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Multi-Objective Optimal Dispatch of Microgrid under Uncertainties via Interval Optimization

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Abstract—This paper presents a model of multi-objective optimal dispatch of microgrid (MODMG) under uncertainties via the interval optimization (IO) approach. In this model, multiple objectives are optimized simultaneously to meet economics, power quality, and security requirements of microgrid (MG) operations. Moreover, in order to adequately consider uncertain power outputs of wind turbines and photovoltaic cells in an MG, they are presented as interval variables. In turn, the MODMG model under uncertainties is formulated as a multi-objective optimization problem via the IO approach, which is then solved by the optimization algorithm of chaotic group search optimizer with multiple producers (CGSOMP). Simulation studies based on a modified IEEE 112-bus MG verify the effectiveness of the proposed optimal dispatch model and the CGSOMP algorithm.

Index Terms—Microgrid dispatch, MODMG model, uncertainty, interval optimization, multi-objective optimization.

NOMENCLATURE

θ_{ij}	voltage angle difference between bus i and j (rad)
B_{ij}	transfer susceptance between bus i and j (p.u.)
G_{ij}	transfer conductance between bus i and j (p.u.)
N_0	total number buses excluding slack bus
N_B	total number of buses
N_C	total number of shunt compensators
N_D	total number of power demand buses
N_E	total number of network branches
N_G	total number of generator buses
N_i	total number of buses adjacent to bus i
N_{PQ}	total number of PQ buses
N_{PV}	total number of PV buses
N_T	total number of transformer branches
P_{D_i}	demand active power at bus i (p.u.)
P_{G_i}	injected active power at bus i , including traditional, renewable and energy storage power output (p.u.)
Q_{C_i}	reactive power source installation at bus i (p.u.)
Q_{D_i}	demand reactive at bus i (p.u.)

P_{D_i}	demand active power at bus i (p.u.)
P_{G_i}	injected active power at bus i (p.u.)
Q_{C_i}	reactive power source installation at bus i (p.u.)
Q_{D_i}	reactive demand at bus i (p.u.)
Q_{G_i}	injected reactive power at bus i (p.u.)
T_k	tap position at transformer k
V_i	voltage magnitude at bus i (p.u.)
S_k	apparent power flow in branch k (p.u.)

I. INTRODUCTION

It is well recognized that renewable power generation is an effective way to resolve environmental concerns and energy crisis throughout the world. For instance, microgrids (MGs) increasingly utilize a mix of different renewable energy resources, such as wind and solar power, and they are deemed as efficient platforms for integrating renewable energy [1]–[3]. However, renewable power generation is fluctuant and weather-dependent. Therefore, the optimal dispatch of MGs to realize its efficient operation with uncertainties of renewable generations remains a challenging topic.

On one hand, MG dispatch is typically a multi-objective optimization problem. This is due to the fact that dispatchers usually attempt to simultaneously reduce generation cost for electricity supply, obtain satisfactory levels of power quality, and guarantee security of the MG [4]–[11]. For instance, economic operation, voltage deviations, and security margin can be considered as multiple objectives, and a multi-objective optimal operation of an MG is established to obtain the optimal dispatch solution.

On the other hand, micro-sources of an MG usually consist of controllable and uncontrollable units. Controllable units include diesel engines (DEs), micro turbines (MTs) and fuel cells (FCs), while uncontrollable sources consist of wind turbines (WTs) and photovoltaic cells (PVs) [6]. Due to the volatility of these uncontrollable sources, it is difficult to schedule an MG under such uncertainties, in an effective way.

At present, four methods are mainly used for power system/microgrid dispatch based on how the uncertain renewable power is represented, i.e., the fuzzy, stochastic and robust and interval optimization methods. In the fuzzy optimization method, the uncertain renewable power is represented as a fuzzy variable, and fuzzy memberships are set for establishing the fuzzy dispatch model. However, specifying values of such memberships is subjectively determined by power system dispatchers. In this way, the obtained optimal solution may be confronted with strong subjectiveness [12]–[14].

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For the stochastic optimization method, uncertainties are regarded as stochastic variables. Their probabilistic distributions are usually assumed as certain standard probabilistic density functions. For instance, Weibull and Beta probability density functions are usually adopted to describe uncertainties of wind speed and solar irradiance, respectively [15]. However, whether it is proper to apply such standard probability density functions in dispatch remains to be examined [16]. In addition, a large number of scenarios need to be generated by specific sampling methods, such as Monte Carlo method [17], using the probabilistic information, which is usually computationally expensive.

Therefore, in recent years, robust optimization has been a popular method to deal with uncertain scheduling problem in power system/microgrid dispatch [18]–[21]. Ref. [18] presents a robust optimization approach to handle the uncertainty of wind power, in which wind power is expressed as an interval variable and a robust unit commitment schedule for thermal generators is obtained for minimizing the total economic cost under the worst wind power output scenario. Ref. [19] discusses a robust energy management approach for an MG which contains highly penetrated wind and solar power, and establishes the formulation to analyze the worst-case amount of renewable power accordingly. Similarly, in [20], an MG dispatch solution is obtained by optimizing the worst-case scenario, which is robust against most possible realizations within the uncertainty set. In addition, a robust two-stage optimization approach is developed to dispatch MG generators, considering uncertain renewable power, for minimizing the expected economic cost while satisfying operational constraints [21]. We can see that robust optimization is based on the worst case analysis, i.e., a solution is evaluated using the realization of uncertainties that is most unfavorable. Therefore, robust optimization is an alternative optimization approach for solving power system/microgrid dispatch problems while considering uncertain renewable power as an interval variable, and it remains computationally tractable [18].

However, robust optimization is usually considered to be too conservative as it always tries to find the worst-case scenario solution which happens at a very low probability [18]. Therefore, another method, interval optimization, is introduced to address uncertainties of renewable power [22]–[26]. That is, it minimizes the interval of dispatching objective rather than the worst case scenario in robust optimization. For instance, Ref. [22] adopts interval optimization for exploring the optimal solution of unit commitment problem under uncertainties, and this uncertain optimization problem is transformed into two extreme deterministic subproblems with respect to upper and lower bounds of the objective function. Ref. [23] proposes a novel unit commitment formulation based on interval optimization to improve the security and economics of power system operation. Ref. [24] presents an interval optimization based model for reactive power optimization, and the linear approximation method is used to solve this problem. Ref. [25] introduces an interval optimization approach to study economic dispatch problems of power systems with uncertain wind power integration, in which the economic risk effects of alternative dispatch solutions are investigated. Ref. [26]

presents an economic dispatch model based on interval optimization to deal with uncertain renewable power via virtual power plants.

