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A robust model for daily operation of grid-connected microgrids during normal conditions

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Bi-level optimization;
Electricity market;
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Robust optimization;
Uncertainty.

Abstract. Microgrids (MGs) are designed to serve their hosting critical load in an island mode in case of major events. However, in normal conditions when MGs are in a grid-connected mode, they may face an opportunity to achieve financial profits through optimization of the operation of energy resources and proper participation in wholesale markets. This paper proposes a model to optimize the participation of MGs in the markets and operation of energy resources. Since MGs usually host renewable energy resources, making decisions without considering uncertainties may put MGs at risk. Therefore, the model considers uncertainties associated with the generation of renewable Distributed Generation (DGs), demand, and market prices via robust optimization technique. The model is formulated as a bi-level max-min optimization problem. The problem is solved in two iterative steps. In the first step, a Genetic Algorithm (GA) finds the worst situation of uncertain parameters such that MG profit is minimized. Then, a mixed-integer linear problem is solved to maximize the profit over MG decision variables considering the values determined in the first step. The steps are iterated to reach convergence to the best solution. To confirm the performance of the approach, it is applied to a typical MG and the results are reported.

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1. Introduction

Microgrid (MG) is defined as a group of interconnected loads, renewable and/or non-renewable Distributed Generation (DG) units, and Energy Storage Systems (ESSs), and it can be employed in both island and grid-connected modes [1]. Since MGs are usually designed to be able to serve their hosting critical load during major events, they may have an opportunity to participate in wholesale markets in the hope of achieving profits in normal conditions. However, the profit is subject to risk by volatile market prices, output

power of intermittent renewable DGs, and uncertain demand. The aim of this article is to present a decision model for a private MG owner who optimizes decisions on participating in the wholesale market, Load Curtailment (LC), and DG units' schedules.

So far, several research studies have discussed MG scheduling and its interactions with wholesale markets. A comprehensive review of the literature on MG operational activities was presented in [2]. Generally, the works presented in this area can be classified into two groups: articles focusing on operational issues and those focusing on market actions. In the former group, the MG scheduling problem minimizes operation costs of local DGs and power exchange with the main grid such that forecasted load is served [2–5]. In [4], a multi-objective optimization problem was developed to minimize fuel costs, changes in power output of diesel generators, and cost of battery life degradation as well

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as to maximize wind power production while maintaining the real-time power balance during operations. In the latter group, the objective is to optimize market activities such that MG owner's profit is maximized. Since MGs usually host a great share of renewable generation, the profit is prone to risk. Therefore, the risk imposed by volatile market prices, intermittent and uncertain renewable generations, and uncertain demand is needed to be considered.

So far, many studies have targeted modeling uncertainties in power systems. In [6], a thorough review of the techniques used to model uncertainties in power system studies was reported. According to the review, stochastic programming and Robust Optimization (RO) are the most popular methods for modeling uncertainties in optimization problems. In [7], a model was developed to optimize MG market activities so that the profit could be maximized. However, uncertainties and their impacts were overlooked in the reported work. In [8], an optimal scheduling model for reconfigurable smart renewable MGs was presented so that the operator's profit could be maximized. In the paper, the wind speed and price of selling and purchasing power to/from the main grid were considered as uncertain parameters, which were modeled by defining scenarios. The obtained optimization problem was solved using a new heuristic method to determine the best combination of MG switches and generation of each DG. Researchers in [9] employed a stochastic bidding strategy for an MG participating in joint energy and reserve markets. The work considered the uncertainty associated with load and renewable DG generation. In this study, the problem was solved in two steps. In the first step, Latin Hypercube Sampling (LHS) method is employed to generate a set of scenarios for MG net demand. Then, bidding strategy is devised such that the expected profit over the generated scenarios is maximized. In [10], a two-stage stochastic model was developed to maximize the expected profit in the wholesale markets and to minimize the MG operation cost based on users' thermal comfort and system technical constraints. In the work, the uncertainties of renewable DGs' generation, load, ambient temperature, and market prices were captured using Monte Carlo simulation approach.

Generally, stochastic programming method is extensively employed to model the uncertainties within the operation research field. This method is, however, heavily dependent on the availability of historical data for modeling uncertainties as random variables with known Probability Distribution Functions (PDFs), which are often unavailable [11]. In contrast, RO technique is usually easier to understand and does not need much information about such uncertain parameters as PDFs, etc. This method models uncertainties by defining parametric sets based on scant information, such as

the lower and upper bounds of uncertain parameters, and helps make the best decision in response to the worst uncertain situation at a predefined interval [11]. Therefore, RO method is widely used for optimization under uncertainty.

Recently, RO has been successfully applied in different power system studies such as unit commitment problem [12–15], transmission expansion planning [11,16–19], and bidding strategy problems [20–28]. In [20] and [23], RO was used to model market price uncertainty in retailers' decision-making. In [24], an RO-based model was proposed for optimal self-scheduling of a price-taker hydro-thermal generating company. In [21], a robust bidding strategy was developed for a wind farm equipped with storage devices considering the uncertainties associated with price and wind power. In [22], an optimal bidding strategy was proposed wherein the uncertainty associated with renewable generation and market prices was modeled via stochastic optimization and RO techniques. In the above research, the uncertain output of intermittent DG and day-ahead market price were modeled in scenarios based on forecast results, while an RO-based model was proposed to limit the unbalanced power in the real-time market considering the uncertainty of real-time market prices. In [25], a multi-objective scheduling approach for MGs was proposed to minimize both operation costs and environmental issues under the worst-case situation of renewable energy production and demand uncertainties, which are captured by robust sets. In [26], an energy management procedure for a residential MG was developed in a day-ahead manner. In this study, a hybrid method based on two-stage stochastic programming and worst-case conditional value-at-risk theory was presented to model the uncertainties in renewable energy production, demand, and energy price. In [27], a RO approach was developed for short-term scheduling of an MG under demand response program and uncertainty of the main grid prices. Moreover, in the paper, the uncertainties in local demand and production of renewable energy sources were modeled by a scenario analysis technique. The study in [28] developed an adaptive robust self-scheduling model for a joint wind farm and compressed air ESS in the day-ahead energy market. This research utilized the max-min-max optimization framework and considered uncertainties in wind output power and market price.

