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Energy storage system impact on the operation of a demand response aggregator

Morteza Vahid-Ghavidel [a,b], Mohammad Sadegh Javadi [a], Sérgio F. Santos [c], Matthew Gough [a,b], Miadreza Shafie-khah [d], João P.S. Catalão [e,*]

[a] Institute for Systems and Computer Engineering, Technology and Science (INESC TEC), 4200-465 Porto, Portugal
[b] Faculty of Engineering, University of Porto, 4200-465 Porto, Portugal
[c] Research on Economics, Management and Information Technologies (REMIT), Portucalense University Infante D. Henrique (UPT), 4200-072 Porto, Portugal
[d] School of Technology and Innovations, University of Vaasa, 65200 Vaasa, Finland
[e] Research Center for Systems and Technologies (SYSTEC), Advanced Production and Intelligent Systems Associate Laboratory (ARISE), Faculty of Engineering, University of Porto, 4200-465 Porto, Portugal

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ABSTRACT

In this paper, we consider a demand response (DR) aggregator responsible for participating in the wholesale electricity market on behalf of the end-users who participated in the DR programs. Thus, the DR aggregator can trade its acquired DR within the short-term electricity markets, i.e., the day-ahead and the balancing (real-time) markets. In the proposed framework, the electricity market prices are considered uncertain, and a robust optimization approach is applied to address the uncertainties to maximize the profit of the DR aggregator. A model for analyzing the impact of the energy storage system (ESS) unit on a DR aggregator's performance is developed to provide more flexibility for the consumers. The direct interactions of a DR aggregator with an ESS are neglected in many models. However, this consideration can lead to improvement in the flexibility of the aggregator and also increase the profit of the entity by trading energy in the short-term markets to charge the ESS during the low-price periods and discharge it to the market while the electricity market prices are high. Hence, it is assumed that the DR aggregator owns an ESS unit and can cover a percentage of its traded power through the ESS. An analysis of the impact of the ESS unit on the DR aggregator's performance is applied to study the most appropriate size of the ESS that can maximize the profit of the aggregator. In addition, renewable energy production is employed for end-users through the installation of rooftop photovoltaic (PV) panels. This demand-side renewable generation can provide more flexibility for the participants in DR programs. Various feasible case studies have been applied to demonstrate the model's effectiveness and usefulness, and conclusions are duly drawn. The numerical results indicate that having an ESS seems necessary when the decision-maker desires to protect its profit from the worst-case scenarios and reduces the negative effect of the uncertain parameter, i.e., the wholesale electricity market prices. Thus, it can be shown that having a greater capacity for the ESS has a significant and direct impact on increasing the profit of the aggregator even in the worst-case scenarios, where the profit rises 20 % when the budget of uncertainty in the robust optimization is equal to 12.

1. Introduction

Due to the significant growth of the gap between the amount of electricity supply and demand in the energy system, demand-side management has received greater attention. Demand response (DR) is one of the most practical approaches to manage this gap between electricity generation and load [1,2]. The Federal Energy Regulatory Commission (FERC) has defined DR as a method to encourage end-user consumers to change their usage patterns in response to proposed electricity prices or incentive payments. The application of DR to the energy system has several advantages, such as balancing electricity generation and demand, increasing flexibility, enhancing the grid's reliability, and reducing CO_2 emissions [3].

Within the energy system, a DR aggregator has emerged whose primary responsibility is to design DR programs to encourage end-users to actively participate in demand-side management, as the volume of DR of each end-user is typically very small. Therefore, the DR aggregator can

* Corresponding author.
E-mail address: catalao@fe.up.pt (J.P.S. Catalão).

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Nomenclature

Indices

t	Time horizon index
p	Periods index
c	Consumer index

Parameters

λ_t^{DA}	Day-ahead market price [€/kWh]
$\lambda_t^{B,+}, \lambda_t^{B,-}$	Imbalance prices in excess/deficit modes [€/kWh]
$\lambda_0(c,p)$	Initial price related to consumer c in period p
$\lambda(c,p)$	TOU price related to consumer c in period p
M	A sufficiently large constant
$\overline{P}_{t,j}^{DR,rw}$	The steps of the reduced load in the reward-based DR program [kWh]
$\overline{R}_j^{DR,rw}(t)$	The steps of incentive in the reward-based DR [€/kWh]
$\eta_{ch}^{ESS}, \eta_{dis}^{ESS}$	The charging/discharging efficiency of the ESS
C_b^{deg}	The degradation cost of the ESS [€/kWh]
$P^{DA,Max}/P^{DA,min}$	The maximum/minimum capacity of the traded power of the DR aggregator in the day-ahead market [kW]
$E^{ESS,Max}/E^{ESS,min}$	The maximum/minimum capacity of the ESS [kWh]
ρ	The coefficient for the SOC of the ESS

Variables

P_t^{DA}	The traded power in the day-ahead market [kWh]
$P_t^{B,+}, P_t^{B,-}$	The traded power in the balancing market [kWh]
P_t^{TOU}	The changes in the electricity usage through the employment of the TOU program [kWh]
$P_t^{ESS,ch}$	The charging power value of the ESS [kW]
$P_t^{ESS,dis}$	The discharging power value of the ESS [kW]
E_t^{ESS}	The energy of ESS [kWh]

Binary variables

$I_j^{DR,rw}(t)$	The reduction level in the reward-based DR program
$I_t^{ESS,ch.}/I_t^{ESS,dis.}$	Binary variable indicating the charging/discharging mode of the ESS

acquire DR from the end-users and trade it within the wholesale electricity markets [4]. Furthermore, another crucial solution for providing flexibility in the energy system is the energy storage system (ESS) [5].

One of the main reasons for using ESSs is to overcome the challenges that can occur due to the high penetration of renewable energy resources in the power system. This significant volume of intermittent energy can lead to instability and low reliability in the network, which these challenges can make it essential to employ ESSs to prevent these issues [6]. The necessities for the application of DR and ESS have been mentioned above. Thus, using both features in a model is more beneficial to the overall system.

Hence, the primary motivation of this paper is to apply an ESS to study its impact on the performance of the DR aggregator in the short-term markets. On the other side, the uncertainty posed by the electricity market prices should be managed and handled to help the aggregator increase its profit. The robust optimization method is also applied to address this uncertainty.

A number of the most recent similar works are reviewed and studied in this section. The DR models that handle uncertain parameters are stated and discussed in the first part. Then, models that utilized a DR aggregator are mentioned. Later, the studies considering both DR and ESS are given detailed attention. For instance, the authors in [7] developed a DR program to determine the solution for minimizing the costs for the third entity and maximizing the social welfare through a game theory approach. Similarly, a game theory approach is proposed in [8] for the optimal scheduling of a DR-enabled energy system.

