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Network-constrained bidding optimization strategy for aggregators of prosumers

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ABSTRACT

The large-scale deployment of smart home technologies will unlock the flexibility of prosumers, which in turn will be transformed into electricity market services by aggregators. This paper proposes a new network-constrained bidding optimization strategy to coordinate the participation of aggregators of prosumers in the day-ahead energy and secondary reserve markets. This bidding optimization strategy consists of a decentralized approach based on the alternating direction method of multipliers, where aggregators negotiate with the distribution system operator to obtain network-constrained energy and secondary reserve bids. For a case study of 2 aggregators and 1 distribution system operator, the results show that the network-constrained bidding strategy computes cost-effective and network-feasible energy and secondary reserve bids, as opposed to a network-free bidding strategy. In addition, the network-constrained bidding strategy preserves the independent roles of aggregators and the distribution system operator, and the data privacy of all agents.

1. Introduction

1.1. Context and motivation

The digitization of the residential sector will introduce internet-of-thing technologies, which will provide unprecedented information and control [1]. This will provide the technical means to unlock the real potential of flexible appliances, such as electric vehicles (EV), photovoltaic systems (PV), and air conditioners. Aggregators will play a central role in transforming the automation of flexible appliances into electricity services with high economic value. Aggregators will optimize and control flexible appliances to provide multiple services in the electricity markets. However, the challenge is big since it will be necessary to develop computational tools to define electricity market services that do not violate distribution network constraints and maintain the independent roles of aggregators and distribution system operators (DSO).

1.2. Related work

Aggregators are energy service providers that gather prosumers with distributed energy resources to transform their generation and load flexibilities into products to be traded in electricity markets [2]. An aggregator may participate in single or multiple day-ahead electricity market sessions, such as energy and/or reserves, depending on its business model. The aggregator relies on optimization tools to define market products under the form of bids. The literature on this topic can be divided into two groups.

The first group covers bidding optimization models that do not constrain the formation of energy and reserve bids by the distribution network. These bidding models are purely economic and are mainly focused on optimizing the aggregator's portfolio to maximize its profit in the electricity market. Typically, these bidding models only optimize one type of flexible resource, such as EV or thermostatically controlled loads. For instance, Bessa and Matos [3–6] proposed a set of bidding optimization models to support the participation of EV aggregators in multiple market sessions, such as

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Nomenclature

Abbreviations

AC	alternating current
ADMM	alternating direction method of multipliers
DSO	distribution system operator(s)
EV	electric vehicle(s)
HV	high voltage
LV	low voltage
MIBEL	iberian market
MV	medium voltage
OPF	optimal power flow
PV	photovoltaic system(s)
TSO	transmission system operator(s)

Indices and sets

$a \in A$	aggregators
$s \in \{E, U, D\}$	scenarios (E – energy, U – upward band activation, D – downward band activation)
(k)	ADMM iteration
$m, n, i \in N$	buses
N_a	buses managed by aggregator a
$(m, n) \in L$	collection of lines from bus m to bus n
$j \in J$	prosumers
$J_n \subset J$	prosumers per bus n
$t, y \in T$	time intervals (h)
$T^{EV} \subset T$	availability of the electric vehicle $[t^{AR}, \ldots, t^{DE}]$
t^{AR}	arrival time of the electric vehicle
t^{DE}	departure time of the electric vehicle

Parameters

$\overline{I}$	maximum current (p.u.)
Pr^{IL}	inflexible load profile (kW)
Pr^{PV}	PV generation profile (kW)
$\overline{P^{EV}}$	maximum power of the electric vehicle (kW)
Q^{I}	reactive power injection (p.u.)
r	resistance (p.u.)
R^{P}	primal residual
R^{D}	dual residual
S^{B}	base power (kVA)
$\overline{SOC}$	maximum state-of-charge (kWh)
$\underline{SOC}$	minimum state-of-charge (kWh)
SOC^{DE}	state-of-charge at departure time (kWh)
SOC^{AR}	state-of-charge at arrival time (kWh)
$\overline{V}$	maximum voltage (p.u.)
$\underline{V}$	minimum voltage (p.u.)
x	reactance (p.u.)
λ^{E}	energy price (€/kWh)
λ^{B}	secondary reserve band price (€/kW)
λ^{D}	downward tertiary reserve price (€/kWh)
λ^{U}	upward tertiary reserve price (€/kWh)
$\varnothing^{U}$	ratio of utilization to availability for upward band
$\varnothing^{D}$	ratio of utilization to availability for downward band
Δt	length of the time interval t in hours $(1\ h)$
ρ	penalty of the augmented Lagrangian (€/kW^2)
η	charging and discharging efficiency
τ	regulates the flexibility of the EV to provide band $(\tau = 2)$

Continuous variables

D^{A}	downward band offered by the aggregator (kW)
D^{EV}	downward band provided by EV (kW)
D^{PV}	downward band provided by PV (kW)
E^{A}	energy bids (kWh)
I	current (p.u.)
P	power variables of the aggregator (kW)
$\widehat{P}$	power variables of the OPF (kW)
P^{E}	energy delivery scenario (kW)
P^{U}	upward band activation scenario (kW)
P^{D}	downward band activation scenario (kW)
$\widehat{P}^{E}$	duplicate variable of P^{E} (kW)
$\widehat{P}^{U}$	duplicate variable of P^{U} (kW)
$\widehat{P}^{D}$	duplicate variable of P^{D} (kW)
P^{+}	charging power of the electric vehicle (kW)
P^{-}	discharging power of the electric vehicle (kW)
P^{PV}	PV generation (kW)
P^{CU}	Generation curtailment (kW)
P^{F}	active power flow (p.u.)
Q^{F}	reactive power flow (p.u.)
SOC	state-of-charge (kWh)
U^{A}	upward band offered by the aggregator (kW)
U^{EV}	upward band provided by EV (kW)
U^{PV}	upward band provided by PV (kW)
V	voltage (p.u.)
X	internal variables of the aggregator's problem
Y	internal variables of the optimal power flow
π	dual variables of the augmented Lagrangian (€/kW)

Functions

f	objective function of the aggregator
g	optimal power flow constraints
h	aggregator constraints
$\mathscr{L}$	augmented Lagrangian

energy [3,4], secondary[1] [5] and tertiary[2] reserves [6]. The bidding optimization models are deterministic, i.e. they model the EV information through point forecasts. To deal with the uncertainty of the EV mobility patterns, Vagropoulos and Bakirtzis [7] proposed a scenario-based stochastic optimization model. Later, Baringo and Amaro [8] considered confidence bounds to model the uncertainty of the EV, instead of using scenarios.

The works [9,10] addressed the participation of aggregators of thermostatically controlled loads in the electricity markets. Chen et al. [9] proposed a stochastic optimization model to define demand bids for the day-ahead energy market. The authors modeled weather and load uncertainties through a set of scenarios. Good et al. [10] also presented a stochastic optimization model to define demand bids. However, the authors included more uncertainty parameters in the optimization problem, such as household

[1] Secondary reserve is known as regulation reserve in U.S. and Australian electricity markets [38,39].

[2] Tertiary reserve is known as non-spinning or replacement reserve in U.S. electricity markets [39].

occupancy and hot water consumption. Later, Iria et al. [11–13] extended the portfolio of the aggregator to multiple types of flexible resources, such as shiftable loads, thermostatically controlled loads, PV, and EV. The authors proposed a set of two-stage stochastic optimization models to support the participation of an aggregator of prosumers in the day-ahead energy [13], secondary [12], and tertiary [11] reserve markets. Ottesen et al. [14,15] studied the participation of aggregators of industrial customers in the energy [14] and tertiary [15] reserve markets. The authors proposed a set of bidding and scheduling models to define energy and tertiary reserve bids.

In short, works [3–15] proposed optimization models to define bids for multiple market sessions through the optimization of multiple types of flexible resources. These works do not consider distribution network constraints. They assume that the DSO must be capable of solving the network problems that may arise from the bidding strategies using technical and market procedures [16]. This premise may increase the cost of operating the electricity system since the DSO may need to acquire flexibility services to solve voltage and congestion problems generated by the bidding strategies.

The second group of works addresses the network problem by proposing a set of network-constrained bidding optimization models. These bidding models define energy and reserve bids constrained by the technical limits of the distribution networks. For instance, the works [17–19] proposed stochastic models to compute energy bids through the optimization of electrical and/or thermal energy storage units. These bidding models use linear equations to constrain network power injections. Nonetheless, these constraints do not ensure the network feasibility of the aggregators' bids, because they do not provide any observability over the line power flows and voltages. On the other hand, works [20–22] developed network-constrained optimization models to support EV aggregators in the definition of energy and secondary reserve bids. These bidding models use linear optimal power flow (OPF) equations to constrain the bids. Linear OPF models present disadvantages, such as generating infeasible physical solutions in scenarios of low voltages [23,24] and reducing the searching space of the bidding optimization models, due to inner approximations [25,26]. Another drawback of [17–22] is to assume that the aggregator has access to the distribution network data. In practice, only the DSO has access to the network data. Aggregators and DSO have independent roles and responsibilities and their roles should remain independent.

1.3. Contributions

This paper proposes a new network-constrained bidding optimization strategy to support the participation of aggregators of prosumers in multiple electricity markets. The bidding optimization strategy maximizes the aggregators' profits in the day-ahead energy and secondary reserve markets while maintaining the security and increasing the utilization of the distribution networks.

The network-constrained bidding optimization strategy consists of a decentralized approach based on the alternating direction method of multipliers (ADMM) [27], where aggregators negotiate with the DSO to obtain solutions that satisfy foreseen network operating scenarios. The ADMM breaks down the network-constrained bidding optimization problem into aggregator and DSO subproblems and solves them iteratively until convergence is reached. Aggregators define day-ahead energy and reserve bids through bidding optimization models. The DSO evaluates the network feasibility of the energy and reserve offers through a series of AC OPF. When ADMM converges, aggregators submit network-constrained energy and reserve bids to the day-ahead markets.

