Optimal Allocation of Distributed Energy Supply System Under Uncertainty Based Improved Gray Wolf Algorithm

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Abstract

In order to improve the economical performance of distributed energy supply system under uncertainty, the improved gray wolf algorithm is constructed for optimal allocation of distributed energy supply system. The relating research progress is summarized firstly, and effect of improved gray wolf algorithm on optimal allocation of distributed energy supply system are studied. The optimal allocation model of distributed energy supply system is constructed considering fuel consumption, operation and maintenance cost, environment penalty cost, and power grid energy exchange function, and the uncertain factor is processed based on scienario method. And then the improved gray wolf algorithm is designed, and the initial strategy of population and the regulated method of main parameters are improved. Finally, simulation analysis is carried out, simulation results show that the proposed model can obtain best optimal allocation effect of system.

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Introduction

With the rapid development of economy, the fossil energy is drying up, a large number of greenhouse gas emissions, which leads further deterioration of the environment. The renewable energy using solar energy and wind energy as main clean energy has been widely concerned. Simultaneous multiple energy complementary integrated energy system has provided theoretical basis for comprehensive utilization of renewable energy. In integrated energy system, all kinds of distribution renewable energy, energy storage devices and auxiliary structures constitute a controllable energy supply system, but it also limits flexibility of system.

The distributed energy supply system is a energy supply system serving user, which can utilize traditional fossil fuels and renewable energy at the same time. When the system configuration and operation strategy design are reasonable, the distributed energy supply system shows better performance than the traditional energy supply system, such as better economy and lower pollutant discharge. Because the devices in distributed energy supply system have wide variety, the structure and energy flow of system are complex, therefore the mathematical programming method can be used to carry out optimal allocation of system, such as linear programming, mixed integer linear/nonlinear programming, mixed integer linear/nonlinear programming, multiple objective optimization method. In addition, the optimal allocation of distribution energy supply system existing many kinds of uncertain factors, such as load demand, energy price, uncertainty of renewable energy intensity, these factors may make allocation form of the system unreasonable, the system operation deviates from the design state, resulting in poor economic performance of the system.

In recent years, optimal allocation of distributed energy system has been concerned by some scientists. Rabbia Siddique et al. carry out optimal allocation of battery energy storage system based on improved non-sorting dominated genetic algorithm [1]. Takele Ferede Agajie et al. proposed the optimal allocation of distributed energy system to improve performance of the system, results showed that the integrating distributed energy system units enhanced the reliability of system [2]. Choton K. Das et al. proposed a strategy for optimal allocation of distributed energy storage systems based on a uniform and non-uniform energy storage system sizes methods, and the system performance was evaluated based on performance indexes [3]. Choton K. Das et al. proposed a method of optimal allocation of distributed energy storage system that was studied based on PQ injection, results showed that the proposed method could enhance the performance of system [4]. Xi Luo et al. proposed a mixed integer linear programming model of optimal allocation of a distributed energy system, results showed that the proposed model can decrease the cost of distributed energy system [5]. Ali-Mohammad Hariri et al. carried out reliability optimization of smart grids, and proposed reliability model of EV/PHEV charging station and presented a novel hierarchical optimization method [6]. Madihah Md Rasid et al. proposed a optimal allocation formulation of renewable energy distribution generation units considering constraints, uncertainties and load variations, and clonal differential evolution was used to optimize the allocation of renewable energy distribution generation units [7]. Gang Chen and Zhongyuan Zhao proposed a algorithm for distributed optimal resource allocation problem, and analyzed the effects of communications delay, proposed the distribution iterative method based on unconstrained resource allocation algorithms [8]. Susan Dominic and Lillykutty Jacob proposed a new distributed energy efficient joint resource block and discrete transmit power allocation method for an underlay device-to-device system. And the performance of the proposed method was assessed [9]. Mohammad-Reza Yaghoubi-Nia proposed evaluation model for optimal allocation of smart grids protective devices and distributed generations considering smart grid's uncertainties, and the precision of the proposed method was verified through experimental analysis [10].

