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Multi-objective distributed generation hierarchical optimal planning in distribution network: Improved beluga whale optimization algorithm

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ABSTRACT

This study constructs a distributed generation (DG) multi-objective hierarchical optimal planning model. A solution method is proposed based on an improved beluga whale optimization algorithm (IBWO). Reasonable planning of the location and capacity of DG access to the distribution network plays an important role in minimizing actual power losses, reducing grid operating costs, and improving voltage distribution. The output power of DG has uncertainties and the demand response on the load side can also affect the DG planning; however, previous studies have ignored these two critical factors. This study aims to determine the optimal location and capacity of DG access to distribution network considering the demand response and the uncertainty of DG output power to improve the economic benefit, power quality and energy utilization efficiency. This study proposes an IBWO algorithm with better performance, aiming at the multi-objective, multi-constrained and nonlinear DG planning problem and a DG multi-objective hierarchical optimal planning model is established. The results show that proposed method can reduce the annual comprehensive cost, total voltage deviation and power loss of system by 11.66%, 40.55% and 38.61%.

1. Introduction

Distributed generation (DG) has the advantages of environmental friendliness, flexible control and low investment cost (Li et al., 2022; Lin and Huang, 2023; Liu et al., 2021), and its access to the distribution network brings clean energy supply to the distribution network and relieves the tension of electric energy (Liu et al., 2021). The access of DG significantly influences tidal flow, network loss and voltage stability of the network (Norouzi et al., 2022). Reasonably determining the installation location and capacity of DG in the distribution network can reduce the negative impact of DG and bring more benefits to the distribution network, such as improving economic efficiency, improving power quality, and reducing active power loss (Ahmed et al., 2023; Hassan et al., 2020). This study is significant to solve the planning problem of DG access to distribution network and plans the DG access to distribution network reasonably.

The power output of DG is random and intermittent (Zhong et al., 2021). This factor needs to be considered when planning DG access to the distribution network to help reduce the negative impact of DG on the distribution network. At present, demand response measures are applied in many areas to increase the reliability of power systems. Demand response implementation on the power user side, usually uses price and economic incentives to guide users to adjust their energy-use strategies. Demand response is an essential strategy for the interaction between the load side and the grid side, and it can transfer or reduce the load of the system during the peak period of electricity consumption, and enhance the operation stability of the distribution network (Pan et al., 2023). Demand response impacts the results of DG planning, so it is necessary to consider demand response when planning DG to meet the actual engineering needs better.

In dealing with the problem, establishing a multi-objective model has more advantages than a single-objective model to make the problem

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more comprehensive analysis and solution (Li et al., 2021). Some studies only consider an optimization objective such as economic benefits (Li et al., 2022), voltage deviation (Shaheen et al., 2022) and network loss (Khan et al., 2023). Some literature does not consider economic indicators, although the proposed model considers two or more optimization objectives (Naderipour et al., 2021; Rathore and Patidar, 2021). Prior models are lacking to comprehensively deal with factors such as demand response and DG output uncertainty when planning DG. In order to make up for the shortcomings of previous studies, this study considered the DG output's uncertainty, demand response, system economy, and power quality, and established a multi-objective DG hierarchical optimization planning model with the goals of total voltage deviation and annual comprehensive cost.

The intelligent algorithm has been an effective method for solving the problem in recent years. It has been applied to many fields to solve some complex problems effectively. For example, intelligent algorithms have penetrated the field of artificial intelligence and can be used for image analysis (Połap, 2023; Prokop et al., 2022), and its performance has proven superior to many traditional analysis methods and may penetrate more fields in the future. The intelligent algorithm can also be combined with machine learning methods such as extreme learning machine to solve more practical engineering problems such as load forecasting (Li et al., 2021) and production energy saving (Li et al., 2020). Intelligent algorithms are more effective than traditional methods. Therefore, this study uses intelligent algorithms as the basic method to solve the problem.

Aiming at the multi-dimensional, multi-objective and multi-constrained problems of DG planning, the model is transformed into a two-layer model to diminish the difficulty of model solving and improve the accuracy of model solving. An improved beluga whale optimization (IBWO) algorithm with better solving ability is proposed to solve the model. A more realistic DG planning scheme with higher economic benefits and power quality is obtained. Finally, the validity of the model and algorithm is verified in the IEEE33 system. The contributions of this study are as follows.

- A multi-objective hierarchical optimization planning model of DG considering demand response and DG output uncertainty is established to effectively determine the location and capacity of DG connected to the distribution network. It can significantly improve the power quality and economic benefits of the network.
- An IBWO algorithm with better performance is proposed. IBWO has faster convergence speed and stronger solving ability. The proposed algorithm solves the DG planning problem compared with many existing excellent intelligent algorithms, effectively.
- Simulation experiments on the IEEE33 system have shown that the proposed algorithm outperforms existing algorithms in terms of solution using the IBWO algorithm to solve the DG programming problem.
- The demand response measures considered include time-of-use electricity price and transferable load. The impact of demand response on DG planning results is also analyzed.

The remaining sections are as follows. The literature review is in Section 2. Section 3 presents the objective function and Constraint conditions of the proposed model, as well as presents the uncertainty modeling of DG. The fourth section introduces the proposed IBWO and compares and performs tests with other single objective algorithms. The fifth section introduces the transformation and solution of the proposed model. In Section 6, the results under three different cases are analyzed and discussed. Section 7 introduces the conclusions of this study and further research directions.

2. Literature review

2.1. Improved beluga whale optimization algorithm

There is an increasing concern on how to reasonably plan DG access to distribution networks with renewable energy development, where planning DG can alleviate the current energy constraint and improve the system's power quality. The traditional DG planning method can no longer meet practical engineering needs with time.

Many methods of planning based on artificial intelligence have been proposed. The classical methods include particle swarm optimization algorithm (Rathore and Patidar, 2021) and genetic algorithm (Cikan and Cikan, 2023). Hemeida et al. (2021) uses manta ray foraging optimization algorithm and Fathy et al. (2021) uses metaheuristic chimp optimizer approach to allocate DG in the radial network to decrease the power loss in the network. The methods optimize only one objective, and the planning results can obtain less benefit. Moreover, single-objective algorithms converge slowly when solving problems and tend to converge to non-optimal solutions, so some studies have improved the intelligent algorithm. Khan et al. (2023) applied arithmetic optimization algorithm to allocate DG in power system to reduce the network loss and the voltage deviation. Cikan and Cikan (2023) determined the location and capacity of various types of DG in the 123-node distribution network through the equilibrium optimizer algorithm. Compared with a variety of effective optimization algorithms, the proposed method achieves the lowest network loss. In order to improve the voltage distribution of the distribution network and reduce the active loss, Ferminus and Saravanan (2023) used the dwarf mongoose optimization algorithm to allocate DG to the distribution network, and the performance of the method is proved by the classical test system. The single objective algorithm has a slow convergence speed when solving problems and can easily converge to non-optimal solutions. Some studies have improved intelligent algorithms for distribution network problem.

Shaheen et al. (2022) proposed an improved heap-based optimization algorithm that can significantly strengthen the global search capacity of the algorithm. Verified the algorithm's validity by test functions and test systems, but only voltage deviation are considered. Haddadian et al. (2023) proposed an improved fuzzy decision-making method to allocate DG in the distribution network, which improves the reliability of the network and reduces the voltage imbalance. However, economic indicators are not taken into account. Mohandas and Devanathan (2021) showed a crossover mutation based Harris Hawk Optimization algorithm to determine the optimal planning scheme of DG but does not consider the economy of the system. Hamidan and Borousan (2022) showed a new method to plan DG using an improved wild horse optimization algorithm, which improves the consistency of the system and decreases the system loss. However, the objective function only considers the network loss.

In addition to improving the algorithm, some literature uses hybrid methods to solve DG planning problems. Hemeida et al. (2021) combined genetic algorithm and stain bowerbird optimization algorithm to constitute a hybrid optimization algorithm, which exerts the advantages of the two algorithms and solves the DG planning problem more effectively. Compared with many existing methods, this hybrid method can effectively decrease the system's power loss and enhance the system's stability. However, the economic indicators considered in optimization are not comprehensive enough. Yehia et al. (2022) proposed a new hybrid fuzzy equilibrium optimization algorithm with faster convergence speed and less solution time than many existing algorithms. The validity of the approach is verified in the test system, but the economy of the system is not considered. The application of multi-objective optimization algorithm in the DG planning method can take into account multiple optimization indicators and bring higher benefits to the system (Ahmadi et al., 2021; Hari Prasad et al., 2023). Kumar and Kumar (2022) applied a multi-objective speed butterfly optimization algorithm for DG allocation to decrease system's network loss, enhance system's economy and improve system's power quality.

2.2. A DG multi-objective hierarchical optimal planning model

Studies have converted multi-objectives into single-objective by setting weights, and solved by some single-objective algorithms with excellent performance, in addition to applying multi-objective algorithms to solve multi-objective problems in terms of DG planning. For instance, Al-Ammar et al. (2021) optimized multiple targets, such as active network loss and power quality, then converted the multi-objectives into single-objective by setting weights. The single-objective is solved by artificial bee colony algorithm. Ahmed et al. (2023) applied the weight method to deal with multiple indicators and convert them into single targets. A hybrid method is proposed to solve the problem combined with two classical algorithms. The example shows that this method can significantly reduce multiple indicators including network loss.

Most studies do not consider the uncertainty of DG output, resulting in a deviation between the planning results and the actual situation. Therefore, some current studies also consider the uncertainty of DG output. Ramadan et al. (2023) applied an effective artificial hummingbird optimization algorithm and uses Monte Carlo simulation and the backward reduction method to deal with the uncertainty of DG output. The planning result is closer to the actual planning, but the performance of the algorithm still has some room for improvement. Aliabadi and Radmehr (2021) aimed to optimize the voltage deviation and network loss of the system, determining the capacity and location of DG and energy storage access hybrid systems. The uncertainty in the system is modeled by probability method. The test results show that considering uncertainty can improve system reliability and network characteristics. Li et al. (2022) constructed a bi-level planning model considering the uncertainty of DG output to simultaneously plan DG and energy storage, which is solved by binary particle swarm optimization algorithm, but only considers the system's economy. Marquez et al. (2022) proposed a stochastic bi-level optimization model for allocating DG to the distribution network. The goal is to maximize the benefits of DG.

