheduling is carried out by both aggregators and DSO. Moreover, Electric Vehicles (EVs) are considered as responsive loads that can participate in ancillary service programs by providing reserve to the system. The efficiency of the proposed method is evaluated on an 84-bus distribution test system. Simulation results show that the integrated scheduling of EVs and renewable generators can mitigate the negative effects related to the uncertainty of renewable generation.

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1. Introduction

The ability to influence electricity demand profile by controlling Electric Vehicles (EVs) in order to cope with intermittent renewable generation and distribution network constraints is a primary capability required to a smart grid. Moreover, an EV, due to its charging/discharging flexibility is a good candidate for supplying ancillary services [1,2]. The energy stored in batteries of EVs can be, indeed, used as a flexible reserve capacity in order to integrate intermittent renewable generation. By using combined on/off charging signals, the system operator can manage a fleet of EVs in order to provide reserve for compensating renewable power generation variability.

1.1. Renewable generation uncertainty

Some of the main limits related to wind and solar power generation are represented by the dispatchability and reliability problems associated with its operation since the output power is determined by the weather conditions. This intermittent generation makes network balance and reserve planning more complex than before and other dispatchable compensating resources are required in order to follow the electrical load demand profile. So, the operator can just provide some reserve capacity in day-ahead scheduling in order to have enough backup resources for making corrective decisions in real-time.

In day-ahead energy and reserve scheduling, renewable generation is mainly modeled as a negative demand [3] and the forecast error of the power generated by renewable units may be modeled by using stochastic or deterministic methods [4–6]. In the deterministic approach, a predefined value for the forecast error for wind and solar generation at each period is taken into account in order to estimate the range of changes for the renewable power generation. The amount of the reserve that is required to counterbalance the variation of renewable generation is calculated based on the values of the forecast error and is usually presented as a percentage of renewable forecasted power in each period. The forecast error value is calculated by weather forecast institutes considering various parameters and historical data.

On the other hand, in most stochastic methods, the amount of reserve requirement for each period is not determined before the energy scheduling [3,6]. In the first step, plausible scenarios of wind and solar generation, with a given probability of occurrence, are created by using a probability distribution function (PDF) of wind or solar generation. The energy and reserve scheduling is carried out for each scenario while the comparison with a base scenario allows assessing all generation variations in order to determine the reserve requirement. Also, in stochastic methods [3,6],

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Nomenclature

Sets
t index of optimization periods, $t = 1, 2, \ldots, 24$
v index of electric vehicles, $v = 1, 2, \ldots, N_{a,v}$
a index of aggregators, $a = 1, 2, \ldots, A$
w index of wind turbines, $w = 1, 2, \ldots, W_a$
pv index of Photovoltaic (PV) units, $pv = 1, \ldots, pv_a$
n, m index of buses, $n, m = 1, 2, \ldots, N$

Variables: (1) Binary variables
$X(v,t)$ binary variable of EV v related to discharge state in period t
$Y(v,t)$ binary variable of EV v related to charge state in period t

(2) Continuous variables
OF total operation cost of an aggregator ($)
$P_S^a(t)$ scheduled power from the main grid in period t (kW)
$P_{EV}^{Dch}(v,t)$ power discharge of EV v in period t (kW)
$P_{EV}^{Ch}(v,t)$ power charge of EV v in period t (kW)
$R_{EV}(v,t)$ scheduled reserve provided by EV v in period t (kW)
$E_s(v,t)$ state of charge related to EV v in period t (kW h)
$SR(a,t)$ accepted reserve capacity of aggregator a in period t (kW)

Parameters
D_t total hourly demand in period t (kW)
$P_{w,t}$ forecasted wind power of turbine w in period t (kW)
$P_{pv,t}$ forecasted solar power of unit pv in period t (kW)
Δt coefficient related to period duration
$C_{Dch}^{v,t}$ discharge price of EV v in period t ($/kW h)
Ω_t hourly electricity price of open market ($/kW h)
ψ_t price of the reserve provided by EV v in period t ($/kW h)
η_v^C grid-to-vehicle charging efficiency coefficient for EV v
η_v^D vehicle-to-grid discharging efficiency coefficient for EV v
$E_{trip}^{v,t}$ required energy for traveling of EV v in period t (kW h)
$P_{Dch,v}^{Max}$ maximum power discharge of EV v (kW)
$P_{Ch,v}^{Max}$ maximum power charge of EV v (kW)
Ψ_v^{max} Maximum level of state of charge for EV v (kW h)
Ψ_v^{min} minimum level of state of charge for EV v (kW h)
$E_{BatCap,v}$ capacity of battery of EV v (kW h)
$Res_{a,t}$ total reserve requirement of aggregator a in period t (kW)
$PR_{a,t}$ purchased reserve from other aggregators for aggregator a in period t (kW)
$SR_{a,t}$ sold reserve to other aggregators by aggregator a in period t (kW)
α_t wind power forecast errors in period t
β_t solar power forecast errors in period t
$O_{a,t}$ price offer for providing reserve in period t submitted by aggregator a ($/kW h)
$R_{a,t}^{max}$ available reserve capacity of aggregator a to sell in period t (kW)

when the probability of scenarios is very low and the cost for providing reserve is very high, an expected load not served term is also considered in order to use involuntary load shedding as a variable in the day-ahead energy resource scheduling optimization. However, it is obvious that in the distribution system operation, it is not acceptable to force some customers to shed their demand due to renewable generation unexpected variation.

Although many forecasting approaches and stochastic scheduling methods exist, there is no guarantee that forecasting values of renewable generation are exactly equal to their actual output power in the real-time [7,8]. So, the day-ahead scheduled quantities may not satisfy all the system constraints in the real-time operation and, in some cases, need to be re-dispatched. For this reason, the real-time scheduling is essential in distribution systems with high penetration of intermittent renewable generation sources. For example, a very short-term wind forecasting for a real world application using data provided by Hydro Tasmania has been presented in [8]. A 2.5 min horizon is proposed in a neuro-fuzzy methodology with less than 4% error. This methodology can be used in real-time operation in order to update the input data of the energy and reserve scheduling optimization in real-time (e.g. 5 min ahead).

Endowing distribution systems with real-time network monitoring and control capabilities [9] offers the opportunity to involve EVs in the provision of the reserve service, thus alleviating the problems determined by renewable energy production variability [10] and also contributing to air pollutant emissions reduction. In [11], for example, a stochastic linear optimization algorithm considering several uncertainties related with the participation of EVs in the day-ahead energy and regulation reserve market has been presented.

However, the compensation of an unexpected decrease in the renewable generation by reserve provided by EVs has not been considered within the distribution energy and reserve scheduling problem in the literature. In this paper, EVs can provide two types of reserve service in order to compensate the wind and solar power variability.

1.2. Electric vehicles and roles of aggregators

Smart grids require a new management philosophy and new operation methods to adequately schedule renewable based generation and Distributed Energy Resources (DER), including EVs as controllable loads [12,13]. On the other end, the large number of EVs significantly increases the number of decision variables that must be considered in the energy resource scheduling problem. Due to the high number of EVs and DERs available in the distribution network, the complexity of the energy resource scheduling problem also increases.

