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Multi-Objective Reactive Power Optimization Based on Improved Particle Swarm Optimization With ε-*Greedy* Strategy and Pareto Archive Algorithm

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ABSTRACT This paper proposes combining an improved particle swarm optimization and Pareto archive algorithm to solve the multi-objective reactive power optimization problem. The idea of ε-*greedy* strategy is adopted and designed to improve particle swarm optimization algorithm. It makes some particles have stronger global search capability, meanwhile, others have stronger local search capability during the whole iteration process. Henceforth, the strategy significantly explores the possibility of optimal solution in local space at the early stage of the iteration, in addition, it mitigates the tendency to fall into the local optimal solution at the later stage of the iteration. The Pareto optimal solution selection problem is solved by minimizing the sum of the difference between each objective function and its optimal solution. The proposed approach is tested on IEEE39-bus and IEEE118-bus system, and it is demonstrated that the proposed approach not only restores the nodes voltage to the normal range and achieves better value for each objective function, but also outperforms other algorithms including standard particle swarm optimization and non-dominated sorting genetic algorithm II(NSGA-II).

INDEX TERMS Multi-objective reactive power optimization, particle swarm optimization, ε-*greedy* strategy, Pareto archive algorithm, voltage control.

I. INTRODUCTION

Too high or too low voltage will directly affect the security and stability of the power system, so voltage control has been paid more and more attention. The researches on solving voltage/var control problem are mainly divided into two categories: 1) Constrained optimal power flow. This category can obtain the solution based on optimal power flow [1]–[3]. This type of method is simple, and the model has adequate interpretability. However, as the scale of the power grid expands, the amount of calculation increases. 2) Machine learning based methods, e.g. reinforcement learning [4]–[6]. They are data-driven methods, which are not limited by the grid models. However, these methods cannot be understood and applied well by human due to inadequate interpretability. At present, the contradiction between the harsh requirements of voltage/var control and the lack of interpretability of machine learning models has become a great obstacle for engineering applications. From the perspective of the first type of research, this paper adopts the reactive power optimization method to solve the static voltage control problem.

Reactive power optimization plays a critical role in the optimal operation of the power system. The static reactive power optimization aims to obtain better secure and economic operation level by changing the number of switching capacitor banks, the location of the on-load tap changers, and generators terminal voltage under a given system operation constraints and load level. In recent years, with the improvement of power system operation requirements, the reactive power optimization has evolved from a single-objective optimization problem to a multi-objective optimization problem [7]. Multi-objective reactive power optimization is a multi-objective, multi-constraint, multi-variable hybrid nonlinear optimization problem [8]–[10]. At present, algorithms

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for addressing multi-objective problems are mainly divided into two categories: conventional algorithms and intelligent algorithms.

A. CONVENTIONAL ALGORITHMS

Conventional algorithms convert the multi-objective problem to single-objective problem, including linear weighting, ε-constraint and so on [11]–[13]. The linear weighting approach assigns a weight to different sub-objectives, and then multiple sub-objectives are linearly weighted into a single objective. However, it is difficult to determine the weight value. The ε-constraint approach selects one of the most concerned sub-objectives as the reference, after which other sub-objectives are constrained to not more than ε. The problem is that it is difficult to obtain the ε. For multi-objective reactive power optimization problems in engineering, conventional algorithms cannot significantly solve them due to the problem that multiple objectives are often conflicting or interacting each other. To solve the problem, a large number of intelligent multi-objective algorithms have been developed.

B. INTELLIGENT ALGORITHMS

Intelligent algorithms can be divided into three categories: the first category is the algorithm based on Pareto optimization, the second category is the algorithm not based on Pareto optimization, and the third category puts forward the concept of external set on the basis of the first two categories, and then it improves the distribution of the optimal solution.

1) THE ALGORITHM BASED ON PARETO OPTIMIZATION

Reference [14] proposes the non-dominated sorting genetic algorithm (NSGA), which utilizes the non-dominant sorting to sort the population. Then niche and morphological algorithms are utilized to obtain optimal individual selection combined with the genetic algorithm. Finally, several Pareto optimal solutions are obtained. The advantage is that the optimal solution is evenly distributed, however, it has the disadvantages of low computational efficiency, high complexity and lack of an elite mechanism. Subsequently, reference [15] proposes the NSGA-II algorithm. Based on the original NSGA, the congestion degree comparison operator is proposed. The congestion degree of individuals is compared in the same non-dominated layer, and the individuals with higher congestion degree are selected. Then, the elite strategy is introduced to expand the sampling space. The NSGA-II algorithm can significantly improve the ability to obtain the optimal solution and the speed of the algorithm. Meanwhile, it preserves the diversity of the population and reduces the complexity. Although NSGA-II has great improvement, it is not fully applicable to the optimization of three or more objectives.

2) THE ALGORITHM NOT BASED ON PARETO OPTIMIZATION

References [16]–[18] propose a multi-objective evolutionary algorithm based on decomposition (MOEA/D). It utilizes the idea of scalarization to decompose the multi-objective problem into multi-scalar sub-problems, and simultaneously optimizes each sub-problem according to its adjacent sub-problems. Then, the optimal solution is obtained. The approach has advantages in solving efficiency and accuracy, and has become the most representative heuristic multi-objective algorithm. Compared with NSGA-II, the MOEA/D has more advantages in time complexity, uniformity and convergence in the case of low dimensional objectives, but its uniformity is worse than NSGA-II in some cases of high dimensional objectives.

