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Research Article

A Hybrid Constraints Handling Strategy for Multiconstrained Multiobjective Optimization Problem of Microgrid Economical/Environmental Dispatch

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Microgrid (MG) economical/environmental dispatch (MGEED) problem is a complex multiobjective optimization topic. Since the generators are diversified and the operation mode changes frequently, the MGEEED problem always has different types of constraints, such as the load balance constraints and the ramp rates constraints, which make it a nonlinear, nonconvex optimization problem. In this paper, the mathematical model of a typical MG system applied in northwest China is established. Then, a hybrid constraints handling strategy (HCHS) based on nondominated sorting genetic algorithm II (NSGAII) is proposed to deal with the typical constraints, by which the constraints violations can be removed in several steps during the evolutionary process. A dimensionality reduction method is introduced to simplify the optimization model. And an individual repair approach is designed for the violations of ramp rates constraints. In order to balance the weights of various types of constraints, the process of constraints handling in standard NSGAII is revised. Thereafter, HCHS-NSGAII is applied to some typical MGEED problems, considering all kinds of typical constraints. The results show that HCHS-NSGAII can obtain feasible Pareto sets with satisfactory convergence and distribution, which is efficient in handling complex practical industrial MGEED problems with the change of constraints combinations.

1. Introduction

With the energy shortage and environmental pollution becoming serious [1–4], the technologies of microgrid (MG) with distributed energy resources (DERs) have been developed rapidly [5–7]. In remote areas of northwest China, the energy requirement is diversified, but the level of energy supply is low [8]. Thus, it is meaningful to establish MG systems by utilizing the local renewable energy such as the wind power and solar energy. Usually, the combined heat and power (CHP) systems like microturbines (MTs) are also needed to provide electricity and heat. As a result, the applications of MGs may cause uncertainty of energy efficiency and environmental pollution if the DERs cannot be dispatched properly. Therefore, solving the multiobjective optimization problem (MOP) of MG economical/environmental dispatch (MGEED) is an important topic to save energy and reduce emissions simultaneously [9–12].

The complexity of the MG system makes MGEED a nonlinear, nonconvex mathematical optimization problem. One of the reasons is that in a practical MG system, there are various types of constraints caused by different distributed generators (DGs), distributed energy storage systems (DESSs), and the whole MG system. Thus, as a MOP, these constraints, such as the equality and inequality constraints and multivariable constraints, make the feasible solutions region distributes unevenly in a high dimension search space, which may make it difficult for the optimization algorithms to reach feasible Pareto fronts [12, 13].

Many researchers have studied the nonlinear optimization methods and their application on MG systems economical/environmental dispatch problems [14–19]. In recent years, multiobjective evolutionary algorithms (MOEAs) have been introduced to deal with the MGEED problems, which is more efficient for solving nonconvex objective functions and more flexible in handling the constraints [10, 18, 20]. However, researchers mainly focused on the accuracy and the efficiency of algorithms instead of constraints handling strategies. Penalty function method (PFM), which is a common, simple, and efficient constraint handling method for constrained optimization problems, is generally used in MOEAs. In [19], the PEM was applied to convert the constrained MG cost optimization problem into an unconstrained one by modifying the objective function with related penalty items. The simulation results showed that PEM could help the optimization approach to find satisfied feasible solutions. However, in that study the amount of the constraints was not large, and the economical and environmental objectives were combined as only one optimization task. In [21], the authors introduced a method to handle the constraints in multiobjective problems taking account of both feasibility and domination, which is called "Deb's constraints handling criteria". It was used in some of the studies [13, 22–24], and the results showed that by using this method considering both feasibility and domination, the proportion of the infeasible solutions could be reduced evidently [13, 23]. However, this method needed to add the overall constraints which were actually of different types and could not be easily quantified. In addition, [20] proposed two frameworks based on MOEAs to solve the multiconstrained MGEED problems, and both of the strategies obtained the feasible Pareto sets. However, the authors only considered some of the common used constraints, and the constraint handling approaches were not customized, which may reduce the efficiency when the optimization frameworks were applied to other MGEED problems with different combinations of constraints.

From the above researches it is obvious that the constraints handling problems of MGEED have not been systematically studied. Most of the studies utilized a general method to deal with the violations. However, as a practical MOP, the MGEED problems have serious challenges to the MOEAs for the following reasons:

(1) MGEED problems have various types of constraints, such as the equality constraints and inequality constraints.

(2) The dimension of the search space is high. Since almost every variable in a solution should meet at least one constraint, the amount of the constraints are always very large, which may make the feasible region in uneven distribution.

(3) When using MOEA as the optimization tool, the generation of constraints violations may appear in different steps of the optimization process.

(4) As a practical MOP, the combinations of the constraints may change in different scenarios.

Considering the above challenges, the single and static constraint handling strategies may not always adapt to the MGEED problems, especially when the constraints are complex. Therefore, it is necessary to study the hybrid approaches in dealing with all kinds of MG constraints.

In remainder of this paper, the system models and objective functions are established in Section 2. The hybrid constraints handling strategy (HCHS) based on nondominated sorting genetic algorithm II (NSGAII) is designed in Section 3. Thereafter, the HCHS-NSGAII is applied to several practical MGEED problems with different constraints combinations to study the efficiency of the proposed hybrid constraints handling strategy in Section 4. Finally, the conclusions of the study are presented.

2. Modeling of MGEED

2.1. MG System Description. The MGEED problem is to allocate the output of every distributed component to meet the predicted electricity and heat load demand without prejudice to any of the constraints through the whole 24-hour process, while maximizing the financial and ecological benefit of the MG system. In this section, the proposed objective functions and constraints are discussed. The structure of the typical MG used in this paper is shown in Figure 1. It can be seen that two kinds of uncontrollable DGs, namely, photovoltaic cells (PVs) and wind turbines (WTs), are considered, of which the mathematical models and related parameters are described in [22, 24]. Two microturbines (MTs) and two fuel cells (FCs) with different parameter settings are considered as the controllable DGs to supply electricity power. A battery bank is also included as the DESS. Besides, the power exchanged with the main grid is considered when the MG system turns to grid connected mode by the PCC (point of common coupling).