Therefore, the large numbers of players requires new management methodologies based on a hierarchical and distributed philosophy. It is also necessary to develop decentralized control and operation of distribution systems in order to improve the efficiency of energy resource scheduling methods aiming at obtaining fast response for optimization problems with many variables.

This challenge motivates the introduction of one or more aggregators as intermediary entities between the DSO and the EVs or DERs owners. Thus, an entity called "aggregator" is considered in this paper that can use the communication and information system provided by the smart grid in order to aggregate the generation/consumption profile of a large number of EVs and renewable generators. Moreover, aggregators can also contribute to ancillary service provision. The concept of EV aggregator using bidirectional communications for direct control over the EV charging process is discussed in [14]. Since each aggregator represents a significant amount of the total load demand in the distribution energy resource scheduling program, it can more efficiently negotiate on behalf of home users and EVs owners with DSO. The current role of aggregators is that of paying a monthly fee to the contracted end-users (mainly industrial ones) in order to gain direct control of their appliances [15,16].

In order to ensure a well-coordinated utilization of DERs, such as distributed renewable generation, demand response and EVs, aggregators can cluster and manage a large numbers of DERs [2]. These may include generation units and stationary loads [17], as well as a large numbers of EVs [18]. Substantial revenue potentials have been found for Vehicle to Grid (V2G) services in different ancillary service markets in the U.S. [19] and in Europe [20].

1.3. Literature review

In [21], a method for tracking the load frequency control signals by groups of plug-in hybrid electric vehicles (PHEVs) is presented. Controllable thermal household appliances under a duty-cycle coordination scheme and combined heat and power units are also taken into account. The distribution of the control actions on the participating units is performed by an aggregator utilizing a predictive control strategy that allows the inclusion of units' and network's constraints. A coordinated charging control problem for EVs with V2G functionality at the residential transformer level is investigated in [22]. In the method, considering an aggregator optimizer and a power distributor, a two-stage charging control strategy is implemented in order to shift the transformer load, while achieving good charging performances for all EVs connected to the network. In the first stage, the optimal charging power for all EVs is carried out by the aggregator. During the second stage, a fuzzy logic control approach is developed in order to allocate the aggregated power from the first stage. Simulation results show that the real-time control strategy can significantly reduce the transformer peak load and fully charge all EVs at the end of the charging process.

In [23], a hierarchical market model for the smart grid is presented where competing aggregators act as intermediate agents between the utility operator and the end users. The utility operator goal is to minimize the smart grid operational costs and this is also achieved by offering rewards to aggregators. Aggregators compete to sell demand response services to the utility operator and provide compensation to end customers in order to modify their preferable consumption pattern. Customers try to optimize the trade-off between incomes received from the aggregator and discomfort due to their pattern modification. A demand response scheme in which an aggregator mediates between the consumer and the market is presented in [24]. The aggregator provides a signal to a smart home control unit that manages the consumer's appliances. The method allows the prediction and shaping of the total demand in order to match it with renewable generation and network constraints. The benefits of the method are a reduced use of peaking plant and a deferral of network reinforcements. An integrated distribution locational marginal pricing method is proposed in [25]. The method is designed to alleviate congestions induced by EV loads in future distribution systems where the DSO determines locational marginal prices by maximizing the social welfare taking into account demand price elasticity and EV aggregators as price takers in the local DSO market. In [26], EVs are introduced as reserve resources where the aggregator's self-scheduling problem for participating in the spinning reserve market is modeled using an agent-based model. The results evidence that the presence of EVs aggregators in spinning reserve market can improve power system reliability and reduce the total costs of the system. A self-regulating distribution system framework for a smart-grid with DER is presented in [27]. The fluctuations of power injection are moderated by bus-level heat pump control, while compliance with both distribution network load flow requirements and consumer comfort constraints are ensured. Applying bus-level DER control improves power and voltage ramping rates, reduces wind power injection variability, and also decreases the energy reserve requirements.

In [5,28], a multiobjective energy and reserve scheduling method has been presented in which the reserve requirement of a distribution system is provided by distributed generation units and responsive loads. In these previous works, EVs have not been considered and the centralized energy and reserve scheduling has been carried out by DSO. In [10], the effect of charge/discharge program of EVs on operational costs and emissions has been assessed. In [29], a method for optimal scheduling and energy management of EVs in a smart parking lot has been presented. In these works, renewable generation uncertainties, as well as the capability of EVs in providing reserve, have not been taken into account.

The integrated operation of EVs and renewable generations has been investigated in [30–32]. In [31], a decision tool for the coordination of EV battery charging has been developed in which a rolling horizon look-ahead stochastic dynamic programming algorithm has been implemented. The results showed that management of renewable generation intermittency, distribution network constraints, and EV charging requirements can result in cost savings, mitigate network congestions, and remove barriers to the widespread adoption of EVs and renewable generation.

In [32] a dynamic behavior analysis of an isolated electricity grid in presence of intermittent wind power generation has been assessed. The objective of the study is to quantify the amount of wind power that can be safely integrated in an isolated electricity grid where EVs are present and in condition of keeping the grid frequency always within the limits defined by the power quality standards. However, in [31,32] the authors do not focus on reserve scheduling provided by EVs within simultaneous energy and reserve short term operational planning.

As shown in [19], electric generators are in use 57% of the time while automobiles are used only 4% of the time. Also, the electric grid has no storage while the automobile fleet inherently must have storage to meet its transportation function. The authors in [19] proposed that V2G could stabilize large-scale wind power with 3% of the fleet dedicated to regulation for wind, plus 8–38% of the fleet providing operating reserves or storage for wind. So, EVs are expected to balance the fluctuation of renewable energy sources. For instance, integration of a plug-in hybrid electric vehicle smart parking lot with renewable energy resources has been proposed in [33]. In [34], the expansion of the electric power system in north-eastern Brazil aiming at enabling the most efficient dispatch of the variable output of the wind farms has been investigated. The study showed that in order to store the electricity surpluses of the wind farms, overnight charging of the EVs for half the year allows avoiding the costs of modifying the electricity system.

In [35], a mixed integer linear programming model for capacity expansion and integrated scheduling of PHEV charging and wind power has been used. The results showed that controlled charging reduces the cost of integrating PHEVs in half. The magnitude of these savings is 5–15% higher in a system with 20% wind penetration compared to a system with no wind power. The assessment of the contribution of V2G systems within small electric energy systems including renewable sources has been investigated in [36]. The uncertainty factors related to renewable power sources and EVs have been taken into account by a robust linear optimization problem and a stochastic programming framework has been used to consider wind power scenarios.

EVs can provide certain ancillary services to the system, such as regulation and spinning reserves. In [37], for example, EVs provide 10-min pinning reserve to the power grid with high penetration of wind power. In [38], the effective generation capacity of three different types of EVs has been used in order to evaluate revenue and costs associated to the electricity supply in three distinct markets, namely, peak power, spinning reserve and regulation.

The capability of EVs in providing reserve capacity has been also investigated in [39–41]. The result evidenced that EV drivers can benefit from cheap charging tariffs when supplying the manual reserve service [42]. EVs can also serve as a fast-response capacity reserve in case of an unbalanced power system resulting from generation outages as addressed in [43]. In addition, EVs can provide regulating power as an ancillary service in case of deviations from production or consumption plans [44]. In [45], a decision support algorithm and a market participation policy for an EV aggregator have been presented. Using dynamic programming, flexible bid scan be cleared as regulation service, as energy, or rejected by the market operator.

