Research on Multi-Objective Reactive Power Optimization of Power Grid With High Proportion of New Energy

YU LINLIN¹, ZHANG LIHUA¹, MENG GAOJUN², ZHANG FENG², AND LIU WANXUN¹

¹State Grid Henan Electric Power Economic and Technological Research Institute, Zhengzhou 450052, China
²School of Electric Power Engineering, Nanjing Institute of Technology, Nanjing 211167, China

Corresponding author: Meng Gaojun (gjun_m@126.com)

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ABSTRACT The integration of large-scale wind power and photovoltaics into the power system will aggravate the voltage fluctuation of grid nodes, while when the reactive power of new energy units participates in the optimization of reactive power and voltage of the system, it will promote the consumption of new energy while effectively improving the stable operation level of the system. In this work, the grey wolf algorithm (GWO) of entropy weight is introduced to solve the optimal compromise solution of multi-objective reactive power optimization of transmission network, and the network loss and voltage deviation and static voltage stability margin are taken as three objective functions to evaluate and make use of the reactive power regulation performance of new energy units. Specifically, the cooperative optimization of reactive power regulation performance of wind turbine and photovoltaic generating set and reactive power compensation of original power system is adopted, the efficient GWO) is incorporated to solve the multi-objective reactive power optimization model, the entropy method is introduced to obtain the optimal compromise solution of reactive power optimization, and a numerical example is analyzed by using IEEE39 transmission network system. Simulation results confirmed that the proposed multi-objective reactive power and voltage optimization model and grey wolf optimization algorithm can effectively improve the system node voltage quality and improve the stable operation level of the system.

INDEX TERMS New energy consumption, voltage fluctuation, multi objective optimization, reactive power compensation.

I. INTRODUCTION

Currently, the rapid development of distributed power sources such as wind power and photovoltaics is showing a blowout growth, which affects the safe and stable operation of the grid after grid connection to a certain extent [1], [2]. The randomness and volatility of new energy output will inevitably affect the power flow distribution of the power grid and the safe and stable operation of the system, and then affect the network loss and power quality of the power system [3].

Considering the connection of new energy sources such as wind power, optoelectronics and traditional reactive power compensation devices to the system, the reactive power optimization of the system becomes a complex, non-convex nonlinear mixed integer programming problem with discrete variables [4], [5]. The power grid with wind turbines and photovoltaic units carries out reactive power optimization to improve the power utilization rate of wind power and photovoltaic units, at the same time, it can effectively reduce the active power loss of the power grid and alleviate the unstable operation caused by the access of new energy to the grid, so as to ensure the safe and stable operation of the power grid and improve the absorption capacity of new energy, which indirectly indicates that it is of great significance to study the reactive power optimization of the power grid with a high proportion of new energy. In [6], the multi-objective reactive
power optimization model of power grid with high proportion of wind farms and photovoltaic power plants is solved by multi-objective sea sheath group algorithm, and the compromise solution of reactive power optimization is selected by using bottle sea sheath group algorithm and improved ideal point method. However, it does not compare the reactive power optimization of the combination of new energy unit reactive power compensation and traditional reactive power compensation. In reference [7], a multi-objective moth algorithm is proposed to solve the reactive power optimization problem of power system. Based on the single-objective moth algorithm, it adds fixed storage, adaptive grid and screening mechanism to effectively store and enhance the non-dominant solution of the reactive power optimization problem of the power system, but it does not consider the variable ratio tap between the new energy unit and the transformer of the transmission network. In [8], the reactive power optimization of distribution network with distributed energy is carried out to improve the voltage quality of the system and improve the capacity of new energy consumption. In [9], the influence of the capacity and geographical location of new energy units on power grid operation is considered, and the risk operation and economic benefits of new energy units connected to the power grid are evaluated. Intelligent algorithm is used to solve multi-objective functions such as operation stability and economic benefits, but the effects of network loss and voltage deviation on the stable operation of the system are not analyzed in detail. In reference [10], [11], [12], [13], considering the randomness of scenery, an intelligent optimization algorithm for multi-objective reactive power optimization of main distribution network to improve the voltage level of distribution network is proposed based on clustering algorithm to generate optimal scenarios and combined with the effect of energy storage device compensation on reactive power optimization. Literature [14] employs a positive distribution crossover algorithm and an improved adaptive mutation NSGA-II algorithm to solve the two-objective optimization, which only considers two reactive power targets: voltage deviation and power loss. In addition, NSGA-II algorithm is vulnerable to local optimization and has deficiencies in the number of iterations, convergence and reliability.