2.2. Objective Functions. In this paper, the total operating cost is considered as one of the objectives to be minimized, which contains the fuel cost, the start-up cost, the maintenance cost, and the outcome, by introducing the power from the main grid. Thus, the objective function for minimum cost can be described below:

$$\min C(\mathbf{X}) = \sum_{t=1}^{T}\left\{\sum_{i=1}^{N_g}\left(\mathrm{CF}_{G,i,t}(\mathbf{X}) + \mathrm{STC}_{G,i,t}(\mathbf{X}) + \mathrm{OM}_{G,i,t}(\mathbf{X})\right) + \sum_{j=1}^{N_s}\left(\mathrm{OM}_{S,j,t}(\mathbf{X})\right) + C_{\mathrm{grid},t}(\mathbf{X})\right\}, \quad (1)$$

where $\mathbf{X}$ is the decision variable vector; T is the number of the time intervals; N_g and N_s are the total amounts of the DGs and DESSs, respectively; $\mathrm{CF}_{G,i,t}$ and $\mathrm{STC}_{G,i,t}$ are the fuel cost and the start-up cost of the ith controllable DG at time t, respectively; $\mathrm{OM}_{G,i,t}$ and $\mathrm{OM}_{S,j,t}$ are the maintenance costs for the ith controllable DG and the jth DESS at time t, respectively; $C_{\mathrm{grid},t}$ is the cost of the purchased power from the main grid. The model functions of $\mathrm{CF}_{G,i,t}$, $\mathrm{OM}_{G,i,t}$, $\mathrm{OM}_{S,j,t}$, $C_{\mathrm{grid},t}$ can be found in [22, 23], and the start-up cost function is described below:

$$\mathrm{STC}_{G,i,t} = \sigma_i + \delta_i\left[1 - \exp\left(\frac{-T_{\mathrm{off},i,t}}{\tau_i}\right)\right]\left(1 - u_i(t)\right), \quad (2)$$

where σ_i and δ_i are the hot start-up cost and cold start-up cost of the ith controllable DG, respectively; $T_{\mathrm{off},i}(t)$ is the

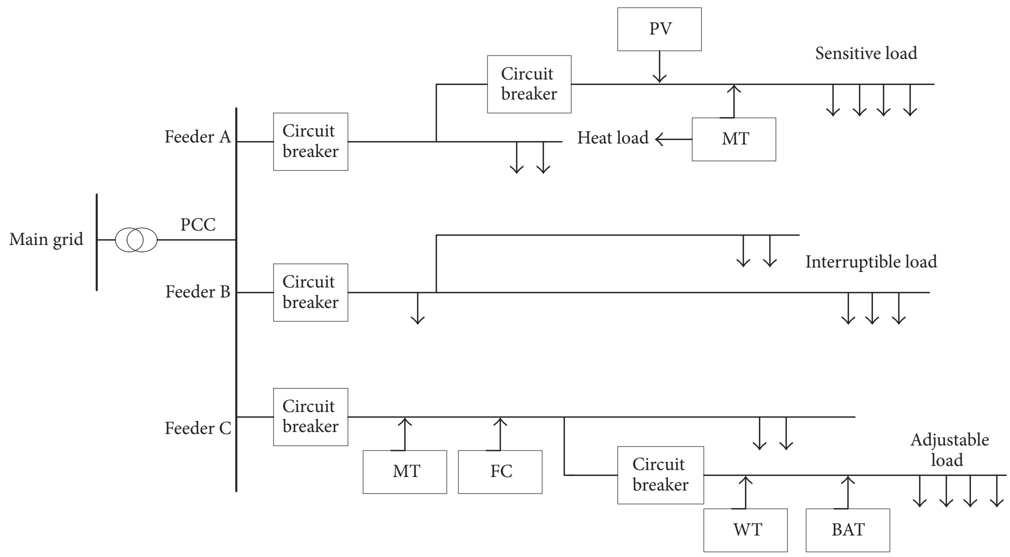

Figure 1: The structure of a typical MG.

time during which the ith controllable DG has been off at the beginning of the tth scheduling period; τ_i and $u_i(t)$ are the cooling time constant and the on/off status of the ith controllable DG, respectively.

Another objective to be optimized is the emission from the MG system, which is shown below:

$$\min E(\mathbf{X}) = \sum_{t=1}^{T} \left\{ \sum_{i=1}^{N_g} E_{G,i,t} + \sum_{j=1}^{N_s} E_{S,j,t} + E_{\text{grid},t} \right\}, \quad (3)$$

where $E_{G,i,t}$, $E_{S,j,t}$, and $E_{\text{grid},t}$ represent the emission of the ith controllable DG, the jth DESS, and the main grid at time t, respectively. In this paper, only the emission production of the controllable DGs is considered, as shown below:

$$E_{G,i,t} = \alpha_i \cdot \text{PW}_{G,i,t}{}^2 + \beta_i \cdot \text{PW}_{G,i,t} + \gamma_i, \quad (4)$$

where α_i, β_i, γ_i are the emission coefficients and $\text{PW}_{G,i,t}$ is the power output of the power generators. The values of the emission coefficients can be found in [25].

2.3. Typical Constraints. As a practical multiobjective optimization problem, the MGEED problem may have various types of constraints. In this paper, some typical ones are mainly introduced as follows.

(1) Rated Power Constraints. Each controllable DG has its maximum and minimum output power constraints. Similarly, the power from the grid is also limited. The constraints are shown below:

$$\text{PW}_{G,i,\min} \leq \text{PW}_{G,i,t} \leq \text{PW}_{G,i,\max}, \quad (5)$$

$$\text{PW}_{\text{grid},\min} \leq \text{PW}_{\text{grid},t} \leq \text{PW}_{\text{grid},\max}, \quad (6)$$

where $\text{PW}_{\text{grid},t}$ is the power exchanged with the main grid.

(2) Electricity Power Balance Constraints. The electricity power generated by all the components from the MG system should exactly meet the total load demands $\sum_{l=1}^{N_L} P_{EL,l}(t)$ at time t, which can be described as

$$\sum_{i=1}^{N_g} \text{PW}_{G,i,t} + \sum_{j=1}^{N_s} \text{PW}_{S,j,t} + P_{\text{grid}}(t) - \sum_{l=1}^{N_L} P_{EL,l}(t) = 0, \quad (7)$$

where $\text{PW}_{S,j,t}$ is the jth charged/discharged power of the DESSs at time t and N_L is the number of electricity load demands. In this paper, $N_L = N_S = 1$.

(3) Heat Power Balance Constraints. The thermal power $Q_{ho,k,t}$ from the MTs should exactly meet the heat load demand $P_{\text{HL},l}(t)$, which is shown below:

$$\sum_{k=1}^{N_m} Q_{ho,k,t} + P_{\text{HL},l}(t) = 0, \quad (8)$$

where $Q_{ho,k,t}$ is the quantity of the exhaust heat of the kth MT at time t and N_m is the number of the MTs in the MG system. The mathematical model and parameter settings of $Q_{ho,k,t}$ can be found in [22].

