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Analog Circuit Fault Diagnosis Approach Based on Improved Particle Swarm Optimization Algorithm

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Abstract: The basic thought of particle swarm optimization is introduced firstly, then particle swarm optimization algorithm model is established. The application of the improved particle swarm optimization algorithm to power supply system fault diagnosis is analyzed in accordance with problem of the algorithm, and migration strategy is added to particle swarm optimization algorithm. Finally the parameters of the wide area damping controller are adjusted by the improved particle swarm optimization algorithm. *Copyright © 2014 IFSA Publishing, S. L.*

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1. The Basic Thought of the Particle Swarm Optimization

It is the same with the other evolutionary algorithms, also based on the concept of "population" and "evolution" through collaboration and competition between individuals, Complete the optimal solution in a complex search space; Meanwhile, PSO and unlike other evolutionary algorithms for individuals as crossover and mutation, selection and other evolutionary operators to operate, Instead group (swarm) is not considered in the individual particles of the mass and volume (particle) in D-dimensional search space, Each movement of the particles to a certain speed in the solution space, and to its optimum position $Pbest$ history and the history of the best location neighborhood $Pbest$ aggregation, Realization of candidate solutions evolve. PSO algorithm has good bio-social context [2] but easily understood, because few and easily achieve the parameters of nonlinear multimodal problems had strong global search capability, which in scientific research and engineering practice, is widespread concern [3-16].

In nature, the various groups of organisms have certain behavior, and one of the main areas of artificial life research is to explore the biological nature of group behavior, in order to build its population model on the computer. Group behavior of birds and fish in nature has been a research interest of scientists, biologists Craig Reynolds made a very influential model of birds gathered in 1987 [11], in his simulations, each individual follows:

1) To avoid colliding with individual neighborhood;

2) Matching the speed of the individual neighborhood;

3) Toward the center of the flock, and the entire group to the target.

Simulation using only these three simple rules, you can be very close to simulate the phenomenon of flying birds. 1990, also proposed biologist Frank Heppner bird model [8], it is different in that: the birds are attracted to the habitat. In the simulation, the beginning of each bird flight are no specific targets, but using simple rules to determine their flight direction and flight speed (every bird in the flock are trying to stay in and do not collide with each other), when there was a bird to the habitat, the birds flying around it will follow the habitat, so that the whole flock will fall habitat.

In 1995, the American social psychologist James Kennedy and Russell Eberhart common electrical engineers proposed PSO on bird populations through behavioral modeling and simulation research results, and their ideas were inspired. Their model and simulation algorithm is mainly on Frank Heppner model was modified to allow the particles to fly in the solution space and landed at the best solution. Kennedy in his book describes the origins of particle swarm optimization thought. Since the 1930s, the development of social psychology reveals: the aggregation behavior of fish or birds to be followed by us. In the constant interaction of people, due to the mutual influence and imitation, they always become more similar to the results on the formation of norms and civilization. Natural human behavior do not like fish and birds, and fish and birds and humans are very similar trajectories in high-dimensional thinking cognitive space. Thinking behind the social phenomenon is very complex than fish and birds gather during graceful movements: first, thinking occurs in the belief space, its dimension is much higher than 3; Secondly, when two ideas converge on the same cognitive space point, we call consensus rather than conflict.

2. The Particle Swarm Optimization Algorithm Model

Given a search space is D dimensional search space, a particle colony is composed of n particles, the location of the i-th particle in the D dimensional search space is as follows:

$X_i = (x_{i1}, x_{i2}, ..., x_{id})^T$, where $i = 1,2,...,n$

The fitness value of the colony is:

$Fitness = f(\mathrm{X_i})$

The flight velocity of the colony is:

$V_i = (v_{i1}, v_{i2}, ..., v_{id})^T$, where $i = 1,2,...,n$

According to the rules of the particle swarm optimization algorithm, the k dimensional component can be transformed by the following formulas:

$$V_{ik}^{t+1} = wV_{ik}^t + c_1R_1(Pbest_{ik}^t - X_{ik}^t) + c_2R_2(Gbest_{ik}^t - X_{ik}^t), \tag{1}$$

$$X_{ik}^{t+1} = V_{ik}^{t+1} + X_{ik}^t, \tag{2}$$

where V_{ki}^t is the k dimensional component of the velocity vector when the i particle moves; X_{ik}^t is the k dimensional component of the position vector when the i particle moves.