The current study develops a mathematical model to optimize the participation of an MG owner in the wholesale market. The model maximizes the profit of the MG owner; accordingly, RO technique is applied to capture the risk caused by volatile market price, uncertain demand, and intermittent and uncertain renewable generation. The problem is modeled as a bi-level optimization problem which is solved in two iterative steps [29]. In the first step, Genetic Algorithm

(GA) determines the worst situation of uncertainties. Then, a deterministic optimization problem is solved such that MG profit is maximized considering the values determined for uncertain parameters in the first step. The two steps are iterated to reach convergence to the best solution. The problem solved in the second step is in a Mixed Integer Linear Programming (MILP) fashion and can be easily solved via available solvers.

The main contributions of this paper are as follows:

- A robust model is developed to optimize the participation of an MG owner in the wholesale market considering renewable energy subsidies;
- The uncertainty associated with market prices, renewables output power, and demand is captured in the model;
- The model is in the bi-level format which is solved in two iterative steps where a GA is used to find the worst-case scenario and an MILP problem is solved to find the best strategy in the worst case scenario found.

The remainder of the paper is organized in the following. Section 2 presents problem formulation for optimal scheduling of an MG owner in the wholesale market. The methodology to solve the problem is also described in this section. Section 3 provides the numerical results and discussions for a case study. Finally, relevant concluding remarks are drawn in Section 4.

2. Proposed methodology

The proposed methodology is presented in this section. In this respect, at first, a deterministic model is described. The model is then extended to consider uncertainties via an RO method. Finally, the solution methodology is explained.

2.1. Deterministic model

2.1.1. Objective function

Generally, MG owners participate in wholesale markets in the hope of achieving maximum profit. Therefore, the objective function of the model is to maximize the profit as follows:

$$\max_{\Lambda_S} Profit = Revenue - Cost, \tag{1}$$

where:

$$\Lambda_S = \left\{ PG_t^{DA}, P_t^{Grid}, P_{i,t}^{DG}, P_{b,t}^{Ch}, P_{b,t}^{Dis}, P_{j,t}^{LC}, SOC_{b,t}, W_{i,t}, I_{i,t}, F_{i,t}, Z_{b,t}^{Ch}, Z_{b,t}^{Dis} \right\},$$

are the problem decision variables. The MG revenue is the total income of the MG due to selling energy

to its customers and to the main grid. It should be mentioned that the selling price of renewable DG power usually contains subsidies in electricity markets and it is higher than the market price. The revenue earned by the MG owner is formulated as follows:

$$Revenue = \sum_{t \in NT} \rho_t^{Disco} . PD_t^{DA} + \sum_{t \in NT} \rho_t^{Market} . PG_t^{DA} + \sum_{t \in NT} \sum_{i \in RE} \rho_t^{RE} . (P_{i,t}^{Wind} + P_{i,t}^{PV}). \tag{2}$$

In Eq. (2), the first term is the revenue achieved by selling electricity to customers. The second term represents the revenue earned by participating in the day-ahead market, while the last term is the revenue of selling the electricity generated by renewable DGs. The cost in Eq. (1) is the total MG cost that is mathematically formulated as follows:

$$Cost = \sum_{t \in NT} \{ \rho_t^{Market} . P_t^{Grid} + \sum_{i \in NDG} \{ (A_i . W_{i,t} + B_i . P_{i,t}^{DG}) + l_{i,t} . CS_i + F_{i,t} . CD_i \} + \sum_{b \in BAT} \{ \alpha_b + \beta_b . (P_{b,t}^{Ch} + P_{b,t}^{Dis}) \} + \sum_{j \in NB} \rho_{j,t}^{LC} . P_{j,t}^{LC} \}. \tag{3}$$

In Eq. (3), the first term denotes the cost of purchasing electricity from the main grid. The second term represents all the costs associated with DGs. The third and fourth terms are ESS and LC costs, respectively. It should be mentioned that the ESS cost depicts a general form of maintenance cost (see [30]).

2.1.2. Constraints

Technical constraints including power balance constraint, DG unit constraints, energy storage constraints, and LC limits are presented hereinafter [31,32].

Power balance constraint. This constraint ensures that the power purchases from the main grid, charging/discharging power of ESSs, and the power provided by DG units (both renewable and non-renewable DGs) can meet the hourly forecasted demand. This constraint is mathematically written as follows:

$$PD_t^{DA} + P_t^{Ex} + \sum_{b \in BAT} P_{b,t}^{Ch} = \sum_{i \in NDG} P_{i,t}^{DG} + \sum_{b \in BAT} P_{b,t}^{Dis} + \sum_{i \in RE} (P_{i,t}^{Wind} + P_{i,t}^{PV}) + \sum_{j \in NB} P_{j,t}^{LC}, \tag{4}$$

where P_t^{Ex} is a free variable as $P_t^{Ex} = PG_t^{DA} - P_t^{Grid}$, which is positive/negative when the MG sells/buys

energy to/from the main grid, to ensure that P_t^{Grid} and $P_t^{DG}^{DA}$ are not nonzero at the same time.

