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Reactive power convex optimization of active distribution network based on Improved Grey Wolf Optimizer

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Abstract: The smart grid concept is predicated upon the pervasive With the construction and development of distribution automation, distributed power supply needs to be comprehensively considered in reactive power optimization as a supplement to reactive power. The traditional reactive power optimization of a distribution network cannot meet the requirements of an active distribution network (ADN), so the Improved Grey Wolf Optimizer (IGWO) is proposed to solve the reactive power optimization problem of the ADN, which can improve the convergence speed of the conventional GWO by changing the level of exploration and development. In addition, a weighted distance strategy is employed in the proposed IGWO to overcome the shortcomings of the conventional GWO. Aiming at the problem that reactive power optimization of an ADN is non-linear and non-convex optimization, a convex model of reactive power optimization of the ADN is proposed, and tested on IEEE33 nodes and IEEE69 nodes, which verifies the effectiveness of the proposed model. Finally, the experimental results verify that the proposed IGWO runs faster and converges more accurately than the GWO.

Key words: active distribution network (ADN), Improved Grey Wolf Optimizer (IGWO), reactive power optimization, second-order cone relaxed convex model

1. Introduction

With the increasing attention to the economic and safe operation of power systems, how to reduce network losses, improved power quality, and improved economic efficiency have become practical problems faced by power researchers under the premise of ensuring safe and reliable operation of the system. Reactive power optimization of a distribution network refers to the rational distribution of reactive power by using various optimization algorithms, so as to achieve reactive power balance and ultimately reduce the active loss of the distribution network. The research on the reactive power optimization of an early distribution network mainly focuses on reactive power optimization intelligent algorithms, such as an artificial bee colony optimization algorithm [1], particle swarm optimization algorithm [2, 3], genetic algorithm [4] and so on. The emergence and development of distributed power sources pose new challenges to the reactive power optimization of distribution networks. As a supplement to the reactive power, distributed power supplies need to be considered in reactive power optimization. With the construction and development of distribution automation, research and demonstration of key technologies for an active distribution network (ADN), more and more active devices and controllable devices in distribution networks [5], and the automation level of distribution networks continuous improving.

In this paper, considering that the reactive power optimization of the ADN is a non-convex nonlinear problem, the reactive power distribution convex model of the ADN is established, and the model is convexly relaxed by the second-order cone relaxation (SOCP) technique. Then the IGWO algorithm is proposed to optimize the model and the simulation experiments are carried out in IEEE33 nodes and IEEE69 nodes. At the same time, compared with the standard The Grey Wolf Optimizer (GWO) algorithm, the effectiveness of the proposed algorithm under different distribution network scales is verified by experimental results.

The remainder of the paper is organized as follows: Section 2 discusses related literature work, Section 3 presents the reactive power optimization convex model and formulates the problem, Section 4 describes the GWO algorithm in detail and proposes the Improved Grey Wolf Optimizer (IGWO). The experimental results were analyzed in Section 5. Finally, Section 6 concludes the paper.

2. Literature work

Reactive power optimization of a distribution network needs new development, and an ADN provides new ideas and means for reactive power optimization of the distribution network. For example, distribution network reconstruction requiring fast communication and control technology [6]; demand side response of intelligent terminals, intelligent measuring instruments, and intelligent control technologies [7]; active and reactive power of distributed power sources according to the real-time operating state of the network real-time scheduling, etc. [8, 9]. At the same time, the ADN can also control the parallel capacitor switching and the on-load tap changer taps in real time and accurately. Yue Yang and Peishuai Li [10, 11] proposed an adaptive robust reactive power optimization model for the unbalanced distribution network caused by distributed generation (DG) power, which alleviated the overvoltage problem and reduced the control cost. However, this model does not consider the coordination of the DG with capacitors, transformers and other equipment. Under normal circumstances, the controlled equipment can be divided into continuous drinking discrete controllable devices. The discrete controllable devices are controlled by switches and should not be adjusted frequently due to their service life and existing manufacturing techniques. Therefore, the total running time of the discrete controllable devices is limited, which leads to the development of dynamic reactive power optimization (DRPO) models [12, 13]. Literature [14] proposed a two-stage multi-period mixed integer convex model, which analyzes the trade-off between risk mitigation and investment cost minimization. In the literature [15], based on the generalized Benders decomposition method, combined with the most conditional decomposition, a multi-period optimal reactive power flow model with voltage safety constraints is proposed. However, due to the large-scale multi-cycle mixed integer nonlinear programming problem, the amount of data increases, which increases the computational burden and time. Recently, the secondary relaxation technique has been studied in the distribution network, which gives a reasonable solution and significantly improves the computational performance [16, 17].

