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Energy Reports 8 (2022) 575–582
www.elsevier.com/locate/egyr

The 8th International Conference on Energy and Environment Research ICEER 2021, 13–17 September

Hour-ahead energy resource scheduling optimization for smart power distribution networks considering local energy market

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Received 17 January 2022; accepted 21 February 2022
Available online 14 March 2022

Abstract

Energy resource management is a concept that should be considered in energy systems due to the significant penetration of dispersed energy resources. Thus, the efficiency in the electrical network operation can be improved and the end-user costs reduced. In this way, an energy resource aggregator plays an important role in managing the demand and generation flexibility which is meant for small producers under market-oriented environments. This research paper presents an energy resource management in intraday (hour-ahead) time horizon considering local market transactions between players. The optimization model is formulated as mixed-integer linear programming and solved in a deterministic way. To exemplify the implementation of the proposed model, a realistic medium voltage distribution network with 180 buses, high penetration of distributed energy resources, energy storage systems, and electric vehicle charging stations is considered. The results show the impact of the forecast errors as well as the contractual constraints between the aggregator and energy storage systems and electric vehicle charging stations in the intraday scheduling costs.

Peer-review under responsibility of the scientific committee of the 8th International Conference on Energy and Environment Research, ICEER, 2021.

Keywords: Aggregator; Electric vehicles; Energy resources management; Local energy market; Hour-ahead; Smart distribution network

1. Introduction

Today's electric power system is an aging system that has difficulty fulfilling the energy needs. It will almost certainly be unable to effectively withstand the large penetration of renewable energy sources (RES). Despite certain benefits, such as distributed generation (DG) that minimizes energy distribution losses, the continuous high integration of distributed energy resources (DER) in the electrical grids [1] can cause major issues for the conventional system. A significant disadvantage of RES is related to its uncertainty and unpredictability, which can cause issues in voltage profiles and frequency stability. To fully use the DER based on RES, investments in smart

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https://doi.org/10.1016/j.egyr.2022.02.253

Peer-review under responsibility of the scientific committee of the 8th International Conference on Energy and Environment Research, ICEER, 2021.

grid technology, such as smart grid communications and smart meters, must be made [2]. Moreover, the end-users must participate actively in the energy community to achieve a sustainable energy system [3,4]. One mechanism that encourages this end-users participation is the local energy markets (LEMs) [5]. The LEM is a market that exchanges electricity produced and consumed in a neighborhood and allows interaction between multiple players, where end-users can also participate [6]. Thus, these exchanges can lead to a reduction in power losses and increase the power quality.

Energy resource management (ERM) problems are being widely studied in energy systems and are essential in the smart grid (SG) context. The ERM problem is highly challenging to solve due to the high level of uncertainty and complexity brought by RES, which leads to high numbers of variables and constraints [7,8]. Artificial intelligence (AI) mechanisms are often used to deal with this complexity, namely computational intelligence (CI) algorithms with a particular emphasis on evolutionary algorithms (EAs) that are being widely applied to the energy field [9,10]. These algorithms can give good solutions in reasonable computational time using a low computational effort to provide these feasible solutions [11].

This paper presents a model to solve the ERM problem in the intraday time horizon (hour-ahead) with 15-min time intervals and considers transactions in the local market. The proposed model also considers the day-ahead methodology proposed in [12] as input data. A two-stage stochastic model formulated as mixed-integer linear programming (MILP) is proposed to solve de ERM problem. This formulation is chosen because efficient MILP solvers are accessible on the market and can obtain the optimum solution in good time for this time horizon (hour-ahead). A medium voltage distribution network with 180 buses with high RES penetration is employed to show the applicability of the proposed approach.

This research paper considers the findings learned from [13] and goes further by including (i) the development of a local energy market transaction in the intraday time horizon energy resource management optimization problem; (ii) more degrees of disturbance in demand forecast and in the non-dispatchable renewable energy sources forecasting to be stressed; (iii) more realistic test case, considering different levels of uncertainty during a day (for each hour) to be stressed.