3) THE ALGORITHM BASED ON EXTERNAL SET

The concept of external set is introduced in the algorithm, which is utilized to preserve all non-dominant individuals. This type of approach can obtain uniformly distributed Pareto solution, and maintain the diversity of the population. Reference [19] proposes the strength Pareto evolution algorithm (SPEA). It utilizes an external set to preserve non-dominated solutions, and evaluates adaptability according to the number of individual external non-dominated solutions. Meanwhile, it controls the size of the non-dominated set combined with clustering approach, so the efficiency of the search in the selection stage can be guaranteed. However, the SPEA has disadvantages of inaccurate fitness allocation and poor diversity. In view of this problem, reference [20] proposes the SPEA-II. Based on a new granularity allocation strategy, it significantly accelerates the convergence speed and enhances the distribution uniformity of the Pareto optimal solution. In addition, the Pareto archive evolution strategy (PAES) is proposed in [21], which is also an approach that utilizes external set. The approach consists of a $1 + 1$ strategy and an external archive scheme, which is a relatively simple MOEA and has a good performance in engineering applications. The above approaches can obtain the optimal solution set. Then, the required solution can be selected according to the practical condition. However, the choice of the final solution is not easy [22]–[24].

The conventional reactive power optimization algorithms will encounter high requirements for initial value and prone to ‘‘dimensional calamity’’. Recently, artificial intelligence algorithms, such as genetic algorithm [25], simulated annealing algorithm [26], tabu search algorithm [27] and particle swarm optimization algorithm [28], [29], have been developed rapidly to solve them. Compared with other algorithms, particle swarm optimization (PSO) is simple and converges fast, however, it is easy to fall into the local optimal solution during iteration [30], [31]. In recent years, researchers have proposed various improved approaches, which are mainly divided into three categories. The first category is to improve the selection of inertia weight: reference [32] shows that the original PSO has poor local search capability. The concept of an inertia weight is developed to better control exploration and exploitation. The inclusion of an inertia weight in the particle swarm optimization algorithm (MeanPSO) is reported in references [33], [34]. Reference [35] utilizes linearly decreasing inertia weight to make all particles have a strong global search capability at the early stage of the iteration, and a strong local search capability at the later stage. It improves the search efficiency of the particle swarm optimization algorithm; Reference [36] proposes to dynamically adjust the inertia weight of all particles nonlinearly, which further improves the processing capability of the algorithm for nonlinear multi-dimensional functions. At present, the shortcoming of searching in a single direction at the later stage is not significantly solved by approaches of adjusting the inertia weight of all particles consistently. They are still easy to fall into the local optimal solution. The second category involves information regarding social sharing. Reference [37] proposes dynamically adjusted neighbourhoods in which directed structures are used for the topology of the initial population and during the subsequent generations edges of the structures are randomly migrated from one source to another. Reference [38] utilizes the additional information of the nearby higher fitness particle that is selected according to fitness-distance ratio (FDR) indicating the ratio of the fitness improvement over the respective distance. These approaches improve the efficiency of particle swarm search to a certain extent, but they increase the amount of calculation. The third improvement approach is to introduce mutation into the process of particle swarm optimization: reference [39] proposes to reinitialize the poorer half of the particles during each iteration, thus increasing the diversity of particles and reducing the possibility of falling into a local optimal solution; References [40], [41] based on the principle of crossover and mutation of genetic algorithm, the velocity and position of each particle are dynamically adjusted, which increases the diversity of particles. Although approaches of random mutation increase the diversity of particles, they increase the amount of calculation, which may reduce the convergence speed and search accuracy.

To solve these problems, this paper proposes a multi-objective reactive power optimization method combining improved particle swarm algorithm and Pareto archive algorithm. The idea of ε-*greedy* strategy is adopted to dynamically adjust the proportion of the global search and the local search of the particles. It enables most particles to have larger inertia weight at the early stage of iteration, and thus has stronger global search capability. Meanwhile, other particles have smaller inertia weight, so they will explore the local space, which can significantly explore the possibility of optimal solution in local space. On the contrary, most particles have smaller inertia weight at the later stage, which makes them have stronger local search capability, meanwhile, other particles have larger inertia weight. It enables them to jump out of the local space for new space, which reduces the possibility of falling into a local optimal solution. The Pareto optimal solution selection problem is solved by minimizing the sum of the difference between each objective function and its optimal solution. Case studies on the modified IEEE39-bus and IEEE118-bus system verify the validity of the proposed approach.

