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RESEARCH ARTICLE

Optimal Configuration of Distributed Generation Based on an Improved Beluga Whale Optimization

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ABSTRACT Large-scale distributed generation (DG) access to the distribution network brings many uncertainties to the distribution network, considering the impact of different types of distributed power supply on the optimization results as well as the uncertainty and correlation of wind energy, photovoltaic power generation, and load. A metaheuristic algorithm the Improved Beluga Whale Optimization Algorithm (IBWO) is used to optimize the capacity and location of DG. This algorithm incorporates the elite reverse learning strategy and cyclone foraging strategy while adjusting the balance factor to enhance the diversity of the algorithm population and further balance local search capability with global search capability. This study optimizes the configuration of distributed energy resources considering the uncertainty and correlation of wind power, photovoltaic power, and load. The optimization objective is to reduce active power loss, improve voltage stability, and minimize investment and operating costs. By conducting simulations on IEEE 33-bus and IEEE 118-bus test cases, the active power network losses are enhanced by 55.49% and 45.39% respectively, and the algorithm outperforms other methods regarding other data, demonstrating its superiority and effectiveness.

INDEX TERMS Distributed generation, distribution network, uncertainty, correlation, improved beluga whale optimization.

NOMENCLATURE

BWO	Beluga whale optimization.
IBWO	Improved Beluga whale optimization.
PSO	Particle swarm optimization.
DG	Distributed generation.
MCS	Monte Carlo simulation.
WT	Wind turbine.
PV	Photovoltaic.
EOBL	Elite opposition-based learning.
CFS	Cyclone foraging strategy.
WOA	Whale optimization algorithm.
MRFO	Manta Ray Foraging Optimization Algorithm.
v	Wind speed.
$v_{in}/v_{out}/v_{rate}$	Cut-in/cut-out/rated speed of WT.
P^r_{WTG}	Rated power of WT.
P_{WT}	Generated wind power at v.
I_r	Rated irradiation intensity.
I	Irradiation intensity.
P^r_{PV}	Rated power of PV.
P_{PV}	Generated solar power at vI.
APL	Active Power Loss.
IOMC	Investment, Operation, and Maintenance Costs of DG.
PPC	Purchased Power Cost from Upper-level Grid.
VSM	Voltage Stability Margin.
N_b	The total branch number.
G_k	The conductance between bus i and bus j.

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U_i	The nodal voltage at bus i.
δ_{ij}	The phase angle between bus i and bus j.
P_{Loss}	Active power loss.
x_i	The type of DG installed at bus i.
C_{D_i}/C_{ri}	Investment cost / operating cost.
P_{DG_i}	The installed capacity of DG is installed at node i.
P_W	The total capacity of the system.
$P_{\sum DG}$	The total active output of DG.
T_{max}	The maximum annual load utilization hours.
$C_{p.u.}$	The electricity price.
B	The first type of voltage stability margin.
L_{ij}	The first type of voltage stability index.
P_i/Q_i	The active/reactive power injected into bus i.
e_i/f_i	The real/imaginary parts of the voltage at bus i.
G_{ij}/B_{ij}	The conductance/conductance between bus i and j.
U_i	The voltage of bus i.
U_{imin}/U_{imax}	The upper and lower limits of voltage at bus i.
I_{ij}	The current allowed for the branch.
I_{ijmax}	The maximum current allowed for the branch.
B_0	A random number between (0,1).
T	Current iteration numbers.
T_{max}	Maximum iteration numbers.
B_f	A balance factor transfer of BWO from the exploration phase to the exploitation phase.
$X_{i,j}^{T+1}$	The new position of the ith beluga whale in the jth dimension.
p_j	Random number between [1, D].
X_{i,p_j}^{T}	The positions of the ith beluga whale at the current iteration.
X_{best}^{T}	The best position of beluga whales.
X_i^T/X_r^T	The current positions for the ith / a random beluga whale.
C_1	The random jump strength of the Levy flight strategy.
Γ	Gamma function.
L_F	The jump length of the Levy flight strategy.
X_{step}	The step size of whale fall.
C_2	The step factor of whale fall.
W_f	The probability of whale fall.
$X_{i,j}^e/\overline{X_{i,j}^e}$	The elite / inverse individual.
K^*	The dynamic coefficient on (0,1).
α_j/β_j	Dynamic boundary.
B_{fmin}/B_{fmax}	The lower/upper bounds of B_f.

I. INTRODUCTION

With the advancement of the economy and society, there will be a significant increase in the energy demand [1]. Conventional methods of power generation such as fossil fuels, nuclear power plants, and hydroelectric power stations require lengthy construction periods, substantial investment costs, and contribute to the growing concern about environmental pollution caused by traditional fossil fuel power generation [2]. In this context, there has been a rapid development of Distributed Generation, particularly wind and photovoltaic power generation, due to their adaptability and environmental friendliness. The integration of DG into distribution networks on a large scale has become a prevailing trend [3]. However, the integration of DG complicates distribution networks, alters network flow to a certain extent, and the optimization and configuration of DG impact the system's network losses, thereby posing significant challenges and complexities to the operation of distribution networks [4]. Nevertheless, an inappropriate configuration of DG can lead to reduced system stability, voltage fluctuations, and increased active network losses [5], as well as adversely affecting the flexibility of grid scheduling [6]. Therefore, researching the optimized configuration of DG in the planning of distribution networks holds immense importance in enabling the distribution network to operate more economically, safely, and reliably [7].

At present, scholars have done many studies on the optimal configuration of DG in distribution networks from different perspectives. They have proposed various DG optimization models and employed diverse methods to solve them. Literature [8] establishes an optimal allocation model considering active network loss cost and user power purchase cost minimization and adopts a cat swarm algorithm improved by using a chaotic search strategy to solve. Literature [9] establishes an optimal allocation model with active network loss, voltage deviation, and voltage stability as the optimization objectives, and adopts an ant-lion optimization algorithm to solve; and literature [10] considers taking into account the interests of both the operator and the user, which constructs the objective function with active network loss, annual investment and operation cost, user power purchase cost and system voltage enhancement, proposes an improved sooty tern algorithm solution model. Literature [11] proposes an optimal allocation model of wind and solar energy storage considering the degradation cost of batteries, and the multi-objective function with the objectives of economy, voltage stability and network loss is solved in the GAMS environment. Literature [12] established an objective function based on the indicators of life-cycle cost, network loss, and voltage deviation. Considering the integration of flexible distribution units, an improved sparrow search algorithm is adopted to solve the model. Literature [13] proposes an improved equilibrium optimizer to optimize the location and capacity of photovoltaic systems in the distribution network to reduce active power network loss. Literature [14] also aims to optimize the location and capacity of photovoltaic systems to reduce network loss. However, unlike [13] and [14] does not model the uncertainty of photovoltaics and uses the Kuhn optimization algorithm to solve the problem. Literature [15] adopts an improved adaptive weighted multi-objective particle swarm optimization (PSO) algorithm to optimize the configuration of DG, aiming to achieve the optimal investment cost of distributed power generation, the lowest network loss, and the best voltage stability. Literature [16] optimizes DG in the distribution network using a hybrid gray wolf optimizer to maximize the reduction of network loss. Literature [17] optimizes the configuration of DG and storage systems (SC) by reducing active power network loss and voltage deviation. Furthermore, an innovative multi-objective MGSA-EE (MMGSA-EE) is proposed to solve the optimization configuration model based on the MGSA-EE.

