

AN INTERVAL MULTI-OBJECTIVE OPTIMIZATION STRATEGY OF ISLAND INTEGRATED ENERGY SYSTEM CONSIDERING MULTIPLE UNCERTAINTIES

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Received January 2023; accepted March 2023

ABSTRACT. *Island integrated energy system (IIES) is an important field in the new energy microgrid. Considering multiple uncertain factors of source-load and energy conversion sides in IIES, an interval multi-objective optimization scheduling strategy is proposed in this paper. First, renewable energy output and load forecasting data are described as interval values, and uncertain models of multi-energy coupling units are presented. After that, aiming at minimizing the daily economic cost and maximizing the renewable energy output, an interval multi-objective optimization scheduling model for an IIES is constructed. Then, a constrained interval multi-objective evolutionary optimization algorithm based on penalty function is developed to directly solve the above model. Finally, the proposed method is tested on a simulation scenario and compared with three state-of-the-art interval multi-objective optimization evolutionary algorithms. The experimental results demonstrate that the proposed strategy can provide a better scheduling scheme and run faster.*

Keywords: Island integrated energy system, Uncertainty, Interval multi-objective optimization, Operation scheduling

1. Introduction. The environmental deterioration caused by energy shortage and the extensive usage of traditional fossil energy has become increasingly prominent. Therefore, an integrated energy system (IES) combining various clean renewable energy sources has attracted much attention [1]. The daily and seasonal cycle of marine energy resources makes it a favorable supplement to other renewable energy sources such as wind and solar. An IES on an island can make the island fully use renewable energy for self-sufficiency and reduce pollution. Therefore, it is of great significance to study the operation scheduling of IIES.

Li et al. analyzed the operation mode, optimized the configuration of the offshore wind power-hydrogen energy system, and used offshore wind power to produce hydrogen to improve wind power consumption and provide offshore clean energy [2]. However, some uncertainties exist in renewable energy generation, energy conversion, and load forecasting, which will negatively affect the scheduling strategy, thus affecting the stability and economy of the system. Considering the uncertainty of the demand response, Zeng et al. proposed an interval multi-objective scheduling model for the energy hub to efficiently utilize renewable energy, which was transformed into a deterministic optimization problem via the interval order relation and possibility degree method and solved by using an improved non-dominated sorting genetic algorithm [3].

At present, few studies consider multi-side uncertainty factors of comprehensive energy. Furthermore, most of them convert the uncertain model into the deterministic one. The

above conversion method may lose effective information, resulting in the optimal strategy not fully reflecting the problem's uncertainty. Therefore, an interval multi-objective optimization scheduling model for an IIES, including hydrogen production from seawater, is constructed, and a penalty function-based constrained interval multi-objective evolutionary optimization algorithm (CIMOEA) is developed to solve the above model. Simulation results verify the effectiveness and efficiency of the proposed method.

The rest of this paper is organized as follows. We introduce the uncertainty model of an IIES in Section 2; Section 3 elaborates on the interval multi-objective scheduling model of IIES and the proposed method. The experiment description and results are provided in Section 4. Section 5 concludes the paper.

2. Modeling Uncertainties of an IIES.

2.1. IIES. The structural diagram of an IIES, including hydrogen production from seawater, is shown in Figure 1. It mainly includes renewable energy generation systems with wind, solar, and wave energy; the energy conversion side of electrolytic cell (EC), hydrogen tank (HT), hydrogen fuel cell (HFC), electric boiler (EB), electric refrigerator (ER), absorption refrigerator (AR), water source heat pump (WSHP), and seawater desalination (SD); the user side includes four types of energy load: electricity, cold, heat, and water.

