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PNN Transformer Fault Diagnosis based on Improved Genetic Algorithm Rough Set Reduction

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Abstract

In order to solve the problem of data redundancy and low diagnosis rate in transformer fault diagnosis, this paper combines the improved genetic algorithm rough set attribute reduction algorithm with probabilistic neural network (PNN), and establishes a PNN neural network transformer fault diagnosis model based on the improved genetic algorithm rough set attribute reduction. In this paper, the traditional genetic algorithm rough set attribute reduction algorithm is improved, the attribute kernel is added to the genetic algorithm population initialization code, and the attribute dependency is added to the genetic fitness function to increase the speed and accuracy of attribute reduction. Through this algorithm, the reduced fault data is smaller and more reliable, and the PNN neural network training simulation can effectively reduce the complexity of the network, reduce the network training time, and improve the practicability and diagnosis rate of transformer fault diagnosis.

Keywords

Transformer fault diagnosis; Genetic algorithm; Rough set attribute reduction; PNN (probabilistic neural network).

1. Introduction

Dissolved gas analysis (DGA) is a common and effective fault diagnosis method for oil immersed power transformer in power system [1,2]. In recent years, many fault diagnosis methods based on the analysis technology of dissolved gas in oil, such as support vector machine [3,4], fuzzy clustering [5], neural network [6] sprang up. In reference [7], PNN neural network is used to replace BP neural network and a transformer fault model is established, which solves the shortcomings of BP neural network such as long training time and retraining when sample changes. Because the neural network is based on the principle of empirical minimization, its structure becomes complex and easy to fall into local minima. Literature [8] and literature [9] respectively apply cultural gene algorithm, wolf swarm algorithm and neural network to diagnosis, and establish intelligent algorithm fault diagnosis model, with good diagnosis effect. However, there are always some uncertainties, redundancy and other problems in transformer fault information data, so there are some diagnosis methods based on information processing [10,11]. Rough sets and support vector machines are combined to diagnose transformer faults, rough sets reduce the characteristic attributes, remove redundant data, and improve the speed and accuracy of SVM in diagnosis and classification in reference [12]. Rough sets perform well in attribute reduction. In recent years, many related algorithms have been proposed around attribute reduction of rough sets [13,17]. Applying these algorithms to the data processing of transformer will greatly improve the fault efficiency of transformer.

Overall, the improved genetic algorithm rough set attribute reduction algorithm is proposed to reduce the transformer fault data, and then the reduced data is trained and simulated by PNN neural network

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to classify and diagnose the transformer in this paper. In this algorithm, attribute kernel is added to the initial population of genetic algorithm to increase the convergence speed, and the dependence of decision attribute on condition attribute is added to the fitness function, so that the algorithm can not only ensure the global optimization characteristic, but also strengthen the local search ability, and obtain the best search effect. The reduced data is more accurate than the neural network in fault diagnosis. The experiment shows that the fault diagnosis model of PNN neural network based on attribute reduction of improved genetic algorithm is well applied and the diagnosis rate is high.

2. Attribute reduction of rough set based on Improved Genetic Algorithm

2.1 Correlation theory of rough set

Theorem 1: decision table: $S=\{U,A,V,f\}$,where, U is the domain, it is the set of all objects; A is the set of attributes, $A=C\cup D$, $C\cap D=\varnothing$ .where, C represents the conditional attribute, D represents the decision attribute; V represents the value domain set of attribute; f is the information function, $f:U\times A\rightarrow V$.

Theorem 2: each attribute subset $P\subseteq A$ determines a binary indistinguishable relation $IND(P)$, namely:

$$\mathrm{IND(P)}=\{f(x,a)=f(y,a)\} \tag{1}$$

In formula (1), $a\in A$, $(x,y)\in U\times U$.

Indiscernible relation is the basic concept of rough set, also known as equivalence relation.

Theorem 3: If X is a subset of U , $X\subseteq U$, R is an equivalence relation of U , then:

$$\underline{R}X=U\{Y\in U/R|\ Y\subseteq X\} \tag{2}$$

$$\overline{R}X=U\{Y\in U/R|\ Y\cap X\neq\varnothing\} \tag{3}$$

Where $\underline{R}X$ and $\overline{R}X$ are called X lower approximation set and upper approximation set of R respectively, and Y is the partition of the equivalence relation R to the domain U .