The above literature has established optimal allocation models with different objective functions from different perspectives, and various algorithms have been used to solve them. However, the aforementioned models did not fully consider the uncertainty and correlation of wind, solar, and load, which can have a significant impact on the DG in distribution networks. Therefore, the resulting optimized configuration may have certain irrationality [18].

Currently, some literature considers the uncertainty and correlation of DG's and loads. Literature [19] established an optimization model with the objectives of distribution network operation cost, pollutant gas emission, and voltage stability, considered the random fluctuation of source load, and used the semi-invariant method and the Cornish-Fisher series expansion to realize the trend calculation; literature [20] considered the uncertainty of load and tariffs, and established an optimization model that considered the investment cost and the operation cost, and used the Monte Carlo sampling for the scenarios, and the optimization configuration is achieved using PSO. Literature [21] firstly constructed probabilistic models for wind, light, and load, and adopted Spearman rank correlation coefficient matrix to describe the correlation, and generated samples for correlation using Latin hypercube and Cholesky decomposition, this paper established a DG optimization configuration model aiming to minimize the annual total cost and risk, and used NSGA-II to achieve it. Literature [22] first modeled the uncertainty of DG output using an improved conditional deep convolution generative adversarial networks (DCGAN). In the model, monthly labels are introduced to generate wind-solar joint output scenarios. The parameters of the Gaussian mixture model (GMM) for the distribution model of the scene are generated, and then a two-layer optimization configuration model for DG is established, aiming to minimize the social comprehensive cost. Finally, an integer genetic algorithm and a wind driven optimization (WDO) algorithm are used to solve the model. Literature [23] models the wind-solar and load using probability distribution functions and simulates scenarios with Monte Carlo simulation(MCS). A K-means algorithm, which incorporates the Davison-Bouldin index (DBI), is used to reduce the clustering of scenarios. A two-level optimization model is established, aiming to minimize the annual comprehensive economic cost and optimize the voltage index. And an IAGA is used to solve the model.

Although the above literature considers the uncertainty and correlation of distributed power sources and uses the parametric method to simulate the generation of scenarios for wind, light, and load, it is based on limited data only, and if the data lack representativeness, the conclusions drawn have certain limitations.

Therefore, in this paper, considering the uncertainty of wind turbine(WT), photovoltaic (PV) output, and load in long time scales, an improved K-means method that considers the initial centroid selection for massive data is used for the optimal allocation scenarios of the distribution network for the aggregation and reduction [24]; while considering the active network loss, the DG investment and operation cost, and the power purchase cost of the distribution network, to improve the voltage quality of the distribution network, the first type of voltage stability margins are introduced indicators [25]; considering the economic indicators with different quantities of active network loss and voltage stability margin, the dimensionless processing was carried out. On this basis, the Beluga Whale Optimization (BWO) algorithm is improved accordingly for the siting and capacity determination problem, which improves the convergence speed and convergence accuracy of the algorithm and improves the search capability, and an Improved Beluga Whale Optimization (IBWO) is proposed and put forward and apply it to the optimal configuration problem of DG.

The main contributions of this paper can be summarized as follows:

1. An optimization model considering the effect of DG types on the optimal allocation results as well as the uncertainty and correlation of wind, solar and load on a long-time scale is established, taking into account active power network loss, DG investment and operational costs, distribution network purchasing costs, and voltage stability as multiple objectives.

2. An improved K-means clustering algorithm, which incorporates a spatial distribution for selecting initial cluster centers, is introduced. The effectiveness of the algorithm in reducing a massive amount of wind-solar load scenarios is validated.

3. An improvement is made to the BWO algorithm for the optimization configuration of distributed generation. This improvement balances its local and global search capabilities, further enhancing the convergence speed and accuracy of the algorithm.

The rest of this paper is organized as follows. Section II introduces the generation of scenarios considering the uncertainty and correlation of distributed power sources and loads, as well as the improved K-means clustering method.

TABLE 1. **Summary of the previous approaches conducted in integrating different DG in distribution network.**

Authors	Year	Type of DG	Target	Algorithm	Test system	
L. Yang et al.[8]	2019	Conventional	-minimize active power loss cost -consumer electricity purchase cost	Modified cat swarm optimization	IEEE 69-BUS	The authors did not consider the impact of DG type on the grid.
E.S. Ali et al.[9]	2017	PV or WT (not installed at the same time)	-educe the power losses -improve the voltage profiles -improve the VSI.	Ant lion optimization algorithm	IEEE 33 and 69-BUS	PV and WT are not installed at the same time.
Y. Xiao et al.[10]	2022	Conventional	-active network loss -annual investment and operation cost -user power purchase cost -system voltage enhancement	Improved sooty tern optimization algorithm	IEEE 33-BUS	The authors did not consider the impact of DG type on the grid.
H. A. Taha et al.[11]	2022	PV or WT (not installed at the same time) , Battery energy storage systems and capacitor banks	-economic index maximization -average power losses minimization -average voltage stability factor maximization	MINOS solver and BONMIN solver	IEEE 33-BUS	PV and WT are not installed at the same time.
X. Yang et al.[12]	2023	Conventional	- life cycle cost -， network loss -voltage deviation	improved sparrow search algorithm	IEEE 33-BUS	Did not consider the impact of DG type
T. T. Nguyen et al.[13]	2022	PV	-reduce active power loss	improved equilibrium optimizer	IEEE33 and 85-BUS	Only PV was considered
L. D. L. Nguyen et al.[14]	2023	PV	-reduce active power loss	Coot optimization algorithm	IEEE 33 and 69-BUS	Only PV was considered
J. Meng et al.[15]	2020	Conventional	-minimizing the distribution network loss -minimizing distributed power costs -maximizing voltage stability	Improved adaptive weight multi-objective particle swarm optimization	IEEE 69-BUS	Did not consider the impact of DG type
R. Sanjay et al.[16]	2017	Conventional	-reduce power loss	hybrid grey wolf optimizer	IEEE 33 and 69-BUS , Indian 85-BUS	Did not consider the impact of DG type
J. Qian et al.[17]	2023	Conventional DG and shunt capacitors	-reducing active power loss -reducing voltage deviation	multi-objective modified gravitational search algorithm with expert experience	IEEE 33 , 69 and 118-BUS	Did not consider the impact of DG type
Z. Cao et al.[18]	2021	PV and WT	-minimizing the annual comprehensive cost	improved particle swarm optimization	IEEE 33-BUS	The approach has been applied on only IEEE 33-bus network
G. Cai et al.[19]	2019	PV, WT, fuel cell and micro-turbine	-cost of distribution network -voltage stability -pollution gas emissions	improved grey wolf optimization	IEEE 33-BUS	The approach has been applied on only IEEE 33-bus network
R. Hemmati et al.[20]	2015	Conventional	-minimizing investment cost -minimizing operational cost	particle swarm optimization	9-bus network and Kianpars–Ahwaz test system as a 72-bus distribution network	considering load and price uncertainties, but did not consider the impact of DG type on the grid.
S. Zhang et al.[21]	2018	PV, WT and micro-turbine	-minimize the annual total cost -minimize the risk of the distribution network	non-dominated sorting genetic algorithm II	IEEE 33-BUS and practical 61-bus distribution network in East China	Modelling PV and WT with just one set of data

Section III presents the DG optimization configuration model. Section IV describes the basic principles of the BWO and the improvements made to it. Section V provides case studies. Section VI concludes the paper.

