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Mechanical Condition Monitoring of Vacuum Circuit Breakers Using Artificial Neural Network

Yongpeng MENG[†a)], **Shenli JIA**[†], ***and*** **Mingzhe RONG**[†], ***Nonmembers***

SUMMARY Using the Vibration signatures obtained during the operations as the original data, a mechanical condition monitoring method for vacuum circuit breaker is developed in this paper. The method combined the time-frequency analysis and the condition recognition based on artificial neural network. During preprocessing, the vibration signature was decomposed into individual frequency bands using the arithmetic of wavelet packets. The signal energy in the main frequency bands was used to form the condition feature vector, which was input to the artificial neural network for condition recognition. By introducing the parameter of approximation degree, a new recognition arithmetic based on Radial Basis Function was constructed. This approach could not only distinguish these conditions that belong to different known condition modes but also distinguish new condition modes.

key words: *vibration signature, wavelet packets, approximation degree, artificial neural network, vacuum circuit breaker*

1. Introduction

Mechanical malfunctions are well known to be one of the major causes for the failure of most circuit breakers. To reduce the costs of preventive maintenance (PM) and improve the life span of circuit breakers, condition based maintenance (CBM) was proposed in the 1970s and has been greatly developed in the 1990s. Because of the noninvasive feature, vibration method has been widely used in the condition monitoring of circuit breakers [1]–[5]. The vibration during operation is the response of the movement and impact of internal components, and theoretically, any slight change of mechanical condition will affect the vibration spectrum. Therefore, abundant condition information in the time-frequency domain can be obtained from the vibration signatures. In recent years, people have brought an increasing focus on techniques about the condition monitoring of circuit breakers by analyzing their vibration signatures.

Many significant works have been carried out by a research group of State University of New York at Buffalo and Electric Power Research Institute [1]. The developed method aims to create an extensive feature database that combines short-time spectra, short-time energy and automatic timing techniques [2]. A single index, Resolution Ratio (RR), is introduced to assess the mechanical condition of circuit breakers, and a reference-based mechanism is proposed for condition classification [3]. Other signal processing techniques are also used, including discrete energy statistics envelope, short-time power spectrum and chi-square based shape test, and the decision-making is accomplished with a voter program [4]. In the research of another team in Norwegian Electric Power Research Institute, the technique called Dynamic Time Warping is adopted to obtain good estimates of timing variations of faulty vibration signatures for classification [5]. To improve the information capacity of the condition recognition, back-propagation (BP) artificial neural network (ANN) is introduced for mechanical condition monitoring of impulsively loaded equipments, and a very accuracy classification of the conditions is achieved after the application of appropriate preprocessing [6].

Actually, Extraction of the characterizing feature vectors from the vibration signature is the key of condition monitoring. The vibration signature of circuit breakers is non-stationary and has a wide frequency band from zero to several tens kHz [7]. This feature requires the decomposition of signature must be localized in both the time and frequency domain, and has a high time resolution in high frequency part and high frequency resolution in low frequency part. However, these methods mentioned above have limited resolution in the time-frequency domain, making it very difficult to balance between the time resolution and the frequency resolution.

Another disadvantage of these methods is that many samples of the feature vector used to compare with the test signatures should be experimentally given before condition recognition. Moreover, the construction of BP network needs more training samples and longer training time. But in practical application, the operation of circuit breakers is often scarce in their life span and only limited samples could be supplied for condition monitoring, which greatly limit the application of these methods.