However, interval optimization is usually used to study a single dispatch objective, such as fuel cost in power system/microgrid dispatch, rather than multiple dispatch objectives, to the best of authors knowledge. Indeed, power system/microgrid dispatch contains multiple objectives, as dispatchers usually attempt to simultaneously reduce generation cost for electricity supply, obtain satisfactory levels of power quality, and guarantee system security [4]–[11]. Therefore, we believe it is worth further investigating the combination of interval optimization and multiple objectives for microgrid dispatch. In this paper, we extend the interval optimization to deal with multi-objective microgrid dispatch, which is the major motivation and novelty of our work.

Therefore, this paper discusses a multi-objective dispatch problem of a MG (MODMG) via the IO approach, which is formulated as a multi-objective optimization model with uncertainties presented by interval variables. A multi-objective optimization algorithm based on chaotic group search optimizer with multiple producers (CGSOMP) is used to achieve Pareto optimal solutions with good computational performance. Furthermore, we quantitatively assess and compare the effectiveness of different Pareto optimal solutions and determine the suitable one. Finally, simulation studies on a modified IEEE 112-bus MG system verify the effectiveness of the proposed MODMG model with the IO approach and the efficiency of the CGSOMP algorithm.

The rest of the paper is organized as follows. Section II introduces the MODMG model with the IO approach. Section III presents the multi-objective optimization algorithm, CGSOMP. Simulation studies on a modified IEEE 112-bus MG system are discussed in Section IV. Finally, the conclusion is drawn in Section V.

II. MULTI-OBJECTIVE DISPATCH OF MICROGRID

A. Problem Formulation

In terms of MG operations, multiple objectives reflecting the aspects of economics, power quality, and operational security usually need to be solved, simultaneously [7], [8], [27]. Indeed, the dispatch of an MG is a multi-objective optimization problem subject to prevailing operational constraints. This problem can be formulated as follows:

$$\min [f_1(\mathbf{x}, \mathbf{u}), f_2(\mathbf{x}, \mathbf{u}), \dots, f_M(\mathbf{x}, \mathbf{u})] \quad (1)$$

$$\text{s.t. } g(\mathbf{x}, \mathbf{u}) = 0 \quad (2)$$

$$h(\mathbf{x}, \mathbf{u}) \leq 0 \quad (3)$$

where $[f_1(\mathbf{x}, \mathbf{u}), f_2(\mathbf{x}, \mathbf{u}), \dots, f_M(\mathbf{x}, \mathbf{u})]$ is the vector of M optimization objectives. g and h represent equality and inequality constraints. $\mathbf{x}$ is the set of decision variables, including power outputs of controllable generators P_G but they exclude the slack generator P_{G_1} , generator terminal voltages V_G , transformer tap settings T , outputs of reactive power compensation sources Q_C , and active and reactive power of energy storage devices (ESDs) P_E and Q_E . Therefore, x can be presented as:

$$\mathbf{x}^T = [P_{G_2}, \dots, P_{G_{N_G}}, V_{G_1}, \dots, V_{G_{N_G}}, T_1, \dots, T_{N_T}, Q_{C_1}, \dots, Q_{C_{N_C}}, P_{E_1}, \dots, P_{E_{N_E}}, Q_{E_1}, \dots, Q_{E_{N_E}}] \quad (4)$$

where N_G , N_T , N_C , and N_E are numbers of controllable generators, transformer branches, reactive power compensation sources, and energy storage devices, respectively.

$\mathbf{u}$ represents uncertain power outputs P_W and P_V of WT and PV units.

$$\mathbf{u}^T = [P_{W_1}, \dots, P_{W_{N_{WT}}}, P_{V_1}, \dots, P_{V_{N_{PV}}}] \quad (5)$$

where N_{WT} and N_{PV} are numbers of WT and PV units, respectively.

B. Objectives

To well describe the requirements of economics, power quality, and security of an MG operation, three objectives are studied in this paper, i.e., economic cost (EC), voltage deviation (VD), and statistic voltage stability index (SVSI).

1) *Minimization of EC*: Economic dispatch is one of the fundamental issues in power system operation, which is targeted to minimize the economic cost, i.e., fuel cost of generation units, while satisfying various constraints [28]. That is, power system dispatchers try to identify the optimal dispatching solution, in order to reduce the economic cost as much as possible. We can see that economic cost can be regarded as a dispatching objective in power system operation. Similarly, in microgrid operation, minimizing economic cost is also pursued [6], [29], [30]. Therefore, we also consider the economic cost as one of objectives in microgrid dispatch in our work, which is formulated as the total fuel costs of DEs, MTs and FCs.

The fuel cost of DEs, f_{DE} , is usually modelled as a quadratic function of its power output [6], which is formulated as follows:

$$f_{DE} = \sum_{i=1}^{N_{DE}} a_i + b_i P_{DE_i} + c_i P_{DE_i}^2 \quad (6)$$

where N_{DE} presents the number of DEs, P_{DE_i} stands for the active power output of the i th DE. a_i , b_i , and c_i are its fuel cost coefficients.

As for an MT, the fuel cost, f_{MT} , is modelled as a linear function of its output, shown in (7).

$$f_{MT} = \sum_{j=1}^{N_{MT}} \frac{c_{ng} P_{MT_j}}{\eta_{MT_j} Q_{LHV}} \quad (7)$$

where c_{ng} is the natural gas price. P_{MT_j} stands for the power output of the j th MT, and N_{MT} is the total number of MTs. η_{MT_j} represents the working efficiency of the j th MT, and LHV is the low-hot value of natural gas [6].

Similarly, the fuel cost of an FC, f_{FC} can be formulated as:

$$f_{FC} = \sum_{k=1}^{N_{FC}} \frac{c_{ng} P_{FC_k}}{\eta_{FC_k} Q_{LHV}} \quad (8)$$

where P_{FC_k} is the power output of the k th FC, and N_{FC} is the number of FCs. η_{FC_k} stands for the operational efficiency of the k th FC [6].

Therefore, the EC of an MG, denoted as f_1 , can be shown as follows:

$$f_1 = f_{DE} + f_{MT} + f_{FC}. \quad (9)$$

2) *Minimization of VD*: Bus voltage deviation is one of the most important indices for operational security and power quality. The sum of VDs of all load buses is presented as the following:

$$f_2 = \sum_{i=1}^{N_D} |V_i - V_{ref}| \quad (10)$$

whose minimization discourages voltage changes from a reference magnitude level, V_{ref} . N_D is the number of load buses, and in general the rated voltage magnitudes are set as reference.