$Pbest_{ik}^t$ is the idiographic particle's position corresponding to the best fitness value of the k dimensional component before changing the i particle's position the t time; $Gbest_{ik}^t$ is the idiographic particle's position corresponding to the best fitness value before changing the positions of all particles the t time.

c_1 and c_2 are acceleration constants; R_1 and R_2 are random numbers from 0 to 1; w is inertial coefficient.

PSO is inspired by foraging birds raised in simulation time. Having made with animal or human cognition to explain the principles of the algorithm found more perfect. Speed update the formula (1) is composed of three parts. The first part is V_{ki}^t, said particles in the solution space according to the original direction and speed of search trends, which can be employing cognitive things are always in the habit of using the inherent explained. The second part is $c_1R_1(Pbest_{ik}^t - X_{ik}^t)$, said particles in the solution space of optimal search past trend towards encountered , when employing this knowledge can be used in the past are always things experiences to explain. Part 3 is $c_2R_2(Gbest_{ik}^t - X_{ik}^t)$, said particles in the solution space towards the optimal solutions throughout the neighborhood in the past encountered search trend, which can total employment at the cognition of things can by learning other people's knowledge that is to share the experience of others to explain. Therefore, PSO is actually borrowed the habit of things when human or animal cognition, experience, and the learning process for Optimization. Particle trajectories in the optimization process are shown in Fig. 1.

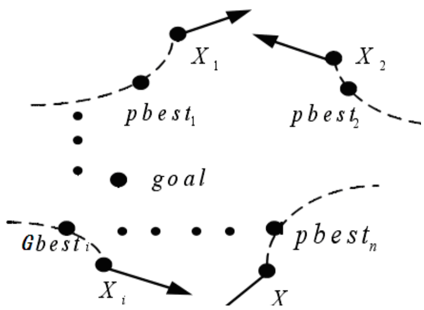


Fig. 1. PSO search schematic.

The implementation steps of the improved particle swarm optimization algorithm are the following:

1) Initialize the swarm: suppose the number of the swarm is m, the initial positions and velocities of the particles are evaluated randomly within proper ranges;

2) Compute the fitness values of the particles: the fitness value of every particle is computed by solving the objective function $f(X_i)$ of the particle;

3) Calculate according to $X_i (i = 1,2,...,n)$, compare $f(X_i)$ with $f(Pbest_i)$, if $f(X_i)$ takes precedence over $f(Pbest_i)$, replace $f(Pbest_i)$ with $f(X_i)$, or else $f(Pbest_i)$ is unaltered;

4) Calculate according to $X_i (i = 1,2,...,n)$, compare $f(X_i)$ with $f(Pbest_i)$, if $f(X_i)$ takes precedence over $f(Pbest_i)$, replace $f(Pbest_i)$ with X_i, or else $f(Pbest_i)$ is unaltered;

5) Adjust the velocity and position of every particle with reference to formula (1) and formula (2);

6) Check the termination conditions of the particle swarm optimization algorithm.

The flowchart of PSO algorithm was shown in Fig. 2.