In this work, the GWO of entropy method is introduced to solve the optimal compromise solution of multi-objective reactive power optimization of transmission network. Taking the network loss, voltage deviation and static voltage stability margin as three objective functions, the reactive power optimization problem of transmission network with new energy power stations is studied by evaluating and making use of the reactive power regulation performance of new energy units, and the multi-objective GWO with efficient optimization performance is used to solve the problem. It is known that GWO has been used in many fields to solve nonlinear optimization problems [15]. In solving the reactive power optimization model of transmission network, the detailed application process of GWO for reactive power optimization is given. A GWO with entropy weight is used to solve the multi-objective reactive power optimization, and compared with the traditional intelligent optimization algorithm, the improved IEEE39 node system is simulated and tested. Simulation results confirm the advantages of GWO in the number of iterations and optimization ability.

II. REACTIVE POWER REGULATION MODEL OF NEW ENERGY GRID CONNECTION

With the advantages of mature power generation technology, convenient installation and clean and environmental protection connection, wind power generation and photovoltaic power generation fully evaluate their reactive power regulation performance and optimize reactive power to promote the safe and stable operation of the power grid.

A. REACTIVE POWER OUTPUT MODEL OF WIND TURBINE

Taking the reactive power control model of wind turbine described by doubly fed induction fan as an example, the input mechanical power $P_m$ of the fan mainly depends on the wind speed, and the active power input $P_g$ of the fan to the power grid is also affected by it [16], [17]. The mechanical power obtained by the fan is as follows:

$$P_m = \frac{1}{2} \rho \pi R^2 C_p(\lambda, \beta) v_w^3$$

where, $\rho$ represents the air density, $R$ represents the radius of the wind turbine, $v$ represents the current wind speed, and $C_p(\lambda, \beta)$ represents the power coefficient related to the tip speed ratio $\lambda$ and the pitch angle $\beta$.

Now, the active power output of the fan is tracked and controlled according to the maximum power point, and the active power input to the power grid can be calculated according to the current wind speed, as shown in Eq. (2).

$$P_g = \begin{cases} 0, & v < v_{in}, v > v_{out} \\ P_w, & v_{in} \leq v < v_N \\ P_w, & v_N \leq v \leq v_{out} \end{cases}$$

where, $v_{in}$, $v_{out}$, $v$ and $v_N$ represent cut-in wind speed, cut-out wind speed, current wind speed and rated wind speed; $P_w$ represents the rated output power of the fan. The active power input by the fan to the power grid is determined by Eq. (2).

The reactive power regulation range of doubly fed fan mainly depends on the reactive power regulation ability of stator-side converter and grid-side converter. When considering the reactive power output of the doubly fed fan, the reactive power limits of both the stator side and the grid side [18] should be considered as shown in the following formula.

$$P_g + (Q_g + \frac{3U_s}{2X_s})^2 \leq (\frac{3X_m}{2X_s} U_s I_s)_{\text{max}}^2$$

$$P_e^2 + Q_e^2 \leq S_w^2$$

where, $P_g$ and $Q_g$ represent the active and reactive power on the stator side of the fan, $U_s$ represents the effective
value of the stator voltage, $X_r$ and $X_m$ represent the stator leakage reactance and excitation reactance respectively, $I_{max}$ represents the maximum specified current on the rotor side, $P_r$ and $Q_r$ represent the active and reactive power capacity of the grid side converter, and $S_w$ represents the grid side converter capacity.

The reactive power regulation range of the wind farm is calculated based on the wind speed meteorological information and combined with the wind turbine grid-connected converter and the stator side converter.

