# Improved Multi-Objective Simulated Annealing Particle Swarm Algorithm for Siting and Capacity Sizing of Distributed Power Supplies

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*Abstract*—**Siting and capacity determination of distributed power supply is a very important part of distribution network planning, which usually involves several factors. In this paper, we consider the investment cost, network loss and voltage stability and establish a three-objective mathematical model, using simulated annealing algorithm combined with particle swarm algorithm to solve the Pareto solution set. The constraints of the model are realized by adding the penalty function to the objective function calculation, and the program not only obtains the multi-objective Pareto solution set, but also gets the best optimization result by calculating the adaptive degree of local optimal solution and assigning weights to the multi-objective approach. The program verifies the effectiveness of the proposed algorithm for distributed power siting and capacity determination with IEEE69 node system.**

***Keywords—Simulated annealing algorithm; Particle swarm algorithm; Distributed power; Siting and capacity determination; Distribution network; Multi-objective optimization***

## I. INTRODUCTION

The rapid development of the global economy and the increasing demand for electricity have led to the depletion of natural resources, mainly fossil energy [1]. Distributed power (DG) is gradually being widely used due to its advantages of green environmental protection, diversified energy utilization, peak shifting effect, and improvement of power quality and reliability [2-4]. Utilizing renewable energy sources such as solar and wind, distributed power supply can reduce environmental pollution and provide additional power during peak power loads to alleviate the pressure of power supply. Therefore, how to determine the access point and installation capacity of distributed power supply in the distribution network to improve the security and economy of the system is the focus of current research.

At present, there are many scholars have carried out research on power source siting. Literature [5] takes into account the characteristics of PV power siting and capacity fixing, and adopts an improved parallel selection method to optimize the location and capacity of PV power supply, in order to achieve the optimal planning of the location and capacity of PV power supply access to the distribution network. Literature [6] uses an improved adaptive genetic algorithm, which enables the crossover operator and the variance operator to change automatically with the degree of adaptation. On this basis, the selection method is further improved, so that the improved adaptive genetic algorithm maintains the diversity of the population while ensuring the convergence of the algorithm. Literature [7] introduced the Levy perturbation in the form of additive stochastic perturbation and proposed the fractional order particle swarm optimization (FPSO) algorithm. The effects of the form of multiplicative and additive perturbations, the number of particles, and the initial positions of the particles on the performance of the algorithm in FPSO are analyzed. The Q-learning algorithm used in the literature [8] utilizes some kind of iterative rule to select the distribution network planning strategy by testing different states to gain rewards and eventually learning recursively to get the best Q value.

However, the above adopted algorithms such as genetic algorithm convergence speed is relatively slow, low accuracy, easy to fall into the local optimum; simulated annealing [9] algorithm is generally longer computation time, low efficiency. Although the particle swarm algorithm converges faster, but the convergence accuracy is lower, easy to fall into the local optimum [10]. Therefore, we think of Simulated Annealing Algorithm (SA) as a stochastic combinatorial optimization method. Under the condition that the initial temperature is high enough and the temperature drop is slow enough, it has asymptotic convergence and can converge to the global optimum with probability 1. Since it accepts the lower point with some probability, it has the ability to jump out of the local optimum solution.

In this paper, an optimization model with investment cost, network loss, and voltage stability as the objective function is first developed, and the node voltage constraints, and the total installed capacity constraints are used as the constraint functions. It can be seen that this is a class of multi-objective multi-variable feasible solution of large-scale optimization problems, for which we usually seek the Pareto optimal solution. Therefore, in this paper, we first use the forward back generation method to calculate the distribution network current, and combine the simulated annealing algorithm with the particle swarm algorithm to obtain the Pareto solution set with three optimal objectives. Then the penalty function is used to find the solution set that satisfies all the constraints, and finally the optimal results are filtered out by assigning different objective weights to the solution set that satisfies the constraints, so as to calculate the optimal power supply capacity and node voltage of each node in this case.

