

Reactive Power Optimization of Distribution Network Based on Dual Population Ant Colony Algorithm

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This paper has further researched on the reactive power optimization algorithm in distribution network aiming at the actual conditions that the reactive-load compensation equipment in the distribution network is insufficient and is in unreasonable distribution and the network loss is too large and the voltage quality needs to be further improvement. At first, this paper uses the minimum loss of the distribution system network as the objective function, establishing a mathematical model of reactive power integrated optimization which fits in with the actual distribution network. Then, aiming at the ant colony algorithm's disadvantage of long searching time and easy to stagnation, this paper proposes that we can carry out reactive power optimization by using dual population improved ant colony algorithm. Based on the ant colony algorithm, this algorithm carries on independent search by leading into two kinds of ant colony, and carries on information communication, breaking the stagnation of the single ant colony's searching in large probability, ensuring the variety of the solution in the algorithm, and raising the global convergence ability. Finally, this paper tests the feasibility and the availability of this algorithm by the simulative calculation of the IEEE6 system and comparing the results and the traditional optimization results.

1. Introduction

The reactive power optimization of the distribution network is the optimization problem of the distribution network's satisfying various constrained conditions and achieving the intended target under certain running mode (Liu et al., 2002). It refers to choosing the reactive-load compensation equipment, confirming the input capacity of the reactive power compensation device (Sarno et al., 2015) and adjusting the transformer's tapping point and the cooperation of the generator terminal voltage, and it is a nonlinear programming problem with multiple constraints. The reactive power optimization has the characteristics of discreteness, nonlinear, large-scale and the convergence depending on the initial value. Aiming at the characteristics of the reactive power optimization, the experts and scholars home and abroad use various optimization algorithms in this field, which can be divided into two kinds of the traditional optimization method and the artificial intelligence method. The traditional optimization method includes linear programming method, nonlinear programming method, and mixed integer programming method, etc (Jwo et al., 1995; Das and Patvardhan, 2002; Abdul-Rahman et al., 1995). The problem of the reactive power optimization is discrete nonlinear problem. The traditional optimization method generally requires differentiable or linearization, but the switching combination of the adjustable tap of the transformer and the compensating capacitor group is graded. Because the traditional method adopts continuous approximation method in dealing with the discrete variable, the problem of the reactive power optimization including the discrete variable may have larger error. For this reason, the researchers use the new method based on the artificial intelligence such as genetic algorithm (Liu et al., 2007), neural network algorithm (Santoso and Tan, 1990), tabu algorithm (Duan and Yu, 2001), expert system, fuzzy set theory (Ng and Salama, 1995) into the research of the reactive power optimization, overcoming the disadvantage of the traditional optimization method and gaining better effect. The most serious problem in the traditional genetic algorithm is the problem of premature convergence. Because the network structure of the distribution network is complicated and changeable, it makes great difficulty to train the nerve net in the neural network algorithm. When the structure of the distribution network is changed, a new shipment of sample

comes into being, so the neural network technique's application in the distribution network is restricted. The optimum seeking speed of the tabu algorithm is faster, but this method is a single point searching method in extending presence, and its convergence is influenced by the initial solution. The method of expert system based on the sensitivity analysis easily is easily immersed in the local extremum region because of the improper selection of the initial point. The fuzzy optimization method is only effective to the analysis of the indeterminacy problems; to the analysis of the exact problem, it will make the problem complicated.

The Ant Colony Search Algorithm is a kind of simulated evolutionary algorithm, which was initially proposed by the Italian scholar M.Dorigo, whose idea took in the behavioral characteristics of real ants, having the advantages of high robustness, intrinsic parallelism and the ability of finding the excellent solution, without any differentiable even continuous require to the function (Dorigo et al., 1996). Based on this, more and more scholars have applied it to the research on the reactive power optimization.