3) *Minimization of SVSI*: This objective is to maintain the voltage stability and move the system far away from the voltage collapse point. It can be achieved by minimizing the maximum statistic voltage stability index, formulated as:

$$f_3 = \max\{\hat{L}_1, \hat{L}_2, \dots, \hat{L}_{N_D}\} \quad (11)$$

where $\hat{L}_k$ ($k = 1, 2, \dots, N_D$) is the voltage stability index for bus k [31]:

$$\hat{L}_i = |1 - \sum_{j=1}^{N_G} F_{ji} \frac{V_i}{V_j}| \quad (12)$$

where F_{ji} is the element of the matrix $\mathbf{F}$, which is obtained by (13).

$$\mathbf{F} = \mathbf{Y}_{LL}^{-1} \mathbf{Y}_{LG} \quad (13)$$

where $\mathbf{Y}_{LL}$ and $\mathbf{Y}_{LG}$ represent sub-matrices of the Jacobian matrix, i.e., admittance elements between load nodes and the ones between load and generator nodes, respectively. It should be mentioned that when the decision variables $\mathbf{x}$ are determined, the statistic voltage stability index for each load bus can be calculated, and the maximum $\hat{L}_k$ ($k = 1, 2, \dots, N_D$) is the SVSI of a power system. The third objective is to minimize SVSI, i.e. to minimize the maximum $\hat{L}_k$, defined as f_3 in (11).

Constraints of MODMG shown in (2) and (3) are composed of both equality constraints $g(\mathbf{x}, \mathbf{u})$ and inequality constraints $h(\mathbf{x}, \mathbf{u})$. $g(\mathbf{x}, \mathbf{u})$ represents the requirements of active and reactive power balance, i.e., the active and reactive power generated by generators must be equal to corresponding load consumptions. As a result, $g(\mathbf{x}, \mathbf{u})$ are listed as follows:

$$0 = P_{G_i} - P_{D_i} - V_i \sum_{j=1}^{N_i} V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) \quad 1 \leq i \leq N_0 \quad (14)$$

$$0 = Q_{G_i} - Q_{D_i} - V_i \sum_{j=1}^{N_i} V_j (G_{ij} \sin \theta_{ij} + B_{ij} \cos \theta_{ij}) \quad 1 \leq i \leq N_{PQ}. \quad (15)$$

The inequality constraints $h(\mathbf{x}, \mathbf{u})$ includes physical limits of electrical power equipment, such as capacity limits of generation units, power transformers and reactive power sources, and power system security constraints such as limits on bus voltages and branch apparent power flows. Therefore, $h(\mathbf{x}, \mathbf{u})$ can be presented in following inequalities.

$$\begin{aligned} P_{G_i}^{\min} &\leq P_{G_i} \leq P_{G_i}^{\max} & 1 \leq i \leq N_G \\ Q_{G_i}^{\min} &\leq Q_{G_i} \leq Q_{G_i}^{\max} & 1 \leq i \leq N_G \\ Q_{C_i}^{\min} &\leq Q_{C_i} \leq Q_{C_i}^{\max} & 1 \leq i \leq N_C \\ T_k^{\min} &\leq T_k \leq T_k^{\max} & 1 \leq k \leq N_T \\ V_i^{\min} &\leq V_i \leq V_i^{\max} & 1 \leq i \leq N_B \\ |S_k| &\leq S_k^{\max} & 1 \leq k \leq N_E \end{aligned} \quad (16)$$

Nomenclature can be referred in this paper.

III. MODEL OF MODMG WITH UNCERTAINTIES VIA INTERVAL OPTIMIZATION

Due to the rapid development of renewable energy, more and more WTs and PVs have been integrated into MGs. However, with the high penetration of such uncertain power sources, it is evident that determining an effective dispatch solution for MG operations is difficult. In this paper, we propose the MODMG model via the IO approach, in which uncertainties are formulated as interval variables while their boundaries can be derived via interval forecasting methods.

Compared with traditional power generating units, wind and solar power are volatile and bring high uncertainties to MGs. When

dealing with the dispatch problem in an MG, dispatchers need to determine a dispatch solution at time t , according to the forecasting information of renewable power during dispatch period T , such as 1 hour. Recently, interval forecasting methods have been proposed [32], [33], which can provide upper and lower forecasting bounds for wind and solar power generations, as shown in Fig. 1(a). Therefore, uncertain renewable energy can be represented as interval variables. In this way, MODMG becomes an interval optimization problem, which is formulated as follows:

$$\begin{aligned} \min \quad & [f_1(\mathbf{x}, \mathbf{u}), f_2(\mathbf{x}, \mathbf{u}), \dots, f_M(\mathbf{x}, \mathbf{u})] \\ \text{s.t.} \quad & g(\mathbf{x}, \mathbf{u}) = 0 \\ & h(\mathbf{x}, \mathbf{u}) \leq 0 \\ & \mathbf{u} \in [\mathbf{u}^L, \mathbf{u}^R]. \end{aligned} \quad (17)$$

Fig. 1. The framework of MODMG via interval optimization: (a) Interval forecasting of renewable power; (b) Comparison of different dispatch solutions; (c) non-dominated sorting; (d) The obtained Pareto front.

It can be seen that $f_1(\mathbf{x}, \mathbf{u}), f_2(\mathbf{x}, \mathbf{u}), \dots, f_M(\mathbf{x}, \mathbf{u})$ are interval numbers with respect to a given dispatch solution $\mathbf{x}$. As shown in Fig. 1(b), the interval values of objective functions corresponding to solutions $\mathbf{x}_1, \mathbf{x}_2$ and $\mathbf{x}_3$ can be obtained. For instance, the value of $f_1(\mathbf{x}, \mathbf{u})$ in terms of x_1 is $[f_{1,1}^L, f_{1,1}^R]$, and $A_{1,1}$ is the mid-point value of the interval, which is used to evaluate qualities of interval solutions [23]. The value $A_{3,1}$ is less than $A_{2,1}$ and $A_{1,1}$, therefore, $\mathbf{x}_3$ performs the best in optimizing the objective function $f_1(\mathbf{x}, \mathbf{u})$.