In [46] an EV aggregation agent, i.e. a commercial middleman between electricity market and EV owners, has been introduced. This agent can bid for purchasing electrical energy and selling secondary reserve where the participation of EVs in day-ahead spot and secondary reserve market has been considered. However, the scheduling of reserve provided by EVs for compensating renewable generation forecast errors has not been considered in the aforementioned studies.

1.4. Innovative contributions

To the best of our knowledge no energy and reserve scheduling method in distribution systems in which EVs provide the reserve requirement for compensating renewable generation fluctuations has been reported in the literature. Although the role of EVs in providing frequency reserve [32] and in mitigating renewable generation intermittency [31] has been studied in the previous literature, management of EVs' charging/discharging within simultaneous energy and reserve scheduling has not been assessed yet. Moreover, the role of the aggregator in supporting the integration of renewable generation units and EVs in the operation of distribution systems has not been considered in previous researches. On this basis, this paper proposes a new architecture and method for the day-ahead optimal management of EVs envisaging the participation of aggregators. The challenges related to the intermittent nature of renewable generation are faced by considering the participation of EVs in ancillary service provision. This paper examines the potential inclusion of EVs in reserve scheduling through an aggregator. Two different types of reserve services provided by EVs are proposed in order to support aggregators to efficiently integrate renewable energy resources.

The rest of the paper is organized as follows: Section 2 describes the system architecture; Section 3 presents the method formulation. The case-study results are presented in Sections 4 and 5 presents the most important conclusions.

2. Day-ahead and real-time operation framework

In this section, the day-ahead and real-time operation framework for scheduling of energy resources is described. Moreover, the types of reserve services to which EVs owners can potentially participate are described.

Energy and reserve scheduling problem of distribution systems including large number of EVs and other DERs, as well as technical constraints of the distribution network, is a large mixed-integer non-linear problem that takes a long computation time and that, in some cases, may be infeasible [47,48]. In the proposed method, in order to reduce the complexity of the problem, the power flow equations (the non-linear part of the problem) are separated from the scheduling problem with binary variables.

2.1. Proposed method framework

In order to monitor and control the EVs charge/discharge procedure, a two way communication infrastructure as well as smart meter systems are required. In this paper, the communication system proposed in [10] has been considered. Each EV owner, in order to participate in energy and reserve programs should submit the information including arrival time, designated departure time, State of Charge (SOC) at arrival, desired SOC at departure, battery size, and the information related to the type of reserve service that can be provided.

At the upper level, DSO provides monetary rewards to aggregators for their reserve services. At the middle level, aggregators provide reserve services to DSO by presenting a total available reserve capacity for each period, as well as the required reserve for the periods in which they have not enough reserve capacity for their scheduling. Each aggregator aims at minimizing its operation costs by optimizing the scheduling of the charge and discharge time of EVs.

At the lower level, EV owners negotiate with the aggregators to receive monetary compensation in order to participate in charge/discharge and reserve service programs. To this end, EV owners submit information, including arrival time, departure time, SOC at arrival, desired SOC at departure, to aggregators in order to participate in a charge/discharge program. Also, the EV owners determine the programs (i.e. only charge, charge/discharge, types of reserve) to which they are willing to participate. Then, aggregators are in charge of all charging issues and pay agreed tariffs to EV owners according to a given program.

Fig. 1 shows the sequence of events and data flow of the proposed method. After that aggregators have received the information of EVs and renewable generation forecast, in the first stage, they calculate the amount of reserve that they need, as well as the amount of available reserve capacity for each scheduling period. Then, aggregators send the information related to required and available reserve for their control area to DSO that checks the reserve requirements and offers of all aggregators and schedules the reserve requirement for each aggregator also according to the reserve offers of other aggregators. Then, DSO informs aggregators with regards to the quantity of their reserve offers that have been accepted. In the second stage, aggregators run the proposed energy

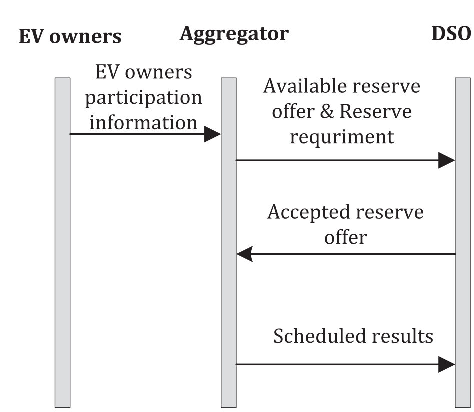

Fig. 1. Events sequence and data flow of the proposed method.

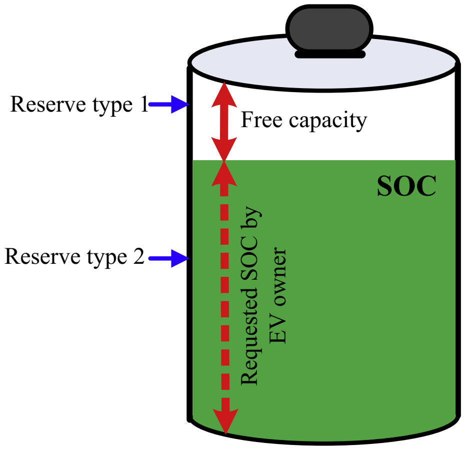

Fig. 2. Types of reserve.

and reserve scheduling in order to determine the amount of required power and charge/discharge status of each EV as well as which set of EVs are scheduled to provide reserve for each period. Finally, the results of optimal energy and reserve scheduling are sent to DSO that should calculate the total required power from the main grid and check the technical constraint.

2.2. Types of reserve

In this paper, two types of reserve that can be provided by EVs are proposed. These two types of reserve are simply shown in Fig. 2. EVs owners determine how much their batteries should be charged when they unplug their vehicle and start to trip. In most cases, EV owners do not need that their vehicles are fully charged. So, some capacity of the battery may remain unused. The first type of reserve refers to the energy stored in the free capacity of the battery. If this type of reserve is used, the desired SOC of an EV in departure time does not change.

The second type of reserve refers to the energy stored in the battery of EVs that is scheduled in order to achieve a final desired SOC. In this case an EV owner accepts to reduce or cancel the trip by receiving a compensation payment [47]. The aggregators will pay the EVs' owners for sharing their energy during system operation. In order to clearly explain this concept, the following example is given. Let assume an EV comprising a battery with a capacity of 16 kW h. The EV owner determines that for the next trip at hour 18:00 the EV should to be charged by 10 kW h. So, the aggregator must provide the state of charge of 10 kW h for this EV until hour 18:00. However, as 6 kW h of the battery capacity are available when the EV is connected to the grid, the aggregator can use this capacity as a reserve capacity. As regards with the second type of reserve, let's assume that the aggregator uses 7 kW h of the 10 kW h stored energy as a reserve at hour 14:00 and provides the EV with only 3 kW h of state of charge at hour 18:00. This means that the EV owner should cancel the trip or shorten the distance of the trip. So, if this type of reserve is used, the aggregator pays a compensation cost to the EV owner due to the trip cancellation or shortening.