B. REACTIVE POWER OUTPUT MODEL OF PHOTOVOLTAIC GENERATOR SET

For the DC output of the photovoltaic module, the photovoltaic power station is connected to the power grid through the inverter. In order to realize the effective use of light energy, the photovoltaic inverter adopts maximum power point tracking control. The output power of the photovoltaic array mainly depends on the current weather conditions such as sunshine and temperature, and its active power output $P_{pv}$ can be calculated as shown in Eq. (5).

$$ P_{pv} = P_{N}^{pv} \left[ 1 + \alpha_{pv} \cdot (T - T_{ref}) \right] \cdot \frac{S_{pv}}{1000} $$  \hspace{1cm} (5)

where and $P_{N}^{pv}$ represent the rated power of the photovoltaic power station; $\alpha_{pv}$ represents the temperature conversion power coefficient of photovoltaic; $T$ represents the current temperature; $T_{ref}$ represents the reference value of temperature; and $S_{pv}$ represents the light intensity.

When the grid-connected inverter adopts maximum power point tracking control, the reactive power output of photovoltaic power station is as follows Eq. (6):

$$ |Q_{pv,\text{max}}| = \sqrt{(S_{pv})^2 - (P_{pv})^2} $$  \hspace{1cm} (6)

where, $|Q_{pv,\text{max}}|$ represents the maximum reactive power that can be generated and absorbed by the photovoltaic power station; $S_{pv}$ represents the capacity of the photovoltaic inverter [19], [20].

C. REACTIVE POWER OPTIMIZATION MODEL CONSIDERING GRID RANDOMNESS

The state estimation is carried out at intervals of 0.5min~1min. Due to the fluctuation of power system, there is a certain random deviation of reactive power and voltage. Therefore, this work needs to deal with the fuzziness of load power and voltage reactive power.

First, a load uncertainty model is established, as shown in Eq. (7):

$$ P = P_0 \left[ a_p \left( \frac{V}{V_0} \right)^2 + b_p \left( \frac{V}{V_0} \right) \right] $$

$$ Q = Q_0 \left[ a_q \left( \frac{V}{V_0} \right)^2 + b_q \left( \frac{V}{V_0} \right) \right] $$  \hspace{1cm} (7)

where, $a_p + b_p = 1$, $a_q + b_q = 1$. $P_0$, $Q_0$ and $V_0$ represent rated active power, rated reactive power and rated voltage, respectively; $P$, $Q$ and $V$ represent actual active power, actual reactive power and actual voltage, respectively.

The theoretical calculation results of the assumed voltage amplitude. The deviation from the actual value obeys the normal distribution with the mean value 0 and the standard deviation $\sigma$, from which the probability density of the actual load is obtained as follows:

$$ f(V) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(V-V_0)^2}{2\sigma^2}} $$  \hspace{1cm} (8)

It is assumed that the probability of occurrence of this condition is $\lambda_2$. Combined with the above two formulas, the expected values of active power and reactive power of the load under this condition can be obtained.

Then, the uncertainty model of generator is established. For PV nodes, the terminal voltage can be calculated by the following formula:

$$ V = V_{for} + \Delta V $$  \hspace{1cm} (9)

where, $\Delta V$ represents the amount of voltage change. Similarly, the probability density of the actual terminal voltage can still be expressed based on Eq. (8). Assuming that the occurrence probability of this condition is $\lambda_2$, the combined Eq. (9) can calculate the expected value of the terminal voltage of the PV node.

Finally, the occurrence probability of each common working condition is solved. The probability distribution function is divided into 7 segments, the probability sum is 1, and the width of each interval is the standard deviation. Based on Monte Carlo random sampling method, the normalized probability $\rho_r(s)$ in the $s$-th scenario is obtained as follows:

$$ \rho_r(s) = \left[ \frac{\sum_{e=1}^{7} (W_{e,s}^L \alpha_e) \sum_{g=1}^{7} (W_{g,s}^R \alpha_g)}{\sum_{s=1}^{N} \sum_{e=1}^{7} (W_{e,s}^L \alpha_e) \sum_{g=1}^{7} (W_{g,s}^R \alpha_g)} \right] [0, 1] $$  \hspace{1cm} (10)

where, $e$ represents the number of load segments, $W_{e,s}^L$ and $\alpha_e$ represent the error interval and error interval probability of the $e$-th load, and $W_{g,s}^R$ and $\alpha_g$ represent the error interval and error interval probability of the $g$ PV nodes, respectively.

