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Robust Optimization-Based Optimal Operation of Islanded Microgrid Considering Demand Response

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Abstract: This paper presents a new robust scheduling model for an islanded microgrid (MG) considering demand response. The model is expressed as a min–max bilevel optimization problem that tries to minimize the total costs of MG including operation cost of conventional distributed generators, energy storages, renewable energy sources (RES), cost of load shifting, and interruptible/non-interruptible load shedding in the worst situation of uncertainties. The uncertainties associated with renewable power generations and MG demand are modeled via robust optimization method. A hybrid method based on the genetic algorithm (GA) and mixed-integer programming technique is utilized to solve the bilevel optimization problem. The proposed model is utilized on a typical MG, and the outcomes are analyzed to show the effectiveness of the proposed method.

Keywords: demand response; islanded microgrid; scheduling; robust optimization

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1. Introduction

The main parts of microgrids (MG) are renewable energy sources (RESs), which are growing, mainly driven by energy policies and incentives [1–3]. For example, a study by the International Energy Agency (IEA) showed that the total installed capacity of RESs in the world will be tripled by 2040, which will produce 41% of the total electricity in the world [4]. In addition, one of the main benefits of MGs is the capability to work in island mode to serve the local loads [5,6]. This application is especially helpful in the case of major events. However, the uncertainties mainly imposed by RESs may affect and reduce the performance of MGs [7]. Therefore, scheduling of MGs in the islanded mode has great importance and must also consider the uncertainties.

So far, MG scheduling has been discussed from different viewpoints by several research works. Parhizi et al. [8] provided a comprehensive review of the literature. The studies in this area focused on (i) grid-connected scheduling of MG, and (ii) scheduling in islanded conditions. In the grid-tied mode, MG can exchange power with the main grid and trade energy in the market. Therefore, the objective is usually to maximize the MG owners' profit [9]. In [9], a robust market-based MG scheduling was presented with the aim of maximizing the profit of MG owners. Shi et al. [10] presented a stochastic bidding strategy for MGs to participate in both energy and reserve markets. Liu et al. [11] proposed a hybrid robust–stochastic model for optimal bidding strategy of MG where the uncertainties in renewable power generation and day-ahead market tariffs were modeled via scenarios, while the supply–demand balance in the real-time market was considered using the robust optimization (RO) method.

Studies considering islanded MGs usually focused on technical issues such as frequency control, load sharing, load shedding, stability, voltage control, and energy management [12–16]. However, there are a few research studies that discussed the scheduling of MGs in island mode. Conti et al. [17] presented a deterministic scheduling model that uses an evolutionary algorithm to minimize the overall MG's operating cost and emissions. Farzin et al. [18] presented a stochastic energy management model during unscheduled islanding events, initiated by disturbances in the upstream network. In the papers presented by Lazar et al. [19], Wu et al. [20], and Zia et al. [21], deterministic models for optimal operation of islanded MGs were proposed that were solved using mixed-integer programming solvers and evolutionary algorithms such as particle swarm optimization (PSO). The authors of [22] presented a secondary control of an islanded MG with a PSO to determine the optimal operation of the biomass and photovoltaic units within an MG. The authors of [23] used a quantum teaching learning-based optimization method to enhance energy flow in an MG. In [24], an intelligent decentralized energy management system (EMS) was presented for an isolated MG to achieve an efficient charging of electric vehicles. The authors of [25] introduced another EMS relying on battery logistics. A tri-stage scheduling method utilizing a quantum adaptive sparrow search algorithm was introduced in [26]. Elgamal et al. [27] designed an optimal next-day power schedule in an isolated MG. The authors of [28] presented a seasonal spinning-reserve schedule for an islanded MG considering contingency conditions. For islanded multiagent MGs, the authors of [29] used the peer-to-peer (P2P) management concept to present an energy schedule. Wahid et al. [30] presented an intelligent control method to share the power among PV-based MG groups with the management of connected loads. In [31], Kumari used the cuttle fish (CFA) and crow search (CSA) algorithms to present an optimal schedule for MGs with multiperiod islanding restrictions. The authors of [32] presented a robust schedule using a two-stage adaptive robust optimization to minimize the total operation expense of networked MGs in the worst-case scenario considering uncertainties.

To offset the power fluctuations, demand-side flexibility is an effective solution [33]. The authors of [34,35] reviewed the flexibility potentials of demand sectors, including residential, industrial, commercial, and agricultural, to smooth the integration of RESs into power systems. Electric vehicles can be leveraged as a distributed and fast-response load in markets to participate in demand response programs for increasing the energy efficiency, providing frequency regulation services, and gaining economic profits [36–41]. An optimized strategy for participation of a demand response aggregator in both day-ahead and balancing markets was developed in [42]. An extension of the previous publication developing a price-maker aggregator to coordinate a large fleet of electric vehicles was proposed to participate in a three-settlement pool-based market [43]. A stochastic optimization method was presented for the energy market operations considering demand response in [44] to design an optimal economic schedule for MGs, and the results confirmed the reduction in operating cost using the proposed method. In [45], a robust control strategy for demand-side management of multicarrier MGs was proposed that employed the model predictive control approach to deal with uncertainties. The model was eventually linearized to attain a mixed-integer linear programming (MILP) problem to be easily solved by commercial solvers. The authors of [46] presented a stochastic multi-objective optimization for the networked microgrids energy management considering demand response programs. A summary of the presented research and our proposed model is presented in Table 1.

Table 1. Taxonomy of related research works.

