IOP Conf. Series: Earth and Environmental Science **170** (2018) 042014 doi:10.1088/1755-1315/170/4/042014

Optimization method of power communication network based on improved particle swarm optimization

He Wang[1,2], Lin Peng[1,2], Zehao Zhang[1,2,*], Jin Sun[3], Yu Xu[4], Jingwei Xiao[4]

[1.]Global Energy Interconnection Research Institute co., Ltd Research Institute of Information Technology& Communication, Nanjing,210003, China;
[2.]State Grid Laboratory of Electric Power Communication Network Technology, Beijing,102209, China;
[3.]Yingda Media Investment Group Company Ltd China electric power press, Beijing,10005, China;
[4.]State Grid Chongqing electric power company, Chongqing,400000, China.

*Corresponding author e-mail:983962749@qq.com

Abstract. For the maintenance of electric power communication network, this paper puts forward a kind of based on improved particle swarm optimization algorithm, a new method for the optimization of electric power communication network to the whole network, the minimum number of nodes and node redundancy transmission capacity as fitness, damaged business in electric power communication network nodes dynamically allocated, make damaged greatly enhance the survivability of the business, to ensure the maximum recovery damaged business, through the contrast can be concluded that the method has good robustness, fast running speed, the advantages of small number of individual relationships with optimal results.

Keywords: Multi objective optimization, Particle swarm optimization, Electric power communication network, Dynamic distribution.

1. Introduction

The current method of electric power communication network maintenance, there are two main research directions: one is to assess the importance of each node, in case of an emergency, according to the importance of the node size sorting, arrange personnel for maintenance. Second, usually leave a certain amount of redundancy in communication ability, when meet emergency, can be right by set, through the optimization algorithm changes the whole through the sequence of each node in the network, to ensure the smooth running of the network. For the second research direction, the existing solutions mostly comes from the fiber optic network optimization, the main research methods are the use of traditional optimization algorithm to solve multi-objective problem, can the artificial default under the weight of multi-objective optimization, although this method solved the optimization problem but at the same time there are two problems: one is single objective optimization algorithm to optimize multi-objective problem when the results of the uncertainty, the second is the optimization goal not fully adapt to the characteristics of the electric power communication network.

In this paper, an optimization algorithm based on multiple targets is adopted to optimize the router's recovery capability by using the minimum node number of the whole network and the redundant transmission capacity of nodes as fitness. Damaged business in electric power communication network nodes dynamically allocated, make damaged greatly enhance the survivability of the business, to ensure the maximum recovery damaged business, compared with other algorithm has good robustness, fast, and the advantages of small number of individual relationships with optimal results.

2. Multi-objective optimization definition.

The multi-objective optimization problem is composed of n decision quantities and m target variables, which satisfy certain constraint conditions to seek the optimal solution of mathematics.
Its mathematical model can be expressed as follows:

$$\begin{aligned} min \quad & F(x) = \left(f_1(x), \ f_2(x), \ \ldots, \ f_m(x)\right)^T \\ s.t \quad & g_i \le 0, i = 1,2,\cdots,q \\ & h_j = 0, j = 1,2,\cdots,p \end{aligned}$$

In the formula, $x = (x_1, x_2, \cdots, x_n)^T$ is the decision vector, which satisfies both the constraints of g_i and h_j. $F(x)$ is the target vector, and we need to find $x^* = (x_1^*, x_2^*, \cdots, x_m^*)^T$ to make $f(x^*)$ satisfy both constraints of g_i and h_j.

Multi-objective optimization problem need to meet the requirements of more child targets at the same time, and may be conflicting between each target, this leads to a multi-objective optimization problem is not only the global optimal solution to make all of the objective function is the same time to achieve the optimal. The core of the multi-objective algorithm is coordinating the relationship between the objective function, to find the optimal solution set make each objective function as larger or smaller, multi-objective optimization problem of the solution is usually not the only, but there is the optimal solution set, the set of elements known as Pareto optimal solution or non-dominated solution, its definition is as follows:

$\exists x^* \in R^n$ and $\nexists x \in R^n$,for every $i = 1,2,\cdots,m$ to make $f_i(x) \le f_i(x^*)$,and there is at least one point to make $f_i(x) < f_i(x^*)$,it is going to call x^* the optimal solution for Pareto.

