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Fault Diagnosis of Power Transformer Based on Gas Characteristic Analysis

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Power transformers are one of the most critical devices in power systems. It is responsible for voltage conversion, power distribution and transmission, and provides power services. Therefore, the normal operation of the transformer is an important guarantee for the safe, reliable, high quality and economical operation of the power system. It is necessary to minimize and reduce the occurrence of transformer failure and accident. The on-line monitoring and fault diagnosis of power equipment is not only the prerequisite for realizing the predictive maintenance of equipment, but also the key to ensure the safe operation of equipment.
Although the analysis of dissolved gas in transformer oil is an important means of transformer insulation monitoring, the coexistence of two kinds of faults, such as discharge and overheat, can lead to a lower positive rate of diagnosis. In this paper, we use the basic particle swarm optimization algorithm to optimize the BP neural network DGA method, select the typical oil in the oil as a neural network input, and then use the trained particle swarm algorithm to optimize the neural network for transformer fault type diagnosis. The results show that the method has a good classification effect, which can solve the problem of difficult to distinguish the faults of the transformer when the discharge and overheat coexist. The positive rate of fault diagnosis is high.

1. Introduction

With the rapid development of national economy, the demand for power supply is increasing. China's power grid construction has formed a pattern of national networking (Zhang et al., 2017). The power system is moving towards ultra-high pressure, large power grids, large capacity and automation. Uninterrupted power supply has become a vital factor in industrial production, defense, military, technological development and people's daily lives. With the increase of grid capacity and the improvement of power supply reliability requirements, the proportion of maintenance costs for power facilities is also increasing. The importance of maintenance management is increasingly apparent. Under the premise of not reducing the reliability, we should adopt the reasonable maintenance strategy and make the scientific maintenance plan to save the maintenance cost. This is becoming an important research topic in the power sector (Wang et al., 2016; Gattuso et al., 2016; Rovense et al., 2016; Cucumo et al., 2016; Yu et al., 2016; Krasnokutskiy et al., 2016; Rosso et al., 2016; Aziz and Kurniawan, 2016).
In recent years, the electric power industry has been actively using the on-line monitoring technology to carry out the condition maintenance, strengthening the routine test and comprehensive analysis of the equipment, thus eliminating the safety hidden trouble of the equipment in time. Failure of power equipment has always been a major factor in the safety of the power grid. The most failure rate is the internal insulation of the power transformer (Wang et al., 2017). The characteristics of the main faults are serious aging of power transformer insulation, bad operating environment and poor quality of power transformer (De Faria et al., 2015). Therefore, how to ensure the safe operation of power transformers has been widespread concern around the world. How to find out the latent fault of power transformer and determine the fault character of power transformer is a matter of great concern to the electric worker (Shekarabi et al., 2017).

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2. Analysis and diagnosis of dissolved gases in transformer oil

The reliable operation of power transformers is the basis for the normal operation of the power industry and other industrial production. The use of dissolved oil in insulating oil to detect the early fault inside the transformer has become an important means of transformer insulation supervision (Jiatang et al., 2016). However, the off-line chromatographic analysis of the gas in the transformer oil has the shortcomings of cumbersome operation procedure and long detection period, and it is difficult to find faults such as inter-turn insulation defects. Therefore, both at home and abroad are committed to the development of on-line detection device to achieve continuous detection and timely detection of failure (Tingfang et al., 2017).
Because of the shortage of the sensor in the detection, the gas chromatograph is used in the actual operation. Chromatography is a physical separation technique, and it was proposed by the Russian botanist M.S. Tswett in 1903. At present, various types of chromatography are made of thermal conductivity and hydrogen flame ionization detector, and the detection sensitivity is very high. It is more important for the existing instruments to control the error caused by the sample before entering the instrument analysis (Tokunaga et al., 2017). Therefore, excessive sensitivity is not necessary.
To sum up, the technology of sampling, gas separation and detection in the transformer on-line detection system is relatively mature, and the sensitivity is high. The better diagnostic method can effectively improve the fault diagnosis rate, so this article is mainly for the diagnosis part. There are many types of transformer faults. High temperature overheating and excessive discharge are the two most representative faults. Because the characteristic gas volume fraction is similar, it is easy to produce misjudgment. In this paper, according to the characteristics of transformer DGA gas content data difference and fault types, the BP neural network based on particle swarm optimization (PSO) is used to diagnose.