## II. OPTIMIZATION MODEL FOR SITING AND CAPACITY SIZING OF DISTRIBUTED POWER SUPPLIES

In this paper, the correlation function is established with the unknown voltage and power supply capacity of each node.

### *A. objective function*

$$\min(S + C + D) \quad (1)$$

Where:S is the total active network loss;C is the total investment and operation cost;D is the voltage stability.

*1) Total Network Loss (TNL)*

$$S = \sum_{k=1}^{N} ({I_k}^2 \times Z_k) \quad (2)$$

Where:N is the number of nodes in the distribution network;$I_k$ denotes the injected current at k nodes;$Z_k$ denotes the resistance at k nodes.

*2) Total investment and O&M costs*

$$C = 10p_g(C_1 \times \frac{r(1+r)^n}{(1+r)^n-1} + C_2) \quad (3)$$

Where: $p_g$ is the total installed capacity of distributed power in the distribution network; $C_1$ represents the investment cost of distributed power; $C_2$ represents the operating cost of distributed power; $r$ is the discount rate of distributed power equipment; $n$ represents the service life of distributed power equipment.

*3) voltage stability*

$$D = \sum_{k=1}^{N} (\frac{U_{kload}-U_e}{U_p})^2 \quad (4)$$

Where: $U_{kload}$ is the load node voltage; $U_e$ is the load node voltage; $U_p$ is the permissible deviation voltage of the load node.

### *B. restrictive condition*

*1) Trend Balancing Constraints*

$$\begin{cases} \sum_j^N e_i(G_{ij}e_j - B_{ij}f_j) - f_i(G_{ij}f_j + B_{ij}e_j) = P_i \\ \sum_j^N f_i(G_{ij}e_j - B_{ij}f_j) + e_i(G_{ij}f_j + B_{ij}e_j) = Q_i \end{cases} \quad (5)$$

Where:N is the number of nodes in the distribution network;$I_k$ denotes the injected current at k nodes;$Z_k$ denotes the resistance at k nodes.

*2) Node voltage constraints*

$$U_i^{min} \leqq U_i \leqq U_i^{max} \quad (6)$$

where: $U_i$ is the voltage at the ith node; $U_i^{max}$、$U_i^{min}$ are the upper and lower limits of the voltage at node i, respectively.

*3) Total capacity constraint for distributed power access*

$$p_g < P \quad (7)$$

where P is the maximum capacity allowed to be installed. In this paper, the maximum power capacity of each node is set to 10 in specific tests.

## III. SOLUTION ALGORITHM

### *A. tidal current calculation*

The model used for distributed power sources connected to the distribution network can be simplified to PV nodes, which usually have better linear convergence using the method of forward back generation for the current calculation. For the standard node data input to the program, we specifically use the following steps to process:

1) After finding the load node, calculate the relevant parameters of the Mississippi value. Specific approach is to set the benchmark power, benchmark voltage, benchmark impedance, the initial value of the voltage and thus calculate the node impedance of the standardized value and then calculated to join the distributed power after the system capacity of the standardized value.

2) Calculate the distribution network current using the forward back generation method. After determining the node and branch information of the distribution network, including the connection relationship between the nodes and the parameters of the branch, set the initial state and establish the node voltage equation and load model.

3) Based on the nodal voltage equation and load model, iterative calculation is performed. First, the voltage value of the unknown node is calculated using the nodal voltage equation, and then the calculated nodal voltage value is substituted into the load model to calculate the power, and then substituted into the nodal voltage equation again for iteration until the convergence condition is satisfied.

4) Calculate branch current and power loss: according to the node voltage and branch parameters, calculate the current and power loss of each branch. Finally, check the convergence of the currents: determine whether the iterative calculation converges, i.e., whether the variation of the node voltage is within the acceptable range. If it converges, the calculation is complete; if it does not converge, return to step 3 for iterative calculation.

