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# A Robust Model for Portfolio Management of Microgrid Operator in the Balancing Market

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**Abstract:** The stochastic nature of renewable energy resources and consumption has the potential to threaten the balance between generation and consumption as well as to cause instability in power systems. The microgrid operators (MGOs) are financially responsible for compensating for the imbalance of power within their portfolio. The imbalance of power can be supplied by rescheduling flexible resources or participating in the balancing market. This paper presents a robust optimization (RO)-based model to maintain the balance of a portfolio according to uncertainties in renewable power generation and consumption. Furthermore, load reduction (LR) and battery energy storage (BES) are considered flexible resources of the MGO on the consumption side. The model is formulated based on the minimax decision rule that determines the minimum cost of balancing based on the worst-case realizations of uncertain parameters. Through the strong duality theory and big-M theory, the proposed minimax model is transformed into a single-level linear maximization problem. The proposed model is tested on a six-node microgrid test system. The main contributions of the proposed model are presenting a robust model for portfolio management of MGO and using BES and LR to improve the flexibility of microgrid. Simulation results demonstrate that using LR and BES could decrease the balancing cost. However, the optimal portfolio management to compensate for the imbalance of power is highly dependent on the risk preferences of MGO.

**Keywords:** battery energy storage; load reduction; microgrid operator; robust optimization; uncertainty

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## 1. Introduction

The imbalance of power is usually caused by fluctuations in consumption or renewable energy generation and unexpected outages of transmission lines or generating units. In power systems, an imbalance of power can result in frequency excursions that could endanger the stability of power systems. Therefore, grid operators try to maintain the balance between generation and consumption by deploying flexible and fast response resources. The microgrid consists of different types of distributed generation resources, and the MGO is financially responsible for the compensation and settlement of imbalance of power within its generation and consumption portfolio [1]. As shown in Figure 1, after the gate closure for the day-ahead (DA) market, the MGO receives the increasing (decreasing) generation (consumption) or decreasing (increasing) generation (consumption) proposals via upward offers and downward bids of microgrid agents, respectively. Based on the forecasted values of renewable generating power and consumption and received upward offers and downward bids, MGO tries to compensate for the imbalance of power by participating in the balancing market or rescheduling the available flexible resources of its portfolio. The settlement period varies depending on the market design, ranging from 15 min (Austria, Switzerland, and Germany) to 30 min (France and United Kingdom) [2].

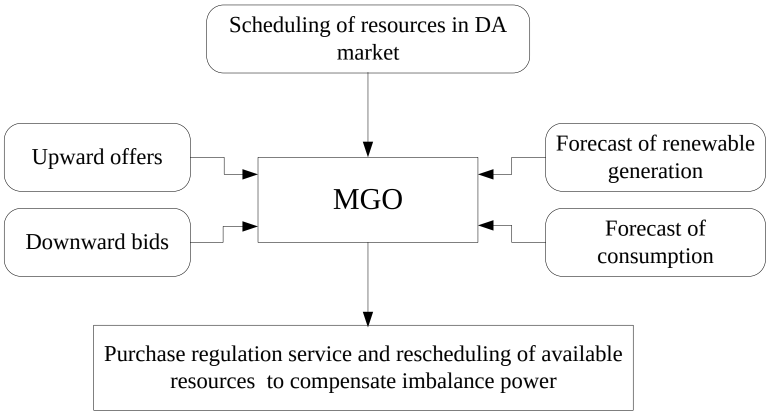


**Figure 1.** Providing the balancing service by MGO.

### 1.1. Literature Review

MGOs need a balance-planning model to determine the optimal strategy for compensating for the imbalance of power over their portfolios. The mechanism of the balancing market and strategies of participants have been analyzed in different literature. In [3], a scheduling model for aggregators who manage the flexible resources of consumers in the balancing market is evaluated. In this work, effects of network constraints on transactions between the aggregator and the transmission system operator (TSO) have been studied. The static study of renewable resources participation level in the balancing market and their impacts on the frequency of the grid are presented in [4]. The proposed hierarchical framework of [5] considers the uncertainty of renewable generating power in the bidding strategy of microgrid aggregators. In the proposed model, the mean-variance method is used to evaluate the impacts of uncertain parameters. In [6], a two-stage model is proposed for the self-scheduling of participants in the balancing market in distribution networks. The follower sub-problem that is formulated as a minimization problem calculates the optimal scheduling of resources. The master sub-problem minimizes the deviation of a scheduled power exchange between the distribution system operator (DSO) and TSO. To solve the proposed model, the two-stage problem is transformed into a single-level optimization problem by Karush–Kuhn–Tucker (KKT) optimality conditions.

The coordination between stochastic consumption, such as by electric vehicles, and the uncertain generation power of wind units to minimize the variations of wind generation is presented in [7]. The participation of distributed resources in the joint DA and real-time markets in the distribution network with multiple microgrids is presented in [8]. To reduce the solution time and increase the convergence speed, the alternating direction method of multipliers (ADMM) approach is proposed to decompose the optimization problem. In [9], a decentralized model is proposed for a DSO to provide a flexible service with dispersed resources. The willingness of market players to participate in the balancing market is studied in the presented model. However, the proposed model only allows the DSO to control the total consumption of the grid. The proposed distributed framework of [10] uses the price sensitivity of consumption to provide flexibility service. In the balancing market, different settlement mechanisms can be used, such as single pricing, dual pricing, additive component, total cost-based pricing, and alternative payment direction [11]. It shall be noted that dual pricing is the most common approach for clearing the balancing market. In this scheme, the market players who put the system off balance (on balance) unintentionally will be penalized (will not be rewarded). Accordingly, the optimal offering strategy of a virtual power plant in the balancing market with the dual pricing mechanism is evaluated in [12]. Based on the presented results [13], the single imbalance pricing leads to less cost for the system operators in comparison with the dual pricing scheme. However, the single pricing scheme could lead to extra profits for participants who deviate from their scheduled values, but their deviations are in the opposite direction of power system imbalances. To maintain the balance of generation and consumption, a demand response program is proposed in [14,15]. According to the presented results, demand response programs decrease the imbalance of power, increase the profit of consumers, and reduce the bills of utilities. In [16], the uncertainty of market price, as well as the degradation cost of energy storage, is considered in the balancing strategy of microgrids.