EVs providing the first type of reserve receive two incomes: the first for sharing the battery capacity to keep reserve and the second one (named discharging tariff) if the reserve is used in the real-time. EVs providing the second type of reserve only receive an income, higher than the first one, if the desired SOC of batteries reduces.

3. Method formulation

In this section, the procedure and optimization method for energy and reserve scheduling in day-ahead and real-time horizon is described. The time horizon of the proposed scheduling method is shown in Fig. 3.

In order to better present the formulation, it is assumed that the variables include parentheses (e.g. $P_{EV}^{Dch}(v,t)$) and the parameters do not include parentheses (e.g. $C_{Dch}^{v,t}$).

3.1. Day-ahead energy and reserve scheduling

The day-ahead energy and reserve scheduling is carried out at both the aggregators and DSO levels. The formulation is described as follows.

3.1.1. Aggregator energy and reserve scheduling

The operation cost of energy and reserve scheduling in the area of each aggregator consists of the cost of the energy from the main grid, the cost of discharging energy and the cost of providing reserve. The scheduling is carried out for day-ahead horizon (next day). The efficient management of the available energy resources requires a multi-period optimization. The presented formulation of the proposed multi-period optimization considers all the costs at different time periods simultaneously (including periods from $t = 1$ to $t = T$) [48]. The cost objective function (OF) related to aggregator a that should be minimized is, therefore, defined as follows:

$$OF = \sum_{t=1}^{T}\left[P_S^a(t)\times\Omega_t + \sum_{v=1}^{N_{a,v}}\left(P_{EV}^{Dch}(v,t)\times C_{Dch}^{v,t} + R_{EV}(v,t)\times\psi_t\right)\right]\times\Delta t \tag{1}$$

The constraints of the aggregator's energy and reserve scheduling are given as follows:

- Load balance

$$P_S^a(t) + \sum_{w=1}^{W_a}P_{w,t} + \sum_{pv=1}^{pv_a}P_{pv,t} + \sum_{v=1}^{N_{a,v}}P_{EV}^{Dch}(v,t) = D_t + \sum_{v=1}^{N_{a,v}}P_{EV}^{Ch}(v,t) \quad \forall t\in\{1,\ldots,T\} \tag{2}$$

where $P_{w,t}$ and $P_{s,t}$ represent the forecasted wind and solar power in period t, respectively; w and pv are the indexes of, respectively and W_a, pv_a and $N_{a,v}$ represent the total number of wind turbines, PV systems and EVs in the area of aggregator a, respectively.

The output power of a wind turbine is calculated by using the wind turbine power curve parameters as described by Eq. (3) [49].

$$P_w = \begin{cases} 0, & 0\leqslant v_f\leqslant v_{ci} \\ P_{rated}\times\frac{(v_f-v_{ci})}{(v_r-v_{ci})}, & v_{ci}\leqslant v_f\leqslant v_r \\ P_{rated} & v_r\leqslant v_f\leqslant v_{co} \\ 0, & v_{co}\leqslant v_f \end{cases} \tag{3}$$

where v_f is the forecasted wind speed; P_{rated} is the rated power of the wind turbine; v_{ci}, v_r and v_{co} are the cut-in speed, rated speed and cut-off speed of the wind turbine, respectively.

The output of PV systems mainly depends on irradiance. Given the forecasted irradiance and irradiance-to-power conversion function, the PV output power can be obtained. The irradiance-to-power conversion function used in this paper is similar to that used in [50]:

$$P_{pv} = \eta^{pv}\times S^{pv}\times si \tag{4}$$

where P_{pv} represents the PV output power (kW) for irradiance si; η^{pv} and S^{pv} are the efficiency (%) and total area (m^2) of the PV system, respectively.

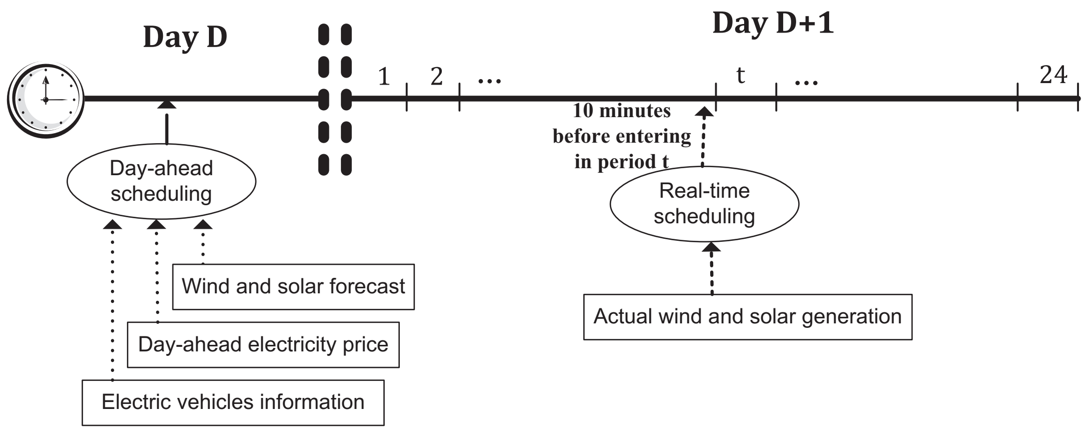

Fig. 3. Time horizon of the proposed energy and reserve scheduling method.

Here, the MV/LV distribution transformer rating constraint at each node is considered. The load of each distribution transformer ($P_{Trans}(n,t)$) in each node n and period t should be lower than the maximum rating of the transformer ($P_{Trans,max}$).

$$P_{Trans}(n,t) \leqslant P_{Trans,max} \quad \forall t \in \{1,\ldots,T\};\ \forall n \in \{1,\ldots,N\} \tag{5}$$

- Reserve requirement

The scheduled reserve prepared by an EV ($R_{EV}(v,t)$) in period t is defined as the amount of discharging power during time period t from the battery of EV v. The total reserve that the aggregator a requires in order to compensate the sudden variations of wind and solar power available in its control area in each period, ($Res_{a,t}$), is assessed on the basis of forecast errors. In this paper, wind and solar forecast errors are defined as a given percentage of their forecasted amount in each period. The amount of reserve that should be scheduled for aggregator a in period t is given as (6):

$$Res_{a,t} = \alpha_t \times P_{w,t} + \beta_t \times P_{s,t} \quad \forall t \in \{1,\ldots,T\} \tag{6}$$

where α_t and β_t are, respectively, the wind and solar power forecast errors in period t.

In each period, the aggregator should match the reserve balance equation as given by (7). It means that the total reserve provided by EVs available in the area of aggregator a plus the purchased reserve capacity from other aggregators ($PR_{a,t}$) minus the sold reserve capacity to other aggregators ($SR_{a,t}$) should be equal to the reserve requirement in period t. If the reserve capacity provided by all EVs available in the aggregator control area is more than its reserve requirement in a period, it can sold its extra reserve capacity, otherwise it must purchase some reserve capacity. So, in each period, the aggregator decides to purchase or sell the reserve capacity according to its available EVs reserve capacity.

$$\sum_{v=1}^{N_{a,v}} R_{EV}(v,t) + PR_{a,t} - SR_{a,t} = Res_{a,t} \quad \forall t \in \{1,\ldots,T\} \tag{7}$$

where $PR_{a,t}$ represents the reserve requirement of the aggregator in period t that should be purchased from other aggregators; $SR_{a,t}$ is the reserve capacity sold to other aggregators in period t which is determined by DSO.