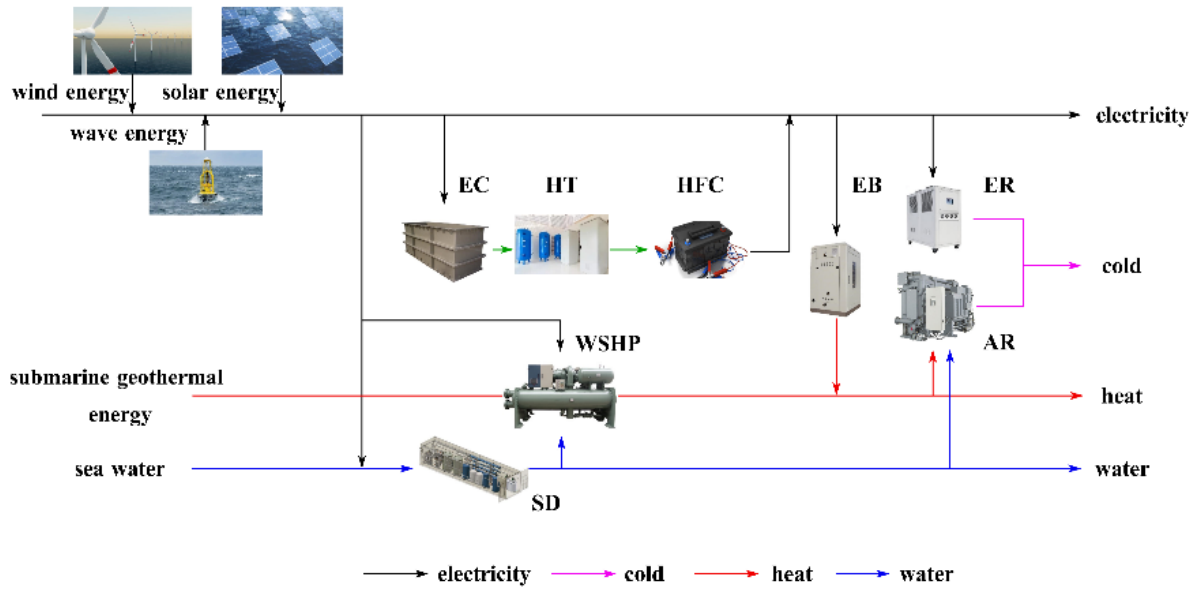


FIGURE 1. The structure of IIES

2.2. Modeling uncertainties of renewable energy generation power and load.

Wind, solar and wave power generations are affected by wind speed, temperature, environment and other factors. Thereby, the output value of each equipment has certain uncertainty. Let $P_w(t)$, $P_{pv}(t)$, and $P_{we}(t)$ denote the prediction data of wind, solar and wave energy output obtained by a prediction method according to the historical data in the t -th period, EP_w , EP_{pv} , and EP_{we} represent the average value of the error between the historical prediction data and the actual data of the three kinds of energy output, and $NP_w(t)$, $NP_{pv}(t)$, and $NP_{we}(t)$ denote the noise disturbance of the three kinds of energy output affected by other factors in the t -th period. The three types of energy output can be expressed as the following interval numbers:

$$\begin{cases} [P_w(t)]^\pm = [P_w^-(t), P_w^+(t)] = [P_w(t) - EP_w - NP_w(t), P_w(t) + EP_w + NP_w(t)] \\ [P_{pv}(t)]^\pm = [P_{pv}^-(t), P_{pv}^+(t)] = [P_{pv}(t) - EP_{pv} - NP_{pv}(t), P_{pv}(t) + EP_{pv} + NP_{pv}(t)] \\ [P_{we}(t)]^\pm = [P_{we}^-(t), P_{we}^+(t)] = [P_{we}(t) - EP_{we} - NP_{we}(t), P_{we}(t) + EP_{we} + NP_{we}(t)] \end{cases} \quad (1)$$

where $[P_w(t)]^\pm$, $[P_{pv}(t)]^\pm$, and $[P_{we}(t)]^\pm$ represent the interval values of wind, photovoltaic and wave energy output in the t -th period, respectively.