In attempt to solve these problems, a new structure of the condition recognition based on an improved radial basis function (RBF) network was introduced, which is shown in Fig. 1. Wavelet packet analysis (WPA) was used to preprocess the vibration signature of a vacuum circuit breaker (VCB) in this paper. The detailed information of WPA was described in our previous research [8]. WPA can supply more subtle analysis for non-stationary signals than traditional methods. RBF neural network was applied to make the condition recognition because of the fast construction. By introducing the parameter of approximation degree, an improved RBF neural network was constructed. The im-

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[†]The authors are with the National Key Laboratory of Electrical Insulation and Power Equipment, Xi'an Jiaotong University, China.
a) E-mail: mengyongpeng@263.net

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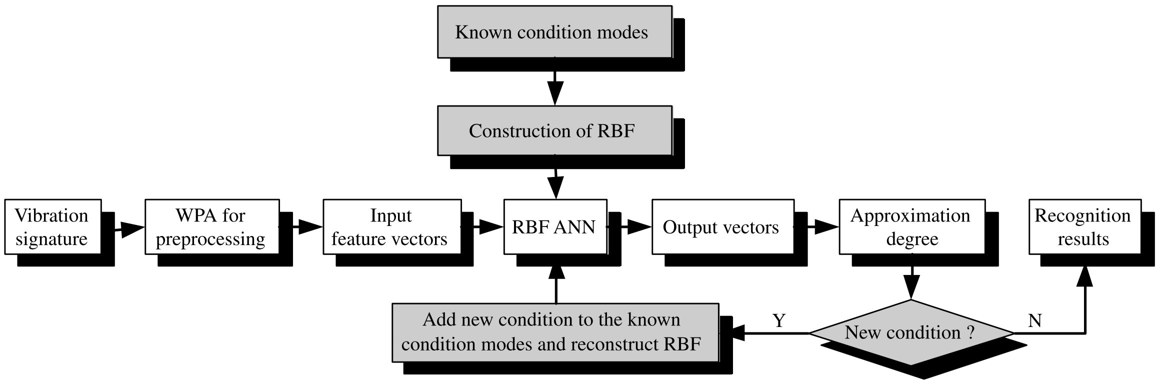


Fig. 1 Structure of the condition recognition based on improved RBF neural network.

proved RBF network has additional feature to recognize a new condition mode that doesn't belong to any of the condition modes used in the construction of ANN.

The purpose of this paper is to determine how well the RBF network can classify certain mechanical condition mode of a VCB using vibration analysis. At present, only conditions with different asynchronous closing time were considered.

2. Preprocessing of the Vibration Signature

WPA algorithm adopts the multi-resolution technique to extract the feature of vibration signatures in the time-frequency domain while retaining the localization properties of wavelet transform. This method further decomposes the high-frequency components that are not dealt with by the dyadic scale wavelet transform. The width of the wavelet packet represents the time resolution and frequency resolution of the decomposition. The desired resolution can be obtained via scaling and shifting the basic wavelet, which effectively improves the time-frequency resolution.

The process of WPA can be expressed as Eq. (1).

$$W_j = \bigoplus_{m=0}^{2^k-1} U_{j-k}^{2^k+m} \quad (j, k, m \in Z) \tag{1}$$

where, U_j^n denotes the orthogonal Hilbert subspace and W_j denotes the wavelet space, variable k equals to $1, 2, \cdots, j$, and m equals to $0, 1, 2, \cdots, 2^k - 1$. The wavelet packet $\{U_n(t)\}$ satisfies the following difference equations Eq. (2) and Eq. (3).

$$u_{2n}(t) = \sqrt{2} \sum_{k \in Z} h(k)\, u_n(2t - k) \tag{2}$$

$$u_{2n+1}(t) = \sqrt{2} \sum_{k \in Z} g(k)\, u_n(2t - k) \tag{3}$$

where, $h(k)$ and $g(k)$ are coefficients of a high-pass filter and a low-pass filter, k denotes a time parameter, j denotes a scale parameter, and n denotes a frequency parameter.

Under the constraint of Eq. (2) and Eq. (3), a discrete signal $x(k)$ can be decomposed into different frequency bands in the time-frequency domain. After the reconstruction of wavelet coefficients, the signal energy in each frequency band can be expressed as Eq. (4).

$$E_n^0 = \sum_{k=1}^{N} \left| x_n^{(j)}(k) \right|^2 \tag{4}$$

where, N is the length of sampling, $x_n^{(j)}(k)$ is the discrete signal under scale parameter of j.