- EVs constraints

In each period of scheduling, the EV charge and discharge are not simultaneous:

$$X(v,t)+Y(v,t) \leqslant 1\ \forall t \in \{1,\ldots,T\};\forall v \in \{1,\ldots,N_{a,v}\};\ X,Y \in \{0,1\} \tag{8}$$

where $X(v,t)$ and $Y(v,t)$ are, respectively, the binary variables of EV v related to power discharge and charge states in period t.

The battery energy balance for each vehicle should be considered. The state of charge variable ($E_s(v,t)$) represents the stored energy in the battery of vehicle v at the end of period t. The state of charge in period t is equal to the state of charge in period $t-1$ plus charged energy or minus discharged energy during period t when the EV is connected to the grid. For driving periods, the state of charge in period t is equal to the state of charge in period $t-1$ minus the energy consumption for travelling in period t ($E_{trip}^{v,t}$) [48,51].

$$E_s(v,t) = E_s(v,t-1) + \eta_v^C \times P_{EV}^{Ch}(v,t) \times \Delta t - E_{trip}^{v,t} - \frac{1}{\eta_v^D} \times \left(P_{EV}^{Dch}(v,t) + R_{EV}(v,t)\right) \times \Delta t \forall t \in \{1,\ldots,T\};\forall v \in \{1,\ldots,N_{a,v}\} \tag{9}$$

The dimension of $E_s(v,t)$ is kW h while the dimension of $P_{EV}^{Ch}(v,t)$ and $P_{EV}^{Dch}(v,t)$ is kW.

The discharge and charge power limits for each EV, considering the battery discharge rate, is given as follows:

$$P_{EV}^{Dch}(v,t) + R_{EV}(v,t) \leqslant P_{Dch,v}^{Max} \times X(v,t) \quad \forall t \in \{1,\ldots,T\};\ \forall v \in \{1,\ldots,N_{a,v}\} \tag{10}$$

$$P_{EV}^{Ch}(v,t) \leqslant P_{Ch,v}^{Max} \times Y(v,t) \quad \forall t \in \{1,\ldots,T\};\ \forall v \in \{1,\ldots,N_{a,v}\} \tag{11}$$

$X(v,t)$ and $Y(v,t)$ are binary decision variables indicating if the EV is in discharging or charging mode. According to Eq. (8), the possible values of (X,Y) for each EV in each period are (1,0), (0,1) and (0,0). When $X(v,t) = 1$ the EV is operating in discharge mode and can thus provide reserve, instead when $X(v,t) = 0$, it cannot operate in discharge mode and in this state, the reserve cannot be extracted from the battery. If $Y(v,t) = 1$ the EV is operating in charging mode and it is assumed here that if the EV is in charging mode, it cannot provide reserve. Consequently, the binary variables (X,Y) directly effect on charge and discharge variables which appear in the objective function. Now, according to Eqs. (10) and (11), if $X(v,t) = 0$ then $P_{EV}^{Dch} + R_{EV} \leq 0$; as P_{EV}^{Dch} and R_{EV} are positive variables, $P_{EV}^{Dch} = 0$. Also, if $Y(v,t) = 0$ then $P_{EV}^{Ch} \leq 0$; as P_{EV}^{Ch} is a positive variable ($P_{EV}^{Ch} \geq 0$), so $P_{EV}^{Ch} = 0$.

To protect the battery from early aging and performance degradation, the battery SOC should be bounded between certain levels. Depletion of EV battery up to a certain minimum level (Ψ_v^{min}) and charging up to a maximum level (Ψ_v^{max}) are ensured by Eqs. (12) and (13) to prevent loss of battery life [52].

$$E_s(v,t) \leqslant \Psi_v^{max} \quad \forall t \in \{1,\ldots,T\};\ \forall v \in \{1,\ldots,N_{a,v}\} \tag{12}$$

$$E_s(v,t) \geqslant \Psi_v^{min} \quad \forall t \in \{1,\ldots,T\};\ \forall v \in \{1,\ldots,N_{a,v}\} \tag{13}$$

where Ψ_v^{min} and Ψ_v^{max} are defined based on the battery capacity limit for each EV and are calculated as follows:

$$\Psi_v^{max} = \phi_v^{max} \times E_{BatCap,v} \quad \forall v \in \{1,\ldots,N_{a,v}\} \tag{14}$$

$$\Psi_v^{min} = \phi_v^{min} \times E_{BatCap,v} \quad \forall v \in \{1,\ldots,N_{a,v}\} \tag{15}$$

where $E_{BatCap,v}$ represents the capacity of the battery of EV; ϕ_v^{max} and ϕ_v^{min} are, respectively, the maximum and minimum percentage of battery capacity considering battery life.

The vehicle battery discharge and charge limits considering, respectively, the battery state of charge, the battery capacity and the energy stored in the previous period are given as follows [48]:

$$\frac{1}{\eta_v^D} \times \left[P_{EV}^{Dch}(v,t) + R_{EV}(v,t)\right] \times \Delta t \leqslant E_s(v,t-1) \quad \forall t \in \{1,\ldots,T\}; \; \forall v \in \{1,\ldots,N_{a,v}\} \tag{16}$$

$$\eta_v^C \times P_{EV}^{Ch}(v,t) \times \Delta t \leqslant \Psi_v^{max} - E_s(v,t-1) \quad \forall t \in \{1,\ldots,T\};\ \forall v \in \{1,\ldots,N_{a,v}\} \tag{17}$$

The stored energy ($E_{trip,q}^{v,t}$) in EVs' battery required to travel the specific distance in each trip is given as follows [10]:

$$E_s\left(v,t_{last}^q\right) \geqslant E_{trip,q}^{v,t} \quad \forall t \in \{1,\ldots,T\};\ \forall v \in \{1,\ldots,N_{a,v}\} \tag{18}$$

where t_{last}^q represents the last period when the EV connected to the grid before start the qth trip in period t_{last}^q+1; $E_{trip,q}^{v,t}$ is the required energy of EV v for trip q in period .

3.1.2. DSO network management

In the first stage, after receiving the available reserve capacity and reserve requirement from all aggregators for all scheduling periods, DSO should match the data and determine how much reserve offers should be accepted for each aggregator. In each period, each aggregator, according to its reserve requirement for compensating renewable generation variation and its maximum available reserve capacity provided by EVs, determines how much reserve is required to purchase ($PR_{a,t}$) or to sell ($R_{a,t}^{max}$). The accepted reserve capacity ($SR(a,t)$) of aggregator a in period t should be lower than the maximum reserve capacity ($R_{a,t}^{max}$) offered by the aggregator. It should be mentioned that in this stage $SR(a,t)$ is a decision variable. After determining the optimal values for $SR(a,t)$, these values are used as a parameters (i.e. $SR_{a,t}$) in the stage where aggregators carry out the day-ahead energy and reserve scheduling.

