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A NOVEL FAULT DIAGNOSIS METHOD OF CIRCUIT BREAKER BASED ON IMPROVED BAYESIAN ALGORITHM

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ABSTRACT

The subject addressed is the fault diagnosis of the circuit breaker based on the coil current in the operating circuit. The characteristics of the coil current in the operating circuit are analyzed at length by extracting eight features. The discretization of continuous variables based on the matrix decomposition is applied to change the eight continuous features into discrete variables. Followed by that, the Bayesian algorithm is used to achieve the fault diagnosis based on the discrete variables. Finally, the accuracy of the improved algorithm is verified by the simulation results.

Keywords: circuit breaker, fault diagnosis, Bayesian algorithm, discretization

NONMENCLATURE

Abbreviations	
DC	Direct Current

1. INTRODUCTION

The circuit breaker is one of the core components of power system relay protection and control system [1-2]. Improper action of the circuit breaker will damage the normal operation of the power system and even cause a cascading fault. Therefore, the study on fault diagnosis of circuit breakers is of great significance to ensure the safe and stable operation of the power system [3].

The coil current waveform in the operating circuit contains much information about the operating state of the circuit breaker. Considering that the operating circuit is the secondary circuit, it is easy to extract the coil current waveform in the operating circuit. Therefore, by monitoring the coil current in the operating circuit, the state of the circuit breaker can be further determined [4].

Based on the coil current in the operating circuit, the artificial intelligence algorithm is widely used in fault diagnosis of the circuit breaker, among which artificial neural network is common [5]. But the results of neural network training are related to the complement of the training samples and sometimes it doesn't converge.

In this paper, the characteristics of the coil current in the operating circuit are analyzed. Followed by that, the discretization of continuous variables based on the matrix decomposition is introduced to apply the Bayesian algorithm to the fault diagnosis of continuous variables and get better diagnosis results. Finally, the improved Bayesian algorithm model is built in MATLAB, and the accuracy of the algorithm is verified by the data samples extracted from the COMSOL model and actual operation process.

2. PAPER STRUCTURE

2.1 *Analysis on the characteristics of coil current in the operating circuit*

This operating circuit can be equivalent to a circuit composed of a DC power, a resistance and an inductance coil [9], and the equivalent circuit diagram is shown in Fig. 1.

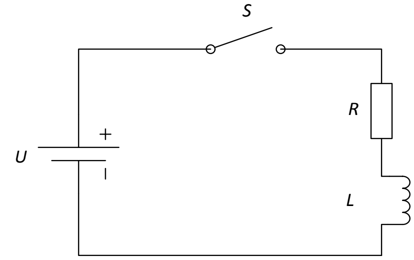

Fig 1 Trip/close coil equivalent circuit diagram

The relation between coil current and voltage can be expressed by equation (1).

$$U = Ri + \frac{d(Li)}{dt} \tag{1}$$

where U is the DC power, R is the equivalent resistance of the coil, L is the equivalent inductance of the coil.

Since the inductance value is related to the air gap of the electromagnet, equation (2) can be further derived from equation (1).

$$U = Ri + L\frac{di}{dt} + i\frac{dL}{d\delta}\cdot v \tag{2}$$

where v is the velocity of the core, δ is the air gap of the electromagnet.

The typical current waveform of the close coil in normal state is shown in Fig. 2 (The current waveform of the trip coil in normal state is similar).

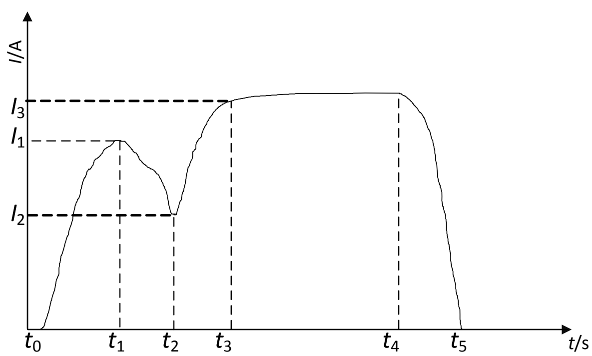

Fig 2 Characteristic waveform diagram of the close coil current

In Fig 2, $t_1 - t_5$ can reflect the movement process of the electromagnet core and the closing process of the contact driven by the operating mechanism. In addition, $I_1 - I_3$ can reflect the power voltage, electromagnet core speed and other information. So $t_1 - t_5$ and $I_1 - I_3$ are features of the current waveform.

The features of the current waveform in the abnormal state are different from that of the normal state. Therefore, different operating states of circuit breaker can be distinguished based on the eight features.

2.2 Principles of Bayesian algorithm

The Bayesian algorithm is a probabilistic method based on statistics [6], which performs well in the fault diagnosis of small-scale data and is often used to deal with discrete multi-classification problems with small sample cases.