III. MULTI-OBJECTIVE REACTIVE POWER OPTIMIZATION MODEL

The reactive power optimization model is the basis for the study of reactive power optimization of power grid. The main purpose of reactive power optimization is to maintain the safe and stable operation of power grid. In this paper, a reactive power optimization model of transmission network with cooperative regulation of reactive power of shunt capacitors and new energy units is established.
A. OBJECTIVE FUNCTION

\[
\begin{align*}
\min F_1(X_1, X_2) & = \sum_{i,j \in N} g_{ij}(V_i^2 + V_j^2 - 2V_iV_j \cos \theta_{ij}) \\
\min F_2(X_1, X_2) & = \sum_{j \in N} (V_j - V^*_{\text{ref}})^2 \\
\max F_3(X_1, X_2) & = 1/\delta_{\text{min}}
\end{align*}
\]

The objective function \( F_1, F_2 \) and \( F_3 \) of the multi-objective reactive power optimization of the transmission network. The optimization results of the objective function can reduce the power line loss, reduce the voltage deviation and keep the system node voltage within the prescribed range. And improve the static voltage stability margin. \( X_1 \) represents optimization variables including generator port voltage, transformer tap stop, shunt capacitor reactive power and new energy unit reactive power. \( X_2 \) represents non-generator node voltage, system node power, etc., \( V_i \) represents the voltage amplitude of node \( i \), \( V_j \) is the voltage amplitude of node \( j \), and \( \theta_{ij} \) represents the phase angle difference between node \( i \) and \( j \), respectively; \( g_{ij} \) represents the admittance between node \( i \) and \( j \), \( \delta_{\text{min}} \) represents the minimum singular value of the Jacobian matrix of the system; \( N_I \) and \( N_B \) represent the number of nodes and branches.

B. CONSTRAINT CONDITION

The multi-objective nonlinear reactive power optimization model mainly considers equality constraints and inequality constraints.

1) EQUALITY CONSTRAINT CONDITION

\[
\begin{align*}
P_{Gi} - P_{Li} & = V_i \sum_{j=1}^{m} V_j (g_{ij} \cos \theta_{ij} + b_{ij} \sin \theta_{ij}) \\
Q_{Gi} - Q_{Li} & = V_i \sum_{j=1}^{m} V_j (g_{ij} \sin \theta_{ij} + b_{ij} \cos \theta_{ij})
\end{align*}
\]

where, \( P_{Gi} \) and \( P_{Li} \) represent the active power injected by node \( i \) and the active power consumed by load, \( Q_{Gi} \) and \( Q_{Li} \) represent the reactive power injected by node \( i \) and reactive power consumed by load, and \( b_{ij} \) represents the admittance of branch \( ij \).

2) INEQUALITY CONSTRAINTS

Inequality constraints include generator constraints, voltage regulating transformer constraints, shunt capacitor constraints and line voltage and current constraints.

\[
\begin{align*}
V_{i_{\text{min}}} \leq V_i \leq V_{i_{\text{max}}} \\
S_{i_{\text{min}}}^1 \leq S_i^1 \leq S_{i_{\text{max}}}^1 \\
P_{i_{\text{min}}}^l \leq P_i^l \leq P_{i_{\text{max}}}^l \\
Q_{i_{\text{min}}}^l \leq Q_i^l \leq Q_{i_{\text{max}}}^l \\
T_{k_{\text{min}}} \leq T_k \leq T_{k_{\text{max}}}
\end{align*}
\]

where, \( V_{i_{\text{min}}} \) and \( V_{i_{\text{max}}} \) represent the minimum and maximum allowable voltage at node \( i \), respectively. \( T_{k_{\text{min}}} \) and \( T_{k_{\text{max}}} \) represent the maximum and minimum of the transformer ratio, \( S_{i_{\text{min}}}^1 \) and \( S_{i_{\text{max}}}^1 \) represent the active power lower limit and upper limit of the balance node, \( P_{i_{\text{min}}}^l \) and \( P_{i_{\text{max}}}^l \) represent the active power lower limit and upper limit of node \( i \) respectively, and \( Q_{i_{\text{min}}}^l \) and \( Q_{i_{\text{max}}}^l \) represent the reactive power lower limit and upper limit of node \( i \) respectively.

