Microgrid distribution system dynamic reactive power optimization based on improved particle swarm algorithms

Wenhao Zhu[1,2], Qiyi Guo[1], Jianyun Lei[3*]

[1] *Department of Electrical Engineering, Tongji University, Shanghai, 200092, China;*

[2] *Schneider Shanghai Low Voltage Terminal Apparatus Co., Ltd. Shanghai, 201109, China;*

[3] *College of Computer Science, South-Central University for Nationalities, Wuhan, 430074, China;*

Received 1 June 2014, www.cmnt.lv

Abstract

Due to the low accuracy and convergence of existing particle swarm algorithm in the micro power dynamic reactive power optimization in distribution system, this paper proposes an improved particle swarm algorithm based on the state of the particle and inertia weight optimization. This algorithm first adjusts the status of the states of the particles. Then using Sigmoid mapping to optimize the search ability of the inertia weight in particle swarms algorithm. Finally, using the optimal learning strategies to improve the convergence of particle swarm optimization algorithm. Through simulation experiments, the proposed improving particle swarm algorithm based on particle state and inertia weight optimization owing better convergence than traditional particle swarm optimization. Only small error was obtained during dynamic reactive power optimization in micro power distribution system.

Keywords: Particle Swarm Algorithm, Dynamic Reactive Power Optimization, Optimal Learning Strategies

1 Introduction

With the high speed economic development and residents' consumption increasing, Chinese power industry development directions becoming slowly towards to a large system, large capacity, long distance and ultrahigh pressure. The structure of the grid system is also becoming more and more complicated [1]. Although the grid supply ability has been greatly improved, but due to the internal long-standing opinion of developing generate electricity ability and ignore the problem such as power supply and utilization of the user. Generally low voltage in the grid becomes an important problem, which could lead to high loss in the network system and increasing serious stability and safety problems. Also, the power quality is difficult to meet the requirements of the power grid. Thus, establish and improve the current system in Chinese power industry becomes very important [2].

Because the power system optimization calculation itself is nonlinear, so the first proposed optimization algorithm applied in power system reactive power was nonlinear programming method. This method is to remove all of the constrained optimization and transfer the problem into an unconstrained optimization[3]. The nonlinear programming method in the optimization of the power system has high calculation precision, but this method needs a large amount of calculation. The process of optimization needs to use many derivation and inversion, which captured more memory of the computer, thus limiting its solving scale. It also has some limitation to solve inequality constraints, so the nonlinear programming method is only suitable for application in some specific cases, are not widely used in the practical application[4]. The basic idea of Mixed Integer Programming (MIP) is the applying the linear programming to solve integer variables and applying the flight planning to deal with non-integer variables. Then gradually narrowing the feasible solution by applying the method of branch defined area, using iteration step by step to reaches global optimization[5]. Dynamic programming is a kind of mathematical programming, which is an effective approach to solve the problem of multi-stage optimization. The basic idea is treating overall objective function according to the time on the stage, optimization of each stage separately and finally find the optimal solution of the problem by comparison [6]. In view of the traditional mathematical programming method to solve the reactive power optimazation problems, people gradually turn their attention to the nature and the human analogy method of Artificial Intelligence (AI), and apply it to reactive power optimazation research. Typical algorithms are mainly genetic algorithm (GA), tabu search algorithm (TS), simulated annealing algorithm (SA), difference evolution algorithm (DE), expert system (ES) and artificial neural network (ANN). Unlike traditional mathematical programming, artificial intelligence algorithm is from an initial population, search the entire space according to certain rule to obtain the optimal solution [7]. Reactive power optimization of power system problem is a complex problem of model optimization. After a lot of analysis and research, scholars applied different algorithms to reactive power optimization, mainly including conventional algorithms and artificial intelligence algorithms[8]. After analysis and comparison, each of them has some drawbacks.

This article optimized the convergence and precision based on the defects of particle swarm algorithm of dynamic reactive power optimization in the distribution system.

[*] ***Corresponding author's*** e-mail: leijianyun@mail.scuec.edu.cn

2 Particle swarm optimization

2.1 DESCRIPTION OF PARTICLE SWARM OPTIMIZATION

Particle swarm optimization algorithm let each individual particle in the group become a no quality and volume of the particles in a multi-dimensional search space. The particle in the search space has a certain speed, and according to the optimal value of their own in the iterative process optimal value *Pbest* and group optimal value *Gbest* to adjust its direction and speed. Thus forming a positive feedback mechanism of optimization [9]. During the optimization problem, the particle's position on behalf of the solution of an optimization problem, the quality of each particle performance depends on the size of the evaluation function for optimization fitness values. Each particle using a velocity vector to determine the flight direction of particles size and rate. Particles is based on the current optimal particle's position and memory himself met the position of the optimal solution, to change their speed and position, in order to complete the search in the solution space [10].