The load is related to the user's personal demand and electricity price, and its uncertainty is small. This paper uses the confidence interval estimation method [4] to reasonably extract the interval value. Let the historical load data of the t -th period obey the normal distribution. $E(L_{load}(t))$ and $D(L_{load}(t))$ represent the mean value and variance of the historical data in the t -th period. When the overall variance is unknown, a confidence interval of the overall mean with the confidence level is expressed as

$$L_{load} (L_{load}^- \leq L_{load} \leq L_{load}^+) = \left[E(L_{load}(t)) - \frac{\sqrt{D(L_{load}(t))}}{\sqrt{n}} t_{\alpha/2}(n-1), E(L_{load}(t)) + \frac{\sqrt{D(L_{load}(t))}}{\sqrt{n}} t_{\alpha/2}(n-1) \right] \quad (2)$$

where $load \in \{e, c, h, w\}$ represents loads including electricity, cold, heat and water. α is the confidence level, and its value is 0.05, indicating the probability that the actual load value within the interval is 95%.

2.3. Modeling uncertainties of multi-energy coupled units.

2.3.1. *Uncertainty model of power to hydrogen (P2H).* Hydrogen is produced by the electrolysis of water in an EC. Hydrogen is stored as supplementary energy for renewable energy. Considering the uncertainty of hydrogen production rate from electrolytic water, the mathematical model for the uncertainty of hydrogen production is established as follows.

(1) Hydrogen production by EC

$$[V_{H_2}(t)]^\pm = \frac{0.0224 P_{H_2}(t) \rho_{H_2}}{4 [v_{H_2}]^\pm M_{H_2}} \quad (3)$$

where $[V_{H_2}(t)]^\pm$ is the interval value of hydrogen production capacity, $P_{H_2}(t)$ is the electric power consumed by the cell in the t -th period, ρ_{H_2} is the density of H_2 , $[v_{H_2}]^\pm$ is the interval value of hydrogen production rate of electrolytic water, and M_{H_2} is the molar mass of H_2 .

$$[E_{H_2}(t)]^\pm = [E_{H_2}(t-1)]^\pm + ([E_{in,H_2}(t)]^\pm - [E_{out,H_2}(t)]^\pm) \quad (4)$$

where $[E_{H_2}(t)]^\pm$, $[E_{H_2}(t-1)]^\pm$, $[E_{in,H_2}(t)]^\pm$, and $[E_{out,H_2}(t)]^\pm$ represent the interval value of hydrogen storage capacity, hydrogen storage and output, respectively.

2.3.2. *Uncertainty model of HFC.* The HFC is the reverse reaction of electrolytic water, and hydrogen is used as fuel to generate electric power. Considering the uncertainty of the working efficiency of HFC, the uncertainty mathematical model is established as follows:

$$[P_{HFC}(t)]^\pm = [\eta_H]^\pm V_{HFC}(t) H_{HV} \quad (5)$$

where $[P_{HFC}(t)]^\pm$ is the interval value of electric power generated by HFC in the t -th period, $[\eta_H]^\pm$ is the efficiency interval of HFC, and $V_{HFC}(t)$ is the hydrogen volume consumed by HFC in the t -th period. H_{HV} is the high calorific value of hydrogen.

2.3.3. *Uncertainty model of EB.* Considering the uncertainty of the heating efficiency of EB, the uncertainty mathematical model is established as follows:

$$[P_{EB,h}(t)]^\pm = P_{EB}(t) [\eta_{EB}]^\pm \quad (6)$$

where $[P_{EB,h}(t)]^\pm$ is the interval value of heating power, $P_{EB}(t)$ is the consumed electric power of EB in the t -th period, and $[\eta_{EB}]^\pm$ is the interval value of the heating efficiency of EB.