(4) State of Charge Constraints. The battery bank (BAT) cannot be overcharged or overused, so the limits of the state of charge (SOC) of the battery bank are as follows:

$$\text{SOC}_{\min} \leq \text{SOC}_t \leq \text{SOC}_{\max}. \quad (9)$$

(5) BAT Charge/Discharge Constraints. The charging/discharging power of the BAT ($P_{\text{char}}/P_{\text{dischar}}$) is limited in order to protect the devices, which can be described as

$$\begin{aligned} P_{\text{char}}(t) &\leq P_{\text{char},\max} \\ P_{\text{dischar}}(t) &\leq P_{\text{dischar},\max}. \end{aligned} \quad (10)$$

The relation between the state of charge and the charging/discharging power of the BAT mentioned above can be expressed as

$$\mathrm{SOC}_t = \mathrm{SOC}_{t-1} + \eta_{\text{char}} P_{\text{char}} \Delta t - \frac{1}{\eta_{\text{dischar}}} P_{\text{dischar}} \Delta t, \quad (11)$$

where η_{char} and η_{dischar} are the charging and discharging efficiencies of the BAT and Δt is the time interval.

(6) Ramp Rates Constraints. The increase/decrease of output power of MTs in unit time is called ramp rate, which reflects the performance of the DGs. The ramp rates cannot exceed a certain value, which can be expressed as

$$\left|\mathrm{PW}_{G,i,t} - \mathrm{PW}_{G,i,t-1}\right| \leq \mathrm{PW}_{G,i,\text{ramp}}. \quad (12)$$

3. HCHS-NSGAII

It can be seen from Section 2 that the MOP of MGEED has complicated solution spaces, due to the complexity of the variable vectors, the objective functions, and the constraints, which makes it difficult for the optimization algorithms to find the optimal Pareto set. Especially, there is a wide variety of constraints, which has strong coupling and nonlinearity. Therefore, one of the keys to solve the MOP of MGEED is to design high efficient optimization algorithms, which can accurately handle the multiple constraints. In this paper, NSGAII is introduced as the core optimization tool to solve the MOP of MGEED. Furthermore, NSGAII is improved with an MG-multiconstraint handling approach to adapt the challenges in this specific multiconstrained MGEED.

3.1. Standard NSGAII. NSGAII was proposed by Deb et al. in 2002 [21], which is one of the most efficient dominance-based MOEAs. The main features of NSGAII are described as follows: (1) elitist based strategy: in this way, the elitist individuals are kept during the evolution procedure; (2) fast nondominated sorting: by utilizing this method, the computational complexity can be reduced; (3) crowding distance calculation: by sorting the individuals in the same Pareto level according to the crowding distance, the diversity of the population is well protected. NSGAII has strong robustness in dealing with complex MOPs and can obtain solutions with good diversities quickly. The process of standard NSGAII can be found in [21].

3.2. Hybrid Constraint Handling Strategy. As mentioned in Section 1, when solving MOPs using NSGAII, Deb's constraints handling criteria are based on the individual feasibility and the violations of the overall constraints in the sorting procedure, which is widely used in many studies. During the constraints handling process, the solutions with smaller overall constraints will be selected if neither of the candidates is feasible. However, in the practical MGEED, different constraints cannot be combined directly and the method in [21] is not able to handle the constraints related to variables generation process. Therefore, this paper proposed a hybrid constraint handling strategy (HCHS) to improve the performance of NSGAII in dealing with the complex constraints, which is described as follows.

3.2.1. Dimensionality Reduction for the Equality Constraints. The equality constraints violations, such as the violations of electricity power and heat power balance constraints, are difficult for the method in NSGAII to completely eliminate, because of the generating ways of the variables in the equalities. Thus, this paper suggests that the output of MT1 and the power exchanged with the grid should be selected to transfer the equalities into inequalities with its own limits, which decreases the difficulties of dealing with the constraints. Take the electricity power balance constraints handling as an example. The transformation procedure is shown below.

First, according to (7), $\mathrm{PW}_{g,1}(t)$ can be expressed as

$$\mathrm{PW}_{g,1}(t) = f_1^{-1}\left(P_{\mathrm{HL},l}(t) - \sum_{k=2}^{N_m} f_k\left(\mathrm{PW}_{g,k}(t)\right)\right). \quad (13)$$

Then, according to (7) and (13), $P_{\text{grid}}(t)$ can be described as

$$\begin{aligned} &P_{\text{grid}}(t) \\ &\quad = P_{EL}(t) \\ &\qquad - \sum_{i=2}^{N_g} \mathrm{PW}_{G,i,t} + f_1^{-1}\left(P_{\mathrm{HL},l}(t) - \sum_{k=2}^{N_m} f_k\left(\mathrm{PW}_{g,k}(t)\right)\right) \\ &\qquad + \sum_{j=1}^{N_s} \mathrm{PW}_{S,j,t}. \end{aligned} \quad (14)$$

Therefore, (6) can be transformed as

$$\begin{aligned} &\mathrm{PW}_{\text{grid,min}} \\ &\quad \leq P_{EL}(t) \\ &\qquad - \sum_{i=2}^{N_g} \mathrm{PW}_{G,i,t} + f_1^{-1}\left(P_{\mathrm{HL},l}(t) - \sum_{k=2}^{N_m} f_k\left(\mathrm{PW}_{g,k}(t)\right)\right) \\ &\qquad + \sum_{j=1}^{N_s} \mathrm{PW}_{S,j,t} \leq \mathrm{PW}_{\text{grid,max}}, \end{aligned} \quad (15)$$

where $\mathrm{PW}_{g,1}(t)$ and $P_{\mathrm{HL},l}(t)$ are the electricity power output of MT1 and the heat load demand, respectively. Equation (15) describes the final inequality constraint after transformation.

By the transformation process above, the equality constraints violations are converted to inequality ones, which are easier to be removed. Furthermore, since one of the variables in the equality has been replaced, the dimensionality of the search space can be reduced. In this way, the optimization model can be simplified.