Many achievements have considered some uncertain factors in distributed energy supply system, at the same time, a variety of uncertain optimization approaches were used to carry out optimal allocation of distributed energy supply system under uncertainty. The common methods concludes the two-stage stochastic programming method and robust optimization method. The two-stage stochastic programming method is used for optimal allocation of distributed energy system. The two-stage stochastic programming method is divided into the decision-making process into two stages. The first stage determines the optimal allocation form of the system, and the second stage determines the optimal operation strategy of the system. The robust optimization method is also used to carry out optimal allocation of distributed energy system, it optimizes the problem based on possible worst case, and can ensure that the obtained solution was reliable to all possible uncertainties. Although the two methods mentioned above can effectively process optimal allocation of distributed energy system under uncertain conditions. The two methods have a single attitude towards risk, and can not consider the multiple attitudes of decision makers toward risk. In stochastic allocation, the uncertainty of parameters can be described by probability density function, the objective function is the expected value of objective quantity, and the attitude towards risk is neural. The robust optimization method is a strategy to keep away from risk and ensure the feasible results. In fact, different decision makers may hold different attitudes toward risk [11]. It is necessary to consider the risk preference of decision makers, so as to make more appropriate choices to reduce the risk of system operation under uncertainty. Therefore it is necessary to select an proper method to obtain the better optimal allocation effect of distributed energy system.

In recent years, the swarm intelligent optimization algorithm has the advantages of simple structure and easy implementation, it is widely used in solving complex problems. The popular algorithms conclude genetic algorithm, particle swarm optimization algorithm, differential evolution algorithm, artificial ant colony algorithm, and fruit fly optimization algorithm, Inpired by predation behavior of gray wolves, Mirjalil et al. proposed a novel swarm intelligent optimization algorithm in 2014 [12]. The gray wolf algorithm can obtain the purpose of optimization by simulating the predation behavior of gray wolf group and based on the mechanism of wolf group and based on the mechanism of wolf group cooperation. This algorithm has the characteristics of simple structure, few parameters to be adjusted and easy to implement. Among them, there are adaptive convergence factors and information feedback mechanism, which can achieve a balance between local optimization and global search. Therefore, the gray wolf optimization algorithm has good performance in problem coping with accuracy and convergence speed [13].

Since gray wolf optimization algorithm was proposed, it has attracted extensive attention of many scholars because of its good performance. In terms of function optimization, it has been proved that the convergence speed and solution accuracy of gray wolf optimization algorithm are better than particle swarm optimization algorithm. Therefore, gray wolf optimization algorithm is widely used in many fields, such as path planning, cluster analysis, feature subset selection, economic scheduling assignment, optimal control of direct control motor and so on [14].

In this research, the uncertainties of load demand, energy price and renewable energy intensity in the optimal allocation of distributed energy supply system are considered. The continuously distributed uncertain parameters are represented by discrete point sets and corresponding probabilities. The scenario sets are designed by orthogonal experimental design method, considering the combination of various uncertain factors, and the probabilities of each scenario are obtained. Through optimization calculation, the optimal system scheme under each scenario is obtained. Each scheme is applied to different scenarios to obtain the economic performance of the system. The gray wolf optimization algorithm is used to select the scheme. Therefore this research can effectively deal with optimal allocation of distributed energy system based on improved gray wolf algorithm, and the analysis efficiency and accuracy can be improved.

1 Theory Model

The aim of optimal allocation of distributed energy system is to reasonably dispatch the output of each power generation unit in the system on the premise of meeting the cooling, heating and power demands of users and taking minimum operation cost as the optimal aim. The operation cost of the system mainly concludes the fuel cost of fossil fuel unit, comprehensive maintenance and management cost during unit operation, environmental pollution punishment cost and power exchange cost with large power grid.