DG constraints. The operation of a non-renewable DG unit is subject to some technical limits including generation limits, minimum down/up time, and ramp-down/ramp-up constraints:

(i) **Generation limits:** These constraints ensure that the power generated by each DG unit is bounded by the corresponding upper and lower generation limits as follows:

$$P_{i,\min}^{DG} \cdot W_{i,t} \leq P_{i,t}^{DG} \leq P_{i,\max}^{DG} \cdot W_{i,t}. \quad (5)$$

(ii) **Ramp-down/up constraints:** The generation of DG units should adhere to the ramp-down/up constraints as follows:

$$P_{i,t+1}^{DG} - P_{i,t}^{DG} \leq R_i^{UP}, \quad \forall i \in NDG, \quad t \in NT,$$

$$P_{i,t}^{DG} - P_{i,t+1}^{DG} \leq R_i^{DN}, \quad \forall i \in NDG, \quad t \in NT,$$

$$P_{i,t}^{DG} |_{t=0} = 0. \quad (6)$$

(iii) **Minimum down/up time constraints:** These constraints guarantee that the operating status of DG units adheres to the minimum down/up time limits as follows:

$$\sum_{t=t'}^{t'+T_i^{UP}-1} W_{i,t} \geq T_i^{UP} \cdot I_{i,t},$$

$$\forall t' = UF_i + 1, \dots, 24 - T_i^{UP} + 1, \quad (7)$$

$$\sum_{t=1}^{UF_i} W_{i,t} \geq UF_i, \quad (8)$$

$$\sum_{t=t'}^{t'+T_i^{DN}-1} (1 - W_{i,t}) \geq T_i^{DN} \cdot F_{i,t},$$

$$\forall t' = DF_i + 1, \dots, 24 - T_i^{DN} + 1, \quad (9)$$

$$\sum_{t=1}^{DF_i} W_{i,t} \geq 0. \quad (10)$$

(iv) **Coordinating constraints:** These constraints ensure that there is no conflict between the model binary variables (i.e., W , I , F), which represent the status of DG units. These constraints are as follows:

$$\sum_{t=t'}^{24} W_{i,t} - I_{i,t'} \geq 0, \quad \forall t' = 24 - T_i^{UP} + 2, \dots, 24, \quad (11)$$

$$\sum_{t=t'}^{24} (1 - W_{i,t} - F_{i,t'}) \geq 0,$$

$$\forall t' = 24 - T_i^{DN} + 2, \dots, 24, \quad (12)$$

$$W_{i,t-1} - W_{i,t} + I_{i,t} - F_{i,t} = 0,$$

$$\forall i \in NDG, t \in NT. \quad (13)$$

ESSs constraints. ESSs should satisfy the stored energy equation, maximum charge and discharge power limits, and the minimum and maximum allowable amounts of stored energy. These constraints are written as follows:

$$0 \leq P_{b,t}^{Ch} \leq P_{b,\max}^{Ch} \cdot Z_{b,t}^{Ch},$$

$$0 \leq P_{b,t}^{Dis} \leq P_{b,\max}^{Dis} \cdot Z_{b,t}^{Dis}, \quad (14)$$

$$Z_{b,t}^{Ch} + Z_{b,t}^{Dis} \leq 1, \quad (15)$$

$$SOC_{b,t+1} = SOC_{b,t} + \frac{\eta_{Ch} \cdot P_{b,t}^{Ch} \cdot d_T}{E_{BAT_{\max}}} - \frac{P_{b,t}^{Dis} \cdot d_T}{\eta_{Dis} \cdot E_{BAT_{\max}}}$$

$$SOC_b^{\min} \leq SOC_{b,t} \leq SOC_b^{\max}. \quad (16)$$

Limit on available LC. This constraint limits the amount of LC by the MG owner as follows:

$$0 \leq P_{j,t}^{LC} \leq P_{j,\max}^{LC}. \quad (17)$$

The above-described model is in MILP format and can be easily solved via available commercial solvers. It, however, does not consider uncertainties associated with market price, customers load, and renewable output power. The next subsection extends the model to fill the gap.

2.2. Robust model

In this work, the wind and PV output powers, demand, and market prices are assumed to be uncertain. Here, it is assumed that the forecasted wind and PV powers, demand, and market prices denoted by $\overline{P_{i,t}^{Wind}}$, $\overline{P_{i,t}^{PV}}$, $\overline{PD_t^{DA}}$, and $\overline{\rho_t^{Market}}$, respectively, are available. According to the uncertainty modeling method, a set of intervals is considered for the uncertainties as follows [16]:

$$P_{i,t}^{Wind} \in [(1 + \alpha_{w,t}^{\min}) \overline{P_{i,t}^{Wind}}, (1 + \alpha_{w,t}^{\max}) \overline{P_{i,t}^{Wind}}],$$

$$P_{i,t}^{PV} \in [(1 + \alpha_{pv,t}^{\min}) \overline{P_{i,t}^{PV}}, (1 + \alpha_{pv,t}^{\max}) \overline{P_{i,t}^{PV}}],$$

$$PD_t^{DA} \in [(1 + \alpha_{PD,t}^{\min}) \overline{PD_t^{DA}}, (1 + \alpha_{PD,t}^{\max}) \overline{PD_t^{DA}}],$$

$$\rho_t^{Market} \in [(1 + \alpha_{\rho,t}^{\min}) \overline{\rho_t^{Market}}, (1 + \alpha_{\rho,t}^{\max}) \overline{\rho_t^{Market}}]. \quad (18)$$