3.2.2. Repair Process after Generation of a New Individual. Since the individuals are generated using some heuristic-based stochastic methods in NSGA-II, the constraint handling method in [21] cannot reduce the violation of some

Input: $PW_{G,i}$
Output: $PW'_{G,i}$
$PW'_{G,i} \leftarrow []$;
for $t \leftarrow 2$ to T **do**
  if $|PW_{G,i,t} - PW_{G,i,t-1}| > PW_{G,i,\text{ramp}}$
    if $PW_{G,i,t} > PW_{G,i,t-1}$
      $PW'_{G,i,t} \leftarrow \min(PW_{G,i,\max}, PW_{G,i,t} + PW_{G,i,\text{ramp}})$;
    else
      $PW'_{G,i,t} \leftarrow \max(PW_{G,i,\min}, PW_{G,i,t} - PW_{G,i,\text{ramp}})$;
    end
  end
end
return $PW'_{G,i,t}$;

Algorithm 1: Repair process.

constraints, such as the ramp rates constraints and the rated power constraints, related to variables generation process. Thus, a repair process is needed after the variable initialization process and the genetic operation process. The pseudocode of repairing the new individuals is presented in Algorithm 1.

It can be seen from Algorithm 1 that the repair process can transfer the infeasible individuals which violate the ramp rates constraints and the rated power constraints into feasible individuals. In this way, the feasibility of the potential solutions is guaranteed. However, the repair process can only handle the violations in the variable generation process, and the computational complexity may be high. It is clear that at the beginning of the evolutionary procedure, the proportion of the infeasible solutions in the population is high, while the population is diversified because of the random generation process. However, at the end of the optimization, the feasibility of the solutions should be guaranteed. Therefore, the repair probability on the infeasible potential solutions is designed to be dynamic depending on the evolutionary generations, as shown below:

$$p_{\text{repair}}(\text{GEN}_{\text{cur}}) = \begin{cases} \left(\dfrac{\text{GEN}_{\text{cur}}}{\text{GEN}_{\text{swi}}}\right)^2, & \text{GEN}_{\text{cur}} \le \text{GEN}_{\text{swi}} \\ 1, & \text{GEN}_{\text{cur}} > \text{GEN}_{\text{swi}}, \end{cases} \quad (16)$$

where GEN_{cur} and GEN_{swi} are the current generation and the switch generation. At the beginning of the evolutionary process, the value of p_{repair} is small and the change speed is slow with the increase of the generation. In this way, a significant number of infeasible solutions can be kept in the population to protect the diversity, which may lead the algorithm to find more feasible regions. When GEN_{cur} is close to GEN_{swi}, the increase speed of p_{repair} is high and most of the infeasible individuals could be repaired. When the number of evolutionary generations is larger than GEN_{swi}, all the infeasible solutions should be repaired to ensure the feasibility of the final solutions. In this paper, GEN_{swi} equals half of the maximum generations.

3.2.3. Normalization and Weighted Sum Process in Selection. For the overall violations combined with different types of constraints, such as the battery SOC constraints and the transferred constraints in Section 3.2.1, each of the subitems should be normalized before being used, which can be calculated as

$$v_{l,k,\text{norm}} = \frac{v_{l,k} - v_{k,\min}}{v_{k,\max} - v_{k,\min}}, \quad (17)$$

where $v_{l,k}$ and $v_{l,k,\text{norm}}$ are the actual and normalized violation values of the kth type of constraint in the lth individual, respectively; $v_{k,\min}$ and $v_{k,\max}$ are the minimum and maximum violation values of the kth type of constraint in the population, respectively. Then, the overall constraints violation of the lth individual can be obtained by

$$v_l = w_1 \cdot v_{l,1,\text{norm}} + w_2 \cdot v_{l,2,\text{norm}} + \cdots + w_c \cdot v_{l,c,\text{norm}}, \quad (18)$$

where w_k is the penalty weight of the kth type of constraint and c is the number of the constraints types using method in [21].

3.2.4. Optimization Procedure of HCHS-NSGAII. The three approaches designed above are combined with Deb's constraints handling criteria to deal with all kinds of constraints violations in the MOPs of MGEED when using NSGAII. In practical day-ahead MGEED, the data may always change with time. Therefore, the forecast load demands and the predicted environmental data should be obtained first. Besides, the structure and the operation mode of the MG may also change [26, 27] according to the operators' requirement, which would cause the change in the optimization models. So the optimization objectives and constraints should also be updated before applying the optimization algorithm. One of the key parts is to classify the constraints using the method proposed in this section, which would guarantee the efficiency of HCHS-NSGAII. Then, the optimization procedure of HCHS-NSGAII starts.

Before running the main program, the optimization models are simplified by the dimensionality reduction methods. Then, after the population initial process, the infeasible

Table 1: The rates of the feasible solutions (%).

Scenarios	HCHS-NSGAII		S-NSGAII		PFM-NSGAII	
	Best	Mean	Best	Mean	Best	Mean
Scenario One	100	98	87	85	78	74
Scenario Two	100	92	33	29	26	23
Scenario Three	98	88	16	13	12	11
Scenario Four	94	86	7	5	2	1

Table 2: The best extreme feasible solutions for the minimum cost and emission using the three algorithms.

Methods		Scenario One	Scenario Two	Scenario Three	Scenario Four
HCHS-NSGAII	for obj1[1]	(20.12, 279.283)	(81.06, 665.581)	(122.47, 864.043)	(183.56, 1012.973)
	for obj2	(98.72, 0.268)	(177.99, 305.079)	(201.47, 721.519)	(242.68, 894.012)
S-NSGAII	for obj1	(20.39, 279.347)	(83.65, 663.062)	(124.67, 866.023)	(185.39, 1000.891)
	for obj2	(99.35, 0.295)	(170.74, 323.159)	(153.87, 775.686)	(205.78, 942.468)
PFM-NSGAII	for obj1	(20.21, 279.436)	(86.00, 674.194)	(126.99, 858.216)	(185.87, 1000.572)
	for obj2	(98.66, 3.617)	(183.51, 326.766)	(139.56, 805.070)	(195.35, 959.465)

[1] obj1 and obj2 represent to the two optimization objectives, namely, the minimum cost and the minimum emission.

individuals are partly repaired according to (16). After that, the main program loop begins. And the normalization and weighted sum methods are applied when using Deb's constraints handling criteria to deal with the violations of the inequality constraints. After the nondominated sorting, the selection, and the genetic operation process, the algorithm will choose whether the partial repair or the total repair process is utilized for the new population according to GEN_{cur}. Then, the new population and the old population will be combined, and the nondominated sorting and the selection will start again. This procedure above is repeated until the termination condition is reached. The flowchart of HCHS-NSGAII is shown in Figure 2.

4. Simulations and Discussion

In this section, the proposed HCHS-NSGAII is tested on a series of MGEED simulation problems. For comparison, another two most used constraints handling methods in solving practical MOPs are also applied. The performances of the three approaches above are discussed.