The signal energy in the main frequency bands is extracted to form the condition feature vector. It is used as the input of a RBF neural network for condition recognition.

The advantages of using WPA to the vibration signature are as follows.

1) The wavelet packet method uses two branches of filters to meet the vibration signatures and provides a richer structure than the conventional wavelet transform.

2) Because of orthogonal decomposition, the coefficients of wavelet packets represent the correlation between the wavelet function and a certain segment of the vibration signature.

3) When the structure of the circuit breaker shifts from one condition to another, the signal energy in the decomposed frequency band will be changed greatly. Therefore, abundant condition information in the time-frequency domain can be obtained from the results of WPA. This method is especially suitable for such a system as circuit breaker that has a wide frequency band in the vibration signature [6].

4) Optimized algorithms are supplied in the MATLAB toolbox, allowing WPA to be easily realized.

3. Condition Recognition

RBF neural network was used in the condition recognition. Compared with BP network, it has better features in approach ability and construction speed [9]. Of several RBF neural networks available, general regression neural network (GRNN) was selected to identify the vibration signatures because it is appropriate for function approach and pattern recognition [10]. The typical RBF network is structured with 3 layers, including input layer, hidden layer, and output layer, which are shown in Fig. 2.

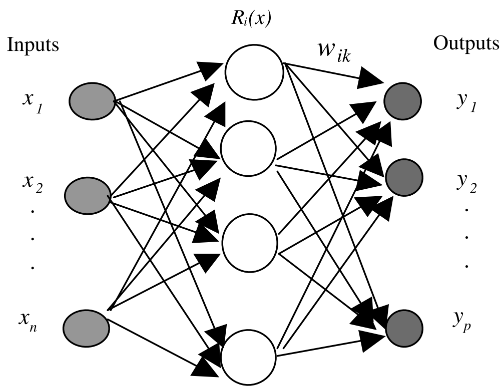


Fig. 2 Three layer structure of RBF neural network.

The input neurons in Fig. 2 transfer the input information, $x_1, x_2, \cdots, x_n$, to the hidden layer. All neurons in the hidden layer are constructed with a basis function, $R_i(x)$, and each output neuron is typically a simple linear function, which is presented with w_{ik}. The basis function has great influence on the local feature of the input information. In the condition recognition, Gauss function was used as the basis function, which can be expressed as Eq. (5).

$$R_i(x) = \exp\left[-\frac{\|x - c_i\|^2}{2\sigma_i^2}\right], \quad i = 1, 2, \cdots, M \tag{5}$$

where, x is the input vector, c_i is the center of the ith basis function and it has the same dimension as x, σ_i is the perception parameter, and M is the number of hidden neurons.

In this paper, the MATLAB function, newgrnn (P, T), was used to construct the RBF neural network. This function creates as many hidden neurons as there are input vectors in P. If there are N input vectors, then there will be N hidden neurons (M=N). Thus, a hidden layer is got, in which each neuron acts as a detector for a different input vector. It is indicated in Fig. 2 that the output layer performs a linear mapping between $R_i(x)$ and y_k, that is expressed as Eq. (6).

$$y_k = \sum_{i=1}^{m} w_{ik} R_i(x), \quad k = 1, 2, \cdots, p \tag{6}$$

where, p is the number of the output vectors.

The integrated process to make condition recognition using an improved RBF neural network can be found in Fig. 3, which are implemented in the MATLAB environment. The input vectors used for constructing the RBF network and the feature vectors used for condition recognition are both obtained from the wavelet packet analysis, as described in the Sect. 2.

To simplify the format of the input vectors, normalization technique is used before the construction of the RBF network. Supposing there are a set of input vectors $\{A_i\}$, $i = 1, 2, \cdots, m$, where m is the number of the vector, and A_i =$\{a_{ij}\}$, $j = 1, 2, \cdots, n$, the normalized input vectors $\{A_i\}$ can be expressed as Eq. (7).

