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Reactive Power Optimization in Power System Based on Improved Multi-agent Ant Colony Optimization

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Abstract: As the disadvantages of the conventional ant colony optimization, such as convergence speed and local optimal value, an improved multi-agent ant colony optimization for reactive power optimization method is proposed. The improved sort-weighted ant colony optimization is combined with multi-agent system to improve convergence speed and calculation accuracy and to avoid falling into local optimal value effectively. Improved algorithm is applied to reactive power optimization in IEEE 30-node systems, the simulation results verify the validity of the algorithm.

Key words: Power system, reactive power optimization, intelligent algorithm

INTRODUCTION

Reactive power optimization which searches the optimal solution in the given constraint situation, plays an important role in power quality, network loss and voltage stability. Scholars have introduced the intelligent optimization algorithm to the field of reactive power optimization to overcome the shortcomings of classic algorithms in recent decades. Evolutionary Programming (EP) which opened up the process of intelligent optimization algorithm was first proposed by L.J. Fogel ect. Evolutionary Strategies (ES) and Genetic Algorithm (GA) presented in 1970s promoted the further development of intelligent algorithm. In 1995, Differential Evolution Algorithm (DE) was discussed by R. Storm and K. Price and at the same time, another branch of intelligent algorithm-swarm intelligent algorithm, especially Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) (Zhang, 2011) are applied widely. Although different optimization algorithms are put forward, they have different scope of application. ACO has no systemic mathematical foundation and analysis methods and the disadvantages such as complex calculation, local optimal value, slowly convergence. Much improvement has been done for ACO. For example, ACO (Tan, 2012) based on chaos theory utilizes the ergodicity of chaotic search and avoids to fall into local optimal value, ACO combined with Immune Algorithm (Bao and Yang, 2007) to improve single search mechanism which enhances global search ability at the expense of the operation time.

A method integrates Multi-Agent System (MAS) with improved ACO to overcome local optimal value and increase convergence speed is discussed in the study which can achieve fast and accurate optimization.

MODEL OF REACTIVE POWER OPTIMIZATION

The mathematical model of reactive power optimization consists of objective function and constraint conditions. The constraint conditions include equality constraints and inequality constraints.

Several constraints such as network loss, voltage quality, reactive compensation capacity and economic benefits ect., should be considered to establish reactive power optimization objective function. Considering these factors comprehensively, the objective function is as follows:

$$\min F = \min\sum_{k=1}^{n} G_{ij}\left[u_i^2 + u_j^2 - 2u_i u_j \cos\left(\delta_j - \delta_i\right)\right] \tag{1}$$

where, F is distribution electric energy loss, n is the total number of branch; G_{ij} is conductance on the i-j branch; δ_i δ_j, respectively stand for phase angles of $node_i$ and $node_j$; $u_i u_j$ stand for voltages of $node_i$ and $node_j$.

As the power flow calculation is used to not only test the results of optimization but also is the main

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component of calculation program in some optimization algorithm, so the power flow equations are treated as equality constraint conditions, it can be expressed as follows:

$$\begin{cases} P_i - U_i \sum_{j=1}^{n} U_j \left(G_{ij} \cos\delta_{ij} + B_{ij} \sin\delta_{ij} \right) = 0 \\ Q_i - U_i \sum_{j=1}^{n} U_j \left(G_{ij} \sin\delta_{ij} - B_{ij} \cos\delta_{ij} \right) = 0 \end{cases} \tag{2}$$

where, P_i and Q_i are the injected active power and reactive power of $node_i$ separately; U_i and U_j stand for voltages of node $_i$ and node $_j$; G_{ij} and B_{ij} are real part and imaginary part of element in the ith row and the jth column in system node admittance matrix.

The reactive power of generator, compensation capacity of reactive power compensation devices and variable ratio of on-load tap changer are selected as controlling variables. Voltages of load node are selected as state variables.