Theorem 4: let U be a domain, P and Q are two equivalent relation clusters defined on U , if the Q independent subset of $P:S\subset P$,then $POS_S(Q)=POS_P(Q)$, S is called Q reduction of P

Theorem 5: the intersection of all reduction of attribute C is called kernel, which is recorded as: $Core(C)=\mathrm{Re}\,d(C)$,the kernel in C is an indispensable attribute set for all reduction.

Theorem 6: the degree of correlation between condition attribute subset $P\subseteq C$ and decision attribute D is as follows:

$$r(P,D)=\frac{|POS_P D|}{|U|} \tag{4}$$

2.2 Attribute reduction of rough set based on Improved Genetic Algorithm

Genetic algorithm is a kind of randomized search method which is based on the evolutionary law of biology and the genetic mechanism of survival of the fittest [18]. It includes five factors: coding, generating initial population, determining fitness function, determining genetic operator and setting control parameters. Genetic reduction algorithm is to use the above factors to reduce data effectively.

1) Encoding

In this paper, binary encoding method is used. Each chromosome encoded represents different sample individuals. Its length is equal to the number of condition attributes in the decision table, and each bit of chromosome corresponds to the condition attribute. In binary encoding, 0 means not selecting the attribute, 1 means selecting the attribute.

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2) Group initialization

In this paper, the kernel of the decision table system is calculated by the above rough set correlation theory and added to the newly generated population individual to ensure that every attribute in the kernel is selected in the chromosome, that means the corresponding position of chromosome is 1. Adding a kernel to the population in advance can improve the speed and accuracy of the algorithm.

3) Fitness function

Fitness function is an important part of the algorithm. It is used to select the optimal individuals that meet the requirements. Its selection is related to the speed and accuracy of evolution. It ensures the accuracy of classification and ensures that the smaller the number of conditional attributes in the Coloring individual, the larger the fitness function value. In this paper, the concept of attribute dependence of rough set $r_C(D)$ is introduced to ensure the convergence speed of the algorithm.

$$f(x)=\frac{L-L_x}{L}+r_C(D) \tag{5}$$

Among them, X represents the chromosome, L is the length of chromosome, and $r_C(D)$ is the dependence of conditional attribute on decision attribute.

4) Genetic operator

a) selection

The roulette strategy is adopted for selection. The probability of each individual inheriting to the next generation is as follows:

$$P(x_i)=\frac{f(x_i)}{\sum_{j=1}^{N} f(x_i)} \tag{6}$$

The fitness value of each individual in $f(x_i)$ population is used to randomly generate values between 0 and 1 to randomly select individuals

b) Variation and crossover

In this paper, we use single point crossover to select two individuals to cross through the crossover probability, and then use them as parents to randomly select a crossover point, and then exchange some of the cross substrings to generate new individuals. Then, individuals were selected by mutation probability to perform mutation operation. Among the selected individuals, except for the unchangeable attribute represented by the kernel attribute, randomly select the bit participating in the mutation in the individual, and reverse the corresponding bit

c) Stop rule

Stop the operation when the number of iteration steps reaches the maximum algebra.

2.3 Specific algorithm steps

Input: information system $S=\{U,A,V,f\}$;

Output: reduction of information system $S=\{U,A,V,f\}$.

Step 1: calculate the core in the information system;

Step 2: a binary population of u is randomly generated. The length of each chromosome is the same as the number of conditional attributes, and the position is corresponding. The nuclear attribute calculated by step 1 corresponds to position 1 in the chromosome, and the rest positions are randomly set to 1 or 0.

Step 3: calculate the fitness of each individual in the population, then select the appropriate individual according to the roulette method, generate two parents in turn according to the crossover probability,

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and then generate new individuals, and randomly select non nuclear attribute bits according to the mutation probability for mutation.

Step 4: calculate the fitness of new individuals, retain the optimal individuals to the next generation, and save the optimal individuals;

Step 5: when the genetic algebra has reached the set value, exit and output the optimal individual, that is, the optimal attribute reduction; otherwise, turn to step 3 to continue running.