IV. GWO APPLICATION REACTIVE POWER OPTIMIZATION SOLUTION

A. BASIC PRINCIPLES OF GWO

GWO is a new swarm intelligence optimization algorithm proposed by Mirjalili et al. by simulating the hierarchical relationship and hunting behavior of GWO, the algorithm has strong detection ability, simple operation, few parameters to be set, good performance and can avoid local optimization [21], [22].

Gray wolves are social animals and have hierarchical relationships. Gray wolves are divided into four grades, namely \( \alpha \) wolf, \( \beta \) wolf, \( \gamma \) wolf and \( \omega \) wolf, corresponding to the optimal solution, optimal solution, suboptimal solution and searcher of the optimization algorithm. The first three types are the first wolf, and \( \omega \) is the lowest gray wolf population.

![FIGURE 1. Schematic diagram of hunting position of GWO gray wolf.](image)

Formula for encircling prey:

\[
D = |C \cdot O_p(t) - O(t)|
\]

\[
O(t + 1) = O_p(t) - A \cdot D
\]

In Eq. (14), \( D \) represents the distance between the hunting position of the gray wolf and the position of the prey; \( t \) represents the current iterative time; \( A \) and \( C \) represent the coefficient of cooperation; \( O_p \) represents the location of the prey; \( C = 2r_2 \) and \( A = 2ar_1 - 1 \) determine that \( A \) and \( C \), \( O \) are the hunting position of the gray wolf, \( \alpha \) is the convergence factor, and \( r_1 \) and \( r_2 \) are random values on \([0, 1]\).

In each iteration of GWO hunting, the whole wolf pack is dominated by \( \alpha \), \( \beta \) and \( \gamma \) wolves, and the other gray wolves are \( \omega \), and the position of continuous renewal is close to \( \alpha \), \( \beta \) and \( \gamma \) populations. The iterative optimization process of
the algorithm:

\[
\begin{align*}
D_α &= |C_1 \cdot O_α - O| \\
D_β &= |C_2 \cdot O_β - O| \\
D_γ &= |C_3 \cdot O_γ - O| \\
O_1 &= O_α - A_1 \cdot (D_α) \\
O_2 &= O_β - A_2 \cdot (D_β) \\
O_3 &= O_γ - A_3 \cdot (D_γ)
\end{align*}
\]  

where, \(D_α, D_β, \) and \(D_γ\) represent the distances between \(α, β, \) and \(γ\) head wolves and their prey respectively, \(O_α\) represents the position of \(α\) head wolf, \(O_β\) represents the position of \(β\) head wolf, \(O_γ\) represents the position of \(γ\) head wolf, \(A_1, A_2, A_3\) and \(C_1, C_2, C_3\) represent random values, and \(O\) represents the current position of the next optimized \(ω\) wolf.

\[
O(t + 1) = \frac{O_1 + O_2 + O_3}{3}
\]

where, \(O(t + 1)\) represents the location of the next optimized \(ω\) wolf.

### B. NON-DOMINANT SOLUTION AND OPTIMAL COMPROMISE SOLUTION OF MULTI-OBJECTIVE FUNCTION

GWO algorithm is used to solve the reactive power optimization problem of power system, and its purpose is to reduce the network loss, reduce the voltage deviation and improve the static voltage stability margin of the power system. In the process of applying the algorithm to solve the multi-objective reactive power optimization function, it mainly solves the storage of non-dominant solution set, control variables, fitness function and optimal compromise solution selection [23].

- a) Introduce fast non-dominant sorting and individual exclusion mechanisms.
- All the solutions of the current population are ranked quickly, and the ones closest to the Pareto frontier are liberated into the solution set. After iterative update, the solution closest to the Pareto front is stored in the solution set repeatedly, and the solution in the final solution set is the optimal Pareto solution set. The individual exclusion mechanism is established, and the over-dense solution is screened by calculating the individual density of the solution, so as to improve the uniformity and extensiveness of the Pareto solution set distribution, so as to improve the global optimization ability and efficiency of the algorithm. By judging the distance between the objective function \(x_i\) and \(x_j\), the objective function distance needs to meet the following conditions. Monte Carlo sampling is used to eliminate some non-dominant solutions based on the number of solution sets.

\[
\begin{align*}
|f_h(x^i) - f_h(x^j)| < D_h \\
D_h &= \frac{f_h^{max} - f_h^{min}}{n_r}
\end{align*}
\]

where, \(D_h\) represent the distance of the \(h\)-th objective function value non-dominant solution, \(f_h^{max}\) and \(f_h^{min}\) represent the maximum and minimum values of the \(h\)-th objective function, and \(f_h\) represent the \(h\)-th objective function value, \(n_r\) represents the limited number of solution sets.

