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Improved adaptive gray wolf genetic algorithm for low-cost and high reliability of photovoltaic intelligent edge terminal optimal configuration

Leijiao Ge [a,*] , Jiaheng Liu[a], Bo Wang[b], Yue Zhou[c], Jun Yan[d], Ming Wang[e]

a School of Electrical and Information Engineering, Tianjin University, Tianjin 300072, China;

b School of Electrical and Engineering, Wuhan University, Wuhan 430072, China;

c School of Engineering, Cardiff University, Cardiff CF24 3AA, UK;

d Concordia Institute for Information Systems Engineering, Concordia University, Montreal, QC H3G 1M8, Canada;

Abstract: Photovoltaic (PV) intelligent edge terminals (IETs) integrate data acquisition, processing, storage and upload functions for intelligent operations of PV power stations. However, the cost of installing a PV IET at one PV station is relatively high. In order to achieve the goal of multiple distributed PV stations sharing one PV IET on the premise of ensuring reliability, the paper proposes a method for the optimal configuration of PV IETs. First of all, considering the economy and reliability of optimizing configuration of PV IET, a two-layer optimization model is established. After that, to solve the nonlinearity of the proposed model, an improved adaptive genetic algorithm and gray wolf optimization (IAGA-GWO) is proposed. Finally, through two application cases of PV IETs, it is proved that the optimized configuration method in this paper can reduce the cost under the premise of ensuring the reliability.

Keywords: distributed photovoltaic; photovoltaic intelligent edge terminal; optimal configuration; improved adaptive genetic algorithm

1. Introduction

1.1 motivation and incitement

With the continuous development of PV technology, today's world has put forward higher requirements for the degree of intelligence in the PV industry. PV Intelligent Edge Terminals (PV IETs) is a new type of high-efficiency equipment, having the functions of data collection, processing, storage, uploading, etc. to ensure the safe and stable operation of the PV power plants. However, a single PV IET is expensive. In practical applications, large-scale PV power plants can afford them, but when applied to distributed PV power plants with a small capacity, the cost is usually high. Therefore, it is difficult to implement the above configuration method for each PV power plant with small capacity in practice. According to the similar characteristics of data acquisition demand of current distributed PV plants, some technicians put forward a method of multiple distributed PV plants share a PV IET. However, because of the scattered and disordered characteristics of the distribution of PV plants, the transformation from a distributed power plant using a PV IET to multiple distributed PV power plants using a PV IET will inevitably reduce the reliability of data acquisition and communication of the PV IET. At present, there are two using schemes to configure PV IETs. The first scheme is to configure the IETs at the distribution network, where the PV power plants are connected to the network; the second scheme is to place IETs in the distributed PV station with other equipment. If the configuration method is unreasonable, it will even seriously affect the function of PV IET, which might lead to increased costs that outweigh the gains. Therefore, how to obtain a better configuration is becoming a significant challenge.

Currently, the challenges facing the rational and optimized configuration of PV IET are as follows: (1) How to describe the reliability and cost loss of PV IET; (2) How to set up a mathematical model for the optimal configuration of PV IET; (3)How to deal with the non-linearity of the mathematical model; (4)There is a strong coupling between the number, location, and connection between PV IET's distributed PV plants. This will lead to the difficulty of solving the model.

1.2 literature review

PV IET is a new type of distributed PV operation and maintenance equipment, and there is less research on the optimal configuration of PV IET. Some research papers on optimal configuration can provide a reference for the modeling of this article. In [1], the hybrid wind power generation microgrid system was optimized, the minimum cost and maximum reliability are the main objectives of optimization; In [2], the wind/PV hybrid power generation system was optimized with the main objective of minimizing the total cost of power generation scheme. In [3], the power management and design of a hybrid Wind/PV generation system with hydrogen energy storage system are optimized. A novel multi-objective optimization algorithm is used to minimize the annualized cost of the system, loss of load expected and loss of energy expected. Reference [4] establishes an uncertain optimization model for the microgrid.

Due to the nonlinearity and complexity of the optimal configuration of PV IETs in distribution networks, metaheuristics as efficient tools of nonlinear problem solvers have been increasingly utilized [5]. Reference [6] uses particle swarm optimization (PSO) to solve the optimization of wind/PV hybrid power generation system. Reference [7] using Grey wolf optimization (GWO) in the tuning of power system stabilizer parameters of a multi-machine system in damping low-frequency oscillations. In addition to the single objective heuristic optimization above, multi-objective algorithms such as Multi-objective particle swarm optimization (MOPSO) [8] and Non-dominated Sorting Genetic Algorithm-II (NSGA-II) [9] have also been used. For example, reference [9] uses NSGA-II to solve distribution network optimization, and reference [10] uses MOPSO to solve microgrid optimization.

Among the solutions, the genetic algorithm (GA) is one of the first evolutionary computation methods applied by [11-12]. It is a random search algorithm that imitates the process of biological evolution in nature. In the search process, all candidate solutions will be tracked until a candidate solution better than the pre-defined standard appears [13]. However, traditional GA soften suffer from slow convergence and low accuracy. Reference [14] claims that an evolutionary algorithm is essentially a dynamic and adaptive process, and thus the use of constant parameters shall be contrary to the idea of natural evolution. In [15], an excellent adaptive GA is proposed to automatically adjust the crossover rate and mutation rate according to the quality of individuals. For good individuals, a lower crossover rate and mutation rate are used to protect them from being destroyed, and on the contrary, a higher crossover rate and mutation rate to bad individuals, in order to accelerate their elimination [16]. However, there are still some limitations in the adaptive method in [17]. When the fitness is close to the optimal fitness of the population, the probability of crossover and mutation is small, and the algorithm may fall into local optima.

1.3 contribution and paper organization

According to the author's knowledge, PV IET is a new type of equipment, and there is no research on its optimal configuration. In order to achieve the goal of multiple distributed PV plants sharing a PV IET, a two-layer optimization model is proposed.

In addition, to improve the performance, this paper proposes an improved adaptive hybrid gray wolf genetic algorithm (IAGA-GWO) to solve the proposed two-layer optimization model. The proposed IAGA-GWO improvement method is as follows: 1) an adaptive strategy to improve the accuracy, 2) the gray wolf algorithm with strong local optimization ability to accelerate the convergence.

The motivation of using propose IAGA-GWO is as follows: The purpose of the optimal question is to obtain the number and location of the PV IET, and the connection mode of each PV IET and PV station. From the perspective of the model characteristics, it is a mixed integer nonlinear programming. From the perspective of the characteristics of the candidate solution, multiple variables in the candidate solution have a strong coupling relationship. Therefore, considering the above-mentioned characteristics of the model and candidate solutions of the PV IET optimal configuration, it is difficult to solve the problem. IAGA-GWO combines the characteristics of high accuracy of GA and fast convergence speed of GWO. Compared with other heuristic algorithms, the IAGA-GWO algorithm has the advantages of high accuracy and fast convergence speed, which is very suitable for dealing with the optimal configuration of PV IET.