In this paper, the basic steps for the calculation of tidal currents using forward back generation are shown in Figure 1 below:

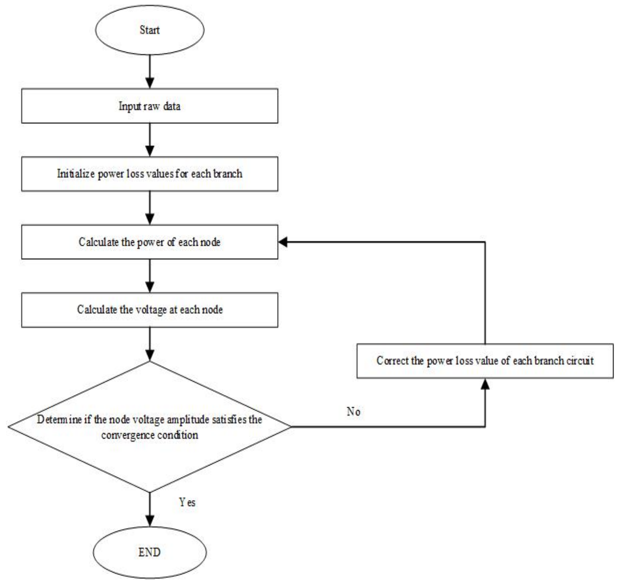


Fig. 1 Calculation of forward and backward generation currents

### *B. Traditional Particle Swarm Improvement Algorithm*

Particle swarm algorithm is an optimization algorithm based on swarm intelligence, which creates a particle swarm by simulating the foraging behavior of biological groups such as flocks of birds, schools of fish, etc., and uses individuals in the swarm to detect the feasible search space Each particle moves in the search space, adjusts itself according to the individual's historical optimal value and the optimal value of its neighbors, and gradually approaches the location of the optimal solution. The process of gradual adjustment of particles is considered to be the process of learning and improvement of particles from the group society. The algorithm has the advantages of simple and easy to implement, fast convergence speed, and can deal with multi-dimensional and high-dimensional optimization problems. The advantage of the particle swarm algorithm lies in its ability to utilize the collaboration and information sharing mechanism among individuals in the group to quickly find the optimal solution.

Simulated annealing algorithm is a heuristic search algorithm that finds the optimal solution by simulating the annealing process of a solid substance in physics. The algorithm excels in global search, is able to find optimal solutions in a large solution space, and is robust and insensitive to the choice of initial parameters. The simulated annealing algorithm is capable of accepting inferior solutions and accepting worse solutions with a certain probability, thus expanding the search range and avoiding falling into local optimal solutions.

Combining the simulated annealing algorithm with the particle swarm algorithm to form a particle swarm algorithm based on simulated annealing can give full play to the advantages of the two algorithms. This hybrid algorithm can search the solution space more comprehensively, avoid falling into local optimal solutions, and improve the global search ability and optimization accuracy. In addition, the particle swarm algorithm based on simulated annealing can further optimize the performance of the algorithm by adjusting the parameters and setting different initial solution strategies to improve the search efficiency and optimization accuracy.

In the combination of simulated annealing algorithm and particle swarm algorithm, a key step is to sample the local optimal solution of each individual by simulated annealing. In this process, appropriate perturbations are first introduced to the local optimal solutions to generate new local optima, which are then screened and updated according to the Metropolis criterion to optimize the local optima. The result thus obtained will be used as the historical optimal solution for each individual in the next-generation population, where the best-performing solution will be selected as the global optimal solution of the particle swarm algorithm. Ultimately, the optimal solution for distributed power access to the distribution network can be obtained by this comprehensive algorithm.

Metropolis Guidelines:

$$\begin{cases} pbest_{old} = pbest_{new} \\ if\ value_{new} < 0\ or\ exp(-value_{new}/T) > rand(0,1) \end{cases} \quad (8)$$

Where: $pbest_{old}$ denotes the past local optimal solution, $pbest_{new}$denotes the present local optimal solution, T denotes the initial temperature of the simulated annealing, and $value_{new}$ denotes the new state value.