According to the literature review, there has not been sufficient attention given to the optimal strategy of the MGO for compensating for the imbalance in power. The comparison between the proposed model and the presented model in the literature is demonstrated in Table 1. This work presents a scheduling strategy for the portfolio management of the MGO. The balancing market, battery energy storage (BES), and load reduction (LR) are considered available resources to supply the imbalance of power. It shall be noted that uncertainty modeling and risk management as well as deploying flexible resources are the main challenging issues in the balancing market. Accordingly, stochastic programming [17–19] and robust optimization (RO) [20,21] approaches are proposed in different technical references. In the stochastic approach, the uncertain parameter is modeled by a probabilistic function. A major disadvantage of this approach is that it depends on assumptions and approximations, which are used to derive the probability function. In the RO, uncertain parameters are modeled by variation intervals and the answer is determined based on the worst-case realization of uncertainties. The risk preference of decision-makers or the level of confidence is specified by the budget of uncertainty. Within the confidence level, the determined strategy is robust against variations in uncertain parameters. RO technique has been used for risk management in different power system problems, e.g., distribution network planning [22], unit commitment [23], self-scheduling of wind producers [24], etc. To the best of our knowledge, this method has not been used for the portfolio management of the MGO in the balancing market.

**Table 1.** Comparison Between the Proposed Model and Literature.

| | MG Portfolio Management | Balance Service | Robust Optimization | Flexible Resources |
|---|---|---|---|---|
| [3,5,6,13–15] | x | ✓ | x | ✓ |
| [4,20,21] | x | ✓ | ✓ | ✓ |
| [7] | x | ✓ | x | x |
| [8] | ✓ | x | ✓ | x |
| [9–12,18] | ✓ | ✓ | x | x |
| [16] | ✓ | ✓ | ✓ | x |
| [17] | x | ✓ | x | x |
| [25] | x | ✓ | ✓ | x |
| Proposed model | ✓ | ✓ | ✓ | ✓ |

### *1.2. Proposed Model*

In this work, the RO is used to model variations of consumption and renewable generation in the portfolio management of MGO in the balancing market. The risk preference of MGO is controlled by the budget of uncertainty. According to the defined budget of uncertainty, the strategy of MGO is calculated based on the minimization of the total operational cost under the worst-case scenario. Therefore, the decision-making problem is developed as a min–max problem. The inner maximization and outer minimization problems determine worst-case realizations of uncertain parameters (that maximize the total operational cost) and optimal values of decision variables to minimize balancing cost, respectively. The inner problem is a convex, linear, and continuous function. In this way, the theory of strong duality is addressed to recast the inner maximization problem as a minimization problem. Accordingly, the min–max problem is rewritten as a MILP that can be solved by commercial solvers. The main contributions of this work are:

– This work presents an innovative mathematical model for the portfolio management of MGO in the balancing market. According to the defined procedure, the optimal strategy of a MGO is represented by a min–max problem that is recast as a minimization problem by the strong duality theorem.

– In the RO-based model, the BES and LR are proposed for MGO to provide the required flexibility of the grid. Moreover, the related technical constraints are modeled in portfolio management. The proposed model enables MGO to use these flexible resources to provide upward and downward balancing services.

The rest of the paper is organized as follows. The deterministic formulations are presented in Section 2. The modeling of uncertain parameters and the RO-based objective function are provided in Section 3. Section 4 presents the dual function and the solution procedure. Numerical simulations and discussions are provided in Section 5. Finally, conclusions and future works are presented in Section 6.

## 2. Deterministic Model for MGO

The MGO can supply the imbalance of power by generation and consumption side resources, as follows:

$$\min_{I^{U/D}_{t,n,i/j},\forall t,\forall n,\forall i,\forall j} \sum_{t\in\Omega_T}\sum_{n\in\Omega_N}\left(\sum_{i\in\Omega_G}\lambda^U_{t,n,i}.I^U_{t,n,i}-\lambda^D_{t,n,i}.I^D_{t,n,i}+\sum_{j\in\Omega_C}\lambda^U_{t,n,j}.I^U_{t,n,j}-\lambda^D_{t,n,j}.I^D_{t,n,j}\right) \tag{1}$$

In (1), the upward offers and downward bids on the generation and consumption sides are represented by first and second terms, respectively. The main constraints of the balancing market problem are represented as follows:

$$\sum_{i\in\Omega_G}(\overline{P}_{t,n,i}+I^U_{t,n,i}-I^D_{t,n,i})-\sum_{j\in\Omega_C}(\overline{P}_{t,n,j}+I^D_{t,n,j}-I^U_{t,n,j})-\sum_{m\in\Omega_{n\leftrightarrow m}}B_{nm}.(\theta_{t,n}-\theta_{t,m})=\mathrm{P}^{imb}_{t,n}:\forall t,\forall n \tag{2}$$

$$0\le I^U_{t,n,i}\le I^{U,\max}_{t,n,i}\quad:\forall t,\forall n,\forall i \tag{3}$$

$$0\le I^D_{t,n,i}\le I^{D,\max}_{t,n,i}\quad:\forall t,\forall n,\forall i \tag{4}$$

$$0\le I^U_{t,n,j}\le I^{U,\max}_{t,n,j}\quad:\forall t,\forall n,\forall j \tag{5}$$

$$0\le I^D_{t,n,j}\le I^{D,\max}_{t,n,j}\quad:\forall t,\forall n,\forall j \tag{6}$$

$$-C_{nm}\le B_{nm}.(\theta_{t,n}-\theta_{t,m})\le C_{nm}\ :\forall t,\forall n,\forall m \tag{7}$$

$$-\pi\le\theta_{t,n}\le\pi\quad:\forall t,\forall n \tag{8}$$

$$\theta_{t,n=1}=0\quad:\forall t \tag{9}$$

The equality constraint (2) provides nodal balancing. In the proposed model, the nodal imbalance power ( $\mathrm{P}^{imb}_{n}$ ) is considered a parameter, which is determined by the MGO. Constraints (3)–(6) demonstrate the maximum power of upward offers and downward bids on the generation and consumption sides, respectively. Constraint (7) limits the power flow of lines. The maximum and minimum limitations of nodal voltage angles are represented by (8). The equality constraint (9) demonstrates that the voltage angle of the reference node is set to zero. As mentioned before, the MGO can compensate for the imbalance of power by utilizing flexible resources on the generation and consumption sides. In this work, BES and LR are considered flexible resources on the consumption side. BES can provide the flexibility service by increasing or decreasing the charging and discharging power. The performance of BES is modeled as follows:

$$E_{t=1,n,j}=E_{ini,n,j}+\Delta t.((\overline{P}^{ch}_{t=1,n,j}+P^{ch+}_{t=1,n,j}-P^{ch-}_{t=1,n,j})-(\overline{P}^{dch}_{t=1,n,j}+P^{dch+}_{t=1,n,j}-P^{dch-}_{t=1,n,j}))\ :\forall t,\forall n,\forall j \tag{10}$$

$$E_{t,n,j}=E_{t-1,n,j}+\Delta t.((\overline{P}^{ch}_{t,n,j}+P^{ch+}_{t,n,j}-P^{ch-}_{t,n,j})-(\overline{P}^{dch}_{t,n,j}+P^{dch+}_{t,n,j}-P^{dch-}_{t,n,j}))\ :\forall t,\forall n,\forall j \tag{11}$$

$$0 \le E_{t,n,j} \le E_{n,j}^{\max}.A_{t,n,j}^{\mathrm{B}} \quad : \forall t, \forall n, \forall j \tag{12}$$

$$0 \le P_{t,n,j}^{dch+} \le P_{n,j}^{\mathrm{B},\max}.A_{t,n,j}^{\mathrm{B}}.\nu_{t,n,j} \quad : \forall t, \forall n, \forall j \tag{13}$$

$$0 \le P_{t,n,j}^{dch-} \le P_{n,j}^{\mathrm{B},\max}.A_{t,n,j}^{\mathrm{B}}.\nu_{t,n,j} \quad : \forall t, \forall n, \forall j \tag{14}$$

$$0 \le P_{t,n,j}^{ch+} \le P_{n,j}^{\mathrm{B},\max}.A_{t,n,j}^{\mathrm{B}}.(1-\nu_{t,n,j}) \quad : \forall t, \forall n, \forall j \tag{15}$$

$$0 \le P_{t,n,j}^{ch-} \le P_{n,j}^{\mathrm{B},\max}.A_{t,n,j}^{\mathrm{B}}.(1-\nu_{t,n,j}) \quad : \forall t, \forall n, \forall j \tag{16}$$

$$0 \le \bar{P}_{t,n,j}^{dch} + P_{t,n,j}^{dch+} - P_{t,n,j}^{dch-} \le P_{n,j}^{\mathrm{B},\max}.A_{t,n,j}^{\mathrm{B}}.\nu_{t,n,j} \quad : \forall t, \forall n, \forall j \tag{17}$$

$$0 \le \bar{P}_{t,n,j}^{ch} + P_{t,n,j}^{ch+} - P_{t,n,j}^{ch-} \le P_{n,j}^{\mathrm{B},\max}.A_{t,n,j}^{\mathrm{B}}.(1-\nu_{t,n,j}) \quad : \forall t, \forall n, \forall j \tag{18}$$

Equations (10)–(12) represent the state of energy and energy capacity of batteries, respectively. It shall be noted that the availability of BES on the consumption side is modeled by the binary parameter $A^{B}$ . Constraints (13)–(18) enforce the upper capacities of upward offers and downward bids in different operational modes, respectively. BES supplies the upward balancing service by increasing/decreasing discharging/charging power. Similarly, the downward balancing service can be provided by decreasing discharging power or increasing the charging power. In the proposed model, it is supposed that the operation mode of BES in the DA market is not changed within the balancing period. Therefore, the status binary variable of BES ( $\nu$ ) is considered a parameter.

The LR is another demand-side resource that can be used by MGO to provide the balancing service. The LR can be represented, as follows:

$$0 \le \Delta L_{t,n,j} \le \Delta L_{n,j}^{\max}.A_{t,n,j}^{L} \quad : \forall t, \forall n, \forall j \tag{19}$$

Constraint (19) limits the maximum capacity of the deployed LR. Moreover, the availability of LR on the consumption side is modeled by the binary parameter $A^{L}$.

On the consumption side, the MGO can provide an upward balance service by increasing the discharging power, decreasing the charging power, and deploying LR. Similarly, the downward balance can be provided by decreasing the discharging power or increasing the charging power. Accordingly, $I_{t,n,j}^{U}$ and $I_{t,n,j}^{D}$ in (1), (2), (5), and (6) are replaced by (20) and (21), as follows:

$$I_{t,n,j}^{U} = P_{t,n,j}^{dch+} + P_{t,n,j}^{ch-} + \Delta L_{t,n,j} \quad : \forall t, \forall n, \forall j \tag{20}$$

$$I_{t,n,j}^{D} = P_{t,n,j}^{dch-} + P_{t,n,j}^{ch+} \quad : \forall t, \forall n, \forall j \tag{21}$$

Accordingly, the optimal deterministic strategy of MGO is represented by a linear problem that the decision variables of optimization problem are represented by $\Omega_{DE}$ ={ $I_{t,n,i}^{U}$ , $I_{t,n,i}^{D}$ , $P_{t,n,j}^{dch+}$ , $P_{t,n,j}^{dch-}$ , $P_{t,n,j}^{ch+}$ , $P_{t,n,j}^{ch-}$ , $\Delta L_{t,n,j}$ , $\theta_{t,n}$ , $E_{t,n,j} : \forall t, \forall n, \forall i, \forall j$ }. In the next section, the uncertain parameters are formulated, and the RO-based model is presented.