The main contributions of this paper are as follows: (1) A reliability evaluation criterion is established and used to estimate the data loss of each distributed PV station. (2) As there is no research on the optimal configuration of PV IETs for multiple distributed PV plants, this paper proposes a two-layer optimal configuration model for PV IETs, which achieve low cost and high reliability of PV IET configuration. (3)A new meta heuristic intelligent optimization algorithm IAGA-GWO is proposed.(4)The results of IAGA-GWO are compared with those of PSO (Particle swarm optimization), GWO (Grey wolf optimization), GA, SCA (Sine cosine algorithm) [18] , SFLS (Hybrid frog leaping algorithm) [19] for different dimensions of test problems.

The rest of the paper is organized as follows. Section 2 introduces the functions of PV IET. It also introduces typical data and data reliability indicators of PV power plants. Section 3 proposes the two-layer configuration model of PV IET and the IAGA-GWO. The validity and superiority of the model and algorithm are verified by the actual case in Section 4. Section 5 concludes the paper.

2. Photovoltaic intelligent edge terminals and calculation of data transmission reliability

2.1. *Photovoltaic intelligent edge terminals*

The PV IET has the function of integration of data acquisition, storage, processing and upload, and supports a variety of communication modes. The function of PV IET is described as follows:

2.1.1 Functions of photovoltaic intelligent edge terminals

1) Collecting the data from inverters of PV power plants.

2) Enabling communication with on-site environmental monitoring instruments in the PV power station and collecting the environmental monitoring data.

3) Enabling communication with PV module managers in the power plants and collecting the PV module data, including the voltage, current and temperature of each module. The PV module managers generally communicate with the PV IETs through the data collectors.

4) Enabling communication with on-site electric energy meters in the power plants.

5) Receiving and analyzing real-time data from the integrated power quality and fault recording device.

6) Storing data in the local database and uploading data to the cloud of distributed PV operation platform.

7) Analyzing and processing the collected PV data, improving the real-time performance of data analysis, and reducing the pressure of data processing in the cloud.

2.1.2 Total daily data of a photovoltaic power station

The power output of a PV power station is both intermittent and volatile. Because of the day and night periodicity of sunlight, a PV power station can only generate electricity in the daytime. At night, when the PV power plant is no longer working, the PV IET will upload the data to the cloud. The total daily data of a PV power station and all the PV power plants in an area can be described in (1)-(3):

$$Q_j = \sum_{s=1}^{D} \beta p_{js} n_{js} e_{js} \tag{1}$$

$$p_{js} = \frac{T_{on}}{T_{js}} \tag{2}$$

$$Q_{\max}=\sum_{i=1}^{M} Q_j \quad [5](3)$$

In (1), Q_j is the total daily data volume of the j-th distributed PV station connected to the distribution network. D is the total number of types of equipment in the distributed PV station. β is to measure the data amount of a single point with a single device for each data acquisition. p_{js} is the collection frequency of equipment s in thej-th PV station. n_{js} is the number of equipment s in thej-th PV power station. e_{js} is the single measurement point of equipment s of the j-thdistributed PVstation,which indicates the number of measuring points of a single device. In formula (2), T_{on} is the daily working time of the PV power station. T_{js} is the collection cycle of thej-th equipment in the PV power station. In formula (3), $Q_{\max}$ is the sum of daily data of M distributed PV power plants.

2.2Reliability evaluation criteria for data

Multiple distributed PV plants using PV IET together will inevitably reduce the reliability of data acquisition. During the process of data transmission from each device in the PV power station to the PV IET, the loss of data is random, so it is difficult to describe the amount of loss accurately, and it can only be estimated roughly. The data collection reliability and communication reliability evaluation criteria of PV IET proposed in this paper are as follows,

$$K=\alpha \mathrm{e}^{-\varepsilon R} \quad (4)$$

where K represents the reliability degree, which refers to the proportion of the data that is retained during the upload the data is uploaded to the PV IET. α and ε are coefficients, which can be obtained by data fitting. R represents the distance between the PV power station and the PV IET.

3. Two-layer model for optimal configuration model of photovoltaic intelligent edge terminals

3.1 Principles for configuration

The purpose of PV IET optimized configuration is to realize the multiple distributed PV stations sharing one PV IET, as shown in Figure 1. To effectively achieve the optimal configuration of PV IETs, this paper establishes a two-layer optimization model. The upper-layer model takes the minimization of costs as the objective function and the maximum number of PV IETs and total funds available at the initial stage of the project as the constraints. The lower-layer model maximizes the reliability of data acquisition and communication as the objective function, The constraints of the model include the maximum storage and processing capacity of PV IETs, the maximum number of communication connections, and the communication distance between the PV power plant and the PV IETs.

3.2 Upper-layer model

(1) Objective function

The total annual equivalent cost of optimized configuration includes the annual equivalent cost of purchase and maintenance of PV IETs. The objective function of the proposed PV IET optimal configuration is as follows:

$$C^{\mathrm{I}}=C^{\mathrm{D}}(1+\rho)A(r,n) \tag{5}$$

$$C^{\mathrm{D}}=P^{\mathrm{T}}N \tag{6}$$

$$A(r,n)=(\frac{r(1+r)^{n}}{(1+r)^{n-1}-1}) \tag{7}$$

where C^{I} is the annual investment/installation cost, C^{D} is the cost of PV IETs purchases, ρ is the proportion of the operation and maintenance cost with respective to the purchase cost of PV IETs, N is the number of PV IETs in the region, P^{T} is the current price of PV IETs in the region, $A(r,n)$ is the factor to measure the economy, the function is to convert the total cost into the cost of each year. r is the annual interest rate, and n is the service life of the PV IET.