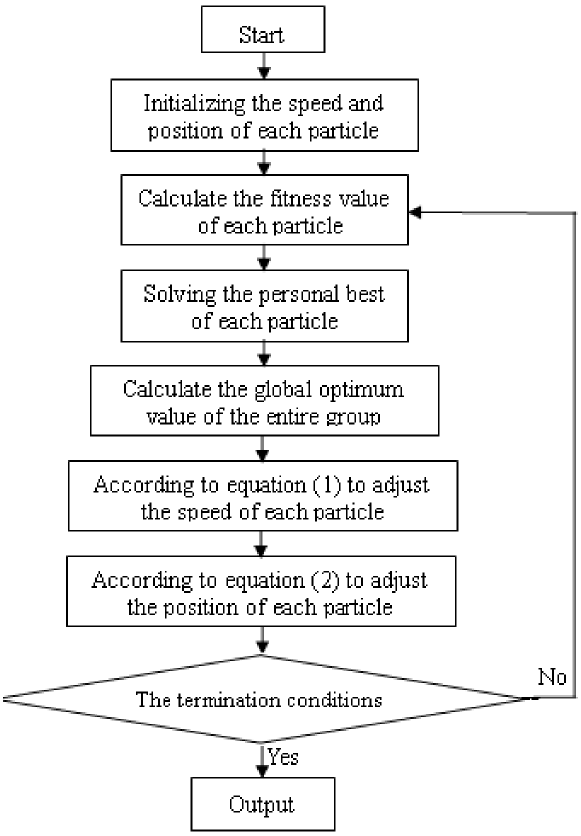


Fig. 2. The flowchart of PSO algorithm.

The velocity of every dimensional particle is restricted to be within boundary velocity, the boundary velocity initially set by the user is between $V_{\max}$ and $V_{\min}$, if the renewed velocity of a dimensional particle oversteps the velocity range from $V_{\min}$ to $V_{\max}$, the upper limit value is set as $V_{\max}$ and the lower limit value $V_{\min}$. The boundary velocity $V_{\max}$ and $V_{\min}$ determine the precision between the current position and the best position, if the boundary velocity value is oversize, the particle could miss the global minimum, or else the particle could reach the local optimum.

3. Two Modes of Particle Swarm Optimization Algorithm

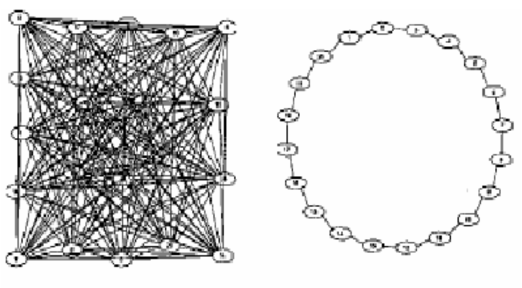
Kennedy, who in the course of observing birds foraging noted, usually birds do not necessarily see all the positions and movements of other birds in the flock [1], often just to see the birds in adjacent positions and movements. So he in the study of particle swarm algorithm, he also developed two models: the global optimum (Gbest) and local optimization (Lbest). Particle Swarm Optimization algorithm is a concrete realization of the global optimum. In the global optimum of each individual is attracted to the optimal solution for any individual found by the population. This structure is equivalent to a fully connected social networks; every individual in the population can now compare the performance of all other individuals, the best imitation of a real individual. Effects of particle swarm all the experience and awareness of all of the particles by the trajectory of each particle.

Global model has a faster convergence speed, but easy to fall into local minima. In local mode, the total particle according to its own information, and the optimal value of neighborhood information to adjust its trajectory, the optimal value information instead of groups of particles, particle trajectory, and only by their cognitive Nearby Effect of particle state rather than affect the state of all the particles. Thus, the particles will not move to the global optimum, but moved to the optimal value of the neighborhood. The final global optimal value from the optimal value of the neighborhood is elected, the highest fitness among the best values in the neighborhood. In the algorithm, two adjacent particles overlap part of the neighborhood, so that two adjacent neighborhood public particles can exchange information between the two neighbors, which helps the particles escape from local optima, global optimum.

Partial model itself there are two different ways. The spatial position of the two to determine the particle "neighbors" is a local optimization method, which is a measure of the distance by the distance between the particles; Another way is the number of methods, PSO particle was prepared before the search to a different number, the ring topology structure of society. For the first approach, after each iteration are required to calculate the distance between each particle and the other particles to determine which particles are included in the neighborhood, which results in enhancement of the complexity of the algorithm, reducing the efficiency of the algorithm; The second way in advance because the particles are numbered, thus iteration of particles in the neighborhood will not change, which resulted in the search process, the current particle with specified "neighbors" particles quickly gathered. And the swarm was divided into several small pieces, on the surface seems to be increasing the scope of the search, in fact, it greatly reduces the convergence rate. Local optimum mode convergence is slow, but it has strong global search capability. For example, the 1st and the 2nd last and adjacent particles in a ring topology, the 2nd particle is adjacent to the 1st, the 3rd, this way is called a neighbor topology defined sense. According to the research of sociologists, the concept of these two neighbors is all social backgrounds.