2.3.4. *Uncertainty model of ER.* Considering the uncertainty of the cooling coefficient of ER, the mathematical model of uncertainty is established as follows:

$$[C_{ER}(t)]^{\pm} = P_{ER}(t) [cop_{ER}]^{\pm} \quad (7)$$

where $[C_{ER}(t)]^{\pm}$ is the interval value of the cooling power, $P_{ER}(t)$ is the consumed electric power of ER in the t -th period, and $[cop_{ER}]^{\pm}$ is the interval value of the cooling coefficient of ER.

2.3.5. *Uncertainty model of AR.* Considering the uncertainty of the cooling coefficient of AR, the uncertainty mathematical model is established as follows:

$$[C_{AR}(t)]^{\pm} = H_{AR}(t) \cdot [cop_{AR}]^{\pm} \quad (8)$$

$$[W_{AR}(t)]^{\pm} = [C_{AR}(t)]^{\pm} [\eta_{AR}]^{\pm} \quad (9)$$

where $[C_{AR}(t)]^{\pm}$ and $[W_{AR}(t)]^{\pm}$ represent the interval value of cooling power and freshwater consumption of AR in the t -th period. $H_{AR}(t)$ is the consumed heat power. $[cop_{AR}]^{\pm}$ and $[\eta_{AR}]^{\pm}$ are the interval values of AR's cooling coefficient and water consumption rate, respectively.

2.3.6. *Uncertainty model of WSHP.* The WSHP converts low-grade heat energy in seawater into high-grade heat energy that can generally be used using a small amount of high-grade electric energy. Considering environmental factors' influence, the mathematical model of uncertainty is established as follows:

$$[P_{WSHP,h}(t)]^{\pm} = P_{WSHP}(t) [\eta_{WSHP,h}]^{\pm} \quad (10)$$

$$[W_{WSHP}(t)]^{\pm} = P_{WSHP}(t) [\eta_{WSHP}]^{\pm} \quad (11)$$

where $[P_{WSHP,h}(t)]^{\pm}$ and $[W_{WSHP}(t)]^{\pm}$ represent the interval value of heating power of WSHP and freshwater consumption in the t -th period. $P_{WSHP}(t)$ is the high-quality electricity consumption in the t -th period. $[\eta_{WSHP,h}]^{\pm}$ and $[\eta_{WSHP}]^{\pm}$ represent the interval value of the heating efficiency coefficient and water consumption rate of WSHP in the t -th period, respectively.

2.3.7. *Uncertainty model of SD.* Considering the uncertainty of the water production rate of SD, the uncertainty mathematical model is established as follows:

$$[W_{SD,w}(t)]^{\pm} = P_{SD}(t) [\eta_{SD}]^{\pm} \quad (12)$$

where $[W_{SD,w}(t)]^{\pm}$ is the interval value of freshwater volume, and $P_{SD}(t)$ is the electric power consumed by the desalination units during the t -th period. $[\eta_{SD}]^{\pm}$ is the interval value of the water production rate of SD.

3. Interval Multi-Objective Scheduling Model of IIES.

3.1. **Objective functions.** For the IIES under consideration, the operation scheduling of the number of each renewable energy equipment aims at minimizing economic cost and maximizing the renewable energy output in the cycle.

Objective function 1: economic cost

The economic cost per cycle includes equipment maintenance cost and energy abandonment cost, as shown in Equation (13).

$$\min[F_1(t)]^{\pm} = [F_{mat}(t)]^{\pm} + [F_{aba}(t)]^{\pm} \quad (13)$$

$$\begin{cases} [F_{mat}(t)]^{\pm} = \sum_{t=1}^T \sum_{i \in k} \sum_{j \in M} (x_{ij}(t) C_{ij}) + \sum_{t=1}^T [P_g(t)]^{\pm} C_g \\ [F_{aba}(t)]^{\pm} = [P_{wd}(t)]^{\pm} C_{wd} \end{cases} \quad (14)$$