However, in the research on the Ant Colony Search Algorithm, it is found that the basic Ant Colony Search Algorithm is easily immersed in the stagnation state. Under the information positive feedback mechanism, a great number of ants choose the same path and make the pheromone concentration on the chosen path largely outweigh other paths, so it makes it difficult for the algorithm to find other excellent solutions in the neighborhood space. This problem is similar to the condition in the genetic algorithm converges to local optimal solution caused by the reason that the species lacks the diversity in the genetic algorithm, so this paper tries to apply the dual population improved ant colony algorithm to the reactive power optimization. Because the ant's choice of the path lies on the state transition probability and the state transition probability is decided by the pheromone concentration, so the distribution of the pheromone concentration in different populations is different, thus the variety of the algorithm's solutions can be kept, at the same time they can exchanged between the two populations regularly, making the best use of the excellent solution and the information.

2. Ant colony algorithm and improved ant colony algorithms

2.1 Ant colony algorithm

Ant colony algorithm is to solve the problem by simulating the behavior of ants' looking for food and returning to their nest. Each ant searches the solution independently in the space of the candidate solution, and leaves pheromone on the way forward. Ant communicates and cooperates with other by leaving the pheromone in order to find a shorter path. The more ants pass through a path, the greater the intensity of the pheromone released on the path. Ants choosing the next path will tend to choose the direction in which the pheromone is in great intensity. In this way, there will be more ants choosing this path, and the intensity of the pheromone on this path will be more and bigger, and the number of ants choosing this path will be more, thus it converges to the optimal path.

The basic principle of ant colony algorithm can be described by the classical traveling salesman problem (A traveling salesman departs from a certain city, visits each city once and only once, and finally returns to the starting city, asking to find a shortest path tour.). We assume that the number of ants is m ; $d_{ij}=(i,j=1,2,\dots,n)$ represents the distance between the city i and the city j ; $\eta_{ij}(t)$ represents the heuristic function, and the value is set to: $1/d_{ij}$; $\tau_{ij}(t)$ represents the amount of pheromone remaining on the city i,j connection at t time; $\Delta\tau_{ij}^k(t)$ represents the amount of per unit length pheromone left by ant k on the city i,j connection; $p_{ij}^k(t)$ represents the transition probability of ant k in the city i to select the next city j at t time. The amount of initial pheromone on each path is equal. $\tau_{ij}=c$ (c is a nonzero constant).

(1) Path selection strategy

In the course of the movement, ant k decides the transfer direction according to the amount of pheromone on each path. The transition probability of ant k in the city i which selects the next city j is:

$$P_{ij}^k(t) = \begin{cases} \frac{\tau_{ij}^\alpha(t)\eta_{ij}^\beta(t)}{\sum_{s \in allowed_k} \tau_{is}^\alpha(t)\eta_{is}^\beta(t)} & j \in allowed_k; \\ 0 & others. \end{cases} \quad (1)$$

In Formula 1, $allowed_k=\{1,2,\dots,n\}-tabu_k$ represents a collection of cities chosen by ants in the next path. α and β are two parameters, which reflect respectively the accumulation of pheromone and the relative influence of heuristic information by ants in the process of moving. The $tabu_k$ list is used to record the city that ants walk through, and has constant dynamic tuning with time in.

(2) Pheromone Updating Strategy

After a traversal of n cities, the ants complete a cycle. The amount of information on each path adjusts according to the following formula:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^m \Delta\tau_{ij}^k(t); \quad \Delta\tau_{ij}^k(t) = \begin{cases} \frac{Q}{L_k} & \text{Ant } k \text{ in this cycle through the } ij \\ 0 & \text{others} \end{cases} \quad (2)$$

In the formula 2, $\rho(0 \leq \rho < 1)$ is the pheromone evaporation coefficient; $1-\rho$ is pheromone residual factor; Q is a constant, which indicates the pheromone intensity released by ants after completing a full path search; L_k represents the total length of the path that ant k has passed in this cycle.