Suppose in a D dimension target search space, particle swarm optimization algorithm is used to randomly initialize a group composed of m particles. The position X_i is for particle i. Then, the potential solution of the optimization problem can be expressed as $\{x_{i1}, x_{i2}, ..., x_{iD}\}$. Put it into the optimization of evaluation function can conclude the fitness value, which used to measure the particle's quality. The corresponding speed can be expressed as $\{v_{i1}, v_{i2}, ..., v_{iD}\}$. In the process of each iteration, the particles by tracking two extreme value to update their speed and position. One extreme value is the optimal solution searched by particle itself, called Individual extremum P_{ibest}, can be expressed as $\{P_{ibest.1}, P_{ibest.2}, ..., P_{ibest.D}\}$. Another extreme value is the optimal solution searched by the group of particles, called global extremum P_{gbest}, representing as $\{P_{gbest.1}, P_{gbest.2}, ..., P_{gbest.D}\}$.

More specifically, When the $k+1$ iterative calculation, particle i changes its speed and position according to formula (1) and (2). The speed limitation is express as (3).

$$v_{id}^{k+1} = \omega \cdot [v_{id}^k + c_1 r_1 (p_{ibest.d}^k - x_{id}^k) + c_2 r_2 (p_{gbest.d}^k - x_{id}^k)] \ , \quad (1)$$

$$x_{id}^{k+1} = x_{id}^k + v_{id}^k \ , \quad (2)$$

$$\begin{aligned} &if\ v_{id}^{k+1} > v_{\max}\ v_{id}^{k+1} = v_{\max} \\ &if\ v_{id}^{k+1} < v_{\min}\ v_{id}^{k+1} = v_{\min} \end{aligned} \ . \quad (3)$$

In those formula: $i = 1,2,...,m$; $d = 1,2,...,D$; ω is the inertia weight; c_1 and c_2 are accelerated factor; r_1 and r_2 are the random number uniformly distributed on the $[0,1]$; $v_{\max}$ and $v_{\min}$ is the speed limit of the particles.

The first part of formula (1) is the inertia behavior of the particle, means the previous inertia velocity of the particle, reflecting the memory ability. The second part is the cognitive behavior of the particle, means the process of particle absorbs their experience knowledge, reflecting the elaborative faculty of the particle. The third part is the social behavior of the particles, means the process of particle learning from other particles in the group, reflecting the information sharing and mutual cooperation between particles.

2.2 THE PROCESS OF PARTICLE SWARM OPTIMIZATION

The process of particle swarm optimization algorithm is as follows:

1) The particle swarm initialization. Including define population size m, particle dimension D, positions of each particle x_i and speed v_i. Individual extreme value of each particle *pbest* set as current position, the collective global extreme *Gbest* is the best value of individual extreme value.
2) Evaluation of the particle swarm. Calculate the fitness value of each particle. If it is better than that of the current individual extremum, then updating individual extremum. If the best individual extremum value superior to the current all the extremum, it updates all the extremum.
3) Update the speed and position of the particle swarm. Update each particle's speed according to formula (1). Update each particle's position according to formula (2).
4) Inspection of end conditions. If the current number of iterations has reached the preset maximum degree or meets the best fitness value threshold or series of fitness value cannot update, the iteration will stop and the output optimal solution. Otherwise, it will continue the iteration by formula (2).

3 Improvement of convergence of particle swarm algorithm

To overcome the inertia weight value ω cannot adjust the premature convergence with the iterative process, this paper considers the use of the state of the algorithm evolution to adjust the inertia weight of ω value.

3.1 PARTICLE STATE OPTIMIZATION BASED ON PERIODIC ADJUSTMENT

This paper firstly optimizes the particle state of each phase, mainly includes the following steps.

1) In the evolution of every stage, calculate the average Euclidean distance between each particle position and all other particle position. This value is the average distance between the particle in the current state of population evolution and other particles. Detail calculation is as follows:

$$d_i = \frac{1}{N-1} \sum_{j=1, j \neq i}^{N} \sqrt{\sum_{k=1}^{D} (x_i^k - x_j^k)^2} \ . \quad (4)$$

2) Mark the average distance between the global optimal particle adn all other particles as d_g. Mark the minimum distance and maximum distance in current population of all the particles average distance as $d_{\max}$ and $d_{\min}$. Then according to the following formula (5) to calculate the evolutionary factors f that represent the current state of the population evolution:

$$f = \frac{d_g - d_{\min}}{d_{\max} - d_{\min}} \in [0,1] \cdot \quad (5)$$

3) Using evolutionary algorithm factor value to represent the different population's states of evolution. The f can

divide into exploration, development, convergence and jump out four states (S1, S2, S3 and S4). According to experience, the evolutionary status factor f in the division of evaluation is blurry and uncertain. Therefore, in this article, we consider using fuzzy classification method to divide the state of the evolution of the population. The key issue of fuzzy classification is to choose the appropriate membership functions, the following membership function is obtained according to experiences.