References	Uncertainty Modeling	Demand Response Program	Solution Method
[17,20,21]	-	-	Metaheuristic algorithms
[18,19]	Stochastic programming	-	MILP solver
[25]	Information gap decision theory	-	Bender decomposition
[26]	Information feedback mechanism	-	Quantum adaptive sparrow search algorithm
[27]	Stochastic programming		Bat algorithm
[32]	Robust optimization	-	Column and constraint generation
[44]	-	✓	Water wave optimization algorithm
[45]	Robust model predictive control	-	MILP solver
[46]	Stochastic programming	✓	Multi-objective compromised program method
Proposed approach	Robust optimization	✓	Hybrid GA–MILP

According to the reviewed papers, in islanded mode, MGs try to minimize the total operation expense to serve the local loads. Thus, in this condition, demand response programs such as load shifting and prioritized load shedding are more important than the grid-connected condition due to lack of supply. Furthermore, the scheduling of islanded MGs should be robust against uncertainties to reduce the negative impacts of unexpected events. In other words, the islanded MGs should be operated according to the worst case of uncertainties to be able to supply as much of the load as possible without curtailment. Therefore, this paper develops a new robust scheduling model for islanded MGs considering the demand response. This framework enables MG owners to make robust decisions for operation and development of MGs. The model minimizes the total operating costs of MGs including operation cost of conventional distributed generators (DGs), energy storage, RESs, cost of load shifting, interruptible/non-interruptible load shedding in worst-case situations of uncertainties in demand, and RES production, which are determined using the RO method. The problem is modeled as a bilevel optimization problem utilizing a hybrid method based on a genetic algorithm (GA) and an available MILP solver. The main contributions of the paper can be summarized as follows:

- A novel robust scheduling model is developed for islanded MGs to withstand the negative impacts of unexpected events.
- The ability of load shedding and load shifting in islanded mode is employed to smooth the transition.

The remainder of the paper is organized as follows: Section 2 presents the mathematical formulation of the scheduling of an islanded MG. The proposed solution methodology is provided in Section 3. Simulation results and discussions are reported in Section 4. Lastly, the summary and conclusions are presented in Section 5.

2. Problem Formulation

In this section, we provide the mathematical formulation of the suggested islanded MG scheduling model illustrated in Figure 1. The islanded MG in this work is a local electrical grid with dispatchable DGs, wind and solar power production units, battery energy storage systems, and two types of electrical loads, i.e., interruptible and non-interruptible loads. The mathematical formulation of the suggested islanded MG scheduling is provided in this section. The model is a bilevel optimization problem. Herein, the first level determines the worst-case scenario of uncertainties, and the second level finds the best action to minimize the MG's operation expense. It should be noted that, without loss of generality, the proposed formulation can be extended to multicarrier energy MGs by adding the constraints for other energy carriers.

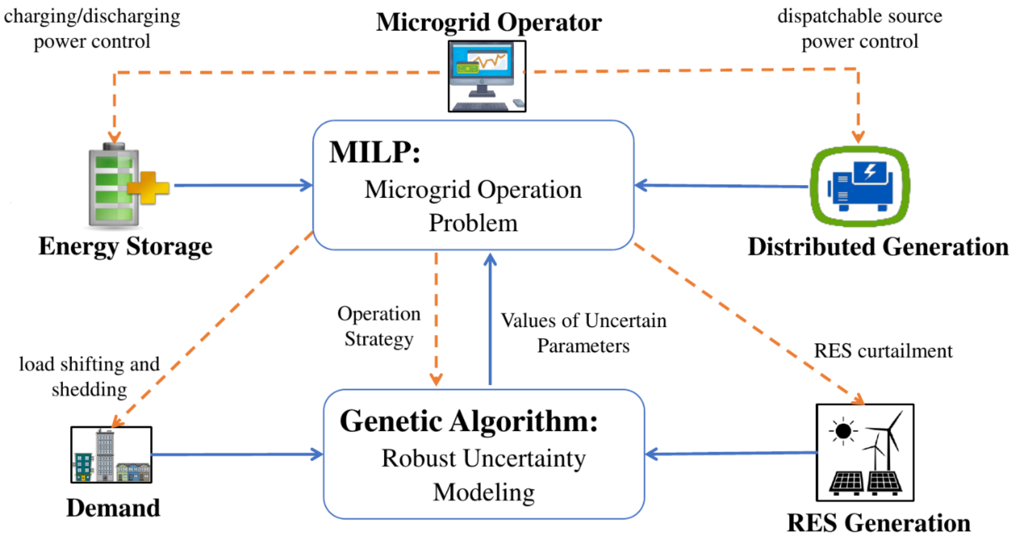


Figure 1. The structure of the proposed robust MG scheduling model.

2.1. First-Level Problem

The mathematical formulation of the first-level problem (FLP) is as follows:

$$\max_{u \in U,\, x \in X} Q(x,u), \tag{1}$$

where u, U and x, X are the index and set of uncertainties and the index and set of decision variables in the second-level problem (SLP), respectively. In this work, the set U consists of the production of wind and solar units ($P_{i,t}^{wt}$, $P_{i,t}^{pv}$) and local loads (PD_t), which are constrained using Equations (2)–(4).

$$\underline{P_{i,t}^{wt}} \le P_{i,t}^{wt} \le \overline{P_{i,t}^{wt}}. \tag{2}$$

$$\underline{P_{i,t}^{pv}} \le P_{i,t}^{pv} \le \overline{P_{i,t}^{pv}}. \tag{3}$$

$$\underline{PD_t} \le PD_t \le \overline{PD_t}. \tag{4}$$

2.2. Second-Level Problem

2.2.1. Objective Function

The mathematical representation of $Q(x,u)$ in Equation (1) is as follows:

$$\begin{aligned} Q(x,u) &= \min_{x\in X} \sum_{t\in T} \rho_t^{sh} PS_t \\ &+ \sum_{t\in T} \left(\sum_{i\in NDG} A_i W_{i,t} + B_i P_{i,t}^{DG} + I_{i,t} CS_i + F_{i,t} CD_i + \sum_{i\in RE} C_i M_{i,t} \right. \\ &\left. + \sum_{i\in BAT} \alpha_i + \beta_i \left(P_{i,t}^{ch} + P_{i,t}^{dis} \right) + \rho_t^{NIL} P_t^{NIL} + \rho_t^{IL} P_t^{IL} \right), \end{aligned} \tag{5}$$

where $X = \left\{ PS_t,\ P_{i,t}^{DG},\ P_{i,t}^{ch},\ P_{i,t}^{dis},\ SOC_{i,t},\ P_t^{NIL},\ P_t^{IL},\ W_{i,t},\ I_{i,t},\ F_{i,t},\ Z_{i,t}^{ch},\ Z_{i,t}^{dis} \right\}$ is the set of SLP decision variables.