Our aim is to find the optimal $\mathbf{x}$ to get the best value of $f_i(\mathbf{x}, \mathbf{u})$, which is an interval number and should be transformed to a deterministic one. Like [23], mid-point values of $f_i(\mathbf{x}, \mathbf{u})$ with respect to different $\mathbf{x}$ are compared, which can be obtained by:

$$f_i^m(\mathbf{x}, \mathbf{u}) = \frac{f_i^L(\mathbf{x}, \mathbf{u}) + f_i^R(\mathbf{x}, \mathbf{u})}{2}. \quad (18)$$

The i th uncertain objective function $f_i(\mathbf{x}, \mathbf{u}) (i = 1, 2, \dots, M)$ can be represented as an interval number $[f_i^L(\mathbf{x}, \mathbf{u}), f_i^R(\mathbf{x}, \mathbf{u})]$, where $f_i^L(\mathbf{x}, \mathbf{u})$ and $f_i^R(\mathbf{x}, \mathbf{u})$ are lower and upper bounds. These bounds can be determined by the following formulations:

$$\begin{aligned} f_i^L(\mathbf{x}, \mathbf{u}) &= \min_{\mathbf{u}} f_i(\mathbf{x}, \mathbf{u}) \\ f_i^R(\mathbf{x}, \mathbf{u}) &= \max_{\mathbf{u}} f_i(\mathbf{x}, \mathbf{u}). \end{aligned} \quad (19)$$

It is noted that $f_i^L(\mathbf{x}, \mathbf{u})$ and $f_i^R(\mathbf{x}, \mathbf{u})$ are the minimum and maximum values within the uncertainty interval $\mathbf{u}$ and corresponding to the dispatch solution $\mathbf{x}$.

However, MODMG considers multiple objectives simultaneously, which may conflict with each other. In fact, it is shown in Fig. 1(b) that although $\mathbf{x}_3$ is the best solution for $f_1(\mathbf{x}, \mathbf{u})$, it shows the worst performance on $f_M(\mathbf{x}, \mathbf{u})$. Therefore, it is difficult to identify which solution is the best for multiple conflicting objectives, as in a multi-objective optimization, a feasible solution that minimizes all objective functions simultaneously may not exist. Instead, this paper intends to derive Pareto optimal solutions. For a Pareto optimal solution, which is also referred to as non-dominated solution, an objective cannot be further improved without degrading at least one of the other objectives. The detailed definition is shown in Part A of Appendix. In order to obtain such Pareto optimal solutions in this paper, the MODMG formulation via the IO approach is shown as follows:

$$\begin{aligned} \min_{\mathbf{x}} \quad & [f_1^m(\mathbf{x}, \mathbf{u}), f_2^m(\mathbf{x}, \mathbf{u}), \dots, f_M^m(\mathbf{x}, \mathbf{u})] \\ \text{s.t.} \quad & (18) - (19) \\ & g(\mathbf{x}, \mathbf{u}) = 0 \\ & h(\mathbf{x}, \mathbf{u}) \leq 0 \\ & \mathbf{u} \in [\mathbf{u}^L, \mathbf{u}^R]. \end{aligned} \quad (20)$$

The multi-objective optimization algorithms are used for assessing Pareto solutions, and the non-dominated sorting is applied for ranking them [34], as shown in Fig. 1(c). Note that Fig. 1(d) presents the curve of objective values ranked as the best, which is the Pareto front that corresponds to Pareto optimal solutions.

IV. CHAOTIC GROUP SEARCH OPTIMIZER WITH MULTIPLE PRODUCERS

In this section, we will present the algorithm of CGSOMP to effectively solve the proposed MODMG model shown in (20). CGSOMP is an improved version of a recent multi-objective optimization algorithm, group search optimizer with multiple producers (GSOMP) [35], [36]. Note that the weighting method based on mathematical programming was firstly adopted to solve the MO problem, which converts the multiple objectives into a single one with the condition that the weights of different objectives sum up to one [37], [38]. However, it was found that the weakness of the weighting method is that it cannot well solve the non-convex MO problem, as not all of the Pareto optimal solutions can be found [37], [38].

In our paper, we study three objectives, i.e., EC, VD and SVSI, which require us to compute AC power flow, as shown in Eq. (14) and Eq. (15). However, the equality constraints of AC power flow are non-convex, which means that the proposed MG dispatch model is also non-convex. Therefore, the weighting method is not suitable to be used in this paper. On the contrary, as multi-objective optimization algorithms, such as CGSOMP and GSOMP, are easy to implement and can solve non-convex optimization problem. Then, these algorithms can be directly used for solving (20). To well introduce CGSOMP, we first provide a brief introduction of GSOMP.

A. Group Search Optimizer with Multiple Producers

GSOMP is based on a single-objective optimization algorithm, i.e., group search optimizer (GSO) [39], which imitates animal searching behavior based on swarm intelligence. It is composed of three types of members, i.e., producers, scroungers and rangers. As shown in Fig. 2, the producer is acting as a leader to hunt for the global optima. Scroungers follow the producer during the searching process, and try to refine solutions near the producer. The rest of members of GSO are rangers, which adopt random walk in the searching area.

GSOMP is a multi-objective optimization algorithm with multiple producers, each of which aims to hunt for the best value corresponding to individual objective functions. In terms of scroungers, they always follow a random producer according to the producer-scrounger model, together with a solution randomly chosen from the already

obtained Pareto optimal solutions. The rest are rangers, who hunt for other resources by random walk.

Fig. 2. The searching mechanism of GSO

B. CGSOMP

However, it is worth mentioning that GSOMP cannot avoid trapping into local optima, as selecting the suitable control parameters, i.e., the ratio of rangers c and the scrounging coefficient r_3 is challenging. c and r_3 are two important control parameters for GSO, which is the basis of GSOMP. r_3 is the scrounging coefficient and it reflects the following extent of scroungers, led by the producer. c is the ratio of rangers, the larger the ratio, the more the rangers. Appropriate control parameters can improve the chance for the algorithm of GSO to escape from local optima. [40] has proposed a method to adaptively adjust their values, however, the proposed method is very complex due to the calculation of Euclidian metric in each iteration. It is reported that chaotic sequences can be used for effectively tuning control parameters of optimization algorithms with limited computation complexity [41], [42]. Therefore, we attempt to employ the chaotic sequences generated by logistic map for dynamically adjusting the ratio of rangers c and the scrounging coefficient r_3 , which are formulated as follows:

$$c(n) = \mu_1 \times c(n-1) \times [1 - c(n-1)] \quad (21)$$

$$r_3(n) = \mu_2 \times r_3(n-1) \times [1 - r_3(n-1)] \quad (22)$$

where n , μ_1 and μ_2 are the iteration number of GSOMP and parameters of logistic map, respectively. The above equations show chaotic dynamics when $\mu_1 = \mu_2 = 4$, and $[c(1), r_3(1)] \notin [0, 0.25, 0.50, 0.75, 1]$. In this paper, c and r_3 are set to be distributed in $[0.2, 0.5]$ and $[0.5, 0.9]$. These values are selected by using the method of investigating effects of control parameters, which aims to find the suitable values [39].