## 3. Robust Scheduling Model for Portfolio Management of MGO

The generating power of renewable resources and demand are two main sources of uncertainty that are considered in this study. In other words, variations of consumption and generating power of renewable resources lead to the nodal imbalance of power, as follows:

$$\sum_{d\in\Omega_D} P_{t,n,d} - \sum_{r\in\Omega_R} P_{t,n,r} = \mathrm{P}_{t,n}^{imb} : \lambda_{t,\mathrm{n}}, \forall t, \forall n \tag{22}$$

In the RO, the possible realizations of an uncertain parameter are modeled by the variation interval. Therefore, the realization sets of uncertain renewable generating power and consumption are defined by (23) and (24), respectively.

$$-\Delta P_{t,n,r} \le P_{t,n,r} - \tilde{P}_{t,n,r} \le \Delta P_{t,n,r} : \mu_{t,n,r}^{\max}, \mu_{t,n,r}^{\min}, \forall t, \forall n, \forall r \tag{23}$$

$$-\Delta P_{t,n,d} \le P_{t,n,d} - \tilde{P}_{t,n,d} \le \Delta P_{t,n,d} : \mu_{t,n,d}^{\max}, \mu_{t,n,d}^{\min}, \forall t, \forall n, \forall d \tag{24}$$

where $\tilde{P}$ and $\Delta P$ are the expected and maximum variation interval of uncertain power.

The value of the budget of uncertainty determines the total variation intervals of uncertain parameters. This parameter represents the conservativeness of the decision-maker based on the normalized values of uncertain parameters. Accordingly, the uncertainty set is represented as follows:

$$\Omega_{UV} = \{\Omega_R, \Omega_D\} \in \left\{ \sum_{t\in\Omega_T} \sum_{n\in\Omega_N} \Big( \sum_{r\in\Omega_R} \left| \frac{P_{t,n,r} - \tilde{P}_{t,n,r}}{\Delta P_{t,n,r}} \right| + \sum_{d\in\Omega_D} \left| \frac{P_{t,n,d} - \tilde{P}_{t,n,d}}{\Delta P_{t,n,d}} \right| \Big) \le \mathrm{B.U.} \right\} : \mu_{B.U}^{\max}, \mu_{B.U}^{\min} \tag{25}$$

The risk-averse MGOs choose a higher budget of uncertainty to consider more realizations of uncertain parameters in the decision-making problem and vice versa. In other words, for $\mathrm{B.U.} = 0$ the risk of uncertainty is neglected, and the optimal strategy is determined based on the expected values of renewable generating power and demand [25]. In the RO approach, the decision is determined based on the worst-case realizations of uncertainties. Accordingly, in real-time operation, it can be guaranteed that the results of the determined strategy are not worse than the expected values. That is the reason that the results of RO are more conservative in comparison with stochastic programming. The objective function (1) is reformulated as a min–max problem, as follows:

$$\begin{aligned} &\min_{\Omega_{DE}} \max_{\Omega_{UV}} \sum_{t\in\Omega_T} \sum_{n\in\Omega_N} \left( \sum_{i\in\Omega_G} \lambda_{t,n,i}^{U}.I_{t,n,i}^{U} - \lambda_{t,n,i}^{D}.I_{t,n,i}^{D} + \sum_{j\in\Omega_C} \lambda_{t,n,j}^{U}.I_{t,n,j}^{U} - \lambda_{t,n,j}^{D}.I_{t,n,j}^{D} \right) \\ &s.t : (2) - (25) \end{aligned} \tag{26}$$

According to the worst-case realizations of uncertainty in (26), the set of primal decision variables is determined in a way that minimizes the balancing cost. In (22)-(25), $\Omega_{UV} = \{\lambda_{t,\mathrm{n}}, \mu_{t,n,r}^{\max}, \mu_{t,n,r}^{\min}, \mu_{t,n,d}^{\max}, \mu_{t,n,d}^{\min}, \mu_{B.U}^{\max}, \mu_{B.U}^{\min}\}$ is the set of dual variables, which is used to recast the min–max problem as a min–min problem. The solution procedure is represented in the next section.

## 4. Solution Procedure

As seen in (26), the inner optimization sub-problem is linear and convex. According to the strong duality theorem, the dual gap is equal to zero and the optimal value of the dual function (minimization) is the lower bound of the primal function (maximization). Therefore, the min–max problem is transformed into a min–min (minimization) problem by substituting the inner minimization problem with its dual problem. The objective function of the MGO is reformulated as a minimization problem, as follows:

$$
\begin{aligned}
&\text{Objective function} = \min_{\Omega_{DE},\Omega_{DV}} \\
&\sum_{t\in\Omega_T}\sum_{n\in\Omega_N}\left(\sum_{i\in\Omega_G}\lambda^{U}_{t,n,i}.I^{U}_{t,n,i}-\lambda^{D}_{t,n,i}.I^{D}_{t,n,i}+\sum_{j\in\Omega_C}\lambda^{U}_{t,n,j}.I^{U}_{t,n,j}-\lambda^{D}_{t,n,j}.I^{D}_{t,n,j}\right)+ \\
&\sum_{t\in\Omega_T}\sum_{n\in\Omega_N}\sum_{r\in\Omega_R}(\Delta P_{t,n,r}-\tilde{P}_{t,n,r}).\mu^{\max}_{t,n,r}+(\tilde{P}_{t,n,r}-\Delta P_{t,n,r}).\mu^{\min}_{t,n,r}+ \\
&\sum_{t\in\Omega_T}\sum_{n\in\Omega_N}\sum_{d\in\Omega_D}(-\Delta P_{t,n,d}-\tilde{P}_{t,n,d}).\mu^{\max}_{t,n,d}+(\tilde{P}_{t,n,d}-\Delta P_{t,n,d}).\mu^{\min}_{t,n,d}+\sum_{t\in\Omega_T}\sum_{n\in\Omega_N}\mathrm{P}^{imb}_{t,n}.\lambda_{t,\mathrm{n}} \\
&(-\mathrm{B.U.}-\sum_{t\in\Omega_T}\sum_{n\in\Omega_N}(\sum_{r\in\Omega_R}\frac{\tilde{P}_{t,n,r}}{\Delta P_{t,n,r}}+\sum_{d\in\Omega_D}\frac{\tilde{P}_{t,n,d}}{\Delta P_{t,n,d}})).\mu^{\max}_{B.U}+ \\
&(-\mathrm{B.U.}+\sum_{t\in\Omega_T}\sum_{n\in\Omega_N}(\sum_{r\in\Omega_R}\frac{\tilde{P}_{t,n,r}}{\Delta P_{t,n,r}}+\sum_{d\in\Omega_D}\frac{\tilde{P}_{t,n,d}}{\Delta P_{t,n,d}})).\mu^{\min}_{B.U}
\end{aligned}
\tag{27}
$$

Subject to the following constraints:

$$-\lambda_{t,\mathrm{n}}-\mu^{\max}_{t,n,r}+\mu^{\min}_{t,n,r}-\frac{\mu^{\max}_{B.U}}{\Delta P_{t,n,r}}+\frac{\mu^{\min}_{B.U}}{\Delta P_{t,n,r}}\geq 0:\forall t,\forall n,\forall r \tag{28}$$

$$\lambda_{t,\mathrm{n}}-\mu^{\max}_{t,n,d}+\mu^{\min}_{t,n,d}-\frac{\mu^{\max}_{B.U}}{\Delta P_{t,n,d}}+\frac{\mu^{\min}_{B.U}}{\Delta P_{t,n,d}}\geq 0\forall t,\forall n,\forall d \tag{29}$$

The dual constraints are represented by Equations (28) and (29). The final model is a MILP problem that is solved by available linear solvers.