A swarm intelligence optimization algorithm is a new bionic algorithm based on the natural survival of the fittest and the special behavior of various biological groups. A number of scholars have tried to improve different optimization algorithms to form an improved intelligent optimization algorithm. The improved intelligent optimization algorithm could overcome the flaws in the original intelligent algorithm with satisfying results.

There is a considerate number of remarkable researches on the improved intelligent optimization algorithm. For example, [18] presents a new technique by hybridizing both the Whale Optimization Algorithm (WOA) and Bat Algorithm (BA), the experimental results show that compared with the WOA, the WOA-BA can achieve better results in fewer iterations. Shamsaldin A.S. [19] *et al*. imitate transportation behavior such as searching and selecting routes for movement by donkeys in the actual world and put forward the Donkey and Smuggler Optimization (DSO) Algorithm Then, the algorithm that is inspired by the bee swarming reproductive process, known as the fitness dependent optimizer (FDO), was developed by [20]. The results are compared with other modern algorithms and reveal that the FDO results show better performance in most cases and comparative results. In order to better handle the classification of employee's behavior, [21] modified particle swarm optimization with a neural network via the Euclidean distance, and the model produced satisfactory results. The Grey Wolf Optimizer (GWO) is a new group social intelligence heuristic technology that can simulate the social rank and hunting behavior of gray wolves in nature [22]. [23] proposed that because the GWO has a good balance between exploration and development, it successfully solved many optimization problems. [24] proposed a new hybrid evolutionary algorithm based on the GWO and the Bees Algorithm, the suggested hybrid method could be efficiently used for wide range problems of global optimization. The Inertia Constant Mean Grey Wolf Optimizer (ICMGWO) Algorithm was developed by S.B. Singh *et al*. [25] for improving search accuracy and convergence speed. In the literature [26], a hybrid model that includes a modified recurrent neural network with an adapted GWO is proposed to forecast students' outcomes, which has the better accuracy when compared with other models.

A great quantity of literature studies have proved that the swarm intelligence optimization algorithm has broad application prospects in all walks of life. Considering the shortcomings of the GWO algorithm, such as easily falling into local optimal solution and slow convergence speed, this paper proposes an improved GWO algorithm to solve the reactive power optimization convex model of an ADN.

3. Active distribution network reactive power optimization convex model

In this section, we introduced the reactive power optimization convex model for an ADN. Section 3.1 describes how to establish the model. In Section 3.2, the convex relaxation of the model is achieved by using SOCP technique.

3.1. Establishment of reactive power optimization model

A distribution network has the advantage of a topological network, so the distribution network power flow can be described by the branch flow formula [27–29]:

$$P_j = \sum_{k\in\delta(j)} H_{jk} - \sum_{i\in\pi(j)} \left(H_{ij} - r_{ij}L_{ij}\right), \quad \forall j \in B, \tag{1}$$

where, P_j is the injected active power of bus j, $\delta(j)$ is the set of bus lines of bus j, $\pi(j)$ is the bus set of bus j, H_{ij} is the active power flow of bus i to j, and r_{ij} is the branch. The resistance of $(i,\ j)$, l_{ij} is the branch current of the branch $(i,\ j)$.

$$Q_j = \sum_{k\in\delta(j)} G_{jk} - \sum_{i\in\pi(j)} \left(G_{ij} - x_{ij}l_{ij}\right) + b_{s.j}U_j^2, \quad \forall j \in B, \tag{2}$$

where, Q_j is the reactive power injected into bus j, G_{ij} is the reactive power flow of bus i to j, x_{ij} is the reactance of the branch $(i,\ j)$, and b_{ij} is the parallel susceptance of bus j to ground.

$$U_j^2 = U_i^2 - 2\left(r_{ij}H_{ij} + x_{ij}G_{ij}\right) + \left(r_{ij}^2 + x_{ij}^2\right) l_{ij}, \quad \forall (i,j) \in E\backslash\Theta. \tag{3}$$

Among them, U_j is the voltage amplitude of bus j, E is the branch set, and Θ is the transformer branch group.