- b) GWO flowchart
- c) Discontinuous variable rounding and fitness function
- In the process of reactive power optimization, the control variables include continuous and discontinuous variables, and the values of continuous variables can be updated with iteration, while the discrete variables such as reactive power compensation and transformer taps are integer programming based on the value space. According to the fitness function of the specific gray wolf, the power flow of the individual gray wolf is calculated, and the value of each objective function and the degree of crossing the boundary are calculated, as shown in the following formula.

\[
f_{fit,h}(x^i) = f_h(x^i) + γ m
\]

where, \(γ\) represents the penalty factor, \(m\) represents the number of constraints that are not satisfied, and \(f_h\) represents the value of the \(h\)-th objective function, \(x_i\) represents the \(i\)-th non-dominated solution, and \(f_{fit,h}\) represents the \(h\)-th objective function value that makes the objective function value satisfy the constraints after introducing the penalty factor.

- d) Entropy method to select the optimal compromise solution

![GWO flow chart](image-url)
Based on the optimal Pareto frontier obtained by GWO, the objective function value of the non-dominant solution is normalized, [19] as follows:

Standardized processing, calculate the proportion of the \( i \)-th sample under the \( j \)-th objective function \( Y_{ij} \) is:

\[
Y_{ij} = \frac{x_{ij}}{\sum_{1}^{n} x_{ij}} \quad (21)
\]

The \( e_j \) information entropy, \( w_j \) weight and \( s_j \) comprehensive score of each objective function are as follows:

\[
\begin{align*}
\ e_j &= -\frac{1}{\ln(n)} \sum_{1}^{n} Y_{ij} \ln Y_{ij} \\
\ w_j &= \frac{1 - e_j}{\sum_{j=1}^{m} (1 - e_j)} \\
\ s_j &= \sum_{j=1}^{m} w_j Y_{ij}
\end{align*}
\quad (22)
\]

The weight \( w_j \) is the amount of information of the objective function [24], and \( x_{ih} \) represents the value of the \( h \)-th objective function in the \( i \)-th non-dominated solution. The corresponding evaluation is carried out based on the three objective functions of power loss, voltage deviation and static voltage stability margin and the corresponding power flow results. The greater the uncertainty of the result of a target change, the higher the corresponding weight, thus the optimal compromise solution can be obtained efficiently.

V. EXAMPLE ANALYSIS

A. ANALYSIS OF IEEE39 NODE SYSTEM

In this paper, the improved IEEE39 node system is used to verify the effectiveness of the algorithm. As shown in Fig. 3, the system is connected to photovoltaic power stations at bus 21, 23, 25, 27, 29, wind farm at bus 1, 4, 7, 8, 20, shunt capacitor at 15 and 24 nodes. The basic parameters and reactive power regulation capacity of wind farm and photovoltaic power station are shown in Table 1. The control variables include the terminal voltage of the traditional generator, the shunt capacitor, the tap gear of the transformer, the reactive power of the fan unit and the reactive power of the photovoltaic unit, the state variables are mainly the node voltage, the node power and the phase difference between the nodes, etc., and the unitary value range of the generator port voltage is [0.98, 1.07]pu. The discrete control quantity of shunt capacitor is respectively \( \{3, 6, 9, 12, 15\} \)MW; transformer tap gear is \( \{0.98, 0.99, \ldots, 1.07\} \)pu, the rest of the system parameters remain unchanged.