2.2 Dual Population Improved Ant Colony Algorithm

The basic idea of dual population improved ant colony algorithm is: the ants in the ant colony algorithm are separated into two populations and carry out independent search, and regularly exchange information and excellent solution, so as to ensure the diversity of the solutions. The realization of the dual population ant colony algorithm needs to solve two basic problems: the first is the content and form of information exchange; the second is how to determine the conditions of information exchange.

(1) Selection of content and form of information exchange

The content of information exchange is reflected mainly in the distribution of pheromone. The pheromone in the single population will tend to be consistent, but the distribution of pheromone in different populations is different. Therefore, we can distribute the information of some excellent solutions in each population to another population, so that the ants of another population can break the stagnant state with greater probability. At the same time, the size of each population can vary, and the optimization parameters of each population can also be different.

(2) Determination of the conditions of information exchange

In general, we can choose to carry out an information exchange after every several generations, and the regular exchange is more intuitive and easy to implement. Too frequent exchanges will make the algorithm close to the single population algorithm, and if the number of exchange is too small, it can not reflect the superiority of the dual population algorithm. So in this paper, the exchange time is 5 in the application of dual population improved ant colony algorithm.

If the distribution of pheromone is different in different two populations after the completion of an optimization iterative process, we can distribute the information of some excellent solutions in each population to another population. That is, we can exchange pheromone. Otherwise, if the search results and the pheromone distribution of the two populations are similar, then the exchange of pheromone is not significant. There is no need to exchange pheromone after the end of the iteration process.

3. Reactive power optimization of distribution network based on Dual Population ant colony

3.1 Mathematical model of reactive power optimization

The mathematical model of reactive power optimization in distribution network includes three parts: the node power constraint equation, the variable constraint condition and the objective function.

(1) Node power constraint equation

In reactive power optimization model, we need to consider the active and reactive power balance constraints of each node. That is, the injected active power and reactive power of each node satisfy the constraint equation of the formula 3.

$$\begin{cases} P_i = P_{Gi} - P_{Li} = V_i \sum_{j=1}^n V_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) \\ Q_i = Q_{Gi} - Q_{Li} - Q_{Ci} = V_i \sum_{j=1}^n V_j (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}) \end{cases} \quad (3)$$

In formula 3, P_i , Q_i , V_i are injected active power, injected reactive power and voltage of the node i , respectively; P_{Gi} , Q_{Gi} are active power and reactive power of generator node, respectively; P_{Li} , Q_{Li} , Q_{Ci} are active load, reactive load and reactive power compensation capacity of the node i , respectively; G_{ij} , B_{ij} , δ_{ij} are conductance, susceptance and voltage phase angle difference between node i and node j , respectively; n is the total number of system nodes.

(2) Variable constraint condition

In general, we choose the generator terminal voltage V_G and reactive power compensation capacity Q_C and the transformation ratio of transformer T_k as control variable, while generator reactive power output Q_G and load node voltage V_D as the state variable.

Inequality constraints of control variables and Inequality constraints of state variables are shown in formula 4.

$$\begin{cases} V_{Gi\min} \leq V_{Gi} \leq V_{Gi\max} & i \in N_G \\ Q_{Ci\min} \leq Q_{Ci} \leq Q_{Ci\max} & i \in N_C \\ T_{k\min} \leq T_k \leq T_{k\max} & i \in N_T \end{cases} ; \begin{cases} Q_{Gi\min} \leq Q_{Gi} \leq Q_{Gi\max} & i \in N_G \\ V_{Dj\min} \leq V_{Dj} \leq V_{Dj\max} & j \in N_{PQ} \end{cases} \quad (4)$$

In formula 4, N_G , N_C , N_T , N_{PQ} are the generator node number and reactive power compensation node number and transformer quantity and load node number, respectively.

(3) Objective function.