Topology of the overall pattern is shown in Fig. 3 a), the partial ring topology pattern in Fig. 3(b) below.

Suganthan proposed PSO model with a neighborhood operation, local extremums defined by each particle current neighborhood, instead of the current global extremum PSO. In the initial stage of the optimization, the neighborhood is defined for each of the particles themselves, as the number of iterations increases, the neighborhood of gradually extended to include all particles. In this case, the local extremum of neighborhood is global extremum. To a certain extent, this model overcomes the PSO model in optimizing search late, with the increase in the number of iterations to overcome the shortcomings of the search results are not significantly improved.



(a) (b)

Fig. 3. Two models of particle swarm algorithm (a) global model; (b) an annular partial model.

4. The Problems of the Particle Swarm Optimization Algorithm

The standard particle swarm optimization algorithm with simple and convenient computation format was proposed in 1995, it has a few parameters and good convergence which made it attract many research specialist staff to carry on a further research [7, 8], the algorithm is extensively applied in many areas. Just like other optimization algorithms, there are limitations in the particle swarm optimization algorithm, the two limitations being mainly improved by research specialist staff is as follows:

1) The local optimum problem of the standard particle swarm optimization algorithm.

The standard particle swarm optimization algorithm could reach local optimum easily because of the following reasons: on the one hand, the parameters of the particles are not enough to retain a diversity of the particles during the computing process, which results in early convergence and locally optimal solution; on the other hand, trial functions have various properties and most of these functions have relatively complex shapes and present themselves as modal functions, nevertheless the standard particle swarm optimization algorithm can't prove strictly which type of global extremum point the algorithm converges to.

2) The slow convergence rate of the standard particle swarm optimization algorithm.

Time cost control is strict in the practical engineering application, whereas the standard particle swarm optimization algorithm often converge slowly, and moreover, the standard particle swarm optimization algorithm updates mainly in accord with single rule, which makes the particles in the good positions play their roles deficiently.

5. The Improved Particle Swarm Optimization Algorithm Based on Migration Ideology

To solve the local optimum problem of the standard particle swarm optimization algorithm, migration strategy is added to the standard particle swarm optimization algorithm, the phenomenon that the individuals of colonies of many generations don't optimize gradually indicates that the particle swarm optimization algorithm reaches local optimum. A target M is set, the particle with best fitness value lead and other particles of the colony migrate towards the target M, the worst particle after migration is substituted with the best particle *Gbest* before migration, then the migration particle swarm optimization algorithm is available.

The migration ideology of the particle swarm optimization algorithm is as follows: a colony is composed of n particles in the D dimensional search space, every particle contains a position vector of D dimension, the vector is denoted by X_{id}, the best particle in the colony is denoted by $Pbest$, and a target point randomly produced is denoted by M. The migration strategy of the particle swarm optimization algorithm adjusts the particles' positions in accord with the following formula:

$$X_{i\_new} = X_i + \sqrt{2-\phi}\,\frac{(M - Pbest_i)}{\left|M - Pbest_i\right|}, \qquad (3)$$

where ϕ is the random number from 1 to 2.

The migration strategy can retain the diversity of the particles to avoid them reaching local extremum. Furthermore, the migration strategy can integrate into all improved particle swarm optimization algorithms. We add migration strategy to the particle swarm optimization algorithm to improve it, the specific calculation process of the improved algorithm is as follows:

1) Initialize the position and velocity of the particle, denoted as X_i, V_i respectively;

2) Compute the fitness value of the particle, denoted as $f(X_i)$;

3) The current position of the particle is denoted as $Pbest_i$, the particle whose position is the best in the initial colony is denoted as $Gbest$;

4) Adjust the position and velocity of the particle following formula (1) and formula (2);

5) Compare the fitness value $f(X_i)$ of the particle's current position with the fitness value $f(Pbest_i)$ of the particle in the best position, if the fitness value $f(X_i)$ of the particle's current position is superior, the current position is the best position; compare every particle's best position $f(Pbest_i)$ with the best fitness value $f(Pbest)$, if $f(Pbest_i)$ is superior, the particle's current position is the best position of all particles in the colony;

6) Check whether the particle swarm optimization algorithm satisfies the convergence conditions, if the algorithm satisfies the conditions, next step is executed, or else $f(Pbest)$ isn't optimized, then the particles in the colony should migrate following the steps mentioned above and the worst particle after migration should be substituted with the best individual $Gbest$;

7) Output the global optimum particle $Gbest$ and the algorithm ends.