The network-constrained bidding optimization strategy presents innovative features that go beyond the current state-of-the-art approaches to support the participation of aggregators of prosumers in electricity markets. The research contributions of the network-constrained bidding strategy are highlighted below:

1. it supports aggregators of prosumers in the definition of network-constrained energy and reserve bids, contrarily to day-ahead bidding optimization approaches focused on defining network-free energy and reserve bids [3–15]. It ensures that the energy and reserve bids are feasible from the DSO perspective;
2. it breaks down the network-constrained bidding optimization problem into aggregator and DSO subproblems, ensuring their independent roles. Each agent solves its optimization problem, in opposition to approaches where aggregators solve the joint network and bidding optimization problems [17–22]. These previous works do not ensure the independent roles of each agent since the aggregators have access to distribution network data and conditions;
3. it exploits ADMM to decompose a large-scale optimization problem into simpler problems, overcoming the computational complexity of solving large-scale AC OPF. The network-constrained optimization problem is broken down into a set of quadratic optimization problems (aggregators' problems) and non-convex optimization problems (DSO problems), making them small enough to be computationally tractable on their own.

1.4. Paper organization

The remaining paper is organized as follows: section 2 describes the frameworks of the aggregators and electricity markets; section 3 describes the network-constrained bidding optimization strategy; sections 4 and 5 presents the aggregator and DSO optimization subproblems; the case study and results are presented in sections 6 and 7; section 8 presents the conclusions.

2. Participation of aggregators in the day-ahead energy and secondary reserve markets

The participation of aggregators in the day-ahead energy and secondary reserve markets follows the rules of the Iberian market (MIBEL) [12]. The MIBEL covers the Portuguese and Spanish control areas. European electricity markets, such as MIBEL, EPEX, and Nord Pool present sequential trading structures, where energy is traded first, and reserves are negotiated afterward. Nonetheless, the proposed approach can be applied to any sequential or joint market (e.g., U.S. or Australia) since the energy and reserve bids are co-optimized.

2.1. Interactions between the electricity market and aggregators

Fig. 1 describes the participation of the aggregators in the day-ahead energy and secondary reserve markets. Before the 12th hour, aggregators submit their energy bids to the day-ahead energy market of MIBEL. The energy bids of MIBEL and other European markets are submitted to the EUPHEMIA platform [28] (European dispatch tool). The EUPHEMIA clears the prices (€/MWh) and quantities (MWh), such that the social welfare is maximal and the power flows between the bidding areas are not exceeded. The clearing prices are published at hour 13. Afterward, the physical bilateral contracts are added to the clearing offers of the day-ahead energy market. Before hour 16, the transmission system operator (TSO) runs congestion management to produce viable energy

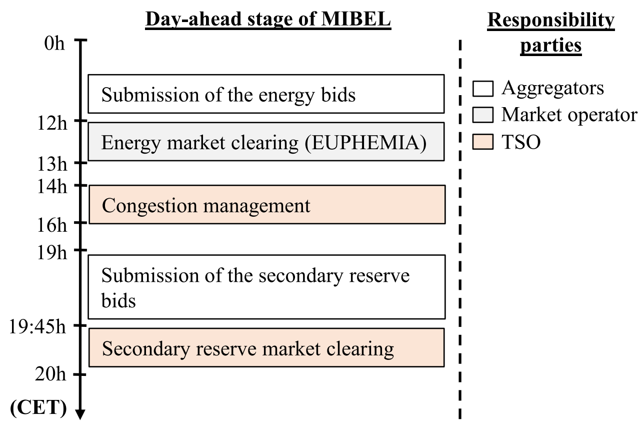

Fig. 1. Sequential timeline of the MIBEL in the day-ahead stage (formulated based on the Portuguese timeline).

schedules.

The secondary reserve bids are submitted between 19:00 and 19:45. The secondary reserve is remunerated under two concepts: band availability and band utilization (in both upward and downward directions). The band availability is traded under the form of bids (MW), which are selected by an economic merit-order and remunerated by a marginal price (€/MW). The TSO is responsible for acquiring band availability in the day-ahead secondary reserve market. During real-time, the TSO dispatches the band acquired in the day-ahead market through an automatic generation control system. The band utilization (MW) is valued at the marginal price (€/MWh) of the tertiary reserve market of MIBEL.

Under the MIBEL framework, aggregators can choose to participate only in the day-ahead energy market (with demand and supply bids) or in both day-ahead energy and secondary reserve markets (with coupled bids of secondary reserve with demand or supply bids). As price-takers, aggregators submit supply and secondary reserve bids at market floor price and demand bids at market cap price.

This paper only addresses the participation of aggregators in the day-ahead energy and secondary reserve markets. The real-time delivery of energy and secondary reserve bids is outside the scope of this paper. This topic is covered in Refs. [29].

2.2. Interactions between aggregators and the distribution system operator

The current framework of the MIBEL does not consider the participation of the DSO. In this work, we propose that aggregators negotiate with the DSO to compute network-secure energy and secondary reserve bids from the distribution network perspective. The proposed bidding strategy is described in section 3.

2.3. Interactions between aggregators and prosumers

Aggregators sign contracts with prosumers to exploit and trade the flexibility of their resources in electricity markets. In exchange, they offer financial rewards, such as cheaper retailing tariffs [3] or monthly bill discounts [12]. To complement the financial rewards, aggregators may also provide gamification services to maximize the interest and participation of prosumers [30]. The remuneration mechanisms and engagement mechanisms are not addressed in this paper. They have been studied in previous works, such as [12].

Aggregators interface with prosumers through home energy management systems [13]. Each prosumer's home energy management system has the following functionalities: metering the consumption and generation of appliances; enabling the exchange of information between aggregators and prosumers; acquiring the state-of-operation of appliances; and controlling the flexible appliances based on the set-points communicated by aggregators. A prosumer may interface with the home energy management system through a mobile or computer application.

This paper considers EV and PV as sources of flexibility. The remaining consumption is considered inflexible. EV are sources of demand and generation flexibilities, while PV are only sources of generation flexibility. Being a source of flexibility means that the resource is capable of decreasing, increasing, or shifting generation and/or consumption.

3. Network-constrained bidding optimization strategy

This section describes the optimization problem used to compute the network-constrained energy and secondary reserve bids. We begin by formulating the joint bidding and network problem in subsection 3.1, and then we decompose the problem into bidding and network subproblems in subsection 3.2.

3.1. Problem formulation

The network-constrained bidding strategy can be represented by optimization problem (1)-(4), which computes network-constrained energy and band bids by minimizing the cost of the aggregators trading in the day-ahead energy and secondary reserve markets.

The objective function of each aggregator a is represented by f_a in equation (1). Variables P_a are the possible scenarios of power exchange between aggregators and the distribution network, due to the participation of the aggregators in the day-ahead energy and secondary reserve markets. Variables X_a are internal inputs of the aggregators. Equations (2) and (3) are the constraint functions of aggregators and DSO (or distribution network), respectively. Variables Y are internal inputs of the distribution network. Variables $\widehat{P}$ are duplicates of the variables P, so that the network and aggregators have their own copies. Constraint (4) enforces the duplicate variables to have the same values and enables the decomposition of optimization problem (1)-(4) into aggregator and DSO optimization problems. Note that we drop all the subscripts of the variables to increase readability.

$$Min \sum_{a \in A} f_a(P_a, X_a) \tag{1}$$

$$h_a(P_a, X_a) \leq 0, \quad \forall\ a \in A \tag{2}$$

$$g(\widehat{P}, Y) \leq 0 \tag{3}$$

$$P - \widehat{P} = 0 \tag{4}$$

3.2. Application of the alternating direction method of multipliers

We use the ADMM algorithm [27] to decompose the optimization problem (1)-(4) into aggregators and DSO optimization problems. The bidding optimization problem of each aggregator a is given by:

$$P^{(k+1)} := \min_{P,X} f_a(P_a, X_a) + \mathscr{L}_a\left(P_a, \widehat{P}_a^{(k)}, \pi_a^{(k)}\right) \tag{5}$$

$$h_a(P_a, X_a) \leq 0 \tag{6}$$

where $\mathscr{L}_a$ is the penalty term of the augmented Lagrangian applied to the equality constraint (4). Equation (7) is the mathematical formulation of the penalty term of the augmented Lagrangian, where π is the vector of dual variables and ρ is the penalty parameter of the augmented Lagrangian.

$$\mathscr{L}\left(P, \widehat{P}, \pi\right) = \pi^T(P - \widehat{P}) + \frac{\rho}{2}||P - \widehat{P}||_2^2 \tag{7}$$

The DSO optimization problem (AC OPF) is given by:

$$\widehat{P}^{(k+1)} := \min_{\widehat{P},Y} \mathscr{L}\left(P^{(k+1)}, \widehat{P}, \pi^{(k)}\right) \tag{8}$$

$$g(\widehat{P}, Y) \leq 0 \tag{9}$$

The ADMM algorithm solves iteratively optimization problems (5)–(6) and (7)–(8) until convergence is reached. The steps of the ADMM algorithm for each iteration k are illustrated in Fig. 2 and described below:

1. aggregators solve their bidding optimization problems (5)–(6) by holding $\widehat{P}^{(k)}$ and $\pi^{(k)}$ constant at their k^{th} values. The aggregators obtain the values of P;
2. the DSO solves an AC OPF (8)–(9) by holding $P^{(k+1)}$ and $\pi^{(k)}$ constant at their $k+1^{th}$ and k^{th} values. The DSO obtains the values of $\widehat{P}$;

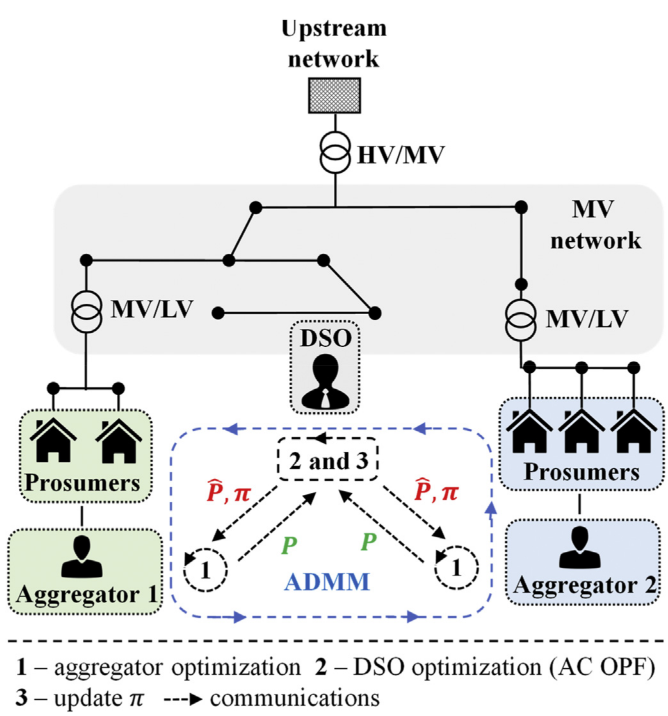

Fig. 2. Schematic overview of the network-constrained bidding optimization strategy.