where $[F_1(t)]^\pm$, $[F_{mat}(t)]^\pm$ and $[F_{aba}(t)]^\pm$ represent the interval value of the total system cost, the maintenance cost and energy abandonment cost in the t -th period. $x_{ij}(t)$ represents the number of the working equipment of the i -th energy and the j -th type in the t -th period. C_{ij} represents the maintenance cost of the working equipment of the i -th energy and the j -th type. $[P_g(t)]^\pm$ is the interval value of output, and C_g is the maintenance cost of each equipment of the energy conversion side in the t -th period. $[P_{wd}(t)]^\pm$ is the interval value of abandoned energy power, and C_{wd} is the penalty cost in the t -th period. $k = \{w, pv, we\}$ indicates that the types of renewable energy output are wind, solar and wave energies.

Objective function 2: renewable energy output

$$\max [F_2(t)]^\pm = \sum_{t=1}^T \sum_{i \in k} \sum_{j \in M} (x_{ij} [P_{ij}(t)]^\pm) \quad (15)$$

where $[F_2(t)]^\pm$ refers to the interval value of the output of renewable energy, and $[P_{ij}(t)]^\pm$ represents the output interval value of the equipment of the i -th energy and the j -th type in the t -th period.

3.2. Constraints. Constraints in the IIES include renewable energy output, the number of renewable energy units, unit climbing, hydrogen fuel cell energy storage operation, and integrated energy system power.

3.3. CIMOEA. This subsection proposes a CIMOEA based on the penalty function [5] and IMOEA [6] to solve the above model accurately and efficiently. The penalty function method deals with the power balance constraints, which are the power balance constraints of electricity, cold, heat and water, respectively. The detailed procedure is as follows.

Step 1: Initialize the relevant parameters of the algorithm and process the output and load forecasting data as interval numbers.

Step 2: Initialize a population and uniformly distributed reference vectors.

Step 3: Input the energy conversion units' parameters, process the energy output, and load data as interval values.

Step 4: Deal with constraints by the penalty function method.

Step 5: Perform evolutionary operations on individuals to get new individuals, calculate the interval aggregation function of the individuals in the current individual neighborhood, and use an interval order relation to update individuals.

Step 6: Output optimal population P when termination condition is reached.

The knee point of the Pareto front is selected as the final optimal solution, thus obtaining an optimal scheduling strategy. To this end, the method of finding the interval knee point of an interval multi-objective problem [7] is used.

4. Experiment. In order to verify the performance of the proposed CIMOEA, IP-MOEA [8], ICMOABC [9] and IMOMA-II [10] were used as comparison algorithms. The following three performance metrics are used to assess each algorithm.

1) The midpoint of a hypervolume on intervals [11] is referred to as the hypervolume, whose reference points are [1, 1] for this problem.

2) Running time is used to evaluate the efficiency of each algorithm.

3) The mean of imprecisions [10] of all individuals in a population is regarded as the average imprecision, the smaller the value, the smaller the interval uncertainty of individuals.

4.1. Basic data. The IIES shown in Figure 1 is simulated and solved in this section. The experiment takes 24 hours as the scheduling cycle and 1 hour as the scheduling period. The unit parameters in the simulation system are from [12]. Figure 2 shows the forecasting