By applying RO method, the deterministic problem described in the previous subsection is solved, while the worst case is considered according to the above parameters and the respective ranges. To do so, the problem is considered as a bi-level model where profit is maximized over the scheduling decisions in the Lower Level (LL) problem and is minimized over the uncertain parameters in the Upper Level (UL) problem. The problem is formulated as follows. The optimal solution of this model provides MG owners with a robust schedule including the power traded in the day-ahead market, DGs commitment and production schedules (renewable/non-renewable DGs and storage devices), and optimal contracts for LCs.

2.2.1. LL problem

The LL optimization problem is:

$$Obj^{LL} = \max_{\Lambda_S} Profit \quad (19)$$

s.t.:

$$\text{Eqs. (4) – (16)}, \quad (20)$$

where *Profit* in Eq. (19) is determined by Eqs. (1) to (3) in which the output power of renewable DG units, demand, and market prices can be calculated as follows:

$$\begin{aligned} P_{i,t}^{Wind} &= (1 + \alpha_{w,t}) \overline{P_{i,t}^{Wind}}, \\ P_{i,t}^{pv} &= (1 + \alpha_{pv,t}) \overline{P_{i,t}^{pv}}, \\ PD_t^{DA} &= (1 + \alpha_{PD,t}) \overline{PD_t^{DA}}, \\ \rho_t^{Market} &= (1 + \alpha_{\rho,t}) \overline{\rho_t^{Market}}. \end{aligned} \quad (21)$$

2.2.2. UL problem

The UL optimization problem is:

$$Obj^{UL} = \min_{\Lambda_U} Obj^{LL}, \quad (22)$$

st.

$$\alpha_{w,t}^{\min} \leq \alpha_{w,t} \leq \alpha_{w,t}^{\max}, \quad (23)$$

$$\alpha_{pv,t}^{\min} \leq \alpha_{pv,t} \leq \alpha_{pv,t}^{\max}, \quad (24)$$

$$\alpha_{PD,t}^{\min} \leq \alpha_{PD,t} \leq \alpha_{PD,t}^{\max}, \quad (25)$$

$$\alpha_{\rho,t}^{\min} \leq \alpha_{\rho,t} \leq \alpha_{\rho,t}^{\max}, \quad (26)$$

where $\Lambda_U = \{P_{i,t}^{Wind}, P_{i,t}^{pv}, PD_t^{DA}, \rho_t^{Market}\}$ are the variables associated with uncertain parameters.

2.3. Solution technique

Generally, bi-level problems are difficult to solve and there is no general step-by-step solution process to ensure finding an optimal solution. Also, due to non-

convexities in the LL objective function and DG and storage constraints with binary variables, the presented bi-level robust model is a non-convex optimization problem. Hence, it cannot be solved by using analytical methods like converting the bi-level formulation into its equivalent single-level formulation derived from Karush-Kuhn-Tucker (KKT) conditions or duality-based technique [33]. Moreover, in this problem, there are identical uncertainties in both objective function and constraints that cannot be reformulated and solved by commercial solvers; this is similar to the condition that many studies existing in the literature have experienced [34].

Here, a robust model is solved via an iterative two-stage approach wherein GA and MILP are used. In this approach, the GA determines a set of values for uncertain parameters that minimize the total profit of the MG owner. Then, LL problem is solved using the values of uncertainties generated by the GA. Figure 1 shows the flowchart of the approach to solving the optimization problem.

According to Figure 1, at first, the input data including forecasted data for uncertain parameters $\overline{P_{i,t}^{Wind}}$, $\overline{P_{i,t}^{pv}}$, $\overline{PD_t^{DA}}$, and $\overline{\rho_t^{Market}}$ are captured by the algorithm. Then, an initial population is randomly generated for $P_{i,t}^{Wind}$, $P_{i,t}^{pv}$, PD_t^{DA} , and ρ_t^{Market} based on Relations (21), (23)–(26) for $t \in NT$. Then, for each individual of the population, the LL problem is solved by an available solver. After that, the obtained results are employed to determine fitness evaluations of individuals in the population and to generate a new population using crossover, mutation, and selection

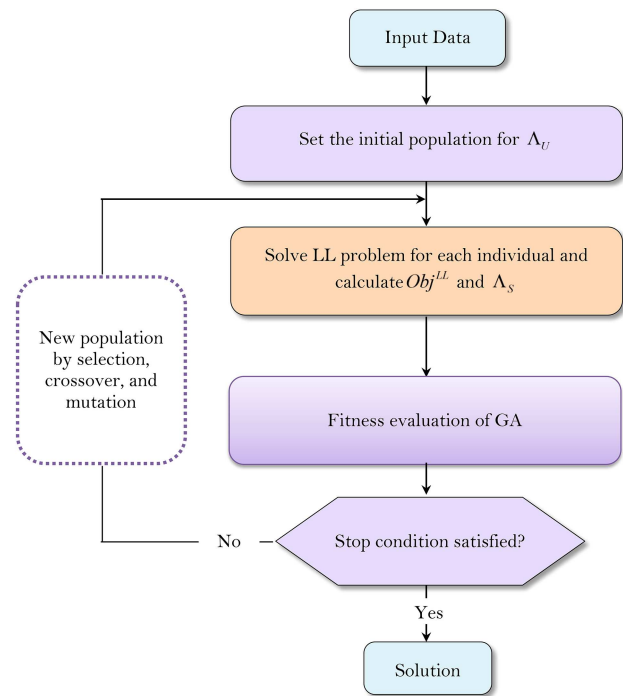


Figure 1. Flowchart of the proposed solution algorithm.

operators. Finally, this process is repeated until the GA’s termination criterion is satisfied.