3.1 Detection stage: Due to the particle distribution in the initial population is sparse at the beginning of the algorithm, which cannot understand the space characteristics of the solution. So if the f value in the range of medium to large, indicating the current population is in the stage of detecting S1. The membership functions are defined as follows:

$$\mu S_1(f)=\begin{cases}0, 0\le f\le 0.4\\ 5\cdot f-2, 0.4<f\le 0.6\\ 1, 0.6<f\le 0.7\\ -10\cdot f+8, 0.7<f\le 0.8\\ 0, 0.8<f\le 1\end{cases}. \quad (6)$$

3.2 Development stage: After continual iteration, the algorithm will be gradually to search the solution space area and the population of particles will slowly close to the optimal area. Thus, when the f value gradually shrink, indicating the current population is in a stage of development S2. The membership functions are defined as follows:

$$\mu S_2(f)=\begin{cases}0, 0\le f\le 0.2\\ 10\cdot f-2, 0.2<f\le 0.3\\ 1, 0.3<f\le 0.4\\ -5\cdot f+3, 0.4<f\le 0.6\\ 0, 0.6<f\le 1\end{cases}. \quad (7)$$

3.3 Convergence stage: After many iterations to find the global optimal solution, all the particles in the population will gather around the optimal solution. Thus, when the small value of f obtained, explaining the particles near the optimal solution in the current population, indicating the population is in S3 convergence stage. The membership functions are defined as follows:

$$\mu S_3(f)=\begin{cases}1, 0\le f\le 0.1\\ -5\cdot f+1.5, 0.1<f\le 0.3\\ 0, 0.3<f\le 1\end{cases}. \quad (8)$$

3.4 Jump out stage: If the algorithm into local optimum, the global optimal solution will deviate from the center of the current population. Thus, when the f value becomes biggest indicating the current population in the jump out stage S4. The membership functions are defined as follows:

$$\mu S_4(f)=\begin{cases}1, 0\le f\le 0.7\\ 5\cdot f-3.5, 0.7<f\le 0.9\\ 1, 0.9<f\le 1\end{cases}. \quad (9)$$

By the above formula (6) to (9), two membership functions will be active when the population at the transitional stage. Use the value of f will determine the current state of the in two evolutionary states. Therefore, it cannot be able to finally determine the current population in the evolution state. In order to be able to eventually determine the population evolution state, this article uses the random "singleton pattern" approach for defuzzification. For example, $\mu S_2(f)>\mu S_1(f)$ can determine the current population is in stage S2.

3.2 INERTIA WEIGHT OPTIMIZATION BASED ON SIGMOID MAPPING

As described earlier, the inertia weight ω is used to balance the global and local search ability. However, the inertia weight ω is not always correct by change over time. It because the evolutionary factor f in detecting state will become larger and in the convergence condition will become small. Therefore, in order to be able to make ω as the population of iterative adaptive adjustment, in this article, set inertia weight ω as the evolutionary factors rather than the time and make the following Sigmoid mapping:

$$\omega(f)=\frac{1}{1+1.5e^{-2.6f}}\in[0.4,0.9], \forall f\in[0,1]. \quad (10)$$

In this way, the inertia weight ω change follows the change of evolutionary factor f rather than time, which is applicable to any state of evolution represented by f .

3.3 CONVERGENCE OPTIMIZATION BASED ON OPTIMIZING LEARNING STRATEGIES

If populations are in a local optimum, certain method has to be taken to jump out of the local optimum, otherwise the system is unable to find the global optimal solution. In this article, learning strategies have been used as an optimization algorithm for jumping out of the local optimum. The main principle of optimizing learning strategies in the global optimal particle is the selection of one dimension (Set the probability of each dimension is equal) and make it following the Gauss perturbation:

$$gBest^d=gBest^d+(X^d_{\max}-X^d_{\min})\cdot Gaussian(\mu,\sigma^2). \quad (11)$$

In the formula, $X^d_{\max}$ and $X^d_{\min}$ represents the maximum and minimum value of each dimension in the current population. The mean of the Gaussian disturbance is 0; the standard deviation is σ , also known as optimal learning rate. It is same as other neural network training strategy, σ will show a linear gradient when the increase of the number of iterations. The calculation method is shown below:

$$\sigma=\sigma_{\max}-(\sigma_{\max}-\sigma_{\min})\frac{gen}{MaxGen}. \quad (12)$$

In this formula, $\sigma_{\max}$ and $\sigma_{\min}$ represents the upper limit and lower limit, indicating the scope of the algorithm learning ability. gen is the current number of iterations, $MaxGen$ is the total number of iterations. According to the experiments, when $\sigma_{\max}$ and $\sigma_{\min}$ choose 1.0 and 0.1, respectively. Most of test functions can achieve well results. Thus, we choose $\sigma_{\max}=1.0$ and $\sigma_{\min}=0.1$ in this article.

