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Research of converter transformer fault diagnosis based on improved PSO-BP algorithm

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Abstract. To overcome those disadvantages that BP (Back Propagation) neural network and conventional Particle Swarm Optimization (PSO) converge at the global best particle repeatedly in early stage and is easy trapped in local optima and with low diagnosis accuracy when being applied in converter transformer fault diagnosis, we come up with the improved PSO-BP neural network to improve the accuracy rate. This algorithm improves the inertia weight Equation by using the attenuation strategy based on concave function to avoid the premature convergence of PSO algorithm and Time-Varying Acceleration Coefficient (TVAC) strategy was adopted to balance the local search and global search ability. At last the simulation results prove that the proposed approach has a better ability in optimizing BP neural network in terms of network output error, global searching performance and diagnosis accuracy.

1 Introduction

The converter transformer is one of the most important electrical equipment in the DC transmission project. The fault and outage of the large converter transformer may bring huge economic loss and social disaster to the power grid and enterprises. Therefore, the fault diagnosis research of the converter transformer is especially important[1]. Dissolved gas analysis (DGA) in oil is the most widely used, most direct and effective technical means for fault diagnosis of converter transformers. It determined the fault type of converter transformer by the content analysis of main characteristics gas come from decomposition of hydrogen(H_2), carbon monoxide (CO), acetylene (C_2H_2) Ethylene (C_2H_4), methane (CH_4), ethane (C_2H_6) and other insulating oil[1-3].

In short, the converter transformer fault diagnosis can be seen as a pattern recognition process. Many artificial intelligence methods have been introduced into the converter transformer fault diagnosis, such as genetic algorithm, artificial neural network, Bayesian classifier and support vector machine, etc. In these methods, the BP neural network becomes a more mature method for performing rheological fault diagnosis because of its good nonlinear mapping ability.

This paper combined with the actual fault diagnosis of converter transformer optimizes from inertia weight and acceleration factor settings, etc. based on the standard PSO algorithm, proposes an improved PSO algorithm, which is combined with BP neural network. The fault diagnosis model of converter transformer is established based on this basis. By comparing the simulation example with the single BP algorithm and the standard PSO-BP algorithm, it is proved that the algorithm proposed in this paper has better optimization performance and higher fault diagnosis rate.

2 PSO algorithm and its improvement

PSO algorithm is an optimization algorithm based on the study of foraging behavior of birds and fish. The algorithm uses the interaction between abstract particles and information sharing to guide the optimal solution in the solution space. Because PSO algorithm is simple, rapid convergence, easy to achieve, etc. So it is widely used to solve the problem of the social and economic, engineering and other needs to optimize, such as function optimization, pattern recognition and decision support, etc.

2.1 Standard PSO algorithm

The standard PSO algorithm principle searched by the usage of the group of N particles in the D-dimensional space at a certain speed flight, follow the optimal particles. The system is initialized to a set of random solutions, which set the velocity range and initial test position of each particle. Each particle updates the individual position according to the individual extremum and the global extremum, and then searches for the optimal value by iteration. The particle swarm algorithm's speed and position update Equation is:.

$$V_{id}^{j+1} = \omega V_{id}^{j} + c_1 r_1 (P_{id}^{j} - X_{id}^{j}) + c_2 r_2 (P_{gd}^{j} - X_{id}^{j}) \qquad (1)$$

$$X_{id}^{j+1} = X_{id}^{j} + V_{id}^{j+1} \qquad (2)$$

Where: j is current iteration times; ω is the inertia weight; V_{id}^{j} is the current velocity of the particle; X_{id}^{j} is the current position of the particle; P_{id}^{j} is the optimal position of the individual particle; P_{gd}^{j} is the optimal position of the whole particle group; c_1 and c_2 are the acceleration factor, r_1, r_2 are a random number within [0,1].