This paper presents the following structure: Section 2 describes the proposed technique and the intraday mathematical formulation. Next, a case study for a 180-bus medium voltage distribution network is provided and studied in Section 3. The relevant results are then presented and discussed in Section 4, and the study findings are then carefully described in Section 5.

2. Proposed methodology

This section contains a detailed discussion of the methods to be used. The mathematical model is offered in Section 2.2, whereas the accepted model for hour-ahead energy resource management scheduling (H-ERM) is detailed in Section 2.1.

2.1. Model for hour-ahead scheduling

The diagram of the energy resource management scheduling in the hour-ahead context is shown in Fig. 1. The aggregator, according to the H-ERM paradigm, must be able to control and manage several DERs in the network or a single grid sector. The model additionally compels a database that has all of the DERs' features, as well as the required projections for the following hours with a 15-min time slot resolution. We now have a decision in hour h for the energy resource scheduling of the hour $h+1$ with a 15-min time slot resolution as an outcome of the model. It is worthy to note that the day-ahead ERM results and the previous hours last time slot are also necessary. The distribution system operator (DSO) is responsible for power network studies and communicates the viable set-point to the aggregator. In this way, the aggregator does not need to consider the network constraints when running an energy resource management. As a result, the problem is MILP - mixed-integer linear programming [14].

2.2. Optimization model

The optimization model used in this work is explained in this section. The following output variables are presented by the optimization model:

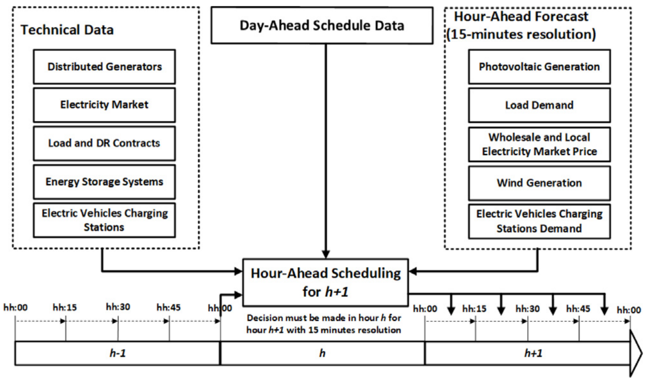

Fig. 1. Proposed methodology diagram .
Source: Adapted from [13].

- External supplier power (producers connected outside the distribution network);
- Dispatchable distributed generators power;
- Energy purchased and sold in the wholesale energy market and local energy market;
- Demand response result;
- Non-supplied power;
- Generation curtailment;
- Energy storage system (ESS) power charge and discharge;
- Electric vehicle (EV) charging station power charge and discharge (CS).

Eq. (1) describes the objective function, representing the predicted hour-ahead operation costs in monetary units (m.u.) and minimized throughout the scheduling horizon T. The scheduling time horizon comprises the four 15-min periods (i.e., one hour) of the day.

$$\sum_{t=1}^{T}\left[\begin{array}{l}\sum_{i\in\Omega_{DG}^{d}} p_{DG(i,t)}\times C_{DG(i,t)}+\sum_{s=1}^{N_s} p_{Supplier(s,t)}\times C_{Supplier(s,t)}+\sum_{i\in\Omega_{DG}^{nd}} p_{DG(i,t)}\times C_{DG(i,t)}+\sum_{l=1}^{N_l} p_{DR(l,t)}\times C_{DR(l,t)}+\\ \sum_{v=1}^{N_v} EV_{Discharge(v,t)}\times EVC_{Discharge(v,t)}+\sum_{l=1}^{N_l} p_{NSD(l,t)}\times C_{NSD(l,t)}+\sum_{e=1}^{N_e} p_{Discharge(e,t)}\times C_{Discharge(e,t)}+\\ \sum_{i=1}^{N_i} p_{GCP(i,t)}\times C_{GCP(i,t)}+\sum_{m=1}^{N_m}\left(p_{Buy(m,t)}-p_{Sell(m,t)}\right)\times MP_{(m,t)}+\sum_{le=1}^{L_E}\left(lem_{Buy(le,t)}-lem_{Sell(le,t)}\right)\times LEM_{(le,t)}\end{array}\right]\times\Delta_t \tag{1}$$