In addition, Xu et al. (2022) considered a variety of economic indicators and constructed a recursive optimization model. The model considers active management measures such as demand response. The effectiveness of the model is verified by an example, but only the economy of the system is considered. Gao et al. (2023) involved the spatiotemporal correlation of DG output power, and establishes a DG multi-objective programming model to maximize annual revenue and stabilize network operation. The effectiveness of the model is proved by experiments. Kashyap et al. (2022) simulated the real load scenario by setting up multiple load scenarios to more accurately determine the location and capacity of DG access to the distribution network, but the optimization index of the model only considers the network loss.

In sum, considering the output uncertainty of DG and demand response can make the planning results of DG more in line with the needs of practical engineering, which is often not considered in some previous literature. Moreover, many studies consider only one objective when planning DG. Considering multiple objectives such as economic and power quality indicators can obtain more effective planning results. Choosing a solution algorithm with superior performance in terms of solving methods is also essential. Therefore, this study constructs a DG planning model that takes the demand response and output uncertainty of DG into account, and considers the improvement of system economic efficiency and power quality, with the annual comprehensive cost and total voltage deviation as the objectives. The model is transformed into a two-layer model, and an IBWO algorithm with excellent performance is proposed to solve the model to reduce the difficulty of solving the model and improve the solving performance.

3. Model description

3.1. Uncertainty modeling of DG

The DG of this study selects WT and PV, assuming that both WT and PV units are constant power control. Since the wind power output is randomly and intermittently affected by wind speed and other factors, uncertainty factors' influence must be considered when modeling the wind power. The Weibull distribution with the ideal two parameters that works best in practical engineering applications is used. The probability density function (PDF) is as follows.

$$f(\upsilon)=\frac{k}{b}\left(\frac{\upsilon}{b}\right)^{k-1}\exp\left(-\left(\frac{\upsilon}{b}\right)^{k}\right) \tag{1}$$

where υ is the real-time wind speed; b and k are the scale and shape parameters of Weibull distribution, depending on the expectation and variance of wind speed.

The output power of the WT is as follows.

$$P^{wt}=\begin{cases}0\upsilon<\upsilon_1,\upsilon>\upsilon_2\\ \dfrac{\upsilon-\upsilon_1}{\upsilon_e-\upsilon_1}P_e^{wt}\upsilon_1<\upsilon<\upsilon_e\\ P_e^{wt}\upsilon_e<\upsilon<\upsilon_2\end{cases} \tag{2}$$

where υ_1, υ_e and υ_2 represent the cut-in wind speed, rated wind speed and cut-out wind speed; P^{wt} is the active power output by the WT at different wind speeds; P_e^{wt} is the rated power of the WT.

Similarly, the output of PV is affected by factors with volatility such as light intensity. The uncertainty of PV is modeled using Beta distribution with PDF as follows.

$$f(l)=\frac{\Gamma(\psi_1+\psi_2)}{\Gamma(\psi_1)\Gamma(\psi_2)}\left(\frac{l}{l_{\max}}\right)^{\psi_1-1}\left(1-\frac{l}{l_{\max}}\right)^{\psi_2-1} \tag{3}$$

where ψ_1 and ψ_2 are the Beta distribution's shape parameters depending on the expectation and variance of the light intensity; l and $l_{\max}$ are the actual and the maximum intensity of illumination.

The output expression of PV is obtained from the intensity of illumination as follows.

$$P^{pv}=\begin{cases}\dfrac{P_e^{pv}l}{l_{\max}}l\leqslant l_{\max}\\ P_e^{pv}l>l_{\max}\end{cases} \tag{4}$$

where P_e^{pv} and P^{pv} are the rate active power and the PV's power output.

According to equation (3), the PDF of PV active output power is obtained as follows:

$$f(P^{pv})=\frac{\Gamma(\psi_1+\psi_2)}{\Gamma(\psi_1)\Gamma(\psi_2)}\left(\frac{P^{pv}}{P_e^{pv}}\right)^{\psi_1-1}\left(1-\frac{P^{pv}}{P_e^{pv}}\right)^{\psi_2-1} \tag{5}$$

The data of illumination intensity and wind speed of a year in a region are collected. K-means clustering algorithm (Ikotun et al., 2023) is used to obtain typical scenes of illumination intensity and wind speed each season. The typical wind speed and light intensity scenes in every season are converted into the corresponding output by the DG output model in this section.

3.2. Objective function

The objectives considered are the annual comprehensive cost and total voltage deviation, and the purpose is to enhance the reliability of the power system while improving the economy of the planning.

3.2.1. Annual comprehensive cost.

$$F_1 = C_{total} = C_l + C_{om} + C_{loss} + C_{en} + C_{dr} \tag{6}$$

3.2.1.1. DG investment cost

$$C_l = \lambda_{wt} \sum_{i=1}^{N_n} \left(c_l^{wt} P_i^{wt}\right) + \lambda_{pv} \sum_{i=1}^{N_n} \left(c_l^{pv} P_i^{pv}\right) \tag{7}$$

$$\lambda_{WT} = \frac{(1+\alpha)^y \alpha}{(1+\alpha)^y - 1} \tag{8}$$

$$\lambda_{pv} = \frac{(1+\alpha)^y \alpha}{(1+\alpha)^y - 1} \tag{9}$$

where λ_{wt} and λ_{pv} are the shape factors of WT and PV; N_n is the number of nodes to be planned for DG; P_i^{wt} and P_i^{pv} are the rated capacity installed at node i; c_l^{wt} and c_l^{pv} are the investment cost per unit capacity; α is the rate of discount; y is the useful life of DG.

3.2.1.2. DG operating cost

$$C_{om} = \sum_{s=1}^{N_s} \sum_{i=1}^{N_n} t_s \left(c_{om}^{wt} P_{i,s}^{wt} + c_{om}^{pv} P_{i,s}^{pv}\right) \tag{10}$$

where c_{om}^{wt} and c_{om}^{pv} are the operating cost per unit of generation for WT and PV; $P_{i,s}^{wt}$ and $P_{i,s}^{pv}$ are the actual active output of WT and PV installed at node i under scenario s; N_s is the number of scenarios simulated to run; t_s denotes the total number of operating days for scenario s.

3.2.1.3. Power purchase cost from superior power grid

$$C_{en} = \sum_{s=1}^{N_s} \sum_{t=1}^{24} d_{s,t} P_{en,s,t} t_s \tag{11}$$

where $P_{en.s,t}$ is the active power of purchasing power from the superior power grid at time t under the scenario s; $d_{s,t}$ is the real-time price of system.

3.2.1.4. Network loss cost.

The network loss is converted into economic indicators to reduce power waste. The conversion equation is as follows.

$$C_{loss} = \sum_{i=1}^{N_s} c_{loss} P_{loss,s} t_s \tag{12}$$

where c_{loss} and $P_{loss,s}$ are the conversion cost of active power loss per unit of electricity and the total network loss in scenario s.

3.2.1.5. Compensation cost of implementing demand response.

There are many measures for demand response. This study selects the transferable load measure, which guides the user to transfer the transferable load from the system peak load period to the trough or other non-peak load period through economic incentives. The calculation equation is as follows.

$$C_{dr} = \sum_{s=1}^{N_s} \sum_{j=1}^{N_n} t_s c_{dr} P_{j,s,dr} \tag{13}$$

where $P_{j,S,dr}$ denotes the transferable load power at load node j under scenario s; c_{dr} denotes the compensation cost of transferable load per unit of power.

3.2.2. Annual total voltage deviation

The annual total voltage deviation is used as an objective to enhance the system's stability and power quality.

$$F_2 = V_{tvd} = \sum_{s=1}^{N_s} \sum_{i=1}^{N_n} \sum_{t=1}^{24} \left|1 - V_{s,i,t}\right| t_s \tag{14}$$

where, $V_{s,i,t}$ is the normalized voltage value of node i at time t in scenario s.

The two objectives considered are combined into a single objective by weight. The equation is as follows.

$$\min F = wF_1 + (1-w)F_2 \tag{15}$$

However, the order of magnitude of the deviation between the annual comprehensive cost and the total voltage deviation is not uniform, which leads to the weight w has little effect on the result of the objective function. Therefore, the correction coefficient Q is introduced to correct the equation (15).

The value of Q is related to the difference in the order of magnitude of the annual comprehensive cost and the total voltage deviation. The objective function obtained after correction is as follows.

$$\min F = wF_1/Q + (1-w)F_2 \tag{16}$$

3.3. Constraint conditions

3.3.1. DG installed capacity constraints

$$\begin{cases} 0 \leqslant P_i^{wt} + P_i^{pv} \leqslant P_{i,DG}^{\max} \\ 0 \leqslant P_i^{wt} \leqslant P_{i,wt}^{\max} \\ 0 \leqslant P_i^{pv} \leqslant P_{i,pv}^{\max} \end{cases} \tag{17}$$

where $P_{i,DG}^{\max}$ denotes the maximum capacity of DGs allowed to be installed at node i to be planned; $P_{i,wt}^{\max}$ and $P_{i,pv}^{\max}$ denote the maximum allowed installation capacity of WT and PV at node i to be installed.

3.3.2. Node voltage constraints

$$U_i^{\min} \leqslant U_i \leqslant U_i^{\max} \tag{18}$$

where U_i is the voltage value at node i; $U_i^{\min}$ and $U_i^{\max}$ are the minimum and maximum node voltage values.

3.3.3. Power balance constraints

$$\begin{cases} U_{i.s} \sum_{i=1}^{N_n} U_{j.s} \left(G_{ij} \cos\theta_{ij.s} + B_{ij} \sin\theta_{ij.s}\right) = P_{i.s} \\ U_{i.s} \sum_{i=1}^{N_n} U_{j.s} \left(G_{ij} \sin\theta_{ij.s} - B_{ij} \cos\theta_{ij.s}\right) = Q_{i.s} \end{cases} \tag{19}$$

where $P_{i.s}$ and $Q_{i.s}$ represents the active power and reactive power flowing into node i at scene s; $U_{i.s}$ and $U_{j.s}$ denote the voltage amplitudes of node i and node j at scene s; G_{ij} and B_{ij} represents the real and imaginary parts of the admittance between node i and node j, and $\theta_{ij.s}$ represents the impedance angle.

3.3.4. Branch capacity constraints

$$0 \leqslant S_j \leqslant S_j^{\max} \tag{20}$$

Where S_j and $S_j^{\max}$ represents the apparent power of line j and its upper limit respectively.

3.3.5. DG penetration rate constraints

$$\sum_{i=1}^{N_n} \left(P_i^{wt} + P_i^{pv}\right) \leqslant \xi P_z \tag{21}$$

where P_z is the system's total load; ξ is the maximum penetration of renewable energy in the system.