2.2.2. Constraints

The first constraint of SLP is the equality of supply and demand:

$$\begin{aligned} \sum_{i\in NDG} P_{i,t}^{DG} + \sum_{i\in BAT} \left(P_{i,t}^{dis} - P_{i,t}^{ch} \right) + PS_t - PS'_t + P_t^{IL} + P_t^{NIL} \\ = PD_t - \sum_{i\in RE} \left(P_{i,t}^{wt} + P_{i,t}^{pv} \right); \forall t \in T, \end{aligned} \tag{6}$$

$$PS_t = PS'_{t+h}\ ; \forall t \in T, \tag{7}$$

$$0 \le PS_t \le PS^{max}\ ;\ \forall t \in [e, e+n-1], \tag{8}$$

$$PS_t = 0\ ; \forall t \notin [e, e+n-1], \tag{9}$$

$$PS_t = PS_{t'}\ ; \forall t,\ t' \in [e, e+n-1], \tag{10}$$

where, Equation (6) is the power balance constraint considering load shifting. Equation (7) gives the amount of load that shifts from t to $t+h$. Equations (8)–(9) enforce the shiftable load limitations. The PS_t is the amount of load that would be cut in the time interval $t \in [e, e+n-1]$, and PS'_{t+h} is the amount of load that would be added in the time interval $t \in [e+h, e+h+n-1]$. Equation (10) ensures that the same amount of load is shifted during the shifting interval $t \in [e, e+n-1]$. For example, assume that we are going to shift a maximum of 200 kW of the load ($PS^{max} = 200$ kW) from interval $t \in [18, 20]$ to interval $t \in [22, 24]$, i.e., $e = 18$, $n = 3$, and $h = 4$. For instance, the optimization may obtain a solution that 120 kW of load at each of $t = 18$, $t = 19$, and $t = 20$ is cut and transferred to each of $t = 22$, $t = 23$, and $t = 24$. Note that, in the model, PS^{max} is introduced as input data.

In the above equations, the demand shift occurs only once during the scheduling time frame. Moreover, we considered only one load with one shifting time interval. However, the model can be easily extended to consider multiple loads with multiple shifts during a day and different shifting time intervals for different loads since shifting time intervals and shiftable loads are considered in the model as input data.

Other constraints of the SLP are the technical limits of conventional DGs, energy storage systems, and load curtailment, as described below.

(1) Conventional DG constraints: Technical constraints of conventional DG units include the upper and lower generation limits (Equation (11)), ramp-up and ramp-down constraints (Equations (12) and (13)), minimum up/down time constraints (Equations (14)–(17)), and the constraints to ensure that the status binary variables (W, I, F) work without any conflicting situation (Equations (18)–(20)).

$$P_{i,min}^{DG} W_{i,t} \le P_{i,t}^{DG} \le P_{i,max}^{DG} W_{i,t}; \forall i \in NDG,\ t \in T. \tag{11}$$

$$P_{i,t+1}^{DG} - P_{i,t}^{DG} \le R_i^{UP}\ ; \forall i \in NDG,\ t \in T. \tag{12}$$

$$P_{i,t}^{DG} - P_{i,t+1}^{DG} \le R_i^{DN}\,;\forall i \in NDG,\ t \in T. \tag{13}$$

$$\sum_{t=k-T_i^{UP}}^{k-1} W_{i,t} \ge T_i^{UP} F_{i,k}\,;\forall k = UF_i + 1,\ \ldots,\ 24 - T_i^{DN} + 1. \tag{14}$$

$$\sum_{t=1}^{UF_i} W_{i,t} \ge UF_i. \tag{15}$$

$$\sum_{t=k-T_i^{DN}}^{k-1} (1 - W_{i,t}) \ge T_i^{DN} I_{i,k}\,;\forall k = DF_i + 1,\ \ldots,\ 24 - T_i^{UP} + 1. \tag{16}$$

$$\sum_{t=1}^{DF_i} W_{i,t} \ge 0. \tag{17}$$

$$\sum_{t=k}^{24} W_{i,t} - I_{i,k} \ge 0\,;\forall k = DF_i + 1,\ \ldots,\ 24 - T_i^{UP} + 1. \tag{18}$$

$$\sum_{t=k}^{24} 1 - W_{i,t} - F_{i,k} \ge 0\,;\forall k = UF_i + 1,\ \ldots,\ 24 - T_i^{DN} + 1. \tag{19}$$

$$W_{i,t} - W_{i,t-1} - I_{i,t} + F_{i,t} = 0\,;\forall i \in NDG,\ t \in T. \tag{20}$$

(2) Energy storage constraints: The technical constraints of energy storage devices are power constraints (Equations (21)–(23)) and energy constraints (Equations (24) and (25)).

$$0 \le P_{i,t}^{ch} \le P_{i,\max}^{ch} Z_{i,t}^{ch}\,;\forall i \in BAT,\ t \in T. \tag{21}$$

$$0 \le P_{i,t}^{dis} \le P_{i,\max}^{dis} Z_{i,t}^{dis}\,;\forall i \in BAT,\ t \in T. \tag{22}$$

$$Z_{i,t}^{ch} + Z_{i,t}^{dis} \le 1\,;\forall i \in BAT,\ t \in T. \tag{23}$$

$$SOC_{i,t+1} = SOC_{i,t} + \frac{\eta_{ch} P_{i,t}^{ch} d_T}{E_{BAT_{max}}} - \frac{P_{i,t}^{dis} d_T}{\eta_{dis} E_{BAT_{max}}}\,;\forall i \in BAT. \tag{24}$$

$$SOC_i^{min} \le SOC_{i,t} \le SOC_i^{max}\,;\forall i \in BAT,\ t \in T. \tag{25}$$