1.1 Unit Fuel Consumption Model

The wind turbine and photovoltaic generator set in the system belong to renewable energy units and do not consume fuel. Therefore, the fuel consumption model is mainly aimed at micro gas turbine and fuel cell, the fuel consumption cost is calculated by [15]

$$C_F = \sum_{t=1}^{T} E_M(t) + \sum_{t=1}^{T} E_C(t) \tag{1}$$

where C_F denotes the fuel consumption cost, $E_M(t)$ denotes the energy consumption of micro gas turbine, $E_C(t)$ denotes the energy consumption of fuel cell.

1.2 Unit Operation and Maintenance Cost

In addition to fuel consumption, regular maintenance of equipment and management training cost of personnel are also needed in the process of unit operation. Considering these costs, according to the empirical data of system, the operation and maintenance costs are calculated by [16]

$$C_{om} = \sum_{t=1}^{T} \sum_{i=1}^{n} \kappa_{i,om} P_i(t) \tag{2}$$

where $\kappa_{i,om}$ denotes the comprehensive maintenance and management cost coefficient for different generation unit, $\kappa_{i,om}$ of wind power unit is equal to 0.0296, $\kappa_{i,om}$ of micro gas turbine is equal to 0.041, $\kappa_{i,om}$ of photovoltaic is equal to 0.0096, $\kappa_{i,om}$ of fuel cell is equal to 0.0293.

1.3 Environmental Penalty Cost

The distributed energy supply system is environmentally friendly, but units of the system using traditional fossil energy as fuel will still produce waste pollution that mainly concludes CO_2, SO_2, NO_X. In order to take into account the environmental protection of distributed energy supply system, this research considers the environmental pollution caused by pollunt emission, and introduces the environmental penalty cost model, the penalty model of pollutant emission established is calculated by [17]

$$C_p = \sum_{t=1}^{T} \sum_{j=1}^{J} \mu_j \lambda_j [P_{MT}(t) + P_{FC}(t)] \tag{3}$$

where J denotes the types of pollutants, μ_j denotes the penalty factor of pollutant, λ_j denotes the emission ability factor of pollutant.

The total pollutant emission of micro gas turbine is higher than that of fuel cell. Photovoltaic power generation and wind power generation do not consume fossil energy, so their emission capacity is zero. Because the traditional power generation mode causes serious environmental pollution, the penalty for pollutant emission is an effective means to improve its environmental protection. For distributed energy generation, environmental penalty cost is also introduced to reflect its fairness and improve environmental protection.

1.4 Power Grid Energy Exchange Function Model

During the operation of distributed energy supply system, it can be connected to the grid or isolated. Under the condition of grid connection, the system has energy exchange with the large power grid. From the perspective of safety and reliability, when the distributed energy supply system fails, the power supply needs to be supplemented by the large power grid in time to ensure the load demand of users. In terms of economic benefits, users should choose the most economical power supply mode in different periods of time. In order to coordinated the balance between power consumption and generation, the system and the large power grid need to exchange energy, and the corresponding function is expressed by

$$C_{ex} = \sum_{t=1}^{T} (p_{t,b} - p_{t,s}) P(t) \tag{4}$$

where $p_{t,b}$ denotes the power purchase price of power grid in period t, $p_{t,s}$ denotes the power sale price of power grid in period t.

Considering the above operation costs, the objective function of multiple energy distributed energy system operation can be obtained as follows [18]:

$$C_t = \eta_1 C_F + \eta_2 C_{om} + \eta_3 C_p + \eta_4 C_{ex} \tag{5}$$

where η_1 denotes the existing coefficient of the fuel consumption cost, η_2 denotes the existing coefficient of unit operation maintenance cost, η_3 denotes the existing coefficient of environmental penalty function, η_4 denotes the existing coefficient of power grid energy exchange function.