3.3.6. DG operation constraints

$$\begin{cases} 1-\omega_{i,DG})P_{i,s,DG}^{\max}\leqslant P_{i,s,DG}\leqslant P_{,i,s,DG}^{\max} \\ 0\leqslant\omega_{i,DG}\leqslant\omega_{i,DG}^{\max} \end{cases} \tag{22}$$

where the types of DG are WT and PV, $P_{i,s,DG}^{\max}$ is the upper limit of active output under the scenario s installed at node i; $\omega_{i,DG}$ and $\omega_{i,DG}^{\max}$ are the active output removal ratio of DG installed at node i and its maximum value.

3.3.7. Load transfer volume constraints

$$0\leqslant P_{i,s,dr}\leqslant P_{i,s,dr}^{\max} \tag{23}$$

where $P_{i,s,dr}$ is the amount of transferable load of node i in scenario s, and $P_{i,s,dr}^{\max}$ is its maximum.

4. Beluga whale optimization algorithm and its improvement

4.1. Beluga whale optimization algorithm

Zhong et al. (2022) observed the habits of beluga whales and are inspired to propose a new BWO algorithm. Its performance has been proved by various tests in the original literature to be superior to most existing heuristic methods. The BWO algorithm has been applied to solve complex problems in some literature and has shown better solving ability (Huang et al., 2023; Li et al., 2023). The BWO algorithm is divided into three stages: exploration phase, development phase and whale falling phase.

4.1.1. Exploration phase

The exploration stage of the beluga whale is the imitation of the swimming behavior of the beluga whale. The expression for updating the position of the beluga whales is as follows.

$$\begin{cases} x_{i,j}^{T+1}=x_{i,Sj}^{T}+\left(x_{r,S1}^{T}-x_{i,Sj}^{T}\right)(1+r_1)\sin(2\pi r_2), j=even \\ x_{i,j}^{T+1}=x_{i,Sj}^{T}+\left(x_{r,S1}^{T}-x_{i,Sj}^{T}\right)(1+r_1)\cos(2\pi r_2), j=odd \end{cases} \tag{24}$$

where T is the current iteration times; (j = 1,2,3,…,D) is a random integer chosen between 1 and D; $x_{i,j}^{T+1}$ is the position of the i_{th} beluga in dimension j after position update; $x_{i,sj}^{T}$ denotes the position of the i_{th} beluga whale in dimension Sj under the current iteration times T; $x_{r,S1}^{T}$ is the current position of the r_{th} beluga whale under the current iteration times (r denotes a randomly chosen beluga whale); r_1, r_2 represent random value between 0 and 1; *even* and *odd* represent even and odd numbers.

The parameter b_f is used to determine whether IBWO is converted from the exploration phase to the development phase. The formula of parameter b_f is as follows.

$$b_f=rand(0,1)\times(1-T/2T_{\max}) \tag{25}$$

4.1.2. Development phase

After the exploration phase, beluga whales need to engage in predatory behavior. The position update equation of the beluga whale at the development phase is as follows.

$$X_i^{T+1}=r_3X_{best}^{T}-r_4X_i^{T}+A\cdot L_F\cdot\left(X_r^{T}-X_i^{T}\right) \tag{26}$$

$$A=2r_4((1-T)/T_{\max}) \tag{27}$$

$$L_F=0.05\times(\delta\times\gamma)/|\mu|^{1/B} \tag{28}$$

$$\gamma=\frac{\sin(\pi B/2)\sin(\pi B/2)}{B\times 2^{(B-1)/2}}\times\frac{\Gamma(1+B)}{\Gamma((1+B)/2)} \tag{29}$$

where X_i^T is the position of the i_{th} beluga whale; X_r^T is the position of a random beluga whale at the current iteration times; r_3, r_4 are random values between (0,1); X_{best}^T denotes the beluga whale's best positioned, i.e., the global optimal position; A represents the random jump strength used to measure the flight strength in the Lévy flight method; $T_{\max}$ is the maximum iterative; L_F denotes the Lévy flight function; δ and μ are random numbers of normally distributed, and B is a constant.

4.1.3. Whale fall

Whale fall simulates the situation that some beluga whales die when they encounter misfortune in the sea. The model of the whale's falling behavior is as follows.

$$X_i^{T+1}=r_5X_i^T-r_6X_r^T+r_7X_s \tag{30}$$

$$X_s=(u_b-l_b)e^{\left(-2\rho_f\times nT/T_{\max}\right)} \tag{31}$$

$$\rho_f=\frac{0.1-0.05T}{T_{\max}} \tag{32}$$

where r_5 , r_6 and r_7 are random number that takes values from 0 to 1; X_s is the unit path length of whale fall; u_b and l_b are the limitations on the location of beluga whales; ρ_f is the probability of occurrence of the whale fall.

4.2. Improved beluga whale optimization algorithm (IBWO)

4.2.1. Improved population position initialization strategy

The BWO algorithm uses random population initialization operation, which causes the generated initial population to be unable to cover the entire solution space. Sobol sequence and Tent mapping are combined as the improved initialization method. The chaotic sequence generated by Tent map has better distribution and randomness, and the point set generated by Sobol sequence in space is relatively uniform. The initial position distribution of the beluga whale population can become more uniform within the constraint range and cover a more extensive spatial range by combining the advantages of the two initialization methods. The proposed initialization strategy can strengthen the exploration performance of algorithm. The function of improving the initialization strategy is expressed as follows.

$$x_{T+1}=\begin{cases} x_T/hx_T\in[0,h] \\ (x_T-1)/(h-1)x_T\in(h,1] \end{cases} \tag{33}$$

where h is the boundary constant with the value of 0.5.

4.2.2. Dynamic self-adaptive feature weight

In the development stage of the IBWO algorithm, dynamic adaptive feature weight is added, and the weight value first increase and then decrease with the increase of iteration times. The weight is small in the early stage of the algorithm, which is conducive to accelerating the optimization speed of the algorithm in the early stage. With the increase of iteration times, the value of the adaptive weight increases continuously and reaches the maximum in the middle stage, which is conducive to the global search of the algorithm. In the later stage of iteration, the search range is determined, the value of adaptive weight is reduced, the optimal solution is found in a certain range, and the convergence speed of the algorithm in the later stage is accelerated. The value of the weights gradually decreases to improve the algorithm's convergence speed to the best solution as iterations increase. The formula of dynamic self-adaptive feature weight is as follows.

$$W=\begin{cases} 2e^{-4(T_{\max}-T)/T_{\max}}T\leqslant T_{\max}/2 \\ 2e^{-4T/T_{\max}}T>T_{\max}/2 \end{cases} \tag{34}$$

After introducing the dynamic self-adaptive feature weight W, the equation for updating the position of beluga whales in the development

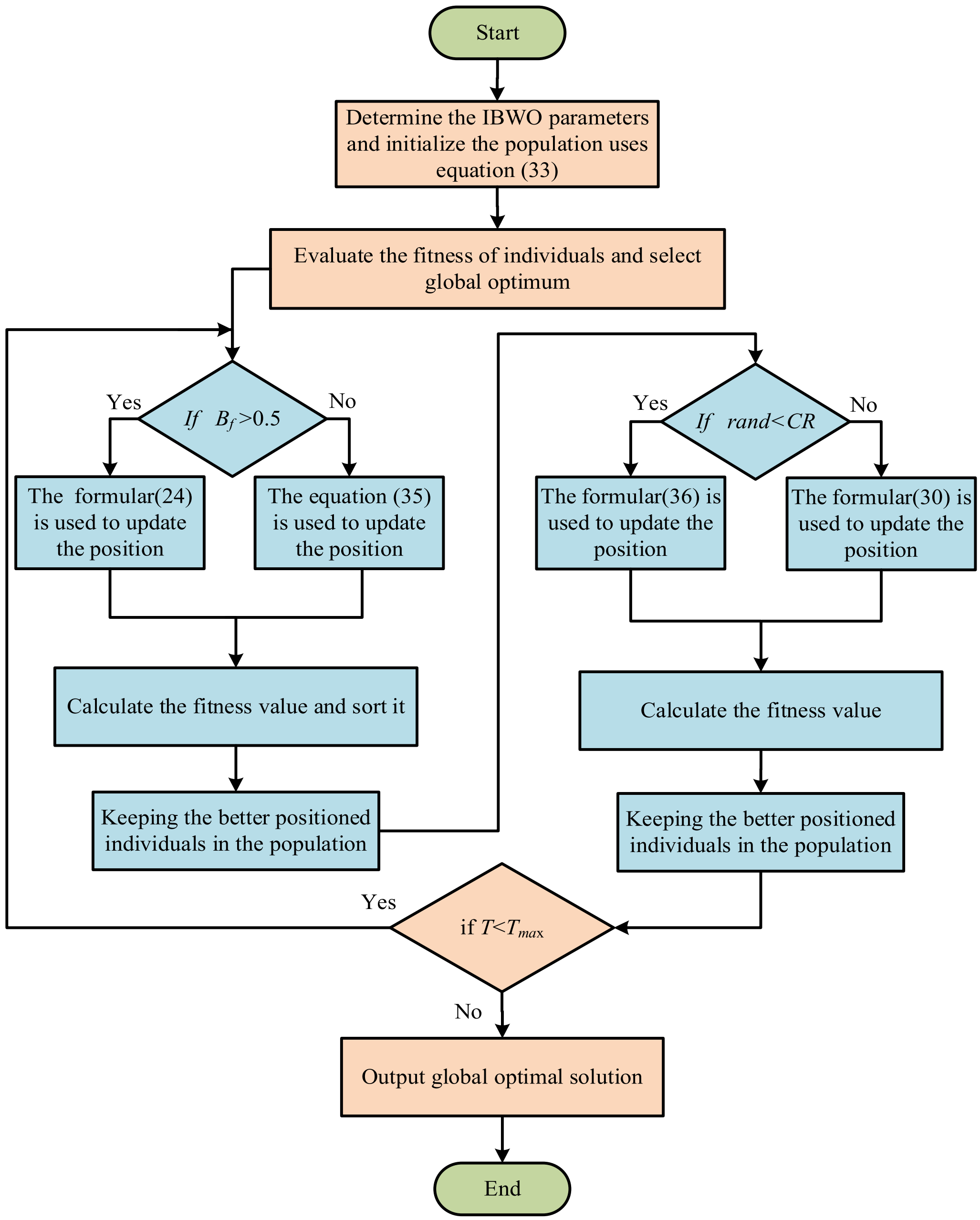

Fig. 1. IBWO algorithm flow chart.