Fig. 3. The varying values of parameters in CGSOMP

Fig. 3 presents varying values of c and r_3 during the searching process of CGSOMP. It can be easily seen that almost all values of the two control parameters in the set ranges are achieved. Consequently,

CGSOMP can easily jump out of local optima, and in turn can effectively overcome the premature convergence problem of GSOMP. This advantage of the CGSOMP will be further verified in simulation studies of Section V. Moreover, the external archive of CGSOMP is set for storing Pareto optimal solutions.

Fig. 4. The illustration of HV in terms of the space of two objectives [43]

The total number of iterations of multi-objective optimization algorithms is usually pre-specified, which is used to stop the computing procedure and obtain the Pareto front [35]. However, choosing a proper value of such iteration number is difficult, which requires many trials. Above all, we cannot observe whether the solutions are converged during the iterative process. Therefore, in this paper, we adopt a more suitable index to check the iterative process, i.e., the hypervolume (HV) indicator, which is used to measure the quality of Pareto set obtained by multi-objective optimization algorithms. It computes the volume of the dominated portion of the objective space relative to a selected reference point R . Mathematically, for each solution $x_i \in \mathbb{X}$ ($\mathbb{X}$ denotes the set of the non-dominated solutions), a hypercube v_i is constructed with reference point R and the solution x_i as the diagonal corners of the hypercube. Then, the union of all hypercubes is referred as HV [44], as shown in Fig. 4, taking two objectives as an example. It can be seen from this figure that for the multi-objective minimization problem, with the process of iteration, the value of HV will be larger and larger. Then it will be kept unchanged for several iterations. In this way, we use HV indicator to check whether the solutions are converged, if its value kept unchanged for a constant number of iterations, set as 50 in this paper, then the algorithm of CGSOMP stops and the Pareto front is obtained.

Consequently, the MODMG model with IO can be solved by CGSOMP as described in the following steps.

Step-1: Initialization

Prepare input parameters of the tested MG system, such as data of DEs, MTs, FCs, ESDs and electricity loads. Then, randomly initialize CGSOMP members x_i ($i = 1, 2, \dots, M$), which stands for the dispatch solutions, and M is the number of initialized members. Afterwards, input the interval forecasting bounds of renewable power $\mathbf{u}$ of WTs and PVs.

Step-2: Update Pareto optimal solutions

In each iteration of CGSOMP, evaluate each scheduling solution x_i using the GSO optimization algorithm, i.e., obtaining the upper and lower bounds of each objective function by optimizing $\mathbf{u}$ in (19). Then, calculate the midpoints of multiple functions in (18). Compare the values of these midpoints with respect to all dispatch solutions x_i ($i = 1, 2, \dots, M$), and determine Pareto optimal solutions by the non-dominated sorting method. These solutions are then saved into the external archive. In addition, new members will be generated at the next iteration for updating obtained solutions.

Step-3: Update CGSOMP members

At the next iteration, the producers are selected by comparing the values of objective functions in (20), and the group members are updated. That is, the producers update their positions by performing the behavior of producing. Then the number of rangers is determined by (21), in this way, the scroungers and rangers are chosen. Scroungers follow the producers and change their positions by (22), and rangers adopt ranging behavior to update themselves.

Fig. 5. The computing procedures of CGSOMP for MODMG

Step-4: Stopping criterion

When the index of HV remains unchanged for 50 iterations, stop the procedure, and the final Pareto optimal solutions are obtained. Otherwise, go back to **Step 2** and **Step 3**, and continue the iterative procedure.

The computing procedure is illustrated in Fig. 5.

V. SIMULATION STUDIES

A. Simulation settings

A modified IEEE 112-bus MG is used to conduct simulation studies, which consists of 50 distributed generators (DGs). They contain 10 DES, 8 MTs and 7 FCs. Their parameters related to operation cost are: $a = 6 \$/h$, $b = 0.012 \$/kWh$, $c = 0.00085 \$/(kWh)^2$, $c_{ng} = 0.3 \$/m^3$, $\eta_{MT} = 0.8$, $Q_{LHV} = 9.7 kWh/m^3$, $\eta_{FC} = 0.9$. Also, this test system is set to contain 25 stochastic DGs, i.e., 10 WTs and 15 PVs, and Table I shows their uncertain renewable power outputs of WTs and PV which can be obtained by the interval forecasting method. The test system is studied at a peak demand of 20.8 p.u. (base power 100 KVA), and the bus information and branch parameters can be referred to [45].

As three distinct objectives are considered in this paper, i.e., economic cost, voltage deviation and static voltage stability index, the following four cases are studied to illustrate the impact of these three objectives: (1) Optimization of both EC and VD; (2) Optimization of both EC and SVSI; (3) Optimization of both VD and SVSI; (4) Optimization of all the three objectives.

Moreover, the performance of CGSOMP is compared with that of GSOMP when conducting the above 4 cases. These optimization algorithms are evaluated in 50 independent runs, and their population sizes are set as 500. The sizes of external repositories for CGSOMP and GSOMP are set as 100 for the Case (1)-(3) and 1000 for Case (4). In addition, the index of HV is used to check the iterative process of the algorithms of CGSOMP. If its value remains unchanged for 50 continuous iterations, the Pareto solutions are converged, and the corresponding Pareto front is obtained.

B. Simulation results and analysis

1) *Case 1: Optimization of both EC and VD*: This case aims to find the Pareto front for effectively representing the trade-off between EC and VD. Fig. 6(a) presents the best Pareto fronts obtained by CGSOMP and GSOMP in 50 independent runs, it can be easily

TABLE I
THE UNCERTAIN RENEWABLE POWER OUTPUTS OF WTs AND PVs IN THE MODIFIED IEEE 112-BUS MG

Bus No.	Type of stochastic DGs	Uncertain power output (p.u.)
6	WT	[0.30,0.40]
7	WT	[0.32,0.42]
13	PV	[0.25,0.33]
14	PV	[0.25,0.33]
19	WT	[0.15,0.25]
24	PV	[0.26,0.31]
25	PV	[0.27,0.32]
33	WT	[0.30,0.40]
38	PV	[0.28,0.32]
42	WT	[0.35,0.43]
45	PV	[0.40,0.45]
46	PV	[0.38,0.46]
47	PV	[0.38,0.46]
52	WT	[0.22,0.29]
58	PV	[0.40,0.47]
59	PV	[0.41,0.48]
65	WT	[0.35,0.45]
78	WT	[0.29,0.39]
87	PV	[0.45,0.52]
88	PV	[0.46,0.53]
95	WT	[0.40,0.49]
99	PV	[0.39,0.44]
100	PV	[0.39,0.44]
112	PV	[0.27,0.36]