2.1 Basic particle swarm optimization algorithm

Particle Swarm Optimization (PSO) is an evolutionary computing technique proposed by Dr. Eberhart and Dr. Kennedy in 1995, which originated from the behavioral study of bird predation. The particle swarm optimization algorithm is similar to the genetic algorithm and is a population-based optimization tool. However, the particle swarm optimization algorithm does not have the crossover mutation in the genetic algorithm, but the particles follow the optimal particles in the solution space to search. Therefore, it has the advantages of being simple and easy to implement and without the need for many parameters to be adjusted.
The algorithm is initialized as a group of random particles (random solutions), and then the optimal solution is found by iteration. In each iteration, the particles update themselves by tracking two "extremes". The first is the particle itself to find the optimal solution, and the solution is called the individual extreme value p_{best}. Another extreme is the optimal solution currently found by the population, and this extreme is the global extremum g_{best}. In addition, it can only use a part of the neighbors as particles without the need for the entire population, then the extreme value in all neighbors is the local extremum. When finding these two optimal values, the particles update their speed and position according to the following formula:

$$v = \omega * v + c_1 * rand() * (p_{best} - p) + c_2 * rand() * (g_{best} - p) \tag{1}$$

$$p = p + v \tag{2}$$

In which, v is the velocity of the particle and p is the position of the current particle. p_{best} and g_{best} as defined earlier, rand () is a random number between [0,1]. c_1 and c_2 are the learning factor. In general, $c_1=c_2=2$.
From the above steps, we can see PSO according to their own speed to decide the search. At the same time, the particles also have an important feature, that is, memory.

2.2 The flow of the basic particle swarm optimization algorithm

The operating steps of the basic particle swarm optimization algorithm are as follows: (1) initialize the position and velocity of the particles within the group; (2) calculate the fitness of each particle; (3) for each particle, its fitness value is compared with the fitness value of the best position p_i experienced by it. If it is better, it will be the best position of the current position, otherwise it will not change; (4) for each particle, the fitness value is compared with the fitness value of the best position p_g experienced by the global. If it is better, it will be the best position of the current global, otherwise it will not change; (5) the velocity and position of the particle are updated according to the velocity and position equations; (6) if the end condition is not satisfied, go back to step 2 until the end condition is satisfied. In general, the end condition takes a good enough fitness value (less than the given error) or reaches the maximum number of iterations.
The flow chart of the algorithm is shown in Figure 1.