phase is as follows.

$$X_i^{T+1} = r_3 X_{best}^T - W X_i^T + A \cdot L_F \cdot \left(X_r^T - X_i^T\right) \tag{35}$$

4.2.3. Optimal neighborhood perturbation

Many intelligent algorithms are easy to converge to non-optimal solutions in the later stage, and the BWO algorithm also suffers from this problem. Interference is applied to the current best solution when the iteration reaches the late stage for enhancing the convergence performance of BWO algorithm in the late iterations. Some new solutions are generated near the current optimal solution. This study proposes a new perturbation, and the equation is as follows.

$$X_i^{T+1} = X_{best}^T + w_2 X_{best}^T \tag{36}$$

$$w_2 = \left[0.6 - 0.3\left(\frac{T}{T_{\max}}\right)\right] \cos\left(\frac{\pi}{2} \times r_5\right) \tag{37}$$

where w_2 represents a variable perturbation factor to decrease with the iteration of the algorithm, which is beneficial for enhancing the convergence accuracy of the algorithm. The proposed optimal neighborhood perturbation alternates with the whale fall, depending on the value of probability factor CR. The whale fall can increase the diversity of solutions in the early and middle stages of the algorithm, but the effect is not significant in the later stages. The probability of optimal neighborhood perturbations increases with the number of iterations, which can improve the algorithm's ability to jump out of the local optimum. The improved location of beluga whales update equation is as follows.

$$\begin{cases} X_i^{T+1} = r_5 X_i^T - r_6 X_r^T + r_7 X_s rand \geqslant CR \\ X_i^{T+1} = X_{best}^T + w_2 X_{best}^T rand < CR \end{cases} \tag{38}$$

where $rand$ is a random value with upper and lower limits are 0 and 1, and CR is a probability factor. The expression is as follows.

$$CR = \cos(\frac{\pi}{2}(1 - \frac{T}{T_{\max}})) \tag{39}$$

Algorithm 1: The pseudo code of IBWO algorithm

Initialize the solutions' positions by Eq. (33)X: $i = 1, \ldots, N$
While $T \leqslant T_{\max}$ do
Obtain weight W by Eq. (34) probability of whale fall ρ_f by Eq. (32) and balance factor b_f by Eq. (25)
for (i = 1 to$N$) do
If b_f (i) > 0.5
// In the exploration phaseChoose a beluga whale X_s, randomly.
Update new position of i-th beluga whale using Eq. (24)
Else If b_f(i) ≤ 0.5
// In the development phase
Update new position of i-th beluga whale using Eq. (35)
End If
Check the boundaries of new positions and evaluate the fitness values
End ForUpdate the probability factor
for (i = 1 to N) do
// the whale fall phaseUpdate the probability factor CR
If b_f (i)≤ρ_f && $rand$ > CRCalculate the step size X_S
Update new position of i-th beluga whale using Eq. (30)
Check the boundaries of new position and calculate fitness value
End If
If b_f (i)≤ρ_f && $rand \leqslant CR$Update the variable disturbance factor w_2
Update new position of i-th beluga whale using Eq. (36)
Check the boundaries of new position and calculate fitness value
End IfEnd While
Output the best solution

In summary, the pseudo-code of IBWO is shown in Algorithm 1, and the flow of the proposed IBWO algorithm is shown in Fig. 1.

1. Set the maximum iteration number of IBWO algorithm, the number of population individuals, dimensions and other related parameters. Establish the initial population according to the improved population location initialization strategy.
2. Calculate the fitness value of beluga whales. Rank belugas according to the magnitude of the fitness value and record the best located beluga whale.
3. Judge the balance factor B_f. If $B_f > 0.5$, use the exploration phase equation (24) to update the position of the beluga whale population. When $Bf \leq 0.5$, use the improved development phase equation (35) to update the position of beluga whales, calculate the updated the fitness value of beluga whales, and retain better individuals in the population.
4. The operation of whale fall is performed on the beluga whale population when the condition of whale fall is reached. If the random number $rand \geq CR$, the equation of whale fall equation(30) is selected to update the beluga whale population. Conversely, $rand < CR$, the neighborhood perturbation equation (36) proposed in this study is selected to update the beluga whale population.
5. Calculate the fitness value of the beluga whales. Better individuals remain in the population by comparing the fitness values of new and original beluga whales.
6. Judge whether the maximum times of iterations is reached. If reached, the white whale with the optimal position is output. Otherwise, continue the iteration.

An important metric for evaluating the performance of an algorithm is the computational complexity. The computational complexity of the initialization process of IBWO is O(N). In the exploration and development phase of the algorithm, the computational complexity is O ($N \times T_{\max}$), and in the improved whale-fall phase, the computational complexity is approximated to be equal to O ($0.2 \times N \times T_{\max}$), subject to parameters such as b_f, ρ_f and CR. the total computational complexity of IBWO is O($N \times (1 + 1.2 \times T_{\max})$).

Table 1
Test functions.

Funcation	Range	opt
$F_1(X) = \sum_{i=1}^{n} X_i^2$	[-100, 100]	0
$F_2(X) = \prod_{i=1}^{n} \lvert X_i \rvert + \sum_{i=1}^{n} \lvert X_i \rvert$	[-10, 10]	0
$F_3(X) = \sum_{i=1}^{n} \left(\sum_{j-1}^{i} X_j\right)^2$	[-100, 100]	0
$F_4(X) = \max_i\{\lvert X_i \rvert, 1 \leqslant i \leqslant n\}$	[-10,10]	0
$F_5(X) = e - \exp(\frac{1}{N}\sum_{I=1}^{n}\cos(2\pi X_i)) + 20(1 - \exp(-\frac{1}{5}\sqrt{\frac{1}{n}\sum_{i=1}^{n} X_i^2}))$	[-32, 32]	0
$F_6(X) = \sum_{i=1}^{11}\left[a_i - \frac{X_1(b_i^2 + b_i X_2)}{b_i^2 + b_i X_3 + X_4}\right]^2$	[-5, 5]	0.0003
$F_7(X) = CompositionFunction2(N = 3)$	–	2200
$F_8(X) = CompositionFunction3(N = 4)$	–	2300
$F_9(X) = CompositionFunction4(N = 4)$	–	2400

Table 2
Parameter settings of each algorithm.

Algorithms	parameters
PSO	$C_1 = C_2 = 2$; $\omega_{min} = 0.1$; $\omega_{max} = 0.9$
WOA	$\beta = 1$
BWO	$B = 1.5$
IBWO	$B = 1.5$; $h = 0.5$
AOA	$p_a = 5$; $r_a = 0.5$
CDO	R_d = rand (0,1)
SCSO	C_l = [0,2]

4.3. Performance analysis of IBWO algorithm

Three measures are used to implement improvements to the BWO algorithm to obtain the IBWO algorithm. Six benchmark functions (F1-F6) and three cec2017 test functions (Abualigah et al., 2022) are selected for the performance testing of the algorithm for verifying the performance of the proposed IBWO algorithm. Among them, F1 to F4 are unimodal test functions that can test algorithm's convergence performance and accuracy to solve the problem. The F5 and F6 are the multi-peak test function can test the global search performance of the algorithm. F7 to F9 are composition functions that can test the ability of the algorithm to solve complex problems. Table 1 shows the expression of the selected test function.

Several heuristic algorithms are selected to compare with IBWO for verifying the solving ability of IBWO algorithm. The classical heuristic algorithms include the particle swarm optimization algorithm (PSO) (Rathore and Patidar, 2021) and whale optimization algorithm (WOA) (Prakash and Lakshminarayana, 2018). Advanced algorithms in recent years include beluga whale optimization algorithm (BWO), arithmetic optimization algorithm(AOA) (Khan et al., 2023), sand cat swarm optimization(SCSO) (Kiani et al., 2023) and Chernobyl disaster optimizer (CDO) (Shehadeh, 2023). C_l is the Sensitivity range in SCSO algorithm.

The parameter settings of every algorithm are shown in Table 2. The parameter setting of the algorithm is consistent with the parameter setting of the corresponding original literature after repeated debugging to solve related problems. c_1 ,c_2 and ω are the learning factor and inertia coefficient in PSO algorithm; β is the spiral coefficient in WOA algorithm; B is the parameter related to position update in BWO and IBWO; h is the boundary constant of IBWO algorithm; p_a and r_a are the sensitive parameter and control parameter to adjust the search process in AOA algorithm; R_d is the radius of radiations propagation in CDO algorithm.

All algorithms' population individuals and iteration times are set to 30 and 500 for fairly comparing the solving ability of IBWO algorithm and other algorithms. All test functions are run 30 times and calculate the average value, optimal value, standard deviation and optimal value

Table 3
Test results of test functions.