4.1. Data and Parameter Settings. The environmental data, including the wind speed, irradiance, and air temperature, can be found in [23]. The curves of heat and electricity load demand on a typical day are shown in Figure 3. In addition, the electricity prices and parameter settings of the objective functions and constraints can be found in [22, 23].

Besides, as described in Section 1, the PFM is one of the most popular constraints handling methods in practical optimization problems. And Deb's constraints handling criteria method applied in the standard NSGAII (S-NSGAII) is the most widely used constraints handling method in solving MOPs. Therefore, these two methods are also applied to the following simulations here with NSGAII as their optimization algorithm. The population size is 100 and the maximum generation number is 500 for the three algorithms. The other parameter settings can be found in [21].

Comparing PFM-NSGAII with S-NSGAII, the only difference is that the fitness function of PFM-NSGAII is modified as

$$F_m\left(\mathbf{x}^{(i)}\right) = f_m\left(\mathbf{x}^{(i)}\right) + G_m\left(\mathbf{x}^{(i)}\right), \qquad (19)$$

where $f_m(\mathbf{x}^{(i)})$ is the objective function value of the ith individual for the mth objective. In this paper, to compare the individuals properly, $G_m(\mathbf{x}^{(i)})$ is calculated as

$$G_m\left(\mathbf{x}^{(i)}\right) = R_m\left(f_{m,\min} + v\left(\mathbf{x}^{(i)}\right)\left(f_{m,\max} - f_{m,\min}\right)\right), \qquad (20)$$

where R_m is the penalty coefficient of the fitness function for the mth objective; $v(\mathbf{x}^{(i)})$ is the overall violation value of the ith individual, which can be calculated by (18); $f_{m,\min}$ and $f_{m,\max}$ are the minimum and maximum value for the mth objective in the population. In this paper, $R_m = 10000$.

4.2. Simulation Experiments. In this subsection, four MG operation scenarios with different constraints are considered. In Scenario One, only constraints expressed in (5), (7), and (9) are taken into account, which means the MTs only generate electricity. In Scenario Two, the constraint in (8) is also used, which shows the effects of heat load on the scheduling results. In Scenario Three, besides the constraints mentioned above, the electricity power limit exchanged with the main grid is considered (6). And in Scenario Four, all the constraints described in Section 2 are applied. The last population and the feasible solutions in the objective space of the four scenarios utilizing the three algorithms are shown in Figures 4–7, respectively. Each method will run 10 times for every scenario, and the best and average results are recorded. The rates of the feasible solutions are shown in Table 1. The best extreme feasible solutions for the two objectives using the three algorithms can be found in Table 2. And the average feasible results of the minimum cost and minimum emission are shown in Table 3.

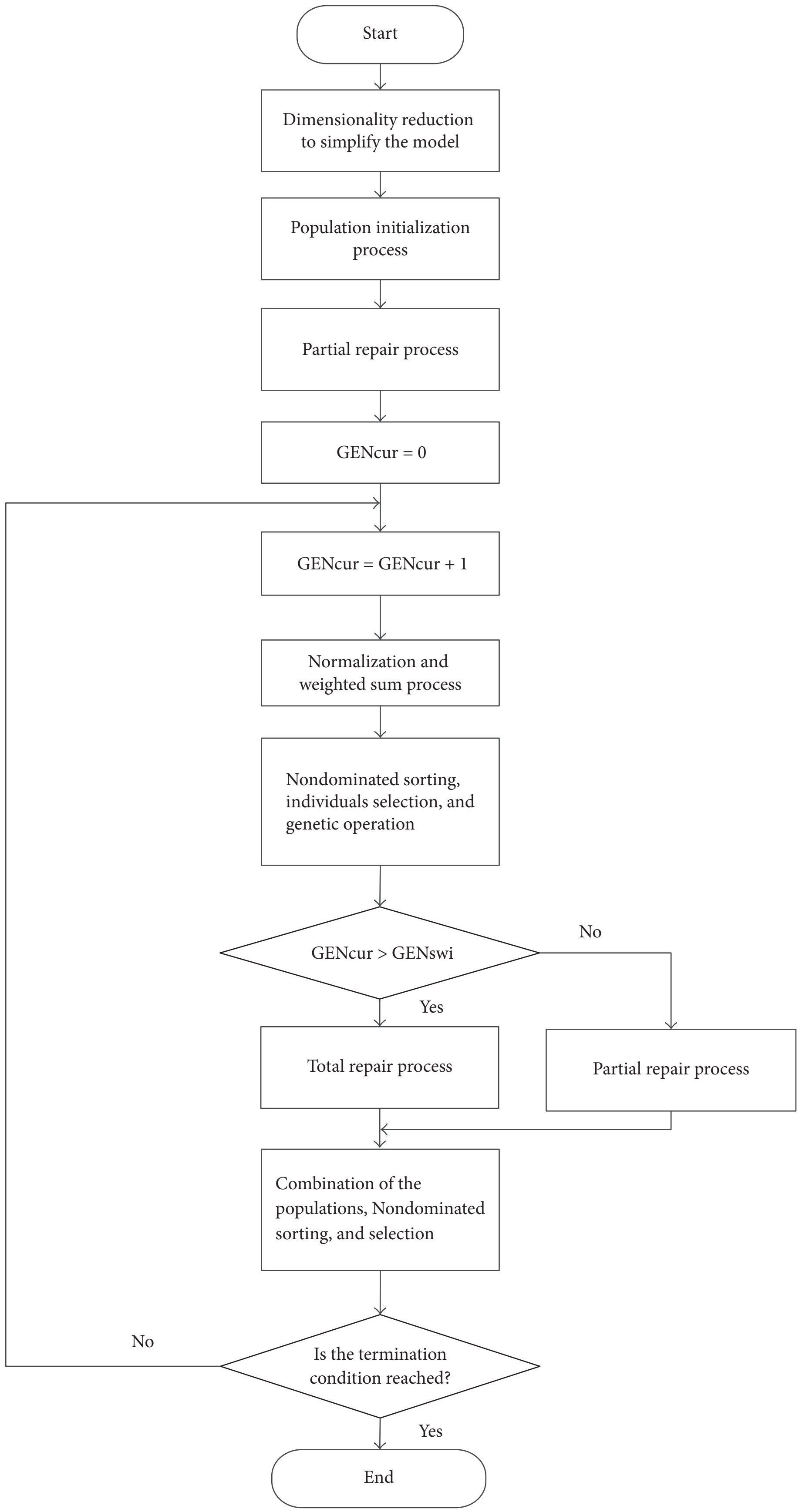

Figure 2: Flowchart of HCHS-NSGAII.