(3) Interruptible and non-interruptible load curtailment limits: In this work, we assume that there are two types of loads: interruptible (controllable) and non-interruptible (non-controllable) [47,48]. The non-interruptible load is a kind of load that the MG owner tries not to curtail. In contrast, the interruptible load in this work refers to a load that can be curtailed with a reasonable price according to a contract between the MG owner and the consumer [47,48]. Equations (26) and (27) limit the amount of load curtailment for interruptible and non-interruptible loads.

$$0 \le P_t^{IL} \le P_{t,\max}^{IL}\,;\forall t \in T. \tag{26}$$

$$0 \le P_t^{NIL} \le P_{t,\max}^{NIL}\,;\forall t \in T. \tag{27}$$

2.2.3. Computational Complexity

The proposed second-level problem of MG scheduling is an MILP optimization problem. Generally, MILP problems can be easily solved using commercial solvers such as CPLEX to reach the guaranteed optimal solution. However, the size of MILP problems limits the computational performance of such solvers. Therefore, Table 2 illustrates the computational complexity of the proposed MILP problem as a function of the number of constraints and variables. In this table, n_T, n_D, and n_B represent the number of time intervals, number of dispatchable DGs, and number of battery energy storage systems in the MG, respectively.

Table 2. Dimension of the proposed MILP formulation.

No. of constraints	$1 + n_T(5 + 11n_D + 6n_B)$
No. of continuous variables	$1 + n_T(3 + n_D + 3n_B)$
No. of binary variables	$3n_D + 2n_B$

3. Solution Technique

The proposed model for scheduling of islanded MG is categorized as a bilevel optimization problem. In the model, the FLP is maximized over the set of uncertain parameters U, while the SLP is minimized over the set of operation variables X. Several methods have been proposed to solve this kind of problem, which usually use Karush–Kuhn–Tucker (KKT) conditions or a strong duality technique to reformulate the original bilevel problem [49,50]. Since, the SLP is a nonconvex and MILP problem, the mentioned methods could not be utilized in this paper. Thus, the hybrid iterative method using GA and an MILP solver, which was presented in [9], is utilized in this paper to solve the proposed model. The reason for choosing GA over other evolutionary algorithm is that the GA is a more mature evolutionary algorithm than others to which a toolbox in the MATLAB is assigned.

According to this algorithm, first, the GA randomly determines a set of values for the wind and solar power production and the load on the basis of Equations (2)–(4). Then, the MILP solver solves Equations (5)–(27), aimed at minimizing the total cost. In the next step, GA sorts the objective functions of MILP for each individual value of $P_{i,t}^{wt}$, $P_{i,t}^{pv}$, and PD_t. Then, a new population is generated for $P_{i,t}^{wt}$, $P_{i,t}^{pv}$, and PD_t using the selection, mutation, and crossover functions of GA. Again, the MILP solver solves the SLP for new values of $P_{i,t}^{wt}$, $P_{i,t}^{pv}$, and PD_t. Lastly, these steps repeated until the maximum iteration number of GA is reached. The flowchart of the solution algorithm is provided in Figure 2, and the steps are described below [9].

1. *Initialization:*
   a. Get the input data including lower and upper bound of wind and photovoltaic generation, and load demand.
   b. Set the initial population for wind and photovoltaic power generation, and load demand using Equations (2)–(4).
   c. Set the iteration counter for GA v = 1.
2. *Solving SLP:* Solve the SLP (Equations (5)−(27)) for each individual of the population.
3. *GA algorithm:*
   a. Calculate the fitness function of Equation (1) using the results of the SLP for each individual.
   b. Generate new population using crossover, mutation, and selection operators while considering Equations (2)–(4).
4. *Convergence checking:*
   a. If the maximum number of iterations is reached, stop the algorithm.
   b. If not, increase the iteration counter of GA v = v + 1, and go back to step 2.

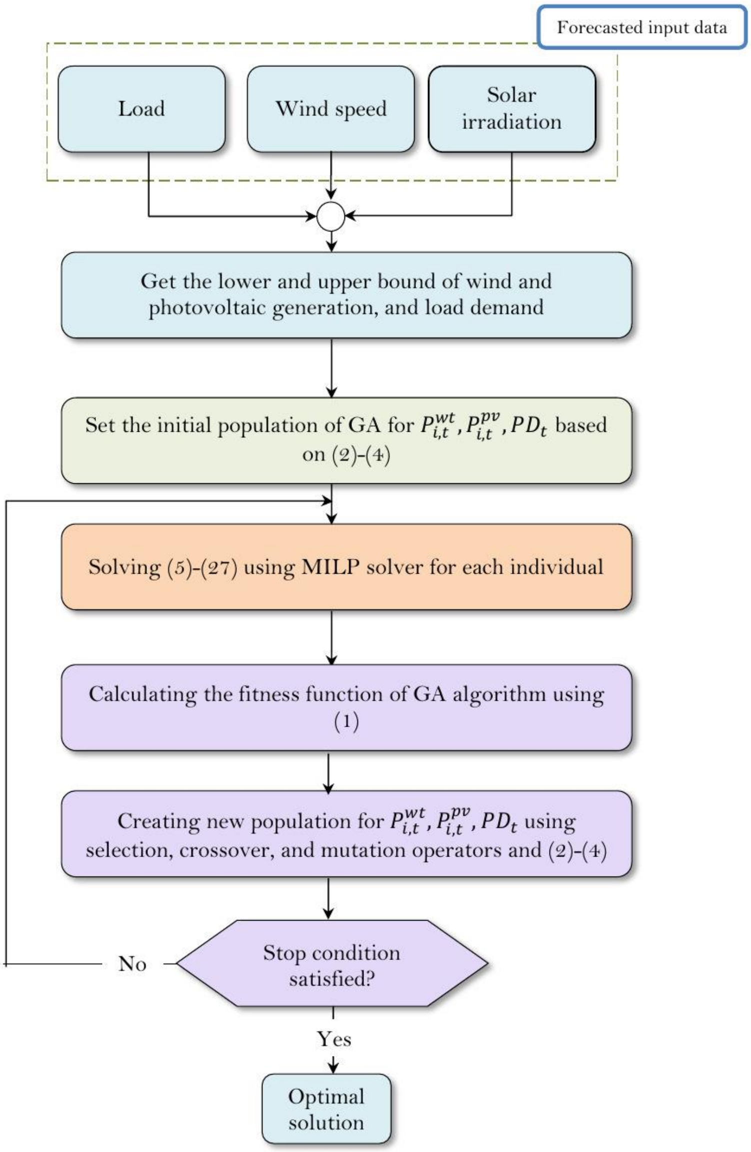


Figure 2. Flowchart of the solution methodology.