TABLE 1. *(Continued.)* **Summary of the previous approaches conducted in integrating different DG in distribution network.**

J. Gu et al.[22]	2021	PV and WT	-minimize the total social cost -maximum consumption of DG output	integer genetic algorithm and wind driven optimization	IEEE 33-BUS	The approach has been applied on only IEEE 33-bus network
Z. Chu et al.[23]	2022	PV and WT	-the annual comprehensive economic cost -voltage level	improved adaptive genetic alogrithm	IEEE 33-BUS	The approach has been applied on only IEEE 33-bus network

II. SCENARIO GENERATION FOR DISTRIBUTED POWER AND LOAD UNCERTAIN AND CORRELATION

Distributed energy represented by WT and PV is more and more accessed to the distribution network, while WT and PV have uncertainty, the wind speed and light intensity and load in the same area also have certain correlations, in order to ensure the rationality of the optimized configuration of DG, it is necessary to consider the uncertainty and correlation of DG and load.

Currently, there are several main approaches to wind speed, light intensity, and load stochasticity:

(1) The wind speed, light intensity, and load are fitted by the parametric method, which is considered to obey Weibull distribution, Beta distribution, and normal distribution, respectively, besides MCS, Latin Hypercube Sampling, and other methods are used to sample and generate the scenarios [18], [23], however, the data relied on by this method is usually limited, and if the data lacks representativeness, the results obtained will have certain limitations.

(2) Fitting wind speed, light intensity, and load by non-parametric methods, such as using kernel density estimation, combined with Copula theory to generate scenarios [26], but the large-scale dataset has high computational complexity.

(3) Based on the prediction error of wind speed, light intensity, and load, the stochasticity of wind speed, light intensity, and load is achieved by modeling and sampling the prediction error [27], [28], but the prediction error brings more limitations.

Considering that solving the distribution function may introduce errors and reduce computation, and that there are natural correlations between wind speed, light intensity, and load at a certain time in the same region, this paper directly combines the wind speed, light intensity, and load data at the same time in the history of a certain place into an original scenario, and adopts a kind of improved K-means method that considers the selection of the initial centroids for a large amount of data to reduce the scenario. for scene reduction. The specific steps are as follows:

Step 1: Combine the wind speed, light intensity, and load data at different moments, set the K value, and perform bubble sorting on the combined data.

Step 2: Filter the data, take the center value of each dimension as the first clustering center, and ensure that this clustering center is in the middle of the data space.

Step 3: Calculate the Euclidean distance between each point in the data space and this cluster center.

Step 4: Randomly select the next clustering center in the data space, calculate the Euclidean distance between it and the previously selected clustering center, and determine whether the distance is greater than or equal to the set interval, or else repeat this step until the requirements are met.

Step 5: Repeat steps 3 and 4 above to select the remaining clustering centers.

Step 6: Calculate the Euclidean distance between all the data and the selected K clustering centers and assign the data to the class cluster closest to the center.

Step 7: Calculate the respective centers of the K class clusters and recalculate the respective centers of the class clusters by the arithmetic mean of the respective dimensions.

Step 8: Calculate the minimization error sum of squares between the new clustering center and the original center for each class cluster, and output the clustering results if the results no longer change or if the upper limit of the number of iterations is reached.

After scenario reduction, wind speed and light intensity are converted into WT and PV output according to (1) and (2) [21].

$$P_{WT} = \begin{cases} 0, & 0 \leq v \leq v_{in} or v_{out} \leq v \\ P_{WTG}^{r} \dfrac{v - v_{in}}{v_{rate} - v_{in}}, & v_{in} \leq v \leq v_{rate} \\ P_{WTG}^{r}, & v_{rate} \leq v \leq v_{out} \end{cases} \tag{1}$$

$$P_{PV} = \begin{cases} P_{PV}^{r} \dfrac{I}{I_r}, & I \leq I_r \\ P_{PV}^{r}, & I > I_r \end{cases} \tag{2}$$

III. DG OPTIMAL CONFIGURATION MODEL

Firstly, establish an optimization configuration model for DG by constructing an objective function incorporating active power losses, investment and operation costs of DG, and system voltage stability margin. The constraints include power balance, nodal voltages, branch currents, and DG installation capacity. Subsequently, plan and optimize the configuration scheme.

A. OBJECTIVE FUNCTION

1. Active Power Loss [10]

$$APL = f_1 = P_{Loss} = \sum_{k=1}^{N_b} G_k \left(U_i^2 + U_j^2 - 2U_i U_j \cos \delta_{ij} \right) \tag{3}$$

where N_b is the total branch number, G_k is the conductance between bus i and bus j, U_i and U_j are the nodal voltage at bus i and bus j, and δ_{ij} is the phase angle between bus i and bus j.

2. Investment, Operation, and Maintenance Costs of DG [10]

$$IOMC = f_2 = \sum_{k=1}^{N_d} x_i \left[\left(\frac{r(1+r)^n}{(1+r)^n - 1} \cdot C_{D_i} + C_{ri} \right) \right] P_{DG_i} \tag{4}$$

where x_i is the type of DG installed at bus i, r is the annual rate of return, which is taken as 0.1; n is the number of years of planning; C_{D_i}, C_{ri} and P_{DG_i} are the investment cost, operating cost, and installed capacity of DG installed at node i.

3. Purchased Power Cost from Upper-level Grid [10]

$$PPC = f_3 = \left(P_W - P_{\sum DG} - \Delta P_L\right) T_{max} C_{p.u.} \tag{5}$$

where P_W is the total capacity of the system; $P_{\sum DG}$ is the total active output of DG; $\Delta P_L = P_{loss} - P'_{loss}$ is the active loss before and after optimization, T_{max} is the maximum annual load utilization hours, and $C_{p.u.}$ is the electricity price.