3. Improved particle swarm optimization algorithm.

For the improvement of particle swarm optimization algorithm, its inspiration mainly comes from the migration flight of wild geese. During the migration of wild geese, the word "-" or "V" will be displayed, and the flight mode will be more than 60 percent higher than that of the wild geese. So, in the improved particle swarm optimization algorithm to each goose equivalent of a flight queue to the particles in particle swarm, the geese strong conditions equivalent to particle degree of the stand or fall of history the best fitness value, the stand or fall of particles according to the history of the optimal fitness value to sort, select the history the best fitness value of the best particle as a leader, and the first good, in turn, to the rear, so that makes the strong geese with relatively weak geese flying, so will be behind the leading wild goose individual extremum as close to the global extremum of geese, namely $gBest_{id} \leftarrow pBest_{(i-1)d}$, the leading wild goose global extreme value for its own individual extremum.This method will not limit in a global extremum values, so as to effectively prevent the all particles direction line state, avoid premature particles of the same, and make the particle diversity changes, effectively expand the search scope.
Updates to speed are as follows:

$$V_{id}^{k+1} = \omega . V_{id}^k + c_1 r_1 \left(pBest_{id}^k - X_{id}^k\right) + c_2 r_2 \left(pBest_{(i-1)d}^k - X_{id}^k\right)$$

Type $i = 1,2,\ldots,M$. and M is the total number of particles, $d = 1,2,\cdots,N$. and N is particle dimension, ω is the inertia weight, c_1, c_2 is constant negative acceleration, usually at the [0,4] between values, r_1, r_2 is random number [0,1], V_{id}^k is the speed of the particles i at the k th iteration, X_{id}^k is the location of the particles i at the k th iteration,, $pBest_{id}^k$ is the location of the particle i at the D individual extremum, $pBest_{(i-1)d}^k$ is the most optimal fitness sorted according to the history, the stronger the wild goose individual extreme value, the speed of the particles in each dimension are confined within the scope of the $[-V_{d\,max}, +V_{d\,max}]$, and $V_{d\,max} = k.X_{d\,max}$, $0.1 \leq k \leq 0.2$

When the geese fly in migration mainly rely on teamwork, in front of geese for flight, can only rely on their own experience in the back of the geese flying experience not only rely on themselves, also can be based on the experience of the in front of the wild goose to fly, and to adapt the current value as the weight value of the reference. So, in addition to the front of the wild goose, its rear geese individual extreme value and the corresponding fitness function value $pBest_i$ weighted average, and will be $f(X_i)$ weighted average of the as other geese individual values, so the case of particle's individual extremum i update as follows:

$$P_a = \frac{\sum_{i=1}^{N} pBest_i \times f(X_i)}{\sum_{i=1}^{N} X_i}$$

After the improvement, each particle can use more information to decide their own behavior, can reduce the probability of algorithm falls into local optimum, and also strengthen the relationship between the individual particles, so as to accelerate the convergence speed of the algorithm. To sum up, the speed and position updating formula of the improved particle swarm optimization algorithm is as follows:

$$V_{id}^{k+1} = \omega.V_{id}^{k} + c_1 r_1 \left(P_{ad} - X_{id}^{k}\right) + c_2 r_2 \left(pBest_{(i-1)d}^{k} - X_{id}^{k}\right)$$

$$X_{id}^{k+1} = X_{id}^{k} + V_{id}^{k+1}$$

Concrete steps to improve particle swarm optimization algorithm:

1. The initialization of particle swarm: set the size of the initial population of M, the dimensions of the space solution for N, within the scope of the permit initialize all the particle's speed $V(i,j)$ and position $x(i,j)$, $i = 1,2 \cdots, M$ $j = 1,2 \cdots, N$ and set up the extreme value of each particle $pBest$ for each particle's current location, get the $pBest$ optimal values for the current global optimal location of particle swarm;

2. Calculate the fitness value of each particle: the fitness value of each particle is obtained through the reference function;

3. Update the optimal value of the individual: compare the current fitness value of each particle with the optimal value of the individual, and update the fitness value if the current fitness value is better; otherwise, it will remain unchanged;

4. Sorting the particle swarm: reordering all the particles according to the optimal fitness value of history, and obtaining the particle with the best fitness value, and using it as the head goose of wild geese;

5. Calculate the optimal value of the new individual: in addition to maintaining the original value of the individual extreme value of the head goose, the individual extreme value of the remaining wild geese is calculated by formula (1).

6. Calculate the new global optimal value: in addition to the global extreme value of the wild goose, the global extreme value of each wild goose is replaced by the individual extreme value of the wild goose in front of it;

7. Update the particle's velocity and position: update each particle's speed V_i and position X_i by formula (2) and (3).

8. Whether the termination condition is satisfied: if the termination condition is met, the update will be stopped, or the reverse step (2) will be resumed.

4. Network optimization of power communication network.

4.1. *Power communication network model.*

In the power communication network, the physical topology is defined as (N, L, C), where N is the node set, which represents the number of network nodes. L is a two-way link set, which represents the logarithm of network optical fiber. Each link is composed of a pair of one-way optical fibers with opposite directions.C is the business circuit set of network optical fiber, which represents the business circuit number of each pair of network fiber. In order to better reflect the performance of this method in network recovery, the main parameters involved are as follows: 1) limit the business volume of each fiber;2) limit the number of incoming and outgoing of each node;3) limit the hop number of routes;4) limit the capacity of optical channels.