The proposed model has the following constraints:

- Power balance — generated power should be equal to consumed power for each t;
- Demand response — through direct load control including an incentive to the consumer;
- Non-supplied power — cannot be higher than the load forecasted l for each t;
- Generation limits for each t;
- Generation curtailment cannot be higher than the generation forecasted in each unit for each t;
- Energy storage systems — power balance, discharge and charge limits, capacity limit, minimum energy stored for each t, and the discharge e charge cannot be simultaneous (guaranteed by two binary variables);
- Wholesale market offers and bids — values are negotiated in day-ahead for each hour, where each 15-min time slot of an hour assume the same value negotiated the day-ahead;
- Local energy market offers and bids for each 15-min time slot;
- Electric vehicle charging stations — power balance, discharge and charge limits, capacity limit, and the discharge e charge cannot be simultaneous (guaranteed by two binary variables).

3. Case study

A realistic medium voltage distribution network with 30 kV, 1 substation (external supplier), and 180 buses [12, 15] was considered to show the applicability of the proposed method presented in Section 2. This network presents large penetration of distributed generator units, resulting in 70% of the total installed capacity power. 40% of that 70% are from PV panels, 35% from wind, and 15% from biomass. In this case study, the 116 DG units, the 7 ESS, 5 EV charging stations, 90 loads, the electricity purchased and sold to the wholesale and local market, as well as the electricity purchased from the external supplier are managed by an aggregator. Furthermore, the loads can be controlled by using direct load control (DLC) with an incentive of 0.05 m.u./kWh, where m.u. is the monetary unit. Moreover, the energy storage systems discharge and electric vehicles discharge costs are 0.01 m.u./kWh and 0.18 m.u./kWh, respectively. Additionally, for the day-ahead time horizon, the results given by the work presented in [12] are used. The energy resources data and prices can be found in [12,13]. Once the work in [12] uses a two-stage stochastic model considering a set of 150 scenarios, we consider a weighted average of the scenarios' results as input of the H-ERM proposed method. Indeed, the weighted average scenario is not ideal. For example, it can result in a tiny variation in the objective function value of day-ahead compared to the one that uses 150 scenarios.

To stress the proposed model, we are considering five test cases listed in Table 1. Moreover, ten degrees of disturbance in load demand forecasting ("Demand disturbance") ranging from −25% to +25%, as well as ten degrees of disturbance in the forecasting of non-dispatchable RES ("Non-dispatchable RES disturbance") ranging from −25 to +25% are used. These disturbances are representing a possible data variation in the intra-day time horizon.

Table 1. Test case list.

Case	Constrained ESS = 10% and CS = 5%	Non-constrained	Demand uncertainty (%) 5, 10, 15, 20, 25 −5, −10, −15, −20, −25	Non-dispatchable RES uncertainty (%) 5, 10, 15, 20, 25 −5, −10, −15, −20, −25
1	Yes	–	Yes	–
2	–	Yes	Yes	–
3	Yes	–	–	Yes
4	–	Yes	–	Yes
5	–	Yes	Variable (Fig. 2a)	5

There are two further constraints, i.e., for ESS and EV charging stations (for cases 1 and 3). Those constraints denote that the aggregator cannot modify more than 10% and 5% of the day-ahead prediction data in the intra-day, respectively. These constraining limits can represent, for instance, a contract between the aggregator and the owners of the resources. The ESS and EV charging stations ability to adjust freely in the intraday, i.e., ignoring the day-ahead forecast, is also investigated. The demand uncertainty for case 5 follows the values presented in Fig. 2(a). (b) shows the day-ahead demand and non-dispatchable RES forecast.