Table 3: The average feasible results of the total cost and emission obtained by the three methods.

Scenarios	HCHS-NSGAII		S-NSGAII		PFM-NSGAII	
	Cost ($)	Emission (kg)	Cost ($)	Emission (kg)	Cost ($)	Emission (kg)
Scenario One	20.37	0.283	20.43	0.311	20.35	3.905
Scenario Two	83.99	312.987	87.35	328.282	92.58	336.987
Scenario Three	126.65	738.001	132.16	790.352	139.24	817.999
Scenario Four	190.87	911.873	199.65	958.981	203.09	987.810

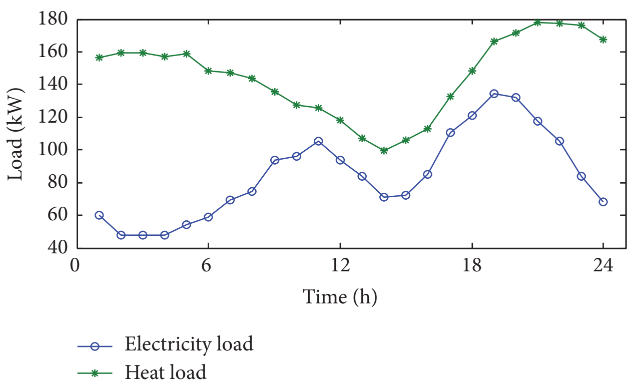

Figure 3: The heat load and electricity load curves.

It can be seen from Figure 4 and Table 1 that when there are only power output limits, battery capacity limits, and electricity power balance constraint, both HCHS-NSGAII and S-NAGAII can solve the MGEED problem well, while HCHS-NAGAII obtains all the feasible solutions as its best record. PFM-NSGAII only gets 78 feasible solutions. All of the three methods reached approximate Pareto fronts. The average amounts of feasible solutions are not much different from their relative highest amounts, which illustrates that the three constraint handling methods have strong robustness in dealing with the MGEED problem in Scenario One. From Tables 2 and 3, it can be seen that the extreme solutions obtained by the three algorithms are similar, and PFM-NSGAII is even better in finding the minimum cost. This means that all of them can manage this MGEED problem.

In Scenario Two, another equality constraint is added. It can be seen from Figures 5(a) and 5(b) that the solutions by HCHS-NSGAII distribute uniformly and all of them are feasible at the best record. However, although some of the solutions by S-NSGAII can dominate those by HCHS-NSGAII (Figure 5(a)), they are actually infeasible. And most of the remaining solutions which are feasible are dominated by those obtained by HCHS-NSGAII (Figure 5(b)). PFM-NSGAII obtains similar results as S-NSGAII, while those by PFM-NSGAII are a little worse since it gets more infeasible solutions according to Figure 5 and Table 1. Tables 2 and 3 also show that HCHS-NSGAII gains the best minimum cost and emission values among the three methods, while the performances of S-NSGAII and PFM-NSGAII are getting worse, especially in the aspects of convergence and distribution. This implies that S-NSGAII and PFM-NSGAII cannot handle the equality constraints violations well, particularly when there are more than one equality constraint. However, by simplifying the optimization model with the dimensionality reduction process, HCHS-NSGAII loses much less feasible solutions than the other two methods.

In Scenario Three, where the MGEED problem becomes more difficult by adding the exchanged electricity power limits, 88% of the population by HCHS-NSGAII is still feasible within 500 generations according to the average result in Table 1, whereas S-NSGAII and PFM-NSGAII just focus on part of the Pareto front according to Figure 6 and only 16% and 12% of the populations are feasible. This is because Deb's constraints handling criteria and the PFM cannot deal with the different kinds of constraints simultaneously, and more infeasible solutions are kept by the elitist based strategy. As a result, most of the solutions converge to an infeasible zone. As for HCHS-NSGAII, the normalization and weighted sum process ensures that all of the constraints violations in different units are taken into account equally, in case that some certain kinds of violations are ignored. Therefore, the approximate Pareto front obtained by HCHS-NSGAII can have good distribution and population diversity.

In Scenario Four, it can be seen from Figure 7 that the results of S-NSGAII and PFM-NSGAII are similar as those in Scenario Three, and only 5% and 1% of the populations are feasible according to the average results. The ramp rates constraints violations are added directly in the overall constraints by the above two constraints handling approaches. Since the violations appear during the variables generation process (which is a random and uncontrollable process), Deb's constraints handling criteria and the PFM cannot remove them completely. Thus, S-NSGAII and PFM-NSGAII cannot lead the algorithm to search a new direction to which the violations can be smaller. Therefore, they cannot directly converge to the feasible approximate Pareto front. For HCHS-NSGAII, according to Figure 7(b) and Table 1, it can get 86 feasible solutions, which is about 17 times and 86 times the feasible solutions obtained by S-NSGAII and PFM-NSGAII, respectively. Obviously, the proposed repair process has avoided the violations of ramp rates constraints and ensured the population diversity.

5. Conclusions

In this paper, a hybrid constraints handling strategy based on NSGAII is proposed for solving the MGEED with various types of constraints. In the HCHS-NSGAII framework, the dimensionality reduction method is employed to simplify the optimization model by transforming the equality constraints

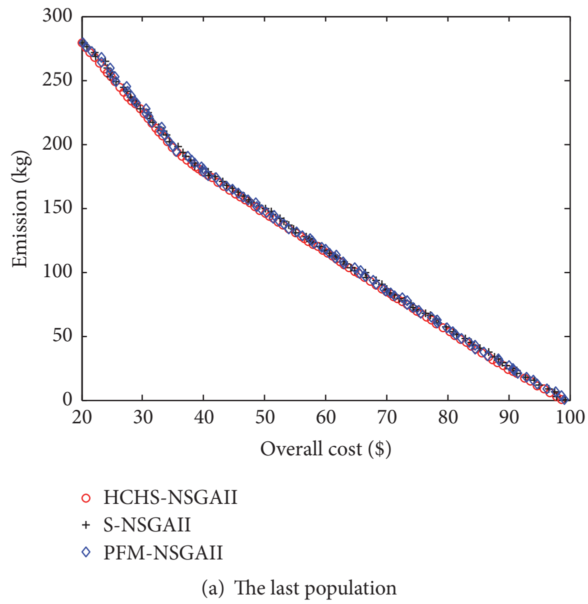

Figure 4: The best optimization results by HCHS-NSGAII, S-NSGAII, and PFM-NSGAII in Scenario One.