3. Case study

In this section, numerical results of the implementation of the proposed robust model on a typical low-voltage MG [7] are presented. The MG is shown in Figure 2. This MG consists of four dispatchable DGs (two micro-turbines and two fuel cells), one ESS unit, three wind turbines and two solar units, and several local

loads. Detailed data of the dispatchable DG, ESS, and renewable wind and solar units can be found in [9,35].

In addition, the MG can exchange power with the main grid under the market rules and has a centralized control system. This system collects the operational information of DG units and decides to participate in the power market sending set points to DG units via communication systems.

The hourly forecasted wind speed, demand, solar radiation, and market prices, which are based on Nordic power market, are shown in Figure 3. Also,

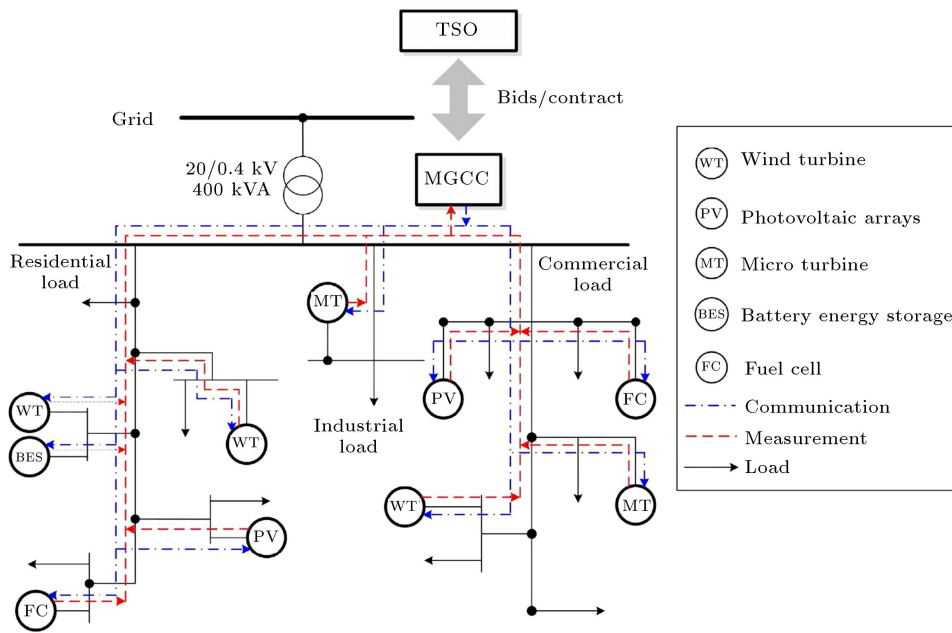


Figure 2. A typical low voltage Microgrid (MG).

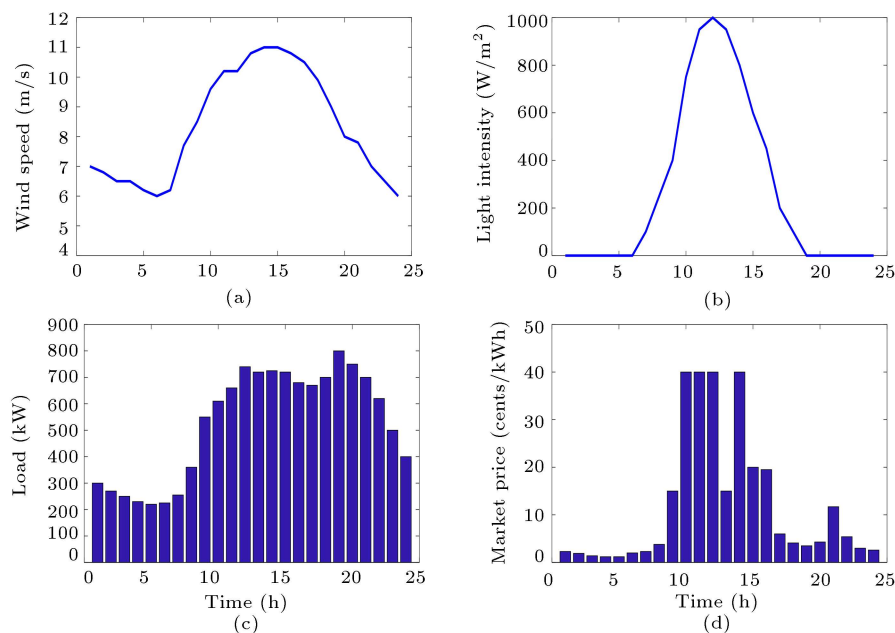
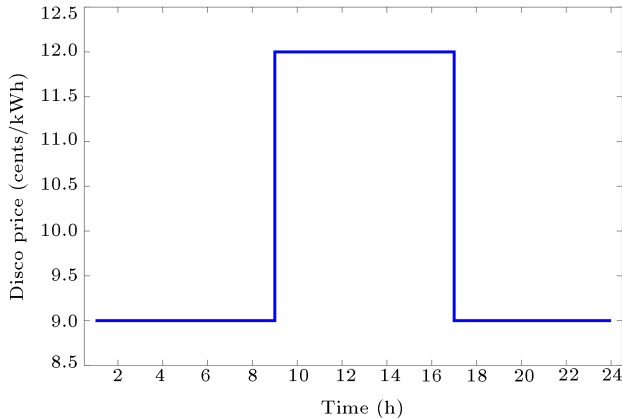


Figure 3. The hourly forecasts: (a) Wind speed, (b) solar irradiation, (c) load, and (d) electricity market price.