3. Attribute reduction PNN network fault diagnosis model based on improved genetic algorithm rough set

3.1 PNN neural network

PNN network is a feedforward neural network developed from radial basis function network. Its theoretical basis is Bayesian decision theory, which is suitable for pattern classification [19]. When the value of spread is close to 0, it forms the nearest classifier; when the value of spread is large, it forms the nearest classifier of several training samples [20]. PNN network model is divided into four layers: input layer, mode layer, summation layer and output layer. The structure of neural network is shown in Figure 1.

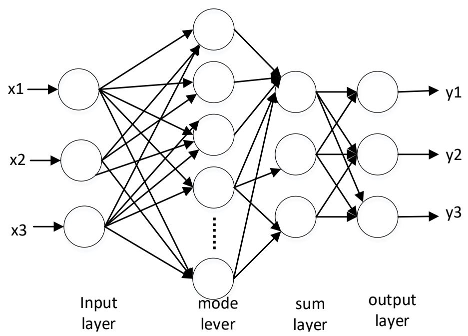

Figure 1. Structure of neural network

3.2 PNN neural network transformer fault diagnosis model based on improved genetic algorithm rough set reduction

The model flow chart is divided into six steps: data information collection, decision table formation, data discretization, attribute reduction by algorithm, final decision table integration, PNN network training and result analysis. The specific flow chart is shown in Figure 2.

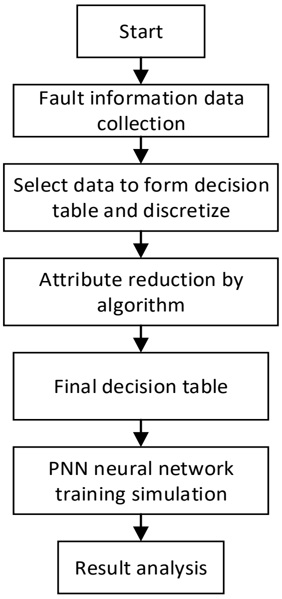

Figure 2. PNN fault diagnosis model based on improved genetic algorithm rough set attribute reduction

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4. Experiment and result analysis

4.1 Construction of decision table

At present, the main method of transformer fault diagnosis is based on the gas content in oil or the ratio of gas content. The collection of samples should be representative, extensive and compact. In this paper, through collecting the historical fault data of multiple transformers, nearly 100 groups of samples are obtained. In this experiment, 29 groups of representative data samples will be selected from the collected sample data, which can be divided into 5 types according to their fault types, as shown in Table 1.

Table 1. Fault type table

number	fault types	fault number
1	Normal	3
2	Low-energy discharge	6
3	High-energy discharge	6
4	Medium and low temperature overheating	6
5	High temperature overheating	8

Each group of data contains 15 gas ratio attribute features. For the convenience of display, the gas attribute features and their corresponding codes in the decision table are shown in Table 2， and TH is the abbreviation of total hydrocarbon.

Table 2. Gas attribute characteristic number table

Gas properties	Coding in decision table
C_2H_2/C_2H_4	a
C_2H_4/C_2H_6	b
C_2H_6/CH_4	c
CH_4/C_2H_4	d
C_2H_2/CH_4	e
C_2H_2/C_2H_6	f
C_2H_2/H_2	g
C_2H_4/H_2	h
C_2H_6/H_2	j
CH_4/H_2	k
CH_4/TH	l
C_2H_4/TH	m
C_2H_6/TH	n
C_2H_2/TH	o
H_2/H_2+TH	p

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The new discretization algorithm[20] combined with natural algorithm and equal frequency discretization method discretizes the above sample data to form the discretized part of the data as shown in Table 3:

Table 3. Decision table of fault information data discretization

attribute / sample	a	b	c	d	e	f	g	h	j	k	l	m	n	o	p	D
1	2	0	2	2	2	2	2	0	2	0	1	0	2	2	1	1
2	1	1	2	2	2	2	2	2	2	2	0	2	1	2	0	1
3	1	0	2	1	1	1	1	0	2	1	0	0	2	1	2	1
4	0	0	2	2	0	0	0	0	0	1	1	0	2	0	2	2
5	0	1	1	2	0	0	0	0	0	1	2	0	2	0	2	2
6	0	0	2	2	0	0	0	0	0	1	1	0	2	0	2	2
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
29	0	2	2	0	1	1	1	2	2	2	1	2	1	1	0	5