The inequality constraints of control variable are:

$$\begin{cases} Q_{Gimin} \le Q_{Gi} \le Q_{Gimax} \\ Q_{Cimin} \le Q_{Ci} \le Q_{Cimax} \\ T_{imin} \le T_i \le T_{imax} \end{cases} \tag{3}$$

The inequality constraints of state variable are:

$$u_{imin} \le u_i \le u_{imax} \tag{4}$$

where, Q_{Gi} is reactive power of $node_i$ generator; Q_{Gimax} and Q_{Gimin} are upper and lower limit of Q_{Gi}; Q_{Ci} is the compensation capacity of the ith reactive power compensation device; upper and lower limit of Q_{Ci} are Q_{Cimax} and Q_{Cimin}; T_i is variable ratio of the ith on-load tap changer; T_{imax} and T_{imin} are upper and lower limit of T_i; u_{imax} and u_{imin} are upper and lower limit of u_i, voltage of $node_i$.

MULTI-AGENT Ant COLONY OPTIMIZATION

Conventional ant colony optimization: Ant Colony Optimization (ACO) is a new simulated evolutionary algorithm which simulates real ants foraging behavior in the nature. But the difference with real ant system is ACO has memory function (Shi, 2008) by exchanging message and cooperation among ants which can get the optimal value of optimized problem which can be equivalent to the shortest path of real ant foraging from the nest to food source.

Traveling salesman problem (TSP) is taken as an example to explain the basic principle of ACO. Initial parameters m is the number of ants, n is the scale of the city, the distance between $city_i$ and $city_j$ is d_{ij} (i,j = 1,2,...,n), the concentration of pheromone that is between the path of $city_i$ and $city_j$ at t moment is $\tau_{ij(t)}$. Ant k (k = 1,2,...,m) decides to visit next city according to the concentration of the pheromone between two cities. $P^K_{ij(t)}$ is probability of ant k from $city_i$ to city $_j$ at t moment, the expression is:

$$P_{ij}^{k} = \begin{cases} \dfrac{\left[\tau_{ij}(t)\right]^{\alpha} * \left[\eta_{ij}(t)\right]^{\beta}}{\sum\limits_{s \in allow_k} \left[\tau_{is}(t)\right]^{\alpha} * \left[\eta_{is}(t)\right]^{\beta}}, & s \in allow_k \\ 0, & s \notin allow_k \end{cases} \tag{5}$$

where, η_{ij} (t) is enlightening function, its value is $1/d_{ij}$ and stands for the expectation from $city_i$ to $city_j$, $allow_k$ expresses set of cities which will be visited by ant k and reduces from n-1 to 0 as time goes on. Pheromone enlightening factor is α and self-enlightening factor is β. The greater the value that is defined between α and β, the greater transfer function between two cities is.

The pheromone among the path of different cities, also gradually disappears when the ants release pheromone. P is defined as volatile coefficient (0<P<1), then real-time concentration of pheromone among the path of cities can be updated when all ants complete the cycle:

$$\tau_{ij}(t+1) = \rho * \tau_{ij}(t) + \Delta\tau_{ij} \tag{6}$$

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{7}$$

$$\Delta\tau_{ij}^{k} = \begin{cases} Q/L_k; & \text{if ant k pass the path (i, j)} \\ 0; & \text{otherwise} \end{cases} \tag{8}$$

where, the increment of pheromone concentration on the searching path (i,j) of ant k is $\Delta\tau^K_{ij}$; the sum of pheromone concentration on the searching route (i,j) of all ants is $\Delta\tau_{ij}$; Q is constant and it is amount of pheromone which is released by ant after circulation; L_k is the length of route that is passed by ant k.

The basic process of ACO is shown in Fig. 1.