## 5. Numerical Results

In this section, the proposed model is tested on a six-node microgrid test system that is shown in Figure 2 [26]. All lines except the line between nodes 2 and 4 have a reactance and capacity of 0.13 p.u. and 100 MW, respectively. The reactance and capacity of line 2–4 are 0.20 p.u. and 15 MW, respectively. Moreover, the expected values of two loads D3 and D6, generation of the wind unit, and amount of reducible loads LR3 and LR6 are 170, 190, 50, 15, and 20 MW, respectively. The upward offers of LR3 and LR6 are 33 and 37 \$/MWh, respectively. In this work, the test system has been extended to include demand-side flexibility resources. The scheduled generating power, upward offers, and downward bids are provided in Table 2 [26]. The data of BESs are presented in Table 3 [27]. For BES 2, the day-ahead offer price 27 \$/MWh is considered.

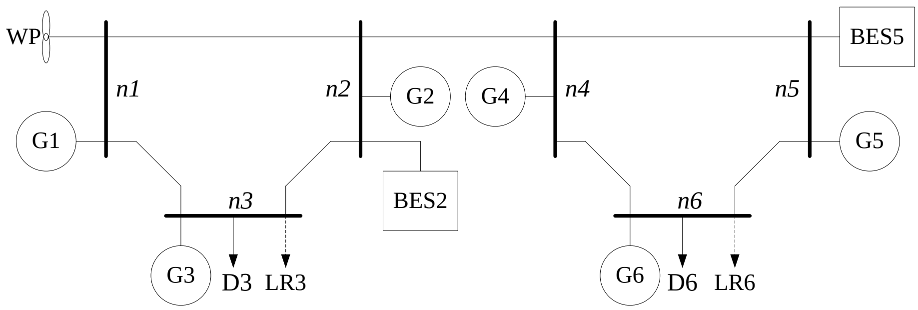


**Figure 2.** Six-node test system.

**Table 2.** DA schedule, upward offers and downward bids of generating units.

| $i$ | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| $\bar{P}$(MW) | 70 | 50 | 50 | 100 | 15 | 100 |
| $I^U$ (MW) | 0 | 20 | 0 | 20 | 20 | 0 |
| $I^D$ (MW) | 0 | 30 | 0 | 30 | 40 | 0 |
| $\lambda^U$ ($/MWh) | - | 35 | - | 38 | 40 | - |
| $\lambda^D$ ($/MWh) | - | 27 | - | 28 | 34 | - |
| DA offer ($/MWh) | 30 | 25 | 10 | 20 | 35 | 31 |

**Table 3.** Data of BES.

| $i$ | $E^{\max}$ (MWh) | $P^{B,\max}$ (MW) | $\bar{P}$(MW) | Mode |
|---|---|---|---|---|
| BES2 | 50 | 50 | 30 | Discharging |
| BES5 | 50 | 50 | 20 | Charging |
| $I^U$ (MW) | $I^D$ (MW) | $\lambda^U$ ($/MWh) | $\lambda^D$ ($/MWh) | $I^U$ (MW) |
| BES2 | 15 | 15 | 32 | 29 |
| BES5 | 10 | 10 | 36 | 32 |

The capacity limitation of the line between nodes 2 and 4 leads to different nodal prices in the test system. Simulation results demonstrate that the marginal prices for Area1 (n1, n2, and n3) and Area2 (n4, n5, and n6) are 30 and 35 $/MWh, respectively. Figure 3 shows realizations of wind generating power, D3, and D6 in real-time for the settlement period of 15 min. It shall be noted that the variation intervals of W.P., D3, and D6 are 20, 15, and 20 MW, respectively.

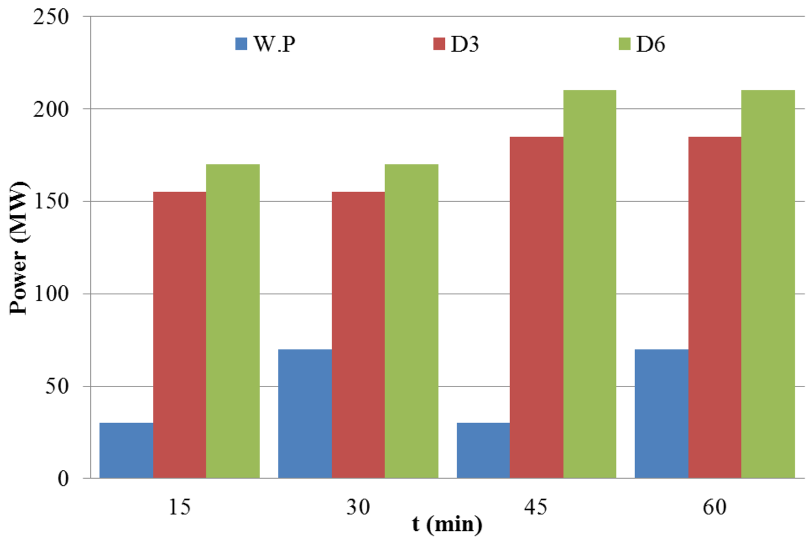


**Figure 3.** Variations of wind power and demand.

Participation levels of flexible resources in the balancing service are presented in Table 4. According to Table 3, the operation modes of BES 2 and BES 5 are discharging and charging, respectively. Therefore, the positive/negative power values for BES2 represent increasing/decreasing the discharging power. Similarly, for BES5 the positive/negative values show decreasing/increasing the charging power. Additionally, the balancing prices in Area1 and Area2 are shown in Figure 4. The presented results demonstrate that the capacity limitation of the line between n2 and n4 increases the balancing cost in Area 2 significantly.