According to the objective function model of multiple energy distributed energy system established above, this research mainly considers the following constraints [19]:

(a) Electric load balance constraint: the system output power (including the exchange power with the power grid) is equal to the user's electric load demand.

$$\sum_{i=1}^{n} P_i(t) - P_l(t) = 0 \tag{6}$$

(b) Heat load balance constraint: the heat (cooling) power output by the system meets the heat (cooling) load demand of users.

$$\sum_{i=1}^{n} Q_i(t) - Q_l(t) \geq 0 \tag{7}$$

(c) Upper and lower limit constraints of unit output: in order to ensure the stability and economy of operation, different generator units have upper and lower limit constraints of power:

$$P_{\min}(t) \leq P(t) \leq P_{\max}(t) \tag{8}$$

(d) The minimum downtime and uptime constraints of units in distributed energy system are listed as follows:

$$[T_{d,on}(t-1) - T_{d,u}][\varphi_d(t) - \varphi_d(t-1)] \geq 0 \tag{9}$$

$$[T_{d,\text{off}}(t-1) - T_{d,d}][\varphi_d(t-1) - \varphi_d(t)] \geq 0 \tag{10}$$

where $T_{d,on}$ denotes the cumulative operation of distributed generation system in time period t, $T_{d,off}$ denotes shutdown time of distributed generation system in time period t. $T_{d,u}$ denotes the minimum start of units in distributed generation system, $T_{d,d}$ denotes minimum stop time of distributed generation system. φ_d denotes the start and stop status of units in distributed generation system.

In this research, the scenario method is used to represent all possible implementations of the output power of wind power generation and photovoltaic power generation, and the combination of Monte Carlo and roulette selection mechanism is used to generate the scenario. The output power of wind power generation and photovoltaic power generation are regarded as a random variables, which are described by a continuous probability distribution function.

The cumulative probability density function of wind power generation system can be calculated by

$$F(P_w(v)) = \begin{cases} 0, & P_w(v) \\ 1 - e - \dfrac{v_i - (v_r - v_i)p_w(v)/p_r}{c} & 0 \leq p_w(v) < p_r \\ \quad + e^{-(\frac{v_o}{c})^k}, & \\ 1, & p_w(c) \geq p_r \end{cases} \tag{11}$$

The probability density function $f(p_s)$ of the output power to the photovoltaic power generation system can be mathematically described as

When $T > 0, T' < 0$,

$$f(p_s) = \begin{cases} \dfrac{D(\sigma_u - (\beta + \beta')/2)}{-\sigma_{tu} B_c \psi T' \beta'} e^{\varsigma(\beta+\beta')/2}, & 0 \leq p_s \leq p_s(k_{tu}) \\ 0, & p_s < 0, or, p_s > p_s(k_{tu}) \end{cases} \tag{12}$$

When $T > 0, T' > 0$,

$$f(p_s) = \begin{cases} \dfrac{D(\sigma_u - (\beta - \beta')/2)}{-\sigma_{tu} B_c \psi T' \beta'} e^{\varsigma(\beta-\beta')/2}, & 0 \leq p_s \leq p_s(k_{tu}) \\ 0, & p_s < 0, or, p_s > p_s(k_{tu}) \end{cases} \tag{13}$$

where

$$\beta = \frac{T}{T'}, \quad \beta' = \sqrt{\beta^2 - 4p_s/\psi T' B_c}.$$

Random sampling is the basis of Monte Carlo method, in this research, the Monte Carlo sampling is applied to generate random numbers, the corresponding expressed is expressed by

$$\sum_{j=1}^{J} \left(\frac{\chi_j}{n_j} \sum_{i=1}^{N} v_i \right) \text{mod} l, \quad \chi_j = 1, 2, \ldots, N, \quad j = 1, 2, \ldots, r \tag{14}$$

where J denotes the number of random variables, N denotes the times of sampling, v_i denotes the column vector concluding d dimensional random, $modl$ is the remainder divided by l. This research divides output power of different unit in distributed energy system into n parts, the mean value of each equal division interval is expressed by M_i, $i = 1, 2, \ldots, n$, and each equal division interval corresponds to a probability value ξ_i, $i = 1, 2, \ldots, n$, The cumulative normalization is carried out for probability value of each bisection interval ξ_i, that is each equal division interval corresponds to a cumulative normalized probability. Then, the roulette selection mechanism is used to generate the output power of wind power generation and photovoltaic power generation. Then, the roulette selection mechanism is used to generate the output power of units in distributed energy system, as shown in the following formula