Improved ant colony optimization: Some scholars introduced the concept of sorting of GA into ACO

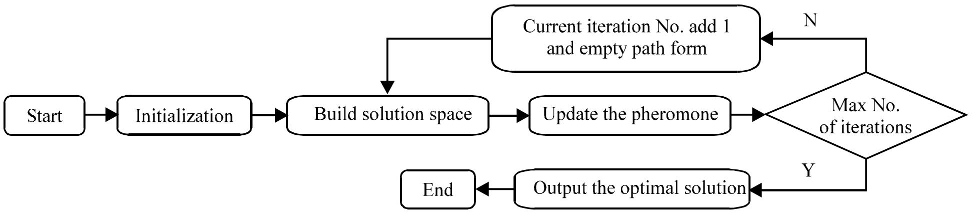


Fig. 1: Basic process of ACO

(Ren, 2006) which improved the algorithm convergence speed in TSP. Based on the thought, the weight coefficient of ACO is adjusted and applied to reactive power optimization to solve convergence speed.

The main idea of improved algorithm is as follows. The paths which are obtained at the end of one ant optimal circulation are sorted according to the length. An ant's contribution of updating pheromone depends on the length of the path. The shorter circulation generates the path, the greater contribution is made by ants to pheromone. The rules of pheromone updating are modified by adding a weighted coefficient $\lambda^K(1\text{-}N/N_{max})$. All the ants have corresponding contribution for global pheromone updating, where the better ants are placed a high value and the effect of worse ants is also weakened during the process of optimization.

In improved algorithm, the path and the global pheromone are updated according to the equation:

$$\Delta\tau_{ij}^{k} = \begin{cases} \lambda^{k}(1-N/N_{max})Q/L_{k}; & \text{if ant k pass the route(i, j) in this cycle} \\ 0 \quad ; & \text{otherwise} \end{cases} \qquad (9)$$

where, $\lambda$is a constant, $0<\lambda<1$; Q is also a constant expressing the amount of pheromone which is released by ant after circulation; k is the No. of optimal ants; L_k is the length of route that is passed by ant k; N and N_{max} are respectively current iteration No. and the maximum iteration No.

When the initial parameters is same, the results of common ACO and improved ACO are shown in Fig. 2.

The advantages of improved ACO over conventional ACO can be summarized from Fig. 2 as follows:

- The improved ACO is able to achieve global optimal value faster than conventional ACO, while satisfying all the power system operation constraints and convergence conditions
- Searching curve of improved ACO is more smooth
- The improved ACO avoids trapping in local optimal value

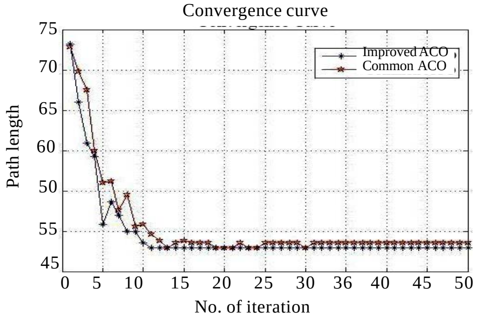
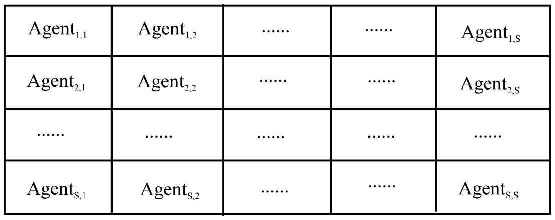


Fig. 2: Comparing results of common ACO and improved ACO



$Agent_{1,1}$	$Agent_{1,2}$	......	......	$Agent_{1,S}$
$Agent_{2,1}$	$Agent_{2,2}$	......	......	$Agent_{2,S}$
......	......	......	......	......
$Agent_{S,1}$	$Agent_{S,2}$	......	......	$Agent_{S,S}$

Fig. 3: Grid structure of agent

Multi-agent Ant colony (MAS) optimization: Multiple-Agent system can solve complex optimal problem by collaborating of each agent. The Agent modules having different functions complete coordinately the task through communication and cooperation with greater flexibility and adaptability (Dagdeviren *et al*., 2011).

Multi-Agent Ant Colony Optimization (MACO) has multiple characters which combine MAS with improved ACO. Any Agent is equivalent to an ant in ACO and it also has a best adaptive value which is decided by optimization.