Through the combination of simulation algorithm and particle swarm algorithm, we can not only introduce more flexibility and diversity in selecting the local optimal solution, but also effectively avoid falling into the dilemma of local optimal solution, so as to find the global optimal solution more likely. However, traditional particle swarm algorithms are mostly used to solve single-objective optimization problems, whereas in practical applications, the siting and capacity determination of distribution networks is often a multi-objective optimization problem that needs to consider multiple factors.

### *C. Improved multi-objective particle swarm algorithm*

In the distribution network siting and capacity determination there are many problems are composed of multiple objectives that conflict with each other and affect each other, such as investment cost and network loss, these objectives can not reach the optimal state at the same time, we usually try to make these objectives to reach the best state in the region, which is multi-objective optimization. So naturally we think of Pareto optimality , based on this this paper proposes a This paper proposes a multi-objective optimization algorithm based on particle swarm optimization.

The Pareto-optimal method searches for the Pareto frontier of the objective function, i.e., the point at which there is no better solution among multiple objectives, by continuously adjusting the decision variables using a mathematical optimization algorithm. The algorithm proceeds iteratively and by constantly updating the set of solutions, a Pareto optimal solution is finally obtained. In this paper, in order to solve the optimal solution containing the three factors of investment cost, network loss and voltage stability, we find the equilibrium point that is optimal under multiple objectives by continuously optimizing the sum of costs, thus achieving the best decision under limited resources.

In the problem of selecting the individual optimal value gbest of particles, in the single-objective problem, it is natural to select by the value of the objective function. However, in multi-scalar optimization problems, it is difficult to determine which particle is better by the value of the objective function, and thus the selection of individual and local optimal values is not possible. A common approach is to select the individual optimum based on the Pareto dominance relation. If the current particle dominates the gbest we update the gbest with the current particle position, otherwise the optimal value remains unchanged.

In dealing with constraints, unlike conventional single-objective particle swarm algorithms, we often implement constraints by means of penalty functions. However, for multi-objective particle swarm algorithms, we usually find the Pareto solution set [11] first, and then find the optimal solution by assigning the weight value, which leads to the difficulty of solving the constraints by means of the penalty function. Therefore, this paper adopts another form of objective function to store the penalty function. In the specific code implementation, we also need to set the penalty function as the objective function, so the number of objective function is set to 4 (one more than the actual objective function), when it is 0 is equivalent to meet all the constraints of the model.

The specific steps for solving the multi-objective optimization model using the improved multi-objective particle swarm algorithm are as follows:

1) Initialization. Including the initial position and number of population particles, the maximum number of iterations, the number of control variables - the capacity of distributed power installed at each node (except for the balanced node), the annealing constant, etc.

2) Calculate the local optimal solution pbest and select the individual global optimal solution gbest from it based on the multi-objective global optimization [12] technique of small habitat technology.

3) Numerical ranking of each objective function. Calculate the fitness of individuals based on their ranking, find the global optimal solution with the best fitness, and output the optimal individual and the optimal individual fitness. Update the velocity and position of the particles. Satisfy the control variable constraints and particle swarm velocity constraints.

4) Update the velocity and position of particles. Satisfy the control variable constraints and particle swarm velocity constraints. Find the objective function value of each

individual to form a mixed population for non-dominated sorting. Select the next generation population. In this paper, particles update their velocity and position in the following way:

$$\begin{cases} v_i(t+1) = v_i(t) + c_1 r_1(t)\left[p_{i,best}(t) - x_i(t)\right] + c_2 r_2(t)\left[g_{i,best}(t) - x_i(t)\right] \\ X_i(t+1) = X_i(t) + v_i(t+1) \end{cases} \tag{9}$$

where $c_1, c_2$ denotes the learning factor; $r_1, r_2$ denotes a random number of [0,1]; $v_i$ denotes the particle velocity.

5) After satisfying the number of iterations, the output is saved in binary code to find the solution that satisfies the constraints. Thus, the optimal individual is selected in the Pareto solution set.