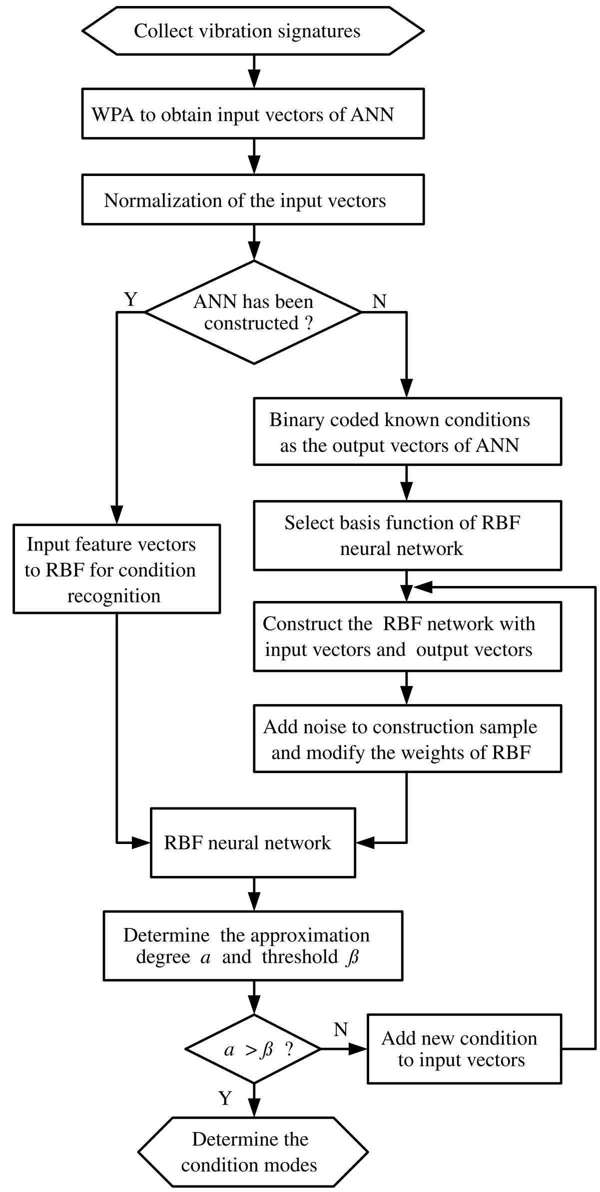


Fig. 3 Flow chart of the condition monitoring that has extended ability to recognize new condition modes.

$$A_i' = \{a_{ij}'\} = \frac{a_{ij}}{\max\limits_{i=1,m}\{a_{ij}\}} \tag{7}$$

The output vectors of the RBF network are optionally defined according to the number of the condition modes. In practical application, they are described with different binary codes. The binary codes have clear meanings with various condition modes and must be convenient for the recognition process. If the number of condition modes is p, each condition can be defined with element 0 or 1 as Eq. (8) and Eq. (9).

$$S_i = \{b_{ij}\}, \quad j = 1, 2, \cdots, p \tag{8}$$

$$b_{ij} = \begin{cases} 0 & j \neq p - i + 1 \\ 1 & j = p - i + 1 \end{cases} \tag{9}$$

where, S_i denotes the ith output vector.

Before the construction of RBF network, it is very difficult to list all condition modes of the circuit breakers, resulting in that the ANN could only recognize the known condition modes. When a new condition mode appears, the correct recognition will not be obtained from the network. To avoid this defect, a parameter called approximation degree, α, is introduced in this paper. This parameter indicates how well the output vector approximates the given condition mode and is described as Eq. (10) and Eq. (11).

$$\alpha = \frac{\max\limits_{j=1,p}\{\left|b'_{ij}\right|\}}{\sum\limits_{j=1,p}\left|b'_{ij}\right|} \tag{10}$$

$$S'_j = \{b'_{ij}\}, \quad j = 1, 2, \cdots, p \tag{11}$$

where, S'_j is the ith output vector of the improved RBF neural network, and p is the number of the output vectors.