$$\frac{U_j^2}{w_{ij}^2} = U_i^2 - 2\left(r_{ij}H_{ij} + x_{ij}G_{ij}\right) + \left(r_{ij}^2 + x_{ij}^2\right) l_{ij}, \quad \forall (i,j) \in \Theta, \tag{4}$$

where, w_{ij} is the branch $(i,\ j)$ transformer tap ratio.

$$H_{ij}^2 + G_{ij}^2 = l_{ij}U_i^2, \quad \forall (i,j) \in E. \tag{5}$$

The objective function is the minimum total network loss for T time periods:

$$\min_{Q_c(t),\rho(t),o(t)} \sum_{t=1}^{T} \sum_{(i,j)\in} \left(r_{ij}, l_{ij}(t)\right). \tag{6}$$

Among them, $Q_{c,(t)}$ is the capacitor running time, $\rho(t)$, $o(t)$ represent the optimal running time of the parallel capacitor and voltage, and T is the total running time.

The boundary constraints are as follows:

$$C_j(t) = C_j^{\min} + s_j\rho_j(t), \quad \forall j \in \Omega_D, \tag{7}$$

$$C_j^{\min} \le C_j(t) \le C_j^{\max}, \quad \forall j \in \Omega_D. \tag{8}$$

Then this paper adopts SOCP for convex relaxation [16, 17].

3.2. SOCP relaxation method of reactive power optimization model

Firstly, let

$$U_j^2(t) = vj(t), \quad \forall j \in B,$$

then constraints are as follows:

$$\frac{1}{2}v_j(t)C_j(t) + Q_{c,j}(t) - Q_{L,j}(t) = \sum_{k\in\delta(j)} G_{jk}(t) - \sum_{i\in\pi(j)} \left(G_{ij}(t) - x_{ij}l_{ij}(t)\right) + b_{s,j}v_j(t), \quad \forall j \in B, \;\; t = 1,\ldots,T. \tag{9}$$

Among them, the voltage square magnitude of v_j bus j:

$$v_j(t) = v_i(t) - 2\left(r_{ij}H_{ij}(t) + x_{ij}G_{ij}(t)\right) + \left(r_{ij}^2 + x_{ij}^2\right) l_{ij}(t), \quad \forall (i,j) \in E/\Theta, \;\; t = 1,\ldots,T, \tag{10}$$

$$\sum_{k=0}^{n_{ij}} \frac{O_{ij,k}(t)}{\left(\omega_{ij,k}\right)^2} v_j(t) = u_i(t) - 2\left(r_{ij}H_{ij}(t) + x_{ij}G_{ij}(t)\right) + \left(r_{ij}^2(t) + x_{ij}^2(t)\right) l_{ij}(t), \tag{11}$$

$$H_{ij}^2(t) + G_{ij}^2(t) = l_{ij}(t)v_i(t), \quad \forall (i,j) \in E, \tag{12}$$

$$\left(U_j^{\min}\right)^2 \le v_j(t) \le \left(U_j^{\max}\right), \quad \forall j \in B. \tag{13}$$

The constraint in (12) leads to a non-convex problem. In order to solve this problem, the second-order cone relaxation technique is adopted.

$$\left\| \begin{matrix} 2H_{ij}(t) \\ 2G_{ij}(t) \\ l_{ij}(t) - u_i(t) \end{matrix} \right\| \le l_{ij}(t) + v_i(t), \quad \forall (i,j) \in E. \tag{14}$$

Each integer variable $\rho_j(t)$ should be recombined into a combination of 0–1 binary variables. Since any integer has a unique binary code, the binary code of $\rho_j(t)$ can use the binary variable $\lambda_{j,0}(t)$, $\lambda_{j,1}(t)$, ..., $\lambda_{j,\tau j}(t)$ which means:

$$\rho_j(t) = 2^0\lambda_{j,0}(t) + 2^1\lambda_{j,1}(t) + \ldots + 2^{\tau j}\lambda_{j,\tau j}(t), \tag{15}$$

where $\lambda_{j,0}(t)$, $\lambda_{j,1}(t)$, ..., $\lambda_{j,\tau j}(t)$ are binary variables representing integer variables ρ_j with binary variables.