The management of the uncertainty posed by the generation of renewables is addressed in this work. Moreover, the uncertainty of DR is taken into account in [9] to enhance the flexibility for scheduling an energy system integrated with an electric vehicle parking lot. While the uncertainty of DR is handled in [10] to assess the congestion issues in the power systems. In these models, different aspects of the utilization of DR in the energy system are considered.

However, most of these works focused on the uncertainties on the demand side, and the uncertainties from the electricity market side are not given comprehensive attention. In addition, it seems crucial to take a closer look at models with an emphasis on applications of DR aggregators [11–15]. A stochastic approach is proposed between a DR aggregator and the end-users in [11] through an incentive-based DR program designation. Additionally, the uncertainty on the demand side is modeled through a Stackelberg Game. Meanwhile, the authors in [13] integrated the DR aggregator with the distributed network operators for residential loads to allocate power consumption from several electrical loads based on the time-of-use (TOU) tariffs.

On the other hand, an optimal trading strategy for a DR aggregator is studied in [16], considering a bottom-up procedure for modeling end-users responsiveness. Peer-to-peer transactions of a DR aggregator with a wind power producer are managed in [14] through a bi-level stochastic programming model combining the day-ahead and balancing markets. An Artificial intelligence (AI) based method is employed for the trading strategy of a DR aggregator in [15] with managing the uncertainty posed by the load and renewable energy resources.

In these studies, despite considering the uncertainties from several sources, the interactions of the aggregator with a direct ESS to improve the flexibility of the aggregator are missing. Nevertheless, a few research works considered the interactions between the DR aggregator and ESS components from the aggregator's viewpoint. For example, an aggregator with an ESS is considered in [17]. The aggregator purchases electricity from the independent system operator (ISO) to serve its customers with the primary objective of minimizing the aggregator's costs. However, the aggregator does not trade its energy within the wholesale electricity markets, and the uncertainty posed by the market side is neglected. While the authors in [18,19] considered the transactions between several components of the network, such as the DR aggregator and ESS in the wholesale markets, the impact of the ESS on the management of the trading strategy of the DR aggregator is not taken into account.

As stated above, several models applied both ESS and DR programs to their models for several purposes. However, the direct impact of the employment of an ESS unit owned by a DR aggregator has not been studied, to the best of our knowledge. Utilization of an ESS by a DR aggregator can lead this entity to increase its profit by trading energy in the short-term markets as well as increasing the flexibility for the aggregator to act as a retailer to charge the ESS during the lower prices periods and discharge it to the market while the electricity market prices are high. On the other side, using renewable energy resources on the demand side can increase the consumers' flexibility to participate in the DR programs. Since the surplus produced energy from the rooftop photovoltaic (PV) panels can be obtained through the DR aggregator. Thus, the decision-maker needs to optimize the characteristics of the ESS unit which directly affects the aggregator's performance to maximize its profit. In most of the works, the impact of the ESS on the DR framework is not analyzed.

Considering the above-mentioned research gap, a DR framework is modeled through robust optimization to study the impact of the ESS on the DR aggregator. The aggregator obtains DR from the end-users through two different DR programs, TOU, and reward-based DR programs. The TOU program is categorized as a price-based DR program, while a reward-based program is known as an incentive-based one. Therefore, the end-users can choose to participate in either DR programs or both based on availability. The end-users are assumed to be from various residential, commercial, or industrial sectors.

On the other side, the aggregator can trade DR in short-term electricity markets, i.e., day-ahead and balancing (real-time) markets. The market prices in both electricity markets are chosen as uncertain parameters. The robust optimization method is applied as a risk measure to handle these uncertainties. This risk-management method can protect the decision-maker against the worst-case market prices.

Hence, the **novel contributions** of the proposed model can be listed below:

- Development of a model for analyzing the impact of the ESS unit on the performance of a DR aggregator on behalf of various end-users such as residential, commercial, and industrial loads participating in the short-term electricity markets, i.e., day-ahead and balancing markets.
- Increasing the flexibility for the end-users to participate in the DR programs through developing the participation roles of the end-users in DR programs through having renewable energy resources on the demand side of the aggregator.

The rest of the paper is organized as follows: Section 2 introduces the proposed optimization model, and then the mathematical formulation is explained. Then, to demonstrate the usefulness and effectiveness of the model, the results are discussed in Section 3. Finally, the paper is concluded by summarizing the most important findings of the studied model in Section 4.

2. Proposed optimization model

The proposed robust optimization approach for the DR aggregator is explained and presented in this section.

The schematic of the DR trading model is illustrated in Fig. 1.

A DR aggregator in the center of the model plays the role of a decision-maker in this framework. The aggregator has employed two DR programs, including TOU and incentive-based DR programs. These programs will be explained in detail in the problem formulation section. The aggregator is responsible for implementing these DR programs for the end users.

This study has three types of end-users, as displayed in Fig. 1; they are the industrial, commercial, and residential sectors. These end-users are equipped with rooftop PV panels that cover a percentage of their usage and allow them to participate in the DR programs. On the other side, there is an electricity pool market that consists of two day-ahead and balancing (real-time) markets where the clearing procedure is based on the regulations indicated in [20].

There is also another component of the proposed framework, namely the ESS. The primary responsibility of this entity is to support the aggregator to avoid economic losses. Thus, the ESS will be controlled and operated by the DR aggregator. There is a bi-directional flow between the components of this framework. In other words, the energy can flow from the end-users to the market through the DR aggregator or vice-versa. Moreover, the ESS can be charged or discharged whenever the aggregator finds it beneficial for the decision-maker, the DR aggregator.

In the second part of Fig. 1, the model's objective and other elements are presented. This problem's objective is to maximize the profit of the DR aggregator. The electricity prices in the pool market, including day-ahead and real-time prices, are chosen as the uncertain parameters. It is worthwhile to mention that the uncertain nature of the wholesale electricity market prices has a significant and direct relation to the profit