4. Voltage Stability Margin [25]

$$VSM = f_4 = B = 1 - max\{L_n\} \tag{6}$$

where B is the first type of voltage stability margin, The smaller $max\{L_1, L_2, \cdots, L_n\}$ is, the larger B is and the more stable the distribution network voltage is; the first type of voltage stability index L_{ij} for the branch between bus i, j is:

$$L_{ij} = 4\frac{\left(P_j X_{ij} - Q_j R_{ij}\right)^2 + \left(P_j R_{ij} + Q_j X_{ij}\right) V_i^2}{V_i^4} \tag{7}$$

5. Objective Function

Considering that each sub-objective function has different magnitudes and conflicts with each other, it is difficult to reach the optimization at the same time, so it needs to be dimensionless.

$$f^* = \frac{f - f_{min}}{f_{max} - f_{min}} \tag{8}$$

$$F = \omega_1 f_1^* + \omega_2 f_2^* + \omega_3 f_3^* + \omega_4 f_4^* \tag{9}$$

where ω_i are weighting factors, $\omega_1 = 0.3$, $\omega_2 = 0.2$, $\omega_3 = 0.3$, $\omega_4 = 0.2$.

B. CONSTRAIN

1) POWER CONSERVATION CONSTRAINT

$$\begin{cases} P_i - \sum_{j=1}^{N} e_i\left(G_{ij}e_j - B_{ij}f_j\right) + f_i\left(G_{ij}f_j + B_{ij}e_j\right) = 0 \\ Q_i - \sum_{j=1}^{N} f_i\left(G_{ij}e_j - B_{ij}f_j\right) - e_i\left(G_{ij}f_j + B_{ij}e_j\right) = 0 \end{cases} \tag{10}$$

where P_i and Q_i are the active and reactive power injected into bus i, e_i and f_i are the real and imaginary parts of the voltage at bus i, G_{ij} and B_{ij} are the conductance and conductance between bus i and j.

2) VOLTAGE CONSTRAINT

$$U_{imin} \le U_i \le U_{imax} \tag{11}$$

where, U_{imin} and U_{imax} are the upper and lower limits of voltage at bus i.

3) CURRENT CONSTRAINT

$$I_{ij} \le I_{\mathrm{ij}max} \tag{12}$$

where I_{ijmax} is the maximum current allowed for the branch.

4) DG LIMITS CONSTRAINT

$$\sum P_{DG} \le \eta \sum P_{Load} \tag{13}$$

IV. IMPROVED BELUGA WHALE OPTIMIZATION

A. BELUGA WHALE OPTIMIZATION

Beluga whale optimization (BWO) is an optimization algorithm proposed by Zhong et al. in 2022 [29]. The algorithm achieves the solution of the optimization problem by simulating the swimming, hunting, and whale fall of beluga whales, which has the characteristics of relatively simple, better global search ability and convergence accuracy. The basic principle of the algorithm is as follows.

The transfer of BWO from the exploration phase to the exploitation phase depends on the balance factor B_f, which is defined as:

$$B_f = B_0\left(1 - T/2 * T_{max}\right) \tag{14}$$

where T and T_{max} are the current and maximum iteration numbers, B_0 is a random number between (0,1) at each iteration, when $B_f > 0.5$, the algorithm is in the exploration phase, when $B_f \le 0.5$, the algorithm is in the exploitation phase.

1) EXPLORATION PHASE

$$\begin{cases} X_{i,j}^{T+1} = X_{i,p_j}^T + \left(X_{r,p_1}^T - X_{i,p_j}^T\right)(1 + r_1)\sin(2\pi r_2) \\ , j = \text{even} \\ X_{i,j}^{T+1} = X_{i,p_j}^T + \left(X_{r,p_1}^T - X_{i,p_j}^T\right)(1 + r_1)\cos(2\pi r_2) \\ , j = \text{odd} \end{cases} \tag{15}$$

where $X_{i,j}^{T+1}$ is the new position of the ith beluga whale in the jth dimension, p_j is a random number between [1, D], X_{i,p_j}^T and X_{r,p_1}^T are the positions of the ith and rth beluga whale at the current iteration, according to the odd or even of the dimension, the beluga whale is swimming synchronously or in mirror.

2) EXPLOITATION PHASE

$$X_i^{T+1} = r_3 X_{best}^T - r_4 X_i^T + C_1 \cdot L_F \cdot \left(X_r^T - X_i^T\right) \quad (16)$$

where X_{best}^T is the best position of beluga whales, X_i^T and X_r^T are the current positions for the ith beluga whale and a random beluga whale, $C_1 = 2r_4 (1 - T/T_{max})$ is the random jump strength of the Levy flight strategy.

$$L_F = 0.05 \times \frac{u \times \sigma}{|v|^{1/\beta}} \quad (17)$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin(\pi\beta/2)}{\Gamma((1+\beta)/2) \times \beta \times 2^{(\beta-1)/2}}\right)^{1/\beta} \quad (18)$$

3) WHALE FALL

$$X_i^{T+1} = r_5 X_i^T - r_6 X_r^T + r_7 X_{step} \quad (19)$$

$$X_{step} = (u_b - l_b) \, exp\left(-C_2 T/T_{max}\right) \quad (20)$$

where X_{step} is the step size of whale fall, $C_2 = 2W_f \times n$ is the step factor of whale fall, W_f is the probability of whale fall, which is defined as:

$$W_f = 0.1 - 0.05T/T_{max} \quad (21)$$

B. IMPROVEMENTS TO BELUGA WHALE OPTIMIZATION

The BWO has the advantages of good stability, strong search capability, and high convergence accuracy. However, it lacks diversity and has the disadvantages of easily falling into local optimum and premature convergence. In order to improve these situations, balance the global and local search multiple abilities, further improve the searchability, increase the diversity of candidate objects, and increase the consistency, the following improvements are made to the BWO.

1) ELITE OPPOSITION-BASED LEARNING

Elite opposition-based learning (EOBL) is to construct a reverse population by elite individuals in the current population, constitute a new population consisting of the reverse population and the current population, and select the optimal individuals from the new population to enter the next iteration [30].

Introducing the EOBL strategy at the beginning of each iteration, can expand the search area and increase the diversity of the population, which can make the algorithm jump out of the local optimum. It can be expressed by:

$$\overline{X_{i,j}^e} = K^* \left(\alpha_j + \beta_j\right) - X_{i,j}^e \quad (22)$$

where $X_{i,j}^e$, $\overline{X_{i,j}^e}$ are the elite individual and the inverse individual, K^* is the dynamic coefficient on (0,1), $\alpha_j = min\left(X_{i,j}\right)$, $\beta_j = max\left(X_{i,j}\right)$ are dynamic boundary.

2) BALANCE FACTOR

In the BWO, B_f is a balancing factor between the exploration and exploitation phase, and the size of B_f has a great impact on balancing the global and local search capabilities. Therefore, iterative modification of B_f is performed to enhance the exploration and development phases of BWO.

$$B_f = B_{fmin} + \left(B_{fmin} - B_{fmax}\right) \cdot exp\left(\ln\left(\frac{B_{fmin}}{B_{fmax}}\right) \cdot \frac{T}{T_{max}}\right) \quad (23)$$

where B_{fmax}, B_{fmin} are the upper and lower bounds of B_f respectively.