According to the boundary constraints of (7) and (8):

$$s_j\left(2^0\lambda_{j,0}(t) + 2^1\lambda_{j,1}(t) + \ldots + 2^{\tau j}\lambda_{j,\tau j}(t)\right) \le C_j^{\max} - C_j^{\min}. \tag{16}$$

By means of the Big-M method, can be linearized, so that:

$$\begin{cases} -M\left(1 - \lambda_{j,k}(t)\right) \le \sigma_{j,k}(t) - v_j(t) \le M\left(1 - \lambda_{j,k}(t)\right) \\ -M\lambda_{j,k}(t) \le \sigma_{j,k}(t) \le M\lambda_{j,k}(t), \quad \forall_j \in \Omega_D, \;\; k = 1,\ldots,\tau j \end{cases}. \tag{17}$$

Substituting (15) into:

$$\sum_{t=2}^{T} \left|\rho_j(t+1) - \rho_j(t) \le \eta_{c.j}, \quad \forall j \in \Omega_D,\right.$$

$$\sum_{t=2}^{T}\left|\sum_{k=0}^{\tau j} 2^k \left(\lambda_{j,k}(t+1) - \lambda_{j,k}(t)\right)\right| \le \eta_{c.j}\,, \quad \forall j \in \Omega_D\,. \tag{18}$$

According to the above formula, the reactive power optimization model can be changed to a standard 01 mixed integer second-order cone scheme:

$$\min_{Q_o(t),\,\lambda(t),\,\lambda_o(t)} \sum_{t=1}^{T} \sum_{i,j\in E} \left(r_{ij} l_{ij}(t)\right). \tag{19}$$

Among them, $\lambda(t) \in \{0,\ 1\}$, $o(t) \in \{0,\ 1\}$, $Q_C \in$ Continous.

4. Improved Grey Wolf Optimizer

In this section, we described how to improve the traditional GWO algorithm. Section 4.1 introduces the strategy of the traditional GWO algorithm. In Section 4.2, we use the weighted distance criterion to improve the performance of the GWO. Then, the computational complexity of the IGWO algorithm is analyzed in Section 4.3.

4.1. Traditional Grey Wolf Optimizer (GWO)

a. Surround the prey

The grey wolf hunts for prey. To simulate the surrounding behavior, the gray wolf algorithm updates the position by:

$$D_i = \left|C_i \cdot X_p(t) - X_i(t)\right|, \tag{20}$$

$$X_i(t+1) = X_p(t) - A_i \cdot D_i\,, \tag{21}$$

where t is the current number of iterations, X_i indicates the position of the gray wolf in the search space, and X_p indicates the position of the prey. The vectors A_i and C_i are calculated as follows:

$$A_i = 2a \cdot r_1 - a, \tag{22}$$

$$C_i = 2 \cdot r_2\,, \tag{23}$$

$$a = 2 - 2t/t_{\max}\,, \tag{24}$$

where A_i and C_i are the coefficient vectors, r_1 and r_2 are the random parameters in [0, 1], and a is a number that linearly decreases from 2 to 0.

b. Prey on prey

In order to search for the best position of the prey, it is assumed that the first three wolves (α, β and δ) have better information on the location of the potential prey, so each wolf can update their position according to the best search agent:

$$D_\alpha = |C_1 \cdot X_\alpha(t) - X_i(t)|\,, \tag{25}$$

$$D_\beta = \left|C_2 \cdot X_\beta(t) - X_i(t)\right|, \tag{26}$$

$$D_\delta = \left|C_3 \cdot X_\delta(t) - X_i(t)\right|, \tag{27}$$

$$X_1 = X_\alpha(t) - A_1 \cdot D_\alpha, \tag{28}$$

$$X_2 = X_\alpha(t) - A_2 \cdot D_\beta, \tag{29}$$

$$X_3 = X_\delta(t) - A_3 \cdot D_\delta, \tag{30}$$

$$X_i(t+1) = (X_1 + X_2 + X_3)/3, \tag{31}$$

where X_α, X_β, X_δ represent the positions of the first three optimal waves, and X_i is the position of the current solution.

4.2. Improved Grey Wolf Optimizer (IGWO)

According to 3.1, when the random value of A is $[-1,\ 1]$, the gray wolf attacks the prey, the local search process begins. When $A > 1$, the wolves are forced to conduct a global search. According to Equation (24), as the number of iterations increases, the parameter a decreases linearly from 2 to 0, which reduces the convergence speed of the algorithm.

$$a = \xi \exp(-\theta \cdot k), \tag{32}$$

where ξ and θ are two parameters that control the convergence characteristics of each point when the GWO algorithm is iterated k times.