By setting a proper threshold for the approximation degree, the ANN can determine whether the output vector belongs to a known condition mode or not. If the approximation degree is lower than the threshold, it is considered as a new condition and is used to construct the RBF network again. By adjusting the weights of the basis function, an improved RBF network is constructed and has additional ability to recognize the new condition. The proper threshold is empirically determined by both considering the error of the recognition algorithm and the dispersion of the construction samples for each condition.

As described in Sect. 2, the construction samples are got experimentally by analyzing the vibration signature of circuit breakers under different conditions. Due to the complexity of working environment, the analyzed input vectors of the ANN are not usually constant but vary in a certain range. Dispersion of the input data can be discovered in repeated tests. If there are enough construction samples, dispersion of the input data can be naturally taken into account in the construction process. In lack of samples, a contaminating technique should be used to increase the construction samples, which adds random noise with different level of amplitudes to the input vectors. The amplitude of random noise is selected from 5 percentage to 10 percentage peak value of the input vectors. This process is very useful for enhancing the adaptability of condition recognition and makes the RBF neural network more suitable for the real situation.

4. Experimental Setup

A 35 kV vacuum circuit breaker has been used as the model circuit breaker. Vibration during closing operation was taken as the original data. Vacuum circuit breaker is often used in the situation of frequent operation. Compared with other types of circuit breakers, it has a special contact structure with a plane impact surface and shorter travel distance, which makes the collision between two contacts in closing operation much stronger than that in opening operation, and abundant condition information are contained in

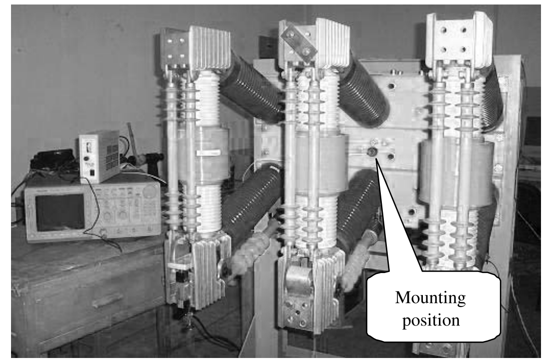


Fig. 4 Mounting position of the acceleration sensor.

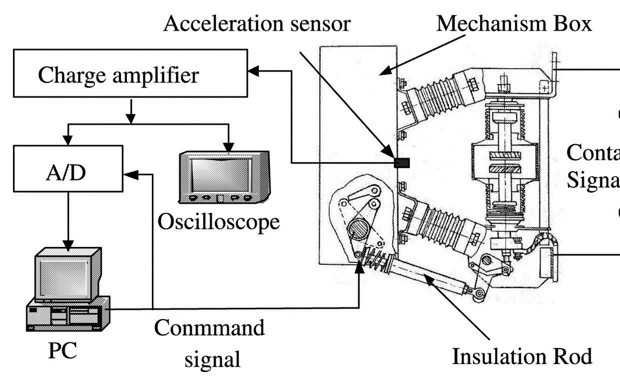


Fig. 5 Diagram of the experimental setup.