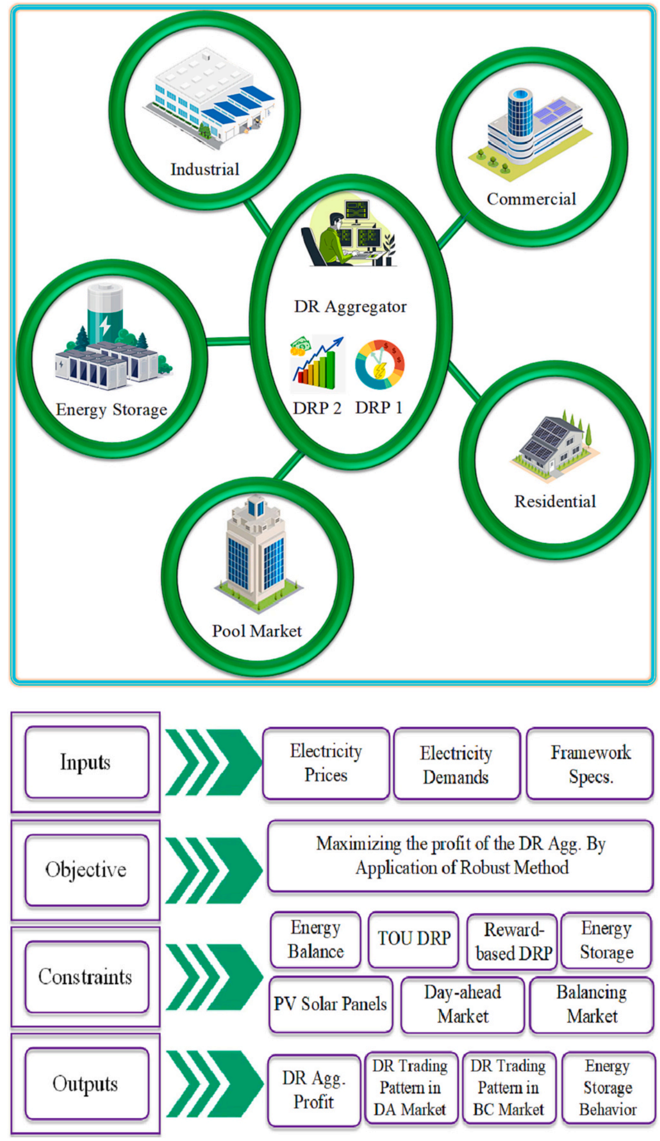

Fig. 1. The schematic of the DR trading model.

of the DR aggregator, where if the uncertainty of the electricity market prices wouldn't be adequately addressed, it may lead to a sharp decline in its profit. A robust optimization model determines the optimal solution to study the case under severe uncertainty, whereas scenario-based methods find the optimal solution based on a limited number of possible price scenarios. Thus, it is crucial to study the uncertainty of market prices to result in the robust scheduling of the DR aggregator in an environment. Therefore, the robust optimization approach is selected to handle this uncertainty and manage the risk associated with electricity market prices. The robust optimization approach in the power system is explained in [21].

The detailed mathematical formulation of the proposed model is expressed as follows:

$$Max\left\{\sum_{t=1}^{T}\left[P_t^{DA}\lambda_t^{DA}+P_t^{B,+}\lambda_t^{B,+}-P_t^{B,-}\lambda_t^{B,-}\right]-\sum_{t=1}^{T}\times\sum_{j=1}^{N_J}P_{t,j}^{DR,rw}R_{t,j}^{DR,rw}-\sum_{t=1}^{T}\left(P_t^{ESS,Ch}\eta_{ch}^{ESS}-\frac{P_t^{ESS,dis}}{\eta_{dis}^{ESS}}\right)C^{Deg}\right\} \quad (1)$$

where this optimization model's objective is maximizing the DR aggregator's profit. The first term of the objective function is the revenue from trading the obtained DR in the day-ahead market which λ_t^{DA} is the day-ahead uncertain price. The following terms refer to the revenue/cost from trading in the balancing markets. Thus, if the aggregator has an excess amount of energy, it can be offered to the balancing market with a positive imbalance price. While if the aggregator has a deficit, it can purchase from the balancing market with the negative imbalance prices. It should be noted that based on the balancing market regulations, the positive imbalance electricity prices are lower than the day-ahead prices, while the negative imbalance prices are greater than the correlated day-ahead prices. This is a reasonable rule to encourage market participants to avoid mismatches in scheduling in the day-ahead market as much as possible. This helps the ISO to have sufficient information about electricity transactions in advance. The imbalance positive and negative prices are also uncertain parameters. The next term in the objective function is the amount of reward that the aggregator pays to the end-users who participate in the reward-based DR program. This is categorized as an incentive-based DR program. There are several steps in each level, as there is a direct relationship between the certain reduced amount of energy and the reward offered. The last element of Eq. (1) relates to the cost of charging or discharging the ESS. The charging and discharging coefficients of the ESS are denoted by η_{ch}^{ESS} and η_{dis}^{ESS}. Finally, C^{Deg} is the degradation cost of the battery. It should be noted that λ_t^{DA}, $\lambda_t^{B,+}, \lambda_t^{B,-}$ are the uncertain parameters which a robust optimization method is selected to handle these sources of uncertainties. When the robust optimization is implemented on the proposed model, the mathematical problem formulation is represented as follows:

$$Max\left\{\sum_{t=1}^{T}\left[P_t^{DA}\widehat{\lambda}_t^{DA,min}+P_t^{B,+}\widehat{\lambda}_t^{B,+,min}-P_t^{B,-}\widehat{\lambda}_t^{B,-,Max}\right]-\sum_{t=1}^{T}\sum_{j=1}^{N_J}P_{t,j}^{DR,rw}R_{t,j}^{DR,rw}-\sum_{t=1}^{T}\left(P_t^{ESS,Ch}\eta_{ch}^{ESS}-\frac{P_t^{ESS,dis}}{\eta_{dis}^{ESS}}\right)C^{Deg}\right\}+\min_{\{t\|t|\le\Gamma\}}\left\{\left(P_t^{DA}\left[\widehat{\lambda}_t^{DA,Max}-\widehat{\lambda}_t^{DA,min}\right]+P_t^{B,+}\left[\widehat{\lambda}_t^{B,+,Max}-\widehat{\lambda}_t^{B,+,min}\right]-P_t^{B,-}\left[\widehat{\lambda}_t^{B,-,min}-\widehat{\lambda}_t^{B,-,Max}\right]\right)\right\} \quad (2)$$

In the robust optimization, the uncertain parameters can deviate from their expected values, i.e., $\{\widehat{\lambda}_t^{DA},\widehat{\lambda}_t^{B,+},\widehat{\lambda}_t^{B,-}\}$. This deviation range can be selected through α where α is a value between 0 and 1 that can adjust the uncertainty level. Hence, the day-ahead market prices, i.e., λ_t^{DA} can deviate between $\widehat{\lambda}_t^{DA,min}$ and $\widehat{\lambda}_t^{DA,Max}$ and $\lambda_t^{B,+}\in\left(\widehat{\lambda}_t^{B,+,min},\widehat{\lambda}_t^{B,+,Max}\right)$ for the positive imbalance price and $\lambda_t^{B,-}\in\left(\widehat{\lambda}_t^{B,-,min},\widehat{\lambda}_t^{B,-,Max}\right)$ for negative imbalance, prices are also considered. In this objective function, the second part of the formula indicated through a min term is considered for wholesale electricity market prices as the uncertain parameters should not exceed Γ. The uncertainty interval of the day-ahead and balancing market prices are taken from a forecasting model [22]. Due to the complexity of this initial form of the robust optimization, the objective function can be handled through the utilization of auxiliary variables χ and y_t. Hence, the objective function presented in Eq. (2) can be equivalently converted into the following mathematical function, i.e., Eq. (3) considering the auxiliary variables.