In this paper, the minimum loss of the active power was regarded as the objective function. The load node voltage constraint and the generator reactive power constraint are introduced into the objective function as penalty function. Expression is as follows:

$$\begin{aligned} \min F &= P_{loss} + \lambda_1 \sum_{j=1}^N \left(\frac{\Delta V_j}{V_M} \right)^2 + \lambda_2 \sum_{k=1}^{N_G} \left(\frac{\Delta Q_k}{Q_M} \right)^2 \\ P_{loss} &= \sum_{i=1, j \in i}^N G_{ij} \left[V_i^2 + V_j^2 - 2V_i V_j \cos \theta_{ij} \right] \end{aligned} \quad (5)$$

In formula 5, N , N_G are system node number and generator node number, respectively; G_{ij} is the conductance of the line ij ; V_i is the voltage of the node i ; λ_1 , λ_2 are the overflow penalty coefficient of load node and the overflow penalty coefficient of the generator reactive power output, respectively. ΔV_j , ΔQ_k as follows:

$$\Delta V_j = \begin{cases} V_j - V_{j\max} & V_j > V_{j\max} \\ 0 & V_{j\min} < V_j < V_{j\max} \\ V_{j\min} - V_j & V_j < V_{j\min} \end{cases} ; \Delta Q_k = \begin{cases} Q_k - Q_{k\max} & Q_k > Q_{k\max} \\ 0 & Q_{k\min} < Q_k < Q_{k\max} \\ Q_{k\min} - Q_k & Q_k < Q_{k\min} \end{cases} \quad (6)$$

$$V_M = V_{j\max} - V_{j\min}; Q_M = Q_{k\max} - Q_{k\min} \quad (7)$$

In the above formula, $V_{j\max}$, $V_{j\min}$ are the upper limit value and lower limit value of voltage of the node j , respectively; $Q_{k\max}$, $Q_{k\min}$ are the upper limit value and lower limit value of reactive power output of the generator node k , respectively.

3.2 Algorithm flow of reactive power optimization of distribution network based on Dual population

The algorithm flow of reactive power optimization of distribution network based on dual population improved ant colony algorithm is shown in figure 1.

4. Example analysis

In this paper, the simulation and calculation on IEEE6 are carried out. IEEE 6 system wiring is shown in Figure 2. The system contains six nodes and seven branches, including two generators and two adjustable transformer and two reactive power compensation points. The reference capacity is 100MVA. We select the node 1 as the balance node and its voltage amplitude is 1.00~1.10; the node 4 and 6 as the reactive power compensation point and the compensation capacity is between 0 ~ 0.55; the transformer tap position adjustment range is 0.9 ~1.1. The parameters in the algorithm are set as follows: the number of ants in the two species is 50; the number of iterations is 100 times; the number of pheromone exchange is 5 times. $\alpha = 1, \beta = 2, \rho = 0.3, Q = 1.0$.