The main contributions of this paper are as follows: 1) The improved particle swarm optimization based on ε-*greedy* strategy and Pareto archive algorithm is first proposed for solving multi-objective reactive power optimization problem. 2) The idea of ε-*greedy* strategy is first adopted and designed to improve PSO algorithm. It increases the diversity of particles, and significantly reduces the possibility of falling into a local optimal solution. 3) The Pareto optimal solution selection problem is solved by the proposed selection criterion. 4) Compared with approaches of random mutation, the proposed approach can increase the diversity of particles as well. Since the proposed approach does not require mutation calculations and operations, it has the advantages of low calculation and avoiding the possible reduction of convergence speed. 5) The simulation results on the IEEE39-bus and IEEE118-bus test system show that the proposed approach restores the nodes voltage to normal range, meanwhile, the performance of the proposed approach is superior to that of standard particle swarm optimization and NSGA-II in terms of multiple objective values.

The remaining parts are organized as follows. Section II introduces multi-objective reactive power optimization model. Section III describes improved PSO algorithm and Pareto archive algorithm. The proposed approach is tested in Section IV on the modified IEEE39-bus and IEEE118-bus system. Finally, conclusions and future work are given in Section V.

II. MULTI-OBJECTIVE REACTIVE POWER OPTIMIZATION MODEL

A. OBJECTIVE FUNCTIONS

The objective function of reactive power optimization has certain differences due to different concerns. It mainly includes economics index and security index. The classical model considering economics takes the minimum active power loss as objective function. The classic model considering system security takes the minimum sum of squares of the system's operating state deviation from the expected value or the maximum static voltage stability as objective function. In addition, there exists the multi-objective models that consider these two or more objectives simultaneously [42].

This paper considers both economics and security of the system. Then the minimum active power loss is regarded as the economics index, and the maximum static voltage stability is regarded as the security index.

1) THE MINIMUM ACTIVE POWER LOSS

The active power loss on transmission lines is generated in the process of power transmission. Reducing the active power loss is an important means to achieve economic operation for power utilities. The transmission loss is regarded as an objective function, as follows:

$$\begin{aligned} \min f_1 &= \min\left(\Delta P_{loss}\right) \\ &= \sum_{i,j \in N_L} G_{ij}\left(V_i^2 + V_j^2 - 2V_iV_j\cos\theta_{ij}\right) \end{aligned} \tag{1}$$

where N_L is the number of branches in the system; G_{ij} is the conductance between node i and node j; V_i and V_j are the voltage value of node i and node j, respectively; θ_{ij} is the voltage phase angle difference between node i and node j.

2) THE MAXIMUM STATIC VOLTAGE STABILITY

Considering the secure operation of power system, voltage instability has become an issue that must be solved. The static voltage stability index can be used to evaluate the voltage stability of power system. It is measured by the smallest singular value $\delta_{\min}$ of the Jacobian matrix. The larger the $\delta_{\min}$, the greater the static voltage stability. Here, the minimum value of reciprocal of the smallest singular value is used to calculate the index. In other words, the smaller $1/\delta_{\min}$, the greater the static voltage stability:

$$\max f_2 = \min\left(1/\delta_{\min}\right) \tag{2}$$

B. CONSTRAINTS

The mathematical formulas of constraints are as follows:

1) POWER FLOW CONSTRAINTS

Since the electricity is generated and consumed at the same time in the power system, so the active power balance and reactive power balance are two basic operating conditions that must be met in power system operation. They are defined as follows:

$$\begin{cases} P_{Gi} - P_{Li} - V_i \sum_{j=1}^{N_s} V_j \left(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}\right) = 0 \\ Q_{Gi} - Q_{Li} - V_i \sum_{j=1}^{N_s} V_j \left(G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}\right) = 0 \end{cases} \tag{3}$$

where N_s is the number of system nodes; P_{Gi} and Q_{Gi} denote the active and reactive power of generator node i, respectively; P_{Li} and Q_{Li} denote the active power and reactive power of load node i, respectively; V_i and V_j are the voltage value of node i and node j, respectively; θ_{ij} is the voltage phase angle difference between node i and node j; G_{ij} is the conductance between node i and node j; B_{ij} is the susceptance between node i and node j.

2) VARIABLE CONSTRAINTS

For the components in the power system, they need to meet certain conditions during normal operation. And the variable constraints are the normal operating range for them, which include constraints of transformer, reactor, generator, voltage value and branch current. They are defined as follows:

$$\begin{cases} T_{i\min} < T_i < T_{i\max} & i \in N_T \\ Q_{ci\min} < Q_{ci} < Q_{ci\max} & i \in N_C \\ V_{i\min} < V_i < V_{i\max} & i \in N_{PQ} \\ V_{Gi\min} < V_{Gi} < V_{Gi\max} & i \in N_G \\ Q_{Gi\min} < Q_{Gi} < Q_{Gi\max} & i \in N_G \\ 0 \le l_{ij} \le I_{ij}^{\max} & i,j \in N_L \end{cases} \tag{4}$$

where N_T, N_C, N_{PQ}, N_G are the number of on-load tap changers, reactor compensation points, PQ nodes, generator nodes, respectively; $T_i, Q_{ci}, V_i, V_{Gi}, Q_{Gi}$ denote the ratio of transformer i, the capacity of reactor i, the voltage value of PQ node i, the voltage value of generator node i, and the reactive power of generator node i, respectively; $T_{i\max}, T_{i\min}, Q_{ci\max}, Q_{ci\min}, V_{i\max}, V_{i\min}, V_{Gi\max}, V_{Gi\min}, Q_{Gi\max}, Q_{Gi\min}$ are the upper and lower limits of the corresponding variable; l_{ij} and $I_{ij}^{\max}$ denote the current and the upper limit of current for the branch from bus i to bus j, respectively.