$$Max\left\{\sum_{t=1}^{T}\left[P_t^{DA}\widehat{\lambda}_t^{DA,min}+P_t^{B,+}\widehat{\lambda}_t^{B,+,min}-P_t^{B,-}\widehat{\lambda}_t^{B,-,Max}\right]-\sum_{t=1}^{T}\sum_{j=1}^{N_J}P_{t,j}^{DR,rw}R_{t,j}^{DR,rw}-\sum_{t=1}^{T}\left(P_t^{ESS,Ch}\eta_{ch}^{ESS}-\frac{P_t^{ESS,dis}}{\eta_{dis}^{ESS}}\right)C^{Deg}\right\}+\min_{\left\{\sum_t\chi\le\Gamma,0\le\chi\le1,\left(P_t^{DA}+P_t^{B,+}-P_t^{B,-}\right)\le y_t\right\}}\left\{\sum_j\left(\left[\widehat{\lambda}_t^{DA,Max}-\widehat{\lambda}_t^{DA,min}\right]+\left[\widehat{\lambda}_t^{B,+,Max}-\widehat{\lambda}_t^{B,+,min}\right]-\left[\widehat{\lambda}_t^{B,-,min}-\widehat{\lambda}_t^{B,-,Max}\right]\right)\bullet y_t\bullet\chi\right\} \quad (3)$$

In addition, by using the duality theory, this formula can be converted into the following objective function and constraints, in which, ξ and β_t are dual variables. A comprehensive explanation for obtaining the robust problem formulation from the initial form is provided in [23].

$$Max\left\{\sum_{t=1}^{T}\left[P_t^{DA}\widehat{\lambda}_t^{DA,min}+P_t^{B,+}\widehat{\lambda}_t^{B,+,min}-P_t^{B,-}\widehat{\lambda}_t^{B,-,Max}\right]-\sum_{t=1}^{T}\times\sum_{j=1}^{N_J}P_{t,j}^{DR,rw}R_{t,j}^{DR,rw}-\sum_{t=1}^{T}\left(P_t^{ESS,Ch}\eta_{ch}^{ESS}-\frac{P_t^{ESS,dis}}{\eta_{dis}^{ESS}}\right)C^{Deg}+\Gamma\xi+\sum_{t=1}^{T}\beta_t\right\} \quad (4)$$

$$\xi+\beta_t\ge\left(\left[\widehat{\lambda}_t^{DA,Max}-\widehat{\lambda}_t^{DA,min}\right]+\left[\widehat{\lambda}_t^{B,+,Max}-\widehat{\lambda}_t^{B,+,min}\right]+\left[\widehat{\lambda}_t^{B,-,min}-\widehat{\lambda}_t^{B,-,Max}\right]\right)y_t \quad (5)$$

$$\left(P_t^{DA}+P_t^{B,+}-P_t^{B,-}\right)\le y_t \quad (6)$$

$$\xi,\beta_t,y_t\ge0 \quad (7)$$

Variables ξ and β_t which are dual variables of the initial problem (3) used to take into account the known bounds of wholesale electricity market prices, i.e., day-ahead and real-time, while y_t is an auxiliary variable used to obtain equivalent linear expressions. To protect the model from uncertainty, another parameter is essential to use in the robust approach, called budget of uncertainty, i.e., Γ. This is an integer parameter that controls the level of conservatism. It can range from 0 to T where T is the maximum number of uncertain parameters. If $\Gamma=0$, the uncertain parameter is precisely equal to its expected value, and the robust approach does not protect the model against uncertainty. However, $\Gamma=T$ indicates that the model is fully protected against uncertainty. In other words, as the decision-maker becomes more risk-averse, higher values for the budget of uncertainty should be chosen. The final form of objective function presents the worst case of uncertain parameters, and market prices can deviate unfavorably equal to the Γ. The constraints of the proposed model can be expressed as follows:

$$\text{s.t}: \quad P_t^{DA}+P_t^{B,+}-P_t^{B,-}=P_t^{DR,rw}-P_t^{TOU}+P_t^{ESS,Ch}-P_t^{ESS,dis}+P_t^{PV},\forall t \quad (8)$$

The power balancing constraint is presented in Eq. (8). Hence, the power traded on the market side of the aggregator should be equal to the amount of power on the consumption side in each time interval. The power traded in the day-ahead market is denoted by P_t^{DA} and power traded in the balancing market denoted by $P_t^{B,+}$ and $P_t^{B,-}$. On the other side, the first two variables indicate the amounts of DR acquired from the end-users. The next two variables are the amount of charging/discharging power from the ESS and the last one is the amount of power generated from the PV panels.

The constraints related to the employed DR programs are given in Eqs. (9)–(14).

$$P_t^{TOU}=\sum_{c=1}^{N}D_0(c,t)\sum_{p=1}^{P}E(c,t,p)\left(\frac{\lambda(c,p)-\lambda_0(c,p)}{\lambda_0(c,p)}\right),\forall t \quad (9)$$

$$P_t^{DR,rw}=\sum_{j=1}^{N_J}\overline{P}_{t,j}^{DR,rw}I_{t,j}^{DR,rw},\forall t,\forall j \quad (10)$$

$$R_t^{DR,rw}=\sum_{j=1}^{N_J}R_{t,j}^{DR,rw},\forall t,\forall j \quad (11)$$

$$\overline{R}_{t,(j-1)}^{DR,rw}I_{t,j}^{DR,rw}\le R_{t,j}^{DR,rw}\le\overline{R}_{t,j}^{DR,rw}\bullet I_{t,j}^{DR,rw},\forall t,\forall j \quad (12)$$

$$\sum_{j=1}^{N_J}I_{t,j}^{DR,rw}=1,\forall t,\forall j \quad (13)$$

$$I_{t,j}^{DR,rw} \in \{0,1\} \tag{14}$$

The implemented TOU program is presented in Eq. (9). According to the definition of the TOU program, the participants are encouraged to reduce their consumption during the peak prices due to the high electricity tariffs, while they can consume more in the off-peak period with lower tariffs. The load profile is denoted by $D_0(c,t)$, where c indicates the type of end-user. The matrix of elasticity is also denoted by $E(c,t,p)$ where p shows the periods that peak and off-peak ones. The electricity usage tariffs before and after employment of the TOU program are $\lambda_0(c,p)$ and $\lambda(c,p)$, respectively.