4 Algorithm performance simulation

In order to verify the effectiveness of the improved algorithm proposed in this paper, we use peaks function as example to simulate the improved particle swarm algorithm. The function curve of Peaks function is shown in figure 1, the simulation results are shown in figure 2.

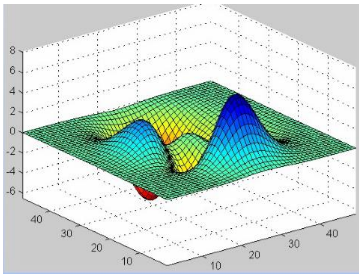

FIGURE 1 The peaks function curve

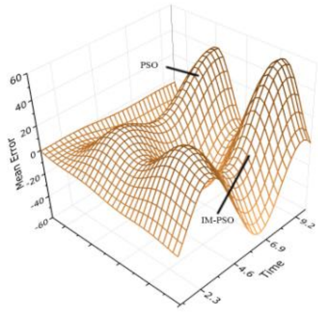

FIGURE 2 Convergence of the simulation results of the improved algorithm

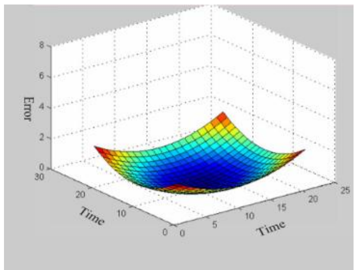

FIGURE 3 Wattless optimization error statistics

It can be seen that, the convergence of improved particle swarm optimization algorithm showed a better performance than traditional particle swarm optimization algorithm. It also showed a small error and higher precision as dynamic reactive power optimization in the distribution system.

5 Conclusion

Power system reactive power optimization is a complicated and nonlinear mathematical programming problem. The reactive power optimization is not only affecting the system voltage quality, also decides the stability and safety of the power grid. Moreover, it also affects the economic benefits of power system. This paper proposed an improved particle swarm optimization algorithm for dynamic reactive power optimization of the distribution system. The simulation results show that the proposed strategies can improve the precision and convergence of particle swarm algorithm.

References

[1] Zhou J and Ding X Q. (2014) Fuzzy optimal model of distribution network based on load reactive power optimization. *Modern Electric Power*, 2 ,46-50.
[2] Zuo Y F. (2014) Research on methods of reactive power optimization based on extended optimal power flow model. *Journal of Shenyang Agricultural University*,45,117-121.
[3] Cai C C. (2014) Dynamic reactive power optimization with distributed generation. *Electrical Measurement &Instrumentation*, 51, 39-44.
[4] Chen Q Y. (2014) Multi-objective reactive power optimization and improvement of particle swarm algorithm. *Relay*, 42, 129-135.
[5] Meng A B. (2014) Of the quantum particle swarm algorithm based on population instead of the wind power grid reactive power optimization. *Electrotechnical Application* ,5, 65-69.
[6] Wang C. (2014) Probability statistics based reactive power optimization of distribution network containing intermittent distributed generations. *Power System Technology*, 38, 1032-1037.
[7] Peng X. (2014) Dynamic reactive-power voltage optimal control strategy based on zoning.*Information and Control* ,43,88-95.
[8] Chen Q Y. (2014) Power system reactive power optimization based on improved PSO algorithm. *Electric power system and its automation* ,26, 8-13.
[9] Liu S Y. (2014) Using chaotic fish distribution network reactive power optimization of the algorithm. *Electric power system and its automation* ,26, 44-48.
[10] Xu P. (2013) Reactive voltage optimization of a complex power grid integrated with large-scale wind power by improved artificial fish swarm algorithm. *Electric Power*, 11,8-11.

Authors

Wenhao Zhu, 8. 10. 1977, China

Current position, grades: A doctoral student at Tongji University, China.
University studies: Master degree in Electronics and Communications Engineering from Fudan University, China in 2007.
Scientific interest: intelligent system in final distribution of smart grid, and communication security and stability.
Publications: over 10 articles.
Experience: 20 patents in intelligent low voltage apparatus area; twice of the Third Prize of National New Technology.

Qiyi Guo, 6.1961, China

Current position, grades: professor and Ph.D. supervisor in electronic information engineering institute at Tongji University, China.
Scientific interest: Electrical equipment failure diagnosis in automation and information engineering.

Jianyun Lei, 9.1972, China

Current position, grades: Associate professor and master degree supervisor in college of computer science at South-central University for Nationalities, China.
Scientific interest: Computer network and information security research.