3. the dual variables π are updated through equation (10). This sequential process is repeated until convergence is reached (otherwise go to step 1).

$$\pi^{(k+1)} = \pi^{(k)} + \rho\left(P^{(k+1)} - \widehat{P}^{(k+1)}\right) \tag{10}$$

The stopping criteria of the ADMM are defined by the primal (11) and dual (12) residuals in line with [31]. The primal residual represents the violation of constraint (4) and the dual residual represents the violation of the Karush–Kuhn–Tucker stationarity constraint. We consider that the problem converges, when the scaled 2-norm of both the primal and dual residuals are smaller than 10^{-3} (<10 W for the primal constraint).

$$R^{P\ (k+1)} = \left(\left(P_1^{(k+1)} - \widehat{P}_1^{(k+1)}\right), \left(P_2^{(k+1)} - \widehat{P}_2^{(k+1)}\right), \ldots\right)^T \tag{11}$$

$$R^{D\ (k+1)} = \left(\rho\left(\widehat{P}_1^{(k+1)} - \widehat{P}_1^{(k)}\right), \rho\left(\widehat{P}_2^{(k+1)} - \widehat{P}_2^{(k)}\right), \ldots\right)^T \tag{12}$$

ADMM has been proven to converge for convex problems [27]. However, recent works [32–34] show that in practice ADMM also converges for non-convex problems, as we demonstrate in this work.

4. Aggregator optimization problem

Each aggregator defines energy and band bids to submit to the day-ahead energy and secondary reserve markets by running the quadratic optimization model (13)–(36). The optimization model computes day-ahead bids $\{E^A, U^A, D^A\}$ and bid delivery scenarios $\{P^E, P^U, P^D\}$, as illustrated in Fig. 3. The bid delivery scenarios define the possible real-time power exchanges between aggregators and the distribution network. The DSO uses the bid delivery scenarios to evaluate the feasibility of the aggregator's offers. We consider the following three scenarios for network feasibility evaluation:

1. the aggregator only delivers the energy traded in the day-ahead market ($P^E = E^A / \Delta t$);
2. the aggregator delivers the energy and maximum upward band traded in the energy and secondary reserve markets ($P^U = E^A / \Delta t - U^A$);
3. the aggregator delivers the energy and maximum downward band traded in the energy and secondary reserve markets ($P^D = E^A / \Delta t + D^A$).

4.1. Objective function

The quadratic optimization model (13)–(36) is formulated as a

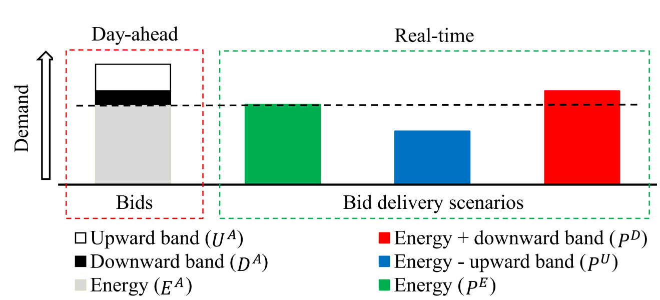

Fig. 3. Output example of the bidding optimization problem of the aggregators.

minimization problem. The aim is to minimize the net cost of the aggregator trading energy and secondary reserve. The objective function (13) is divided into two main terms:

1. the first term f_t is the net cost of the aggregator trading energy and secondary reserve. Equation (14) divides the first term into energy $\lambda_t^E E_t^A$ and secondary reserve $-\lambda_t^B(U_t^A+D_t^A)+(\lambda_t^D \varnothing_t^D D_t^A - \lambda_t^U \varnothing_t^U U_t^A)\Delta t$ components. The energy term represents the net cost of buying ($E_t^A > 0$) and selling ($E_t^A < 0$) energy at price λ_t^E in the day-ahead energy market. The secondary reserve term is divided into two components. The first component is the revenue of selling band $U_t^A + D_t^A$ at price λ_t^B in the day-ahead secondary reserve market. The second component is the expected net cost of mobilizing downward D_t^A and upward U_t^A bands during real-time at tertiary reserve prices λ_t^D and λ_t^U. The parameters $\varnothing_t^D$ and $\varnothing_t^U$ are the forecast ratios of utilization to band availability;
2. the second term $\mathscr{L}_{n,t}^s$ is the penalty term of the augmented Lagrangian. It is used to penalize distribution network violations. Therefore, it is only positive in bid delivery scenarios $s \in \{E, U, D\}$ that produce network violations.

$$Min \sum_{t\in T}\left[f_t + \sum_{s\in\{E,U,D\}}\left(\sum_{n\in N_a}\mathscr{L}_{n,t}^s\right)\right] \tag{13}$$

$$f_t = \lambda_t^E E_t^A - \lambda_t^B\left(U_t^A + D_t^A\right) + \left(\lambda_t^D \varnothing_t^D D_t^A - \lambda_t^U \varnothing_t^U U_t^A\right)\Delta t \tag{14}$$

$$\mathscr{L}_{n,t}^s = \pi_{n,t}^{s\ (k)}\left(P_{n,t}^s - \widehat{P}_{n,t}^{s\ (k)}\right) + \frac{\rho}{2}\left(P_{n,t}^s - \widehat{P}_{n,t}^{s\ (k)}\right)^2 \tag{15}$$

The energy and band bids are defined for the optimization horizon $t \in T$ and each time interval has the duration 1 h Δt (h). The prosumers of aggregator a are in the nodes $n \in N_a$ of the MV distribution network.

4.2. Day-ahead bidding constraints

Constraint (16) defines the energy bids of the aggregator. The energy bids result from the sum of the energy consumed by EV $P_{j,t}^+$ and inflexible appliances $Pr_{j,t}^{IL}$, and the energy generated by EV $P_{j,t}^-$ and PV $P_{j,t}^{PV}$.

$$E_t^A = \sum_{j\in J}\left(P_{j,t}^+ - P_{j,t}^- + Pr_{j,t}^{IL} - P_{j,t}^{PV}\right)\Delta t, \quad \forall\ t\in T \tag{16}$$

Constraints (17) and (18) define the band bids for upward and downward directions. The upward band U_t^A defines the flexibility of the EV and PV to decrease load or increase generation during real-time. The downward band D_t^A defines the flexibility of the EV and PV to increase load and decrease generation during real-time.

$$U_t^A = \sum_{j\in J}\left(U_{j,t}^{EV} + U_{j,t}^{PV}\right), \quad \forall\ t\in T \tag{17}$$

$$D_t^A = \sum_{j\in J}\left(D_{j,t}^{EV} + D_{j,t}^{PV}\right), \quad \forall\ t\in T \tag{18}$$

4.3. Secondary reserve constraint

Constraint (19) splits the secondary reserve band according to the bidding rules of MIBEL (2/3 for upward and 1/3 for downward) [5,12].

$$U_t^A = 2\cdot D_t^A, \quad \forall\ t\in T \tag{19}$$

4.4. Bid delivery constraints

Constraints (20)–(22) define the three bid delivery scenarios $\{P_{n,t}^E, P_{n,t}^U, P_{n,t}^D\}$. The bid delivery scenarios are disaggregated by the distribution network nodes $n \in N_a$.

$$P_{n,t}^E = \sum_{j\in J_n}\left(P_{j,t}^+ - P_{j,t}^- + Pr_{j,t}^{IL} - P_{j,t}^{PV}\right), \quad \forall\ n\in N_a,\ \ t\in T \tag{20}$$

$$P_{n,t}^U = P_{n,t}^E - \sum_{j\in J_n}\left(U_{j,t}^{EV} + U_{j,t}^{PV}\right), \quad \forall\ n\in N_a,\ \ t\in T \tag{21}$$

$$P_{n,t}^D = P_{n,t}^E + \sum_{j\in J_n}\left(D_{j,t}^{EV} + D_{j,t}^{PV}\right), \quad \forall\ n\in N_a,\ \ t\in T \tag{22}$$

4.5. Electric vehicle constraints

The charging and discharging of the EV are defined by equations (23–27). Constraints (23) and (24) bound the charging power $P_{j,t}^+$ and discharging $P_{j,t}^-$ power of the EV. Constraints (25) and (26) set the state-of-charge $SOC_{j,t+1}$ within its technical limits $\left[\underline{SOC_j}, \overline{SOC_j}\right]$. Constraint (27) ensures that the SOC at departure time t_j^{DE} is satisfied. The aim is to guarantee that the preferences of the prosumers $j \in J$ are always satisfied. The preferences include availability T_j^{EV} and state-of-charge at departure time SOC_j^{DE}.

$$0 \le P_{j,t}^+ \le \overline{P_j^{EV}}, \quad \forall\ j\in J,\ \ t\in T_j^{EV} \tag{23}$$

$$0 \le P_{j,t}^- \le \overline{P_j^{EV}}, \quad \forall\ j\in J,\ \ t\in T_j^{EV} \tag{24}$$

$$SOC_{j,t+1} = SOC_{j,t} + \left(P_{j,t}^+\eta_j - \frac{P_{j,t}^-}{\eta_j}\right)\Delta t, \quad \forall\ j\in J,\ \ t\in T_j^{EV} \tag{25}$$

$$\underline{SOC_j} \le SOC_{j,t+1} \le \overline{SOC_j}, \quad \forall\ j\in J,\ \ t\in T_j^{EV} \tag{26}$$

$$SOC_{j,t_j^{DE}} \ge SOC_j^{DE}, \quad \forall\ j\in J \tag{27}$$

The upward and downward bands provided by the EV are defined by equations (28–32). Constraints (28) and (29) limit the downward $D_{j,t}^{EV}$ and upward $U_{j,t}^{EV}$ bands to the available charging and discharging powers, respectively. Constraints (30) and (31) guarantee that the EV only supply upward and downward bands if the SOC is within the interval $]\underline{SOC}_j, \overline{SOC}_j[$. Constraint (32) forces the EV to have availability to charge in the time intervals subsequent to the provision of upward and downward bands. So, it increases the robustness of the bidding problem and reduces the risk of reserve shortage in real-time.