Table 1. The results of deterministic scheduling strategy.

Hour	MT1	MT2	FC1	FC2	BAT	Main grid	LC	Wind	PV
1	0	0	0	0	0	235.9	0	64.09	0
2	0	0	0	0	0	210.1	0	59.9	0
3	0	0	0	0	0	195.9	0	54.1	0
4	0	0	0	0	-88.9	264.8	0	54.1	0
5	0	0	0	0	0	171.3	0	48.7	0
6	0	0	0	0	0	179.7	0	45.3	0
7	0	0	0	0	0	191.3	0	48.7	15
8	0	0	0	0	0	242.2	0	80.3	37.5
9	150	150	100	100	0	-112.3	0	102.3	60
10	150	150	100	100	0	-324.6	0	139.1	112.5
11	150	150	100	100	0	-343.1	0	162.6	142.5
12	150	150	100	100	72	-366.6	0	162.6	150
13	150	150	100	100	-88.9	-22.5	183	188.9	142.5
14	150	150	100	100	72	-382.7	198	198.2	120
15	150	150	100	100	0	-68.2	222	198.2	90
16	150	150	100	100	0	-76.4	0	188.9	67.5
17	150	150	100	100	0	-35.4	217.5	175.4	30
18	0	0	0	0	0	534.5	0	150.5	15
19	0	0	0	0	-88.9	770.9	0	118	0
20	0	0	0	0	0	661.9	0	88.1	0
21	150	150	100	100	72	45.2	0	82.8	0
22	150	150	100	100	0	55.9	0	64.1	0
23	0	0	0	0	0	445.9	0	54.1	0
24	0	0	0	0	18	336.7	0	45.3	0

**Figure 4.** The retail energy price for end-users based on TOU program.

power conversion models and parameters of wind and PV resources were adopted from [9]. In addition, the retail price for local consumers of the MG is shown in Figure 4. It should be mentioned that only 30% of the load can be curtailed with interruption cost at 30 cents/kWh, and the selling price of renewable DGs output power consists of 20% subsidies, i.e., 20% higher than market prices.

3.1. Deterministic model

In this section, the scheduling problem is solved using the forecasted values of uncertain parameters for the afore-mentioned case study. To this end, the optimiza-

tion problems (Relations (1)–(17)) are solved using CPLEX solver in GAMS environment. The expected profit of the MG owner based on the forecasted values is equal to k\$139. Table 1 shows the results of the deterministic model in detail. As can be seen, during the hours 9–17, 21, and 22 when the price of energy market is high, the DG units operate at their maximum level for selling as much power as possible to the energy market. Also, during hours 13–17, the MG prefers to reduce its demand and sell greater power to the market. Another observation is that during hours 18–20, the demand of the MG is at the highest level and renewable DGs produce less power, but non-renewable DGs are off due to lower market prices.

3.2. Robust model

In this section, the bi-level problems (Relations (19)–(26)) are solved by the method described in Section 2.3 considering the input parameter data and uncertainties. The allowable changing ranges of uncertain parameters are considered identical and equal to 5%, i.e., $-0.05 \leq \alpha_{w,t}, \alpha_{pv,t}, \alpha_{PD,t}, \alpha_{\rho,t} \leq 0.05$ for $t = 1 : 24$ hour.

The obtained results for the robust and deterministic models are provided in Figure 5 and Table 2. As can be observed from Figure 5, the worst case occurs when the wind and PV output powers are close to the LL and the demand is close to the UL for peak hours and to the LL for off-peak hours. Also, in the worst