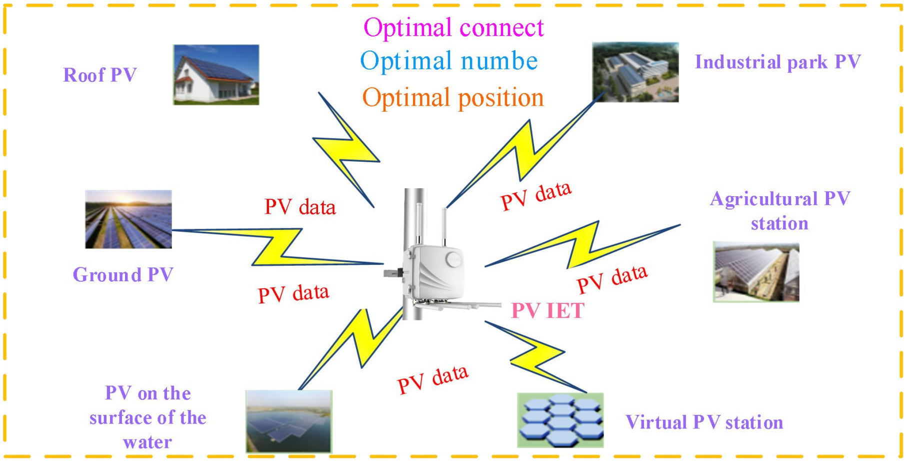


Fig.1 multiple distributed PV stations sharing one PV IET

PV data can reduce unnecessary fault losses . If there are missing or incomplete data, the cost of operation and maintenance will increase. The relationship between the amount of data loss and the increase in cost is as follows,

$$C^{loss}=\eta Q^{loss} \tag{8}$$

where C^{loss} represents the cost because of data loss. η is the coefficient, indicating the economic loss caused by the loss of 1MB data. Q^{loss} (MB) is the total amount of missing daily data.

Therefore, the final objective function can be expressed as,

$$\min C = C^{I} + C^{loss} \tag{9}$$

(2) Constraints

All data of a PV power plant only needs to be uploaded to one PV IET, and the number of PV IET should not exceed the number of PV power plants that need to upload data, as described below,

$$N \leq M \tag{10}$$

where N is the number of PV IETs and M is the number of PV power plants.

The cost of purchasing and maintaining PV IETs shall not exceed the total investment fund available for the project,as described below,

$$C^{I} \leq C^{\mathrm{K}} \tag{11}$$

where C^{K} is the total investment capital available at the initial stage of the project.

3.3 Lower-layer model

(1) Objective function

Given the missing data during data acquisition, it is necessary to analyze the amount of missing data finally collected by PV IETs and ensure that the configuration of PV IETs will not sacrifice the reliability of data collection and communication. In the lower-layer optimization, the objective function is set as the minimization of final data loss, shown as follows,

$$\min Q^{loss} = \sum_{i=1}^{N}\sum_{j=1}^{M} A_{ij}(1\text{-}K_{ij}w_{j})\ Q_{j} \tag{12}$$

where A_{ij} is a binary variable, if the PV IET i establishes a communication connection with the PV power station j , A_{ij} is 1, otherwise A_{ij} is 0. Q_j is the total amount of daily data of the PV power station j . K_{ij} is the reliability of data acquisition and communication between the PV IET i and PV power station j . M and N are the numbers of PV power plants and installed PV IETs, respectively. w_j is the weight to measure the importance of data quality of the j-th PV power station, the weight can be determined by evaluating the importance of each distributed PV station.

(2) Constraints

Any PV power station can only establish one communication connection with a PV IET,as described below,

$$\sum_{i=1}^{N} A_{ij} = 1 \tag{13}$$

To ensure the quality of data collection and processing, the amount of data collected by PV IETs should not exceed the maximum amount that can be stored and processed,as described below,

$$\sum_{j=1}^{M} A_{ij}Q_{j} \leq Q_{\max} \tag{14}$$

where $Q_{\max}$ is the maximum amount of data that can be collected, stored and processed by PV IETs every day.

To ensure the normal data collection of the PV IETs, the communication distance between a PV IET and the PV power station must be within a certain range,as described below,

$$A_{ij}R_{ij} \leq R_{\max} \tag{15}$$

where $R_{\max}$ is the maximum communication distance allowed; R_{ij} is the communication distance between the PV IET i of and the PV power station j .

PV IETs can support multiple wireless and wired communication modes, and collect data of distributed PV station in different ways. However, the number of connections in each communication mode is limited, and the number of connections with distributed PV station equipment cannot exceed the maximum number of connections in a certain communication mode of PV IETs. This observation can be represented by the following constraint,

$$\sum_{j=1}^{M} \gamma_{ji}^{\ l} \leq J_{l\max} \tag{16}$$

where $\gamma_{ji}^{\ l}$ is a binary variable: if the distributed PV station. j establishes a communication connection with PV IET i in the l -th communication mode, it is 1, otherwise it is 0. $J_{l\max}$ is the maximum connection number of PV IET in the l -th communication mode.

The proposed two-layer optimization model and the corresponding input and output is shown in Figure 2.

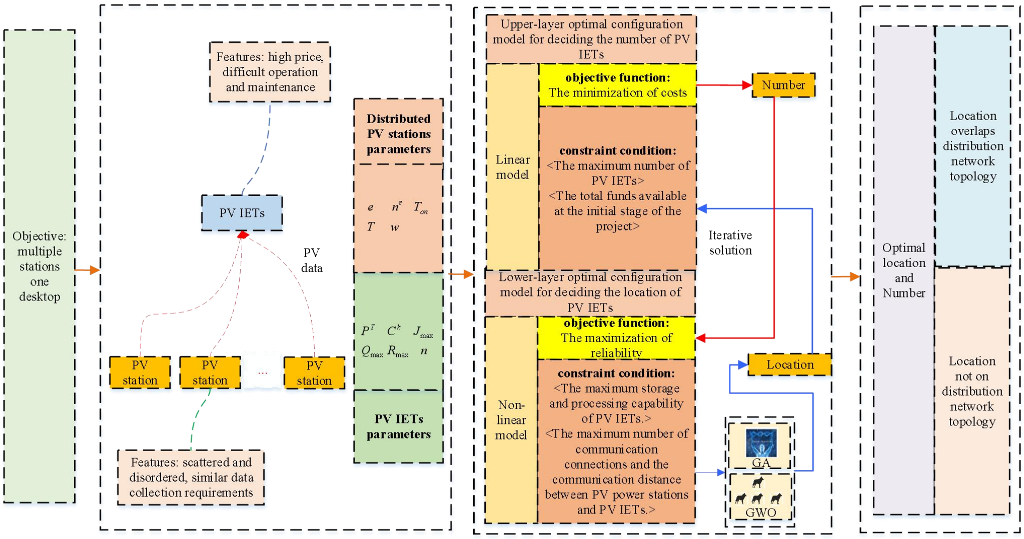


Fig. 2 The proposed two-layer optimization model and the corresponding input and output.