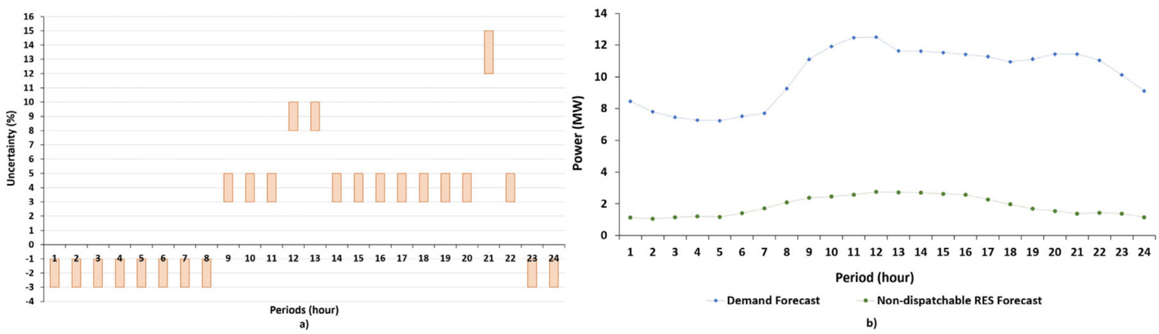

Fig. 2. (a) Demand uncertainty for case 5; (b) Day-ahead forecast for power demand and non-dispatchable renewable energy sources.

The capacity day-ahead projection for the 5 charging stations evaluated in this study is shown in Fig. 3(a). (b) shows the wholesale market electricity price to buy and sell, the external supplier electricity price to buy, and the local electricity market price to buy and sell in each 15 min intraday period.

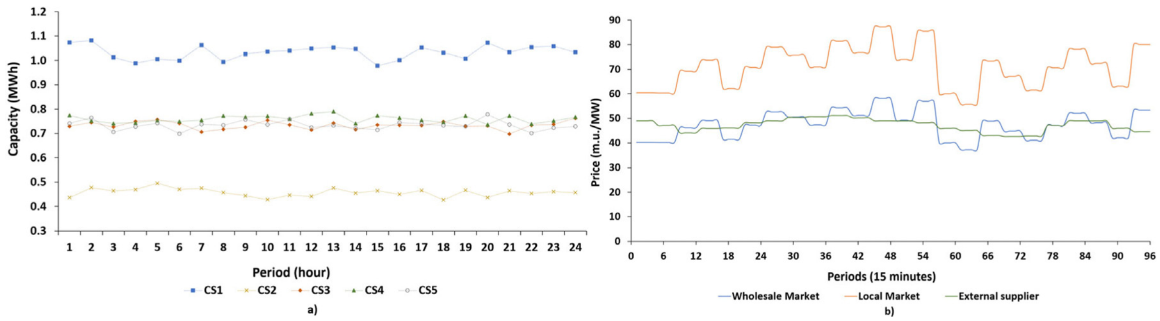

Fig. 3. (a) Charging stations day-ahead forecast capacity; (b) Wholesale, local market and external supplier electricity price day-ahead forecast.

4. Research work results and comments

A workstation with one Intel Xeon E5-2620 v2 processor and 16 GB of RAM running Windows 10 Pro with MATLAB R2016a and TOMLAB[1] 8.1 64 bits with CPLEX[2] solver were used to develop this research work.

On average, the studies presented 2848 variables (104 integer variables), 208 constraints, and 0.057 s of execution time for each four 15-min time slots. A memory test was done to evaluate the computer system resource impact using the MATLAB memory profiler tool. As a result, peak memory reached 1844 kB, which is more than plenty for today's computers. These outcomes show that the proposed model is aligned with the time frame for the intraday ERM.