C. PROCESSING OF DISCRETE VARIABLES

Since the ratio of the transformer and the compensation of the reactor are discrete variables, they need to be converted into continuously changing integer variables. For the ratio, it can be transformed into a continuously changing tap gear. Similarly, the compensation capacity of reactor can be transformed into a continuously changing switching gear. Assuming that the transformer i has a total of k_i taps, and its step length of the gear is a_i. Hence, the relationship between the transformation ratio T_i and the corresponding gear B_i $(1 \le B_i \le k_i)$ is:

$$T_i = T_{i\min} + a_i \times round\ (B_i - 1) \tag{5}$$

Assuming that the single group capacity of the reactor at node i is c_i, and n_i groups can be connected in total. Similarly, the relationship between the reactor compensation capacity Q_{ci} and its corresponding switching gear D_i $(0 \le D_i \le n_i)$ is:

$$Q_{ci} = c_i \times round\ (D_i) \tag{6}$$

III. IMPROVED PSO ALGORITHM AND PARETO ARCHIVE ALGORITHM

A. STANDARD PSO ALGORITHM

The PSO algorithm is an intelligent optimization algorithm proposed by Kennedy and Eberhart in 1995. It utilizes the collaboration and information sharing among individuals for the optimal solution [43]. Each particle updates its velocity and position by tracking individual extreme values and global extreme values in each iteration. The update formulas of particle i at the $k+1$ *th* iteration are as follows:

$$\begin{cases} v_{id}^{k+1} = w \cdot v_{id}^{k} + c_1 \cdot r_1^k \cdot \left(p_{best}^k - x_{id}^k\right) + \\ \quad c_2 \cdot r_2^k \cdot \left(g_{best}^k - x_{id}^k\right) \\ x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \end{cases} \tag{7}$$

where i denotes the number of the particles; d denotes the dimensional component of the search space; k denotes the number of current iteration; w denotes the inertia weight, which is a fixed value; v_i and x_i denote velocity and position of the particle, respectively; p_{best} denotes the individual extreme value of the particle, g_{best} denotes the global extremum of the particle swarm; c_1 and c_2 denote the learning factor; r_1 and r_2 are random numbers in (0,1).

The inertia weight determines the capability of the particle's global search and local search. The larger the inertia weight, the stronger the global search capability; the smaller the inertia weight, the stronger the local search capability.

B. IMPROVE PSO ALGORITHM BASED ON ε-GREEDY STRATEGY

The ε-*greedy* strategy achieves a balance of exploration and exploitation based on probability. Set a probability $\varepsilon(0 < \varepsilon < 1)$, when the agent is making a decision, it explores an unknown action with a small probability ε. Furthermore, it selects the maximum action from the previous actions with a probability of 1-ε [44]. The ε-*greedy* strategy aims for execution of all the possible actions in a certain state, thereby ensuring continuous exploration.

Inspired by the ε-*greedy* strategy, the strategy is modified to improved PSO algorithm. The specific improvement processes are as follows: assign a random probability to each particle, and set the probability ε, where the ε increases from 0.1 to 0.9 following the number of iterations. When the probability of particle i satisfies $P_i \geq \varepsilon$, the particle is given a larger inertia weight, which makes its global search capability stronger. When it satisfies $P_i < \varepsilon$, the particle is given a smaller inertia weight, which makes its local search capability stronger. Since the ε is small at the early stage of the iteration, most of the particles have a stronger global search capability. Meanwhile, other particles will search in the local space, which can significantly explore the possibility of the optimal solution in the local space. With the proliferation of iteration, the ε gradually increases. The ε is larger at the later stage, thus most of the particles have stronger local search capability. Meanwhile, other particles have larger inertia weight. It enables them to jump out of the local space for new space, which reduces the possibility of falling into a local optimal solution. Since each particle is given a random probability, they can have larger or smaller inertia weight in the process of iteration. The mathematical formulas are as follows:

$$\varepsilon = \varepsilon_{\min} + \frac{iter}{MaxIter} \times (\varepsilon_{\max} - \varepsilon_{\min}) \tag{8}$$

$$w_i = \begin{cases} w_l\ , & if\ P_i \geq \varepsilon \\ w_s\ , & if\ P_i < \varepsilon \end{cases} \tag{9}$$

where $\varepsilon_{\min} = 0.1$, $\varepsilon_{\max} = 0.9$; *iter* is the number of current iteration, *MaxIter* is the maximum number of iterations, w_i is the inertia weight of particle i, w_l is the larger inertia weight, w_s is the smaller inertia weight, P_i is the random probability of particle i.

C. PARETO ARCHIVE ALGORITHM

The PSO algorithm cannot directly solve the multi-objective reactive power optimization problem. It is necessary to transform the multi-objective function into a single objective function or combine the intelligent algorithm to solve. Combined with the Pareto archive algorithm, each objective function value and the optimal solution set can be obtained. With them, the solution can be selected according to the practical condition.