4. Improved adaptive hybrid gray wolf genetic algorithm

4.1 Genetic algorithm

GA is an algorithm that simulates the evolution mechanism of natural organisms and uses a random search technology following the rule of survival of the fittest. In the search process, all kinds of candidate solutions will be tracked until a more suitable solution appears than the pre-defined standard. The main steps include chromosome coding, population initialization, fitness calculation, selection, crossover, and mutation. It is worth mentioning that the GA in this paper adopts real coding. The cross operation is as follows:

$$X(i) = rand_1 X(i) + rand_2 X(i+1) \tag{17}$$

$$X(i+1) = rand_3 X(i) + rand_4 X(i+1) \tag{18}$$

where $rand_p (p = 1,2,3,4)$ are constants in (0,1),

The mutation operation is as follows:

$$X(i)_j = lb + (ub - lb) rand_5 \tag{19}$$

4.2 Traditional gray wolf optimization algorithm

Grey wolf optimization algorithm (GWO) is a new type of swarm intelligence optimization algorithm, which simulates the social hierarchy mechanism and hunting behavior of gray wolfs in nature. In the gray wolf group, there is a strict social hierarchy. The mathematical model for encircling the prey can be expressed by (20) and (21),

$$D = \left| CX_p(t) - X(t) \right| \tag{20}$$

$$X(t+1) = X_p(t) - AD \tag{21}$$

where $t+1$ represents the next iteration; X represents the position of one wolf; X_p represents the position of the prey. A and D are the coefficient vectors. The calculation method is shown as,

$$A = 2ar_1 - a \tag{22}$$

$$C = 2r_2 \tag{23}$$

where r_1 and r_2 are random numbers in [0,1], a is a variable, linearly decreasing from 2 to 0 over the course of iteration.

When the wolves determine the position of prey, the α wolf, β wolf and δ wolf will lead the wolves to surround the prey, and the other wolves in the group will move according to the position of the three wolves, which is mathematically expressed by the (24), (25) and (26),

$$D_\alpha = \left| C_1 X_\alpha - X_\alpha \right| \tag{24}$$

$$D_\beta = \left| C_1 X_\beta - X_\beta \right| \tag{25}$$

$$D_\alpha = \left| C_1 X_\delta - X_\delta \right| \tag{26}$$

where X_α , X_β and X_δ represent the three best solutions in the iterative process . The location of the prey is updated as follows,

$$X_1 = \left| X_\alpha - A_1 D_\alpha \right| \tag{27}$$

$$X_2 = \left| X_\beta - A_2 D_\beta \right| \tag{28}$$

$$X_3 = \left| X_\delta - A_3 D_\delta \right| \tag{29}$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \tag{30}$$

where $X(t+1)$ is the new location of prey and is the average of the three best solutions in the population.

4.3 Adaptive crossover and mutation rate

Crossover and mutation are important parts of GA. However, If the crossover probability is too large, it will destroy the excellent individuals; if the crossover probability is too small, the algorithm will be slow or even difficult to converge. Similarly, a high probability of mutation will damage the excellent individuals, while a small probability of mutation will reduce the diversity of the population.

To solve the above problems, an adaptive GA is proposed in [16]. When the fitness of the population tends to be the same, the probability of crossover and mutation will be increased automatically to prevent the premature of the algorithm caused by the convergence of population individuals; At the same time, for the individuals whose adaptability is higher than the average, lower crossover rate and mutation rate should be given to protect the excellent individuals from being destroyed [17]. The adaptive rules can be described as follows,

$$P_c = \begin{cases} \dfrac{k_1(f_{\max} - f)}{f_{\max} - f_{avg}}, f \geq f_{avg} \\ k_2 \qquad\qquad\qquad f < f_{avg} \end{cases} \tag{31}$$

where P_c is the crossover rate of GA. $f_{\max}$ is the optimal adaptive value of individuals in the population. f_{avg} is the average adaptive value of individuals in the population. f is the better one of the two individual adaptive values to be crossed, and $k_i (i = 1, 2)$ is a constant between (0,1).

$$P_m = \begin{cases} \dfrac{k_3(f_{\max} - f')}{f_{\max} - f_{avg}}, f' \geq f_{avg} \\ k_4 \qquad\qquad\qquad f' < f_{avg} \end{cases} \tag{32}$$

where P_m is the mutation rate of GA; f' is the adaptive value of individual variation, and $k_i (i = 3, 4)$ is a constant between (0,1).

Still, problems exist in the above adaptive rules due to the large difference between individuals in the early stage of population and the large similarity between populations in the later stage of the population. The problems in the early and later stages of the algorithm are analyzed as follows.

In GA, the elite retain strategy is used to retain the optimal individuals in the population, so as to ensure that the optimal individuals in the population can inevitably enter the next generation. In the early stage of the adaptive GA, due to the large difference between the population individuals, the crossover rate and mutation rate of the excellent individuals can be considered as 0. This leads to the algorithm not only to retain the optimal individuals but also to retain multiple elite individuals. Although it helps protect the genes of the excellent individuals from being destroyed, excessive reservation of excellent individuals may destroy the diversity of the population and increase the risk of fall into local optima.

In the later stage of the algorithm, after multiple choices, the individuals in the population have a high degree of similarity. The optimal individuals account for a large proportion of the population, and there is no need to protect it. In the adaptive method, the crossover rate and mutation rate of the optimal individual are 0, that is, the optimal individuals will not have crossover and mutation, which will cause the search process of the whole population to almost stagnating.

In this paper, to tackle the problems existing in the pre-period and post-period of the adaptive method, a better improvement is proposed using the cosine function to adjust the probability of crossover and mutation. This method solves the problem of low cross rate and mutation rate between the elite individuals in the early stage and the optimal individuals in the later stage. The calculations are shown in the formulas (33) (34) and (35),

$$P_c=\begin{cases}\dfrac{k_1(f_{\max}-f)}{f_{\max}-f_{avg}}+k_5\lambda, f\ge f_{avg}\\ k_2 \qquad f<f_{avg}\end{cases} \tag{33}$$

$$P_m=\begin{cases}\dfrac{k_3(f_{\max}-f')}{f_{\max}-f_{avg}}+k_6\lambda, f'\ge f_{avg}\\ k_4 \qquad f'<f_{avg}\end{cases} \tag{34}$$

$$\lambda=1+\cos(\pi(\frac{t}{t_{\max}}+1/2)) \tag{35}$$

where $k_i(i=3,4)$ are constants in (0,1), $t_{\max}$ is the maximum number of iterations, and t is the current number of iterations.

4.4 Hybrid optimization based on gray wolf algorithm

The adaptive method proposed above improves the accuracy of the algorithm, but also reduces the convergence speed of the algorithm. In order to balance the accuracy and speed of the algorithm, a hybrid optimization of GWO and GA is designed in this paper. In the GA, crossover and mutation are performed randomly, while in the GWO, the population is guided by three superior wolves to change its position. The introduction of the GWO in the GA allows some individuals in the population to evolve based on the GWO instead of cross-mutation to a random position, which improves the local search ability of the algorithm and speeds up the convergence of the algorithm.