seen that CGSOMP can find more convergent and evenly distributed Pareto front. The Pareto front found by CGSOMP is in the range of $[500.03, 555.85] \times [0.1591, 0.5615]$, wider than that of GSOMP $[500.82, 555.73] \times [0.1921, 0.5442]$. We denote the Pareto optimal solutions obtained by CGSOMP as $a_1, a_2, \dots, a_{99}, a_{100}$. It can be easily observed that a solution that minimizes both EC and VD simultaneously does not exist. Specifically, Fig. 6(b) shows objective values of selective Pareto optimal solutions, i.e., $a_1, a_{10}, \dots, a_{91}, a_{100}$, as it is impossible to show the objective values of all solutions. Their objective values are also listed in Table II. a_1 has the lowest EC, i.e., 500.03 $\$/h$. However, the corresponding VD is as high as 0.561, while the value for a_{100} is merely 0.1591. Nevertheless, it may not be reasonable to choose a_{100} as the dispatch solution due to the fact that its EC is too high, i.e., 555.85 $\$/h$. Note that Fig. 6(c) presents the values of HV indicator during the iterative process of CGSOMP, and the reference point for calculating HV is set to be $[600, 0.8]$. It can be easily seen that the obtained Pareto solutions are converged as the value remains unchanged after the 70th iteration.

Fig. 6. (a) Pareto fronts obtained by CGSOMP and GSOMP; (b) Values of EC and VD with respect to different Pareto optimal solutions; (c) Values of the HV index during the iterative process of CGSOMP

As EC and VD conflicts with each other, we should give a comprehensive consideration of both of them. In our work, we adopt the fuzzy decision making method, which can well assess Pareto optimal solutions with respect to multiple objectives. The detailed

formulations of this method is presented in Part B of Appendix in this paper. As the objective of VD is more important than ED for MG operations, we set the weight factors of them to be 0.7 and 0.3, respectively. The final ranking values obtained by the fuzzy decision method are shown in Table II, and a_{76} is selected as the final dispatch solution.

To further illustrate the outperformance of a_{76} , we randomly select power output samples of WTs and PV from the interval information shown in Table I, using a sampling method, i.e., Latin hypercube sampling with Cholesky decomposition (LHS-CD) [34], and the number of samples is chosen as 400, suggested by [46]. Then, 400 values of economic costs and voltage deviations with respect to these samples, corresponding to three solutions of a_1 , a_{76} and a_{100} are shown in Fig. 7. It is obvious that solution a_{100} gets the largest EC values. On the other hand, it obtains lowest VD values, which means solution a_{100} puts more emphasis on considering this objective.

In comparison, solution a_1 obtains the least averaged EC under the uncertain environment, which can be regarded as the most economic solution. However, the values of VD range in [0.4723, 0.6514], which are much higher than those of a_{76} and a_{100} . This implies that a_1 is the best choice when the economic operation is merely pursued. Therefore, to well balance the interests of these two conflicting objectives, solution a_{76} is selected by the fuzzy decision making method, and its objective values of EC and VD are 539.28 \$/h and 0.2173 on average. From Fig. 7, we can see that the samples of these two objective values are in the range of those of a_1 and a_{100} , which verifies that the selected solution has a balanced performance between the two objectives. This also verifies the importance of considering multiple objectives to conduct MG dispatch, for instance, VD could be unacceptably high if the minimization of EC is merely pursued.

Fig. 7. The samples of EC and VD in terms of a_1 , a_{76} and a_{100}

2) *Case 2: Optimization of both EC and SVSI:* In this case, the objectives of EC and SVSI are minimized simultaneously. The best Pareto fronts of 50 independent runs obtained by CGSOMP and GSOMP are shown in Fig. 8(a). It is easily observed that CGSOMP obtains better convergent and more distributed Pareto optimal solutions, and the objective values of selected solutions, $b_1, b_{11}, \dots, b_{91}, b_{100}$, are listed in Table II. We can see that the smallest EC is 501.05 \$/h, obtained by b_1 . However, its value of SVSI is as high as 0.3924, which is much larger than that of b_{100} . On the other hand, although the SVSI corresponding to b_{10} is only 0.1305, its EC is too high, i.e., 560.96 \$/h. Moreover, the trade-off between EC and SVSI is clearly captured according to Fig. 8(b), which shows their values of selective solutions $b_1, b_{11}, \dots, b_{91}, b_{100}$. Fig. 8(c) illustrates the varying process of the HV indicator during the iteration of CGSOMP, which verifies that this algorithm is converged and can obtain the Pareto optimal solutions. Note that the reference point for calculating the HV indicator is set as [600, 0.5].

In order to balance the interests of these objectives, we also use

Fig. 8. (a) Pareto fronts obtained by CGSOMP and GSOMP; (b) Values of EC and SVSI with respect to different Pareto optimal solutions; (c) Values of the HV index during the iterative process of CGSOMP

the fuzzy decision making method and set the weighting factors of EC and SVSI as 0.2 and 0.8 as the latter objective is much more important. The detailed ranking values are also shown in Table II, and solution b_{87} is chosen as the final dispatch solution. Furthermore, the sampling analysis is used for further illustrating the effectiveness of the selected solution under uncertain environment. We calculate 400 values of EC and SVSI for 400 random power output samples of WTs and PV using the forecast information in Table I. The values are illustrated in Fig. 9, which also verifies that solution b_{87} has a better performance for leveraging the two objectives simultaneously.

Fig. 9. The samples of EC and SVSI with respect to solutions of b_1 , b_{87} and b_{100}

3) *Case 3: Optimization of both VD and SVSI:* The objectives of VD and SVSI are minimized in this case to investigate the relationship between them. The Pareto fronts obtained by CGSOMP and GSOMP are presented in Fig. 10(a), which clearly manifests the trade-off between these two objectives. It is also seen that the Pareto front derived by CGSOMP is in the range of $[0.2102, 0.6042] \times [0.1336, 0.4154]$, wider than that of GSOMP, i.e., $[0.2147, 0.5982] \times [0.1599, 0.4147]$. The extreme solutions of the obtained Pareto optimal solutions by CGSOMP are denoted as c_1 and c_{100} ,