DSO carries out the reserve scheduling based on reserve cost minimization. It means that DSO prefers to purchase reserve capacity from aggregators that offer reserve at lower prices. The reserve cost objective function (F_R) used by DSO is given as follows:

$$Minimize\ F_R = \sum_{t=1}^{T}\left(\sum_{a=1}^{A} SR(a,t) \times O_{a,t}\right) \times \Delta t \tag{19}$$

where $O_{a,t}$ represents the offer price for providing reserve in period t submitted by aggregator a.

The objective function should be minimized subject to the following constraints:

$$SR(a,t) \leq R_{a,t}^{max} \quad \forall t \in \{1,\ldots,T\} \tag{20}$$

$$PR_{\bar{a},t} = \sum_{a \neq \bar{a}} SR(a,t) \quad \forall \bar{a} \in \{1,\ldots,A\};\ \forall t \in \{1,\ldots,24\} \tag{21}$$

where $PR_{\bar{a},t}$ represents the reserve requirement of aggregator $\bar{a}$ in period t that should be provided by the reserve capacity made available by other aggregators ($a \neq \bar{a}$). Bar is used to show a specific aggregator among other aggregators.

It should be noted that the available reserve capacity provided by EVs may be lower than the total reserve requirement of the distribution network in a specific period. In this case, the operator can procure the reserve requirement from the electricity market.

The DSO should also check the technical constraints of the distribution network in order to ensure that the whole distribution system remains in safe operational bounds. By receiving the result of scheduling from all aggregators, DSO can calculate the power flow in the whole network. The power flow equations are given as follows:

$$P_{inj}(n,t) = \sum_{m=1}^{N} |V(n,t)||V(m,t)||Y_{n,m}| \cos(\delta(m,t) - \delta(n,t) + \theta_{n,m}) \quad \forall n,t \tag{22}$$

$$Q_{inj}(n,t) = -\sum_{m=1}^{N} |V(n,t)||V(m,t)||Y_{n,m}| \sin(\delta(m,t) - \delta(n,t) + \theta_{n,m}) \quad \forall n,t \tag{23}$$

where N is the total number of buses; n and m are index for buses; $|V(n,t)|$ is the voltage amplitude at node n; $\delta(n,t)$ is the voltage angle at node n; $|Y_{n,m}|$ is an element (n,m) of the admittance matrix; $\theta_{n,m}$ is the angle of $Y_{n,m}$; $P_{inj}(n,t)$ and $Q_{inj}(n,t)$ are the net active and reactive power injected into node n, respectively.

The other network operation constraints are as follows:

$$|S(n,m,t)| \leqslant S_{n,m}^{max} \quad \forall t \in \{1,\ldots,24\};\ \forall n,m \in \{1,\ldots,N\} \tag{24}$$

$$V_n^{min} \leqslant V(n,t) \leqslant V_n^{max} \quad \forall t \in \{1,\ldots,24\};\ \forall n \in \{1,\ldots,N\} \tag{25}$$

$$P_{grid}(t) \leq P_{sub}^{max} \quad \forall t \in \{1,\ldots,24\} \tag{26}$$

where $|S(n,m,t)|$ is the apparent power flow from node n to m; $S_{n,m}^{max}$ is the capacity of the line/cable between node n and node m; V_n^{max} and V_n^{min} are the maximum and minimum voltage magnitude at node n, respectively; $P_{grid}(t)$ is the total power imported from the transmission network through the main substation in period t; P_{sub}^{max} is the maximum power drawn from the main substation.

3.2. Real-time operation

In real-time, there are three different cases according to renewable generation actual status:

(1) the unexpected loss of renewable generation is lower or equal to the scheduled reserve;
(2) the renewable generation is more than the predicted value; and
(3) the unexpected loss of renewable generation is more than the amount of scheduled reserve.

In case 1, the aggregators use the scheduled reserve in order to compensate the loss of renewable generation. So, the balance between generation and consumption can easily be settled. In case 2, when the amount of actual renewable generation is more than its predicted value, the aggregators use the extra energy for charging some EVs having discharged batteries. The extra energy stored in EVs can be used in the following hours as an extra reserve capacity.

Case 3 is known as the worst one since the loss of renewable generation is more than the scheduled reserve. It means that the actual forecast error is more than the one considered in the day-ahead scheduling. In this case, firstly, by comparing the loss of renewable and the scheduled reserve, aggregators calculate the power required to keep the generation and consumption balance.

Then aggregators use the second type of reserve of EVs in order to keep the balance between generation and consumption.

4. Simulation

The proposed method was applied to a modified version of the 84-bus 11.4-kV radial distribution system given in [53] and illustrated in Fig 4. The eleven feeders are supplied by two 30 MVA 33/11.4 kV transformer (in compliance with the U.K. security of supply regulations [54]). The maximum load levels for each bus are given in [53]. Voltage limits are taken to be ±6% of nominal. Table 1 provides the hourly electricity price of the open electricity market according to [55]. The forecasted load profile of the test system for a 24-h period is shown in Fig. 5. In the test distribution system, four aggregators represented by A1, A2, A3 and A4 in Fig. 4 have been considered.

The driving patterns were based on a statistical survey in a real town carried out by the authors. The information consists of trip duration of each type of customer, start and end time of their trip and average distance travel. The summaries of the driving pattern information are given in Table 2.

It is assumed that the wind speed and solar irradiance forecasts for areas of aggregators 1 and 2 are different from the ones for areas of aggregators 3 and 4. The real hourly wind speeds information have been taken from Willy Online Pty Ltd whether forecast website and shown in Fig. 6 [56]. All wind turbines installed in the test system are of the same type and of 1 MW, with cut-in speed of 4 m/s, nominal speed of 14 m/s, and cut-out speed of 25 m/s. Six 100 kW PV systems are installed in the test system: each of them is composed of 10×10 kW solar PV panels with $\eta = 18.6\%$ and $S^{PV} = 10\ m^2$ [57]. The average hourly solar irradiance is shown in Fig. 7 [58]. Wind turbines and PV systems are assumed to have fixed power factors equal to 1.

A 24 kW h battery capacity for EVs is selected according to Nissan Leaf [59]. Battery chargers have some losses and therefore the energy requirement from the grid is actually greater than the stated battery capacity. Typical battery charge and discharge efficiency are assumed (i.e. 90% and 95%, respectively [60]). In order to optimize EV battery life, depletion of EV battery up to 85% of the rated battery capacity is assumed.

Table 1
Hourly electricity price of open market.

t	1	2	3	4	5	6
\$/kW h	0.033	0.027	0.020	0.017	0.017	0.029
t	7	8	9	10	11	12
\$/kW h	0.033	0.054	0.215	0.572	0.572	0.572
t	13	14	15	16	17	18
\$/kW h	0.215	0.572	0.286	0.279	0.086	0.059
t	19	20	21	22	23	24
\$/kW h	0.050	0.061	0.181	0.077	0.043	0.037

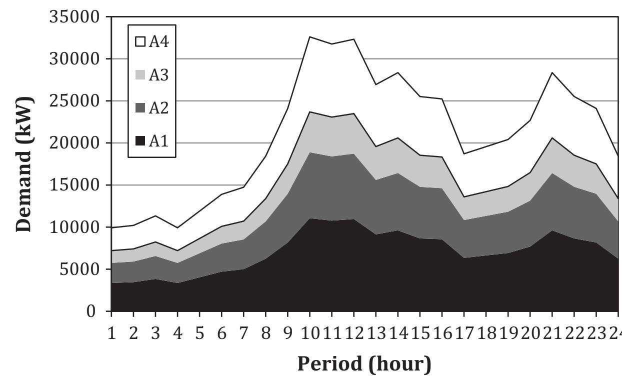

Fig. 5. Hourly forecasted load demand of the test system.