**Table 4.** Scheduling of flexible resources in balancing market (MW).

| $\Delta t$ $(min)$ | G2 | G4 | G5 | LR3 | LR6 | BES2(Dch) | BES5(Ch) |
|---|---|---|---|---|---|---|---|
| 0–15 | 0 | 0 | −20 | 0 | 0 | 5 | 0 |
| 15–30 | −20 | 0 | −20 | 0 | 0 | −15 | 0 |
| 30–45 | 5 | 0 | 0 | 15 | 10 | 15 | 10 |
| 45–60 | 0 | 0 | 0 | 0 | 10 | −5 | 10 |

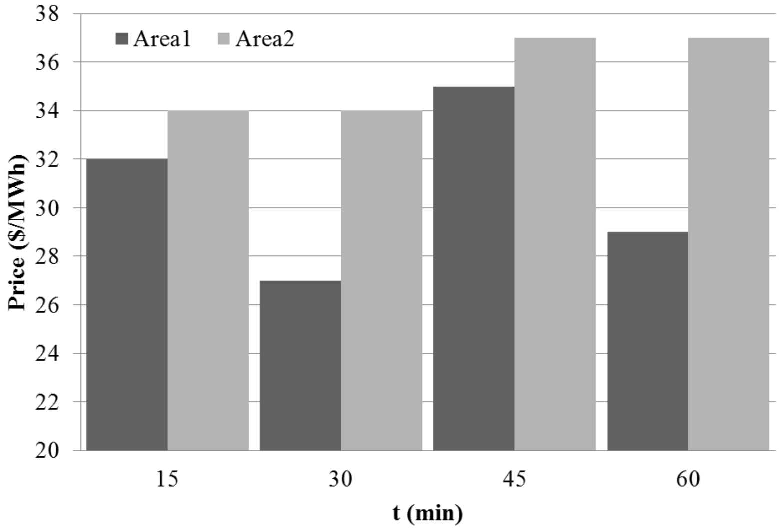


**Figure 4.** Balancing prices in Area1 (n1,n2,n3) and Area2 (n4,n4,n6).

To evaluate the impact of line capacity on balancing settlement, the balance prices for different capacities of line n2-n4 are presented in Figure 5. In this work, clearing the day-ahead market is not considered. Simulation results show that by increasing the capacity of the tie line between n2 and n4, the MGO can utilize flexible resources more effectively and, consequently, reduce balancing costs.

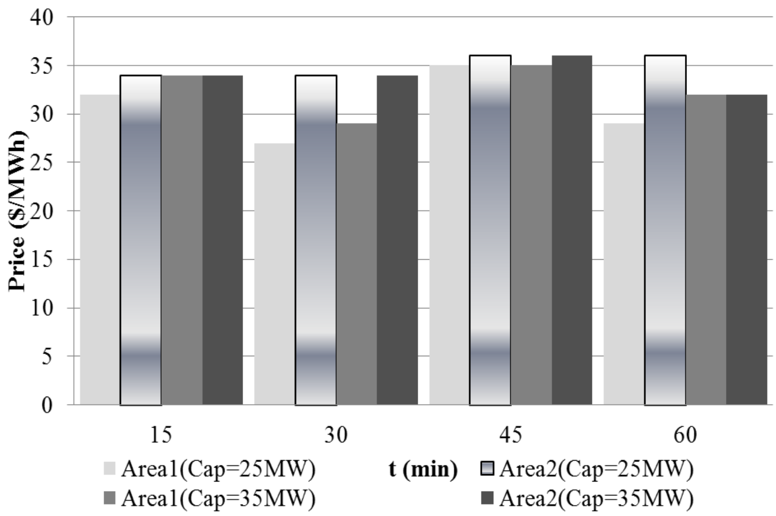


**Figure 5.** Impact of tie-line capacity on balance price.

This study uses a dual pricing scheme to calculate the cost and payment to each participant, which is provided in Table 5. The upward/downward balance price is higher/lower than the day-ahead price. Therefore, participation in the balancing market leads to a higher profit for flexible resources. For example, within the period (15–30), G2 sells back 5 MWh to the MGO. The income of G2 in this period is $150. In other words, G2 gains more profit. Simulation results demonstrate that, in the dual pricing scheme, increasing the uncertain demand and decreasing the renewable generation leads to the worst-case situation for the MGO (period 30–45).

**Table 5.** Cost and payment of resources in the balancing market ($).

| | 0–15 (min) | 15–30 (min) | 30–45 (min) | 45–60 (min) |
|---|---|---|---|---|
| G2 | 0 | −135 | 0 | 0 |
| G4 | 0 | 0 | 0 | 0 |
| G5 | −170 | −170 | 0 | 0 |
| LR3 | 0 | 0 | 131.25 | 0 |
| LR6 | 0 | 0 | 92.5 | 92.5 |
| BES2 | 40 | −101.25 | 131.25 | 0 |
| BES5 | 0 | 0 | 92.5 | 92.5 |
| D3 | 112.5 | 101.25 | −131.25 | −108.75 |
| D6 | 160 | 160 | 185 | 185 |
| WP | −160 | 135 | −175 | 145 |

Impacts of the budget of uncertainty variations (B.U.) on the balancing cost and price are demonstrated in Figure 6. As discussed previously, by increasing the budget of uncertainty, more realizations of uncertain parameters are considered in the optimization problem. To compensate for real-time variations of uncertain parameters, MGO will use more expensive flexible units. As shown in Figure 6, a higher budget of uncertainty leads to a higher balancing price and cost. It shall be noted that in the proposed model, the centralized optimization approach is used. Accordingly, increasing the solution time is the main limitation of the model that could happen in large-scale problems. Comparison with [18,19] demonstrates that the simulation results are independent of the approximations and assumptions which are used to model the uncertain parameters. In other words, the results are robust against the forecasting scenarios. However, in the presented model, the impacts of the conservativeness of the decision-maker or B.U. shall be considered in choosing the optimal strategy. Additionally, comparing the results of the proposed portfolio-management strategy with the individual participation of flexible resources [25] demonstrates that the proposed model decreases the operational cost of a microgrid by 11.2%. The main reason for the cost reduction is the supplying of the required flexibility of microgrids by the local resources.