4. Simulation Results

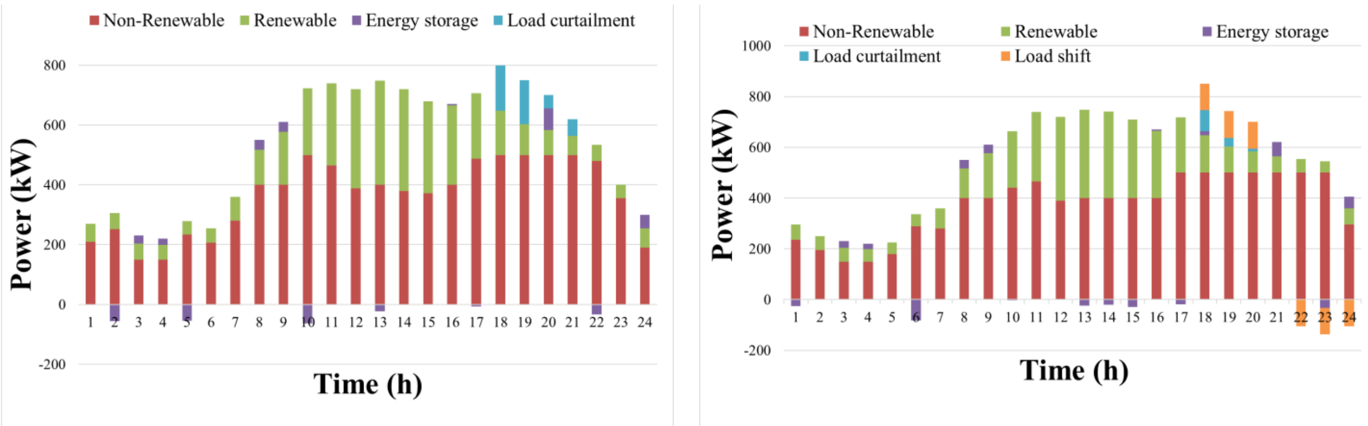
The numerical results of the proposed model on a typical MG [9,10] are presented in this section. This MG consisted of four conventional DGs, three wind units, two solar units, and one energy storage system. The detail data for the generation units and the hourly forecasted data of local load, as well as wind and solar power outputs, can be found in [9,10]. It was assumed that only 30% of the load was interruptible with an interruption cost of 330 cents/kWh. Furthermore, the penalty for interruption of remaining loads was 3000 cents/kWh. It should be mentioned that the scheduling problem was solved for 24 h.

4.1. Deterministic Model Results

In this section, the results of the proposed scheduling scheme without considering uncertainties is reported for two cases: (i) no load shifting allowed; (ii) maximum of 120 kW of the load at time intervals [18,20] can be shifted for 4 h (i.e., $PS^{max} = 120$ kW, $n = 3$, $e = 18$, and $h = 4$). To do this, the Equations (5)–(27) were executed in the GAMS environment and solved using the CPLEX solver. Table 3 shows the summary of the scheduling results. Furthermore, Figure 3 presents the hourly production of MG resources. According to the results, the expected costs of scheduling are k$ 167 and k$ 90 without and with load shifting, respectively. As can be seen, shifting 105 kW of load in hours 18, 19, and 20 to hours 22, 23, and 24 decreased the total scheduling cost for 46%. Moreover, it decreased the load curtailment by about 66%.

Table 3. The deterministic scheduling model's results.

	Without Load Shifting	With Load Shifting
Non-renewable DG production	8698 kWh	8961 kWh
Renewable DG production	3557 kWh	3557 kWh
Energy storage charging	235 kWh	235 kWh
Energy storage discharging	235 kWh	235 kWh
Interruptible load curtailment	400 kWh	136 kWh
Non-interruptible load curtailment	0	0
Load shifting	0	315 kWh
Total MG cost	k$ 167	k$ 90



(**a**) Without load shifting (**b**) With load shifting

Figure 3. The hourly production of MG resources for the deterministic model.

4.2. Robust Model Results

The results of the proposed robust scheduling model (Equations (1)–(27)) are presented in this section. It was assumed that the uncertain parameters could vary from 95% to 105% of their forecasted values. The model was solved using the method described in Section 3. The number of chromosomes, population size, and maximum number of iterations for GA were assumed to be 72, 150, and 100, respectively. Moreover, we considered the maximum iteration as the stopping criterion and the Gaussian function for GA mutation. Table 4 illustrates the results for cases with and without consideration of load shifting, similar to the previous section. Furthermore, Figure 4 presents the hourly production of MG resources for the robust model. According to the results, the costs of scheduling in the worst-case situation are k$ 272 and k$ 174 without and with load shifting, respectively. As can be seen, shifting 110 kW of load in hours 18, 19, and 20 to hours 22, 23, and 24 decreased the total scheduling cost by about 36%. Moreover, it decreased load curtailment by about 46%.

Table 4. The results of the robust scheduling model.