2.2 Improved PSO algorithm

2.2.1 Inertia weight improvement. In the standard PSO algorithm, the inertia weight ω is usually set as a fixed constant, which proves that this setting limits the trend of particle expansion search space and the ability to explore the new region, which is not conducive to the global optimization and fast convergence of the algorithm. In order to further improve the performance of the algorithm, the dynamic linear adaptive strategy proposed in literature [4] is used to adjust the inertia weight ω, which is linearly attenuated as the iterative process increases, thus accelerating the convergence speed of the algorithm. The inertia weight modification Equation is as follows:

$$\omega = \omega_{\max} - j\left(\frac{\omega_{\max} - \omega_{\min}}{j_{\max}}\right) \qquad (3)$$

Where: $\omega_{\max}$, $\omega_{\min}$ are the upper and lower limits of the inertia weight, respectively, j, $j_{\max}$ are the current iterations number and the maximum iterations number.

On the basis of this literature[5], three kinds of nonlinear weight attenuation methods of concave function curve, convex function curve and exponential curve are proposed. The results show that the nonlinear attenuation method based on concave function compared with the attenuation method of linear function is more effective to avoid premature convergence of PSO algorithm. Therefore, this paper adopts the attenuation strategy based on concave function, and improves the Equation (3)

2.2.2 Introduction of time-varying acceleration factor. In PSO algorithm, c_1, c_2 are the cognitive acceleration factor and social acceleration factor, respectively, reflecting the particle's own experience and social experience ratio, determine the particle movement direction and the final convergence results of the algorithm. c_1 is responsible for adjusting the particle to fly to their best position direction step, if c_1 is too small, then the particle lacks of their own experience, it is easy to fall into the local optimum. c_2 is responsible for adjusting the particles to the best position the flight step of the overall, if c_2 is too small, the exchange of information between the particles is too weak, it only rely on their own experience to search, the probability of obtaining the global optimal solution is very small.

Therefore, the literature[6] proposed a PSO improved algorithm for accelerating factors, the algorithm used in the particle velocity update, adopt time-varying acceleration factor (TVAC), the cognitive acceleration factor c_1 with the linear acceleration of the iteration process at the same time, social acceleration factor c_2 is linearly reduced, so as to avoid the local optimization of the particles in the early stage of the algorithm, and encourage the particles to search the global optimal solution at the end of the algorithm:

$$c_1 = c_{1i} + (c_{1f} - c_{1i})(j / j_{\max}) \tag{4}$$

$$c_2 = c_{2i} + (c_{2f} - c_{2i})(j / j_{\max}) \tag{5}$$

Where c_{1f} and c_{1i} are the initial value of the acceleration factor, c_{2f} and c_{2f} are the final value of the acceleration factor; $j_{\max}$ is the maximum number of iterations; j is the current number of iterations.
In this paper, it introduces the time-varying acceleration factor (TVAC), considering the influence of all particles on the search, we can balance the local optimal search in the early algorithm and global optimal convergence of in the late algorithm, enhance the global optimal solution searching ability.

3 Improved PSO Algorithm for BP Neural Network

3.1 Standard BP Neural Network

BP neural network is a multi-layer feedforward neural network, which has more powerful computing ability and self-learning ability compared with other neural networks. BP neural network is generally composed of input layer, hidden layer, output layer, and its learning rule is used of the gradient descent method, the learning process is composed of forward and reverse propagation. The signal is first input by the input layer and passed through the activation function of the hidden layer node to the output layer. If the error of the forward propagation output does not reach the expected precision, the error is propagated backwards, and the error is distributed to all the elements of the layer. The weights and thresholds of each layer of neurons are repeatedly modified according to the negative direction of the error signal, and the output error of the network is reduced to the set error range. The BP neural network model is shown in Fig.1.

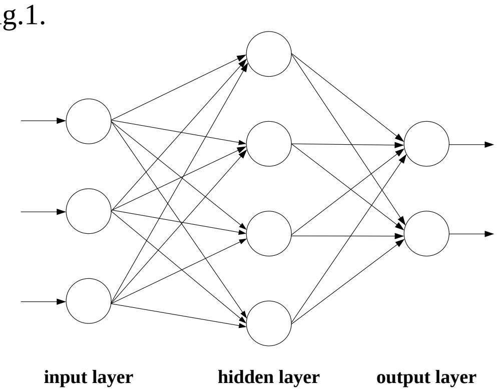

Fig 1: BP neural network algorithm model

3.2 Optimization of Improved PSO Algorithm to BP Neural Network

The standard BP neural network uses the gradient descent method to modify the weight and threshold, but the gradient descent algorithm usually has the disadvantage of easy to fall into the local minimum, easy to oscillate and slow convergence. The optimization of PSO algorithm to BP neural network combines BP neural network with PSO algorithm. The optimal threshold of BP network is used to correspond to the position of PSO. The output error of neural network corresponds to the fitness function of PSO, The optimal network threshold is obtained by finding the optimal particle position, so as to realize the optimization of BP network. The fitness function is given by equation (6)

$$J=\frac{1}{n}\sum_{j=1}^{n}\left|\sum_{k=1}^{m}(q_{jk}-y_{jk})^2\right| \qquad (6)$$