Function	Algorithm	Average	Std	Best fitness	Worst fitness
$F(x_1)$	IBWO	0	0	0	0
	BWO	3.523e-260	0	1.571e-271	8.595e-259
	WOA	5.986e-86	2.002e-85	2.600e-100	8.651e-85
	CDO	8.318e-124	3.359e-123	7.160e-133	1.504e-122
	SCSO	7.408e-109	3.291e-108	1.412e-123	1.472e-107
	PSO	15.1130	2.23240	8.33050	18.93501
	AOA	0.00055	0.00130	8.113e-56	0.00509
$F(x_2)$	IBWO	5.957e-241	0	3.223e-247	2.977e-240
	BWO	1.100e-131	3.393e-131	2.051e-137	1.536e-130
	WOA	6.027e-53	3.060e-52	3.702e-60	1.687e-51
	CDO	8.021e-65	2.300e-64	8.498e-68	1.047e-63
	SCSO	2.447e-56	1.077e-55	1.490e-61	4.822e-55
	PSO	16.43240	0.90430	14.73420	18.33650
	AOA	1.063e-159	4.755e-159	3.466e-271	2.126e-158
$F(x_3)$	IBWO	0	0	0	0
	BWO	5.432e-244	1.320e-128	3.362e-256	1.629e-242
	WOA	2.993e + 04	1.192e + 04	4.029e + 03	5.060e + 04
	CDO	6.339e-82	2.784e-81	3.084e-108	1.490e-80
	SCSO	1.548e-95	6.883e-95	1.787e-105	3.773e-94
	PSO	68.23050	14.20810	40.85050	99.11030
	AOA	0.09142	0.07600	0.01378	0.40530
$F(x_4)$	IBWO	4.552e-231	0	5.635e-235	9.813e-230
	BWO	1.613e-128	8.209e-128	4.243e-132	4.506e-127
	WOA	4.41530	3.21650	3.499e-06	8.67670
	CDO	1.262e-59	3.331e-59	2.290e-63	1.499e-58
	SCSO	3.558e-49	1.250e-48	1.054e-55	6.734e-48
	PSO	1.52370	0.13650	1.10740	1.80710
	AOA	0.04806	0.01180	0.01882	0.07276
$F(x_5)$	IBWO	8.881e-16	0	8.881e-16	8.881e-16
	BWO	8.881e-16	0	8.881e-16	8.881e-16
	WOA	4.914e-15	2.233e-15	6.820e-16	7.993e-15
	CDO	4.440e-15	0	4.440e-15	4.440e-15
	SCSO	8.881e-16	0	8.881e-16	8.881e-16
	PSO	4.26740	0.18770	3.71160	5.51000
	AOA	8.881e-16	0	8.88e1-16	8.881e-16
$F(x_6)$	IBWO	3.332e-04	1.294e-05	3.105e-04	3.562e-04
	BWO	3.876e-04	1.209e-04	3.108e-04	8.241e-04
	WOA	0.00080	0.00050	0.00030	0.00220
	CDO	0.00050	0.00030	0.00030	0.002000
	SCSO	0.00050	0.00030	0.00030	0.00120
	PSO	0.00470	0.00870	0.00070	0.02030
	AOA	0.00430	0.00890	0.00030	0.02030
$F(x_7)$	IBWO	3561.7360	1695.7645	2638.1669	7897.2985
	BWO	8825.1920	565.1208	8166.2175	9578.3733
	WOA	8139.1795	1599.1864	3080.3053	9819.9767
	CDO	10125.5561	1176.6243	6701.5849	11146.3474
	SCSO	4312.4913	1654.6874	2668.8903	8737.0084
	PSO	7632.8459	1968.0239	2417.8518	10361.0982
	AOA	8844.1071	1015.9593	5998.6553	10124.2821
$F(x_8)$	IBWO	2896.4686	30.7400	2822.0848	2949.9302
	BWO	3340.8318	61.4377	3160.5037	3457.3315
	WOA	3166.1595	97.2591	2990.8024	3350.5569
	CDO	3766.8289	72.8195	3614.7037	3944.4211
	SCSO	2951.0017	72.6442	2838.0725	3162.2994
	PSO	3503.4813	168.6428	3180.3171	3850.8514
	AOA	3580.3529	150.5003	3316.666	3984.949
$F(x_9)$	IBWO	3103.9573	30.7063	3004.9572	3187.9747
	BWO	3627.8830	79.3385	3484.3567	3770.8788
	WOA	3252.9791	102.3259	3077.4364	3482.9715
	CDO	3844.2587	42.1161	3768.8770	3950.9648
	SCSO	3107.5783	73.8982	3017.1077	3308.9014
	PSO	3426.7729	141.1093	3179.9532	3797.5649
	AOA	3913.4547	206.3471	3427.8652	4346.4647

Table 4
Friedman test results.

Algorithm	Average rank	Total rank
IBWO	1.6573	1
BWO	2.9793	3
WOA	4.6889	4
CDO	5.2678	5
SCSO	2.3592	2
PSO	5.6189	7
AOA	5.4286	6

of 30 experiments for reducing the contingency of the results.

Table 3 shows the test results of the seven optimization algorithms on the test functions F1-F9. In the test results of the unimodal test function, the test results of the IBWO algorithm are significantly better than other algorithms, showing the best optimization effect. Whether the average value or the optimal value of the IBWO algorithm is closest to the optimal solution of the test functions and even reaches its optimal value in the F1 and F3 test functions. It is proved that IBWO has the highest convergence accuracy compared with other algorithms. In the test results of the multimodal test function, the average and optimal values obtained by the IBWO algorithm are the smallest, which proves that IBWO algorithm has strong optimization ability and the ability to jump out of local optimum. The test results of composition test functions prove that IBWO algorithm has strong performance in dealing with complex problems. The results of standard deviation can be used to evaluate the stability of the algorithm. Except for F7, the standard deviation of IBWO algorithms is the smallest. In the test functions F1-F5, the standard deviation of IBWO algorithm is 0, indicating that IBWO algorithm has high stability.

This study also performed the Friedman test on the average data obtained after 30 runs of all algorithms. Table 4 shows the results of the Friedman test. The IBWO algorithm ranks first in both average ranking and total ranking, and it is proved that the algorithm has strong robustness and solving ability.

Fig. 2 is the boxplot of 30 independent runs of all algorithms. IBWO is closest to the global optimum on all test function that has the best global exploration ability, and higher accuracy than other algorithms, by comparing the median and range of fitness.

Fig. 3 shows the iterative curves of all algorithms. The convergence speed of IBWO is significantly faster than other comparison algorithms in the unimodal test function results. The optimization results of IBWO and BWO are similar, but still superior to BWO and other algorithms in the test results of multimodal test functions. IBWO has the fastest convergence speed, and the average value and the optimal value are the closest to the global optimum of the test functions. The results of composition functions show that although the convergence speed of IBWO algorithm is not as fast as SCSO algorithm and the accuracy is better than other algorithms. Compared with other comparison algorithms, IBWO with adaptive weights, neighborhood perturbation and other strategies has stronger global search performance and the ability to jump out of local optimum. Overall, the improved IBWO algorithm combined with multiple strategies has better optimization ability.

5. Transformation and solution of the model

The model is transformed into a two-layer architecture according to the optimization idea of hierarchical coordination, which can significantly reduce the complexity and difficulty of solving models. This study optimizes the DG's total operating cost while planning the location capacity of DG to minimize the total operating cost of DG, thus reducing the annual comprehensive cost of DG planning. Fig. 4 shows the hierarchical model architecture and its solving process. The upper and lower layers have different objectives and constraints. The upper layer model determines the installation type, size, and location of DGs, with optimization objectives of total voltage deviation and annual comprehensive cost and constraints of DG installation capacity and permeability. The lower layer model is the optimization sub-problem of the system in each scenario. The objective of lower layer model is to minimize the DG's total operating cost, and the constraints are power flow constraints, DG operation constraints and system constraints. These two layers are interconnected and transmit variables to each other.

On the right side of Fig. 4 shows the process of solving the model. The IBWO algorithm solves the upper layer of the model, and the CPLEX solver solves the lower layer of the model. Firstly, input the data and initial the planning scheme (type, size and location of DG). Then, the upper layer model passes the planning scheme of DG to the lower layer operation sub-problem. After the lower layer model receives the planning scheme, The CPLEX solver is used to get the total operating cost of DG in each scenario, and the calculation results are transmitted to the upper layer to calculate the objective function of the upper layer model. If the max iteration times of the model are not reached, the DG planning scheme is updated and the iteration continues; otherwise, the optimal planning scheme is output. The upper and lower layers of the model transmit information and coordinate with each other, which can degrade the complexity and difficulty of solving models, improve the speed of solution, and improve the accuracy of solution. Finally, the optimal DG planning scheme is obtained.

6. Case analysis

IEEE33 is selected as the test system. The structure of IEEE33 is shown in Fig. 5. The system's total active and reactive load is 3715 + j2350 kVA, and the reference voltage of the system is 12.66 kV. The system parameters are default parameters (Li et al., 2022). The types of DG to be selected are WT and PV. Some parameters of DG are shown in Table 5. The nodes to be installed for the WT are set to 13, 17, and 25, and the maximum total capacity of the WT installed in the system is set to 1000 kW. The nodes to be installed for the PV are set to 4, 7, and 27. The maximum DG installed capacity for each node is 800 kW. The upper limit of the total capacity of DG is set to 1700 kW. This study implements time share tariff and transferable load measures for all nodes of the system. The time-of-use electricity price is shown in Table 6, and Table 7 shows some other parameters of the system.

This study is necessary to get the value of correction coefficients Q to ensure the performance of the model. According to the order of magnitude of annual comprehensive cost and total voltage deviation, the model can achieve good performance when the value of Q is 537.4. The value of w in the fitness function of the upper model is gradually increased from 0 intervals 0.05 to 1, and IBWO algorithm solves the model with different w values. The number of individuals and the iteration times are set to 30 and 100. The Pareto solution set under different w values is shown in Fig. 6. The red ring represents the compromise solution of the model when the w value is different. Blue pentagram is the optimal solution, and the model performance is optimal when w is 0.50.

Several classical methods such as PSO algorithm, grey wolf optimization (GWO) algorithm (Emiroglu et al., 2023), WOA algorithm, and the methods used in the latest literature such as dwarf mongoose optimization (DMO) (Ferminus and Saravanan, 2023) algorithm, arithmetic optimization algorithm (AOA) (Khan et al., 2023) are selected to compare with the IBWO algorithm in order to test the performance of the proposed IBWO algorithm. The number of individuals in population and the maximum iteration times of all algorithms are set to 30 and 100. The optimization curves of different algorithms are shown in Fig. 7. Compared with other four algorithms, IBWO algorithm has the fastest convergence speed and the highest accuracy.