Agent environment: The survival environment of agent can be simplified to a grid structure in constrained condition. Agent must carry pheromone in ACO and has corresponding response. "Grid" structure is demonstrated in Fig. 3, S stands for the size of grid structure and S*S is ant colony scale.

	$\text{Agent}_{i-1,j}$	
$\text{Agent}_{i-,j-1}$	$\text{Agent}_{i,j}$	$\text{Agent}_{i,j+1}$
	$\text{Agent}_{i+1,j}$	

Fig. 4: Local environment of non-boundary agent

	$\text{Agent}_{i1,j}$	
$\text{Agent}_{i-,j1}$	$\text{Agent}_{i,j}$	$\text{Agent}_{i,j\ 2}$
	$\text{Agent}_{i\ 2,j}$	

Fig. 5: Local environment of boundary agent

Local environment and competitive-cooperative operations: Every agent competes and cooperates with its neighbors, then takes corresponding action strategies independently combined with ant colony searching. Thus, the local environment of Agent is significant (Zhao and Cao, 2005). For the non-boundary $\text{Agent}_{i,j}$, its neighbors are shown in

Figure 4 and can be expressed as:

$$\text{Neighbor}_{i,j} = \{\text{Agent}_{i-1,j}\text{Agent}_{i+1,j}\text{Agent}_{i,j-1}\text{Agent}_{i,j+1}\} \tag{10}$$

where, i and j are both positive integer and I, j∈ (1,2,3…,S) For boundary Agent, namely i,j = 1 or S. Its neighbors are shown in Fig. 5. The value of row index:

$$\begin{cases} i_1 = Si_2 = i+1; & \text{when } i = 1 \\ i_2 = 1i_1 = i-1; & \text{when } i = S \end{cases} \tag{11}$$

In the same way, the value of column index:

$$\begin{cases} j_1 = Sj_2 = j+1; & \text{when } j = 1 \\ j_2 = 1j_1 = j-1\,; & \text{when } j = S \end{cases} \tag{12}$$

Agents are enlightened by pheromone which is left by ants and cooperate and compete with their neighbors. The agent with optimal adaptive value keeps its original location, then exchanges pheromone to all ants at the same time. This algorithm increases the speed of transfer and can search the global optimal solution quickly.

Self-iearning operation: Self learning operation search in small scope and don't introduce ant colony searching mechanism. Self-learning operation is only used to optimal agent to enhance searching speed effectively.

Optimizing steps of MACO: The steps of the improved algorithm is as follows:

- **Step 1:** Set the upper and lower limit of initial parameters and constraints and define the specified control parameters and the maximum number of iterations in the algorithm
- **Step 2:** Create the Agent "survival" environment, "grid" structure and initial Agent, the initial number of iteration is 0
- **Step 3:** Evaluate the adaptive value of each Agent by Newton-Raphson power flow algorithm
- **Step 4:** Every agent and its neighbors are competitive and cooperative, then updating Agents in the whole environment
- **Step 5:** Carry out the improved ACO in the MAS and update position of each Agent in the solution space for the second time afterwards
- **Step 6:** Evaluate the adaptive value of Agent again;
- **Step 7:** Search the optimal adaptive value of Agent, (search the minimum network loss value in this article) and update the location of Agent in the solution space for the third time according to self-learning operation of Agent
- **Step 8:** times of iteration add 1
- **Step 9:** Judge whether the termination conditions is reached, that is, maximum number of iterations or convergence condition; if not, jump to Step 3. Otherwise, terminate the iterations and output the optimal value of optimization

EXAMPLE ANALYSIS

The improved algorithm is applied to IEEE 30-node system (Liu, 2010) analysis to verify the feasibility and validity. IEEE 30-node system is shown in Fig. 6.

The power reference in the system is S_B = 100MVA. There are 6 generators, 38 branches, 4 transformers, 9 sets of parallel capacitor and 21 load nodes. The total load active power is P_{total} = 2.834 and reactive power is Q_{total} =1.262. Parameters are set in Table 1 and 2.