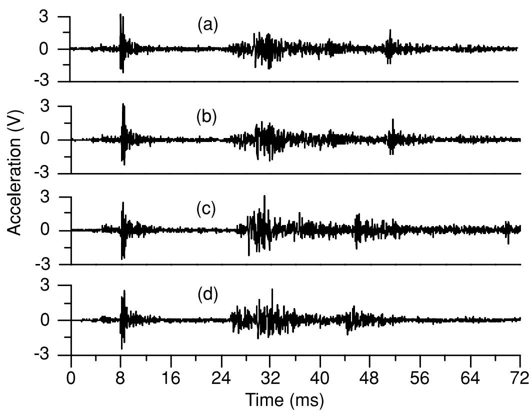
the vibration signature. Asynchronous closing time is an important parameter of vacuum circuit breakers. The asynchronous closing time is often changed much during the service, which indicates the shift of the mechanical condition. In this paper, conditions with different asynchronous closing time were considered in the experiments. The acceleration sensor was mounted at a fixed point almost in the middle of the whole framework, as shown in Fig. 4. This location was optimized in order to obtain the maximum amplitude of the vibration signature. Fourier spectrum indicates that the frequency components of the vibration signature for this type VCB are concentrated within 10 kHz. According to the Shannon's theorems, the sampling frequency was set as 25 kHz in data acquisition.

The diagram of the experimental setup is shown in Fig. 5. Four kinds of asynchronous conditions during closing operation were simulated. The simulation was accomplished by extending the insulation rod of one pole (A, B or C) to different length while the other two insulation rods were kept in the original length (390 mm). The simulated conditions are shown in Table 1, which were presented with N, A, B, and C respectively.

For the 35 kV vacuum circuit breaker investigated, the asynchronous closing time in normal condition is less than 3 ms. Hence, condition mode N represents a normal case. It is clear that mode A, B and C are all under abnormal conditions with excess asynchronous closing time. The typical vibration signatures of each condition are respectively

Table 1 Different conditions for experiment.

Condition mode	Length of insulation rod /mm	Asynchronous closing time /ms
N	390 (all 3 poles)	2.5 (Normal)
A	390+5 (pole A)	4.0 (Abnormal)
B	390+10 (pole B)	5.0 (Abnormal)
C	390+10 (pole C)	4.5 (Abnormal)



(a)–Condition mode N (b)–Condition mode A
(c)–Condition mode B (d)–Condition mode C

Fig. 6 Vibration signatures under different conditions.

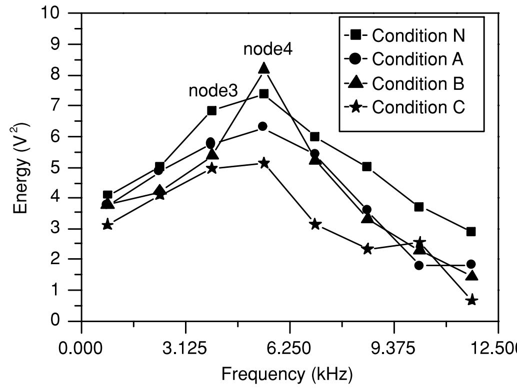


Fig. 7 Frequency band energy under different conditions.

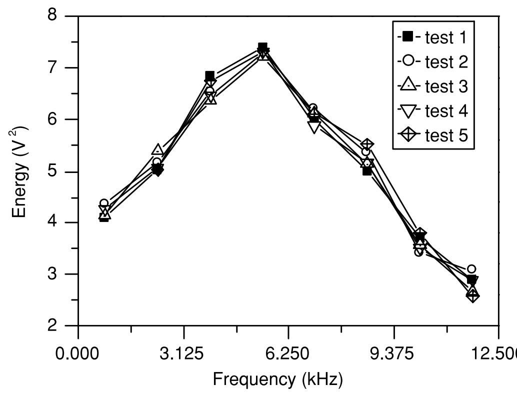


Fig. 8 Frequency band energy under conditions N.

Table 2 Binary codes of different conditions.

Condition mode	Output vector			
N	0	0	0	1
A	0	0	1	0
B	0	1	0	0
C	1	0	0	0

shown in Fig. 6. Obviously, it is hard to distinguish different conditions only from the original vibration signatures. The vertical axis in Fig. 6 represents the amplitude of vibration signature, which is directly expressed with the output voltage of the charge amplifier.