In this paper, the flow of the improved simulated annealing particle swarm algorithm for solving the multi-objective distributed power source siting and capacity determination problem is shown in Fig. 2.

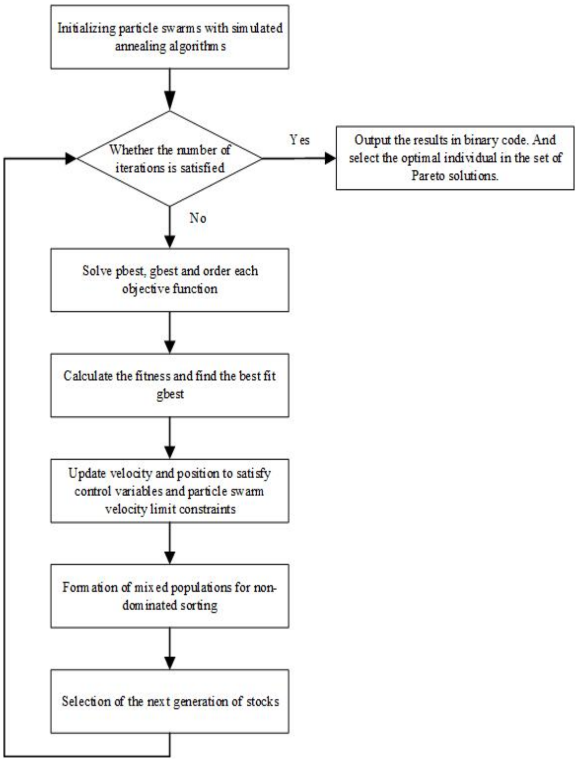


Fig. 2 Flowchart for solving the multi-objective optimization model

## IV. CALCULUS ANALYSIS SUMMARIZE

The IEEE69 node system [13] is used in this algorithm and its network architecture is shown in Fig. 3. The standard IEEE69 node distribution system is simplified using the coding strategy, which contains 5 loops, 69 nodes in the network with 73 branches, a rated voltage of 12.66kV, a base value of system power of 10MVA, and a total load of the entire network of 3802.19+j2694.6KVA.

After reading the data of 69 nodes (first node, last node, resistance, reactance, active Kw, reactive Kva), first find its load node, set the benchmark power as 100MVA benchmark voltage as 12.66Kv and calculate the standardized value of the relevant parameters, and then use the method of forward and backward generation to calculate the distribution network trend, and in this paper, set the number of iterations as 20 times.

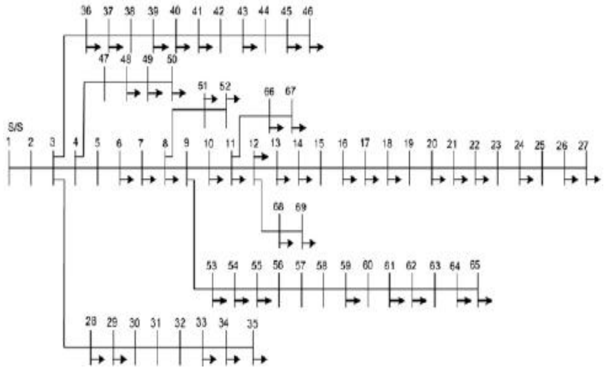


Fig. 3 Network architecture of IEEE69 node system

When using the improved multi-objective simulated annealing particle swarm algorithm to solve the multi-objective optimization problem, the initial parameters of this paper are set as follows: the number of population particles is 90; the maximum number of iterations is 200; the annealing constant is taken to be 0.5; the investment cost of the unit of distributed power supply is taken to be 0.12, and the operation cost is taken to be 0.2; the service life of the distributed power supply equipment is 20, and the discount rate is 0.1; the expected voltage of the load node is 1, and the voltage Allowable deviation 0.05; node voltage minimum value is set to 0.95, maximum value is set to 1.05 for solving.