4.2 Experiment and result analysis

Firstly, the data in the above decision table is processed by the attribute reduction algorithm based on improved genetic algorithm rough set, and the final decision table is obtained after reduction. Among them, the data in the decision table is reduced from the original 15 attribute features to 6 attributes, namely: C_2H_2 / C_2H_4, CH_4 / C_2H_4, C_2H_4 / H_2, CH_4 / total hydrocarbon, C_2H_4 / total hydrocarbon, H_2 / H_2 + total hydrocarbon; after the algorithm is processed, redundant attributes are removed, the scale of the decision table is reduced, and the speed of subsequent neural network processing is accelerated. After the final decision table is input and trained by PNN neural network, the effect and error diagram after PNN network training and simulation are shown in Figure 3. Then, 11 groups of test samples are sent to PNN for simulation, and the renderings are shown in Figure 4.

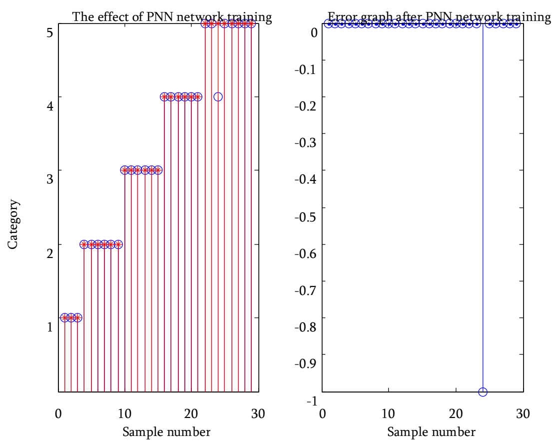

Figure 3. PNN training effect after rough set reduction by improved genetic algorithm

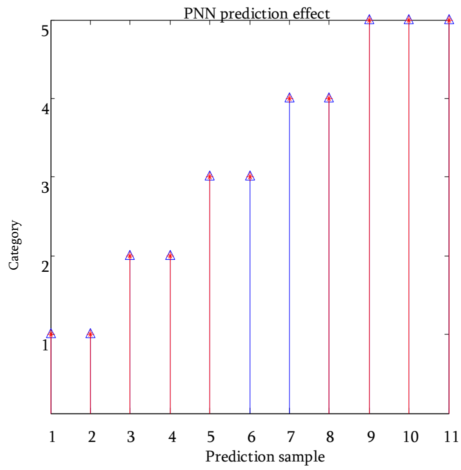

Figure 4. PNN prediction rendering

An error indicates a diagnostic error. As shown in Figure 3, a diagnostic error has occurred. When using the trained network to test samples, it can be seen from Figure 4 that the prediction effect is good. In order to more clearly show the effect of the improved genetic algorithm rough set attribute reduction algorithm proposed in this paper applied to transformer fault diagnosis, this paper uses the diagnosis model of rough set combined with PNN, and the standard genetic algorithm rough set PNN

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fault diagnosis is tested under the same conditions, and the diagnosis effect comparison is shown in Table 4.

Table 4. Transformer fault diagnosis effect under different algorithms

fault diagnostic method	accuracy rate
RS-PNN	72.7%
standard GA-RS-PNN	81.8%
diagnosis model of this paper	90.9%

To sum up, we can see that the improved genetic algorithm rough set attribute reduction algorithm proposed in this paper is more accurate than the final attribute reduction table obtained by the previous algorithm, and has better effect and higher diagnosis rate after PNN neural network training and simulation. It can be seen that the proposed PNN neural network transformer fault diagnosis model based on improved genetic algorithm rough set attribute reduction is more efficient and practical than the previous intelligent algorithm and neural network combined fault diagnosis model.

5. Concluding remarks

There are some problems in transformer fault data, such as uncertainty, redundancy and so on. When the transformer fault method based on intelligent algorithm is applied to transformer fault diagnosis, the reduction algorithm is complex, difficult to realize and difficult to get the optimal reduction. In this paper, based on the previous research, a rough set attribute reduction algorithm based on improved genetic algorithm is proposed, and on this basis, a new attribute reduction algorithm based on improved genetic algorithm is established The neural network model of transformer fault diagnosis based on rough set attribute reduction of genetic algorithm. The test results show that the effect of fault diagnosis of transformer is better, which effectively improves the practicability and accuracy of transformer fault diagnosis.

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