$$0 \le D_{j,t}^{EV} \le \overline{P_j^{EV}} - P_{j,t}^{+}, \;\; \forall \; j \in J, \;\; t \in T_j^{EV} \tag{28}$$

$$0 \le U_{j,t}^{EV} \le \overline{P_j^{EV}} - P_{j,t}^{-}, \;\; \forall \; j \in J, \;\; t \in T_j^{EV} \tag{29}$$

$$U_{j,t}^{EV}, D_{j,t}^{EV} \le \frac{\overline{SOC_j} - SOC_{j,t+1}}{\eta_j \Delta t}, \;\; \forall \; j \in J, \;\; t \in T_j^{EV} \tag{30}$$

$$U_{j,t}^{EV}, \; D_{j,t}^{EV} \le \frac{\left(SOC_{j,t+1} - \underline{SOC}_j\right)\eta_j}{\Delta t}, \;\; \forall \; j \in J, \;\; t \in T_j^{EV} \tag{31}$$

$$\sum_{y \in T_{j,t}^{EV}} \left(D_{j,y}^{EV} + U_{j,y}^{EV}\right) \le \sum_{y \in T_{j,t}^{EV}} \left(\frac{\overline{P_j^{EV}} - P_{j,y}^{+} - P_{j,y}^{-}}{\tau}\right), \;\; \forall \; j \in J, \;\; t \in T_j^{EV} \tag{32}$$

4.6. Photovoltaic system constraints

The generation of the PV is defined by equations (33) and (34). Constraint (33) sets the PV generation $P_{j,t}^{PV}$. Constraint (34) bounds the curtailment power $P_{j,t}^{CU}$ of the PV. The maximum power output of the PV is defined by the forecasted power profile $Pr_{j,t}^{PV}$.

$$P_{j,t}^{PV} = Pr_{j,t}^{PV} - P_{j,t}^{CU}, \;\; \forall \; j \in J, \;\; t \in T \tag{33}$$

$$0 \le P_{j,t}^{CU} \le Pr_{j,t}^{PV}, \;\; \forall \; j \in J, \;\; t \in T \tag{34}$$

The upward $U_{j,t}^{PV}$ and downward $D_{j,t}^{PV}$ bands are defined by equations (35) and (36).

$$0 \le U_{j,t}^{PV} \le P_{j,t}^{CU}, \;\; \forall \; j \in J, \;\; t \in T \tag{35}$$

$$0 \le D_{j,t}^{PV} \le Pr_{j,t}^{PV} - P_{j,t}^{CU}, \;\; \forall \; j \in J, \;\; t \in T \tag{36}$$

5. DSO optimization problem

The DSO evaluates the network feasibility of the bid delivery scenarios $s \in \{E, U, D\}$ computed by the aggregators by running the AC OPF (37)–(43). The aim is to ensure that the delivery of the aggregators' offers does not violate the distribution network constraints.

5.1. Objective function

The AC OPF is formulated as a minimization problem. The aim is to minimize the penalty term of the augmented Lagrangian for a set of bid delivery scenarios $s \in \{E, U, D\}$ and bidding horizon $t \in T$. Note that $\widehat{P}_{n,t}^{s}$ is the duplicated variable of $P_{n,t}^{s}$. In this case, $\widehat{P}_{n,t}^{s}$ is a free variable and $P_{n,t}^{s}$ is a parameter.

$$Min \sum_{s \in \{E,U,D\}} \sum_{t \in T} \sum_{n \in N} \left({\pi_{n,t}^{s}}^{(k)} \left({P_{n,t}^{s}}^{(k+1)} - \widehat{P}_{n,t}^{s} \right) + \frac{\rho}{2} \left({P_{n,t}^{s}}^{(k+1)} - \widehat{P}_{n,t}^{s} \right)^2 \right) \tag{37}$$

5.2. Distribution network constraints

We model the distribution network constraints (38)–(43) using the branch flow formulation of the AC OPF in the non-convex form [23]. Constraints (38)–(41) are the power flow equations. For each line $(m, n) \in L$, let $P_{s,t,m,n}^{F}$ and $Q_{s,t,m,n}^{F}$ denote the active and reactive power flows. Let $r_{m,n}$ and $x_{m,n}$ be the resistance and reactance. For each node $n \in N$, let $\widehat{P}_{n,t}^{s}$ and $Q_{s,t,n}^{I}$ denote the active and reactive power injections. The active power injection $\widehat{P}_{n,t}^{s}$ is negative for generation and positive for consumption. Let S^b be the base power.

$$P_{s,t,m,n}^{F} = \frac{\widehat{P}_{n,t}^{s}}{S^B} + \sum_{i:n \to i} P_{s,t,n,i}^{F} + r_{m,n} I_{s,t,m,n}^{2}, \quad \forall \; s \in \{E, U, D\}, \;\; t \in T, \;\; (m,n) \in L \tag{38}$$

$$Q_{s,t,m,n}^{F} = Q_{s,t,n}^{I} + \sum_{i:n \to i} Q_{s,t,n,i}^{F} + x_{m,n} I_{s,t,m,n}^{2}, \quad \forall \; s \in \{E, U, D\}, \;\; t \in T, \;\; (m,n) \in L \tag{39}$$

$$V_{s,t,n}^{2} = V_{s,t,m}^{2} - 2\left(r_{m,n} P_{s,t,m,n}^{F} + x_{m,n} Q_{s,t,m,n}^{F}\right) + \left(r_{m,n}^{2} + x_{m,n}^{2}\right) I_{s,t,m,n}^{2}, \quad \forall \; s \in \{E,U,D\}, \; t \in T, \; (m,n) \in L \tag{40}$$

$$I_{s,t,m,n}^{2} V_{s,t,m}^{2} = {P_{s,t,m,n}^{F}}^{2} + {Q_{s,t,m,n}^{F}}^{2}, \quad \forall \; s \in \{E, U, D\}, \;\; t \in T, \;\; (m,n) \in L \tag{41}$$

Constraint (42) sets the limits of the voltage magnitude $V_{s,t,n}$ between $\underline{V_n}$ and $\overline{V_n}$. Constraint (43) maintains the current magnitude $I_{s,t,m,n}$ within a prescribed region.

$$\underline{V_n} \le V_{s,t,n} \le \overline{V_n}, \;\; \forall \; s \in \{E, U, D\}, \;\; t \in T, \;\; n \in N \tag{42}$$

$$0 \le I_{s,t,m,n} \le \bar{I}_{s,t,m,n}, \;\; \forall \; s \in \{E, U, D\}, \;\; t \in T, \;\; (m,n) \in L \tag{43}$$

5.3. AC OPF implementation

The AC OPF problem (37)-(43) was decomposed by time-step $t \in T$ and bid delivery scenario $s \in \{E, U, D\}$ since there is no time coupling constraints and dependency constraints between bid delivery scenarios. In addition, the variables $V_{s,t,m}^{2}$ and $I_{s,t,m,n}^{2}$ were replaced by linear equivalent variables [23,35]. These two modifications reduced the computational time of solving the problem (37)-(43) without compromising the quality of the solutions.

6. Case study

The case study covers the participation of two aggregators in the energy and secondary reserve markets of MIBEL on November 30th, 2015. The aggregators represent and optimize the flexibility of 24450 prosumers. The network location of the prosumers and flexible resources under the management of each aggregator is described in Fig. 4.

6.1. DSO data

The DSO data includes information on the 11-kV distribution network. The voltage bounds are 0.9 and 1.1 p.u., and slack bus voltage is 1.0 p.u. The resistance and reactance of the branches can

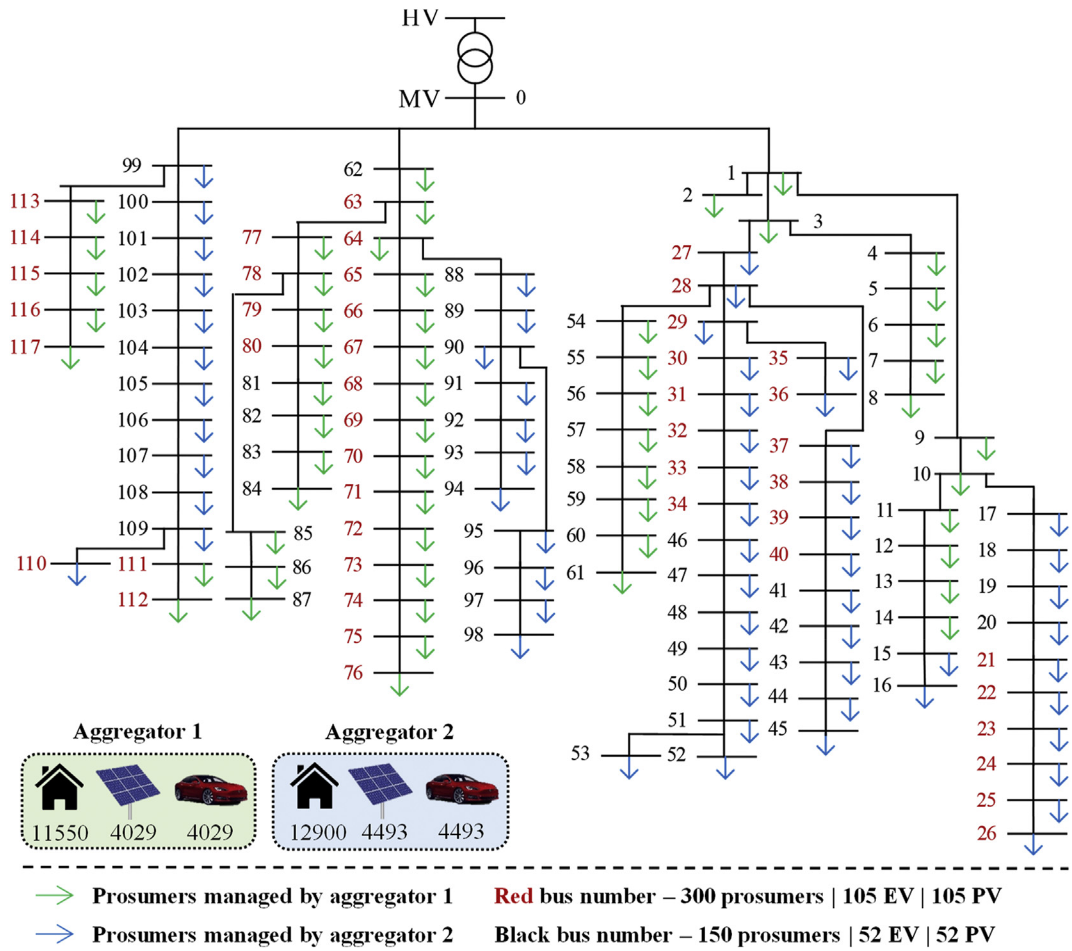

Fig. 4. 118-bus distribution network with two aggregators.

be found in Ref. [36].