The constraints regarding the reward-based DR program are stated in Eqs. (10)–(14). The amount of demand reduced in each time interval is denoted by $P_t^{DR,rw}$. The correlated reward is given to the end-users based on the reduced amount of demand, i.e., $R_t^{DR,rw}$ is calculated through Eq. (11). The next equation indicates that the reward amount can change in a stepwise pattern. The last two constraints show that in each time interval, one step can be chosen, and this is indicated by a binary variable denoted by $I_{t,j}^{DR,rw}$.

$$P^{min} \le P_t^{DA} \le P^{Max}, \forall t \tag{15}$$

$$0 \le P_t^{B,+} \le P_t^{DR,rw} - P_t^{TOU} + P_t^{ESS,Ch} - P_t^{ESS,dis} + P_t^{PV}, \forall t \tag{16}$$

$$0 \le P_t^{B,-} \le P^{Max}, \forall t \tag{17}$$

The power that can be traded in the day-ahead market through the DR aggregator has a specific capacity presented in Eq. (15). Similarly, the positive imbalance power should be lower or equal to the amount of available power for the DR aggregator as the maximum amount of power that can be available for the aggregator in the excess mode happens if the aggregator does not trade its whole available DR in the day-ahead market as declared in Eq. (16). Whereas the imbalance negative power limits are shown in Eq. (17), where no DR is available, the aggregator schedules its maximum capacity to be offered in the market. The ESS constraints are written as follows:

$$E_t^{ESS} = E_{t-1}^{ESS} + \left(P_t^{ESS,Ch}\eta_{ch}^{ESS} - P_t^{ESS,dis}/\eta_{dis}^{ESS}\right) \tag{18}$$

$$E^{ESS,min} \le E_t^{ESS} \le E^{ESS,Max} \tag{19}$$

$$E_{t=1}^{ESS} = E_{t=T}^{ESS} \tag{20}$$

$$E_{t=1}^{ESS} = \rho E^{ESS,Max} \tag{21}$$

$$0 \le P_t^{ESS,Ch} \le P_{Max}^{ESS,Ch} I_t^{ESS,Ch} \tag{22}$$

$$0 \le P_t^{ESS,dis} \le P_{Max}^{ESS,dis} I_t^{ESS,dis} \tag{23}$$

$$0 \le I_t^{ESS,ch} + I_t^{ESS,dis} \le 1 \tag{24}$$

$$I_t^{ESS,ch}, I_t^{ESS,dis} \in \{0,1\} \tag{25}$$

The amount of energy stored in the ESS unit is calculated in Eq. (18), where it is dependent on the previous level of energy plus the amount of power charged/discharged at time t with ESS charging/discharging coefficients, i.e., η_{ch}^{ESS} and η_{dis}^{ESS}.

It should be noted that the ESS has a minimum and maximum energy level declared in Eq. (19). Moreover, it is assumed that the ESS unit's initial and final level of the ESS unit in each time horizon should be equal. Also, Eq. (20) indicates that the stored energy level in the ESS directly relates to its maximum capacity. The initial amount of energy available at the beginning of the scheduling period is determined by Eq. (21). The amount of charging/discharging power in each time interval is limited, as stated in Eqs. (22) and (23). In addition, $I_t^{ESS,ch}$ and $I_t^{ESS,dis}$ are the binary variables that are used to indicate that the ESS cannot charge or discharge simultaneously.

$$P_t^{PV} = \left(G_t^a/G_0^a\right)\left[\overline{P}_0^M + \mu\left(T_t^a + G_t^a\frac{NOCT-20}{800} - T_0^M\right)\right] \tag{26}$$

$$P_t^{PV} = P_t^{PV\to c} + P_t^{PV\to ESS} + P_t^{PV\to DRA} \tag{27}$$

Finally, the hourly PV generation constraints are presented in Eqs. (26) and (27). Rooftop PV generation is wholly dependent on solar irradiance. Besides that, other factors can affect the generation value, such as the temperature and the characteristics of the panel (26) [24]. The PV panels' generated power can be exploited by either the end-users, ESS or the DR aggregator to be traded within the short-term electricity markets.

3. Case study

3.1. Data preparation

In this section, the employed data from the case study is explained in detail. The proposed model is aimed at profit maximization, mathematically formulated as a mixed-integer linear programming (MILP). It is simulated and solved in GAMS optimization software through the CPLEX solver. The problem was solved in a personal computer with 6 GB RAM and 2.41 GHz CPU speed. It is considered that the peak period of residential and commercial consumers is from 9:00 to 22:00 during the day, while the peak period for industrial consumers is from 9:00 to 18:00. The rest of the time is an off-peak period. These load profiles are taken from a real case study in March 2016 from São Miguel, Portugal. It is noteworthy to mention that the peak and off-peak periods of the studied cases are chosen based on their daily initial load profiles which they are presented in a figure that illustrates the influence of application of the TOU program in the simulation result section. The expected day-ahead market prices are taken from the Portuguese wholesale electricity market [25]. The maximum value for the available power of the DR aggregator that can be exchanged in the day-ahead market is equal to 1000 kW.

The data for the TOU and reward-based DR programs are similar to the reward steps and tariffs. The values used for the steps of the reward-based DR program are presented in Fig. 2. In our model, it is assumed that there are 25 unique steps for the reward-based DR program for each consumer type, such as residential, commercial, and industrial. The DR aggregator offers the obtained DR to the pool market during the peak period and purchases during the off-peak hours. As the pool market prices are assumed to be uncertain, robust optimization is selected as the risk management method, and 20 % is chosen as the price variations from the expected day-ahead market prices. The expected electricity prices in the balancing market are assumed to be 10 % higher or 10 % lower than day-ahead prices for the negative or positive imbalance values, respectively [4].

Moreover, it is assumed that the end-users in all three sectors are equipped with rooftop PV panels and their total generation for each section in the studied time horizon is illustrated in Fig. 3. Regarding the ESS, it should be mentioned that three different cases are considered for the ESS to observe and study its impact on the profit of the DR aggregator. The degradation cost of the battery is assumed to be 0.07 €/kWh. The battery's efficiency for both charging and discharging modes is 88 %. The remaining employed ESS data for each case is presented in Tables 1 and 2.