$$W_{t,s} = \{S^i_{1,t,s}, \ldots, S^i_{n_l,t,s}\}, \quad t = 1, \ldots, T, \quad s = 1, \ldots, n_l \tag{15}$$

where $S^i_{i,t,s}$ denotes switch parameter, which indicates whether ith equal interval of the output power of units in distributed energy system is selected.

2 Optimal Method

In order to solve the optimal allocation model of distributed energy system considering uncertain factors, the gray wolf algorithm is used in this research.

The wolf is considered as the apex predator, which is at the top of the food chain. The gray wolf generally likes to live in groups, and each group has five to twelve wolves on average. They have strict social hierarchy. The first level is the leader of group, which is defined by ρ. In wolf group, ρ is the individual with management ability, who mainly is responsible for various decision-making things in the wolf group, such as hunting, sleep time and location, food distribution. The second level is think tank team, which is defined by ϑ, which mainly is responsible for assisting ρ in decision-making. When ρ of the whole wolf group remains vacant, ϑ will replace ρ. The dominance of ϑ is second in line to ρ. The third level is defined by γ, who follows orders of ρ and ϑ. They mainly are responsible for sentry, investigation and nursing. The collective hunting is a charming social behavior of gray wolf, the social hierarchy of gray wolf plays an important role in collective hunting, and the predation process is complete with leading of ρ. The hunting of wolf group concludes three stages, the first stage is to track, chase and approach prey; the second stage is to hunt, surround, harass prey until it stops moving; The final stage is to attack the prey.

In process of hunting, the behavior of gray wolves rounding up the prey is defined by [20]

$$\vec{R} = |\vec{B} \cdot \vec{L}_P(t) - \vec{L}(t)| \tag{16}$$

$$\vec{L}(t+1) = \vec{L}_P(t) - \vec{F} \cdot \vec{R} \tag{17}$$

where $\vec{R}$ denotes the distance between individual and prey, the location of gray wolf can be updated according to expression (17). $\vec{B}$ and $\vec{F}$ are coefficient vector, $\vec{L}_P(t)$ denotes the location vector of prey, $\vec{L}(t)$ denotes the location vector of gray wolf. The calculation formulas of $\vec{B}$ and $\vec{F}$ are listed as follows:

$$\vec{B} = 2\vec{b} \cdot \vec{s}_1 - \vec{b} \tag{18}$$

$$\vec{F} = 2\vec{s}_2 \tag{19}$$

where $\vec{b}$ represents the convergence factor, which decreases from 2 to 0 with iteration times, $\vec{s}_1$ and $\vec{s}_2$ are random number between 0 and 1.

The gray wolf can identify the location of prey and surround it. When the gray wolf identify the location of prey, ϑ and γ can surround the prey with the leading of ρ. In decision space of optimal allocation, the best location of prey can not be confirmed initially. Therefore, in order to simulate the hunting behavior of gray wolves, we assume that ρ, ϑ and γ better understand the potential location of prey. We save the three optimal solutions obtained so far, and use the positions of the three to judge the position of the prey. At the same time, we force other gray wolf individuals to update their positions according to the position of the optimal gray wolf individuals, and gradually approach the prey.