Table 2
EVs information and availability.

Aggregator	Number of EVs	Available time	Desired SOC (%)
A1	120	1:00–7:00 & 17:00–24:00	80
A2	180	8:00–17:00	100
A3	150	1:00–7:00 & 16:00–24:00	75
A4	200	1:00–18:00	90

A standard single-phase 230 V, 16 A socket (Italian standard) is assumed as charging point in home or work place. For this analysis, a fixed charging power of 4 kW is selected because this may be

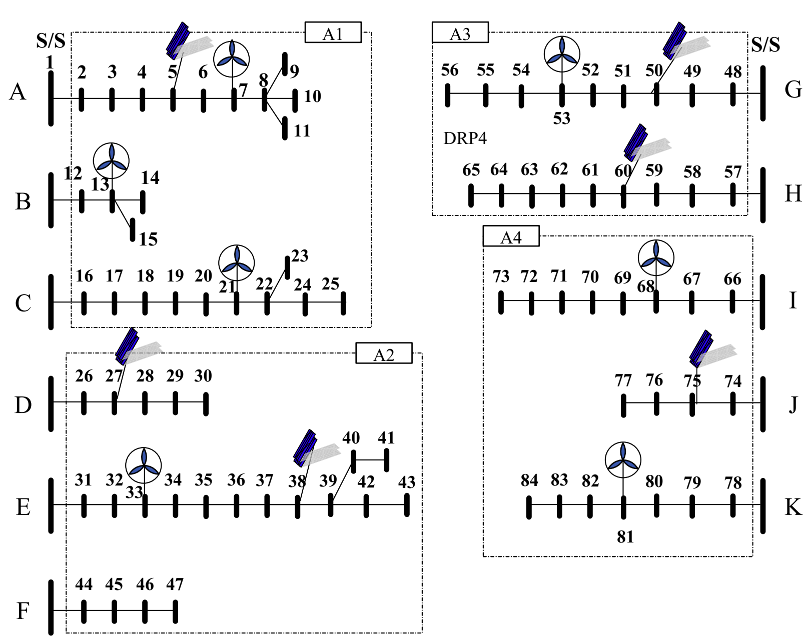

Fig. 4. 84-Bus distribution test system.

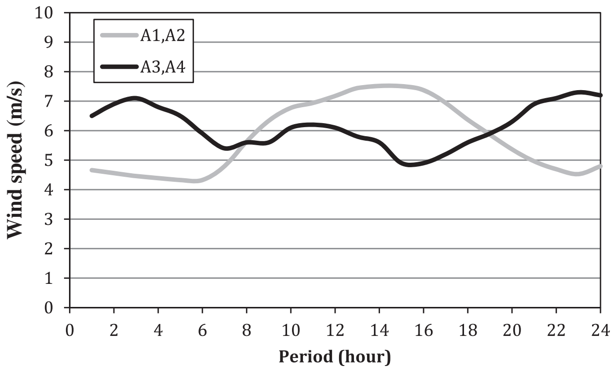

Fig. 6. Hourly wind speed forecast.

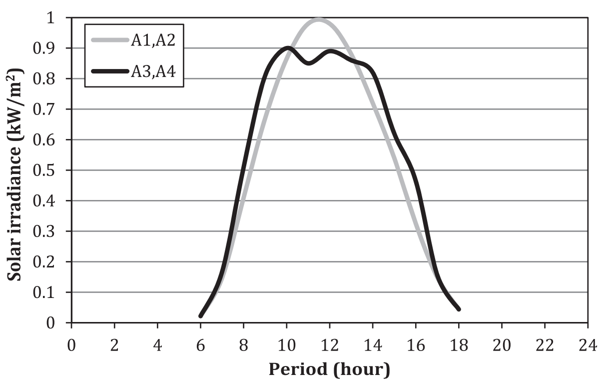

Fig. 7. Hourly solar irradiance forecast.

commonly available in most single-phase residential households having a 6 kW contract (e.g. in Italy), without having to reinforce wiring [61,62].

The above formulation has been implemented in GAMS using Mixed-Integer Linear Programming (MILP) solver Cplex [63] on a PC with 2.27 GHz CPU and 4 GB of RAM.

In the first stage, after that the aggregators received the available time and duration of EVs and renewable generation forecasts for the day-ahead, they calculate the amount of reserve in order to compensate the renewable power generation variability. Then, the time period and the amount of required reserve for themselves and the available reserve capacity for other aggregators are submitted to DSO. Table 3 shows the amount of available and required reserve capacity submitted by each aggregator for each period of the next day. DSO schedules the reserve according to cost minimization objective in order to match the reserve offers and requirements. Then, DSO communicates to each aggregator the accepted reserve capacity.

According to Eqs. (19)–(21), the DSO's reserve scheduling results are given in Fig. 8 and explained as follows. The offered reserve of aggregator 1 has been accepted in hours 18–24 in order to provide the reserve requirement of aggregators 2 and 4 while the offered reserve of aggregator 2 has been accepted in hours 8–16 in order to provide the reserve requirement of aggregator 1. Moreover, the offered reserve of aggregator 3 has been accepted in hours 1–7 in order to provide the reserve requirement of aggregator 2 and the offered reserve of aggregator 4 has been accepted in hours 8–15 in order to provide the reserve requirement of aggregator 3.

When aggregators receive the accepted amount of their reserve offers by DSO, they run the proposed energy and reserve scheduling for the day-ahead. The required power form the main grid, as well as the load demand at each bus, are communicated to DSO. The charge/discharge program of EVs for each aggregator is shown in Fig. 9. According to the cost minimization objective, simulation results evidence that EVs charging is carried out during the hours when the electricity prices are low. On the other hand, EVs discharging is carried out during the hours when the electricity prices are relatively high.

The scheduled reserve of the aggregators is illustrated in Fig. 10. As shown, during hours 12–17 the amount of scheduled reserve increased due to high wind and solar power generation.

The required power of the aggregators for each period of the day-ahead scheduling has been shown in Fig. 11. The solid and dash curves show, respectively, the load demand of the whole

Table 3
Required and available reserve offer of aggregators (kW).