In [20], an elite wolf retention strategy is proposed to strengthen the elite learning strategy for the dominant wolves to prevent the misleading of the low-level wolves. Each wolf in the population only follows the higher-ranking wolf, but this method does not change the trend that all individuals in the population still tend to the average position of the three dominant wolves. This paper proposes another strategy to overcome the shortcomings of GWO. To reduce the damage of excellent individuals, the elite wolf strategy is introduced to keep the former S individuals from entering the GWO, while the remaining individuals after the first T individuals are not entering the GWO to prevent the convergence of population individuals, maintain the diversity of the population, and finally, the S-T individuals in the fitness order of the wolf group enter the GWO. This way of entering the gray wolf algorithm can ensure the algorithm has good robustness and solution quality.

S and T are calculated as follows:

$$S=\tau_1 D \tag{36}$$

$$T=\tau_2 D \tag{37}$$

Where τ_1 and τ_2 are constants related to the number of individuals entering the gray wolf algorithm, and round represents rounding.

The flow chart of IAGA-GWO is summarized as follows:

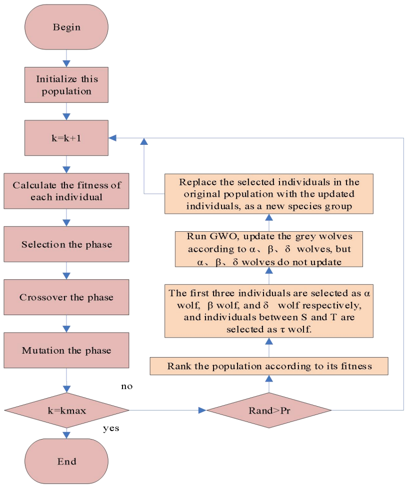


Fig. 3 Improved adaptive hybrid gray wolf genetic algorithm

4.5 Validation of the proposed IAGA-GWO

In this section, the performance of the algorithms presented in this paper is verified. To verify the effectiveness of the proposed IAGA-GWO, it is applied to different benchmark functions f1-f6 [5], among which f1 to f3 is unimodal (UM) function and f4 to f6 is multimodal (MM) function; and the results are compared with other algorithms, such as PSO, GWO, GA, SFLS, SCA based on the best standard deviation (STD), average (AVG), minimum value (MIN). The parameters of the algorithm are shown in Tab.1.

Tab.1.

parameters of the algorithm:

Algorithm	Parameter	Value	Algorithm	Parameter	Value
SCA	Convergence constant *a*	[2 0]	GA	Crossover probability pc	0.6
GWO	Convergence constant *a*	[2 0]		Mutation probability pm	0.2
PSO	Inertia weight *w*	0.5	IGA-GWO	Adaptive factor K1	0.4
	Learning factor c1	2		Adaptive factor K2	0.6
	Learning factor c2	2.5		Adaptive factor K3	0.1
SFLS	m	5		Adaptive factor	0.2

		K4	
Number of offsprings	3	Adaptive factor K5	0.2(k2-k1)
Maximum number of iterations	5	Adaptive factor k6	0.1(k4-k3)
step size	2	Threshold w	0.8

The parameter spaces of F1 to F6 are shown in Figure 4 [8]. All benchmark functions have a dimension of 30. The adopted equations for the algorithm validation with the corresponding dimensions are given in Tab. 2:

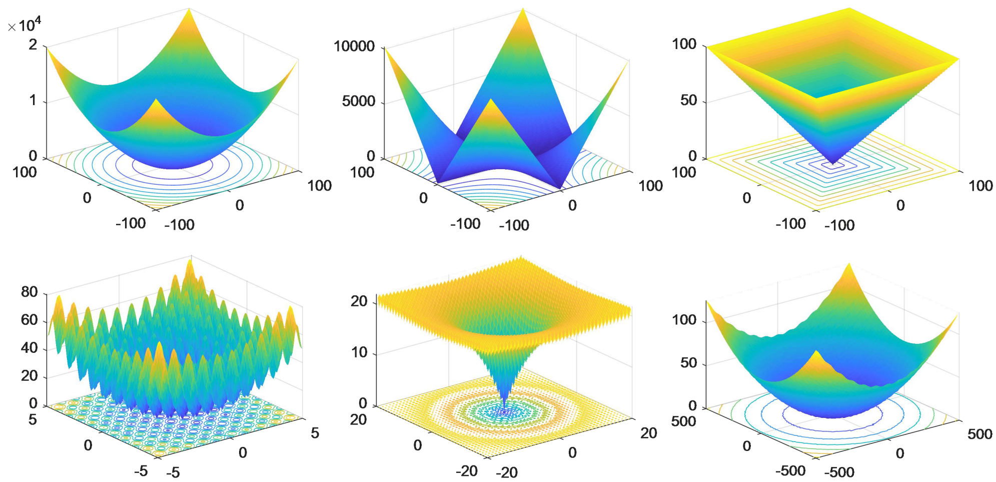


Fig. 4 The parameter space of F1 ~ F6

Tab 2:

Description of benchmark functions.

Function	Range	fmin
$f_1(x)=\sum_{i=1}^{n} x_i$	[-100,100]	0
$f_2(x)=\sum_{i=1}^{n}\lvert x_i\rvert+\prod_{i=1}^{n}\lvert x_i\rvert$	[-10,10]	0
$f_3(x)=\sum_{i=1}^{n}(\sum_{j-1}^{i} x_j)^2$	[-100,100]	0
$f_9(x)=\sum_{i=1}^{n}[x_i^2-10\cos(2\pi x_i)]$	[-5.12,5.12]	0
$f_{10}(x)=-20\exp(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2})-exp(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i))+20+e$	[-32,32]	0
$f_{11}=\frac{1}{4000}\sum_{i=1}^{n}x_i^2-\prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}})+1$	[-600,600]	0

To eliminate the influence of randomness of heuristic algorithms and ensure absolute fairness, each algorithm was run 30 times independently, and all results were recorded and compared in Tab. 3. All experiments were run for 1000 iterations.

In Tab. 3, we can find that the IAGA-GWO proposed in this paper has excellent optimization results in f1-f6, and the performance of the algorithm is generally better than other algorithms. For unimodal function f1-f3, IAGA-GWO is better than PSO, GWO, GA, SFLS and SCA in terms of mean, standard deviation and minimum value, which reveals that IAGA-GWO improves the performance of GA and GWO in unimodal function. For multimodal function f4-f6, it is found that IAGA-GWO is still better than PSO, GWO, SFLS, SCA in the mean value and standard deviation, but the difference compared to GA is less significant, especially in f4 and f6, where IAGA-GWO and GA both reach the theoretical optimal value. IAGA-GWO shows excellent results in unimodal function and multimodal function and always keeps the advantage.

Tab 3.

Results of benchmark functions (F1–F6), with 30 dimensions.