Table 8 presetned the results of different algorithms. The optimal value of every objective is marked as bold. The objective function value obtained by IBWO algorithm is the lowest, and the total voltage deviation and the annual comprehensive cost obtained by the IBWO algorithm are also the smallest. The proposed IBWO algorithm has the best

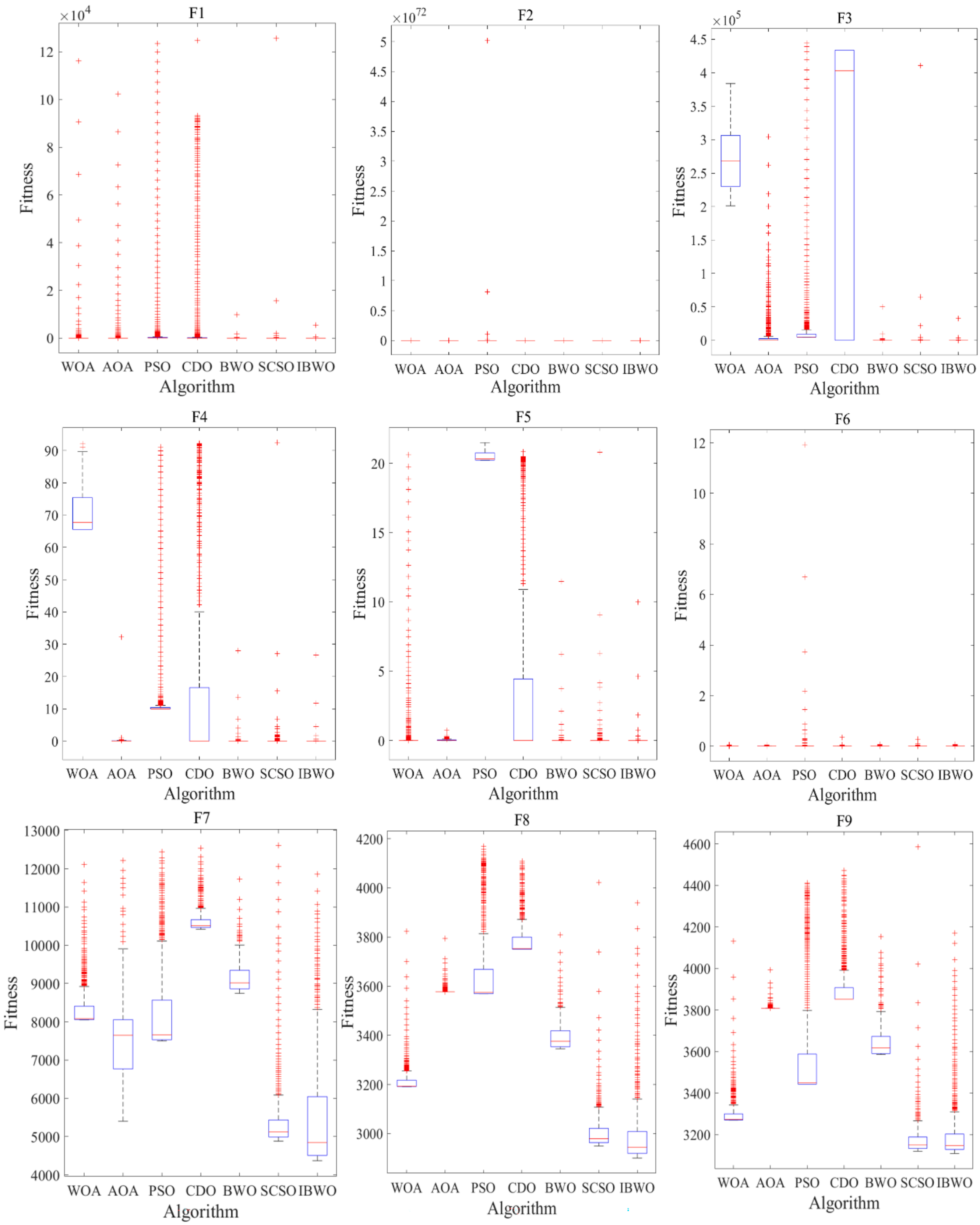

Fig. 2. boxplot of algorithm test.

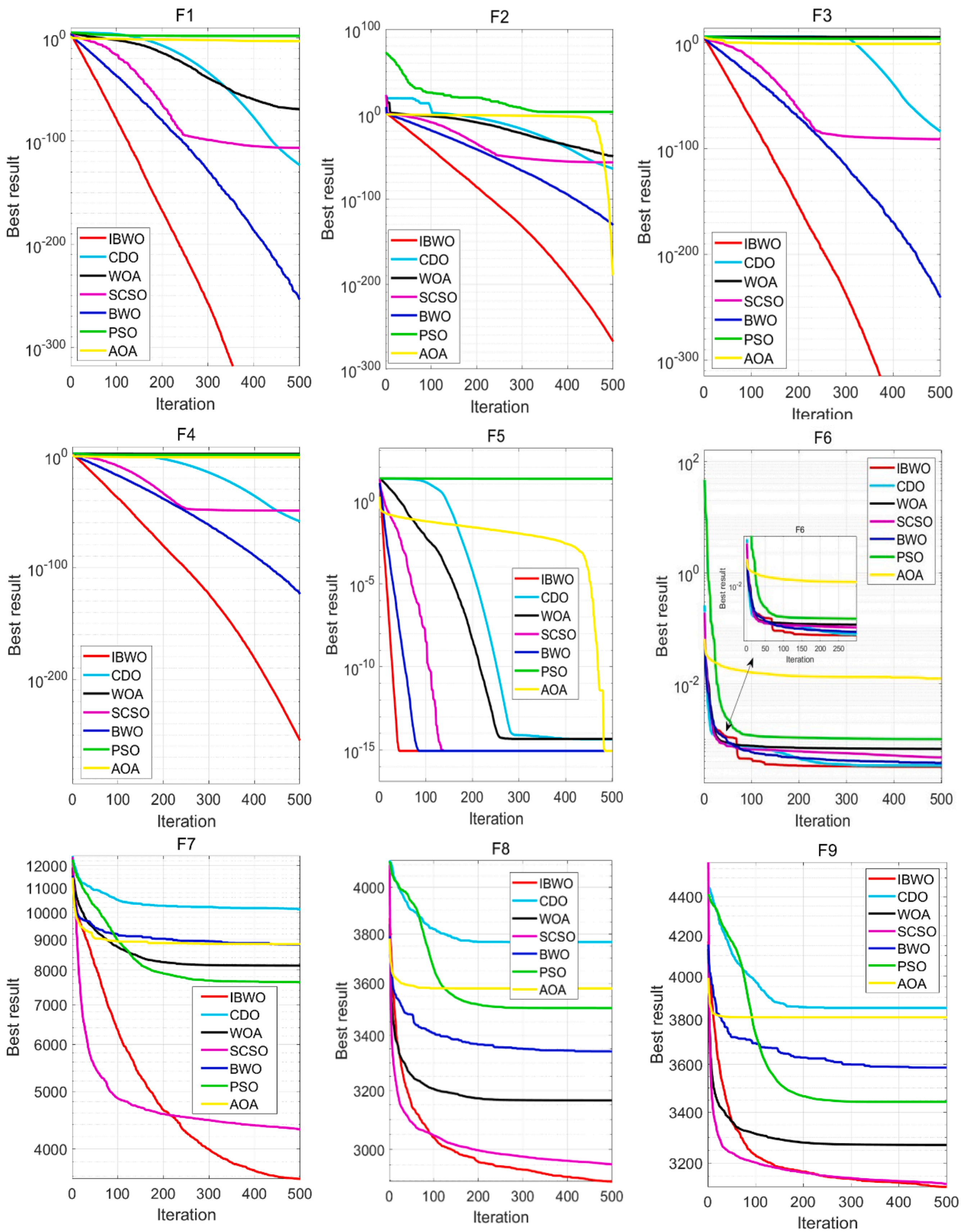

Fig. 3. Iterative curve of algorithm test.

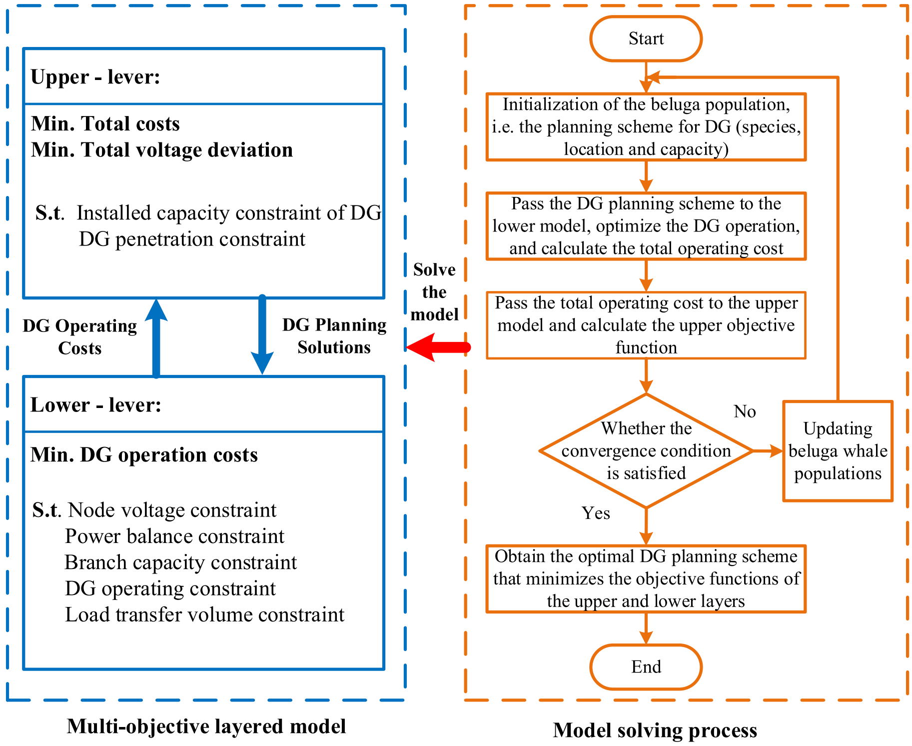

Fig. 4. Layered architecture of the model and model solving process.

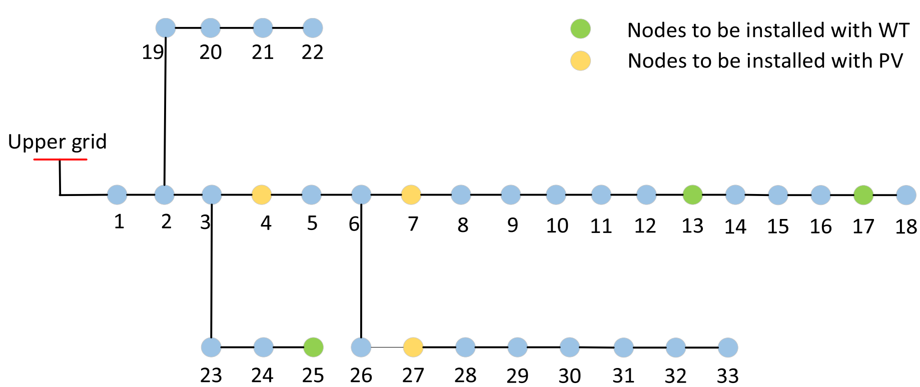

Fig. 5. IEEE33 test system structure diagram.

Table 5
Parameters of DG.

Parameters	WT	PV
investment cost (¥/kWh)	6200	7000
operating and maintenance cost (¥/kWh)	0.2	0.2
Maximum useful life (year)	20	20
Present value coefficient	0.06	0.06

Table 6
Time-of-use electricity price list.