3.2. Simulation results

The electricity pool prices are chosen as the uncertain parameters, and through the implementation of a robust optimization approach, the uncertainty budget, i.e., Γ, is an integer number that indicates the optimization level. As Γ increases, the robustness of the model against

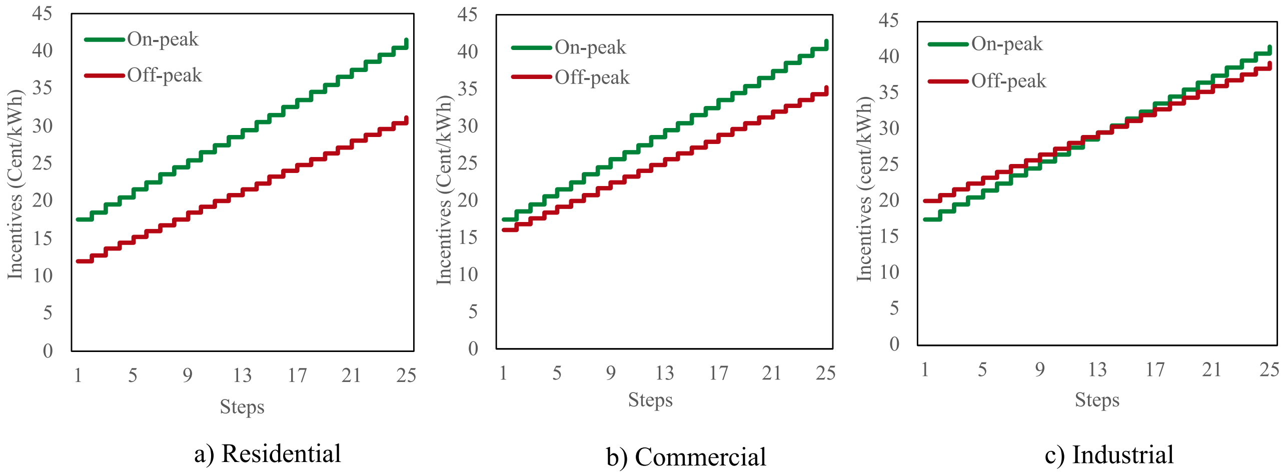

Fig. 2. The values for each step of the reward-based DR program.

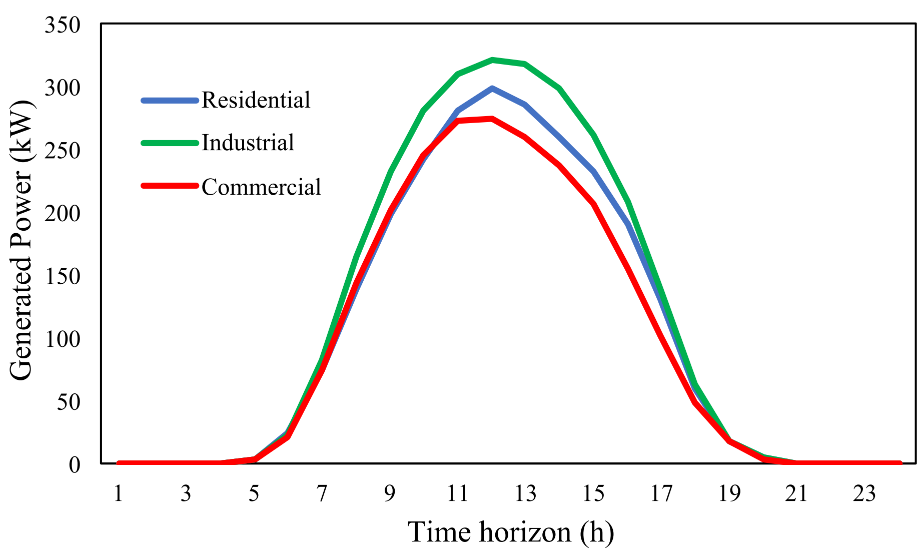

Fig. 3. The PV generation for each sector of the consumers.

Table 1
The general input parameters of the ESS unit.

C^{Deg}	0.07 €/kWh
η_{ch}^{ESS}	88 %
η_{dis}^{ESS}	88 %
ρ	0.5

Table 2
The characteristics of the ESS for three studied cases.

ESS	$E^{ESS,Max}$ (kWh)	$E^{ESS,Min}$ (kWh)	$P_{Max}^{ESS,Ch}$ (kW)	$P_{Max}^{ESS,dis}$ (kW)
Case 1	100	40	20	20
Case 2	200	40	40	40
Case 3	400	40	80	80

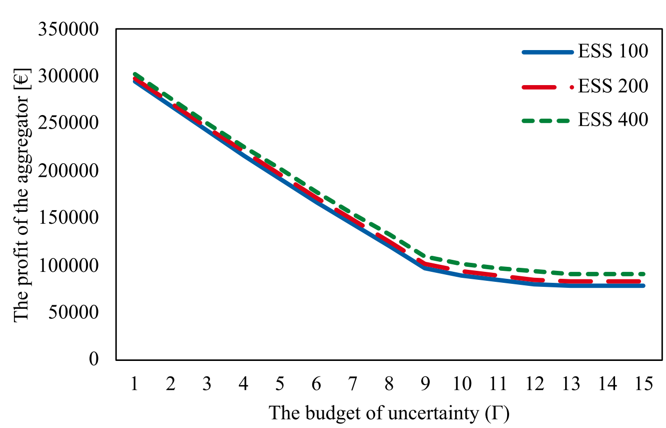

Fig. 4. The sensitivity analysis of the proposed robust model for various ESS capacities.

the worst-case scenarios increases as well. The sensitivity analysis of the proposed robust model for various ESS capacities is depicted in Fig. 4.

Fig. 4 illustrates the profit of the DR aggregator against several values for the budget of uncertainty. There are two significant findings from this result. First, when the level of robustness is low, there is small protection against the uncertain parameter that leads very sharp decrease in the profit of the aggregator. While it reaches a specific budget of uncertainty, i.e., $\Gamma = 9$, the model becomes almost fully robust against the price uncertainty. Hence, this robustness protects the profit of the aggregator from unfavorable scenarios for the electricity market prices.

Meanwhile, it can be seen that when the budget of uncertainty is low, the impact of ESS on the DR aggregator's profit is insignificant. However, as the model becomes more robust against the electricity market prices, the impact of the ESS grows meaningfully. Thus, to show the importance of the ESS in detail, a table provides data regarding the profit of the aggregator in two conditions, which is when our model is less protected against the price uncertainty, $\Gamma = 2$. The following condition is when our proposed model is protected against the uncertain parameter and is fully robust, $\Gamma = 12$, i.e., Table 3. According to the data shown in this table, when there is no ESS, the profit of the aggregator is €266,187 if the budget of uncertainty is equal to two.

By increasing the capacity of the ESS, it can be observed that the aggregator's profit is also increasing. Thus, when the ESS capacity is 400 kWh, the profit of the aggregator is €275,502 which is 3.5 % higher than the case study without any ESS. On the other side, the profit of the aggregator increases by 20 % when the budget of uncertainty is equal to 12. In other words, having a greater capacity for the ESS significantly impacts the DR aggregator's profit, even in the worst-case scenarios.