In the initial conditions, $\sum P_G$ and $\sum Q_G$ are 2.8691 and 1.3807 respectively by power flow calculation. Network loss is P_{loss} which equal to 0.035. The initial parameters of the improved algorithm are set as follows. Total environment size is S = 10, namely, ant population scale is 100, the largest number of iterations is N_{max}= 50, pheromone enlightening factor is α = 1, self-enlightening factor is β = 2, volatile coefficient is P = 0.1, weighting coefficient is λ = 0.3, self-learning environment size

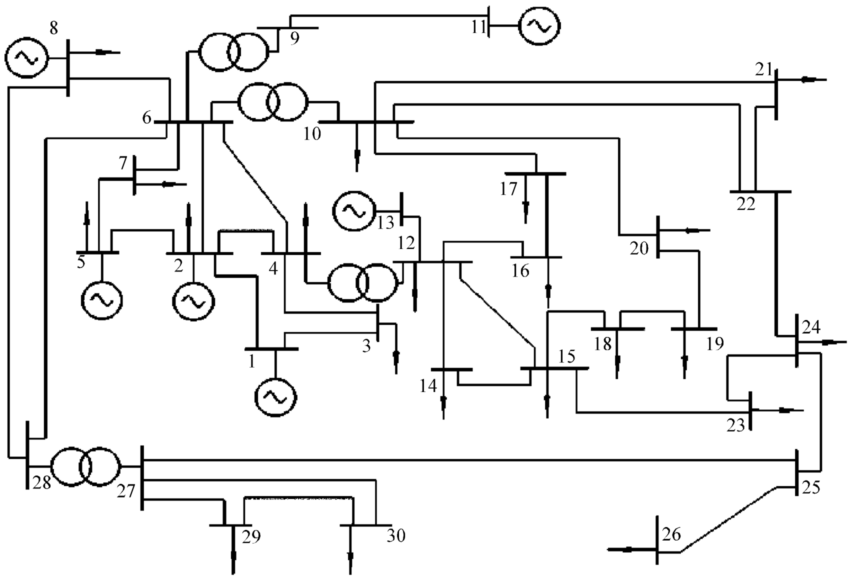


Fig. 6: IEEE 30-node system

Table 1: Generator parameters

Veriables	Q_{G1}	Q_{G2}	Q_{G5}	Q_{G8}	Q_{G11}	Q_{G13}	Voltage
Lower limit	-0.20	-0.20	-0.15	-0.15	-0.10	-0.15	0.9
Upper limit	0.60	0.60	0.63	0.50	0.40	0.45	1.1

Table 2: Transformer ratio parameters

Head node	End node	Initial value	Location	Upper limit	Lower limit
6	9	1.025	9	1.1	0.9
6	10	0.975	6	1.1	0.9
4	12	1.000	12	1.1	0.9
28	27	0.950	28	1.1	0.9

Table 3: Contrastive results of optimization

			Balance bus power		
Algorithm	Network loss	Descent rate (%)	Active	Reactive	Run-time (sec)
Initial	0.035	—	0.308	0.352	—
GA	0.023	≈34.29	0.294	0.289	38.9
MACO	0.017	≈51.43	0.288	0.221	36.5

is s = 4, searching radius of self-learning sR = 0.4. The comparison result of MACO and GA in the same initial conditions is demonstrated in Table 3.

In Table 3, the power network is optimized by MACO, network loss is 0.017 which is much less than GA and initial. Compared with GA, there is a 17% increase in network loss descent rate and the computing time is shorter. By means of power flow calculation, the reactive power of balance bus become much less than before. The results fully show effectiveness of MACO by taking economic condition and the result of optimization into consideration.

CONCLUSION

The reactive power optimization is a important technique to ensure power system running safely and economically. An improved multi-agent ant colony algorithm is discussed to realize reactive power optimization which overcomes the disadvantage of slow convergence and falling into local optimal solution by modifying the pheromone weight. The improved algorithm is combined with multi-agent system and applied to IEEE-30 node system, the results demonstrate that the computation speed and accuracy are all increased.

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