A comparison of objective functions is made, taking into account the studies listed in Table 1. In addition, a comparison is also conducted with the day-ahead objective function resulted from [12]. As shown in Fig. 4(a) and (b), the variations between H-ERM and day-ahead objective function findings tend to increase as the error forecast increases. It has also been confirmed that the variations are greater when the demand forecast error is positive, requiring the aggregator to perform more demand response operations and more energy stored in the energy storage systems.

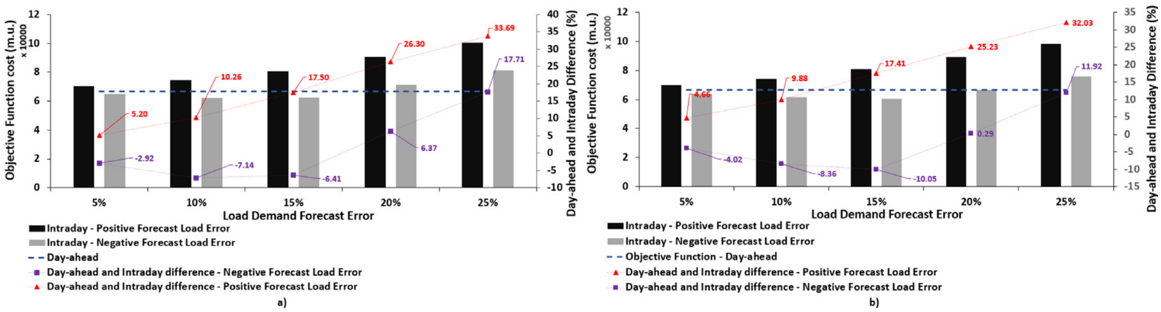

Fig. 4. Objective functions outcomes and variations between the day-ahead and intraday forecast values for: (a) Case 1; (b) Case 2.

When non-dispatchable renewable generation disturbances are taken into account, the objective function values for day-ahead and hour-ahead, as well as the variations between them, are shown in Fig. 5(a) and (b). These charts show that the differences between the hour-ahead objective functions values compared to the day-ahead values present a small significance (the higher difference is verified when the non-dispatchable generation forecast error is +25% - around 3%). This occurs because the ESSs and demand flexibility reduces the effects of the impact of the disturbances.

1 https://tomopt.com/tomlab/.
2 https://tomopt.com/tomlab/products/cplex/.

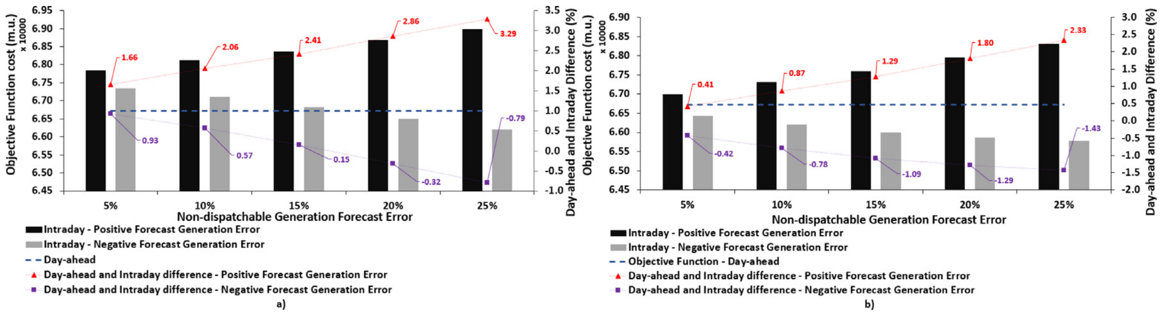

Fig. 5. Objective functions results and differences between the day-ahead and intraday forecast values for: (a) Case 3; (b) Case 4.