Where q_{jk} is the expected output value, y_{jk} is the actual output value, n is the network output node number, m is the number of training samples. The optimization steps of PSO algorithm to BP neural network are as follows:

Step 1: Initialize the improved PSO algorithm parameters, set the number of particles P, particle dimension d , the maximum number of iterations $j_{\max}$ and network error accuracy, inertia weight ω and time-varying acceleration factor upper and lower limits.

Step 2: Establish correspondence of an improved PSO algorithm and BP network: determine the layer number of neural networks, the number of neurons per layer, and the particle dimension that need to optimize.

Step 3: Calculate the fitness of each particle, update the optimal position P_{id}^{j} of the individual particles and the optimal position in the whole particle group according to the fitness value.

Step 4: According to the Equations (1) and (2) to adjust the flight speed of the particles and the position in the whole particle group, adjust the inertia weight value and the time-varying acceleration factor according to equations (4) to (6), recalculate the particle fitness.

Step 5: Check whether the termination condition is reached. If the current fitness satisfies the error accuracy requirement or reaches the maximum number of iterations, the iteration is stopped and the global optimal value of the current particle population is output, that corresponds to the final weight and threshold of the BP neural network, or jump to step (3) to continue execution.

4 Simulation examples

In this paper, five kinds of characteristic gas contents in converter oil such as hydrogen (H_2), acetylene (C_2H_2), ethylene (C_2H_4), methane (CH_4) and ethane (C_2H_6) are input as BP neural network. The output status is five states of normal state, high energy discharge, low energy discharge, low temperature and medium temperature fault. In order to reduce the difference in the numerical content between the various gases and the impact of dispersion, the original gas data were normalized[7]. Therefore, the network structure uses 5 input, 5 output structure.

4.1 Parameter setting

4.1.1 Setting BP neural network parameters. In the BP neural network, construct of 5-l-5 neural network structure, the hidden layer neurons are estimated by using the Equation (7):

$$l=\sqrt{n+m}+a \qquad (7)$$

Where m indicates the nerve node number of the input layer; n indicates the nerve node s of output layer; a is any integer between 0 to 9.

Use the standard BP algorithm for loop testing, comparing the final error size after 200 learning, according to the error size to determine the optimal value of the network to find the final mean square error of each l value, the results shown in Table 1, when the number of nodes is 9 , the error is minimum, so $l = 9$.

Table 1: Results of different nodes of hidden layers BP network

nodes	final error	nodes	final error
4	0.0866	9	0.0391
5	0.0745	10	0.0453
6	0.0669	11	0.0536
7	0.0621	12	0.0614
8	0.0442	13	0.0716

4.1.2 Setting PSO algorithm parameters. The number of particles is P = 20, the particle dimension is $d = l\times m+l\times n+m+n$ =100, the maximum number of iterations is 200, the location range of the particle swarm is [-1,1], and the velocity range of the particle swarm is [-2,2]. The most important parameters of the PSO algorithm are the inertia weight ω and the acceleration factor c_1, c_2. According to the literature[8], the standard PSO algorithm is best diagnosed when the inertia weight is in the range of $\omega_{\max} = 0.9$, $\omega_{\min} = 0.4$, acceleration factor $c_1 = c_2 = 2$. For the improved PSO algorithm proposed in this paper, the upper and lower limits of the time-varying acceleration factor are $c_{1i} = 2$, $c_{1f} = 0.2$, $c_{2f} = 0.2$, $c_{2f} = 2$, and the range of inertia weight is the same as the standard PSO's.