Five closing operations under each asynchronous condition were conducted. Total of twenty vibration signatures were got. WPA method was used to process all signatures. Daubechies 10 wavelet was selected because it is sufficiently smooth and regular to provide high decay rate for decomposition [11]. Shannon entropy was used to get the optimum hierarchical tree. When the original sampling rate is 25 kHz, decomposition in 3 level subspaces is appropriate and 8 independent nodes are obtained under this condition. The frequency step between two adjacent decomposition nodes is 1.5625 kHz. Each node denotes an independent frequency band. The signal energy in the frequency band is calculated according to Eq. (4) and arranged in the frequency sequence, as shown in Fig. 7.

It is shown in Fig. 7 that node3 and node4 denote the main frequency bands presented with N_3 and N_4 respectively, in which most of the signal energy is distributed. Moreover, the energy distributions under different conditions are not the same. We process all signatures in this manner. The results show that under each condition, the band energy distribution has definite repeatability within a certain range of dispersion, which ensures the feasibility of using the vibration method. Figure 8 shows the repeatability of test under condition N. On base of that, energy in N_3 and N_4 are extracted to form the condition feature vector.

All feature vectors are normalized with Eq. (7) and used as the input feature vectors for constructing the RBF neural network. According to these feature vectors and Eq. (8) and Eq. (9), the binary codes of each condition are obtained and used as the output vectors of the construction process. The corresponding output vectors are shown in Table 2. Each output vector denotes a known condition mode, which is N, A, B, and C respectively.

All input vectors of the RBF network generated from STE analysis are listed in Table 3. Vectors 1 to 12 are used as the samples to construct the RBF network. Vectors 13 to 16 are results of the 4th test under conditions N, A, B, and C, respectively, and vectors 17 to 20 are results of the 5th test. However, Vector 21 is got under a new condition that the insulation rod of pole A is extended by 10 mm, the corresponding asynchronous closing time of which is 4.5 ms. After the RBF network was constructed, all vectors including 1 to 12 are input to test the validity of the network. The threshold of the approximation degree, β, is set as 0.7. The recognition results of the RBF network are shown in Table 4. The output value approximately equals to 0 if it is less than 0.5 and 1 if it is great than 0.95, which is listed in the followed parentheses. The maximum value of each output vector is outstanding with boldface. In this manner, the network output is used to compare with the binary codes of known condition modes (Table 2) and finally determine which condition it really belongs to.

It is showed in Table 4 that for the known condition modes, i.e., N, A, B and C, the network has a correct recognition. It is also indicated a high level of approximation degrees (α >0.95). However, the output of vector 21 doesn't belong to any of the known condition modes because the approximation degree is 0.523 and less than the given threshold (β=0.7). It is determined by the RBF network as a new condition and described with mode D. Because the condition D is not included in the known condition modes, the RBF network itself could not determine which physical condition the circuit breaker is really in. It should be discovered by skilled personals in later maintenance process and added to the information database of known condition modes. The new condition, D, is then used together with N, A, B and C to reconstruct the RBF network. The output vectors are also recoded, which are shown in Table 5. After reconstruction, the RBF network has extended ability to recognize the new condition D well.

Additional three operations have been carried out under the new condition D. After preprocessing of WPA, the feature vectors were input to the improved RBF neural network. Correct recognition results and high approximation degree were also obtained, which are 0.987, 0.989 and 0.989, respectively. The results indicate the validity of the improved RBF neural network.

Table 3 Input vectors for RBF neural network.

Condition mode		Number	Input vector	
			N_3/V^2	N_4/V^2
Input vectors for RBF construction (known condition modes)	N	1	6.8344	7.3739
		2	6.5331	7.2203
		3	6.3504	7.2091
	A	4	5.7764	6.2906
		5	5.7458	6.5998
		6	5.6636	6.2614
	B	7	5.3865	8.1861
		8	5.4261	8.2496
		9	5.6005	7.9210
	C	10	4.9734	5.1319
		11	5.1470	5.4542
		12	4.8589	5.3063
Input vectors for recognition		13	6.4603	7.2982
		14	5.7035	6.3871
		15	5.5309	8.0152
		16	5.0278	5.2194
		17	6.7335	7.3168
		18	5.5432	6.3086
		19	5.2703	8.2250
		20	4.9068	5.3726
New condition		21	5.5335	5.0218

Table 5 New binary codes for the RBF network.