From (23), as the number of iterations increases, B_f decreases exponentially. B_f declines more gently at the beginning of the algorithm iteration, which facilitates the algorithm to perform a global search; it declines more at the end of the iteration, which enhances the local search capability.

3) CYCLONE FORAGING STRATEGY

Cyclone foraging strategy (CFS) is a foraging behavioral strategy observed in the field of animal behavior, in which individual animals forage in a cyclone-like motion. It has been demonstrated in the Whale Optimization Algorithm (WOA) and the Manta Ray Foraging Optimization Algorithm (MRFO) [31]. To further enhance the development phase of the BWO, the cyclone foraging strategy in the MRFO is introduced to improve this phase. The updated formula for the improved exploitation phase is:

$$X_i^{T+1} = \begin{cases} X_{best}^T + r_8\left(X_{best}^T - X_i^T\right) \\ +\beta \cdot C_1 \cdot L_F\left(X_{best}^T - X_i^T\right), \; i = 1 \\ \\ X_{best}^T + r_8\left(X_{i-1}^T - X_i^T\right) \\ +\beta \cdot C_1 \cdot L_F\left(X_{best}^T - X_i^T\right), \; i = 2, \ldots, n \end{cases} \quad (24)$$

$$\beta = 2e^{r_9 \frac{T-t+1}{T}} \cdot \sin(2\pi r_9) \quad (25)$$

C. THE PROCEDURE OF IBWO

The flow chart and pseudo code of the IBWO to solve the optimal configuration of distributed generation are shown in FIGURE 1 and TABLE 2. The specific optimization steps are as follows:

(1) Initialize the maximum iterative number, population size, B_{fmax} and B_{fmin} and other related parameters, initially generate the initial position of the beluga whale population, and calculate the fitness value according to the objective function.

(2) Further optimize the position of beluga whale populations according to the EOBL strategy and calculate the fitness value after position update.

(3) Calculate B_f and W_f by (23) and (21), if $B_f > 0.5$, then enter the exploration phase and update the population position according to (15), otherwise enter the exploitation phase and update the population position according to (24); Calculate the fitness value and keep the optimal solution of the current cycle.

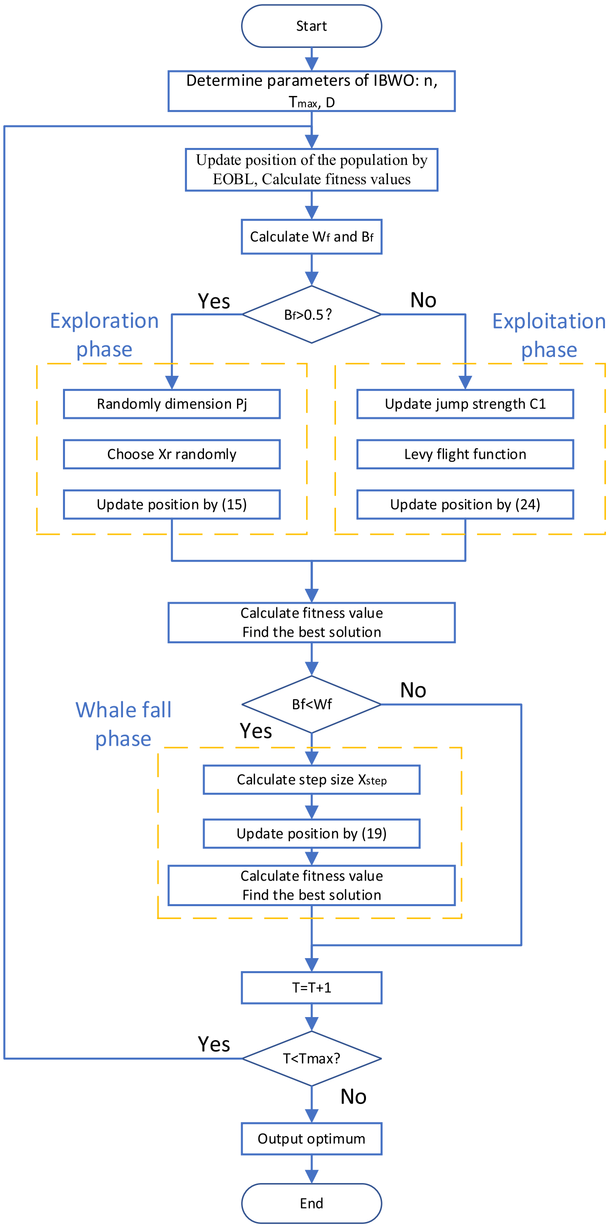

FIGURE 1. Process of IBWO.

(4) If $B_f < W_f$, then enter the whale fall, update the position according to (19), calculate the fitness value, and keep the optimal solution of the current cycle; otherwise, skip this process.

(5) Determine whether the current iteration reaches the maximum iteration, if it does, output the optimal solution and end the program; otherwise, return to step 2.

V. CASE STUDIES

A. SCENARIO REDUCTION RESULTS

Select the 2021 annual wind speed, light intensity and load data (one point per hour) of the region where a place in China as a sample (As shown in FIGURE 2), taking into account the calculation speed and accuracy of the clustering is reduced to four typical scenarios, in order to the wind turbine and photovoltaic model in (1) and (2), using the abovementioned wind turbine and photovoltaic-related parameters, the wind speed and light intensity data are converted into the wind and light out of the power, and finally, the wind, light and load scalarization is obtained by taking into account the correlation of the wind, light and load of the scenarios. The reduction of the corresponding scenes before and after the reduction is shown in FIGURE 3.

In terms of the correlation of win light and load, they in each scenario show a certain correlation. Scene a and scene b have the characteristics of higher wind speed, long sunshine time and high light intensity, although they also have summer characteristics from the view of wind and light output, but the load of scene a is lower and the load of scene b is higher, which can be seen that scene b is the summer season, and scene a is the transition season; scene c has higher wind speed and higher light intensity, which can be seen as the characteristics of the transition season; scene d shows the characteristics of winter in the place. less wind and low light intensity and higher loads. It can be seen that the typical scenarios generated by the improved K-means method based on the long time scale historical wind speed, light intensity and load scenarios can better simulate the stochasticity and correlation of wind speed, light intensity and load in the region, which is conducive to the optimal allocation of DG access to the distribution network.

B. BASIC PARAMETERS

Based on generated typical scenarios, this paper conducted tests on IEEE 33-bus and IEEE 118-bus distribution systems, as shown in FIGURE 4 and 5.

Each distributed power source is treated as a negative PQ node, and is connected to the distribution network using constant power factor control, with the power factor taken as 0.9, the planning period of 20 years, the maximum annual load utilization hours = 3200 h, and the unit electricity price C = 0.5 yuan/kWh. It is assumed that the DGs have the candidate installation locations of nodes 3, 6, 8, 13, 17, 19, and 31 and that the rated capacity of a single DG is 50 kW, and the number of accesses to each node is capped at 10 units. The upper limit of the number of accesses at each node is 10 units.