	Without Load Shifting	With Load Shifting
Non-renewable DG production	9334 kWh	9664 kWh
Renewable DG production	3198 kWh	3198 kWh
Energy storage charging	159 kWh	108 kWh
Energy storage discharging	174 kWh	132 kWh
Interruptible load curtailment	740 kWh	400 kWh
Non-interruptible load curtailment	0	0
Load shifting	0	330 kWh
Total MG cost	k$ 272	k$ 174

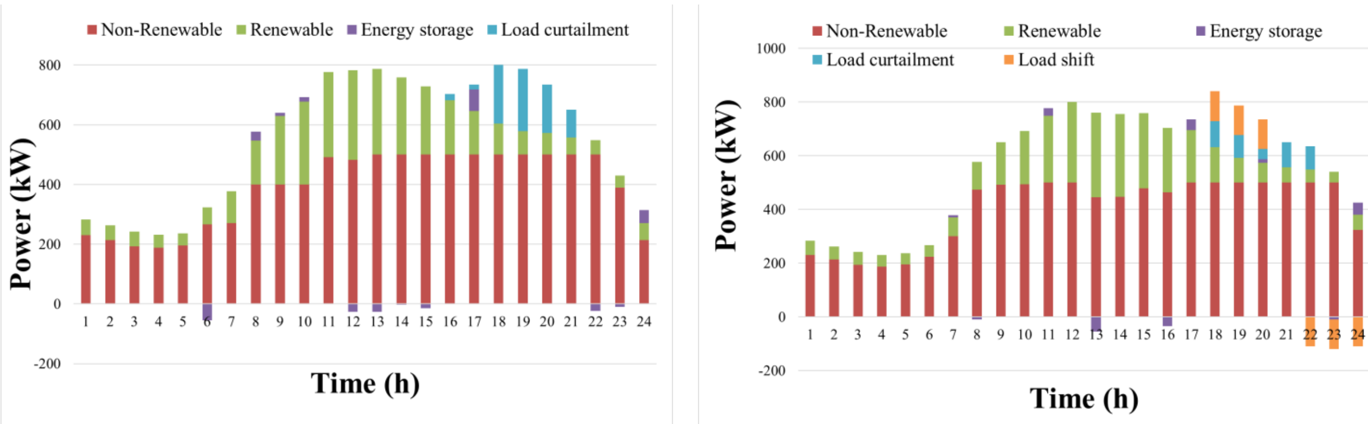
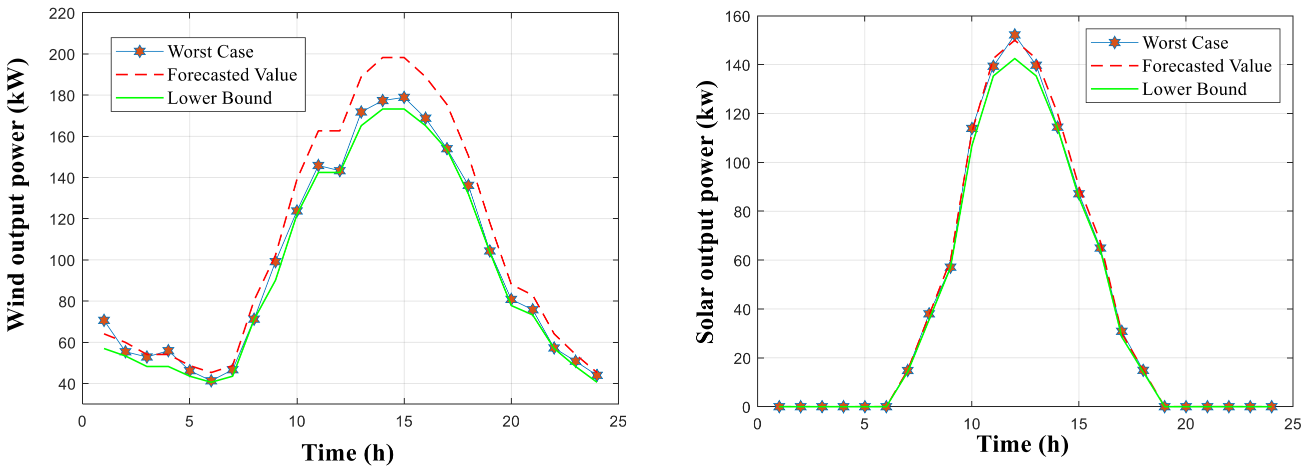


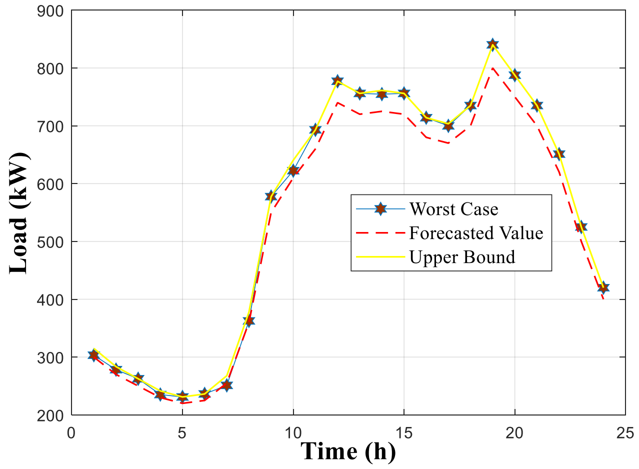
Figure 4. The hourly production of MG resources for robust model.

Figures 5 and 6 represent the worst situation of uncertainties for cases with and without considering load shifting, respectively. As can be observed in the figures, the worst situation of wind and solar resources was close to the lower bound most of the time, while it was near the upper bound for the load. The results show that wind outputs had the most distance between the forecasted and worst situation most of the times for both cases. However, the forecast of solar output was more accurate than other uncertainties. The reason is that solar units did not generate energy for at least one-third of a day.