Period	Aggregator 1		Aggregator 2		Aggregator 3		Aggregator 4	
	Requirement	Available	Requirement	Available	Requirement	Available	Requirement	Available
1	–	461	4	–	–	515	–	790
2	–	459	5	–	–	514	–	789
3	–	461	5	–	–	515	–	790
4	–	464	4	–	–	516	–	792
5	–	464	4	–	–	516	–	792
6	–	461	5	–	–	515	–	790
7	–	435	12	–	–	507	–	777
8	100	–	–	771	28	–	–	749
9	153	–	–	754	45	–	–	721
10	178	–	–	753	46	–	–	710
11	189	–	–	750	49	–	–	704
12	217	–	–	742	57	–	–	690
13	249	–	–	735	64	–	–	674
14	254	–	–	734	65	–	–	672
15	268	–	–	731	68	–	–	665
16	258	–	–	734	–	454	–	671
17	–	244	–	740	–	460	–	682
18	–	281	50	–	–	470	–	700
19	–	315	41	–	–	478	82	–
20	–	354	31	–	–	488	62	–
21	–	383	24	–	–	495	48	–
22	–	408	18	–	–	501	36	–
23	–	423	14	–	–	505	28	–
24	–	388	23	–	–	496	46	–

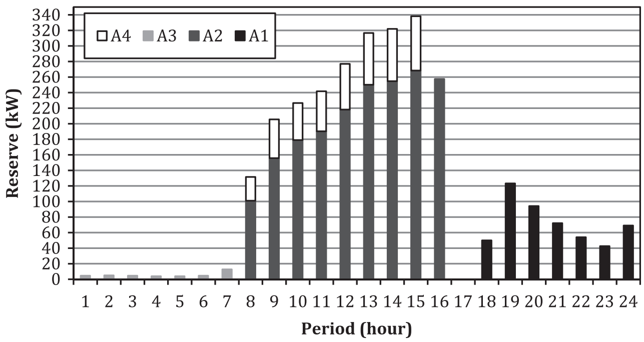

Fig. 8. Reserve capacity of aggregators accepted by DSO.

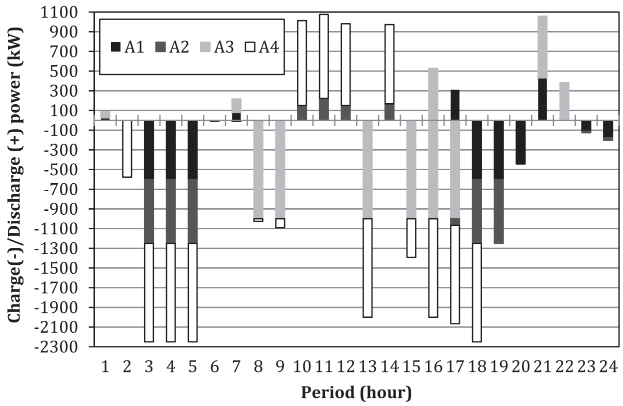

Fig. 9. Scheduled charge/discharge power.

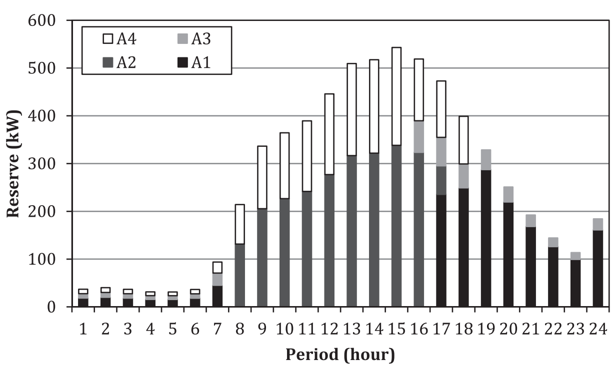

Fig. 10. Scheduled reserve of aggregators.

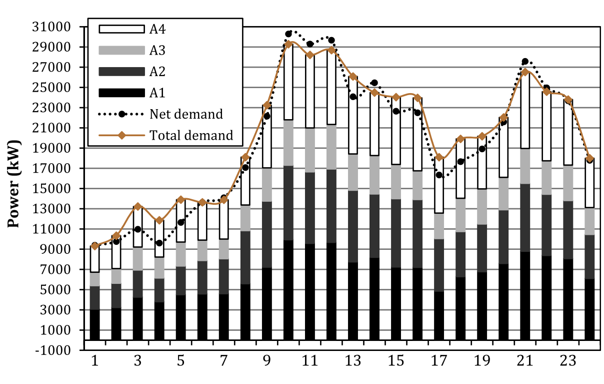

Fig. 11. Power required by aggregators.

distribution system with and without considering EVs electricity demand. The net load demand is defined as the total consumers' electricity demand minus available renewable generation in each period, without considering demand of EVs, while the total load demand is defined as the sum of the net load demand and the EVs' demand. As shown in Fig. 11, the total electricity demand pattern during the scheduling horizon has not been severely increased due to EVs demand. In other words, by implementing the proposed charge/discharge method, the peak load demand of the system did not increase due to EVs. Instead, EVs played an important role in smoothing the load demand profile.

4.1. Real-time operation

In order to evaluate the real-time operation, hour 12:00 has been considered. The total forecasted wind and solar power in this hour are 2539 kW and 109 kW with forecast errors of 17% and 13%, respectively. Also, the scheduled reserve for this period in day-ahead scheduling is 445 kW. In order to evaluate the real-time operational scheduling, three different cases are considered during period 12:00. The actual wind and solar powers are respectively 2312 kW and 100 kW in case 1, 2721 kW and 115 kW in case 2 and 1954 kW and 85 kW in case 3.

In case 1, a decrease of 236 kW of renewable power generation occurs if compared to the scheduled generation and consumption in this period. As the scheduled reserve is enough for compensating the renewable power reduction, the aggregators send an advice to those EVs selected to provide reserve for this period. So, using the energy stored in the EVs, the balance between generation and consumption is settled.

In case 2, there are 188 kW of extra power generation, if compared to the scheduled generation and consumption in this period. In this case, the aggregators find a set of EVs that can store this extra energy that can be used in the following hours.

In case 3, a decrease of 609 kW of renewable power generation occurs. As a scheduled reserve of 455 kW has been considered, additional 154 kW are required to keep the generation and consumption balance. In this case, the aggregators should use the second type of reserve provided by EVs. To this end, a set of EVs, that have enough stored energy in their batteries, has been selected to operate in discharge mode. Also, an information signal is sent to EVs owners selected to provide a second level reserve.

In view of an optimal solution, dividing a big problem into small sub-problems may result in locally optimal solutions. To compensate this loss, an additional conventional (centralized) optimization can be applied at the end, with having the previously optimized solution as the initial solution for the centralized optimization.

In order to prove that the proposed model is able to find the global optimum solution, the case study is also solved using the centralized energy and reserve scheduling method carried out by DSO without the participation of aggregators. The centralized energy and reserve scheduling framework presented in [10,64] has been utilized in this case. The total operation costs of energy and reserve scheduling in the two cases have been reported in Table 4. In the proposed method, the sum of the operation costs of all aggregators has been considered as total operation cost. As shown, the total operation costs are equal. However, as the

Table 4
Comparison with a centralized scheduling.

	Total operation cost ($)	Computation time (s)
Centralized scheduling	104,508	1256
Proposed method	104,508	6

centralized method is a mixed-integer non-linear programming problem, it takes much more computation time.

5. Conclusion

In this paper, an integrated scheduling of distribution energy resources, including electric vehicles and renewable generation, has been presented. The main contribution of this work is that it provides a better understanding of the role of EVs in providing reserve capacity, especially for compensating the intermittent nature of renewable generation in the future smart grids. We focused on a hierarchical distribution operation structure and investigated the interactions between EVs owners, DSO and several aggregator entities that act as intermediaries. The results evidenced that the distribution load profile can be flattened by scheduling the charge/discharge time of EVs. Moreover, renewable generation fluctuations could be easily managed by the reserve capacity provided by EVs.

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