Therefore, according to the data shown in Fig. 4 and Table 3, the necessity of having an ESS seems more reasonable when the decision-maker desires to protect its profit from the worst-case scenarios and reduces the uncertainty's negative effect. The influence of the implementation of the TOU DR program is expressed in Fig. 5. In this figure, there are two columns for each hour. The first column indicates the initial amount of the total load. Meanwhile, the second column in each hour presents the new load values after the application of the TOU program. Each column shows the share of each sector, such as residential, commercial, and industrial in the total load amount. As presented in this figure, there is an increase in consumption compared to the typical energy usage without consideration of the TOU program during the off-peak period. On the other side, there is a reduction in the consumption of the end-users during the peak period.

Based on these results, the influence of industrial loads in implementing this DR program is almost ten times greater than the reasonable residential and commercial sectors due to the high consumption profile of the industrial loads. Based on this program, the end-users are encouraged to reduce their usage during the peak period and compensate for this reduction during the off-peak period with lower tariffs.

The robust results of the problem when the DR aggregator is trading the day-ahead and balancing markets are depicted in Figs. 6 and 7, respectively. To analyze the scheduling of the aggregator in the short-term markets in a robust condition, the chosen budget of uncertainty is equal to 12. Thus, the profit of the aggregator is protected against the worst-case scenarios that could happen in the day ahead and balancing market prices.

According to Fig. 6, the aggregator purchases energy from the day-ahead market at total capacity. On the other side, when the peak period starts, the aggregator offers the acquired DR to the day-ahead market, which is indicated in the figure as positive values. As presented, the performance of the aggregator in the day-ahead market when ESS maximum capacity is 100 kWh is entirely different from the other case studies. Thus, the trading behavior of the aggregator during the off-peak period of residential and commercial end-users is almost the same. At 18:00, the off-peak of the industrial section starts while the residential and commercial sectors are still in their peak period. Thus, the values shown in the figure from 18:00 to 22:00 are the total energy traded in the day-ahead market. During these hours, the residential and commercial sectors are reducing their demand by participating in the reward-based DR program while the industrial sector increases its usage as it is in the off-peak period. Therefore, the participation of the industrial sector in the reward-based DR program is in the opposite direction of the other sectors from 18:00 to 22:00. After 22:00, the trading behavior becomes similar as all three sectors are again in the same period, i.e., the off-peak period.

Table 3
The profit of aggregator for different ESS cases.

ESS max capacity (kW)	The profit of DR aggregator (€)	
	$\Gamma = 2$	$\Gamma = 12$
0	266,187	77,883
100	268,542	81,060
200	271,458	85,904
400	275,502	93,471

The trading manner of the aggregator in the balancing market is illustrated in Fig. 7. The aggregator trades the imbalance within the balancing market depending on whether it has a deficit or excess. The positive values in the figure indicate that the aggregator has an excess and is offering its surplus energy in the balancing market with the positive imbalance prices that are 10 % lower than the day-ahead market prices. On the other side, the negative values state that the aggregator has a deficit and is required to purchase energy from the balancing market with the negative imbalance prices that are 10 % higher than the day-ahead market prices. Therefore, the DR aggregator trades its energy during the day-ahead market to avoid economic losses. The entity does not desire to purchase its required energy during higher-price periods and sell the excess during lower-priced periods. Hence, based on the data shown in Fig. 7, the aggregator gains more profit when its ESS maximum capacity is 400 kWh. The imbalance values during the peak and off-peak periods are lower than in the other cases. And the behavior of the aggregator with 100 kWh ESS is the worst as in many time slots; it is in the deficit or excess mode.

Finally, the behavior of ESS in the proposed model for three different cases is displayed in Fig. 8. The green bars express the day-ahead market prices, while the lines show the current level of the ESS for different cases. Increasing the energy level means that the ESS is charging, and a decrease in the level of the ESS energy indicates the ESS is discharging. The first apparent outcome is the ESS's dependency on market prices. Thus, when the market prices increase, the ESS is discharging to cover a percentage of the required energy of the aggregator to avoid economic losses. If there was no ESS, the aggregator must purchase the whole amount of energy from the electricity markets at high prices. Therefore, owning an ESS allows the aggregator to charge it during low prices and discharge it during high prices, further supporting the aggregator to maximize its profit.

Another critical point is about the different capacities of the ESS employed by the aggregator. It can be seen that the initial level of energy of Case 3 is higher than the other cases. Hence, Case 3 starts discharging at 5:00 while Case 1 and Case 2 start discharging at 6:00. The main reason for beginning the earlier discharge for Case 3 is that the initial level of energy is high enough to cover the percentage of the aggregator's required energy. It can also charge up to its maximum capacity, which is 400 kWh. The ESS starts discharging for the second time at 18:00, which is when the peak period of the industrial sector ends. Therefore, because of high day-ahead market prices during the afternoon, it is more beneficial for the aggregator with 400 kWh ESS to cover a percentage of its demand.

4. Conclusion

An optimal electricity trading model for a DR aggregator was developed in this work with a focus on the impact of the ESS unit that the aggregator owns. The DR aggregator was responsible for trading the available energy within the wholesale electricity markets, i.e., day-ahead and balancing (real-time) markets. The electricity market prices were assumed to be uncertain and a robust optimization approach was applied as the risk measure for these sources of uncertainty. On the demand side, three types of end-users were considered: residential, commercial, and industrial sectors. Two DR programs were implemented to allow end-users to participate in DR programs actively. Meanwhile, end-users were equipped with rooftop PV panels that could improve their participation in DR programs. In addition, three cases

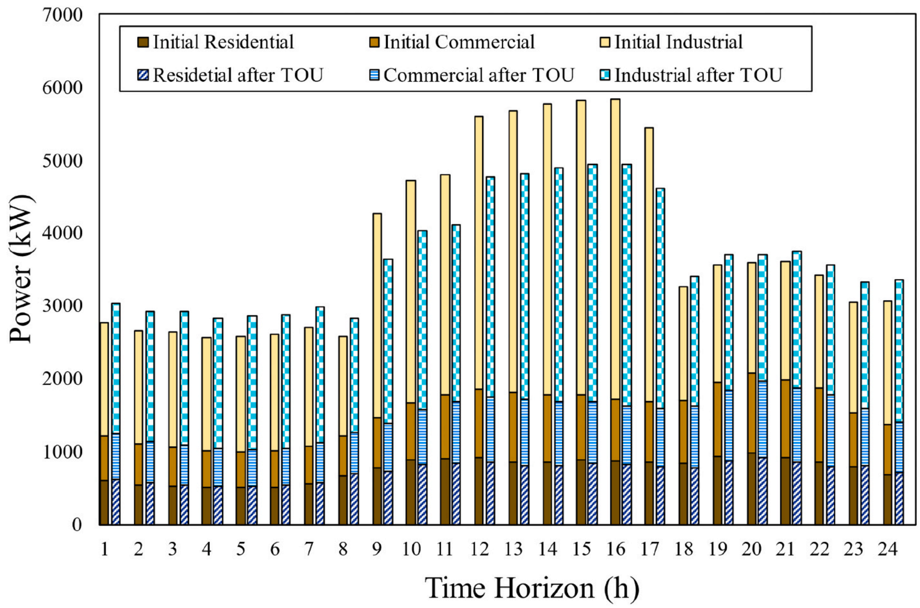

Fig. 5. The influence of the TOU program on the usage amounts of the end-users during the studied time horizon.