6.2. Aggregator data

The data of aggregators includes information about the prosumers and electricity markets. The prosumer data comprises parameters of inflexible load, EV, and PV generation. The parameters are divided into fixed and dynamic, as shown in Table 1. The fixed parameters are provided by the manufacturing companies. The dynamic parameters are computed by the aggregators and assume the form of point forecasts. The prosumer data can be found in Ref. [13].

The electricity market data includes point forecasts of energy price λ^E, secondary reserve price λ^B, tertiary reserve prices for upward λ^U and downward λ^D directions, and ratios of utilization to availability for upward $\varnothing^U$ and downward $\varnothing^D$ bands. Fig. 5 presents the electricity market data forecasted for November 30th, 2015. The point forecasts were computed using the forecasting algorithms described in Ref. [12].

Table 1
Prosumer data.

Parameters	Electric vehicles	PV generation	Inflexible load
Dynamic	t^{DE}; t^{AR}; T^{EV}; SOC^{DE}; SOC^{AR}	Pr^{PV}	Pr^{IL}
Fixed	η; $\overline{P^{EV}}$; $\underline{SOC}$; $\overline{SOC}$	–	–

7. Results

The proposed network-constrained bidding strategy is compared to a network-free bidding strategy. Table 2 describes the main characteristics of the two day-ahead bidding strategies. The network-constrained bidding strategy computes network-constrained energy and secondary reserve bids. The network-free bidding strategy computes energy and secondary reserve bids without considering distribution network constraints, like the network-free approaches [3–15]. Both bidding strategies ensure the independent roles of aggregators and DSO. Under the network-constrained bidding strategy, the exchange of information between aggregators and DSO is minimal to ensure data privacy. The aggregators do not have access to the network data and the DSO does not have access to the data of the prosumers.

The results presented in the next subsections evaluate the participation of two aggregators in the energy and secondary reserve markets of MIBEL on November 30th, 2015. Nonetheless, the results can be replicated for any other day, beyond November 30th, 2015.

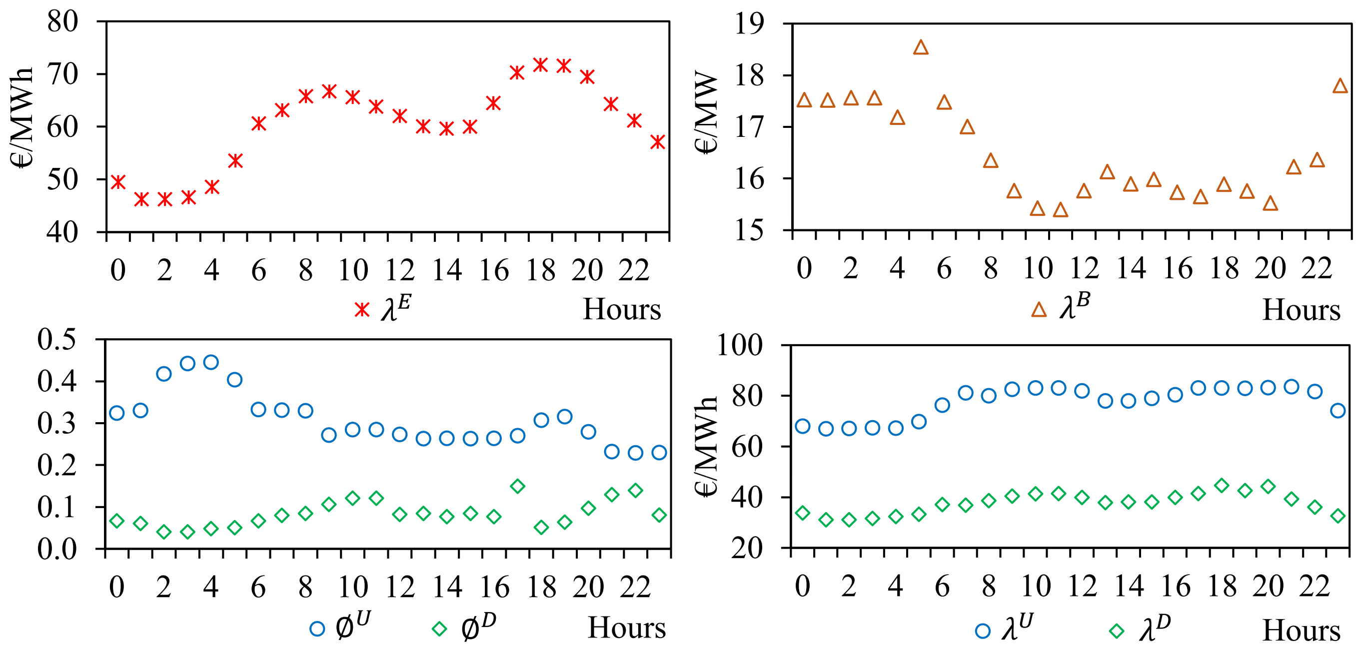

Fig. 5. Forecasted electricity market data for November 30th, 2015 [12].

Table 2
Main characteristics of the two day-ahead bidding strategies.

Bidding strategy	Participant agents	Optimization model
Network-constrained	Aggregators and DSO	Optimization model described in sections 3, 4, and 5
Network-free	Aggregators	Optimization model (13)–(14) and (16)–(36)

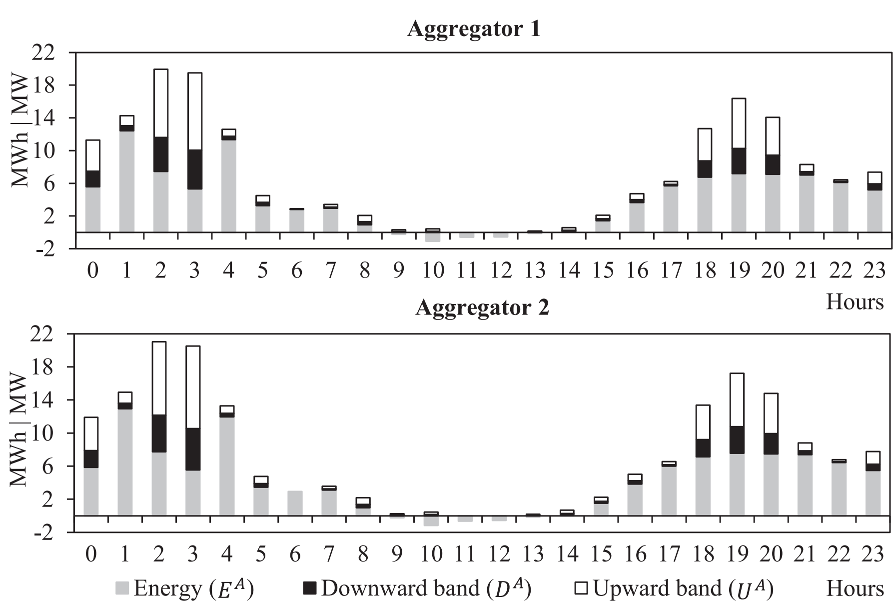

Fig. 6. Energy and band bids computed by the network-free bidding strategy.

7.1. Comparison of the bid placement results

Fig. 6 and Fig. 7 illustrate the energy and band bids submitted by aggregators 1 and 2 to the day-ahead energy and secondary reserve markets. The energy and band bids were computed by the network-free bidding strategy (Fig. 6) and network-constrained bidding strategy (Fig. 7). We can observe four combinations of bids: only supply bids at hours 11 and 12; only demand bid at hour 6; supply bid coupled with band bid at hour 10; and demand bids coupled with band bids at hours 2 and 3. Demand and band bids assume

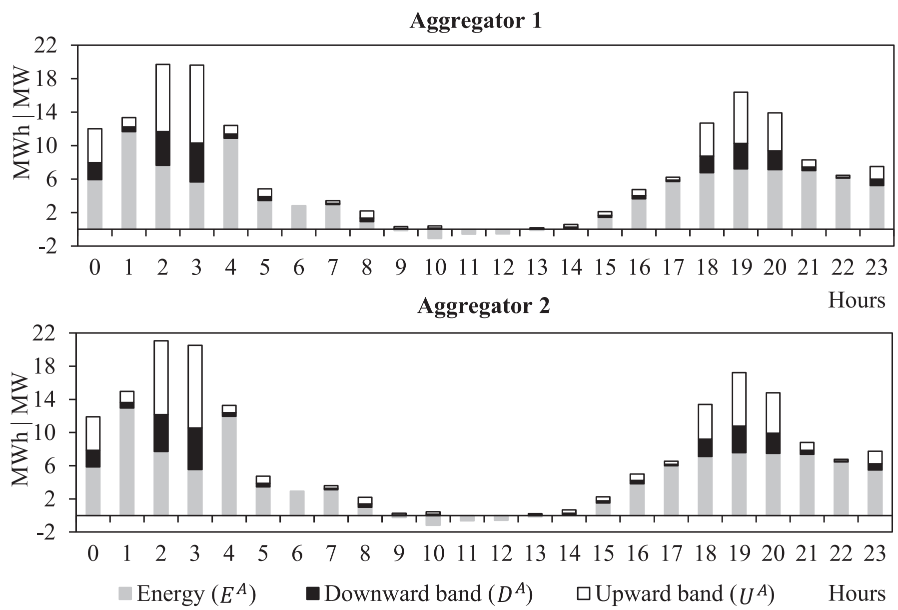

Fig. 7. Energy and band bids computed by the network-constrained bidding strategy.