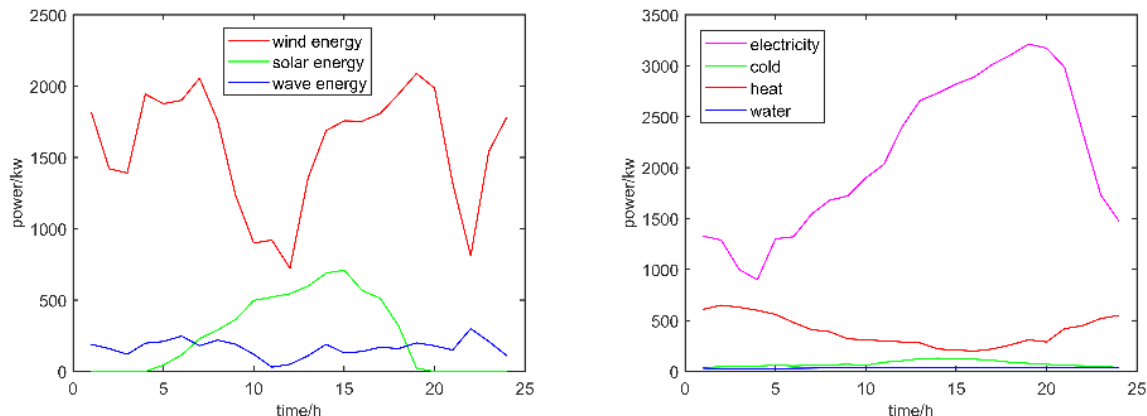


FIGURE 2. (color online) Forecasting data of renewable energy output and daily load

data of wind, solar and wave energy output [13] and the daily load of electricity, cold, heat, and water [5].

Algorithm parameters: N is the size of the population, $N = 50$. Gen is the size of the evolutionary generations, $Gen = 20$. T is the size of the neighborhood, $T = 5$. N is the number of the reference vectors as well. In this paper, the results of multiple running are taken to form an approximation of the Pareto front, and the interval knee point on the front is selected as the optimal scheduling strategy.

4.2. Experimental result. According to the renewable energy output and load forecast data, the interval multi-objective scheduling model for the IIES constructed in Section 3.1 is solved to minimize the daily economic cost and maximize renewable energy output. The Pareto front is shown in Figure 3.

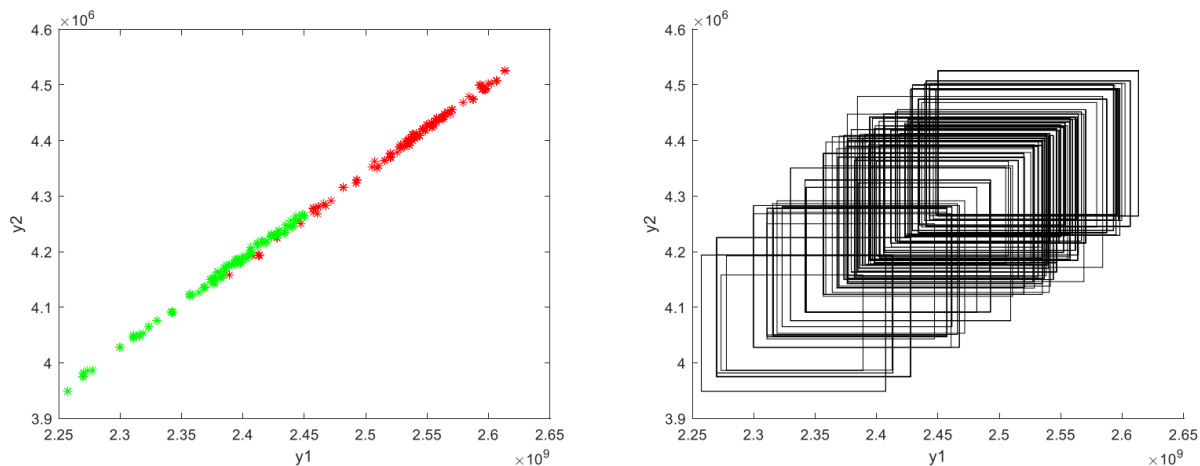


FIGURE 3. (color online) Pareto front

According to the method of finding the interval knee point introduced in Section 3.3, the optimal scheduling strategy of the IIES is obtained, as shown in Figure 4. It indicates that the system is supplied by wind, solar and wave energy. There is a complementary relationship between them. When the system's supply exceeds the electricity consumption, the system stores the electricity in the hydrogen fuel cell. If the hydrogen fuel cell cannot store the electricity, the cost of energy abandonment will be generated. Otherwise, the hydrogen fuel cell is used as supplementary energy for energy supply to ensure the regular operation of the units in the system.