The application of the particle swarm optimization algorithm to the fault optimization of power supply system.

The optimization problem of power supply system is complex and nonlinear, the peculiarity that its continuous variables intermix with discrete ones makes the problem difficult to solve. The research specialist staff has long tried to solve the problem based on the traditional optimization methods such as nonlinear programming method, linear programming method and dynamic programming method which have defects like strong dependence on model and high requirement for the initial points and continuous variables [9, 10]. The intelligent algorithms extensively used in recent years can overcome the shortcomings of the traditional optimization methods. The swarm intelligent algorithm is a heuristic algorithm based on multipoint random search, it fast converges to a point in the space through multipoint parallel searching and information exchanging between particles in the colony. As the number of the parameters adjusted is small, the algorithm is applicable to power engineering optimization.

Firstly, the improved particle swarm optimization algorithm is employed to optimize the fault problem of power supply system with reactive power optimization. The static voltage stability is set as optimizing index and then multi-objective reactive power optimization model is established in consideration of the active power loss minimization, voltage level optimization and static voltage stability maximization. The particle swarm optimization algorithm is employed to optimize the functions in the model. The experiment results show that the particle swarm optimization algorithm can realize the economic operation of power supply system and increase the stability of the system, which indicates that the particle swarm optimization algorithm is uniquely superior and effective.

Secondly, the improved particle swarm optimization algorithm is employed to optimize the multi-objective scheduling model of the power supply system fault problem, researches show that the improved particle swarm optimization algorithm can greatly increase the feasibility of the decision making of power supply system and powerfully support the decision maker, which indicate that the algorithm is applicable to multi-objective scheduling optimization of large power supply system.

Thirdly, to solve the peculiar active power loss problem of power supply system, a variance of the improved particle swarm optimization algorithm is employed to optimize multi-objective with reactive power optimization. A large number of experiments indicate that the particle swarm optimization algorithm can express the specific relationship between voltage deviation and active power loss of power supply system and provide various alternative solutions of uniform distribution for the users. The superimposition of several results proves the reliable stability of the algorithm. The numerical experiments on the improved particle swarm optimization algorithm show the search capability and convergence capability of the improved algorithm which overcomes the defects of the standard particle swarm optimization algorithm.

In summary, the improved particle swarm optimization algorithm is employed to solve the power supply system fault problem, which decreases the number of the parameters and increase the optimization maneuverability. Accordingly, the parameters of the wide area damping controller are adjusted by the improved particle swarm optimization algorithm.

6. Adjust the Improved Parameters of the Wide Area Damping Controller by the Improved Particle Swarm Optimization Algorithm

1) The design of the wide area damping controller.

The wide area system provides various parameters including shaft speed, rotor angle and source voltage. Shaft speed is the input signal to the wide area damping controller, as shown in the Fig. 4.

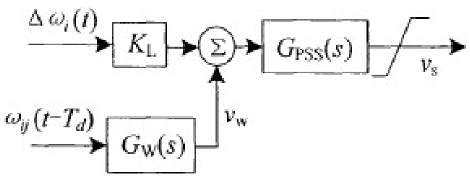


Fig. 4. The wide area damping controller of generator i .

2) The lead-lag compensator.