TABLE II
OBJECTIVE AND RANKING VALUES FOR THE SELECTIVE SOLUTIONS AND THE FINAL DISPATCH SOLUTION

Case 1	Solutions	a_1	a_{11}	a_{21}	a_{31}	a_{41}	a_{51}	a_{61}	a_{71}	a_{81}	a_{91}	a_{100}	a_{76}
Objectives	EC (\$/h)	500.03	502.38	506.46	514.39	522.16	526.73	535.26	538.55	542.96	550.65	555.85	539.28
	VD	0.5615	0.4733	0.3771	0.3310	0.2874	0.2598	0.2280	0.2185	0.1958	0.1724	0.1591	0.2173
Rank	Ranking values	0.00471	0.00703	0.00936	0.00963	0.01042	0.01093	0.01104	0.01111	0.01122	0.01117	0.11121	0.11134
Case 2	Solutions	b_1	b_{11}	b_{21}	b_{31}	b_{41}	b_{51}	b_{61}	b_{71}	b_{81}	b_{91}	b_{100}	b_{87}
Objectives	EC (\$/h)	501.05	501.73	504.55	507.99	512.95	521.76	522.67	533.35	538.94	553.50	560.96	547.84
	SVSI	0.3924	0.3622	0.3136	0.2926	0.2578	0.2290	0.2122	0.1941	0.1785	0.1679	0.1305	0.1577
Rank	Ranking values	0.00269	0.00390	0.00577	0.00648	0.00769	0.00847	0.00894	0.00939	0.00977	0.01001	0.01076	0.01094
Case 3	Solutions	c_1	c_{11}	c_{21}	c_{31}	c_{41}	c_{51}	c_{61}	c_{71}	c_{81}	c_{91}	c_{100}	c_{46}
Objectives	VD	0.2102	0.2259	0.2573	0.2942	0.3566	0.4030	0.4518	0.4873	0.5329	0.5499	0.6042	0.3709
	SVSI	0.4154	0.3457	0.2931	0.2667	0.2316	0.2080	0.1906	0.1691	0.1588	0.1482	0.1336	0.2186
Rank	Ranking values (\$/h)	0.00637	0.00848	0.00976	0.01006	0.01024	0.01029	0.01009	0.01025	0.00986	0.00995	0.00956	0.01045
Case 4	Solutions	d_1	d_{101}	d_{201}	d_{301}	d_{401}	d_{501}	d_{601}	d_{701}	d_{801}	d_{901}	d_{1000}	d_{287}
Objectives	EC (\$/h)	685.26	632.13	651.79	574.57	513.14	526.27	539.82	634.45	564.49	535.32	514.97	523.52
	VD	0.5876	0.2781	0.3247	0.3257	0.6515	0.3325	0.3939	0.5662	0.3396	0.3752	0.3866	0.3440
	SVSI	0.1324	0.2799	0.1856	0.2048	0.5426	0.3697	0.2570	0.1506	0.2951	0.2533	0.5186	0.2628
Rank	Ranking values (\$/h)	0.00074	0.00102	0.00107	0.00117	0.00029	0.00098	0.00105	0.00083	0.00102	0.00116	0.00069	0.00129

respectively. c_1 gets the least VD, 0.2102, while the maximum value of SVSI, i.e., 0.4154. For solution c_{100} , on the other hand, the minimum value of SVSI and the highest VD are obtained, i.e., 0.1336 and 0.6042, respectively. The detailed objective values for $c_1, c_{11}, \dots, c_{91}, c_{100}$ are also listed in Case 3 of Table II. It can be also seen from Fig. 10(b) and Fig. 10(c) that these two objectives conflict with each other, and CGSOMP can obtain the convergent Pareto optimal solutions.

Fig. 10. (a) Pareto fronts obtained by CGSOMP and GSOMP; (b) Values of VD and SVSI of Pareto optimal solutions; (c) Values of the HV index during the iterative process of CGSOMP

The fuzzy decision making method is then used, and c_{46} is selected as the best dispatch solution when weighting factors of these two objectives are set as 0.4 and 0.6. The corresponding values of VD and SVSI are 0.3709 and 0.2186, also shown in Case 3 of Table II. Therefore, c_{56} is chosen as it well balances the tradeoff between these two objectives. Afterwards, we adopt the sampling analysis and illustrate 400 values of these two objectives in Fig. 11. It can be seen again that c_{46} has a balanced performance in terms of these two objectives, compared with those of c_1 and c_{100} .

4) *Case 4: Optimization of EC, VD and SVSI*: Fig. 12(a) shows Pareto fronts obtained by CGSOMP and GSOMP when optimizing all the three objectives, i.e., EC, VD and SVSI. It can be

Fig. 11. The samples of VD and SVSI with respect to solutions of c_1 , c_{46} and c_{100}

observed that CGSOMP obtains more convergent Pareto front than that of GSOMP. Also, the varying values of HV index shown in Fig. 12(b) verify that the Pareto optimal solutions obtained by CGSOMP are convergent. However, note that the trade-off relationship of these solutions is difficult to be manifested due to the 3 dimensions. Therefore, we adopt a helpful visualization tool, named parallel axis plot [47]. It displays each objective on a separate axis, whose scale is normalized to the range of scales given in the objective values. Each of Pareto optimal solution is plotted as a line across the axes, with the objective function value of each objective plotted on its respective axis. Crossing lines represent trade-off effect of two different solutions for conflicting objectives. Key benefits of parallel axis plots are their ability to scale to an unlimited number of dimensions and to present different coordinates in a uniform manner. Therefore, a parallel axis plot for the 10 selective Pareto optimal solutions, which are denoted as $d_1, d_{101}, d_{201}, \dots, d_{901}, d_{1000}$, is presented in Fig. 13, and “id” stands for the serial number of these solutions. It is easily seen that crossing lines exist corresponding to each pair of solutions, which shows that they are non-dominated with each other and proves the trade-off effect of EC, VD and SVSI. The detailed values of these three objectives with respect to the selected Pareto optimal solutions are presented in Case 4 of Table II. The fuzzy decision making method is applied to select the best solution, i.e., d_{287} when the weighting factors of EC, VD and SVSI are set as 0.2, 0.35 and 0.45.

Fig. 12. (a) Pareto fronts of all the objectives obtained by CGSOMP and GSOMP; (b) Values of the HV index during the iterative process of CGSOMP

Fig. 13. Parallel axis plot of 3 objective values

C. Comparison with Optimistic and Pessimistic cases

It can be seen from (20) that IO aims to minimize the midpoints of each objective. However, it is interesting to find (20) becomes an optimistic or a pessimistic case when $[f_1^m(\mathbf{x}, \mathbf{u}), f_2^m(\mathbf{x}, \mathbf{u}), \dots, f_M^m(\mathbf{x}, \mathbf{u})]$ is replaced by $[f_1^R(\mathbf{x}, \mathbf{u}), f_2^R(\mathbf{x}, \mathbf{u}), \dots, f_M^R(\mathbf{x}, \mathbf{u})]$ or $[f_1^L(\mathbf{x}, \mathbf{u}), f_2^L(\mathbf{x}, \mathbf{u}), \dots, f_M^L(\mathbf{x}, \mathbf{u})]$, respectively. In the optimistic case, the objectives are in the form of “min-min”, which aims to obtain the best performance under the best case of uncertainties. However, the objectives of the pessimistic case are expressed as “min-max” to pursue the best performance under the worst case of uncertainties.