The mathematical model of gray wolf individual tracking prey position is described as follows:

$$\vec{R}_\rho = |\vec{B}_1 \cdot \vec{L}_\rho - \vec{L}| \tag{20}$$

$$\vec{R}_\vartheta = |\vec{B}_2 \cdot \vec{L}_\vartheta - \vec{L}| \tag{21}$$

$$\vec{R}_\gamma = |\vec{B}_3 \cdot \vec{L}_\gamma - \vec{L}| \tag{22}$$

where $\vec{R}_\rho$, $\vec{R}_\vartheta$ and $\vec{R}_\gamma$ are distances between ρ, ϑ and γ and other individuals, $\vec{L}_\rho$, $\vec{L}_\vartheta$ and $\vec{L}_\gamma$ are current location of ρ, ϑ and γ, $\vec{B}_1$, $\vec{B}_2$ and $\vec{B}_3$ are random vector, $\vec{L}$ denotes the location of current gray wolf.

$$\vec{L}_1 = \vec{L}_\rho - \vec{F}_1 \cdot \vec{R}_\rho \tag{23}$$

$$\vec{L}_2 = \vec{L}_\vartheta - \vec{F}_2 \cdot \vec{R}_\vartheta \tag{24}$$

$$\vec{L}_3 = \vec{L}_\gamma - \vec{F}_3 \cdot \vec{R}_\gamma \tag{25}$$

$$\vec{L}(t+1) = \frac{\vec{L}_1 + \vec{L}_2 + \vec{L}_3}{3} \tag{26}$$

Equation (24) respectively defines step and direction of other wolf individual to ρ, ϑ and γ, Equation (25) defines the final position of other wolf individual.

In theory, the following points should be paid attention to when using GWO algorithm to solve optimization problems:

(1) Gray wolf's social hierarchy helps GWO algorithm to save the best solution obtained so far in the iterative process;
(2) The surround mechanism defines a circular neighborhood around the solution, which can be extended to a higher dimensional hypersphere;
(3) Random parameters $\vec{B}$ and $\vec{F}$ assist candidate solutions to obtain hyperspheres with different random radii;
(4) The proposed hunting method allows candidate solutions to locate the possible location of prey;
(5) Adaptive $\vec{b}$ and $\vec{B}$ ensure local optimization and global optimization;

(6) The adaptive values of parameters $\vec{b}$ and $\vec{B}$ allow gray wolf optimization algorithm to transition smoothly between exploration and development;

In order to improve the computing efficiency, the search mechanism is improved. The initial package of each phase is generated based on the best solution found in the previous phase: in the first phase, the best solution is saved as $\vec{L}_{best}$; In the next step, a new wolf pack is selected from the adjacent area of the found $\vec{L}_{best}$, so the $\vec{L}_{best}$ is converted into a new package. The rest are randomly selected as follows:

$$L_j = N(L_{best}, \tau L_{best}) \tag{27}$$

where $(L_{best}, \tau L_{best})$ represents a random normal distribution, the average value is L_{best}, the standard deviation, τ denotes the random ranging from 0 to 1.

The parameter $\vec{b}$ can be regulated according to the following expression:

$$\vec{b}(t) = \frac{1 - t_I/t_{I,\max}}{1 - \varepsilon \cdot t_I/t_{I,\max}} \tag{28}$$

where t_I denotes the current iteration times, $t_{I,\max}$ denotes the maximum iteration times, ε denotes nonlinear regulating index, $0 < \varepsilon < 3$.

3 Case Study

In order to verify the effectiveness of the proposed model, a distributed energy system is selected to carry out simulation. This system concludes diesel generators, micro gas turbines, fuel cells, photovoltaic power generation and wind power generation units, and the energy storage unit is composed of batteries. The micro smart grid system adopts a centralized hierarchical control architecture. During its normal operation, it passes through three levels: distribution network level, micro grid system level and micro power supply unit level, from top to bottom, The coordinated operation of distributed energy system is controlled from coarse to accurate

The main parameters of micro gas turbine, fuel cell, battery, photovoltaic power generation and wind power generation in microgrid system are shown in Tables 1–4. Parameters M, N and U in Table 1 represent the coefficients of quadratic term, primary term and constant term between the operating cost and output power of diesel generator, micro gas turbine and fuel cell respectively.