(31) is weighted in each iteration and can be re-described as follows:

$$\omega_1 = A_\alpha \cdot C_\alpha, \quad \omega_2 = A_\beta \cdot C_\beta, \quad \omega_3 = A_\delta \cdot C_\delta, \tag{33}$$

$$X(k+1) = \frac{\omega_1 \cdot X_1 + \omega_2 \cdot X_2 + \omega_3 \cdot X_3}{\omega_1 + \omega_2 + \omega_3}. \tag{34}$$

4.3. Computional complexity analysis

The computational complexity of the proposed improved GWO is discussed as follows: firstly, calculating the fitness value f_i of N gray wolf individuals requires N operations, and the complexity of the fitness function is $O(D)$, the individuals who select the top three fitness values need at most $3N-3$ operations, recording the optimal solution X_α and the number of operations plus one. Next, calculating the distance between the remaining individuals ω and X_α, X_β, X_δ according to Equations (25)–(27) requires $3(N-3)$ perations, updating the position of the wolf and prey needs $3D+1$ calculation according to (28)–(31). Afterwards, for the entire gray wolf population, calculating the distance between the gray wolves requires at most $\dfrac{N(N-1)}{2}$ operations. At last, since the algorithm performs at most t times (t is the set maximum number of iterations), the time complexity of the algorithm is approximately

$$o\left[t \cdot (D+2) \cdot \frac{N(N-1)}{2}\right] \approx o\left[\frac{N^2 Dt}{2}\right]$$

by approximating and simplifying the calculation.

5. Results analysis

In this section, the proposed algorithm is simulated on the IEEEE33 node distribution network and the IEEE69 node power distribution system.

The total active load of the IEEE33 node system is 3715.0 kW, the total reactive load is 2 300 kvar, the node voltage threshold is 0.95–1.05 pu, and the rated normal operation capacity of the branch is 5 MVA. The voltage at the 17-node is greatly branched and the voltage reaches the lowest value. Therefore, the distributed generation (DG) power supply is installed here to improve the reactive power support. The DG rated capacity is 800 kW, and the power factor is adjustable from −0.95 to 0.95. The total active load of the IEEE69 node system is 3802.19 kW, the total reactive power is 2694.60 kvar, the node voltage standard value is 0.95–1.05 pu, and the rated normal operation capacity of the branch is 5 MVA. The capacitors are installed at three nodes of 18, 47, and 52. Each node is installed with up to ten groups of 50 kvar each. The DG access points are 26, 49, 68 to improve reactive support.

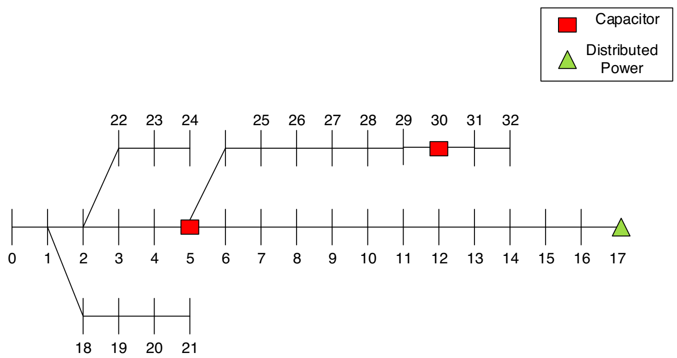

Fig. 1. Improved 33 bus test system

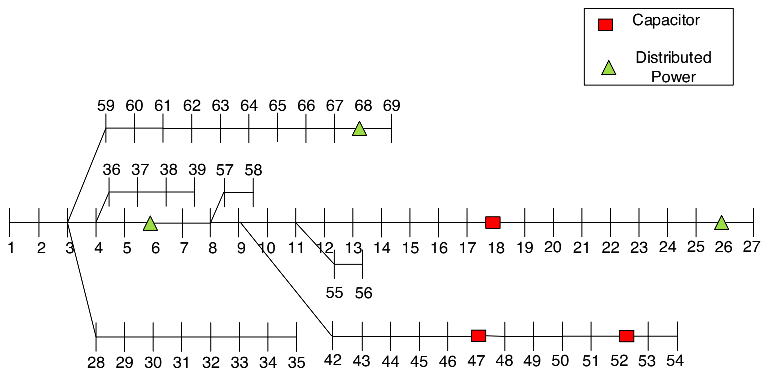

Fig. 2. Improved 69-node test system

The program code is written in Matlab 2014 software, running on a microcomputer with Intel Celeron G550, 2.6 GHz CPU, and 2 GBRAM. The selected parameters are adjusted to be:

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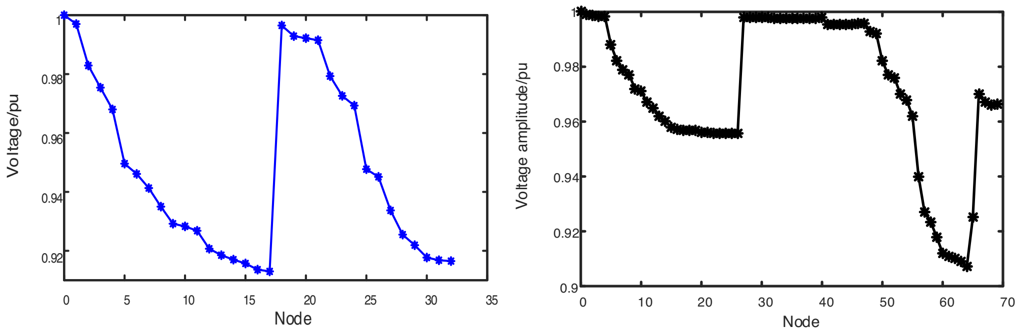
the maximum number of iterations $t_{\max} = 100$, the population number is 50, and the allowable voltage limit 0.9, 1.05 pu.

Table 1 shows the evaluation between the standard GWO and IGWO in terms of the best fitness function, standard deviation, and average fitness function. It can be seen that the standard deviation of the IGWO is obviously smaller than that of the GWO, so the IGWO algorithm is more stable.

Table 1. The evaluation between GWO and IGWO

	GWO	**IGWO**
Best fitness function	$f_{11}(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	$f_{21}(x) = \sum_{i=1}^{n} (\lvert x_i + 0.5 \rvert)^2$
Average fitness function	$f_{12}(x) = \sum_{i=1}^{n} x_i^2$	$f_{21}(x) = \max_{1} \{ \lvert x_i \rvert,\ 1 \le i \le n \}$
Standard deviation	0.2755	0.0551

In this experiment, the original network power flow calculation (ONPFC) has no capacitor and the distributed generation (DG) power supply in the network, as well as the transformer tap position is 0. DG-free reactive power optimization (NDGRPO) is the traditional reactive power optimization, it changes the capacitor switching amount and transformer gear position to achieve the minimum network loss; fixed DG reactive power optimization (FDGRPO) is the initial smart grid reactive power optimization, the DG is added to the network, but the DG output is fixed. The ADN reactive power optimization (ADNRPO) includes the simulation results of all the active management measures mentioned above. They are in Table 1.



(a) 33-node network power flow calculation voltage distribution curve

(b) 69-node network power flow calculation voltage distribution curve

Fig. 3. Curve of voltage distribution calculation of original network power flow of different nodes in IEEE

It can be seen from Table 2 that on the IEEE33 node system, the ADNRPO is reduced by 5.96% compared with the FDGRPO, which is 65.85% lower than the traditional reactive power optimization network loss. It can be seen from Table 2 that at the IEEE69 node, the ADNRPO loss is 17.06% lower than the loss with the FDGRPO, which is 70.87% lower than that of the NDGRPO. It can be seen that the IGWO algorithm has a better effect on reactive power optimization in the large-node system, lower network loss, and gives better results.

Table 2. IGWO optimization results in different reactive power optimization methods (33-node system)

Reactive power optimization	**Network loss/kW**	**Capacitor switching/kvar**		**Transformer gear**
		Node 5	**Node 30**	
ONPFC	200.612	Null	Null	Null
NDGRPO	111.35	450	450	+4
FDGRPO	40.291	450	350	+4
ADNRPO	38.026	400	300	+4

Table 3. IGWO algorithm optimization results in different reactive power optimization methods (69-node system)

Reactive power optimization	**Network loss/kW**	**Capacitor switching/kvar**			**Transformer gear**
		Node 18	**Node 47**	**Node 52**	
ONPFC	224.999	Null	Null	Null	Null
NDGRPO	148.386	450	450	450	+5
FDGRPO	52.112	450	350	350	+4
ADNRPO	43.218	400	300	350	+5

This paper proposes the following four specific optimization strategies to conduct experiments, and verify the validity of this model by narrowing the difference between the proportions of each optimization strategy. $P_0 = [0, 0, 0]$ (original network); $P_1 = [0.7, 0.2, 0.1]$ (lower level of system intelligence); $P_1 = [0.5, 0.3, 0.2]$ (the level of system intelligence has improved); $P_1 = [1/3, 1/3\ 1/3]$ (the system reaches the level of ADN intelligence). It can be seen from Fig. 4. that although the DG is added, in the case of P_1 and P_2, the DG reactive support is insufficient, resulting in low voltage under P_1 and P_2; the adjustment of P_1 and P_2 optimization strategies is basically the same, mainly capacitors. With the transformer, the two voltage curves do not change much; P_3 is a combination of three optimization strategies, the specific gravity is equal, and the voltage of each node is greatly improved.