Another important point to note is that the difference between the day-ahead and hour-ahead objective function values is lower in several studies (e.g., Fig. 4(a) for −5%, −10%, and −15%) in the previous figures (Figs. 4 and 5). This shows that in those cases, the H-ERM is much closer to the optimal solution found in the day-ahead with 150 scenarios. Meaning, that this is a better scenario than the weighted average scenario in terms of the objective function. Fig. 6depicts the variations between the constrained ESS and EVs generated from day-ahead results and the unconstrained ESS and EVs (see Table 1). When the demand forecast error is verified, the objective function changes become more obvious, particularly in the negative forecast error.

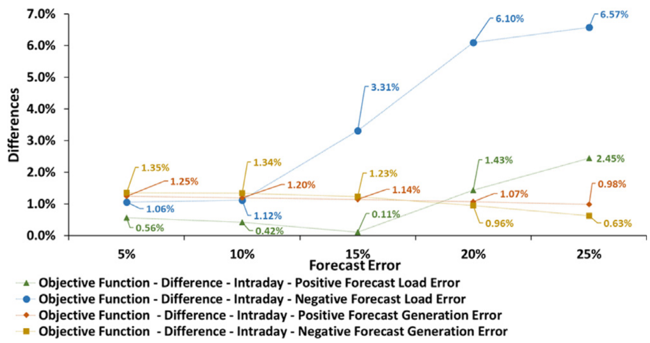

Fig. 6. ESS and charging stations constrained to day-ahead results *vs.* ESS and charging stations not constrained to day-ahead results.

To show H-ERM results, the authors used case 5 (Table 1). For this case, in each period, +5% of non-dispatchable generation uncertainty and random uncertainty values generated between the minimums and the maximums presented in Fig. 2(a) are considered. Fig. 7 presents the energy resource management for hour-ahead.

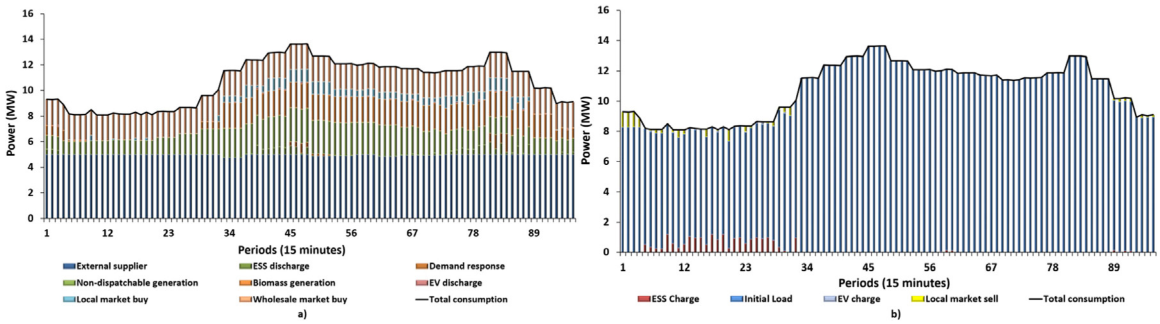

Fig. 7. Energy resource management – (a) generation; (b) consumption.

Fig. 7(a) shows the results of energy resource management (in terms of generation). The total external supplier acquisition is 119.23 MWh, while non-dispatchable generation (PV and Wind) and biomass are 42.79 MWh and 31.82 MWh, respectively. The total ESS discharge is 3.85 MWh, the EV discharge (charging stations) is 0.49 MWh, while the total scheduled demand response is 1.61 MWh. The total wholesale market and local market purchases are 48 MWh and 10.25 MWh, respectively. Fig. 7(b) presents the energy resource management results (in terms of consumption). The ESS charge, local market sale, EV charge (charging stations) are 5.12 MWh, 2.32 MWh, and 0.20 MWh, respectively.