Benchmark		IAGA-GWO	GWO	PSO	GA	SCA	SFLS
F1	AVG	**1.36E-239**	3.48E-70	1.85E+03	1.9406e-158	1.85E-03	9.26E-29
	STD	**0.00E+00**	6.84E-70	1.01E+03	1.06E-157	4.16E-03	1.23E-28
	MIN	**9.30E-267**	1.50E-73	3.93E+02	2.2567e-195	9.59E-08	6.66E-31
F2	AVG	**1.41E-115**	6.30E-41	2.39E+01	1.90E-89	1.20E-05	6.55E-16
	STD	**7.73E-115**	7.85E-41	8.37E+00	1.04E-88	2.68E-05	1.61E-15
	MIN	**9.00E-132**	2.95E-42	5.90E+00	6.60E-116	1.34E-08	1.01E-17
F4	AVG	**2.76E-133**	1.82E-17	1.79E+01	4.66E-95	1.85E+01	9.42E-04
	STD	**1.20E-132**	2.10E-17	3.78E+00	1.94E-94	1.18E+01	9.59E-04
	MIN	**3.02E-151**	4.07E-19	1.13E+01	1.83E-113	4.83E+00	1.44E-04
F9	AVG	**0.00E+00**	0.4542	1.34E+02	**0.00E+00**	8.68E+00	6.86E+01
	STD	**0.00E+00**	1.7502	3.04E+01	**0.00E+00**	1.49E+01	1.75E+01
	MIN	**0.00E+00**	0.00E+00	8.65E+01	**0.00E+00**	2.09E-06	4.28E+01
F10	AVG	**8.88E-16**	1.33E-14	1.16E+01	**8.88E-16**	1.19E+01	3.85E-02
	STD	**0.00E+00**	2.76E-15	2.37E+00	**0.00E+00**	9.25E+00	2.11E-01
	MIN	**8.88E-16**	7.99E-15	8.53E+00	**8.88E-16**	1.98E-05	7.99E-15
F11	AVG	**0.00E+00**	0.0021	1.96E+01	**0.00E+00**	2.11E-01	7.63E-03
	STD	**0.00E+00**	0.006	1.41E+01	**0.00E+00**	2.82E-01	1.12E-02

MIN	**0.00E+00**	0.00E+00	5.98E+00	**0.00E+00**	1.03E-05	0.00E+00

To test the global and local convergence of IAGA-GWO, the convergence curve of the test function F1-F6 on 30 dimensions is listed in Fig. 5. The y-axis is plotted on the logarithmic scale for better visibility. For unimodal function f1-f3, IAGA-GWO is superior to other algorithms in convergence speed and accuracy. For multimodal function f3-f6, IAGA-GWO and GA also show excellent performance, indicating that IAGA-GWO also has strong global and local search capabilities. For function f3-f6, it is clear that both IAGA-GWO and GA will converge to the same result eventually, but IAGA-GWO converges faster than GA. It is proved that the improved strategy proposed in this paper can accelerate the convergence speed without affecting the optimization accuracy. The adaptive strategy in this paper also avoids the local shortcomings of the gray wolf algorithm. Therefore, in general, IAGA-GWO achieves better performance through the proposed optimization.

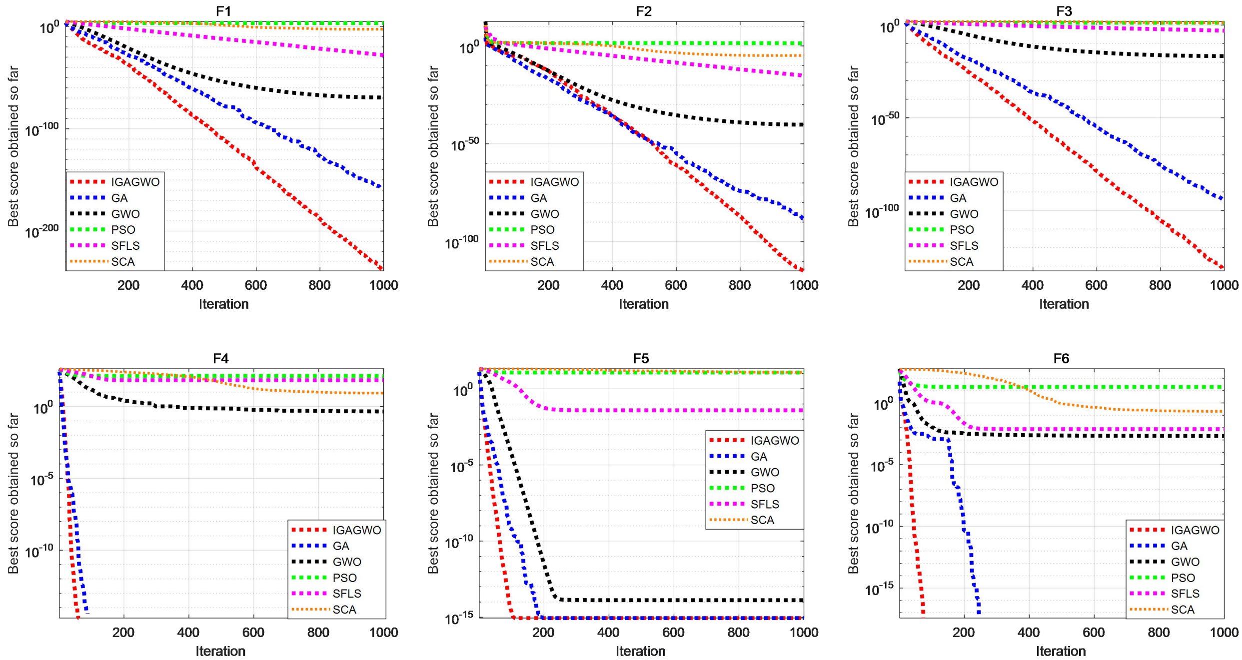


Fig. 5 The convergence curve of f1-f6

4.6 Solution method of the two-layer model

In Section 3, it can be seen that the upper-layer model obtains the number of PV IETs, which acts as a constraint of the lower-layer model. The lower-layer model obtains the optimal location of PV IETs and feeds back to the upper-layer model to obtain the accurate total cost. The upper-layer and lower-layer models are solved iteratively until the final solution is obtained.

4.6.1 Solution method of the upper-layer model

The upper-layer model is a linear optimization model, which is solved by classical linear programming methods.

4.6.2 Solution method of the lower-layer model

The lower-layer model is a nonlinear optimization model, which can be solved by the proposed IAGA-GWO.

4.7 Solution of the two-layer model for the optimal configuration of PV IETs

In this paper, the solution steps of the two-layer model are summarized as follows,

Step 1: Algorithm initialization - input the original basic data of the two-level optimization model.