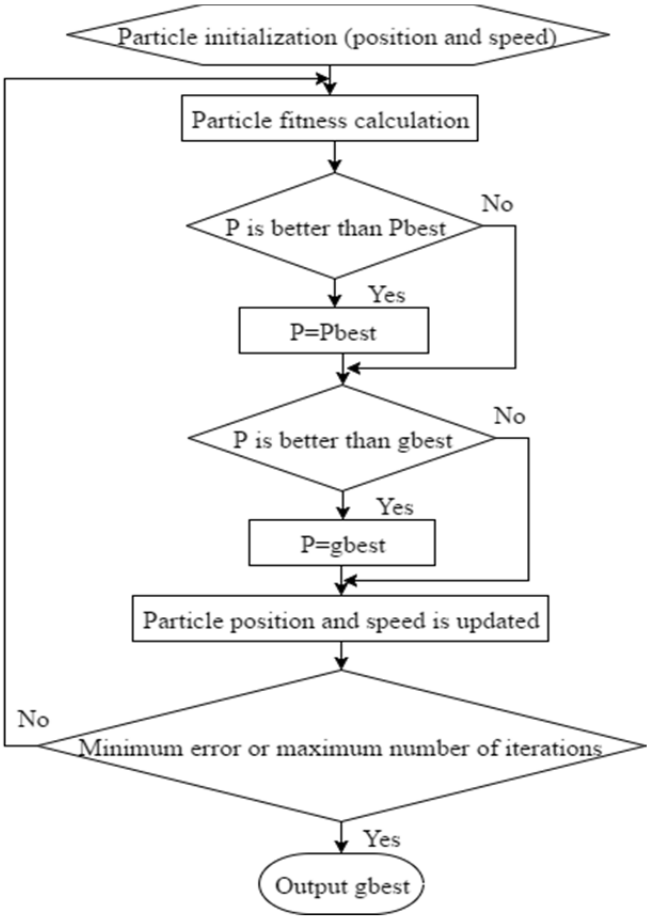

Figure 1: Diagram of PSO algorithm

2.3 Optimization of BP neural network by PSO algorithm

BP model is a multi-layer feedforward network. The algorithm is divided into two stages: the first stage (forward process) is the input information. The output values of the units are calculated from the input layer by the hidden layer. The second stage (reverse propagation process) output error layer by layer to calculate the hidden layer of the unit error, and use this error to correct the weight of the previous layer and closed value. Such positive and negative calculations are repeated until the global square error of the network reaches the expected accuracy. The algorithm is based on the gradient descent, which is inherently easy to fall into the local optimal, slow convergence and easy to cause local oscillation and other shortcomings.

The PSO algorithm is used to optimize the BP neural network, and the object particles to be optimized are the weights and thresholds of the BP neural network. First, we should make all the weights and closed values of the neural networks to be optimized form a real array and assign them random numbers between [0,1]. Then, according to the selected network structure, the neural network output corresponding to each input sample is calculated by the forward algorithm. Here, the activation function of the BP network is selected as the Sigmoid function, and then the optimal position is searched by the PSO algorithm, so that the mean square error index (fitness function) is minimized.

3. Application of basic particle swarm optimization algorithm in transformer fault diagnosis

3.1 Design of the input layer

The input of the training network is the relative content (volume fraction) of the characteristic gas. There are 20 kinds of combustible and non-combustible gases produced by thermal decomposition of the transformer. Therefore, it is very important to select the necessary gas as the analysis object in order to facilitate the internal fault diagnosis of the transformer. At present, the gas objects that analyzed at home and abroad are not uniform, as shown in Table 1.

Table 1: Examples of analysis objects

Number of gases	Analysis of the target gas
7 kinds of gas	H_2, CH_4, C_2H_6, C_2H_4, C_2H_2, CO, CO_2
8 kinds of gas	O_2, H_2, CH_4, C_2H_6, C_2H_4, C_2H_2, CO, CO_2
9 kinds of gas	N_2, O_2, H_2, CH_4, C_2H_6, C_2H_4, C_2H_2, CO, CO_2
11 kinds of gas	N_2, O_2, H_2, CH_4, C_2H_6, C_2H_4, C_2H_2, CO, CO_2, C_3H_6, C_3H_8
12 kinds of gas	N_2, O_2, H_2, CH_4, C_2H_6, C_2H_4, C_2H_2, CO, CO_2, C_3H_6, C_3H_8, i-C_4H_{10}

The purpose of the different gas analysis is not the same. O_2 is mainly used to understand the degree of degassing and sealing. H_2 is mainly used to understand the heat source temperature, partial discharge and moisture. CO_2 is mainly used to understand the solid insulation aging or the average temperature. CO is mainly used to understand the thermal decomposition of solid insulation. CH_4, C_2H_6, C_2H_4 is mainly used to understand the heat source temperature. C_2H_2 is mainly used to understand the condition of the discharge or high temperature heat source. Without prejudice to the accuracy of judgment and analysis of the object as little as possible, we select seven kinds of gas: H_2, CH_4, C_2H_6, C_2H_4, C_2H_2, CO, CO_2.

3.2 Data preprocessing

Taking into account the huge differences between the various components of the gas composition and dispersion, the DGA raw data were "normalized" treatment to reduce the mutual exclusion between gases. For the input vector normalization, this model uses the class S fuzzy membership function with offset:

$$A(x) = (1 + \exp(-a\frac{(x - x_C)}{x_C}))^{-1} \tag{3}$$

In which, x is the component content, x_c is the value of the hydrocarbon gas in the normal transformer oil, and a is the gain factor.
All components of the DGA are semi-definite, and component growth indicates that the fault is exacerbated. Therefore, the basic principles of the algorithm x_c and a are: when x=0, A(x) approaches zero. When $x>1.5x_c$, A (x) will saturate to 1. The attention value of dissolved gas of regular transformer is shown in Table 2.