This method mainly considers the two situations of the power communication network. The first is that the communication nodes of each business circuit set are as few as possible so as to improve the compactness of the topology. In the second case, the minimum redundant communication capacity of all nodes should be as large as possible in the power communication network topology, so as to retain certain robustness. For the first case, you can change $\mathrm{D1} = \mathrm{Arg\,min}\left(\sum_{i=1}^{Nd} X_i\right)$ to $\mathrm{D1} = \mathrm{Arg\ max}\left(\frac{1}{\sum_{i=1}^{Nd} X_i}\right)$, where Nd represents all the business Numbers, and X_i is the number of communication nodes passed by the ith business number. For the second case, $\mathrm{D2} = \mathrm{Arg\ max\,min}(DC_1 - DT_1), (DC_2 - DT_2), \dots, (DC_n - DT_n)$, where DC_1 is the maximum communication capacity of the first node, DT_1 is the communication data volume of the first node, and n is the number of all nodes. Therefore, the fitness Arg $\max(\mathrm{D1}, \mathrm{D2})$of this project can be obtained.

4.2. The performance tests

In the model simulation of the power communication network in a province, the target is changed to take and the minimum value for the convenience of calculation, which is as follows:

$$Arg\ min(F) = Arg\ min(F1 + F2)$$

$$F1 = \frac{1}{D1} = \left(\sum\nolimits_{i=1}^{Nd} X_i\right)$$

$$F2 = \frac{1}{D1} = max(1/(DC_1 - DT_1),\ \ 1/(DC_2 - DT_2)\ ,\ \ \dots,\ \ 1/(DC_n - DT_n))$$

Among them, for the target $F1$, be able to get reliable data, but for the target $F22$, did not obtain the real data, so will make the following assumptions: (1) places the communication capacity of 10 unit of network node;(2) the communication capacity of network nodes in county-level cities is 5 units;(3) there is at least one random business of 0.01 unit between each node. In this way, the virtual data of target $F2$ can be obtained. Don't add a new business, the start node to the existing 100 random operations and flow rate of 0.01 overall business restructuring, 100 times and path optimization, optimization results are shown in table 1.

Table 1 Results of network optimization of power communication network in a province.

Number	Methods	Optimize the number of optimizations.	The optimal average algebra.	The optimal average time.
1	MOGA	82	73.8	41.7
2	MOGPSO	72	52.3	5.1

Among them, the recognition of the results is judged by expert analysis. The number of population of the multi-objective wild geese algorithm (MOGPSO) is 40, $c_1 = c_2, \omega = 0.729$.The population number of multi-objective genetic algorithm (MOGA) is 40, and the crossover probability is 0.5, roulette method. total of 100 experiments were evaluated by experts.

5. Conclusion

The multi-objective particle swarm optimization algorithm is applied to the restoration process of electric power communication optical fiber network, using multi-objective his algorithm is verified on the performance of the electric power communication network optimization, to ensure that when the business can redistribute the business when damaged, restore to the largest degree. Compared with other algorithms, the algorithm has the advantages of fast computing speed and good robustness and can achieve better results in the application of the restoration of power communication network.

Acknowledgments
The project is in the global energy Internet research institute co., LTD., with the support from the institute of information and communication, electric power communication network is mainly studied the network optimization method, the multi-objective particle swarm optimization algorithm is applied to electric power optical fiber communication network in the process of recovery of the algorithm is verified using the algorithm of multi-target his performance of the electric power communication network optimization, and combined with the province company for electric power communication network simulation model, and obtained ideal results.

References
[1] Bou-Harb E, Fachkha C, Pourzandi M, et al. Communication security for smart grid distribution networks[J]. IEEE Communications Magazine, 2016, 51(1):42-49.
[2] Gungor V C, Lambert F C. A survey on communication networks for electric system automation[J]. Computer Networks, 2016, 50(7):877-897.
[3] Rodriguez A, Laio A. Clustering by fast search and find of density peaks[J]. Science, 2014, 344(6191):1492.
[4] Zhang M, Luo C, Li J. Estimating Available Bandwidth Using Multiple Overloading Streams[C]// IEEE International Conference on Communications. IEEE, 2016:495-502.
[5] Guerrero C D, Labrador M A. On the applicability of available bandwidth estimation techniques and tools[J]. Computer Communications, 2017, 33(1):11-22.
[6] Huang S C. Online option price forecasting by using unscented Kalman filters and support vector machines[J]. Expert Systems with Applications, 2015, 34(4):2819-2825.
[7] Wonga W K, Chu W C. Adaptive neural network model for time-series forecasting[J]. European Journal of Operational Research, 2016, 207(2):807-816.