The Pareto archive algorithm saves the optimal solutions in an external archive. The core is to determine whether the optimal solution can be stored in the external archive. The criterion for judgment is whether the scale of the external archive exceeds its specified maximum value during the process of iteration. If it does not exceed, then the optimal solution generated can be directly saved in the external archive. If it exceeds and the original solution in the external archive is dominated by the newly generated optimal solution, then the new optimal solution will be added to the external archive, meanwhile, the original dominated solution will be deleted. If the original solution is not dominated, the new optimal solution will not be added to the external archive.

D. SELECTION AND IMPROVEMENT OF OPTIMAL SOLUTION

The Pareto optimal solution set is obtained by the improved PSO algorithm and Pareto archive algorithm. The final solution needs to be selected from the set according to the practical condition. The general selection approaches are random selection and weight coefficient. The random selection approach selects a pair of solutions randomly, while the weight coefficient approach performs a weighted summation of each optimization objective, and then the overall evaluation index is obtained. Finally, it utilizes the overall index to select the optimal solution.

Since the random selection approach selects the optimal solution by chance, and the weight of the weight coefficient approach is difficult to be determined, this paper defines a new optimal solution selection approach: the pair of solutions, which has the minimum sum of the difference between each objective function and its optimal solution, is the final optimal solution. By doing like this, it takes into account of better performance of each objective function. What's more, in order to eliminate the influence of dimension and magnitude, the value of each objective function needs to be standardized before calculation. The mathematical formula is as follows:

$$W = \left(f_1' - f_{1\min}'\right) + \left(f_2' - f_{2\min}'\right) \tag{10}$$

where W denotes the optimal solution selection index; f_1' and f_2' denote the value of the standardized objective function 1 and objective function 2, respectively; $f_{1\min}'$ and $f_{2\min}'$ denote the optimal value of the standardized objective function 1 and objective function 2, respectively.

E. MULTI-OBJECTIVE REACTIVE POWER OPTIMIZATION STEPS

The flow chart of multi-objective reactive power optimization based on the improved PSO algorithm and Pareto archive algorithm is shown in Fig. 1. The steps are as follows:

Step 1: Initiation of particle swarm S and calculation of each particle's fitness, and then the optimal solutions are added to the external archive.

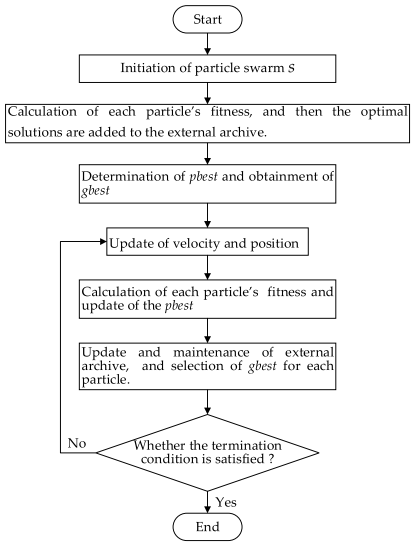

FIGURE 1. Flow chart of reactive power optimization.

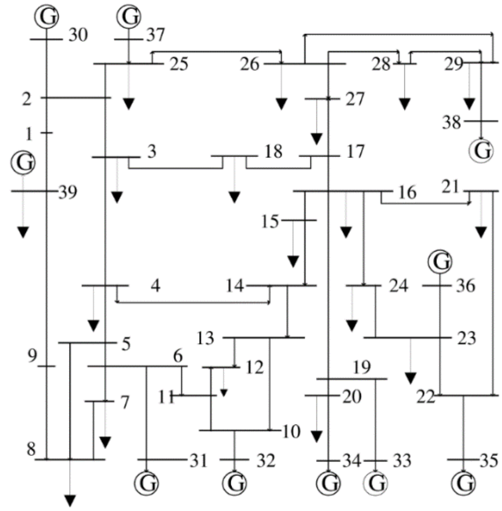

FIGURE 2. Chart of IEEE 39-bus single line.

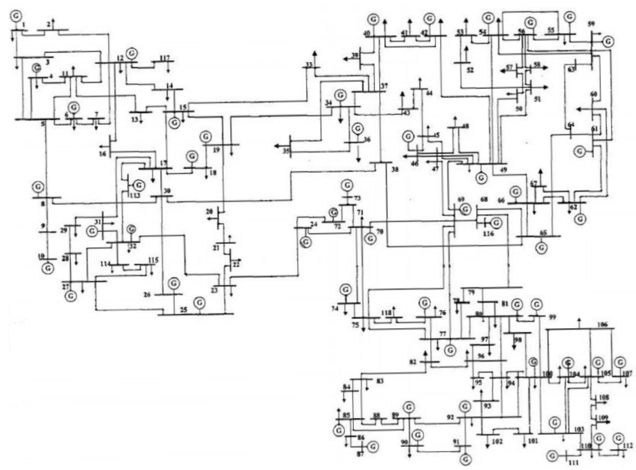

FIGURE 3. Chart of IEEE 118-bus single line.

Step 2: Determination of each particle's optimal position *pbest*, and then global optimal position *gbest* is obtained according to the *pbest*.

Step 3: Update of velocity and position of the particles, and reselection of the *pbest*.