Fig. 5 shows that the ADNRPO loss is only 17.06% lower than the loss with the FDGRPO, so the voltage difference between the two curve nodes is not large. The node voltage of the original network appears to be out of limits, and other reactive power optimization methods can ensure that the voltage is within the constraint range.

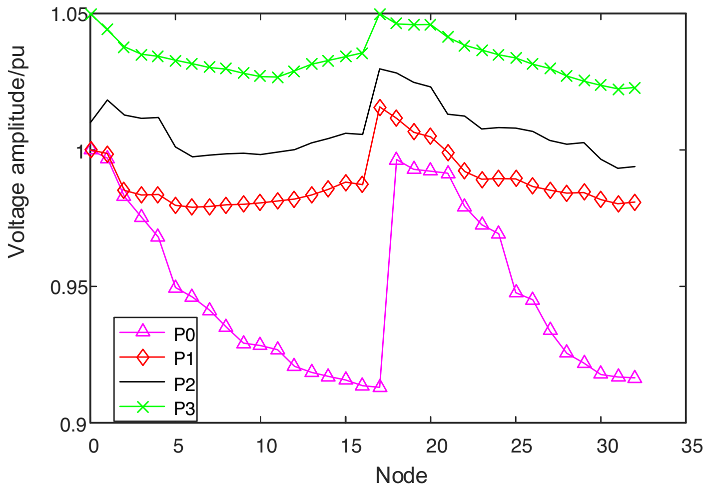


Fig. 4. Voltage distribution curve of 33 nodes with different optimization strategies

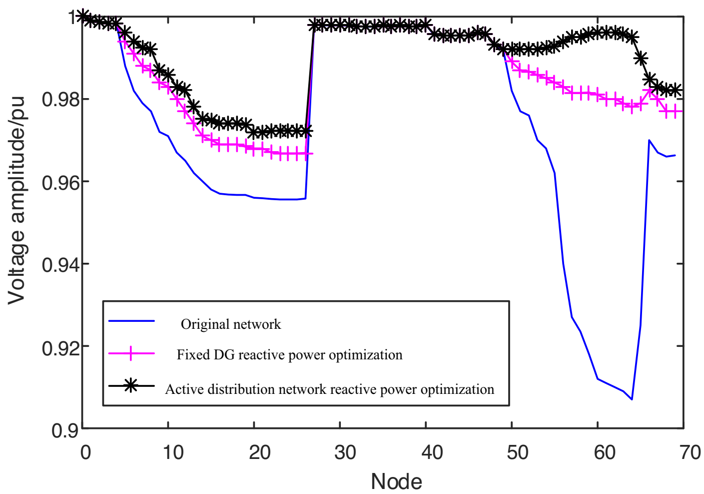


Fig. 5. Voltage distribution curve of IGWO algorithm under different reactive power optimization modes (69 nodes)

Table 4 shows that when $Q_{DG.\max}$ = 1400 kvar, the DG reactive power is less than the maximum value, and there is no out of bounds; when $Q_{DG.\max}$ = 800 kvar, the DG reactive power is close to the upper limit, and when $Q_{DG.\max}$ = 600 kvar, the DG reactive power appears to be out of bounds. From the voltage amplitude of the DG access node, it can be seen that as $Q_{DG.\max}$ gradually decreases, the voltage amplitude of the DG access node value is also gradually decreasing, indicating that the DG reactive support is reduced. As can be seen from Fig. 6, as $Q_{DG.\max}$ decreases, the node voltage level of the entire system is decreasing.