The cut-in wind speed of WT is $v_{in} = 3.5m/s$, the rated wind speed of WT is $v_{rate} = 9.5m/s$, the cut-out wind speed of WT is $v_{out} = 20m/s$. The rated light intensity of PV is $I_r = 1000W/m^2$. The investment cost of WT and PV is 6300 yuan/kW and 8000 yuan/kW respectively, and the operation and maintenance cost of fan and photovoltaic is 0.27 yuan/kWh and 0.28 yuan/kWh respectively.

The algorithm parameters were set as follows: to verify the superiority and effectiveness of IBWO in solving problems, IBWO, standard BWO, and PSO were tested and compared. In the IEEE 33-node case, the population size of the three

TABLE 2. The pseudo-code of IBWO.

Algorithm: IBWO

Input: Algorithm parameters (population size, maximum iteration, parameter dimension)
Output: The best solution

Initialize the population and evaluate fitness values, obtain the best solution (P^*)
While $T \le T_{max}$ **Do**
  Update position by EOBL, evaluate the fitness values
  Obtain the probability of whale fall W_f by (21) and balance factor B_f by (23)
  For each beluga whale (X_i) **Do**
    If $B_f > 0.5$
      //In the exploration phase
      Generate p_j randomly
      Choose a beluga whale X_r randomly
      Update the new position of the population by (15)
    Else If $B_f \le 0.5$
      //In the exploitation phase
        Update the random jump strength C_1 and calculate the Lexy flight function
      Update position by (24)
    End If
    Check the boundaries of new positions and evaluate the fitness values
  End For
  For each beluga whale (X_i) **Do**
    //the whale fall phase
    If $B_f < W_f$
      Update the step factor C_2 and calculate the step size X_{step}
      Update the new position of the population by (19)
      Check the boundaries of new positions and evaluate the fitness values
    End If
  End For
  Find the current best solution P^*
  $T = T + 1$
End While
Output the best solution

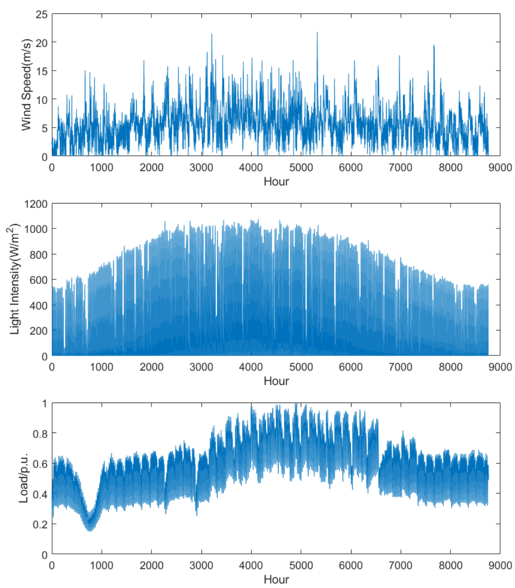

FIGURE 2. Wind speed, light intensity and load data.

algorithms was set as 100, and the maximum number of iterations was set as 100. The inertia weight of the PSO algorithm was set as 0.95, and the learning factors were set as 2. In the IEEE 118-node case, the population size of the three algorithms was set as 100, and the maximum number of iterations was set as 200. The inertia weight of the PSO was set as 0.95, and the learning factors were set as 2.

C. IEEE 33-BUS

The data for the IEEE 33-bus system is referenced from the case_ieee33 file in Matpower 7.1. The total load of the system is 3715kW and 2300kvar, Without the installation of DG, the active power network loss is 211.92 kW, the minimum voltage is 0.913 p.u., and the average voltage is 0.948 p.u. It is assumed that the DGs have the candidate installation locations of nodes 3, 6, 8, 13, 17, 19, and 31 that the rated capacity of a single DG is 50 kW, and the upper limit of the number of accesses at each node is 10 units.

Combined with the generated typical scenarios, three algorithms, namely IBWO, standard BWO algorithm and PSO, are run for DG optimization configuration calculation respectively, the optimization results of different algorithms are shown in TABLE 3, and the comparison of optimization effect is shown in TABLE 4.

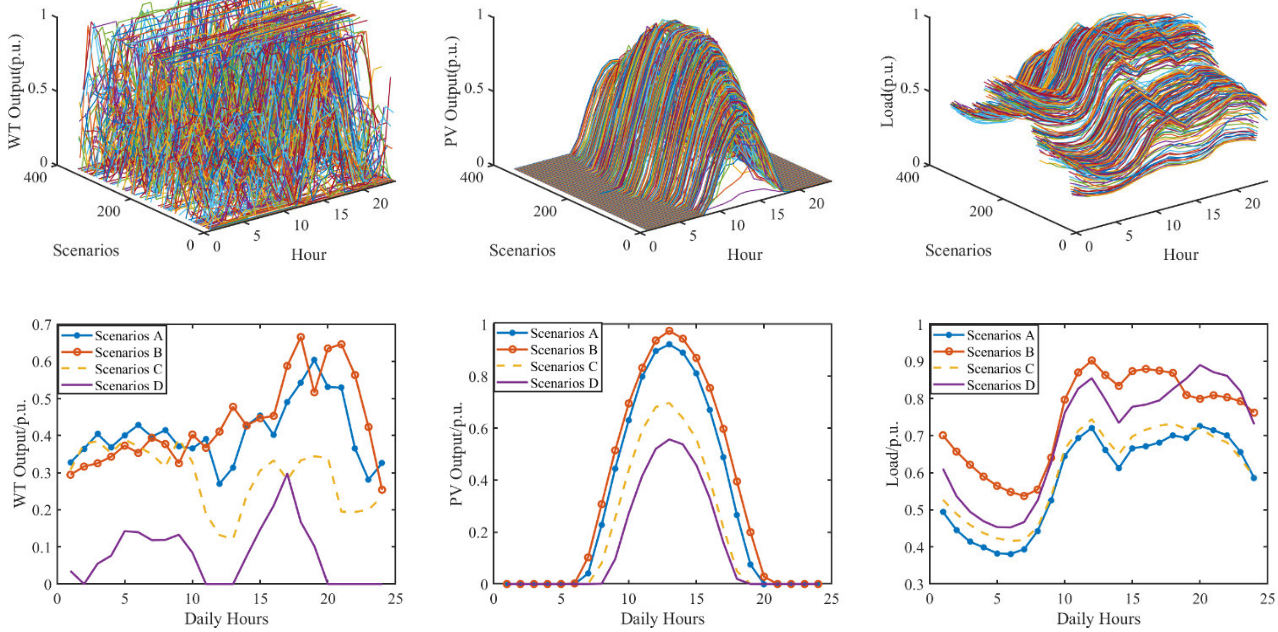

FIGURE 3. Scenes before and after clustering.