Step 4: Update and maintenance of external archive, and selection of *gbest* for each particle.

Step 5: Judging whether the maximum number of iterations is reached, if it reaches, then the result is output; otherwise, go to step 3) to continue the loop calculation.

IV. CASE STUDY

The proposed approach is tested on the IEEE39-bus and IEEE118-bus system. The simulations are conducted the MATLAB 2018b on a 64-bit laptop with 2.60 GHz CPU and 16.0 GB RAM.

In order to make the IEEE39-bus and IEEE118-bus system more complete, this paper adjusts the standard IEEE39-bus and IEEE118-bus system according to case39 and case118 in the Matpower7.0 software [45], [46], respectively. The upper and lower limits of generators active power and reactive power are added, as well as the upper limit of branches current. Furthermore, in order to verify the voltage regulation capability of the proposed approach, the IEEE39-bus and IEEE118-bus system are adjusted to the light-load system by reducing loads' power and active power of generators. As a result, the PQ nodes voltage will be high when the power flow converges. In order to verify the performance of the approach proposed in this paper, it is compared with the following two approaches: 1) standard PSO algorithm combined with Pareto archive algorithm; 2) NSGA-II algorithm.

A. CASE PARAMETERS

The single-line diagram of the IEEE39-bus and IEEE118-bus system are shown in Fig. 2 and Fig. 3, respectively. Except for the balance node, the generator nodes are treated as PV nodes, and the other nodes are PQ nodes. In the modified IEEE39-bus system, the total active power of loads is 2456.3MW, and reactive power is 561.7Mvar. In the modified IEEE118-bus system, the total active power of loads is 573.2MW, and reactive power is 210.0Mvar. The normal range of PQ nodes voltage is 0.95-1.05 pu. Assuming that the upper and lower limit of the transformers' ratio are 1.1 and 0.9, respectively. The adjustment range of the ratio is $1 \pm 0.0125 \times 8$, and the transformer gear is 17 in total. The adjustment range of the generators terminal voltage is 0.9-1.1 pu. Due to the voltage of PQ nodes is high under light load, reactors need to be used to reduce the voltage. The range of reactor switching groups is set to $0 \sim 5$, and the single group capacity is -8Mvar. The number of particles in the population is 100, and the maximum number of iterations is 100. The range of ε is $0.1 \sim 0.9$, the larger inertia weight w_l is 0.9, and the smaller inertia weight w_s is 0.4. The maximum number of Pareto optimal solutions that can be stored in the external archive is