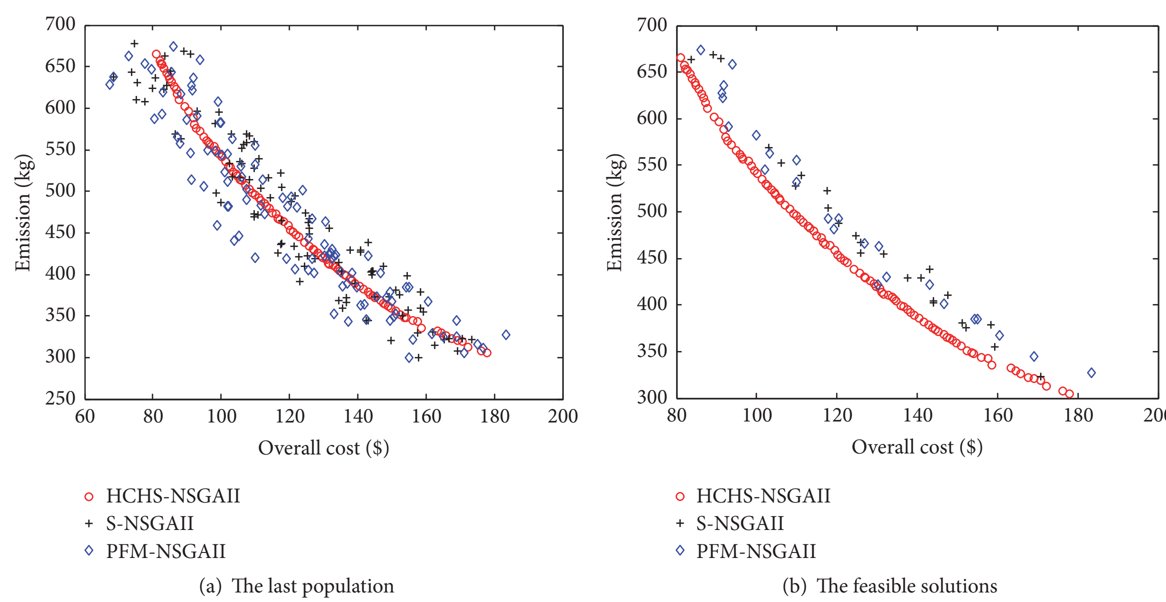

Figure 5: The best optimization results by HCHS-NSGAII, S-NSGAII, and PFM-NSGAII in Scenario Two.

into inequality ones. Meanwhile, a repair process is suggested to handle the ramp rates constraints after the generation of new individuals, which is a dynamical process to ensure the population diversity and the solutions feasibility. In addition, the normalization and weighted sum approaches are introduced to balance the weights of different kinds of constraints. And then HCHS-NSGAII is applied to a series of MGEED problems with different combinations of MG constraints and the results are compared with those obtained by S-NSGAII and PFM-NSGAII. The results show that by utilizing HCHS, NSGAII can gain feasible Pareto sets with satisfactory convergence and distribution in different scenarios, while the widely used constraints handling methods lose the feasible solutions and fall into local optimum with the increase of the MOPs complexity. It is evident that for a complicated industrial MGEED problem which may have various types of constraints, a hybrid constraints handling strategy is more efficient than single methods. And it is better to remove the violations of different constraints in several steps during the evolutionary process, instead of converting them into

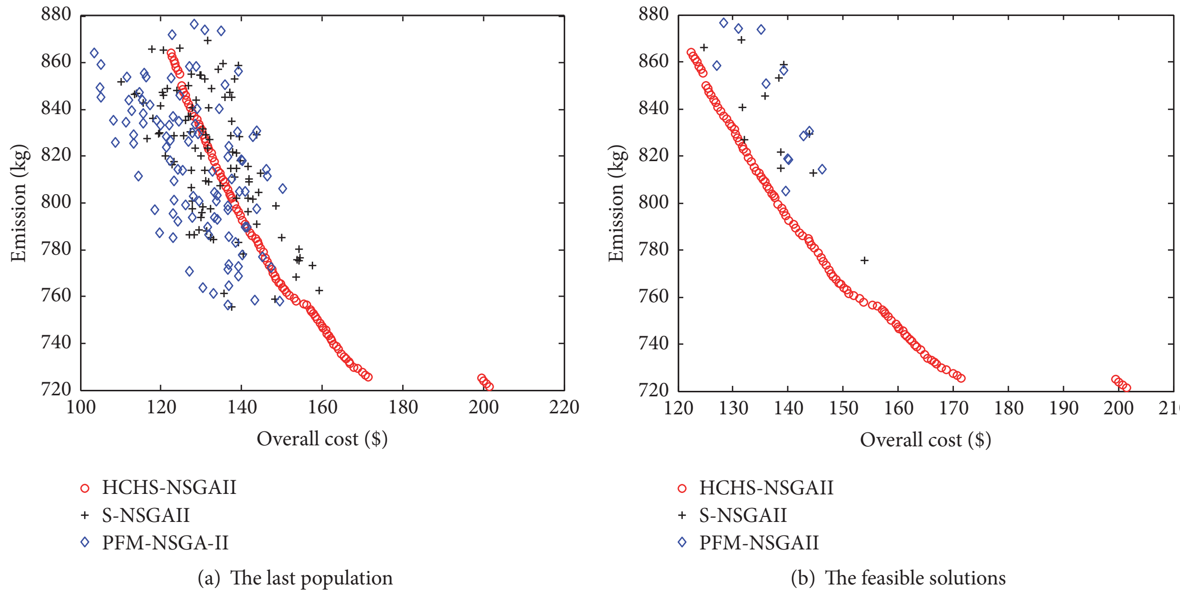

Figure 6: The best optimization results by HCHS-NSGAII, S-NSGAII, and PFM-NSGAII in Scenario Three.