	Unit price (¥/kWh)	Time period
Electricity	0.2	23:00–7:00
	0.4	7:00–10:00, 15:00–16:00, 17:00–18:00, 21:00–23:00
	0.45	10:00–11:00, 13:00–15:00, 18:00–21:00
	0.56	11:00–13:00, 16:00–17:00

Table 7
Same parameters of the system.

Parameters	Value
System voltage limitation (p.u)	0.95 ~ 1.05
Branch circuit capacity limit (MVA)	0 ~ 7
Unit demand response compensation costs (¥)	0.2
Maximum transferable load of the node (kW)	37.15
Unit network loss costs (¥)	0.5
Maximum Renewable Energy Penetration	45%

solving ability and can effectively solve the planning problem of DG.

The output curve of WT and PV in summer scenario is shown in Fig. 8. The output of WT is greater than other time periods from 3 pm to 8 pm, and the output of PV reaches the maximum at 3 pm. Because the installed capacity of WT is greater than the installed capacity of PV, the overall output of WT is greater than the output of PV, and WT can output power throughout the day, the PV does not output power at night, and the PV fluctuates more in terms of output stability.

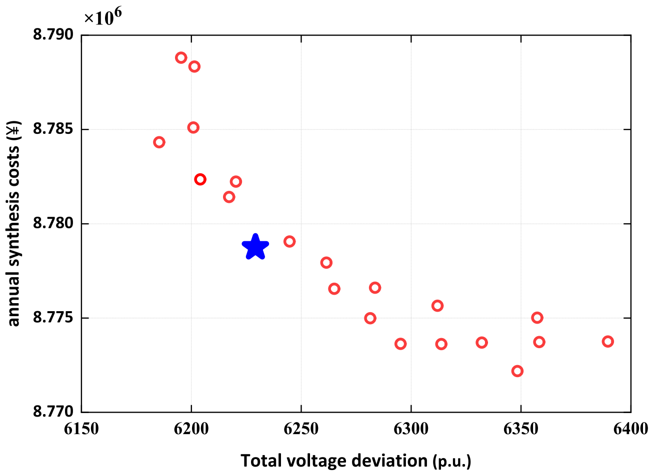

Fig. 6. Pareto solution set of IBWO algorithm in test system.

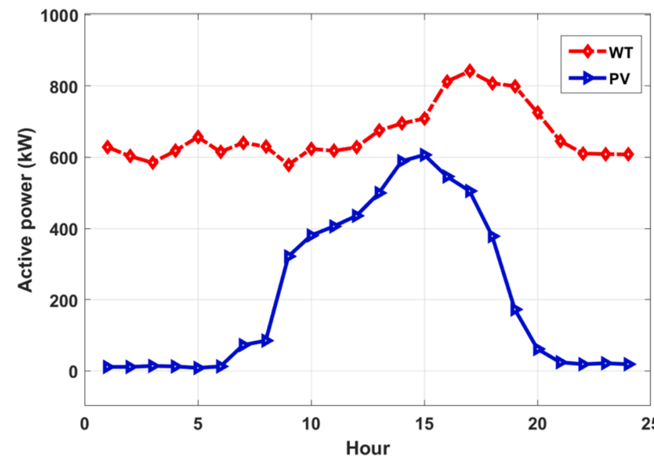

Fig. 8. The output curves of WT and PV in summer scenes.

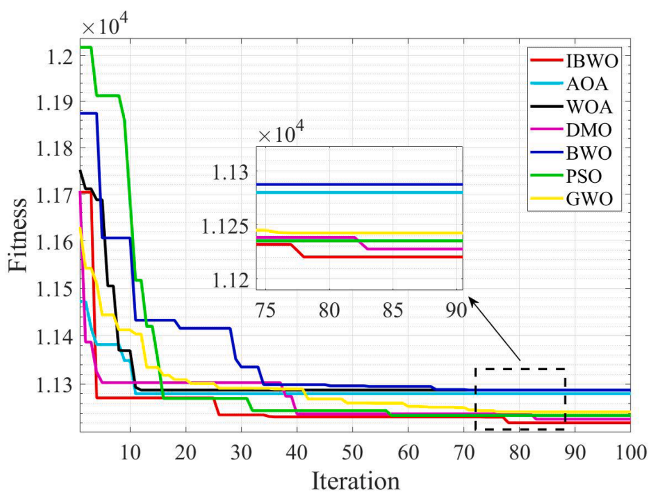

Fig. 7. Convergence curves of different algorithm.

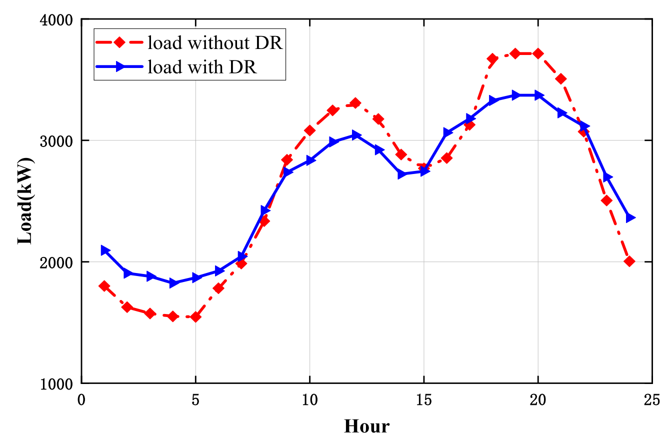

Fig. 9. Load curve with or without implementation of demand response measures.

The demand response measures considered in this study include time-of-use electricity price measures and transferable load measures. Both can decrease the load pressure of the system during the peak period. The latter encourages users to shift the flexible load from the peak period to other periods by giving users compensation, so as to achieve peak load shifting. Fig. 9 showed the load curve with or without the implementation of demand response measures.

The peak-valley difference of the load curve with the demand response is significantly reduced, which reduces the power supply pressure of the system and increases the system's reliability.

The IEEE33 system is evaluated from two aspects: economy and power quality. The smaller the annual comprehensive cost and total voltage deviation are, the higher the economic benefit and power quality of the system. The validity of the proposed model is verified by

Table 9
The operation results of three cases.

Case	$\{WT\}^{bus}$ (k W)	$\{PV\}^{bus}$ (kW)	C_{total}(¥)	V_{tvd} (p.u)
Case1	—	—	9.934 E-06	1.045 E-04
Case2	$\{147.2\}^{13}\{800.3\}^{17}$	$\{183.2\}^{4}\{68.2\}^{7}\{494.5\}^{27}$	8.686 E-06	6.382E-03
Case3	$\{413.6\}^{13}\{580.3\}^{17}$	$\{554.8\}^{4}\{121.1\}^{7}$	8.775 E-06	6.215 E-03

Table 8
The running results of different algorithms.

Algorithm	$\{WT\}^{bus}$(kW)	$\{PV\}^{bus}$ (kW)	Fitness	C_{total} (¥)	V_{tvd} (p.u)
IBWO	$\{413.6\}^{13}\{580.3\}^{17}$	$\{554.8\}^{4}\{121.1\}^{7}$	1.120E-04	8.775 E-06	6.215 E-03
PSO	$\{413.6\}^{13}\{580.4\}^{17}$	$\{554.8\}^{7}\{124.1\}^{27}$	1.123E-04	8.782 E-06	6.224 E-03
BWO	$\{197.5\}^{13}\{800\}^{17}$	$\{80.7\}^{7}\{561.1\}^{27}$	1.123E-04	8.796E-06	6.216 E-03
WOA	$\{147.5\}^{13}\{800\}^{17}$	$\{800\}^{7}$	1.128E-04	8.801E-06	6.302 E-03
GWO	$\{167.6\}^{13}\{800\}^{17}\{31.3\}^{25}$	$\{523.1\}^{7}\{177.7\}^{27}$	1.124E-04	8.778 E-06	6.255 E-03
AOA	$\{183.3\}^{13}\{800\}^{17}$	$\{352.2.1\}^{7}\{283.2\}^{27}$	1.128E-04	8.807 E-06	6.273 E-03
DMO	$\{187.3\}^{13}\{800\}^{17}$	$\{655.0\}^{7}\{51.2\}^{27}$	1.122E-04	8.781 E-06	6.220 E-03

Table 10
Cost components of the three cases.

Case	Cost (¥)				
	C_I	C_{om}	C_{en}	C_{loss}	C_{dr}
Case1	—	—	9.46 E-06	4.74 E-05	0
Case2	5.15 E-05	1.40 E-06	6.52 E-06	3.03 E-05	0
Case3	5.04 E-05	1.43 E-06	6.33 E-06	2.91 E-05	2.23 E-05

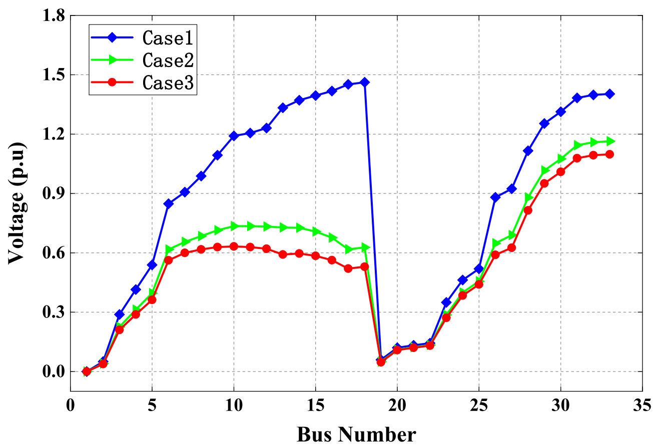

Fig. 10. Total voltage deviation for the summer scenario for the three cases.

setting three cases for comparative experiments.

- Case 1: DG is not installed in the system, and demand response is not considered.
- Case 2: The proposed model and algorithm are used to install DG in the system without considering demand response.
- Case 3: The proposed model and algorithm are used to install DG in the system and consider demand response.

The results of the three cases are shown in Table 9, and the bold characters represent the optimal value of each objective. Case 1 is the initial case, and DG is not planned. Compared with the initial case 1, the annual comprehensive cost of case 2 is reduced by 12.56%, and the total voltage deviation is reduced by 38.95%. Compared with the initial case 1, the annual comprehensive cost of case 3 is reduced by 11.66%, and the total voltage deviation is reduced by 40.55%. Case 3 implements load transfer measures and needs to compensate power users. Compared with Case 2, Case 3 increases the compensation cost and the annual comprehensive cost, but improves the power quality and reliability of the system and reduces the total voltage deviation.