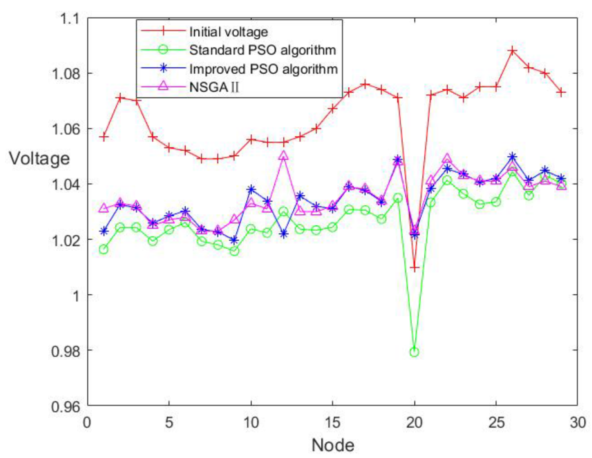

FIGURE 4. **Comparison chart of PQ nodes voltage values.**

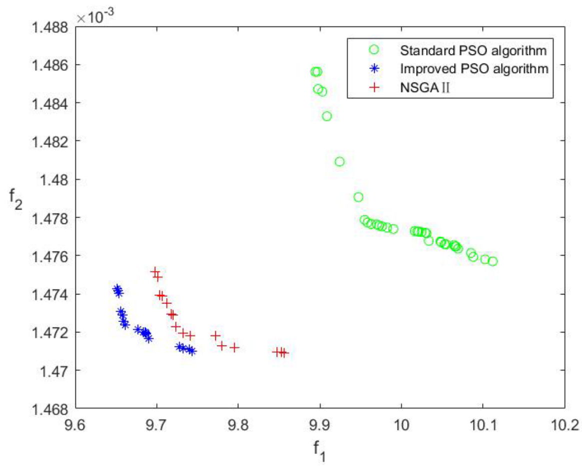

FIGURE 5. **Comparison chart of Pareto optimal frontier.**

TABLE 1. **Voltage values of PQ nodes.**

PQ nodes	Initial voltage (pu)	Standard PSO combined with Pareto archive algorithm (pu)	NSGA-II algorithm (pu)	Improved PSO combined with Pareto archive algorithm (pu)
V_1	1.057	1.016	1.031	1.023
V_2	1.071	1.024	1.033	1.032
V_3	1.070	1.024	1.032	1.031
V_4	1.057	1.019	1.025	1.026
V_5	1.053	1.023	1.027	1.028
V_6	1.052	1.026	1.028	1.030
V_7	1.049	1.019	1.023	1.024
V_8	1.049	1.018	1.023	1.023
V_9	1.050	1.016	1.027	1.020
V_{10}	1.056	1.024	1.033	1.038
V_{11}	1.055	1.022	1.031	1.034
V_{12}	1.055	1.030	1.050	1.022
V_{13}	1.057	1.024	1.030	1.036
V_{14}	1.060	1.023	1.030	1.032
V_{15}	1.067	1.024	1.032	1.031
V_{16}	1.073	1.031	1.039	1.039
V_{17}	1.076	1.031	1.038	1.038
V_{18}	1.074	1.027	1.034	1.034
V_{19}	1.071	1.035	1.048	1.049
V_{20}	1.010	0.979	1.023	1.022
V_{21}	1.072	1.033	1.041	1.038
V_{22}	1.074	1.041	1.049	1.045
V_{23}	1.071	1.036	1.043	1.043
V_{24}	1.075	1.033	1.041	1.041
V_{25}	1.075	1.034	1.041	1.042
V_{26}	1.088	1.044	1.046	1.050
V_{27}	1.082	1.036	1.039	1.041
V_{28}	1.080	1.043	1.041	1.045
V_{29}	1.073	1.040	1.039	1.042

100. The inertia weight in the standard PSO algorithm is set to 0.73, and the maximum number of iterations of the standard PSO algorithm and NSGA-II are both 100.

B. RESULTS AND ANALYSIS

1) IEEE39-BUS SYSTEM

Table 1 shows the PQ nodes voltage values obtained by three approaches, and the corresponding voltage values comparison chart is shown in Fig. 4. It can be seen from Table 1 and Fig. 4: 1) The initial voltage values of the PQ nodes are generally high; 2) By adjusting the generators terminal voltage, the transformers ratio and switching reactors, three optimization approaches can restore the PQ nodes voltage to the normal range. 3) The deviation between the voltage value of each node obtained by the standard PSO algorithm and the rated voltage value is obviously better than that of NSGA-II and the proposed approach. Meanwhile, voltage value of each node obtained by NSGA-II and the proposed approach is very close. The reason for this phenomenon is that the minimum voltage deviation and the minimum active power loss or the maximum static voltage stability cannot be considered simultaneously. They are contradictory objective functions.

TABLE 2. **Extremum of two objective functions.**

Algorithms	$f_{1\max}$ (MW)	$f_{1\min}$ (MW)	$f_{2\max}$ ($\times10^{-3}$)	$f_{2\min}$ ($\times10^{-3}$)
Standard PSO combined with Pareto archive algorithm	10.1119	9.8943	1.4856	1.4757
NSGA-II algorithm	9.8566	9.6983	1.4752	1.4709
Improved PSO combined with Pareto archive algorithm	9.7435	9.6515	1.4743	1.4710

Table 2 shows the extreme values of the two objective functions obtained by three optimization approaches. Fig. 5 shows the Pareto optimal frontier comparison chart of three approaches, where the abscissa denotes the value of the active power loss f_1, and the ordinate denotes the value of the static voltage stability index f_2. According to Table 2 and Fig. 5, the minimum values of the active power loss and the static voltage stability index obtained by the proposed

TABLE 3. Voltage values of PQ nodes.

PQ nodes	Initial voltage (pu)	Standard PSO combined with Pareto archive algorithm (pu)	NSGA-II algorithm (pu)	Improved PSO combined with Pareto archive algorithm (pu)
V_{45}	1.059	1.016	1.030	1.029
V_{47}	1.052	1.030	1.037	1.040
V_{48}	1.053	1.030	1.032	1.038
V_{50}	1.054	1.034	1.038	1.044
V_{67}	1.071	1.036	1.033	1.050
V_{94}	1.059	1.022	1.033	1.035
V_{95}	1.084	1.034	1.048	1.045
V_{96}	1.077	1.025	1.042	1.038
V_{97}	1.098	1.030	1.049	1.048
V_{98}	1.089	1.025	1.046	1.045
V_{101}	1.063	1.037	1.042	1.045

approach are 9.6515MW and 0.001471, respectively. We can obtain the following conclusions: 1) Compared with standard PSO and Pareto archive algorithm: the minimum values of two objective functions are smaller than the standard algorithm, respectively. In addition, the maximum values of two objective functions obtained by the proposed approach are smaller than the minimum values of standard algorithm, respectively. As a result, the Pareto optimal frontier of proposed approach is better. 2) Compared with NSGA-II algorithm: the minimum and maximum values of the active power loss obtained by the proposed approach are both smaller. Meanwhile, the static voltage stability obtained by the two algorithms is very close. As a result, the Pareto optimal frontier obtained by the proposed approach is more ideal, so the performance of the proposed approach is better. In a word, the improved approach proposed in this paper significantly improves the efficiency of particle swarm search. It can obtain better value of the objective function and a more ideal Pareto optimal frontier.

Finally, with the proposed optimal solution selection approach, a pair of solutions considering both the active power loss and the static voltage stability is obtained: $f_1 = 9.6590$ MW, $f_2 = 0.001473$. In summary, for the reactive power optimization problem of the power system, the proposed approach can bring better economics and security to the operation of the power grid.