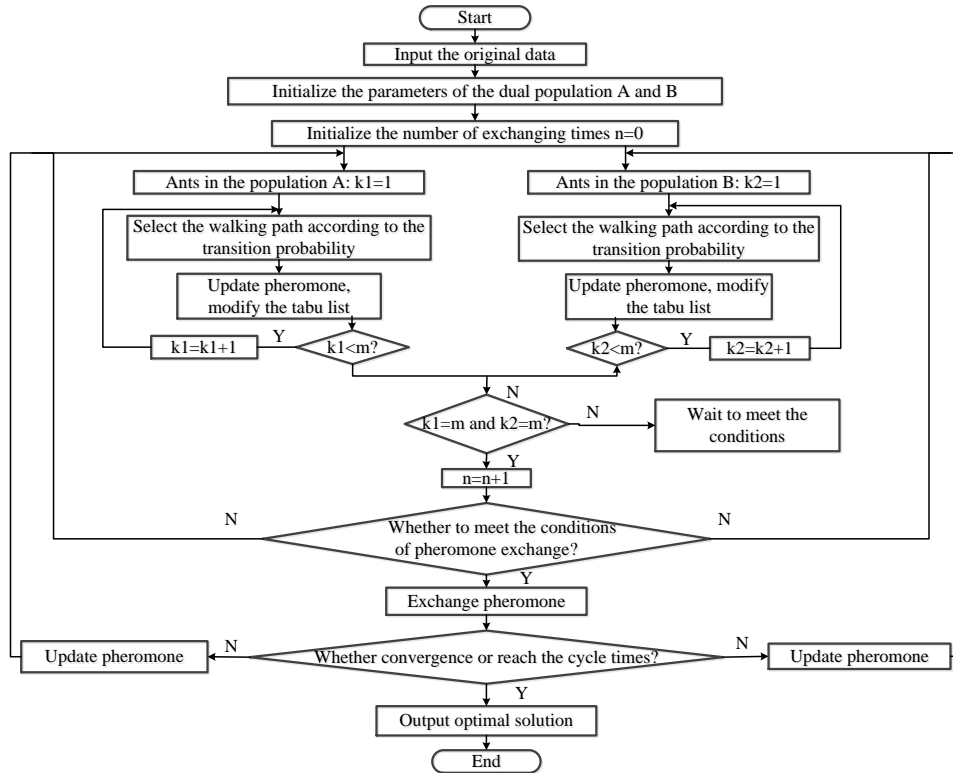


Figure 1: The algorithm flow chart

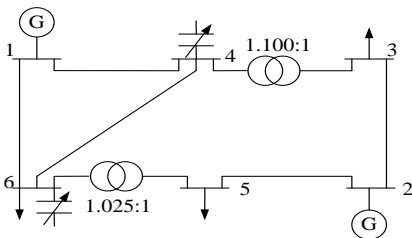


Figure 2: IEEE 6 system wiring chart

Table 1: Optimization results and comparison of IEEE6 nodes (p.u.)

Variable name	Comparison of the results of each algorithm		
	Initial power flow	Ant colony algorithm	Dual population ant colony
T_{43}	1.100	0.984	1.025
T_{65}	1.025	0.950	1.000
V_{G1}	1.0500	1.1000	1.1000
V_{G2}	1.1000	1.1411	1.1471
Q_{C4}	0.0000	0.0500	0.0500
Q_{C6}	0.0000	0.0550	0.0550
Q_{G1}	0.3812	0.3922	0.4028
Q_{G2}	0.3481	0.1649	0.1741
V_{D3}	0.8551	0.9811	0.9932
V_{D4}	0.9527	0.9622	1.0013
V_{D5}	0.9008	0.9125	0.9494
V_{D6}	0.9331	0.9312	0.9843
P_{loss}	0.11613	0.08852	0.08825

The optimization results of the dual population improved ant colony algorithm are compared with the results of the initial power flow and the basic ant colony algorithm, as shown in Table 1.

In the result of the initial power flow, the active power network loss is 11.613MW, the node 3 voltage is the lowest, and its standard value is 0.8551 which is less than the lower limit value 0.9. After the optimization of the improved ant colony algorithm, the active power loss of the system compared with the initial power flow reduces 24.007%, without voltage and reactive overflow node, and the minimum voltage of the load node is increased from the initial state 0.8551 to 0.9932 (p.u.).

5. Conclusion

According to the current situation and characteristics of reactive power optimization of distribution network and under the premise of satisfying the network performance requirement of reactive power of generator and load node voltage, this paper has established a mathematical model of reactive power integrated optimization which fits in with the actual distribution network, using the minimum of the distribution system network loss as the objective function. Based on the analysis of a large number of intelligent algorithms, the ant colony algorithm has been selected as the optimization algorithm and the shortcomings of the algorithm has been improved, with the dual population improved ant colony algorithm having been obtained. And this algorithm has applied in IEEE6 system for experimental simulation. The results have shown that the improved ant colony algorithm overcomes the shortcomings of the ant colony algorithm in premature, stagnation and so on. The whole optimization process has high precision and reliability, and the optimization results and convergence performance have been greatly improved.

Acknowledgements

This work was supported by Baoding Science and Technology Research and Development Project (11ZG029).

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