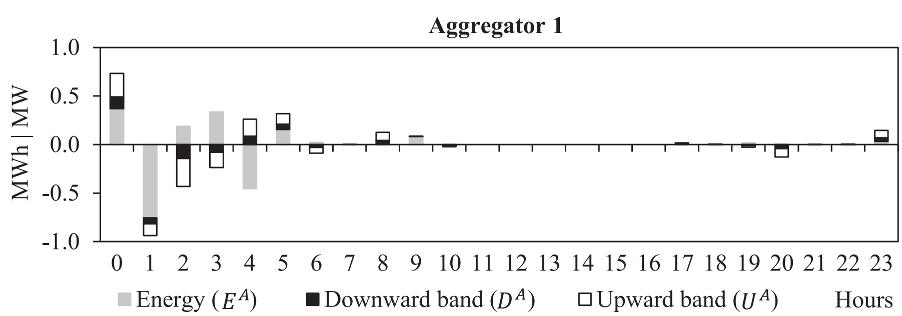

Fig. 8. Bid differences between network-constrained and network-free strategies.

positive values. Supply bids assume negative values.

The network-free and network-constrained bidding strategies present a similar placement behavior. Both strategies place most of the demand bids in the periods of low energy prices λ^E and the supply bids in the periods of forecasted PV generation. The demand bids placed in the early hours of the day (0–5 h) result from the optimization of EV charging, as shown in Fig. 13. The hours 1 and 4 are examples of this bidding behavior with energy prices of 46.3 and 48.6 €/MWh. In addition, both bidding strategies place most of the band bids in the periods of high band prices λ^B and high product between upward tertiary reserve prices and ratios of utilization to availability for upward bands $\lambda^U \varnothing^U$. The hours 2 and 3 are examples of this bidding behavior with identical band prices of 17.6 €/MW, and products of 28.9 and 29.8 €/MWh. The electricity market data can be observed in Fig. 5.

The quantities of energy and band bids computed by the network-free and network-constrained bidding strategies can be different in case of the offers violating the distribution network constraints. Fig. 8 illustrates the bid differences between the two strategies for aggregator 1. Positive differences mean that the aggregator placed more bids with the network-constrained bidding strategy than with the network-free bidding strategy. Negative differences mean the opposite. The results suggest that the network-free bidding strategy produced network infeasible energy and band bids since the bid differences between the two bidding strategies is observed. A more detailed analysis of the network feasibility of the energy and band bids computed by aggregator 1 is made in section 7.2. Regarding aggregator 2, no-bid differences are observed. This means that the bidding strategy of the aggregator 2 does not generate distribution network problems.

7.2. Impact of the bidding strategies in the distribution network

Under the network-constrained bidding strategy, the DSO evaluates the network feasibility of the bid delivery scenarios $\{P^E, P^U, P^D\}$ through the AC OPF (37)–(43). The network-free bidding strategy does not evaluate the network feasibility of the bid delivery scenarios. This lack of network observability of the network-free strategy may produce voltage violations and line congestions in real-time.

Fig. 9 shows that the 3 bid delivery scenarios computed by the network-free strategy generate undervoltage problems at hours 1, 2, 4, 19, and 20. The undervoltage problems are observed at buses [69, 76]. The lowest voltage value is observed at hour 1 and bus 76 (0.87 p.u.) under the downward band activation scenario. These undevoltage problems are generated by the bidding strategy of

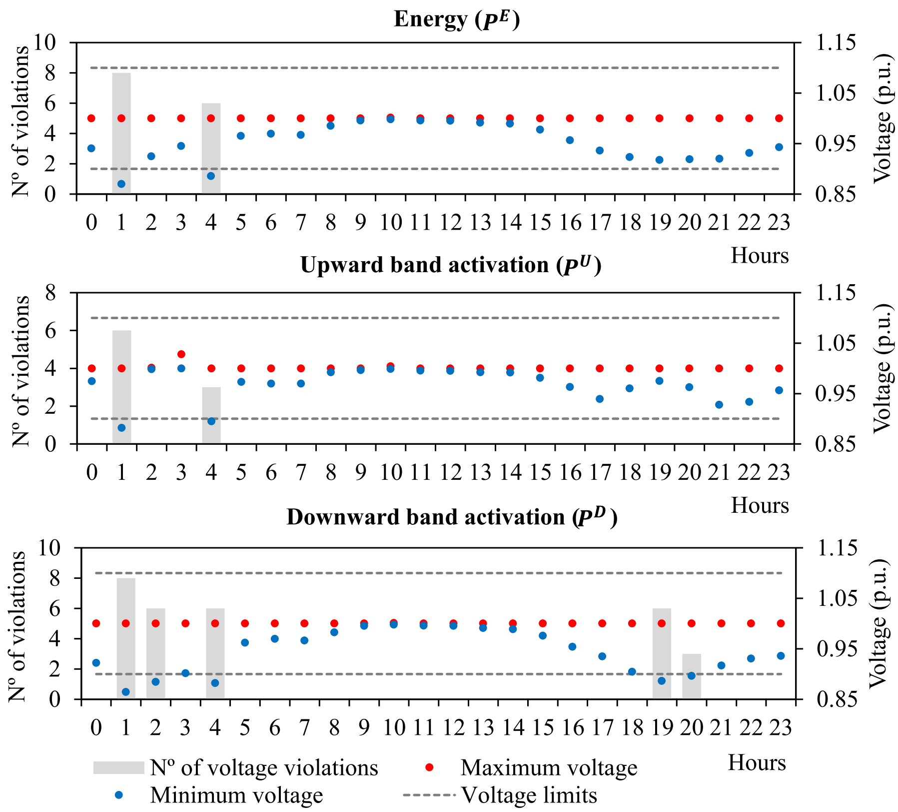

Fig. 9. Distribution network voltages generated by the network-free bidding strategy for the three bid delivery scenarios.

aggregator 1 since the prosumers of buses [69, 76] are managed by it. Therefore, the energy and band bids computed by the aggregator 1 are network-infeasible under the network-free bidding strategy.

The network-constrained bidding strategy comprises negotiations between aggregators and DSO to obtain energy and secondary reserve band bids that satisfy the distribution network constraints. Fig. 10 shows that the network-constrained bidding strategy computes network-feasible energy and secondary reserve band bids since no voltage violations are observed for any of the bid delivery scenarios. We can also observe in Fig. 8 that the aggregator 1 modified the quantities of energy and band bids at hours 1, 2, 4, 19, and 20 to avoid the undervoltage problems. For instance, the aggregator 1 reduced the quantities of energy and band bids at hour 1 by 7%, in order to avoid the undervoltage value of 0.87 p.u. observed under the network-free bidding strategy.

As mentioned before, the network-free bidding strategy does not have any observability over the distribution network. This may generate line congestion during real-time, as illustrated in Fig. 11. The 3 bid delivery scenarios generated congestion in the line 68–69 at hours 1, 2, and 4. The maximum congestion is observed at hour 1 (3073 kVA) for the scenario of downward band activation. The line 68–69 is in the network area managed by aggregator 1.

Fig. 12 illustrates the power flows in line 68–69 produced by the network-constrained bidding strategy. The 3 bid delivery scenarios do not violate the limit of the line at any hour of the day. We can observe that the limit of the line is not a binding constraint. The power flows are being limited by the voltage bounds of buses [69, 76].

7.3. Disaggregation of the bidding results per resource

This section discusses the disaggregation of the energy and band bids of the aggregator 2 per type of resource. The energy and band bids were computed by the network-free bidding strategy.

Fig. 13 illustrates the disaggregation of the energy bids per type of resource. The EV demand is placed in the periods of low energy prices (see Fig. 5). The PV generation and inflexible load are placed in the periods of expected realizations. The inflexible load is the main source of consumption with 111.2 MWh (79%) followed by the EV with 29.2 MWh (21%). PV are the main source of generation with −35.5 MWh (99%) followed by EV with −0.3 MWh (1%).

The EV are the main sources of upward and downward bands, as illustrated in Fig. 14. They provide 93% (22.3 MW) of the total downward band and 100% (47.9 MW) of the total upward band. Most of the upward and downward bands offered by the EV are placed in the period between the hours 18 and 5. These hours correspond to the period when the EV are available to charge or discharge. The PV only provide downward band (7%, 1.7 MW) in the periods of expected generation.

The disaggregation of the bidding results shows us that the EV are generating the line congestion and undervoltage problems observed in the distribution network.

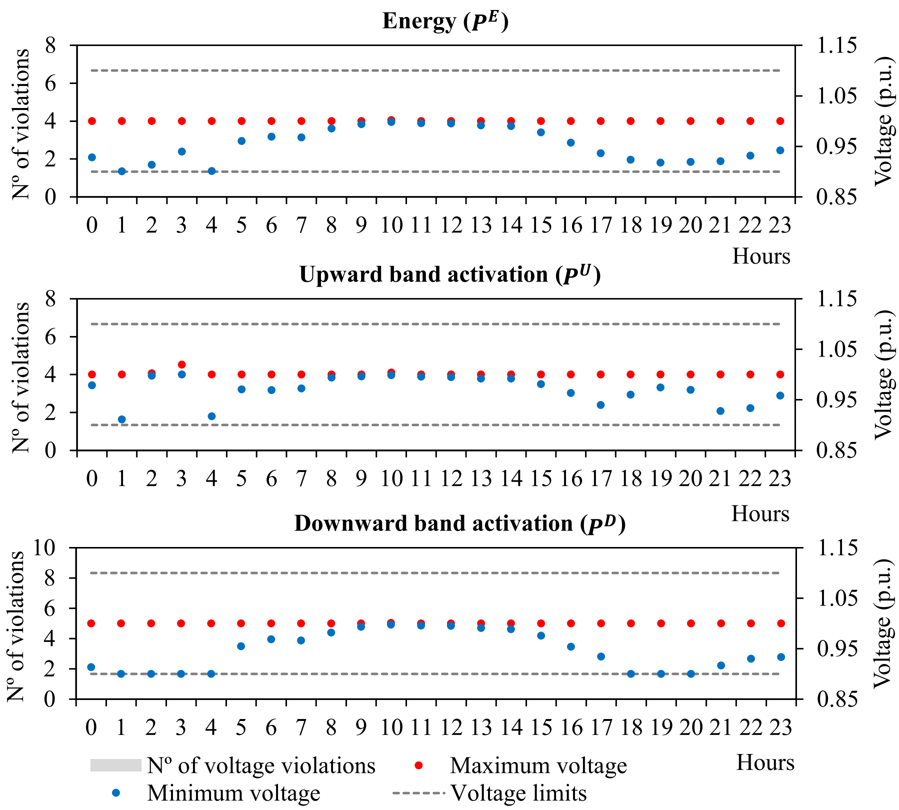

Fig. 10. Distribution network voltages generated by the network-constrained bidding strategy for the three bid delivery scenarios.