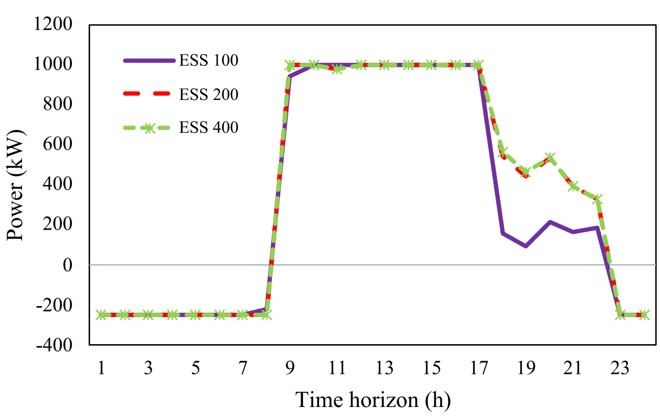

Fig. 6. The power traded in the day-ahead market for various ESS capacities.

with different ESS characteristics were studied to evaluate better the impact of the ESS on the profit of the DR aggregator. Thus, it was demonstrated that an ESS with higher capacity was required as the decision-maker desires to be increasingly protected against unfavorable scenarios for uncertain parameters. By increasing the capacity of the ESS, it is shown that the aggregator's profit also increases. For instance, when the ESS capacity is 400 kWh, the profit of the aggregator is €275,502. This represents a 3.5 % increase compared to the case study without any ESS, assuming a budget of uncertainty (Γ) equal to 2. On the other hand, if the Γ is equal to 12 in a case with an ESS capacity of 400 kWh, the profit of the aggregator increases by 20 % from a case without an ESS unit. In other words, having a greater capacity for the ESS significantly impacts the DR aggregator's profit, even in the worst-case scenarios. Moreover, the results showed that the capacity of the ESS had a significant impact on the trading strategy of the aggregator in day-ahead and balancing markets. Hence, as the aggregator chooses an ESS with higher capacity, its transactions within the day-ahead market will increase. Therefore, the aggregator will require less power to be traded

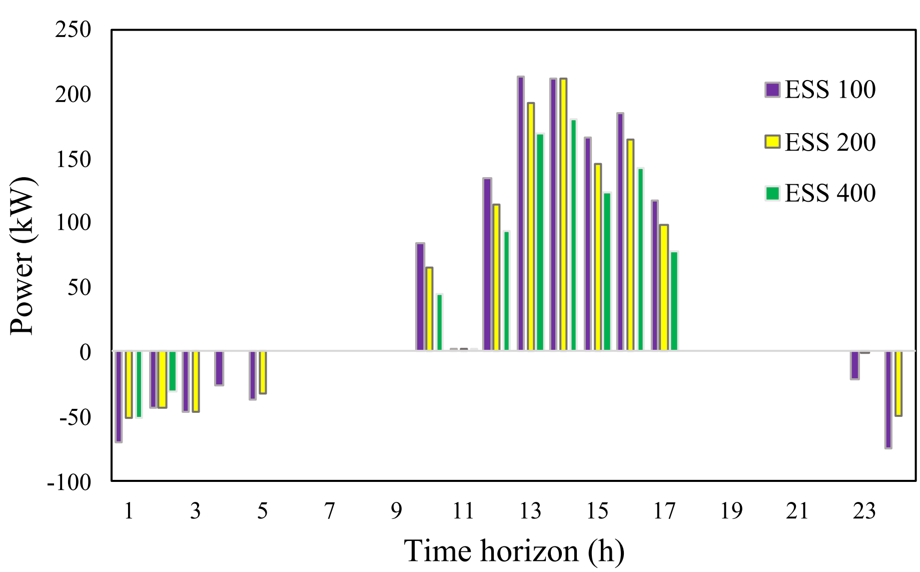

Fig. 7. The power traded in the balancing market for various ESS capacities.

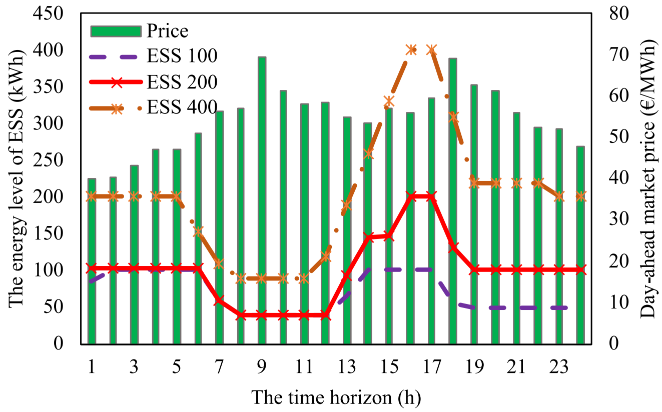

Fig. 8. The optimal performance of the ESS with different capacities based on the DA electricity market prices.

in the balancing market, which is desirable to prevent economic losses. The robust optimization method is suitable for risk-averse and conservative decision-makers who desire to investigate the worst-case scenarios that can occur. However, for better investigation of favorable changes in the uncertain parameter, it is suggested to implement other risk measures such as information-gap decision theory or stochastic programming that can generate several scenarios, including the favorable scenarios for the risk-seeking decision-makers. The role of the DR aggregator entity can be upgraded to a distributed energy resources aggregator that provides the control and management of several components of the energy system such as multiple renewables, on-site distributed generations, and DR programs to this entity. This upgrade can lead to more flexibility for the aggregator and make the model more comprehensive in optimizing its profit which can be worked as future work. Thus, the performance of the ESSs in such a system can be improved as the aggregator has several components under its control.

CRediT authorship contribution statement

Morteza Vahid-Ghavidel: Methodology, Investigation, Data curation, Writing –original draft. **Mohammad Sadegh Javadi:** Formal analysis, Validation. **Sérgio F. Santos:** Conceptualization, Visualization. **Matthew Gough:** Writing – review & editing. **Miadreza Shafie-khah:** Supervision, Validation. **João P.S. Catalão:** Supervision, 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.

Data availability

Data will be made available on request.

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