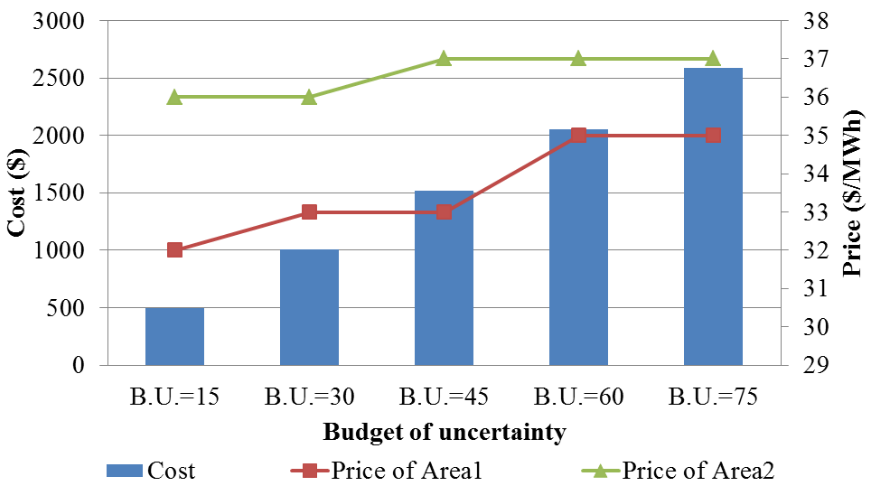


**Figure 6.** Impact of budget of uncertainty (MW) on balancing cost and price.

## 6. Conclusions

This paper presents an RO-based model for MGO to manage its portfolio in the balancing market. In this model, demand and renewable generating power are considered uncertain resources. Furthermore, LRs and BESs are proposed as demand-side flexible resources that can be used by the MGO to compensate for the imbalance of power. In this paper, the optimal scheduling of resources is determined based on the worst-case scenario of uncertainties. Accordingly, the objective function is represented by a min–max problem. To solve the proposed problem, the strong duality theorem is used to recast the inner maximization problem as a minimization problem. Moreover, the budget of uncertainty is addressed to control the conservativeness of MGO. Numerical simulations show that increasing the conservativeness of MGO leads to a higher balancing cost. Moreover, the limitations of microgrids, such as the capacity of lines, increase the balancing cost significantly. However, the MGO can relieve the negative impacts of line congestion by deploying the LR resources. Moreover, the BES can participate in the balancing market in both charging and discharging modes that improve the flexibility of the grid. Comparison with the available stochastic models demonstrates that the results of the presented robust model are independent of initial approximations and assumptions which are used to model the uncertain parameters. Moreover, deploying flexible resources such as LR and BES decreases the flexibility cost of microgrids. In future works, to improve the accuracy of the results, the authors will consider AC economic dispatch constraints and limitations of reactive power in the robust portfolio management problem.

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## Nomenclature

**Index and set**

| | |
|---|---|
| $i, \Omega_G$ | Index and set of generation resources. |
| $j, \Omega_C$ | Index and set of consumption resources. |
| $r(r'), \Omega_R$ | Index and set of uncertain renewable generation. |
| $d(d'), \Omega_D$ | Index and set of uncertain demand. |
| $n, \Omega_N$ | Index and set of nodes. |

| | |
|---|---|
| $m, \Omega_{n \leftrightarrow m}$ | Index and set of nodes which are connected to $n$. |
| $t, \Omega_T$ | Index and set of time. |
| $\Omega_{UV}$ | Set of uncertain variables. |
| $\Omega_{DE}$ | Set of decision variables. |
| $\Omega_{DV}$ | Set of dual variables. |

**Parameter**

| | |
|---|---|
| $\lambda^{U/D}$ | Up/down balance price ($/MWh). |
| $\tilde{P}_r$ | Expected value of renewable power (MW). |
| $\tilde{P}_d$ | Expected value of demand (MW). |
| $\Delta P_r$ | Maximum variation intervals of renewable power (MW). |
| $\Delta P_d$ | Maximum variation intervals of demand (MW). |
| $\Delta t$ | Time interval (min). |
| $\overline{P}$ | Scheduled value of power (MW). |
| $P_n^{imb}$ | Expected nodal imbalance power (MW). |
| $B_{nm}$ | Susceptance between $n$ and $m$ (siemens). |
| $C$ | Capacity of line (MW). |
| $A^{B/L}$ | Binary parameter that represents availability of battery/reducible load (1: available, 0: else). |
| $V$ | Binary parameter that represents operation mode of battery (1: discharging, 0: charging). |
| B.U. | Budget of uncertainty. |
| $I^{U/D,\max}$ | Maximum upward offer/downward bids (MW). |
| $P^{B,\max}$ | Power capacity of battery (MW). |
| $E^{\max}$ | Energy capacity of battery (MWh). |

**Variable**

| | |
|---|---|
| $I^{U/D}$ | Upward offer/downward bid (MW). |
| $\theta$ | Angle of voltage (rad). |
| $P_r$ | Realization of renewable power (MW). |
| $P_d$ | Realization of renewable power/demand (MW). |
| $E$ | Energy level of battery (MWh). |
| $P^{ch+/-}$ | Increased/decreased charging power (MW). |
| $P^{dch+/-}$ | Increased/decreased discharging power (MW). |
| $\Delta L$ | Flexible consumption (MW). |
| $\lambda, \mu$ | Dual variables. |

**Abbreviation**

| | |
|---|---|
| ADMM | Alternating direction method of multipliers |
| BES | Battery energy storage |
| DA | Day ahead |
| MGO | Microgrid operator |
| LR | Load reduction |
| MILP | Mixed integer linear programming |
| KKT | Karush–Kuhn–Tucker |
| RO | Robust optimization |
| TSO | Transmission system operator |