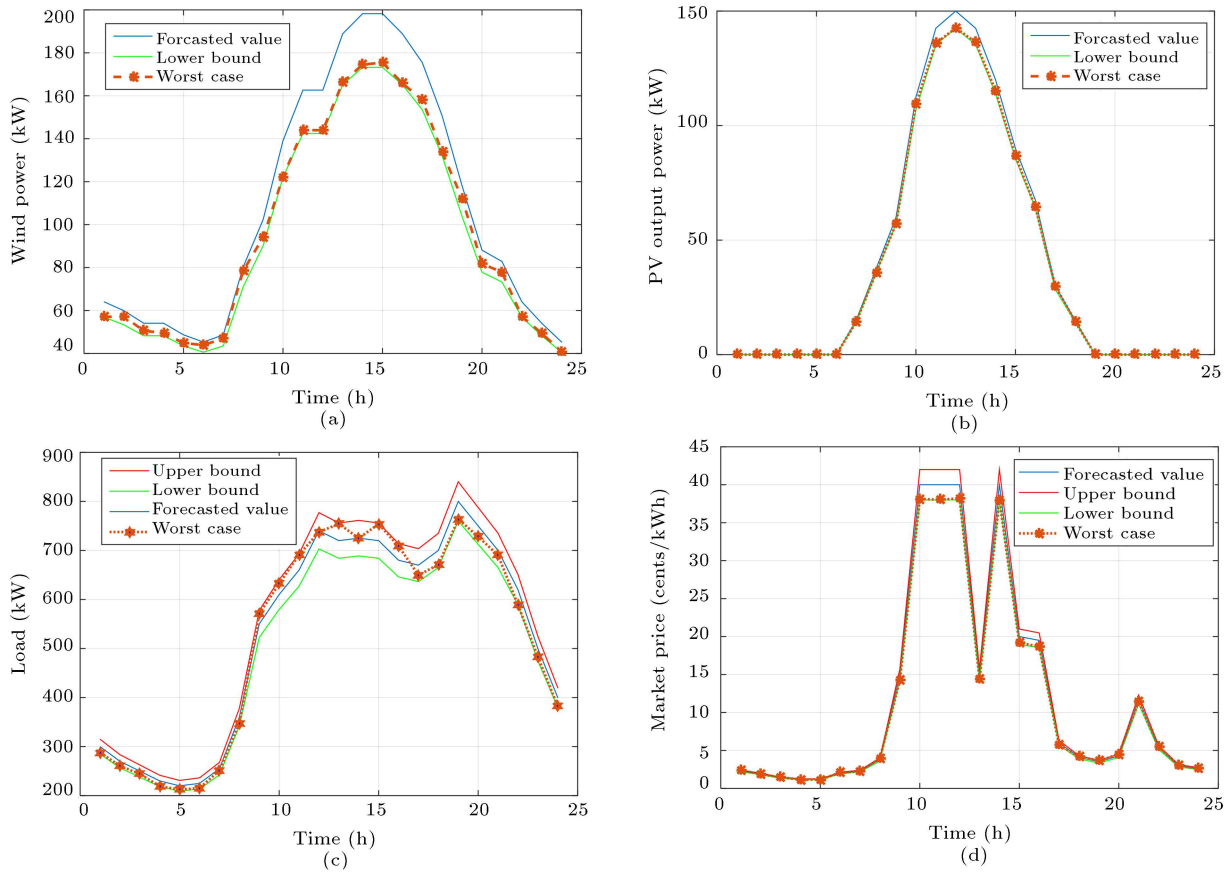


Figure 5. The result of deterministic and robust models: (a) Wind output power, (b) PV output power, (c) load, and (d) electricity market price.

Table 2. The results of robust scheduling strategy and percent of load procurement.

	Deterministic model	Robust model
Utility (%)	22.15	23.78
Non-renewable DG (%)	43.35	43.65
Renewable DG (%)	28.03	25.94
Load curtailment (%)	6.47	6.63
MG's profit ($10^3\$$)	138.98	125.15
MG's cost ($10^3\$$)	5.36	17.16
MG's revenue ($10^3\$$)	144.33	142.31

case, the electricity market prices are almost at a LL during peak periods and at a higher level during off-peak hours. Also, a deeper observation indicates that the uncertainties are not exactly located within the boundaries for the worst case and they are changing during the 24 hours.

On the other hand, according to the table, the minimum profit of the MG for the robust model is k\$125, which is guaranteed if none of the uncertain parameters is deviated by more than 5%. In other words, if the actual wind and PV output powers,

demand, and market prices deviate by no more than 5% of their forecasted values, the profit gained by the MG's owner will be at least k\$125. In addition, by comparing the results of deterministic and robust models, the revenue of both of the models is almost equal; however, the cost of the robust model is higher than that of the deterministic one. This situation occurs because the production of renewable DGs in the robust model is reduced due to uncertainties and the MG must increase the LC invocation and utility share. This indicates that having a level of robustness in scheduling increases the costs of the MG and, consequently, leads to lower profits in the worst situation.

3.3. Sensitivity analysis

In this section, the effects of uncertainties on the profit and scheduling of the MG are investigated. In this regard, four cases are considered in which the allowable changing ranges of uncertain parameters are considered identical and equal to 5%, except for one which is considered 15%, as depicted in Table 3.

Table 4 shows the results of the sensitivity analysis based on the above scenarios. As can be observed, the minimum profits of the MG for Scenarios 1, 2, 3, and 4 are k\$111, k\$119, k\$112, and k\$115, respectively.

Table 3. The allowable changing range of uncertain parameters.

Scenario 1	$\alpha_{pv,t}, \alpha_{PD,t}, \alpha_{\rho,t} \in [-0.05, 0.05]$ and $\alpha_{w,t} \in [-0.15, 0.15]$; $\forall t = 1 : 24$
Scenario 2	$\alpha_{w,t}, \alpha_{PD,t}, \alpha_{\rho,t} \in [-0.05, 0.05]$ and $\alpha_{pv,t} \in [-0.15, 0.15]$; $\forall t = 1 : 24$
Scenario 3	$\alpha_{w,t}, \alpha_{pv,t}, \alpha_{\rho,t} \in [-0.05, 0.05]$ and $\alpha_{PD,t} \in [-0.15, 0.15]$; $\forall t = 1 : 24$
Scenario 4	$\alpha_{w,t}, \alpha_{pv,t}, \alpha_{PD,t} \in [-0.05, 0.05]$ and $\alpha_{\rho,t} \in [-0.15, 0.15]$; $\forall t = 1 : 24$

Table 4. Sensitivity analysis results.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Utility (%)	28.40	24.68	23.12	25.67
Non-renewable DG (%)	43.41	43.56	43.65	41.93
Renewable DG (%)	21.40	24.96	25.84	26.62
Load curtailment (%)	6.79	6.80	7.39	6.78
MG's profit (10^3 \$)	111.46	119.57	112.18	115.44
MG's cost (10^3 \$)	29.94	22.50	31.99	26.27
MG's revenue (10^3 \$)	141.41	142.07	144.17	141.71

This indicates that PV uncertainty is of lower significance than the others. This makes sense since no solar power is available during night times. Besides, it can be because of lower PV capacity in the MG. Also, the wind and load uncertainties are almost the same and have the greatest effect on profit and scheduling of the MG. Unexpectedly, the bound of market price uncertainty has less effect than wind and load and the revenue obtained in Scenarios 1 and 4 is equal, but the cost of Scenario 1 is higher than that of Scenario 4. This could be due to the lack of wind power at some hours and use of conventional DGs or buying greater power from the upstream grid to cover the load.