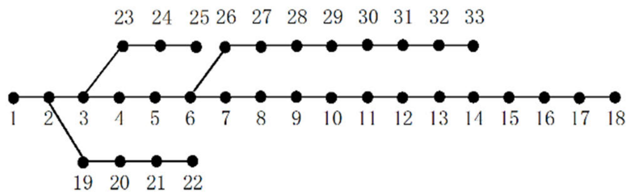

FIGURE 4. IEEE 33 bus distribution network.

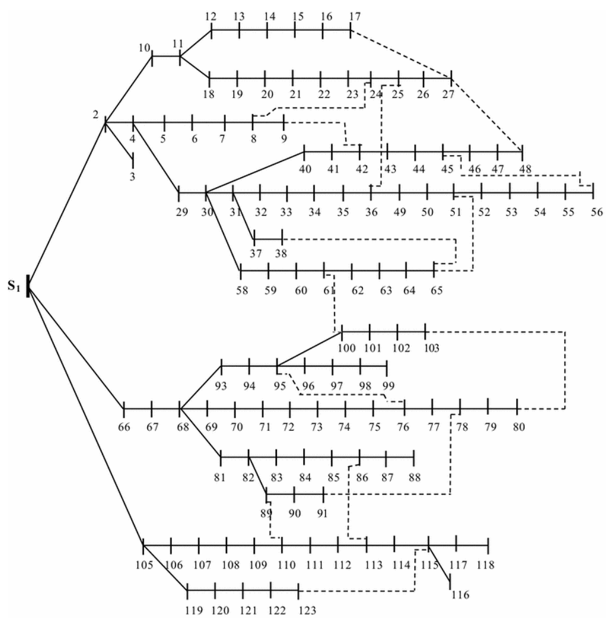

FIGURE 5. IEEE 118-bus distribution network.

From TABLE 3, it can be concluded that the active network loss of the system after DG access to the system using the IBWO algorithm is reduced from 211.92 kW to 94.323 4 kW, loss decreases by 55.49%, which is a significant reduction in active network loss. While applying PSO and BWO active network loss is reduced by 51.77% and 50.47% respectively, which are smaller than IBWO. The investment operation cost when IBWO is applied is significantly higher than the other two algorithms, which is due to the fact that the number of DGs accessed is higher than the number of DGs in the other algorithms. In terms of the power purchase cost of the distribution network after accessing DGs, the power purchase cost when using IBWO is lower than applying the PSO and

TABLE 3. Optimization results of different algorithms.

Algorithm	DG Planning results
No DG	—
PSO	6(10,0); 8(10,0); 17(0,3); 31(10,0)
BWO	8(9,1); 13(8,2); 31(10,0)
IBWO	6(6,0); 8(8,2); 17(3,0); 31(9,1)

note: 6(10,0) indicates that bus 6 has 10 WTs installed and no PVs.

TABLE 4. Comparison of optimization effects of different algorithms.

Algorithm	APL (kW)	IOMC (10^3yuan/year)	PPC (10^3yuan/year)	VSM
No DG	211.92	0	622.386 4	0.908 70
PSO	102.201 3	316.363 8	337.152 2	0.951 49
BWO	104.963 3	283.394 4	361.594 1	0.948 05
IBWO	94.323 4	340.073 3	311.891 7	0.955 08

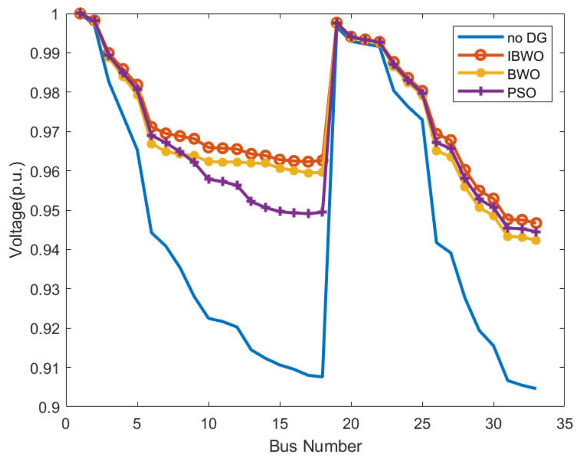

FIGURE 6. Bus voltage profile.

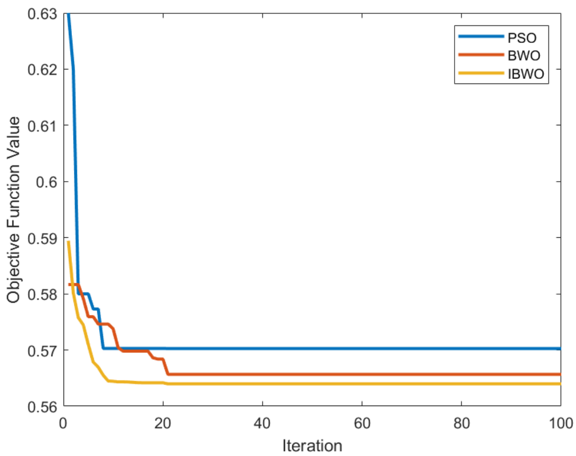

FIGURE 7. Convergence characteristics curves of different algorithms.

the BWO. FIGURE 4 shows the scalar values of the bus voltages of each bus with different algorithms for the optimal configuration of DGs before and after accessing the DGs, and the bus voltages of the distribution network are improved, with the lowest voltage being 0.946 7 p.u. and the average voltage being 0.972 2p.u. From the comparison of the voltage stability margin values in TABLE 4 as well as in FIGURE 6, IBWO has the best degree of improvement of the system voltages. The convergence characteristic curves of the three algorithms are shown in FIGURE 7, which shows that the PSO stabilizes around the tenth iteration, the IBWO similarly stabilizes around the tenth iteration, while the BWO stabilizes in the twentieth iteration, with the slowest convergence speed, which indicates that the elite inverse learning curves introduced in this paper to the BWO improves the quality and diversity of the populations, which makes the algorithm converge at a higher speed at the beginning of iteration, and the improvement of the balancing factor helps to balance the exploration stage and the development stage, it helps

TABLE 5. Comparison of simulation time for different algorithms.

	algorithm	Average simulation time (s)	Minimum simulation time (s)	Maximum simulation time (s)	stability
IEEE33	PSO	38.596 1	32.484 4	44.046 9	6.835 3
	BWO	17.171 9	16.234 4	19.250 0	2.682 9
	IBWO	16.733 6	15.578 1	18.953 1	0.474 2
IEEE118	PSO	45.340 6	42.093 8	53.525 6	6.4264
	BWO	45.682 0	44.750 0	52.562 5	2.811 0
	IBWO	43.512 5	42.2969	50.1563	2.6257

TABLE 6. Optimization results of different algorithms.