The detailed cost composition of each case is shown in Table 10. Case 1 is not installing DG into the system, so most of the cost comes from purchasing power from the superior power grid. Compared with case 1, case 2 and case 3 increase the operation cost and investment cost because of the planning of DG. The power purchase cost has reduced significantly by 31.08% and 33.09%, and the cost of active power loss conversion has reduced by 36.08% and 38.61%. Case 3 considers demand response, so it increases the compensation cost of implementing demand response more than case 1. Compared with case 2, the power loss conversion cost and the purchase electricity cost are reduced in case 3, and the demand response compensation cost is increased.

Fig. 10 shows the comparison of the total voltage deviation distribution for each node of the three cases during one day in the summer scenario. The blue curve is the voltage deviation curve of the initial case1 without DG installation, and the total voltage deviation value of each node is relatively large, and the largest total deviation value reaches 1.46p.u. With DG installation in case 2 and case 3, the total voltage deviation value of most nodes decreases significantly, especially in nodes 6 to 18. Case 3 improves the system reliability by considering demand response compared to case 2, and the overall system has less node voltage deviation and higher power quality.

Fig. 11 shows the 24-hour active power loss of the three cases in the summer scenario. Compared with the initial case without DG, the network loss of case 2 and case 3 is significantly reduced. Compared with case 2, the power loss of case 3 considering demand response is further reduced at most nodes, and the total power loss is reduced. The conclusion shows that both installing DG and implementing demand response can reduce network loss and energy waste.

Fig. 12 is the three-dimensional voltage distribution map of each case in the summer scene. In case 1, DG is not installed, and the voltage fluctuation of the system is significant. Many node voltages are below 0.95p.u. The node voltage value is too low, and the power quality is poor. In case 2, DG is installed but demand response is not considered. The minimum node voltage in 24 h is about 0.93p.u. The overall voltage fluctuation is more stable than in case 1, and only a tiny part of the voltage value is below 0.95p.u. In case 3, DG is installed and demand response is considered. Compared with case 2, the proportion of node

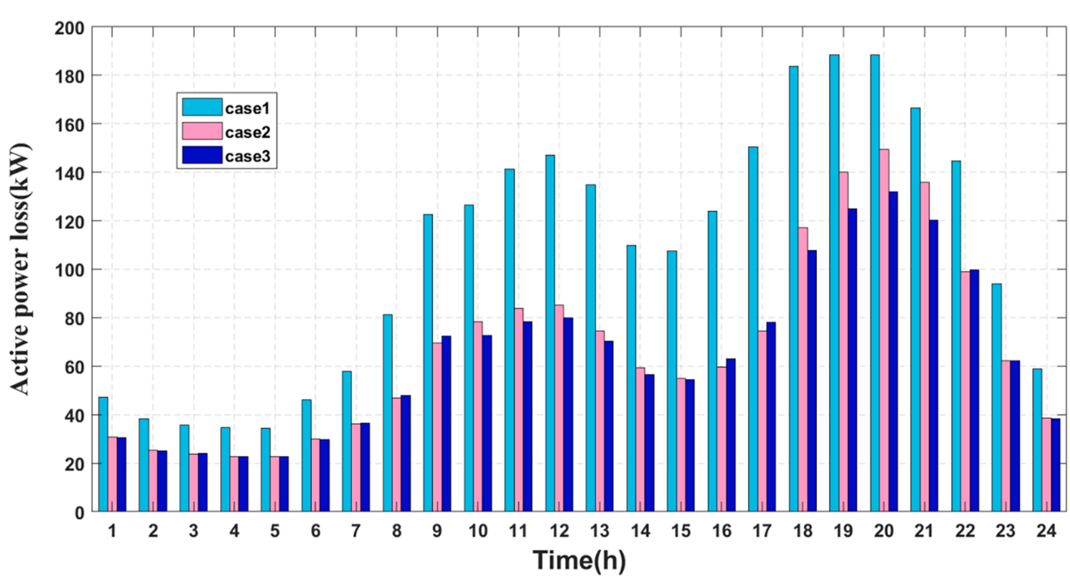

Fig. 11. 24-hour power loss of three cases.

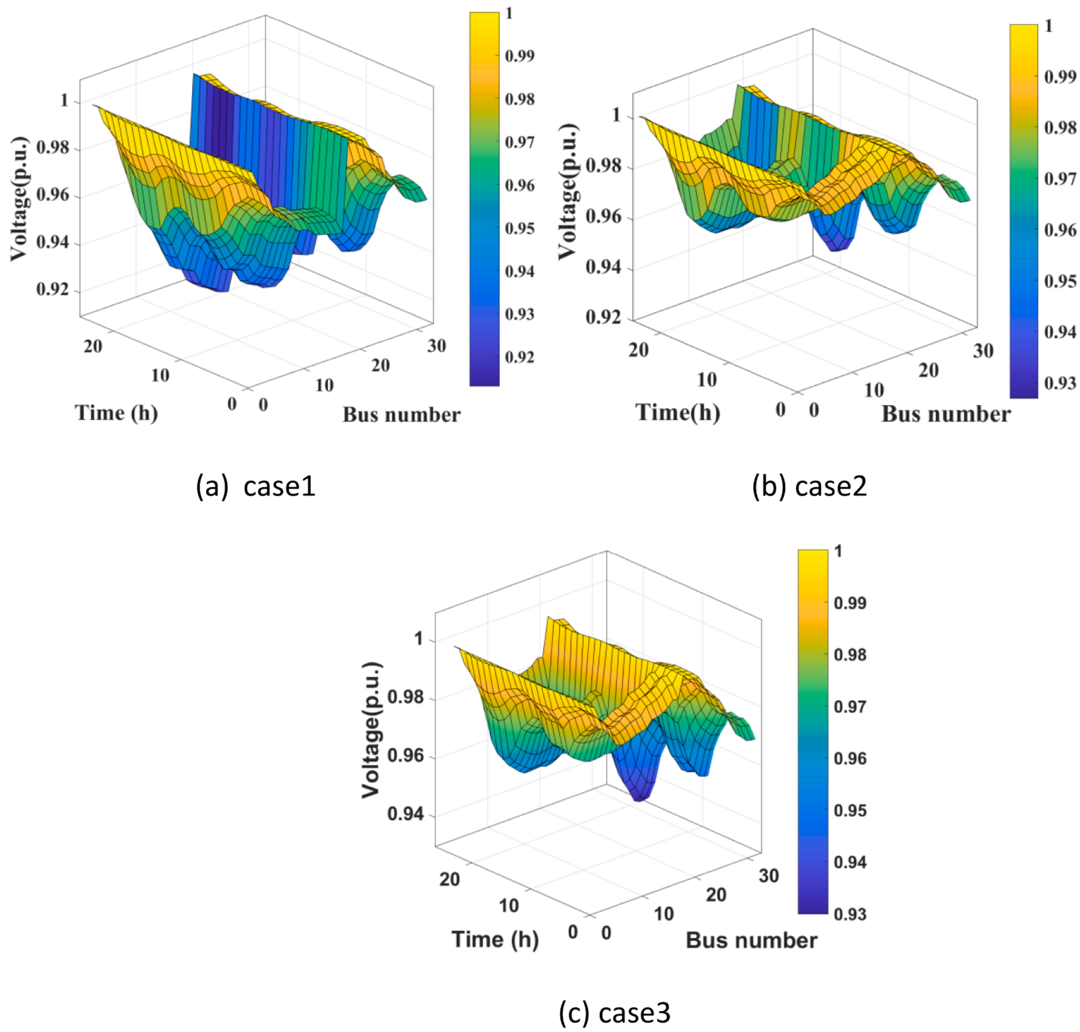

Fig. 12. Three-dimensional voltage distribution of three cases.

voltage value near 0.99p.u increases significantly, only a few node values are below 0.95p.u, the node voltage value is higher as a whole, the voltage fluctuation is more stable and the power quality is improved.

7. Concluding remarks

This study aims to obtain the best location and capacity of DG access to the distribution network to get the maximum benefit. Renewable energy generation has gradually replaced traditional fossil energy generation due to its environmental friendliness and easy availability of resources. This study establishes a multi-objective hierarchical optimal planning model considering demand response and the uncertain output of DG. An IBWO algorithm with excellent performance is proposed to solve the model. Set up several cases in the IEEE33 test system to verify that the proposed method can effectively solve the DG planning problem and bring considerable benefits to the system.

- The initialization strategy, adaptive weight and optimal neighborhood perturbation are used to improve the performance of the BWO algorithm. An IBWO algorithm with excellent performance is proposed. The performance of the proposed algorithm is verified by test functions. Its convergence speed and convergence accuracy are better than other algorithms.
- A multi-objective hierarchical optimal planning model is established considering demand response and the uncertain output of DG, and the annual comprehensive cost and total voltage deviation of the system are taken as objectives. The IEEE33 example verifies that the model can effectively solve the DG planning problem and significantly improve the economic benefits, power quality and reliability of the system.
- In the IEEE33 system, compared with the initial state, the annual comprehensive cost, total voltage deviation, active network loss and power purchase cost of the proposed IBWO algorithm are reduced by 11.66 %, 40.55 %, 38.61 % and 33.09 %, respectively. Compared with the system without demand response, the system with demand response is more stable, the total voltage deviation and network loss are reduced, and the node voltage fluctuation is smaller.

This study is significant in promoting the transformation of traditional distribution network and the development of renewable energy. Renewable energy grid-connected technology is essential in the current energy shortage environment. An IBWO algorithm with excellent performance is proposed, and an effective multi-objective hierarchical optimal planning model is constructed, which provides an effective solution and idea for reasonably determining the scheme of DG access to distribution network. However, some things could be improved in this study. The performance of the solution method can be further improved. The model does not consider the influence of time-varying load on DG planning results. The correlation between wind speed, light intensity and load is not considered. In future studies, in terms of algorithms, the algorithm used can be used in combination with other excellent *meta*-heuristic algorithms or machine learning methods to enhance solution performance. In terms of models, the impact of different load models on DG planning problems should be analyzed in the future. The spatio-temporal correlation of wind-photovoltaic-load should also be considered to make the method more suitable for practical engineering needs.

CRediT authorship contribution statement

Ling-Ling Li: Conceptualization, Writing – original draft, Writing – review & editing. **Xing-Da Fan:** Conceptualization, Writing – original draft, Writing – review & editing. **Kuo-Jui Wu:** Conceptualization, Writing – original draft, Writing – review & editing. **Kanchana Sethanan:** Conceptualization, Writing – original draft, Writing – review & editing. **Ming-Lang Tseng:** Conceptualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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