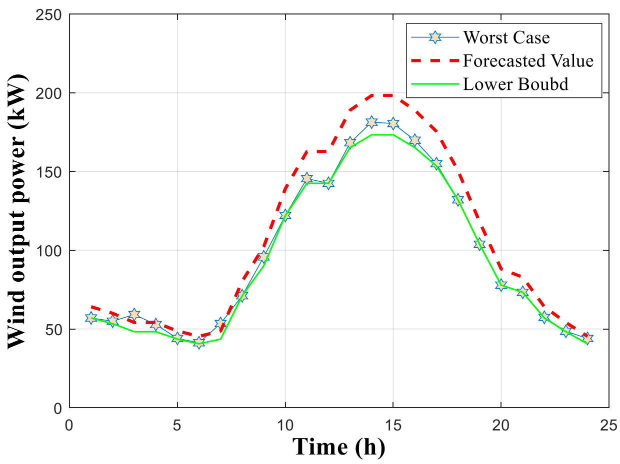
(**a**) Wind output power (**b**) Solar output power

Figure 5. *Cont.*

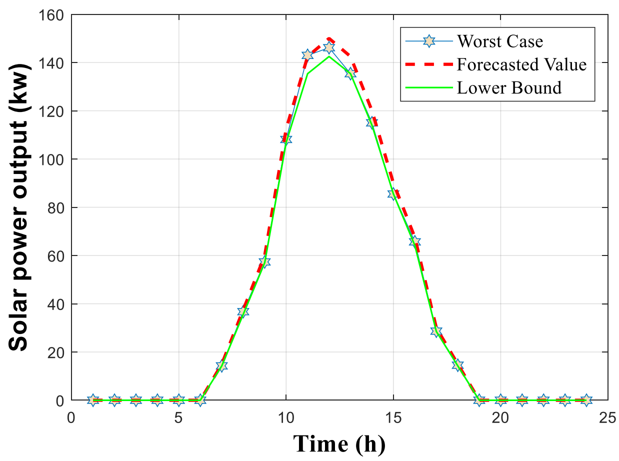


(**c**) Load

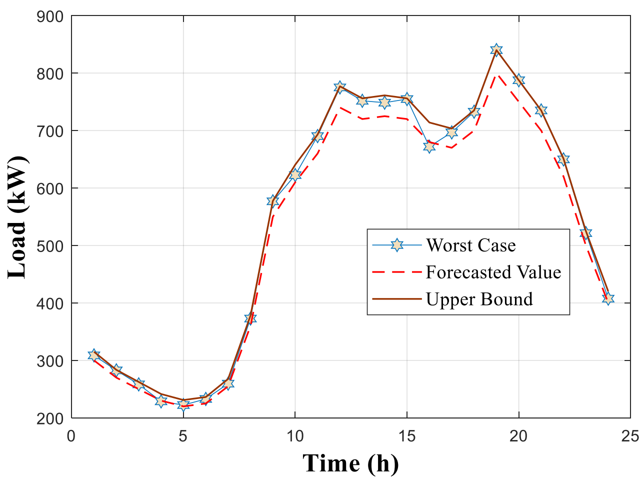
Figure 5. The worst-case scenario of uncertain parameters for the case with load shifting.



(**a**) Wind output power



(**b**) Solar output power



(**c**) Load

Figure 6. The worst-case scenario of uncertain parameters for the case without load shifting.

Furthermore, the fitness graph with and without load shifting cases is shown in Figure 7. As can be seen, the proposed model converged in fewer than 15 iterations.

Additionally, evolutionary algorithms such as GA may not reach the global optimal solution with one run due to their random starting nature. Therefore, we ran the proposed model several times with a different population size and maximum number of iterations. Table 5 shows the statistical results of running the GA-MILP model with and without load shifting. As can be seen, the standard deviation of running the model was really low, indicating that the utilized GA-MILP method could reach the optimal solution most of the time.

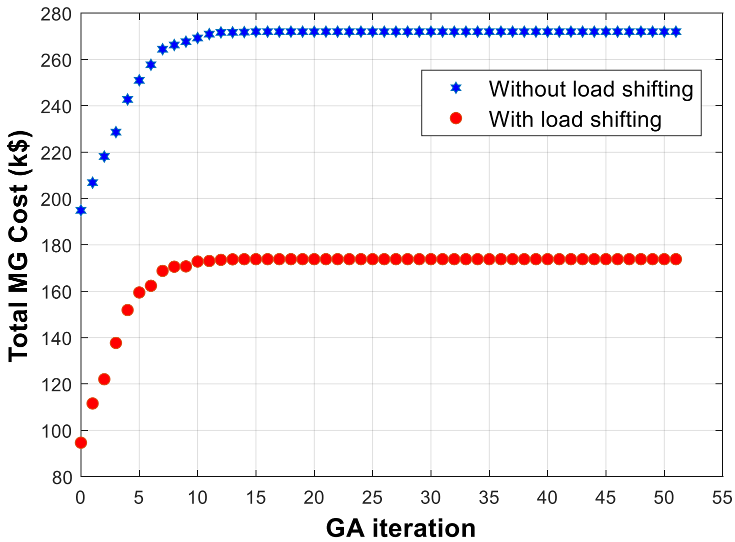


Figure 7. Convergence process of the GA-MILP algorithm.

Table 5. The statistical total costs of the robust scheduling model.

	Without Load Shifting	With Load Shifting
Minimum value	k$ 257	k$ 169
Maximum value	k$ 272	k$ 174
Mean value	k$ 268	k$ 172
Standard deviation	0.66%	0.26%

4.3. Results Verification and Sensitivity Analysis

In this section, the results of the proposed model were analyzed to make sure that the determined GA values for the uncertainties were the true worst-case situation. For this purpose, 10,000 scenarios for uncertain parameters were randomly generated in the range of 95% to 105% of the forecasted values. Moreover, the objective values of the heuristic worst case (i.e., wind and PV set to minimum and load to maximum bound) are reported along with the deterministic and robust schedules. Table 6 presents the min, max, and mean values of the objective function for generated scenarios. As can be seen, the maximum objective value of generated scenarios was k$ 241, which is less than the value of the objective function in the robust model. In other words, the obtained values for the uncertainties using our method led to worse situations than the generated scenarios. Additionally, the mean value of the generated scenarios was close to the value of the objective function in deterministic model. Furthermore, the objective values of the heuristic worst-case situation were close to those of the robust schedules.