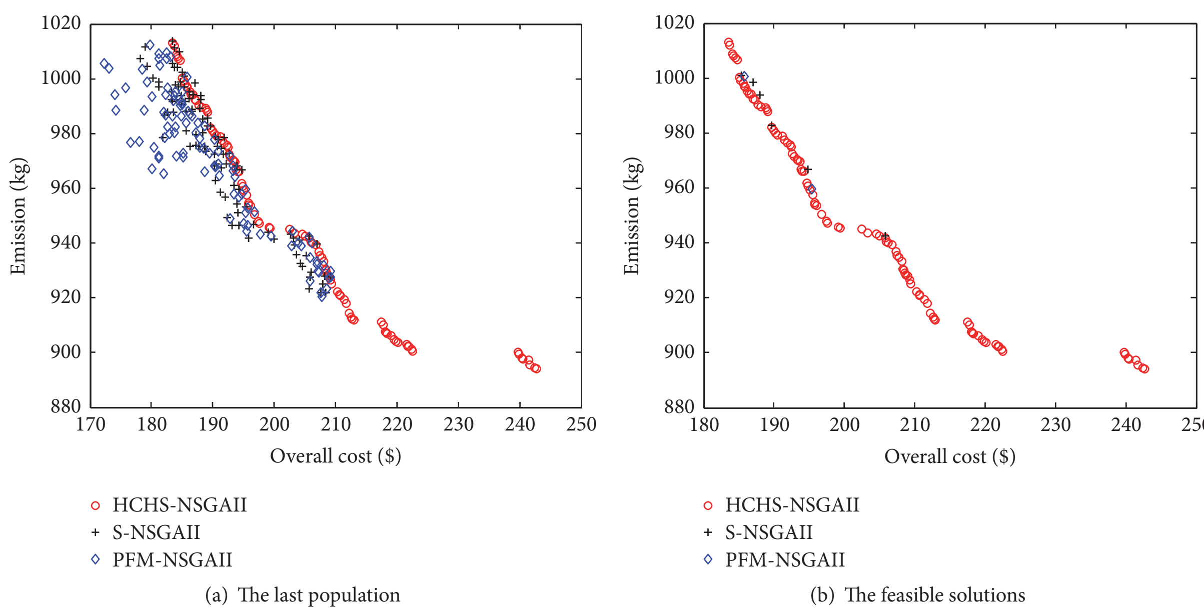

Figure 7: The best optimization results by HCHS-NSGAII, S-NSGAII, and PFM-NSGAII in Scenario Four.

an overall constraints violation. Further studies are needed for designing more efficient algorithms to solve the MGEED problems with the proposed HCHS.

Nomenclature

MG: Microgrid
DERs: Distributed energy resources
CHP: Combined heat and power
MT: Microturbine
MOP: Multiobjective optimization problem
MGEED: MG economical/environmental dispatch
DG: Distributed generator
DESS: Distributed energy storage system
MOEA: Multiobjective evolutionary algorithm
PFM: Penalty function method
HCHS: Hybrid constraints handling strategy
NSGAII: Nondominated sorting genetic algorithm II
PV: Photovoltaic
WT: Wind turbine
FC: Fuel cell
PCC: Point of common coupling
SOC: State of charge

S-NSGAII:	Standard NSGAII
BAT:	Battery
$C_{\text{grid},t}$:	Cost of the purchased power from the main grid ($)
σ_i/δ_i:	Hot/cold start-up cost of the ith controllable DG ($)
$T_{\text{off},i}(t)$:	Time during which the ith controllable DG has been off at the beginning of the tth scheduling period ($)
τ_i:	Cooling time constant of the ith controllable DG (s)
$u_i(t)$:	On/off status of the ith controllable DG
$E_{G,i,t}/E_{S,j,t}$:	Emission of the ith controllable DG/ jth DESS at time t (kg)
$E_{\text{grid},t}$:	Emission of the main grid at time t (kg)
$\text{PW}_{\text{grid,min}}/\text{PW}_{\text{grid,max}}$:	Maximum and minimum power exchanged with the grid (kW)
$\text{PW}_{G,i,t}$:	Power output of the power generators (kW)
$\text{PW}_{G,i,\min}/\text{PW}_{G,i,\max}$:	Maximum/minimum output power of the ith controllable DG (kW)
$\alpha_i, /\beta_i, \gamma_i$:	Emission coefficients
$E(\cdot)$:	Total emission of the MG (kg)
$C(\cdot)$:	Total operating cost of the MG ($)
$\mathbf{X}$:	Decision variable vector
T:	Number of the time intervals
N_g/N_s:	Total amounts of the DGs/DESSs
$\text{CF}_{G,i,t}$:	Fuel cost of the ith controllable DG at time t ($)
$v_{l,k}/v_{l,k,\text{norm}}$:	Actual/normalized violation values of the kth type of constraint in the lth individual
$\text{OM}_{G,i,t}/\text{OM}_{S,j,t}$:	Maintenance cost for the ith DG/ jth DESS at t ($)
$f_m(\mathbf{x}^{(i)})$:	Objective function value of the ith individual for the mth objective
R_m:	Penalty coefficient of the fitness function for the mth objective
$v(\mathbf{x}^{(i)})$:	Overall violation value of the ith individual
$\text{PW}_{\text{grid},t}$:	Power exchanged with the main grid (kW)
N_L:	Number of electricity load demands
$\text{PW}_{S,j,t}$:	The jth charged/discharged power of the DES- Ss at time t (kW)
$Q_{ho,k,t}$:	Quantity of the exhaust heat of the kth MT at time t (kW)
N_m:	Number of the MTs in the MG system
SOC_t:	Amount of stored energy inside the BAT at time t (Ah)
$\text{SOC}_{\min}/\text{SOC}_{\max}$:	Maximum/minimum amount of stored energy inside the BAT (Ah)
$P_{\text{char}}(t)/P_{\text{dischar}}(t)$:	Charging/discharging power of the BAT at time t (kW)
$P_{\text{char,max}}/P_{\text{dischar,max}}$:	Maximum/minimum charging/discharging power of the BAT at time t (kW)
$\eta_{\text{char}}/\eta_{\text{dischar}}$:	Charging/discharging efficiencies of the BAT
Δt:	Time interval
$\text{PW}_{G,i,\text{ramp}}$:	Ramp rate of the ith controllable DG (kW)
$\text{PW}_{g,1}(t)$:	Electricity power output of MT1 (kW)
$P_{\text{HL},l}(t)$:	Heat load demand (kW)
$p_{\text{repair}}(\cdot)$:	Repair probability
$\text{GEN}_{\text{cur}}/\text{GEN}_{\text{swi}}$:	Current/switch generation
$\text{STC}_{G,i,t}$:	Start-up cost of the ith controllable DG at time t ($)
$v_{k,\min}/v_{k,\max}$:	Minimum/maximum violation values of the kth type of constraint
v_l:	Overall constraints violation of the lth individual
w_k:	Penalty weight of the kth type of constraint
c:	Number of the constraints types
$f_{m,\min}/f_{m,\max}$:	Minimum/maximum value for the mth objective.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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