## References


1. Lezama, F.; Soares, J.; Faia, R.; Vale, Z.; Kilkki, O.; Repo, S.; Segerstam, J. Bidding in local electricity markets with cascading wholesale market integration. *Int. J. Electr. Power Energy Syst.* **2021**, *131*, 107045.
2. Scherer, M.; Haubensak, O.; Staake, T. Assessing distorted trading incentives of balance responsible parties based on the example of the Swiss power system. *Energy Policy* **2015**, *86*, 792–801.
3. Hu, J.; Yang, G.; Ziras, C.; Kok, K. Aggregator operation in the balancing market through network-constrained transactive energy. *IEEE Trans. Power Syst.* **2019**, *34*, 4071–4080.
4. Khojasteh, M.; Faria, P.; Vale, Z. Scheduling of battery energy storages in the joint energy and reserve markets based on the static frequency of power system. *J. Energy Storage* **2022**, *49*, 104115.
5. Pei, W.; Du, Y.; Deng, W.; Sheng, K.; Xiao, H.; Qu, H.; Optimal bidding strategy and intramarket mechanism of microgrid aggregator in real-time balancing market. *IEEE Trans. Industr. Inform.* **2016**, *12*, 587–596.
6. Du, Y.; Li, F. A hierarchical real-time balancing market considering multi-microgrids with distributed sustainable resources. *IEEE Trans. Sustain. Energy* **2020**, *11*, 72–83.
7. Vayá, M.G.; Andersson, G. Self scheduling of plug-in electric vehicle aggregator to provide balancing services for wind power. *IEEE Trans. Sustain. Energy* **2016**, *7*, 886–899.
8. Jalali, M.; Zare, K.; Seyedi, H.; Alipour, M.; Wang, F. Distributed model for robust real-time operation of distribution systems and microgrids. *Electr. Power Syst. Res.* **2019**, *177*, 105985.
9. Morstyn, T.; Teytelboym, A.; McCulloch, M.D. Designing decentralized markets for distribution system flexibility. *IEEE Trans. Power Syst.* **2019**, *34*, 2128–2139.
10. De Paola, A.; Angeli, D.; Strbac, G. Price-based schemes for distributed coordination of flexible demand in the electricity market. *IEEE Trans. Smart Grid* **2017**, *8*, 3104–3116.
11. Van der Veen, R.A.; Abbasy, A.; Hakvoort, R.A. Agent-based analysis of the impact of the imbalance pricing mechanism on market behavior in electricity balancing markets. *Energy Econ.* **2012**, *34*, 874–881.
12. Mazzi, N.; Trivella, A.; Morales, J.M. Enabling active/passive electricity trading in dual-price balancing markets. *IEEE Trans. Power Syst.* **2019**, *34*, 1980–1990.
13. Shinde, P.; Hesamzadeh, M.R.; Date, P.; Bunn, D.W. Optimal dispatch in a balancing market with intermittent renewable generation. *IEEE Trans. Power Syst.* **2021**, *36*, 865–878.
14. Wang, S.; Bi, S.; Zhang, Y.J.A. Demand response management for profit maximizing energy loads in real-time electricity market. *IEEE Trans. Power Syst.* **2018**, *33*, 6387–6396.
15. Talari, S.; Shafie-Khah, M.; Chen, Y.; Wei, W.; Gaspar, P.D.; Catalao, J.P. Real-time scheduling of demand response options considering the volatility of wind power generation. *IEEE Trans. Sustain. Energy* **2019**, *10*, 1633–1643.
16. Liu, Y.; Li, Y.; Gooi, H.B.; Jian, Y.; Xin, H.; Jiang, X.; Pan, J. Distributed robust energy management of a multimicrogrid system in the real-time energy market. *IEEE Trans. Sustain. Energy* **2019**, *10*, 396–406.
17. Song, M.; Amelin, M.; Wang, X.; Saleem, A. Planning and operation models for EV sharing community in spot and balancing market. *IEEE Trans. Smart Grid* **2019**, *10*, 6248–6258.
18. Hakimi, S.M.; Hasankhani, A.; Shafie-khah, M.; Catalão, J.P. Stochastic planning of a multi-microgrid considering integration of renewable energy resources and real-time electricity market. *Appl. Energy* **2021**, *298*, 117215.
19. Appino, R.R.; Wang, H.; Ordiano, J.A.G.; Faulwasser, T.; Mikut, R.; Hagenmeyer, V.; Mancarella, P. Energy-based stochastic MPC for integrated electricity-hydrogen VPP in real-time markets. *Electr. Power Syst. Res.* **2021**, *195*, 106738.
20. Xie, Y.; Guo, W.; Wu, Q.; Wang, K. Robust MPC-based bidding strategy for wind storage systems in real-time energy and regulation markets. *Int. J Electr. Power Energy Syst.* **2021**, *124*, 106361.
21. Khojasteh, M.; Faria, P.; Vale, Z. A robust model for aggregated bidding of energy storages and wind resources in the joint energy and reserve markets. *Energy* **2022**, *238*, 121735.
22. Amjady, N.; Attarha, A.; Dehghan, S.; Conejo, A.J. Adaptive robust expansion planning for a distribution network with DERs. *IEEE Trans. Power Syst.* **2018**, *33*, 1698–1715.
23. Amjady, N.; Dehghan, S.; Attarha, A.; Conejo, A.J. Adaptive robust network-constrained AC unit commitment. *IEEE Trans. Power Syst.* **2017**, *32*, 672–683.
24. Attarha, A.; Amjady, N.; Dehghan, S.; Vatani, B. Adaptive robust self-scheduling for a wind producer with compressed air energy storage. *IEEE Trans. Sustain. Energy* **2018**, *9*, 1659–1671.
25. Khojasteh, M.; Faria, P.; Vale, Z. Energy-constrained model for scheduling of battery storage systems in joint energy and ancillary service markets based on the energy throughput concept. *Int. J. Electr. Power Energy Syst.* **2021**, *133*, 107213.
26. Delikaraoglou, S.; Morales, J.M.; Pinson, P. Impact of inter-and intra-regional coordination in markets with a large renewable component. *IEEE Trans. Power Syst.* **2016**, *31*, 5061–5070.
27. Vespermann, N.; Delikaraoglou, S.; Pinson, P. Offering strategy of a price-maker energy storage system in day-ahead and balancing markets. In Proceedings of the IEEE Manchester PowerTech, Manchester, UK, 18–22 June 2017.