Table 1 Main parameters of distributed energy system

Term	Diesel Generator	Micro Gas Turbine	Fuel Cell
Upper limit of power	28	28	5
Lower limit of power	8	8	48
M	0.453	3.47	0.22
N	0.256	0.43	0.438
U			
Price cocient	0.0695	0.0137	0.0164

Table 2 Controlling parameters of distributed energy system

Term	Diesel Generator	Micro Gas Turbine	Fuel Cell
Minimum start time/min	25	15	15
Minimum start time/min	25	15	15
Cold start cost/Y	6.5	6.5	3.6
Hot start cost/Y	4.5	3.0	2.0
Cooling time/min	30	25	25

Table 3 Main parameters of battery

Term	Battery	Term	Battery
Upper limit of power/kW	25	Lower limit of power/kW	15
Upper limit of electric quantity/kW	55	Lower limit of electric quantity/kWh	25
Charging or discharging efficiency/kW/h	0.90	Degradation cost/Y/kW	1.5

Table 4 Interactive power parameters between external distribution network and microgrid

Term	Battery
Upper limit of power/kW	45
Lower limit of power/kW	35

In this research, the probability density function of the output power of wind power generation and photovoltaic power generation is determined according to the above methods. 1000 groups of scenes are generated by the scene generation method, and the scenes are reduced to 10 groups by the scene reduction method. The generated output power scenes of wind power generation and photovoltaic power generation are shown in Tables 5–6 and Figure 1.

Table 5 Wind power output scenario

Scenario	Wind Power/kW										
	t = 2 h	t = 4 h	t = 6 h	t = 8 h	t = 10 h	t = 12 h	t = 14 h	t = 16 h	t = 18 h	t = 20 h	t = 22 h
1	1.22	1.14	1.25	1.10	1.06	1.03	1.07	0.94	0.97	0.83	0.75
2	1.25	1.32	1.20	1.15	1.18	0.94	0.86	0.90	0.76	0.79	0.82
3	1.16	1.22	1.14	0.98	1.05	0.89	0.94	1.02	0.88	0.67	0.79
4	1.19	1.26	1.20	0.95	1.05	0.95	0.99	0.79	1.05	1.01	0.93
5	1.15	1.19	1.08	1.05	1.09	0.95	0.99	0.89	0.85	0.79	0.83
6	1.14	1.08	1.12	0.99	0.85	0.93	0.75	0.79	0.82	0.91	0.79
7	1.10	0.98	1.04	0.88	0.92	0.79	0.76	0.82	0.92	0.80	0.77
8	1.05	0.95	0.89	0.91	0.84	0.79	0.82	0.76	0.83	0.86	0.78
9	1.03	0.97	0.85	0.92	0.84	0.86	0.79	0.83	0.81	0.77	0.82
10	0.98	1.04	0.96	0.92	0.88	0.91	0.83	0.81	0.75	0.84	0.79

Table 6 Photovoltaic power output scenario

Scenario	Wind Power/kW									
	t = 6 h	t = 7 h	t = 8 h	t = 9 h	t = 10 h	t = 11 h	t = 12 h	t = 13 h	t = 14 h	t = 15 h
1	0	0.93	0.88	0.79	0.69	0.73	0.66	0.64	0.74	0
2	0	0.92	0.86	0.85	0.78	0.82	0.84	0.78	0.75	0
3	0	0.88	0.89	0.92	0.79	0.76	0.74	0.79	0.83	0
4	0	0.90	0.87	0.84	0.80	0.78	0.77	0.82	0.69	0
5	0	0.92	0.85	0.76	0.65	0.56	0.76	0.69	0.64	0
6	0	0.78	0.83	0.86	0.82	0.78	0.72	0.67	0.54	0
7	0	0.75	0.68	0.79	0.82	0.85	0.82	0.75	0.68	0
8	0	0.68	0.75	0.78	0.83	0.84	0.75	0.71	0.65	0
9	0	0.65	0.70	0.74	0.82	0.80	0.75	0.72	0.68	0
10	0	0.76	0.78	0.83	0.85	0.80	0.73	0.66	0.62	0