Table 6. The verification results of generated scenarios.

		Without Load Shifting	With Load Shifting
Objective values of generated scenarios	Minimum	k$ 137	k$ 49
	Mean	k$ 190	k$ 92
	Maximum	k$ 241	k$ 139
Deterministic objective value		k$ 167	k$ 90
Heuristic worst-case objective value		k$ 268	k$ 171
Robust objective value		k$ 272	k$ 174

In addition, a sensitivity analysis on the uncertainties was performed to determine which of the uncertain parameters had the most impact on the scheduling problem. Accordingly, three cases were considered in which only one of the uncertain parameters could vary between 95% and 105% of its forecasted values:

- Case1: Production of wind and photovoltaic units was equal to forecasted values, and the load could vary between 95% and 105% of its forecasted values.
- Case2: Production of wind unit and the load was equal to forecasted values, and the solar unit production could deviate between 95% and 105% of its forecasted values.
- Case3: Production of the solar unit and the load was equal to forecasted values, and the wind unit production could vary between 95% and 105% of its forecasted values.

Table 7 shows the results of the above cases. As can be seen, cases 1 and 2 had the highest and lowest objective values, respectively. In other words, the uncertainties in load and production of the solar unit had the greatest and least impact on the model. This is obvious since no solar power was available in at least one-third of the day. Furthermore, the values of objective functions for case 2 and the deterministic model were almost the same.

Table 7. The objective values of cases 1–3.

	Without Load Shifting	With Load Shifting
Case 1	k$ 246	k$ 149
Case 2	k$ 191	k$ 89
Case 3	k$ 209	k$ 105

5. Summary and Conclusions

In this paper, a robust scheduling model was proposed for islanded MGs considering load shifting. The uncertainties in local load and power production of wind and solar resources were captured using a robust optimization method. The obtained bilevel MILP optimization problem was solved using a hybrid method based on the GA and a typical MILP solver. The results of applying the represented model on a typical low-voltage MG were reported, and a sensitivity analysis on uncertainties was provided. The results demonstrated that load shifting could reduce the total cost of scheduling in all cases. Moreover, the results elaborated that the worst case occurred when the renewable DG generations were the lowest while the load took the highest values. Moreover, it was shown that the uncertainties in load and solar output power had the greatest and least effect on MG cost.

The proposed scheduling model in this paper could be developed and extended for multicarrier energy MGs. Moreover, another future direction would be to propose a suitable linearization and convex relaxation approach to combine both FLP and SLP to improve the computational performance and accuracy of the proposed model.

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Nomenclature

Symbol	Description
t, t', k	Indices of time intervals
i	Index of generation units
T	Set of time intervals
NDG	Set of conventional DG units
RE	Set of renewable DG units
BAT	Set of energy storage

Parameters and Constants

Parameters	Description
$\underline{P_{i,t}^{wt}}$, $\overline{P_{i,t}^{wt}}$	Power production's lower and upper limits in wind unit i at time interval t, respectively
$\underline{P_{i,t}^{pv}}$, $\overline{P_{i,t}^{pv}}$	Power production's lower and upper bound in each solar unit i at time interval t, respectively
$\underline{PD_t}$, $\overline{PD_t}$	Lower and upper bound of load profile at hour t, respectively
A_i, B_i	Cost function parameters of conventional DG unit i
CS_i, CD_i	Start-up and shut-down expenses of conventional DG unit i, respectively
α_i, β_i	Cost function parameters of energy storage i
C_i	Fixed cost of renewable generator i
ρ_t^{sh}	Cost of shifting load at time interval t
ρ_t^{IL}	Cost of load curtailment for interruptible load at time interval t
ρ_t^{NIL}	Penalty of load shedding for non-interruptible load at time interval t
PS^{max}	Maximum allowable load shifting
$P_{i,\max}^{DG}, P_{i,\min}^{DG}$	Upper and lower generation limits of conventional DG unit i
R_i^{UP}, R_i^{DN}	Ramp-up and ramp-down bounds for conventional DG unit i
T_i^{UP}, T_i^{DN}	Minimum up and minimum down time of conventional DG unit i
UF_i, DF_i	Required up and required down time of conventional DG unit i at the beginning of the horizon, respectively
$P_{i,\max}^{ch}, P_{i,\max}^{dis}$	Limits on charge and discharge of energy storage unit i, respectively
SOC_i^{max}, SOC_i^{min}	Upper and lower state of charge of energy storage unit i, respectively
η_{ch}, η_{dis}	Charge and discharge efficiency of energy storage units, respectively
E_{BATmax}	Installed capacity of energy storage devices
d_T	Duration of each time interval t, e.g., 1 h
$P_{t,\max}^{IL}, P_{t,\max}^{NIL}$	Maximum allowable load curtailment for interruptible and non-interruptible loads at time interval t, respectively
n	The maximum number of sequential hours that the load can be shifted
h	The shifting hours for shiftable loads
e	The beginning hour to shift the load

Functions and Variables

Variables	Description
PD_t	Power demand at hour t
$P_{i,t}^{wt}$, $P_{i,t}^{pv}$	Power production of wind and photovoltaic unit i at hour t
W, I, F	Commitment status (start-up and shutdown) of DGs
$P_{i,t}^{DG}$	Generated power of conventional DG unit i at time interval t
$P_{i,t}^{ch}$, $P_{i,t}^{dis}$	Energy storage charge and discharge ratio i at time interval t, respectively
$SOC_{i,t}$	State of charge of storage unit i
$Z_{i,t}^{ch}$, $Z_{i,t}^{dis}$	Binary variables denoting charging and discharging status of energy storage unit i at time interval t, respectively
P_t^{IL}, P_t^{NIL}	Load curtailment for interruptible and non-interruptible loads at time interval t, respectively
PS_t	The amount of shifted load at time interval t

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