Table 4. Reactive power optimization results when DG reactive power $Q_{DG.\max}$ is different

Q_{DG}/kvar	DG active kW/no use kvar output (maximum)	System network loss/kW	DG access node voltage amplitude/pu (6/26/68)
1400	1401.5/1056.3	43.218	(0.9800/0.9517/0.9811)
800	1281.3/798.6	59.694	(0.9773/0.9486/0.9778)
600	959.3/600	71.226	(0.9591/0.9412/0.9600)

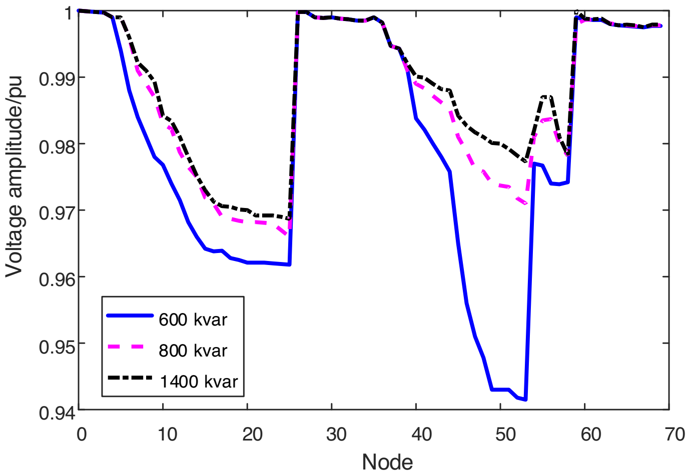
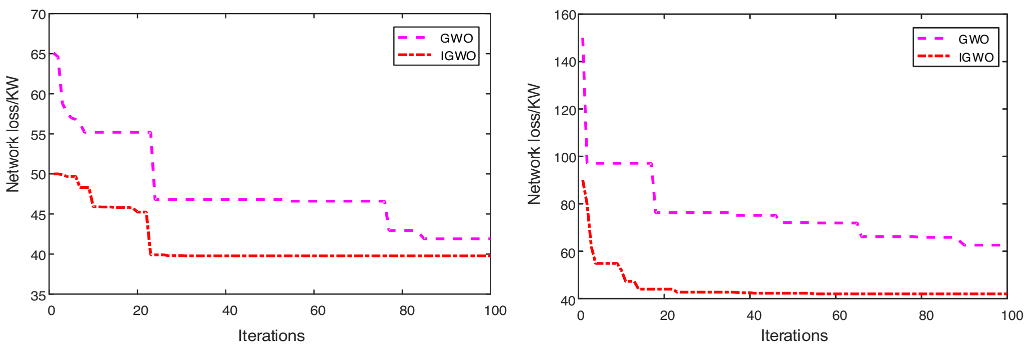


Fig. 6. Node voltage distribution when DG reactive power $Q_{DG.\max}$ is different

It can be seen from the Fig. 7 that the objective function does not suddenly oscillate. The lower stationary convergence to the optimal solution proves the reliability of the proposed method.



(a) 33 node convergence graph of IGWO and GWO

(b) 69 node convergence graph of IGWO and GWO

Fig. 7. Comparison of convergence between the proposed algorithm and the original algorithm on different node systems

Also, the IGWO has fewer iterations than the original GWO, because the IGWO uses an improved exploration-development balance to accelerate the convergence of the algorithm.

Table 5 shows that in the IEEE33 node system, the running time of the IGWO is 17.54% faster than that of the GWO, while in the IEEE69 node system, the running time of the IGWO is 22.28% faster than that of the GWO, which shows that the IGWO can be applied to a large node system.

Table 5. The running time of algorithms for different node systems (/h)

Algorithm	**IEEE33 node system**	**IEEE69 node system**
GWO	33.23	51.4
IGWO	27.4	40

In summary, it can be seen from the experimental results that the stability of an IGWO algorithm is better than that of the traditional GWO algorithm, and when running on the same node system, the IGWO converges faster and has fewer iterations. In addition, the running time of the IGWO algorithm is obviously faster than that of the GWO algorithm on large-node system. Therefore, the IGWO algorithm proposed in this paper has better performance in the reactive power optimization of an ADN.

6. Conclusions

In this paper, the Gray Wolf Optimization algorithm is improved, then the improved GWO algorithm and the Statistical Online Computational Resource (SOCR) is applied to solve the ADN reactive power optimization model established in the previous paper. The advantages of a weighted distance strategy have been used in an IGWO algorithm to create the balancing between the exploration and exploitation process. Finally, the simulation results verify the effectiveness of the proposed method.

At the moment, there are some limitations of the proposed IGWO algorithm. For example, the efficiency and robustness of the algorithm in solving other optimization problems have not been verified and its running speed needs to be further improved. In the future, the parallelization method can be used to improve the running speed of the algorithm. Then the improved method could be applied to power optimization problems with larger data and faster operation speed.

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