Step 2: Calculate the number of PV IETs by conventional linear programming methods and transfer the optimized results to the lower layer.

Step 3: Use the results of the upper-layer optimization to calculate the objective function of the lower-layer model. The proposed IAGA-GWO is used to solve the lower-layer model to find the optimal position of the PV IETs, and the result of the lower-layer model is passed to the upper-layer model.

Step4: Record the result as the current optimal solution, return to step 2 and repeat the above steps. If the newly calculated cost is lower than the current optimal solution, replace the current optimal solution with this new cost. When the upper optimization model is solved, go to step 5.

Step5: Output the optimal configuration scheme that meets the requirements of low cost and high reliability, and the algorithm ends.

5. Case study

5.1 Case 1: For the optimal configuration of using scheme I

1) Input data

The scheme I is to configure the PV IETs at the distribution network node where the PV power plants are connected to the network. In case 1, not every distributed network node where the PV power plants are connected to the network is equipped with PV IET, but a few nodes in the distribution network are equipped with PV IET to achieve the goal of multiple distributed PV plants using a PVIET together, and these nodes can have no distributed PV connection. The IEEE 69-node distribution network is used as an example. The distance between 69 nodes can be calculated according to the impedance of each line in the IEEE 69-node systems. The connection points of distributed PV plants are placed according to [21], and the connection nodes are 9, 20, 26, 28, 29, 38, 42, 55, and 64. The parameters in the mathematical model are shown in Tab.4. The numbers of equipment in each distributed PV station are shown in Tab.5. In the PV power station: the collection cycle of inverter meters, environmental monitors, power quality recorders, and component managers is 5s 900s 60s 5s 60s.

Tab 4.

Results of benchmark functions (F1–F6), with 30 dimensions.

Parameters	Value	Parameters	Value	Parameters	Value	Parameters	Value

P^{T}	￥15,000	r	0.1	n	15 years	ρ	0.2
$Q_{\max}$	20,000MB	C^{K}	￥100,000	α	1	β	0.001171
η	40	ε	0.03	$J_{l\max}$	4	$R_{\max}$	50km

To distinguish the importance of each distributed PV station, the weight w from distributed PV station A to distributed photovoltaic power station I is 0.05, 0.1, 0.15, 0.05, 0.05, 0.1, 0.12, 0.18 and 0.2, respectively.The results of Case 1 are is shown in Tab. 6

Tab.5

Basic information of distributed PV plants

	Coordinates	The number of equipment in the distributed PV plants and the number of single measuring point											
		Inverter		Data collector		Energy meter		Environment monitor		Power quality recorder		Component manager	
		PV station	single measuring point	PV station	single measuring point	PV station	single measuring point	PV station	single measuring point	PV station	single measuring point	PV station	single measuring point
a	(-20,-10.2)	4	80	4	47	1	1	1	10	1	21	188	188
b	(-12,-23.8)	8	176	6	40	1	8	1	13	1	20	242	240
c	(-25.4,21.6)	6	144	5	46	1	12	1	11	1	20	232	230
d	(21.2,12.7)	4	72	3	47	4	36	1	9	1	22	142	141
e	(15.2,14.9)	4	84	6	45	1	10	1	9	1	18	270	270
f	(21,27.3)	8	144	5	45	1	10	1	10	1	19	224	225
g	(0.5,24.8)	5	90	4	50	1	13	1	8	1	23	201	200
h	(20.5,-20.5)	7	161	8	41	1	9	1	11	1	20	326	328
i	(11.1,-13.2)	9	171	8	43	1	9	1	11	1	20	344	344

Table 6

Comparison of configuration results of photovoltaic intelligent edge terminal in different way in case 1

Way	Number of PV IETs / set	Nodes where PV IETs are connected	Connection mode	Data loss / MB	Equivalent annual cost / ￥10,000
No optimized configuration	9	9,20,26,28,29,38,42,55,64	9-9.20-20,26-26,28-28,29-29,38-38,42-42,55-55,64-64	0	2.42
IAGA-GWO	4	20,38,55,64	9-55,20-20,26-20,28-38,29-55,38-38,42-55,55-55,64-64	118.8	1.5504
GA	4	21,38,55,64	9-55,20-21,26-21,28-38,29-55,38-38,42-55,55-55,64-64	120.4	1.5570
GWO	4	1,20,55,64	9-1,20-20,26-20,28-1,29-55,38-1,42-1,55-55,64-64	196.1	1.8560

In Case 1, the location of PV IETs in the IEEE69 bus system is shown in Fig. 6. PV IETs of the same color and distributed PV power stations represent that they are interconnected. when the number of PV IETs is 4, the fitness curve of each algorithm is shown in Fig.7:

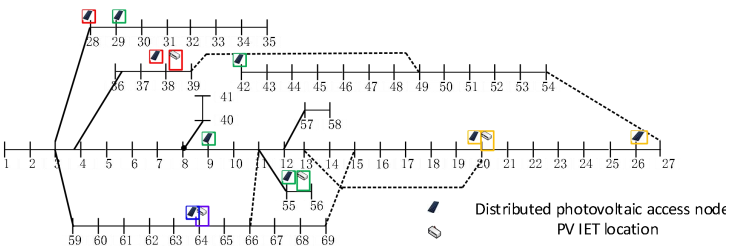


Fig. 6 The topology of distributed PV and PV IETs in IEEE69 bus system obtained by IAGA-GWO

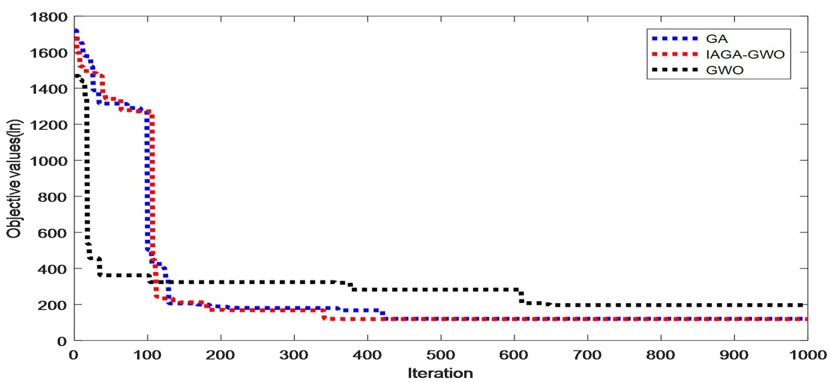


Fig 7. The fitness curve of the three algorithms for the lower level location optimization in Case 1

The following observations can be drawn from the experimental results above:

Before the PV IETs optimization configuration, the required number of PV IETs is 9. Using the configuration method in this paper, the required number of PV IETs is 4. It significantly reduces the configuration number of PV IETs.