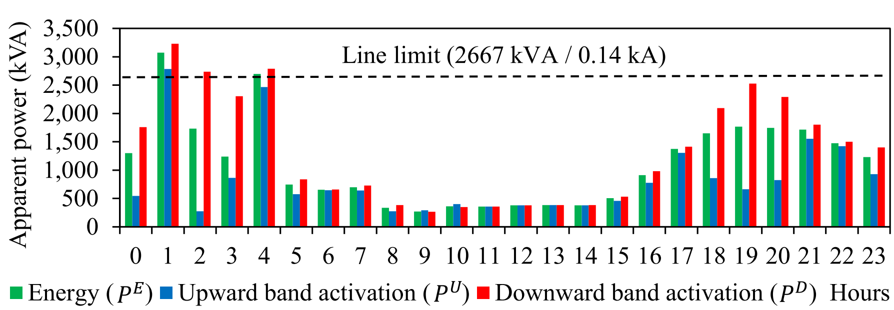

Fig. 11. Power flows in line 68–69 produced by network-free bidding strategy.

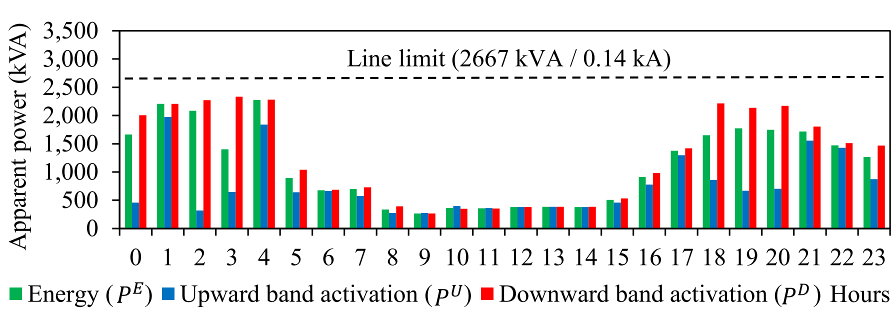

Fig. 12. Power flows in line 68–69 produced by network-constrained bidding strategy.

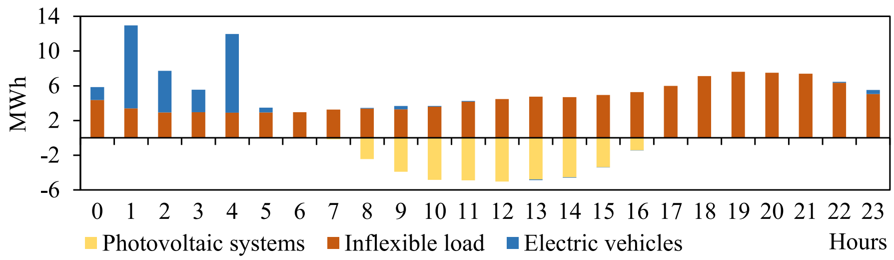

Fig. 13. Disaggregation of the energy bids of the aggregator 2 per type of resource. The load is positive, and the generation is negative.

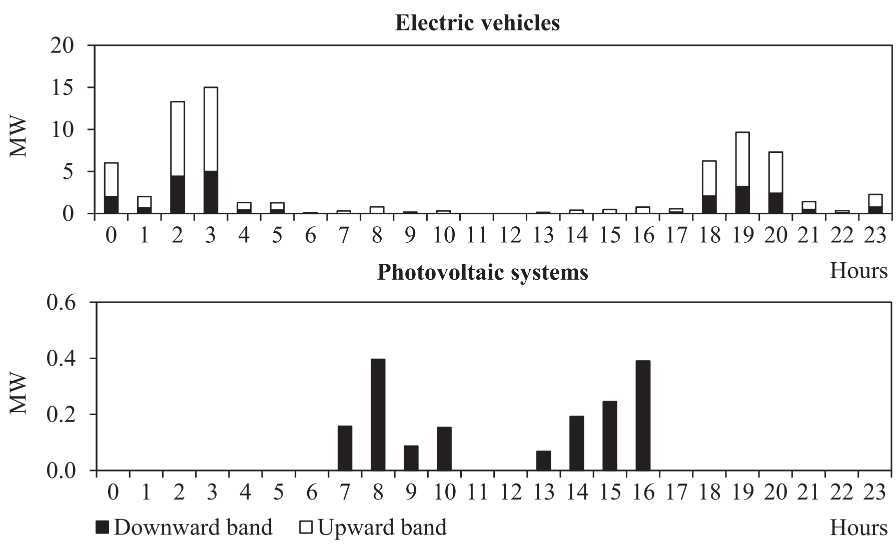

Fig. 14. Disaggregation of the band bids of the aggregator 2 per flexible resource.

Table 3
Cumulative energy and power bidding results.

Bidding strategy	Network-free		Network-constrained	
Aggregator	1	2	1	2
Demand bids (MWh)	99.7	104.7	99.7	104.7
Band bids (MW)	67.9	71.8	67.9	71.8

Table 4
Cumulative financial bidding results.

Bidding strategy	Network-free		Network-constrained	
Aggregator	1	2	1	2
Energy cost (€)	5763.8	6056.1	5768.0	6056.1
Secondary reserve revenue (€)	−2263.1	−2391.8	−2260.2	−2391.8
Total net-cost (€)	**3500.7**	**3664.3**	**3507.8**	**3664.3**

7.4. Comparison of the cumulative bidding results

Table 3 compares the cumulative energy and power results of the two bidding strategies. Both bidding strategies submit the same quantities of demand and band bids to the day-ahead energy and secondary reserve markets. However, the placement of the demand and band bids varies along of the day for the aggregator 1, as illustrated in Fig. 8. The demand and band bids computed by the network-free bidding strategy violate the voltage and line constraints at hours 1, 2, 4, 19, and 20, as shown in Figs. 9 and 11. The demand and band bids placed by the aggregator 2 are equal for both bidding strategies since they do not violate any distribution network constraint.

Table 4 compares the economic performance of the two bidding strategies. The total net cost is computed by equation (14). The other revenue and cost terms are components of the equation (14). Positive values are costs and negative values are revenues.

Both bidding strategies present the same net-cost of 3664.3 € for aggregator 2 since the bidding strategy of aggregator 2 does not violate any network constraint. Regarding aggregator 1, the network-free bidding strategy presents the lowest net-cost of 3500.7 €, outperforming network-constrained bidding strategy with a net-cost of 3507.7 €. However, the energy and band bids computed by network-free bidding strategy are infeasible from the distribution network perspective, as shown in section 7.2. So, the distribution network constraints increased the cost of aggregator 1 by 7.1 € (0.2%). The cost of purchasing demand in the market increased by 4.2 € and the revenue of selling secondary reserve decreased by −2.9 €.

7.5. Computational performance

The optimization problems were implemented in Python and solved on a machine with an Intel®Core™ i7-9700 CPU clocked at

Table 5
Average sizes and execution times of the subproblems of the network-constrained bidding strategy for 1 ADMM iteration. The ADMM needed 29 iterations to converge.

Agent	Aggregator 1	Aggregator 2	DSO (AC OPF[a])
Type of optimization problem	Quadratic programming	Quadratic programming	Nonlinear programming
Equations	(13)–(36)	(13)–(36)	(37)–(43)
Number of variables	346,792	366,260	581
Number of constraints	568,088	599,944	586
Computational time	11.4 s	11.0 s	0.2 s

[a] AC OPF decomposed by time-step and bid delivery scenario.

Table 6
Sizes and execution times of the optimization problems of the network-free bidding strategy.

Agent	Aggregator 1	Aggregator 2
Type of optimization problem	Linear programming	Linear programming
Equations	(13)–(14) and (16)–(36)	(13)–(14) and (16)–(36)
Number of variables	346,792	366,260
Number of constraints	568,088	599,944
Computational time	55.3 s	38.4 s

3.0 GHz with 32 GB RAM. The aggregator and DSO problems were solved by the CPLEX 12.9 and Ipopt 3.12.8 optimizers, respectively.

Tables 5 and 6 present the execution times and sizes of the two bidding optimization approaches. Table 5 shows that the ADMM algorithm needs at least 11.6 s (max (11.4, 11.0) + 0.2) to run an iteration if the aggregators and DSO problems are solved in parallel (without considering communications). The ADMM algorithm took 29 iterations to converge. This means that the network-constrained bidding problem can be solved in 5.6 min. The network-free strategy is faster. It only needed 55.3 s and 38.4 s to solve the optimization problems of the aggregators 1 and 2, as described in Table 6. Nonetheless, both bidding strategies present suitable execution times for MIBEL.

8. Conclusion

This paper proposes a new network-constrained bidding optimization strategy to support the participation of aggregators in the day-ahead energy and secondary reserve markets. The bidding strategy uses ADMM to break down the network-constrained bidding problem into aggregator and DSO subproblems and solve them iteratively. Aggregators compute energy and secondary reserve bids through bidding optimization models. The DSO evaluates the network feasibility of the bids through AC OPF. After ADMM convergence, aggregators obtain network-constrained energy and secondary reserve bids to submit to the day-ahead markets.

The numerical results compare the network-constrained bidding strategy to a network-free bidding strategy. Five main conclusions can be drawn. First, both bidding strategies place most of the flexible demand bids in the hours of low energy prices. Second, both bidding strategies place most of the band bids in the hours of high band prices and high product between upward tertiary reserve prices and ratios of utilization to availability for upward band. Third, the energy and band bids computed by the network-free bidding strategy can be network-infeasible in cases of high integration of distributed energy resources. Fourth, the network-constrained bidding strategy computes cost-effective and network-feasible energy and band bids. Fifth, the network-constrained and network-free bidding strategies present the same aggregators' costs in cases of no network violations. However, the network-constrained bidding strategy presents slightly higher costs in cases of foreseen network violations under the network-free bidding strategy.

Future work consists of developing and studying the impact of modeling the bidding problem of the aggregators, as a stochastic problem. Stochastic optimization may reduce slightly the settlement cost of the aggregators [37], but may also significantly increase the computational time.