The peculiar transfer functions of the lead-lag compensator are as follows:

$$G_W(s) = K_W\left(\frac{1+\alpha_W T_W s}{1+T_{W}s}\right), \tag{4}$$

$$G_W(j\omega) = \left|G_W(j\omega)\right| e^{j\phi W}, \tag{5}$$

where K_W is the gain, K_W is the constant, α_W is the time constant, ϕ_W is the angle, $n = 1, 2, 3$. Oscillation period is defined as 360 degree, as the existence of communication time delay in power supply system is inevitable, suppose that the angle lag between the wide area control signal transmitted from wide area measurement system and the initial signal is ϕ_{lag} .

The lead-lag compensator mainly compensate for the time lag of the wide area signal to get the wide area control signal which should be equal to the initial signal.

If the angle lag ϕ_{lag} is at the range from 0 degree to 80 degree, the specific parameters of the lead-lag compensator must satisfy the conditions $K_W > 0$ and $\phi_W > 0$;

If the angle lag ϕ_{lag} is at the range from 80 degree to 180 degree, the specific parameters of the lead-lag compensator must satisfy the conditions $K_W < 0$ and $\phi_W < 0$;

If the angle lag ϕ_{lag} is at the range from 180 degree to 260 degree, the specific parameters of the lead-lag compensator must satisfy the conditions $K_W < 0$ and $\phi_W > 0$;

If the angle lag ϕ_{lag} is at the range from 260 degree to 360 degree, the specific parameters of the lead-lag compensator must satisfy the conditions $K_W > 0$ and $\phi_W < 0$.

3) Adjust the parameters of the lead-lag compensator

According to formula (4), the parameters n , K_W , α_W should be adjusted as follows:

1. The angle lag ϕ_{lag} is computed in accord with the time lag T_d and the oscillation period $\omega_{ij}(t)$;

2. The parameter ϕ_W is computed according to the correlative rules;

3.The parameter n of the lead-lag compensator is calculated from the parameter ϕ_W ;

4. The parameters K_W and α_W are computed in accord with formula (6) and formula (7):

$$\alpha_W = \frac{1+\sin(\phi_W / n)}{1-\sin(\phi_W / n)}, \tag{6}$$

$$T_W = \frac{1}{\omega_{osc}\sqrt{\alpha_W}}, \tag{7}$$

where $\omega_{osc} = 2\pi f_{osc}$, oscillation frequency of $\phi_{ij}(t)$ is f_{osc} .

4) Adjust the gain of the wide area damping controller by the improved particle swarm optimization algorithm.

The improved particle swarm optimization algorithm is employed to adjust the gain of the wide area damping controller, the gain is denoted as K_W .

Presume that the power supply system is composed of m generators, the wide area damping controllers are installed in $m-1$ generators, the gain of the wide area damping controller installed in every generator is to be determined, consequently, there are $m-1$ parameters.

The gain value of the wide area damping controller is expressed by means of the coordinate values of every particle's position $x_1, x_2, ..., x_{(m-1)}$ and therefore every particle have $x_1, x_2, ..., x_{(m-1)}$ coordinates.

The performance index of the gain of the wide area damping controller is the fitness value of the particle's position, the index is denoted as $f(X_i)$. The time is weighted to get the weighted average error integral which is the performance index. In the case of $m-1$ gains of the wide area damping controllers, the performance index value is available by analyzing the differential equation of the power supply system.

$$\begin{aligned} J_I = \int_0^f t[w(v_{W1}^2 + v_{W2}^2 + ... + v_{W(m-1)}^2) + \\ \omega_{1m}^2 + \omega_{2m}^2 + ... + \omega_{(m-1)m}^2]dt \end{aligned}, \tag{8}$$

where w is the weight.

The improved particle swarm optimization algorithm is employed to optimize the fitness value $f(X_i)$, the optimization result X_i corresponding to the particle's position is the minimum performance index which corresponds to the gain value of the wide area damping controller.

7. Conclusion

In conclusion, many fault problems in the integrated power system, especially the problem like low frequency oscillation, have seriously influenced the stable operation of the integrated power system and have restrained mutual transmission of the supple networks. In this paper, based on its basic optimizing principle, we improve the particle swarm optimization algorithm by adding migration strategy to the algorithm and prove that the algorithm has a good optimizing capability. In addition, the improved particle swarm optimization algorithm is utilized to adjust the parameters of the wide area damping controller in the power supply system.

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