Algorithm	DG Planning results	
No DG	—	
	WT	PV
PSO	7(9);87(3);19(11)	21(13);51(30);111(29);74(30)
BWO	51(30);19(0);37(19)	73(22);40(30);97(30);81(7)
IBWO	74(30);6(30);71(30)	111(30);52(25);110(30);50(30)

to balance the global and local searches. The convergence speed is higher, and the improvement of the balancing factor helps to balance the exploratory stage and the development stage of the algorithm, i.e., it helps to balance the global and local search. Meanwhile, it is easy to see that IBWO has the highest convergence accuracy due to the introduction of the cyclone foraging strategy of the manta ray foraging optimization algorithm, which enhances the algorithm's local search capability. Twenty simulations of IEEE 33-bus are performed by three algorithms and the results of simulation time are shown in TABLE.5 and the stability is indicated by the variance of the 20 simulation times. IBWO is better than the remaining two algorithms in terms of average simulation time, minimum simulation time, maximum simulation time and stability.

D. IEEE 118-BUS

The data for the IEEE 118-bus system is referenced from Zhang [32]. The total load of the system is 22,709.7 kW and 17,041.1 kvar. Without installing DG, the active power network loss is 1,298.0916 kW, and the minimum voltage value is 0.8688 p.u. The average voltage is 0.9556 p.u.

In the IEEE 118-bus case, assuming no designated locations for DG, it is assumed that three nodes will install WT and four nodes will install PV. The rated capacity of each DG is 100 kW, and the maximum number of DGs connected to each node is 30.

Three algorithms, IBWO, standard BWO, and PSO, are respectively run for DG optimization configuration calculation, the optimization results of different algorithms are shown in TABLE. 6, and the comparison of optimization effect is shown in TABLE. 7.

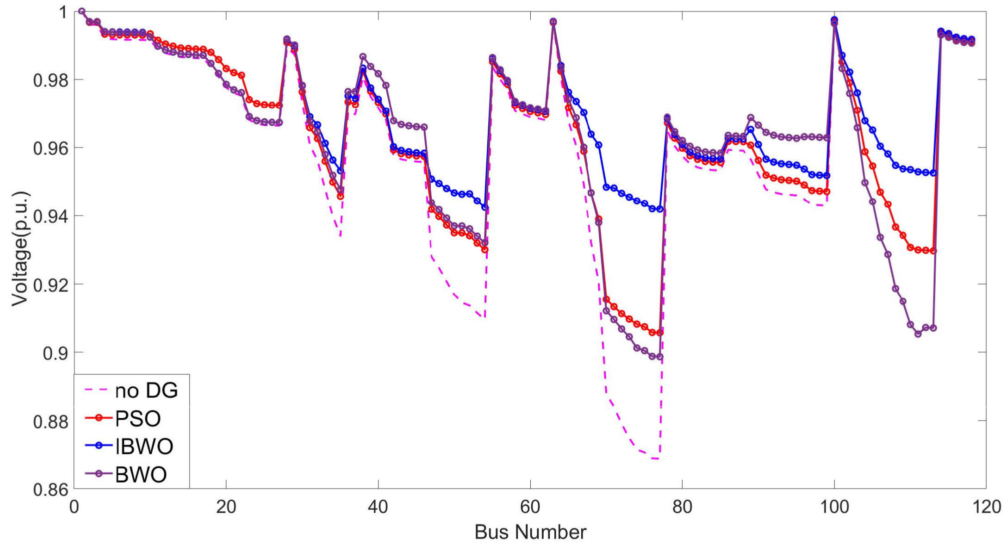

FIGURE 8. Bus voltage profile.

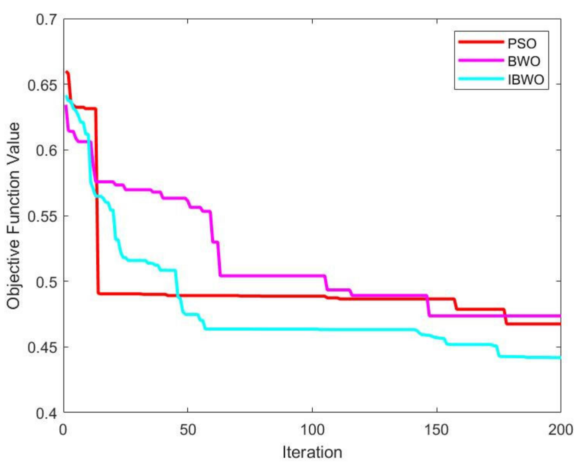

FIGURE 9. Convergence characteristics curves of different algorithms.

TABLE 7. Comparison of optimization effects of different algorithms.

Algorithm	APL (kW)	IOMC (10^3yuan/year)	PPC (10^3yuan/year)	VSM
No DG	1 298.091 6	0	38 412.498 6	1-2.230 4e-06
PSO	903.581 6	3 332.510 8	3 1382.790 5	1-1.025 7e-07
BWO	969.773	3 000.214 7	3 0647.350 3	1-6.898 9e-08
IBWO	704.245 8	3 961.941 7	2 6579.28	1-7.314 7e-07

The active network loss of the system is reduced from 1298.0916kW to 704.245 8kW after the DG is connected to the system using the IBWO, and the active network loss decreases by 45.39%, while the active network loss of the PSO and the BWO decreases by 30.39% and 25.29%, respectively, and the voltage stability margin is smaller than that of the IBWO.

Minimum voltage raised from 0.8688 p.u. to 0.9421 p.u. and the average voltage is raised to 0.9690 p.u. FIGURE. 8 shows the voltage distribution of 118-bus and it can be seen that there is a considerable enhancement compared to the schemes given by BWO and PSO. FIGURE.9 gives the convergence curves of IBWO, standard BWO, and PSO and it can be seen that the convergence speed and convergence accuracy of IBWO are better than the other two algorithms. TABLE. 5 gives 20 simulation times of the three algorithms under IEEE 118-bus. IBWO is better than the remaining two algorithms in terms of average simulation time, maximum simulation time and stability.

VI. CONCLUSION

In this paper, considering the stochasticity and correlation of wind speed, light intensity and load, based on the historical data of long time scale, and considering the amount of data and computation, a kind of improved K-means square for massive data is used to cut down the scenarios, and the typical scenarios generated by this method can better simulate the stochasticity and correlation of wind speed, light intensity and load of the planning area.

We consider constructing an optimal allocation model of DG with active network loss, investment and operation cost of DG, power purchase cost of distribution network and voltage stability indexes, and transforming it into a single-objective problem for solving under satisfying constraints after normalization.

This paper proposes to improve the beluga optimization algorithm for the distribution network optimization allocation problem, incorporating the elite reverse learning strategy, the cyclone foraging strategy, and improving the balance factor of the beluga optimization algorithm, which improves the convergence speed and convergence accuracy of the algorithm. The simulation in IEEE 33 and 118-bus system shows that the constructed model can effectively improve the voltage distribution of the distribution network, reduce the active network loss, reduce the power purchase cost of the distribution network, and improve the economics of the distribution network operation. IBWO has a clear superiority in solution quality, accuracy and simulation time.

There are some limitations to the current study. For example, the data selected in this paper is only for one year, which makes it difficult to take into account the increase in load demand due to economic growth, as well as the impact of extreme weather in various situations. In the subsequent study, we will fully consider the impact of these factors and further improve the optimal allocation of DG.

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