Table 2: The attention value of dissolved gas of regular transformer

Group	H_2	CH_4	C_2H_6	C_2H_4	C_2H_2	CO	CO_2
Content	150	60	4	70	10	400	4500

The statistical limit content is based on the recommended value of D/L722-2000, which is consistent with the domestic transformer failure rate over the years. According to the value of attention, if some kind of gas content does not reach the value of attention, the value of the normalized value will be smaller, so as to avoid mistakes and errors.

3.3 Design of the output layer

There are two types of transformer faults: discharge type and overheat type. However, considering the fact that the actual fault type of the transformer has the same situation of discharge and overheating, this paper adds two kinds of faults to the output layer, which makes up the shortage of the method. After comprehensive consideration, the output layer is divided into seven kinds of fault types, such as high temperature, medium temperature, low temperature, low temperature, partial discharge or damp, low energy discharge, high energy discharge, discharge and overheating, which is encoded as 1~7.

3.4 Diagnostic examples

In this paper, the data of gas volume fraction collected in 127 sets of transformer faults are collected. The error data is cut off. The gas data of 118 sets of fault transformers are obtained.
Firstly, the data of the selected samples are pre-processed, coded and trained, in order to produce the trained network. Then, the samples were tested with different training samples. The parameters of PSO algorithm are as follows: the number of particles is 40, c_1=c_2=2.0, w decreases linearly with the number of iterations from 0.9 to 0.3. The number of iterations is 150. The best fitness curve is shown in Figure 2.

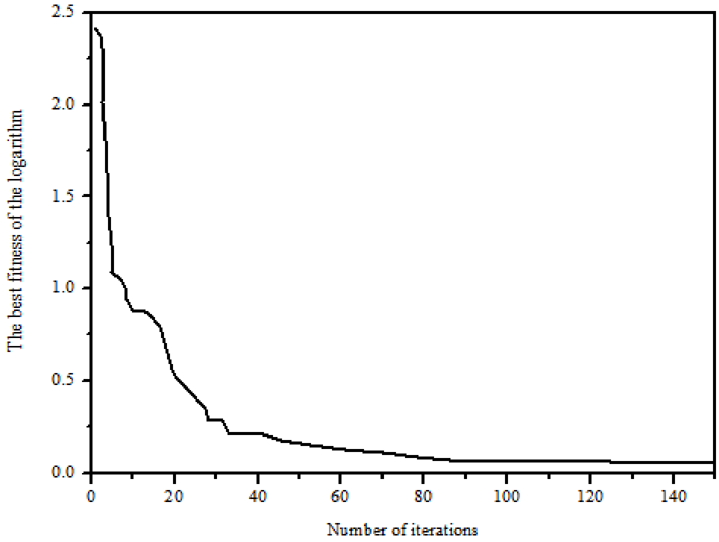

Figure 2: Optimal fitness curve of PSO.

After repeated debugging, the number of hidden nodes in the neural network is determined as 5, and the test results are shown in Table 3 and Table 4.
In Table 4, the meaning of 1~7 digital coding has been mentioned in the design of the output layer, which represent seven types of faults, respectively. It can be seen from Table 3 that this algorithm is superior to BP neural network. As can be seen from Table 4, the main reason for the emergence of Table 2 situation is the neural network will misjudge the two similar faults of high temperature overheating and overheating and discharge. However, the neural network can solve the problem better after the neighborhood PSO optimization. The main reason for its misjudgment is that the sample data of the fault is too small. Therefore, the method that proposed in this paper can improve the positive rate of fault diagnosis.

Table 3: Statistical results of diagnosis

	PSO-BP	BP
16 sets of test samples diagnostic accuracy (%)	93.75	75

Table 4: Statistical results of diagnosis

	Fault type							
True value	6	7	6	6	6	6	6	6
PSO-BP	6	7	6	6	6	6	6	6
BP	7	7	6	6	6	7	7	6
True value	6	5	6	6	1	5	2	3
PSO-BP	6	5	6	6	2	5	2	3
BP	6	5	6	6	2	5	2	3

4. Conclusions

In this paper, the application of BP algorithm based on PSO optimization in gas analysis and diagnosis (DGA) of power transformer oil was studied. The results show that the optimized BP algorithm is applied to the neural network training, which overcomes the shortcomings of BP algorithm training time and easy to fall into local convergence. At the same time, in view of the problem that the input data of several fault types are relatively close and the number of faulty samples is less, the problem of difficult to distinguish between similar fault types is solved effectively, which improves the positive probability of transformer DGA fault.

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