5. Conclusions

This research provides aggregators with an approach for dealing with the complex challenge of large-scale energy resource scheduling in a smart grid over an hour-ahead time horizon. The observed results allowed the analysis of the impact of forecast inaccuracies and contractual limits between the aggregator and ESSs and EV charging stations on hour-ahead scheduling expenses. Furthermore, when comparing the outcomes of cases 1 and 2, there are significant differences between the day-ahead and hour-ahead horizons. These differences grow from 5.20% (5% of forecast error) to 33.62% (25% of forecast error) on case 1, namely in positive forecast errors, and from 4.66% (5% of forecast error) to 32.03% (25% of forecast error) on case 2 also in positive forecast errors. Thus, the findings point to the necessity for appropriate tools to cope with the uncertainties in energy resource scheduling challenges. Therefore, as part of a future study, a two-stage stochastic optimization model for distribution system operator and aggregator coordination is being created in a competitive environment, taking into account numerous aggregators and a model for distribution system operator and aggregator coordination.

Nomenclature

Ω_{DG}^{d}	Dispatchable DG units set
Ω_{DG}^{nd}	Non-dispatchable DG units set
$p_{DG(i,t)}$	DG unit i forecast in period t [MW]
$C_{DG(i,t)}$	DG unit i generation cost in period t [m.u./MWh]
$p_{Supplier(s,t)}$	External supplier s power scheduled in period t [MW]
$C_{Supplier(s,t)}$	External energy supplier s cost in period t [m.u./MWh]
N_l	Loads quantity
$p_{DR(l,t)}$	Load l reduction due to demand response event in period t [MW]
$C_{DR(l,t)}$	Load l reduction cost due to demand response event in period t [m.u./MWh]
N_v	EV charging stations quantity
$EV_{Discharge(v,t)}$	EV charging station v discharge in period t [MW]
$EVC_{Discharge(v,t)}$	EV charging station v discharging cost in period t [m.u./MWh]
$p_{NSD(l,t)}$	Non-supplied demand of load l in period t [MW]
$C_{NSD(l,t)}$	Non-supplied demand for load l cost in period t [m.u./MWh]
N_e	ESS units quantity
$p_{Discharge(e,t)}$	ESS e discharge in period t [MW]
$C_{Discharge(e,t)}$	ESS e discharging cost in period t [m.u./MWh]
N_i	Generation units quantity
$p_{GCP(i,t)}$	DG unit i power generation curtailment in period t [MW]
$C_{GCP(i,t)}$	DG unit i power generation curtailment cost in period t [m.u./MWh]
N_m	Wholesale markets quantity
$p_{Buy(m,t)}$	Wholesale market m power bought in period t [MW]
$p_{Sell(m,t)}$	Wholesale market m power sold in period t [MW]
$MP_{(m,t)}$	Price of the wholesale energy market [m.u./MWh]
L_E	Local energy markets quantity
$lem_{Buy(le,t)}$	Local energy market le power bought in period t [MW]
$lem_{Sell(le,t)}$	Local energy market le power sold in period t [MW]
$LEM_{(le,t)}$	Price of the local energy market [m.u./MWh]

CRediT authorship contribution statement

Bruno Canizes: Conceptualization, Investigation, Formal analysis, Validation, Writing – original draft. **João Soares:** Conceptualization, Investigation, Formal analysis, Validation, Writing – original draft, Project administration, Funding acquisition. **José Almeida:** Formal analysis, Data curation, Writing – review & editing. **Zita Vale:** Supervision, Writing – review & editing, Project administration, Funding acquisition.

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.

Acknowledgments

This research has received funding from FEDER funds through the Operational Programme for Competitiveness and Internationalization (COMPETE 2020) and National Funds through the FCT Portuguese Foundation for Science and Technology, under Projects PTDC/EEI-EEE/28983/2017 (CENERGETIC), CEECIND/02814/2017 (Joao Soares grant), and UIDB/000760/2020.

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