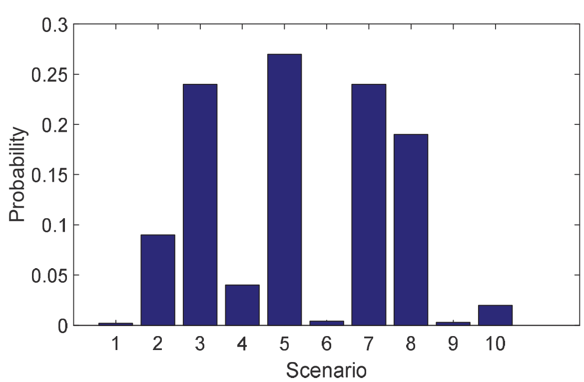

Figure 1 Probabilities of reduced scenarios.

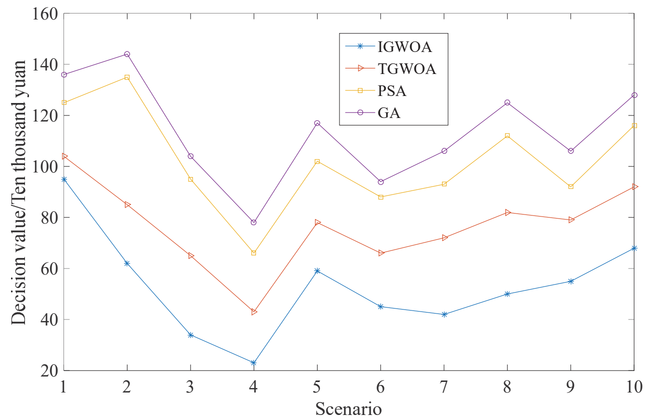

Figure 2 Total cost of different scenario based on different algorithm.

Table 7 Install capacities of different devices

	Install capacity/kW							
Scenario	Heat Accumulator	Cold Accumulator	Absorption Refrigerator	Electric Refrigerator	Gas Fired Boiler	Waste Heat Boiler	Wind Power Generation	Internal Combustion Engine
1	1002	950	6302	2504	5203	4695	3864	1402
2	830	760	5305	2204	4950	4596	3495	1354
3	734	830	5400	2030	4670	4403	3305	1289
4	670	740	4930	2105	4500	4304	3200	1200
5	690	780	5043	2260	4705	4450	3506	1350
6	800	930	6701	2439	4896	4629	3704	1435
7	740	850	6893	2649	5023	5042	3849	1503
8	780	850	6304	2530	5293	4956	3806	1649
9	1030	1100	7320	2704	5407	4892	4036	1754
10	1200	1205	6690	2803	5028	5025	3995	1699

In order to verify the improved gray wolf optimization algorithm (IGWOA), the particle swarm algorithm (PSA), the genetic algorithm (GA), and traditional gray wolf optimization algorithm (TGWOA) are also used to carry out optimal allocation of distributed energy system, and the decision value obtained based on different algorithm is shown in Figure 2.

As seen from Figure 2, the IGWOA can obtain the least decision value among all algorithms, therefore it can obtain best economical performance of optimal allocation of distributed energy system.

For different scenario, the install capacities of different devices are listed in Table 7. As seen from Table 7, the install capacities of different devices for scenario 4 are least among all scenario, therefore, the demand of electricity, heat and cold load is least, and the price of energy is least, the distributed energy system in scenario has least total cost.

4 Conclusions

The uncertainty of load requirement, energy price and renewable energy is considered in this research, and the corresponding optimal model of distributed energy system is established. The scenario method is used to process uncertainty of power distribute energy system. The improved gray wolf optimization algorithm is constructed to solve the optimal model. A distributed energy system is selected to carry out simulation, results show that the proposed model can obtain best optimal allocation of distributed energy system, and the economy of distributed energy system can be improved.

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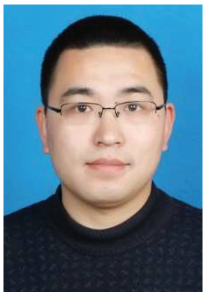
Biographies



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