2) IEEE118-BUS SYSTEM

In order to further verify the performance of the proposed approach in a large system, we choose the IEEE118-bus system for testing. Meanwhile, in order to simplify the comparison, we only show the high voltage PQ nodes and the optimized voltage values, as shown in Table 3. The comparison chart of the corresponding voltage values is shown in Fig. 6. Some similar conclusions with IEEE39-bus system can be drawn: 1) Three optimization approaches can restore the PQ nodes voltage to the normal range. 2) The deviation between each node voltage value and the rated voltage value: the standard PSO algorithm is the smallest, and NSGA-II is very close to the approach proposed in this paper. Therefore,

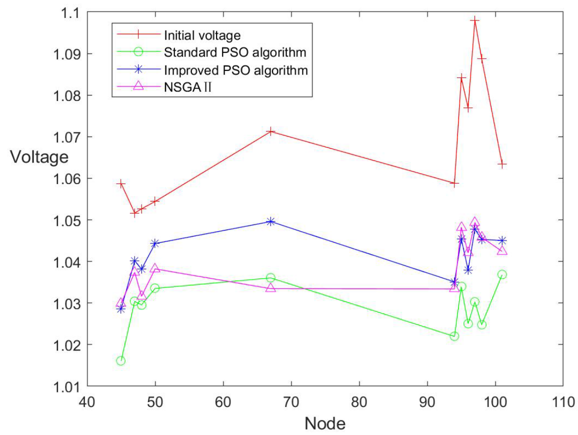

FIGURE 6. Comparison chart of PQ nodes voltage values.

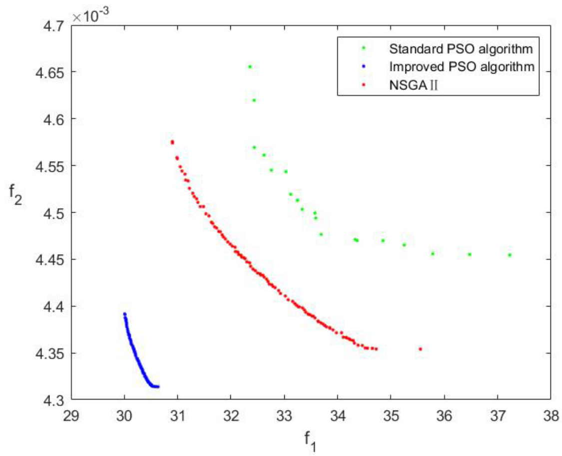

FIGURE 7. Comparison chart of Pareto optimal frontier.

TABLE 4. Extremum of two objective functions.

Algorithms	$f_{1\max}$ (MW)	$f_{1\min}$ (MW)	$f_{2\max}$ ($\times 10^{-3}$)	$f_{2\min}$ ($\times 10^{-3}$)
Standard PSO combined with Pareto archive algorithm	37.2263	32.3564	4.6555	4.4544
NSGA-II algorithm	35.5518	30.9004	4.5755	4.3540
Improved PSO combined with Pareto archive algorithm	30.6323	30.0075	4.3915	4.3138

the proposed approach can still adjust the voltage to the normal range in a larger system, indicating that the approach has excellent voltage regulation capability.

Table 4 shows the extreme values of the two objective functions obtained by three optimization approaches. The Pareto optimal frontier comparison chart of three approaches is shown in Fig. 7. According to Table 4 and Fig. 7, the minimum values of the active power loss and the static voltage stability index obtained by the proposed algorithm are 30.0075MW and 0.004314, respectively. We can obtain the following conclusions: 1) Compared with the other two approaches, the proposed approach can achieve a smaller objective function value. 2) The Pareto optimal frontier obtained by the proposed approach is more ideal. Therefore, even in a large system, the proposed approach can still explore and obtain a better value of the objective function. Meanwhile, it obtains a more ideal Pareto optimal frontier. In a word, the proposed approach has excellent reactive power optimization capability.

Finally, with the proposed optimal solution selection approach, a pair of solutions considering both the active power loss and the static voltage stability is obtained: $f_1 = 30.6323$ MW, $f_2 = 0.004314$ MW.

V. CONCLUSION AND FUTURE WORK

This paper proposes an improved PSO algorithm based on the ε-*greedy* strategy. It significantly explores the possibility of optimal solution in local space at the early stage of iteration, in addition, it mitigates the tendency to fall into the local optimal solution at the later stage. Meanwhile, in order to solve the multi-objective reactive power optimization model, this paper introduces an algorithm combining the Pareto archive algorithm and the improved PSO algorithm. The simulation results verify that the proposed approach can be well applied to the multi-objective reactive power optimization of the power system. It not only restores the nodes voltage to the normal range, but also explores to achieve the better objective function value, which can significantly reduce the active power loss and improve the static voltage stability of the system.

The Pareto optimal solution selection problem is solved by minimizing the sum of the difference between each objective function and its optimal solution. The obtained optimal solution considers the performance of each objective function. For the decision-maker, it provides a good basis for the selection of the optimal solution.

The improved PSO algorithm enables few particles to randomly explore the local space at the early stage of iteration and global space at the later stage of iteration. In the future work, it is necessary to study that each particle can explore more intelligently, thereby further improving the efficiency of the particles for the optimal solution.

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