In order to verify the stability and accuracy of GWO optimization, gray wolf optimization algorithm and particle swarm optimization algorithm are used to compare the optimization. Take the calculation results of GWO algorithm and PSO algorithm to make the convergence curve of the objective function as shown in Fig. 4. The results show that the proposed algorithm has better convergence than the simple PSO algorithm, and can find the global optimal solution better. After taking improvement measures, from the 90th generation, the objective function value of this algorithm has been reduced to less than 0.1120, and has been searching towards the optimization goal, the convergence speed is obviously faster than the PSO algorithm, and the optimal solution found is 0.1115, which is better than the optimal solution 0.1126 of the PSO. According to the search efficiency and search results, the proposed algorithm has better comprehensive performance than PSO algorithm.

B. ANALYSIS OF OPTIMIZATION RESULTS

When the optimization objectives are only voltage deviation and power loss, the non-dominant solution set result distribution maps of GWO algorithm and particle swarm optimization algorithm are compared. According to Fig. 5, compared with the Pareto frontier distribution obtained by the
traditional particle swarm optimization algorithm, the spatial distribution of the Pareto solution set solved by the GWO algorithm shows good uniformity and diversity. Therefore, the two-objective reactive power optimization model solved by GWO can provide a more widely distributed Pareto optimal solution for power grid operation.

When the optimization objectives are three objectives, it can be seen from Fig. 7 that in sufficient iterations, the non-dominant solution set obtained by the traditional particle swarm optimization algorithm is partially concentrated, while the non-dominant solution set obtained by GWO is more uniform, indicating that GWO can get rid of the local optimal solution, and also has a good global optimization performance for three-objective model optimization. As shown in Fig. 6 and Fig. 8, entropy weight method is used to select the optimal compromise solution for both two-objective optimization and three-objective optimization results, the advantage of the entropy weight method is to eliminate the dimensional differences between multiple targets and perform a unified comparison of weights. According to the normalization and standardization of each objective function value, and according to the corresponding variation degree of each objective function change and GWO optimization power flow result, the proportion of weight coefficients corresponding to each objective is obtained respectively, thus the best compromise solution is found.

GWO is used to solve the optimal solution set of the multi-objective model, and on this basis, the entropy weight function is introduced. According to the corresponding variation degree of each objective function and the optimization result of the algorithm, the specific index weight of each target is obtained, and the entropy weight (compromise solution) is compared with other calculation results.

According to Table 2, the synthesis of the optimal compromise solution obtained by the entropy weight function is better, and the individual solution distribution space is wider and the distribution density is more uniform. It is based on information entropy, so it can better coordinate the objective weights before the three goals and avoid over-optimizing a
single goal. According to Table 2, the optimal compromise solution is more in line with the practical application.

In order to further verify the reactive power optimization performance of the improved GWO, Table 2 compares the Pareto frontier comparison results of the GWO and the traditional particle swarm optimization (PSO) algorithm in the test system. There is a greater difference between the minimum and maximum values of the improved GWO, indicating that the Pareto frontier obtained is more widely distributed, and that the algorithm has a strong ability to explore and use optimization.

In order to effectively discuss the influence of reactive power regulation of new energy units on system reactive power optimization, three schemes are proposed:

1. **Scheme 1.** The original system solves the system power flow.
2. **Scheme 2.** Using GWO algorithm and entropy method to analyze the power flow results of traditional system reactive power regulation and analyze the system network loss and voltage deviation, etc.
3. **Scheme 3.** The GWO algorithm and entropy method are used to combine the reactive power regulation of the traditional system with new energy units to obtain the results of power flow calculation and analyze the system network loss and voltage deviation.

Comparing the influence of the change of the system network loss under the three schemes, as shown in Fig. 9, it can be seen from the figure that the total network loss of Scheme 3 is obviously better than that of the former two schemes, and the network loss of Scheme 2 is also significantly improved compared with the system loss of Scheme 2.

According to Fig. 10, compared with before optimization, the total network loss of scheme 2 and scheme 3 using GWO algorithm and entropy weight is significantly reduced, and the optimization scheme of new energy unit combined with traditional reactive power compensation of the system has the smallest network loss. Affected by the output of new energy units at some nodes, the network loss of some branches is significantly reduced after optimization of the corresponding branch, indicating that the optimization can effectively reduce the system network loss.

According to the comparative analysis of the system node voltage under the three schemes, Fig. 10 provides the voltage distribution of the whole network under the three schemes. Obviously, through the optimization of new energy units and reactive power compensation, the voltage deviation of the system is obviously reduced, and the quality of voltage stability is obviously improved. In addition, this improves the system node voltage quality, the system stationarity is significantly improved, and all node voltages meet the above safe operation constraints.