To make a comparison, we obtain solutions to the optimistic case and the pessimistic case for MODMG in optimizing EC, VD and SVSI respectively. Note that these cases are also solved by CGSOMP with the same procedure of IO, and the fuzzy decision making method is used to select the dispatch solution.

In order to verify that IO is more effective for MG dispatch under uncertainties, the sampling analysis is conducted for comparing the performances of d_{287} (i.e., the best solution obtained in Case 4) and solutions to the optimistic case and the pessimistic case, which are denoted as O and P respectively. Specifically, 400 power output samples of WTs and PV units are randomly generated, and EC, VD and SVSI values of those samples are shown in Fig. 14.

It is observed that the solution O can obtain the lower bounds of interval values of EC, VD and SVSI, as it merely pursues the optimistic operations of an MG under uncertainties. However, the sampling values of these three objectives are scattered much more widely than those of P and d_{287} . This means that the solution of optimistic case is of high risk as it is possible to have large values of EC, VD and SVSI, up to 557.82 \$/h, 0.5915 and 0.3896 under

Fig. 14. The samples of EC, VD and SVSI with respect to solutions O , d_{287} and P

the uncertain environment. In terms of the pessimistic case, it merely optimizes upper bounds of EC, VD and SVSI, then the obtained bounds are lower than those of other cases. However, this case is based on the worst case analysis to immune against uncertainty, and we can see that the ranges of sampling values are much smaller, which verifies the conservativeness of the pessimistic case. The IO case optimizes the midpoints of each objective, and considers both the lower and upper bounds, which makes it more flexible. Therefore, it is easily to be observed that d_{287} gets the lowest averaged values of these three objectives, compared with those of the optimistic and pessimistic cases.

VI. CONCLUSION

In this paper, the model of multi-objective dispatch under uncertainties in microgrid via the interval optimization approach has been proposed. Three objectives, i.e., economic cost, voltage deviation and static voltage stability index are considered in the model. Uncertain power outputs of renewable energy are presented as interval variables, which derives a multi-objective interval optimization problem. We further propose an improved multi-objective optimization algorithm, i.e., the chaotic group search optimizer with multiple producers. It adopts chaotic sequences to tune parameters adaptively and help the algorithm easily jumping out of local optima.

A modified IEEE-112 bus microgrid is used to conduct numerical case studies for illustrating the effectiveness of the proposed model and solution approach. The obtained Pareto fronts have shown that the improved optimization algorithm obtains better convergent solutions, compared with the traditional one. Furthermore, we comprehensively assess and compare the effectiveness of different solutions based on the sampling analysis. It has been verified that multiple objectives should be considered for dispatch, instead of only optimizing a single objective. Numerical results also demonstrate that the interval optimization approach is more flexible compared with the optimistic and pessimistic cases for microgrids with uncertain renewable energy. In the future work, we will use historical power output data of WTs and PVs to analyze correlations of their uncertainties, and study a high-order statistic model for simulating such correlations with high accuracy. This could further improve the optimal operation of microgrids and enhance the utilization of renewable energy.

VII. APPENDIX

A. Concept of Pareto solutions

Pareto solutions are used for reflecting the trade-off between multiple objectives, which is based on non-dominated ranking. For

instance, in a minimization problem with n objectives f_i ($i = 1, 2, \dots, n$), it can be observed that a solution $\mathbf{x}_1$ dominates $\mathbf{x}_2$ if and only if the following two relationships are satisfied simultaneously:

$$\begin{aligned} \forall i \in 1, 2, \dots, n \quad & f_i(\mathbf{x}_1) \leq f_i(\mathbf{x}_2) \\ \exists i \in 1, 2, \dots, n \quad & f_i(\mathbf{x}_1) < f_i(\mathbf{x}_2) \end{aligned}$$

The non-dominated solutions are also referred to as Pareto solutions.

B. Fuzzy decision making method

When using this decision making method, a fuzzy membership function can be defined:

$$\mu_i = \begin{cases} 0 & \text{if } f_i \geq f_i^{\max} \\ \frac{f_i^{\max} - f_i}{f_i^{\max} - f_i^{\min}} & \text{if } f_i^{\min} < f_i < f_i^{\max} \\ 1 & \text{if } f_i \leq f_i^{\min} \end{cases}$$

where μ_i is the membership value corresponding to the i th function f_i , $f_i^{\max}$ and $f_i^{\min}$ are the maximum and minimum values in terms of the obtained Pareto solutions.

Then for each alternative k in the Pareto solutions, the normalized membership value can be obtained by the following equation:

$$\mu[k] = \frac{\sum_{i=1}^n \omega_i \mu_i[k]}{\sum_{k=1}^m \sum_{i=1}^n \omega_i \mu_i[k]}$$

where m represents the number of Pareto solutions, and n is the number of multiple objectives. ω_i is the weight factor representing the importance of the i th objective, which is set by the decision maker. In turn, the Pareto optimal solution which has the largest value of $\mu[k]$ is selected as the best one [9].

C. Optimistic and Pessimistic cases

Optimistic case:

$$\begin{aligned} \min_{\mathbf{x}} \quad & [f_1^L(\mathbf{x}, \mathbf{u}), f_2^L(\mathbf{x}, \mathbf{u}), \dots, f_M^L(\mathbf{x}, \mathbf{u})] \\ \text{s.t.} \quad & f_i^L(\mathbf{x}, \mathbf{u}) = \min_{\mathbf{u}} f_i(\mathbf{x}, \mathbf{u}) \\ & g(\mathbf{x}, \mathbf{u}) = 0 \\ & h(\mathbf{x}, \mathbf{u}) \leq 0 \\ & \mathbf{u} \in [\mathbf{u}^L, \mathbf{u}^R] \end{aligned}$$

Pessimistic case:

$$\begin{aligned} \min_{\mathbf{x}} \quad & [f_1^R(\mathbf{x}, \mathbf{u}), f_2^R(\mathbf{x}, \mathbf{u}), \dots, f_M^R(\mathbf{x}, \mathbf{u})] \\ \text{s.t.} \quad & f_i^R(\mathbf{x}, \mathbf{u}) = \max_{\mathbf{u}} f_i(\mathbf{x}, \mathbf{u}) \\ & g(\mathbf{x}, \mathbf{u}) = 0 \\ & h(\mathbf{x}, \mathbf{u}) \leq 0 \\ & \mathbf{u} \in [\mathbf{u}^L, \mathbf{u}^R] \end{aligned}$$

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