4.2 Algorithm comparison

The DGA data of 104 sets of converter transformers were collected, 60 sets of them were used to train the BP neural network, and 44 sets of data were used as test samples. After the parameters were set, the standard BP algorithm, PSO-BP algorithm and the improvement PSO-BP algorithm in this paper proposed are used to simulate. Training error of three methods and fault diagnosis accuracy shown in Table 2, the network output error curve shown in Figure 2, figure 3 is the fitness curve of PSO and improved PSO algorithm to BP neural network parameter optimization.

Table 2: Training error and diagnosis precision of three methods

method	output error	diagnosis precision
BP	0.0386	81.8%
PSO-BP	0.0174	86.4%
improved PSO-BP	0.0112	93.2%

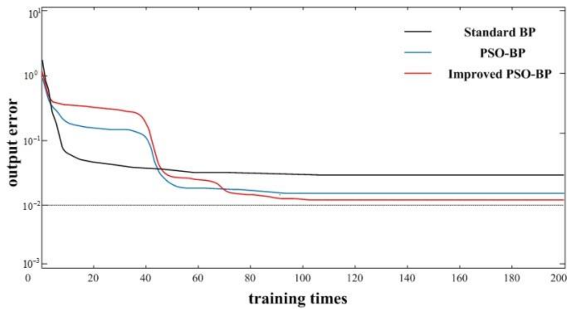

Fig 2: network output error curve

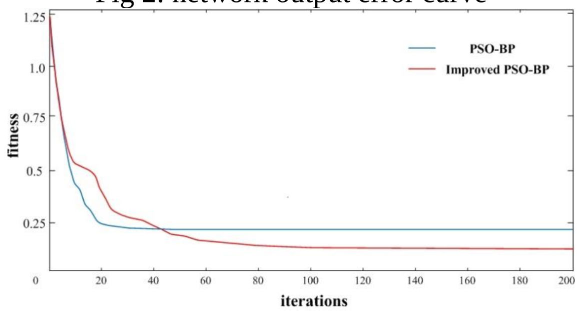

Fig 3: fitness curves

As shown in Figure 2, the output error of the standard BP neural network began to decline rapidly, the decline rate reached the maximum when the number of training is 11 times, and then gradually decline gentle in the curve, training 57 times has reached convergence, the late reduction is minimal, the minimum training error is 0.0386, the diagnostic accuracy of 81.8% is the lowest among the three. The other two PSO-optimized BP algorithms show considerable performance in the early iteration. In the first 30 times training, avoid the standard BP algorithm premature convergence into disadvantages of local optimization. In the 35 times training, the gradient of the left and right sides dropped into the depth optimization. But the PSO-BP algorithm also failed to jump out of the local optimum. The curve was stabilized at 60 times, and the training error was 0.0174. The training error was reduced by 50% compared with the standard BP algorithm. The diagnostic accuracy rate also increased to 86.4%. In this paper, the improved PSO-BP algorithm curve is reduced again in the short-term second gentle and then into the global optimization. Finally, it converges at 101 times, the training error is 0.0112, and the fault accuracy rate of 93.2% is the highest in three.

In addition, the fitness curves of the two PSO optimization algorithms are shown in Fig. 3. It can be seen that the fitness curve of PSO-BP converges rapidly in the first 20 iterative periods, but it is basically gentle in the later period, and the fitness value is no longer change. And the early convergence of improvement of the PSO-BP's fitness curve is not as fast as the unmodified PSO-BP, but it has been in the descending state. It shows that the algorithm can effectively balance the global and local optimal performance of the particle during the training process, So that the particles have been searching, the final fitness value is smaller than the unmodified PSO algorithm, resulting in better training error and fault accuracy.

5 Conclusion

In this paper, combine PSO algorithm and BP neural network to research on fault diagnosis of converter transformer. In view of the inherent shortcomings of standard PSO algorithm, the inertia weight Equation is improved, and the time-varying acceleration factor is introduced at the same time. The simulation results show that the improved PSO-BP algorithm can effectively balance the contradictions between global and local search of the particles, avoid the premature convergence of the standard PSO algorithm into the local optimal solution, and enhance the global optimal solution search ability, effectively improve the fault diagnosis rate of converter transformer. The improved PSO-BP algorithm proposed in this paper can be applied to the actual engineering combined with the experience of field maintenance personnel, which is a simple and effective method to solve the fault diagnosis problem of converter transformer.

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