By taking the investment cost, network loss and voltage stability as the objective function, we can get a Pareto solution set. This solution set shows each feasible solution set that minimizes the sum of the three costs, as shown in Fig. 4. For the derived feasible solution set find the solution whose penalty function is 0, i.e., the solution set that satisfies all the constraints. Since the Pareto solution set is not unique, we then filter out an optimal solution that satisfies the weights by assigning different weights to its weights multi-objective, and calculate the value of the population particles to obtain an optimal result, as shown in Fig. 5, for the capacity of the distributed power supply installed at each node (set the maximum value to 10). Finally, the node voltage diagram after installing distributed power supply at each node is calculated and analyzed, and the result is shown in Fig. 6.

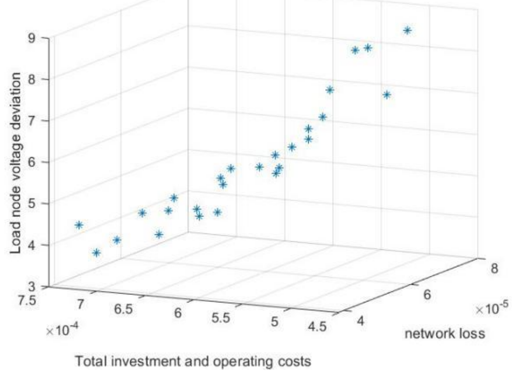


Fig. 4 The set of Pareto solutions for the three objectives

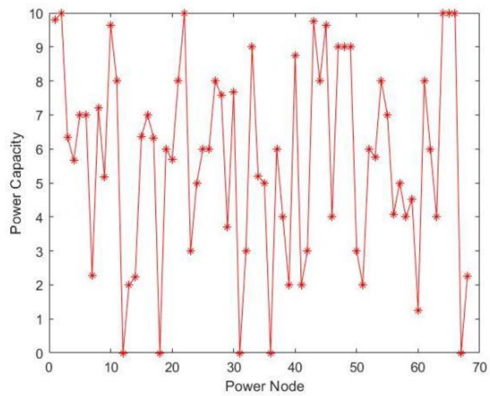


Fig. 5 Distributed power capacity installed at each node

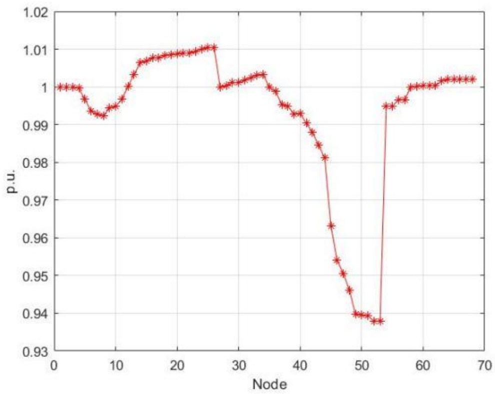


Fig. 6 Nodal voltage diagram of the optimal node

## V. SUMMARIZE

This paper proposes a solution method for a multi-objective mathematical model based on three objectives: investment cost, network loss, and voltage stability. The computational method for solving the distributed power siting and capacity-setting problem is computed by forward back generation method for calculating the distribution network currents and the improved particle swarm algorithm with hybrid simulated annealing algorithm. For the realization of constraints in the process of solving the Pareto solution set, the penalty function is added to the objective function to find the relevant solution that makes the value of the function 0, i.e., the solution that satisfies the constraints. For the optimal solution set obtained, the final result is filtered by solving its adaptability, additional weights, etc., and finally the optimal battery capacity and node voltage of each node are calculated to determine the installation of DG.

Through experimental analysis, this method not only solves the Pareto solution set of the multi-objective model, but also suppresses the shortcomings of the simulated annealing algorithm, such as the long computation time, the particle swarm algorithm, which has a slower convergence accuracy and is easy to fall into the local oscillations, and greatly improves the algorithm's speed of convergence to the globally optimal solution and the convergence accuracy. The results of the specific arithmetic example of IEEE69 nodes show that the algorithm is feasible in practical applications.

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