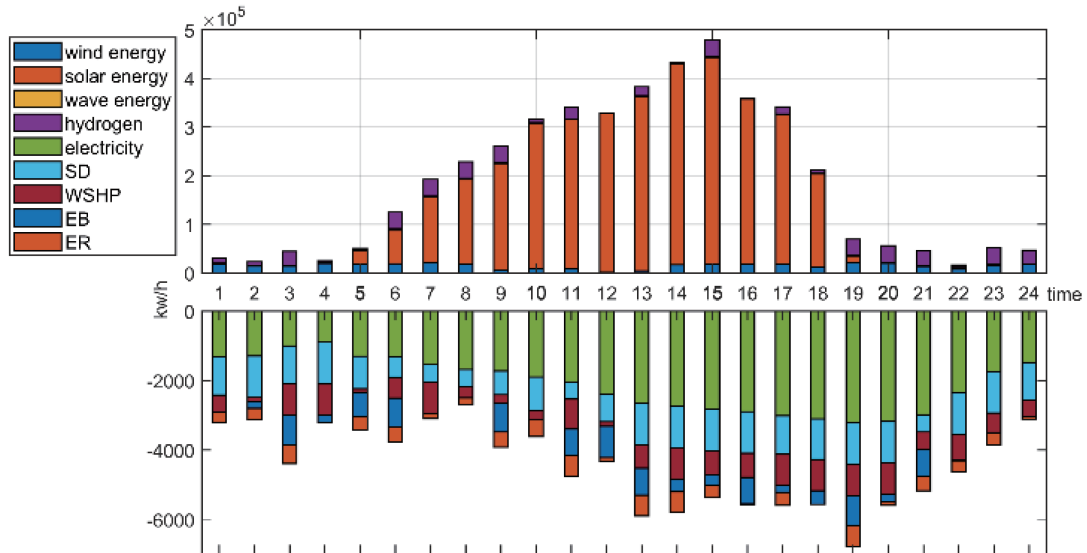


FIGURE 4. (color online) Optimal scheduling scheme

TABLE 1. Comparisons between CIMOEA and other algorithms

	Hypervolume	Time(s)	Imprecision
IP-MOEA	0.4864	16366	19.7635
ICMOABC	0.4515	12803	26.3377
IMOMA-II	0.4846	16278	26.6577
CIMOEA	0.4947	2147.5	1.6793

Table 1 lists the normalized hypervolume, time and imprecision obtained by the four algorithms. It reports that CIMOEA has a higher hypervolume value, which implies that the proposed algorithm can derive optimal solution sets with better convergence and distribution. CIMOEA is significantly superior to the other three algorithms for the running time. Moreover, CIMOEA has a lower imprecision value than other algorithms, indicating that the interval uncertainty of the population calculated by this algorithm is smaller. In summary, CIMOEA can generate an approximate PF with better distribution and convergence, and its population has less uncertainty. Furthermore, the running speed is the fastest while dealing with the scheduling of IIES.

5. Conclusion. Considering the uncertainty factors of source, load and energy conversion side, a multiple uncertainties IIES optimization scheduling model is established. CIMOEA, based on the penalty function, solves the above model directly, which is different from the existing research that converts the uncertain model into the deterministic one. Finally, the proposed CIMOEA is compared with three state-of-the-art intervals MOEAs. The experimental results show that it provides a better scheduling scheme and runs faster than the other three algorithms.

Acknowledgment. This work is partially supported by National Key R&D Program of China with grant no. 2021YFE0199000, National Natural Science Foundation of China under grant nos. 61873105 and 62133015, Qinglan Project of Jiangsu Province of China and 521 Talents Project of Lianyungang of China.

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