4. Conclusion

In this paper, a robust scheduling approach was presented from the viewpoint of Microgrids (MG) owners with emphasis on uncertainties. The uncertainties in demand, market price, and output power of renewable Distributed Generation (DG) units were modeled using an Robust Optimization (RO)-based method. The problem was formulated as a bi-level Mixed Integer Linear Programming (MILP) optimization problem and was solved using an iterative two-step approach. The approach was applied to a typical MG to illustrate its performance. As demonstrated by the obtained results, when the MG owner decides to reduce his/her own risks, the expected profit is reduced. Therefore, having a level of robustness in scheduling increased the MG costs and, consequently, led to lower profits in the worst situation. In addition, it was shown that the worst case was related to the situation in which the wind and PV output powers were lower. The load and market prices were higher and lower during peak

periods and lower and higher during off-peak hours, respectively. Also, it was found that the uncertainties were not exactly located on the boundaries for the worst case and they were changing during the 24 hours. Moreover, it was shown that the wind and load uncertainties had the highest effect on MG profit and scheduling and the PV was of lower significance.

Nomenclature

Set and indices

t, t', NT	Indices and set of operating hours
i, NDG	Index and set of DG units in the MG
RE	Set of renewable DG units in the MG
b, BAT	Index and set of energy storages in the MG

Parameters and Constants

ρ_t^{Disco}	Price of power for end-use customers at hour t
ρ_t^{RE}	Price of renewable DG unit i at hour t in electricity market
ρ_t^{LC}	Price of power decreased by load curtailment at hour t
A, B	Cost function parameters of DG units
CS, CD	Start-up and shut-down costs of DG units
α_b, β_b	Cost function parameters of energy storage b
$P_{i,max}^{DG}, P_{i,min}^{DG}$	Maximum and minimum output of DG unit i
R_i^{UP}, R_i^{DN}	Ramp-up/down limits for DG unit i
UF_i, DF_i	Minimum up/down times of DG unit i

T_i^{UP}, T_i^{DN}	Required up/down times of DG unit i at the beginning of the time horizon, respectively
$P_{b,\max}^{Ch}, P_{b,\max}^{Dis}$	Upper limit on charge and discharge of ESS b
SOC_b^{\max}	Maximum of state of charge of ESS b
SOC_b^{\min}	Minimum of state of charge of ESS b
η_{Ch}, η_{Dis}	Charge and discharge efficiency of ESS
$E_{BAT,\max}$	Installed capacity of ESS
d_t	Duration time of bidding interval, e.g. 1 hour
P_{\max}^{LC}	Maximum allowable power decreased by load curtailment
$\overline{P_{i,t}^{Wind}}$	Forecasted wind power output of unit i at hour t
$\overline{P_{i,t}^{pv}}$	Forecasted solar power output of unit i at hour t
$\overline{PD_t^{DA}}$	Forecasted consumer active power demand at hour t
$\overline{\rho_t^{Market}}$	Forecasted electricity market price at hour t
$\alpha_{w,t}^{\max}, \alpha_{w,t}^{\min}$	Upper and lower bound of $\alpha_{w,t}$ at hour t
$\alpha_{pv,t}^{\max}, \alpha_{pv,t}^{\min}$	Upper and lower bound of $\alpha_{pv,t}$ at hour t
$\alpha_{PD,t}^{\max}, \alpha_{PD,t}^{\min}$	Upper and lower bound of $\alpha_{PD,t}$ at hour t
$\alpha_{\rho,t}^{\max}, \alpha_{\rho,t}^{\min}$	Upper and lower bound of $\alpha_{\rho,t}$ at hour t
Variables	
ρ_t^{Market}	Electricity market price at hour t .
PD_t^{DA}	End-use active power demand at hour t .
PG_t^{DA}, P_t^{Grid}	Active power sold/purchased to the market at hour t .
P_t^{Ex}	Active power exchanged with the main grid at hour t .
$P_{i,t}^{Wind}, P_{i,t}^{pv}$	Wind and solar power output of unit i at hour t .
W, I, F	Binary variables denoting DG units' commitment status, start-up, shut-down decisions, respectively.
$P_{i,t}^{DG}$	Active power generated from DG unit i at hour t .
$P_{b,t}^{Ch}, P_{b,t}^{Dis}$	Charge and discharge power energy storage b at hour t .
$SOC_{b,t}$	State of charge of battery energy storage b at hour t .
$Z_{b,t}^{Ch}, Z_{b,t}^{Dis}$	Binary variables denoting status of ESS unit b at hour t .

P_t^{LC}	Active power decreased by load curtailment at hour t .
$\alpha_{w,t}, \alpha_{pv,t}$	Decision variable to model wind and PV output power uncertainty at hour t .
$\alpha_{PD,t}$	Decision variable to model demand uncertainty at hour t .
$\alpha_{\rho,t}$	Decision variable to model market price uncertainty at hour t .

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