The Bayesian algorithm process starts with a set of attribute variables $X = [X_1, X_2, \cdots, X_n]$ and a fault category variable C. $\mathrm{Val}(X_i)$ represents the value range of the attribute variables and Val(C) represents the value range of the fault category variable. Then, $t = [x_1, x_2, \cdots, x_n, c_i]$ represents training samples and $a = [x_1, x_2, \cdots, x_n]$ represents test samples, where $x_i \in \mathrm{Val}(X_i)$, $c_i \in \mathrm{Val}(C)$. At this point, the probability of the classifier c_i given the attribute a can be carried out by equation (3).

$$P(c_i \mid x_1, x_2, \cdots, x_n) = \frac{P(c_i)\cdot\prod_{j=1}^{n} P(x_j \mid c_i)}{P(x_1, x_2, \cdots, x_n)} \tag{3}$$

where $P(x_j \mid c_i)$ is the probability that the attribute x_j will occur with respect to the classifier c_i, $P(c_i)$ is the probability of the learned classifier which was trained before the existence of the attributes, $P(x_1, x_2, \cdots, x_n)$ is the probability of the attributes $x_1, x_2, \cdots, x_n$ based on the classifier.

The conventional Bayesian discretization method is interval discretization. By judging the relationship between a certain data and each threshold value, the data is classified into a certain interval and the data within the same interval are given the same value.

However, for the data far from the threshold value, interval discretization will cause data deviation and reduce the accuracy of fault diagnosis.

Therefore, the discretization of continuous variables based on the matrix decomposition is introduced to improve the conventional Bayesian algorithm.

2.3 Discretization of continuous variables based on the matrix decomposition

First, the discretization of continuous variables based on the matrix decomposition should reasonably select the standard state $e_x = [e_{x1}, e_{x2}, \cdots, e_{xn}]$ to form the discretization result with a high degree of discrimination. Then, according to the selected standard state, the probability decomposition matrix P_x is calculated, where P_x is an $m \times n$ order matrix, $P_x(m,n)$ represents the probability that the attribute value x_j of the mth sample belongs to the nth standard state.

Since each data is only assigned into two adjacent standard states, so P_x can be calculated in equation (4).

$$\begin{cases} \sum P_x(i,:) = 1 \\ P_x(i,k) = 0, k \neq j, k \neq j+1 \\ P_x(i,j)\cdot e_{xj} + P_x(i,j+1)\cdot e_{xj+1} = x_i \end{cases} \tag{4}$$

Through equation (4), each value is decomposed into continuous probability and discrete standard state, which can solve the problem of data deviation in the process of data discretization. In the process of small sample fault diagnosis, this method can effectively improve the accuracy.

Considering the discrete output variable, the output matrix of fault category $p_x(i,j)$ is defined to indicate whether the *i*th sample belongs to the *j*th fault category, where $p_x(i,j)=0$ means it does not belong to and $p_x(i,j)=1$ means it belongs to.

Therefore, the posterior probability can be directly calculated in equation (5) according to the equation (3).

$$P(x=e_{xi}\,|\,y=e_{yj},z=e_{zl},\cdots)=\frac{\sum_{k=1}^{m}p_x(k,i)\cdot P_y(k,j)\cdot P_z(k,l)\cdots}{\sum_{k=1}^{m}P_y(k,j)\cdot P_z(k,l)\cdots} \tag{5}$$

where, p_x is the output matrix of the fault category, P_y and P_z are the probability decomposition matrixes.

According to the equation (5), the posterior probability of the test sample for all fault categories is calculated, and the fault category with the maximum posterior probability is the fault category of the test sample.

2.4 Simulation results

2.4.1 Diagnosis based on COMSOL data

Because the on-line monitoring technology of circuit breaker operating circuit is not yet mature in China, it is difficult to obtain a large number of samples of coil current in the operating circuit, so data samples are extracted from COMSOL model firstly.

The number and fault category of samples are shown in Table 1. The examples of sample data are shown in Table 2.

In order to analyze the fault diagnosis performance under the condition that the number of training samples decreases, the number of training samples respectively takes 15, 18, 21, 24, 27 and 30. Then, 10 sets of data are randomly selected as the test samples from the remaining sets of data. The conventional Bayesian algorithm, the improved Bayesian algorithm and the artificial neural network are applied to fault diagnosis of circuit breaker respectively. The diagnosis process is repeated for 30 times and the average value is taken. The fault diagnosis accuracy is shown in Fig 3.