CRediT authorship contribution statement

José Iria: Conceptualization, Methodology, Formal analysis, Investigation, Software, Writing - original draft, Writing - review & editing. **Paul Scott:** Methodology, Writing - review & editing, Project administration, Funding acquisition. **Ahmad Attarha:** Methodology, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] GhaffarianHoseini AH, Dahlan ND, Berardi U, GhaffarianHoseini A, Makaremi N. The essence of future smart houses: from embedding ICT to adapting to sustainability principles. Renew Sustain Energy Rev 2013;24: 593–607. https://doi.org/10.1016/j.rser.2013.02.032.
[2] Amini MH, Talari S, Arasteh H, Mahmoudi N, Kazemi M, Abdollahi A, Bhattacharjee V, Shafie-khah M, Siano P, Catalão JPS. Demand response in future power Networks : panorama and state-of-the-art. Sustain. Interdependent networks II Stud. Syst. Decis. Control. Cham, Switzerland: Springer International Publishing; 2019. p. 167–91. https://doi.org/10.1007/978-3-319-98923-5_10.
[3] Bessa RJ, Matos MA. Global against divided optimization for the participation of an EV aggregator in the day-ahead electricity market. Part I: theory, Electr. Power Syst. Res. 2013;95:309–18. https://doi.org/10.1016/j.epsr.2012.08.007.
[4] Bessa RJ, Matos MA. Global against divided optimization for the participation of an EV aggregator in the day-ahead electricity market. Part II: numerical analysis, Electr. Power Syst. Res. 2013;95:319–29. https://doi.org/10.1016/j.epsr.2012.08.013.
[5] Bessa RJ, Matos MA. Optimization models for an EV aggregator selling secondary reserve in the electricity market, Electr. Power Syst. Res. 2014;106: 36–50. https://doi.org/10.1016/j.epsr.2013.08.006.

[6] Bessa RJ, Matos MA. Optimization models for EV aggregator participation in a manual reserve market. IEEE Trans Power Syst 2013;28:3085–95. https://doi.org/10.1109/TPWRS.2012.2233222.
[7] Vagropoulos SI, Bakirtzis AG. Optimal bidding strategy for electric vehicle aggregators in electricity markets. IEEE Trans Power Syst 2013;28:4031–41. https://doi.org/10.1109/TPWRS.2013.2274673.
[8] Baringo L, Sánchez Amaro R. A stochastic robust optimization approach for the bidding strategy of an electric vehicle aggregator. Elec Power Syst Res 2017;146:362–70. https://doi.org/10.1016/j.epsr.2017.02.004.
[9] Chen S, Chen Q, Xu Y. Strategic bidding and compensation mechanism for a load aggregator with direct thermostat control capabilities. IEEE Trans. Smart Grid. 2018;9:2327–36. https://doi.org/10.1109/TSG.2016.2611611.
[10] Good N, Karangelos E, Navarro-Espinosa A, Mancarella P. Optimization under uncertainty of thermal storage-based flexible demand response with quantification of residential users' discomfort. IEEE Trans. Smart Grid. 2015;6:2333–42. https://doi.org/10.1109/TSG.2015.2399974.
[11] Iria JP, Soares FJ, Matos MA. Trading small prosumers flexibility in the energy and tertiary reserve markets. IEEE Trans. Smart Grid. 2019;10:2371–82. https://doi.org/10.1109/TSG.2018.2797001.
[12] Iria J, Soares F, Matos M. Optimal bidding strategy for an aggregator of prosumers in energy and secondary reserve markets. Appl Energy 2019;238:1361–72. https://doi.org/10.1016/j.apenergy.2019.01.191.
[13] Iria J, Soares F. A cluster-based optimization approach to support the participation of an aggregator of a larger number of prosumers in the day-ahead energy market, Electr. Power Syst. Res. 2019;168:324–35. https://doi.org/10.1016/j.epsr.2018.11.022.
[14] Ottesen SØ, Tomasgard A, Fleten SE. Prosumer bidding and scheduling in electricity markets. Energy 2016;94:828–43. https://doi.org/10.1016/j.energy.2015.11.047.
[15] Ottesen SØ, Tomasgard A, Fleten S-E. Multi market bidding strategies for demand side flexibility aggregators in electricity markets. Energy 2018;149:120–34. https://doi.org/10.1016/j.energy.2018.01.187.
[16] Soares FJ, Almeida PMR, Lopes JAP. Quasi-real-time management of electric vehicles charging. Elec Power Syst Res 2014;108:293–303. https://doi.org/10.1016/j.epsr.2013.11.019.
[17] Good N, Mancarella P. Flexibility in multi-energy communities with electrical and thermal storage: a stochastic, robust approach for multi-service demand response. IEEE Trans. Smart Grid 2019;10:503–13. https://doi.org/10.1109/TSG.2017.2745559.
[18] Correa-Florez CA, Michiorri A, Kariniotakis G. Optimal participation of residential aggregators in energy and local flexibility markets. IEEE Trans. Smart Grid. 2020;11:1644–56. https://doi.org/10.1109/TSG.2019.2941687.
[19] Wang H, Riaz S, Mancarella P. Integrated techno-economic modeling, flexibility analysis, and business case assessment of an urban virtual power plant with multi-market co-optimization. Appl Energy 2020;259:114142. https://doi.org/10.1016/j.apenergy.2019.114142.
[20] Neyestani N, Damavandi MY, Shafie-khah M, Bakirtzis AG, Catalao JPS. Plug-in electric vehicles parking lot equilibria with energy and reserve markets. IEEE Trans Power Syst 2017;32:2001–16. https://doi.org/10.1109/TPWRS.2016.2609416.
[21] Moghaddam SZ, Akbari T. Network-constrained optimal bidding strategy of a plug-in electric vehicle aggregator: a stochastic/robust game theoretic approach. Energy 2018;151:478–89. https://doi.org/10.1016/j.energy.2018.03.074.
[22] Vatandoust B, Ahmadian A, Golkar MA, Elkamel A, Almansoori A, Ghaljehei M. Risk-averse optimal bidding of electric vehicles and energy storage aggregator in day-ahead frequency regulation market. IEEE Trans Power Syst 2019;34:2036–47. https://doi.org/10.1109/TPWRS.2018.2888942.
[23] Iria J, Heleno M, Cardoso G. Optimal sizing and placement of energy storage systems and on-load tap changer transformers in distribution networks. Appl Energy 2019;250:1147–57. https://doi.org/10.1016/j.apenergy.2019.04.120.
[24] Gan L, Li N, Topcu U, Low SH. Exact convex relaxation of optimal power flow in radial networks. IEEE Trans Automat Contr 2015;60:72–87. https://doi.org/10.1109/TAC.2014.2332712.
[25] Mashayekh S, Stadler M, Cardoso G, Heleno M, Madathil SC, Nagarajan H, Bent R, Mueller-Stoffels M, Lu X, Wang J. Security-constrained design of isolated multi-energy microgrids. IEEE Trans Power Syst 2018;33:2452–62. https://doi.org/10.1109/TPWRS.2017.2748060.
[26] Luo L, Wu Z, Gu W, Huang H, Gao S, Han J. Coordinated allocation of distributed generation resources and electric vehicle charging stations in distribution systems with vehicle-to-grid interaction. Energy 2020;192:116631. https://doi.org/10.1016/j.energy.2019.116631.
[27] Boyd S, Parikh N, Chu E, Peleato B, Eckstein J. Distributed optimization and statistical learning via the alternating direction method of multipliers. Found. Trends® Mach. Learn. 2010;3:1–122. https://doi.org/10.1561/2200000016.
[28] Lam LH, Ilea V, Bovo C. European day-ahead electricity market coupling: discussion, modeling, and case study, Electr. Power Syst. Res. 2018;155:80–92. https://doi.org/10.1016/j.epsr.2017.10.003.
[29] Iria J, Soares F. Real-time provision of multiple electricity market products by an aggregator of prosumers. Appl Energy 2019;255:113792. https://doi.org/10.1016/j.apenergy.2019.113792.
[30] Koivisto J, Hamari J. The rise of motivational information systems: a review of gamification research. Int J Inf Manag 2019;45:191–210. https://doi.org/10.1016/j.ijinfomgt.2018.10.013.
[31] Attarha A, Scott P, Thiebaux S. Affinely adjustable robust ADMM for residential DER coordination in distribution networks. IEEE Trans. Smart Grid. 2019;3053. https://doi.org/10.1109/tsg.2019.2941235. 1–1.
[32] Scott P, Thiébaux S. Distributed multi-period optimal power flow for demand response in microgrids. Proc. 2015 ACM Sixth Int. Conf. Futur. Energy Syst. - e-energy '15. New York, New York, USA: ACM Press; 2015. p. 17–26. https://doi.org/10.1145/2768510.2768534.
[33] Mhanna S, Verbic G, Chapman AC. Adaptive ADMM for distributed AC optimal power flow. IEEE Trans Power Syst 2019;34:2025–35. https://doi.org/10.1109/TPWRS.2018.2886344.
[34] Scott P, Gordon D, Franklin E, Jones L, Thiebaux S. Network-aware coordination of residential distributed energy resources. IEEE Trans. Smart Grid. 2019;10:6528–37. https://doi.org/10.1109/tsg.2019.2907128.
[35] Farivar M, Low SH. Branch flow model: relaxations and convexification (parts I, II). IEEE Trans Power Syst 2012;28:2554–64. https://doi.org/10.1109/TPWRS.2013.2255317.
[36] Zhang D, Fu Z, Zhang L. An improved TS algorithm for loss-minimum reconfiguration in large-scale distribution systems, Electr. Power Syst. Res. 2007;77:685–94. https://doi.org/10.1016/j.epsr.2006.06.005.
[37] Iria J, Soares F, Matos M. Optimal supply and demand bidding strategy for an aggregator of small prosumers. Appl Energy 2018;213:658–69. https://doi.org/10.1016/j.apenergy.2017.09.002.
[38] Riesz J, Gilmore J, MacGill I. Frequency control ancillary service market design: insights from the Australian national electricity market, electr. J 2015;28:86–99. https://doi.org/10.1016/j.tej.2015.03.006.
[39] González P, Villar J, Díaz CA, Campos FA. Joint energy and reserve markets: current implementations and modeling trends. Elec Power Syst Res 2014;109:101–11. https://doi.org/10.1016/j.epsr.2013.12.013.