Fig. 11 is scheme 3, and the optimal solution of the three-objective model is solved by GWO algorithm and entropy weight, and the output diagrams of new energy units and shunt capacitors of the system are obtained by power flow calculation. Fig. 12 is the tap application scheme of 12 transformers under the three schemes, which shows that transformers also play a key role in the reactive power optimization of the system.

In order to further verify the adaptability of the proposed method to the randomness of the power grid, taking the system operation data disturbed by uncertain factors as an example, the reactive power and voltage optimization calculation is carried out with the goal of maximum overall intentionality.

### TABLE 2. Comparison of Pareto statistical results of IEEE39 node system.

| Target          | Standard | GWO      | PSO      |
|-----------------|----------|----------|----------|
| Grid loss/MW    |          |          |          |
| Optimal         | 41.59740 | 42.39131 |          |
| Worst           | 47.95192 | 50.33346 |          |
| Mean            | 44.40786 | 45.33603 |          |
| Compromise      | 42.3454  | 43.8329  |          |
| Solution        |          |          |          |
| Optimal         | 0.0071   | 0.0083   |          |
| Worst           | 0.0490   | 0.0589   |          |
| Mean            | 0.0209   | 0.0287   |          |
| Compromise      | 0.0199   | 0.0324   |          |
| Solution        |          |          |          |
| Optimal         | 1.1121   | 1.1026   |          |
| Worst           | 1.0407   | 1.0423   |          |
| Mean            | 1.0745   | 1.0658   |          |
| Static voltage  |          |          |          |
| Stability       |          |          |          |
| Margin/pu       |          |          |          |
| Compromise      | 1.0858   | 1.0676   |          |
| Solution        |          |          |          |

**FIGURE 9.** Comparison of power grid loss before and after optimization by algorithm.

**FIGURE 10.** Comparison of node voltage changes before and after algorithm optimization.
VI. CONCLUSION

In this work, a multi-objective reactive power optimization method based on entropy weight and GWO algorithm is proposed, and a multi-objective nonlinear reactive power optimization model is established. GWO and entropy weight are used to solve the optimal compromise solution of reactive power optimization.

1) The reactive power optimization model of new energy participating in reactive power regulation is built, which makes full use of the reactive power output of wind farm and photovoltaic power station to reduce the instability of power grid caused by the connection of new energy units to the transmission grid. Coordinate the reactive power regulation characteristics of new energy units and system, achieve the reduction of network loss in the power grid, effectively improve the voltage, and improve the power utilization rate of new energy units.

2) GWO algorithm is proposed to solve the multi-objective reactive power optimization model of transmission network. Discontinuous variable rounding and fitness function optimization are introduced to improve the convergence speed and global optimization ability of the algorithm. The simulation results of IEEE39 node system show that the proposed algorithm can effectively improve the efficiency of reactive power calculation and achieve efficient global optimization.

3) The introduction of the entropy weight method theory can obtain the optimal compromise solution for multiple objectives, and effectively avoid the optimization results from focusing too much on a certain objective. The objective weight coefficient obtained based on information entropy can meet the actual reactive power optimization requirements of the power grid, and it flexibly mobilizes reactive power compensation, thus enabling the system to run stably.

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YU LINLIN was born in 1984. She received the master’s degree from Xi’an Jiaotong University. She is currently a Senior Engineer. Her research interests include power electronics and advanced energy storage technology.

ZHANG LIHUA was born in 1981. She received the master’s degree from Guangxi University, and the Ph.D. degree. She is currently a Senior Engineer. Her research interests include energy storage technology and efficient utilization.

MENG GAOJUN was born in 1987. He received the Ph.D. degree from Southeast University. He is currently an Associate Professor. His research interests include power electronics and advanced energy storage technology.

ZHANG FENG was born in 1996. He is currently pursuing the master’s degree with the Nanjing Institute of Technology, China. His research interests include energy storage technology and efficient utilization.

LIU WANXUN was born in 1981. He received the master’s degree from the Huazhong University of Science and Technology, and the Ph.D. degree. He is currently a Senior Engineer. His research interest includes new energy power generation.

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