Table 1 The number and fault category of samples

Circuit breaker status serial number	Number of samples	Fault category of samples
1	10	Normal
2	10	Low operating voltage
3	10	Stuck at the operation of core
4	10	Stuck at the operating mechanism
5	10	Circuit breaker structure aging

Table 2 The examples of sample data

Category	I1/A	I2/A	I3/A	t1/ms	t2/ms	t3/ms	t4/ms	t5/ms
1	3.70	3.37	4.23	5.92	7.22	15.12	58.91	76.43
2	3.34	2.94	3.12	9.33	12.53	15.2	60.12	76.38
3	3.86	3.44	4.21	11.35	20.20	26.61	60.10	75.78
4	3.70	3.38	4.23	5.89	7.28	15.18	62.60	80.30
5	3.58	3.22	3.89	6.40	7.91	15.11	60.00	73.92

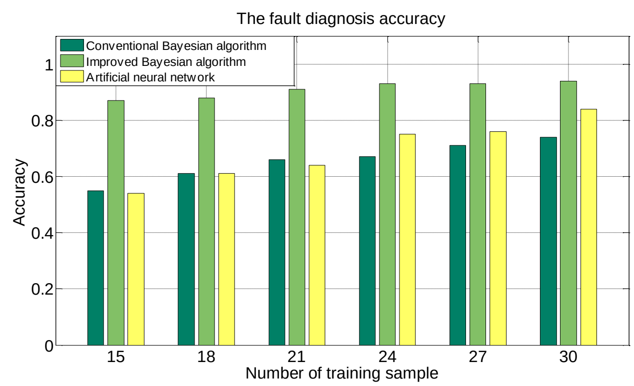

Fig 3 The fault diagnosis accuracy

As is seen in Fig 3, the fault diagnosis accuracy of the method described in this paper is greatly improved. Because the improved Bayesian algorithm introduced in this paper discretizes the continuous data into discrete probability based on the matrix decomposition, which can reduce the data deviation in the discretization process and improve the accuracy of fault diagnosis.

At the same time, it can be seen that the method described in this paper is still effective in the fault diagnosis of small sample data. The accuracy of fault diagnosis will not decrease significantly with the decrease in the number of training samples, reaching 93.6% when the number of training samples is 15 sets.

2.4.2 Diagnosis based on actual operation data

In order to verify the applicability of the method described in this paper for different circuit breakers, ZN42. 27. 5 indoor single-phase high voltage vacuum circuit breaker manufactured by Sichuan high voltage electrical appliances co. LTD provides 30 sets of data.

The number and fault category of samples in Table3. The examples of sample data are shown in Table 4.

Table 3 The number and fault category of samples

Circuit breaker status serial number	Number of samples	Fault category of samples
1	5	Normal
2	5	Low operating voltage
3	5	Stuck at the beginning of closing
4	5	Stuck at the operating mechanism
5	5	Excessive core air travel
6	5	Poor contact of auxiliary switch action

Table 4 The examples of sample data

Category	I1/A	I2/A	I3/A	t1/ms	t2/ms	t3/ms	t4/ms	t5/ms
1	2.21	1.59	1.18	24.37	37.83	43.32	46.54	50.21
2	1.88	1.25	0.94	23.73	36.64	42.24	45.74	50.13
3	2.24	1.52	1.02	30.22	43.43	48.18	52.54	56.25
4	2.24	1.73	1.28	24.24	37.62	43.38	49.87	54.22
5	2.24	1.67	1.18	24.19	39.86	42.66	45.81	49.81
6	2.24	1.63	1.18	23.98	37.64	43.36	48.23	52.17

The number of training samples respectively takes 10, 12,14, 16, 18 and 20. Then, 10 sets of data are randomly selected as the test samples from the remaining sets of data. The conventional Bayesian algorithm, the improved Bayesian algorithm and the artificial neural network are applied for fault diagnosis of circuit breaker respectively, and the diagnosis process is repeated for 30 times and the average value is taken. The fault diagnosis accuracy is shown in Fig 4.

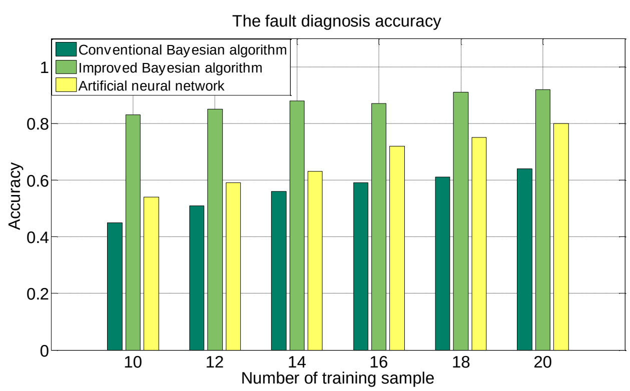

Fig 4 The fault diagnosis accuracy

As is seen in Fig 4, the method described in this paper is suitable for fault diagnosis of different circuit breakers.

2.5 Conclusions

In this paper, the characteristics of the coil current in the operating circuit are analyzed. On this basis, an improved Bayesian algorithm is introduced to finish the fault diagnosis of the circuit breaker, and the following conclusions are drawn:

First, the discretization of continuous variables based on the matrix decomposition is used to change current features into discrete variable, reducing the data deviation in the discretization process and improving the accuracy of fault diagnosis.

Besides, the improved Bayesian algorithm is an algorithm based on the principle of statistics, which avoids the difficulty in convergence caused by insufficient data completeness in the artificial intelligence method that relies on data training for state classification (such as the artificial neural network). As a result, the algorithm still has a high accuracy rate for the fault diagnosis of small sample data.

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