(1)After adopting the optimal configuration method in this paper, although the data loss is increased, compared with the total amount of data collected by PV IETs every day, the total data loss remains low, which will not have a significant impact on the application nor the reliability.

(2)Taking into account the cost loss caused by reliability reduction, the equivalent annual cost under the proposed PV IE configuration method is ￥15504, ￥15570and ￥18560, respectively, while the equivalent annual cost of the PV IETs under the traditional method is ￥24,200, which shows that the proposed method can significantly reduce the annual cost, improve the economy, and verify the effectiveness and feasibility of the model in this paper.

(3)In the comparison of the three algorithms in Fig 7, GWO is weaker than the other two algorithms in both the accuracy and the convergence. The traditional GA and IAGA-GWO in this paper can finally find similar solutions, but the convergence of the traditional GA is slightly slower than the algorithm proposed in this paper. The results show that the proposed IAGA-GWO algorithm has excellent performance.

5.2 Case 2: For the optimal configuration of using scheme II

1) Input data

The scheme II is to place IETs in the distributed PV station with other equipment. In case 2, the PV IET can be configured not only in the distributed PV station but also outside the distributed PV station. According to the geographical location of each distributed PV station, a certain number of PV IETs can be installed in the appropriate location.

2) Results of Case 2

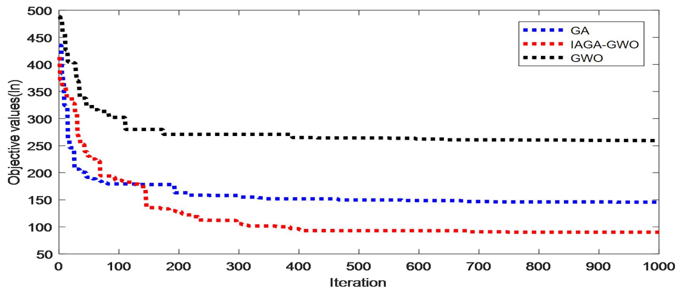
In Case2,the results are is shown in Tab. 7. The fitness curve of each algorithm is shown in Fig.8:

Tab 7

Comparison of configuration results of photovoltaic intelligent edge terminal in different modes in case 2

way	number of PV IETs	PV IETs coordinates / km	Corresponding connection mode	Data loss / MB	Equivalent annual cost / ￥10000
No optimized configuration	9	A(-20,-10.2)B(-12,-23.8)C(-25.4,21.6) D(21.2,12.7)E(15.2,14.9) F(21,27.3) G(0.5,24.8)H(20.5,-20.5)I(11.1,-13.2)	a-A, b-B, c-C, d-D, e-E, f-F, g-G, h-H, i-I	0	2.42

IAGA-GWO	4	A(11.4,-13.3)B(20.4,27.2)C(-12.4,-23.8) D(-25.4,21.3)	a-C, b-C, c-D, d-B, e-B, f-B, g-B, h-A, i-A	90.2	1.44
GA	4	A(10.6,-13.8)B(-24.7,-23.2)C(20.4,25.5) D(20.0,-20.6)	a-A-b-D, c-B, d-C, e-C, f-C, g-C, h-D, i-A	145.7	1.66
GWO	3	A(11.1,-13.2)B(0,-22.1)C(0.3,24.8)	a-B, b-B, c-C, d-B, e-C, f-C, g-C, h-A. i-A	225.4	1.71



.**Fig 8.**The fitness curve of the three algorithms for the lower level location optimization in Case 2

According to the above experimental results, the following conclusions can be obtained:

(1) No matter Case 1 or Case 2, the results of the optimized configuration of PV IETs proposed in this paper are still better than those without optimized configuration, which proves the effectiveness and feasibility of the model.

(2) It can be seen from Fig 8 that the GWO falls into the local optimal solution, indicating that the GWO has a strong local search ability but a weak global search ability. Although the convergence ability and accuracy of the traditional GA solution is higher than that of GWO, it also falls into the local optimum in the final stage, which shows that the accuracy of traditional GA is weak.

(3) Through comparison, it is found that the IAGA-GWO inherits the advantages of traditional GWO and GA but overcomes their limitations. The accuracy and the convergence of the algorithm proposed in this paper have demonstrated clear advantages.

6 Conclusion

In order to achieve the goal of multiple distributed PV plants sharing one PV IET. In this paper, a two-layer optimal configuration model is proposed to decide the optimal number and location of PV IETs with low cost and high reliability. To deal with the nonlinearity of the model, an adaptive hybrid gray wolf genetic algorithm is proposed, which can reduce the chance of falling into the local optimum, prevent the premature of the algorithm and improve the convergence speed of the algorithm. By comparing the results before and after the optimal configuration of two PV IET using schemes, the effectiveness and superiority of the model and algorithm are verified. The method proposed in this paper can realize that multiple distributed PV plants share one PV IET.

The model and algorithm proposed in this paper provide a reference for users of PV IET. However, the method in this paper may not be perfect, and there will inevitably be some problems in practical application. In the future, scholars can combine the practical problems in the large-scale use of PV IET, and continue the relevant research on the basis of the optimization configuration method in this paper, and propose a more comprehensive optimization configuration method.

Declaration of Competing Interest

None.

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Supplementary material

Leijiao Ge received Ph.D. degree in electrical engineering from Tianjin University, Tianjin, China, in 2016. He is currently a lecturer in the school of electrical and information engineering at Tianjin University. His main research interests are smart distribution network, cloud computing and big data.

Jiaheng Liu is pursing a master majoring in electrical engineering of Tianjin University. His research interests are distributed photovoltaic data collection and transmission.

Bo Wang received the Ph.D. degree in computer science from Wuhan University, Wuhan, China, in 2006. He did a Postdoctoral Research with the School of Electrical Engineering, Wuhan University, from 2007 to 2009, where he is currently a Professor with the School of Electrical Engineering. His research interests include power system online assessment, big data, integrated energy systems.

Yue Zhou received the B.S., M.S., and Ph.D. degrees in electrical engineering from Tianjin University, Tianjin, China, in 2011, 2016, and 2016, respectively. He is currently a Postdoctoral Research Associate with the School of Engineering, Cardiff University, Cardiff, U.K. His research interests include demand response, peer-to-peer energy trading and block-chain technology.

Jun Yan received the M.S. and Ph.D. (with Excellence in Doctoral Research) degrees in electrical engineering from the University of Rhode Island, USA, in 2013 and 2017, respectively. He is currently an Assistant Professor in the Concordia Institute for Information Systems Engineering, Concordia University, Montreal, Canada.

Ming Wang obtained the qualification of assistant engineer in 2017. Now he is the general manager of O&M department of Meteocontrol Electric Power Development Co., Ltd. His main research direction is intelligent PV system O&M technology.