Condition mode	Output vector				
D	0	0	0	0	1
N	0	0	0	1	0
A	0	0	1	0	0
B	0	1	0	0	0
C	1	0	0	0	0

Table 4 Recognition results of RBF neural network.

Number	Network output								Condition mode	α
1	3.5e-003	(0)	7.5e-130	(0)	3.3e-025	(0)	**0.99654**	(1)	N	0.996
2	2.9e-003	(0)	5.7e-136	(0)	5.7e-021	(0)	**0.99703**	(1)	N	0.997
3	2.0e-002	(0)	3.3e-128	(0)	6.3e-017	(0)	**0.98015**	(1)	N	0.980
4	3.2e-035	(0)	1.7e-080	(0)	**0.99711**	(1)	2.9e-003	(0)	A	0.997
5	3.8e-033	(0)	5.7e-089	(0)	**0.99942**	(1)	4.3e-004	(0)	A	0.999
6	9.2e-028	(0)	2.4e-086	(0)	**0.99937**	(1)	5.2e-004	(0)	A	0.999
7	5.5e-135	(0)	**0.99867**	(1)	1.4e-003	(0)	1.3e-105	(0)	B	0.998
8	4.1e-133	(0)	**0.99853**	(1)	1.5e-003	(0)	3.9e-102	(0)	B	0.998
9	2.7e-130	(0)	**0.99921**	(1)	1.0e-003	(0)	8.2e-107	(0)	B	0.999
10	**0.99511**	(1)	3.4e-130	(0)	5.3e-028	(0)	4.8e-003	(0)	C	0.995
11	**0.99637**	(1)	2.5e-133	(0)	2.7e-030	(0)	3.7e-003	(0)	C	0.996
12	**0.99831**	(1)	1.6e-130	(0)	8.5e-029	(0)	1.7e-003	(0)	C	0.998
13	2.1e-002	(0)	5.5e-130	(0)	2.2e-020	(0)	**0.97835**	(1)	N	0.978
14	1.5e-030	(0)	5.2e-090	(0)	**0.98477**	(1)	1.5e-002	(0)	A	0.985
15	3.0e-132	(0)	**0.99733**	(1)	2.7e-003	(0)	1.8e-102	(0)	B	0.997
16	**0.97483**	(1)	2.2e-130	(0)	1.6e-028	(0)	2.5e-002	(0)	C	0.975
17	1.8e-002	(0)	7.2e-128	(0)	3.1e-022	(0)	**0.98223**	(1)	N	0.982
18	6.6e-031	(0)	2.3e-088	(0)	**0.99545**	(1)	4.5e-003	(0)	A	0.995
19	5.2e-130	(0)	**0.98911**	(1)	1.1e-002	(0)	7.3e-105	(0)	B	0.989
20	**0.98843**	(1)	8.2e-128	(0)	2.3e-027	(0)	1.2e-002	(0)	C	0.988
21	0.26122	(0)	0.20685	(0)	7.0e-003	(0)	**0.52263**	(0)	D(new)	0.523

5. Conclusions

1. As an effective tool for time-frequency decomposition, Wavelet packet analysis is well used in preprocessing of the vibration signatures because of its high resolution in the time-frequency domain.
2. RBF neural network was used for condition recognition because of its simple structure and rapid construction. By introducing the parameter of approximation degree, a modified algorithm is proposed to construct an improved RBF network. The improved RBF network could not only recognize the known condition modes but also new conditions modes.
3. A good condition recognition result was obtained from the experiments on a 35 kV vacuum circuit breaker. This may also be a useful method for the condition monitoring of other kind of circuit breaker.

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Yongpeng Meng received the B.S. and M.SC. degrees from the Department of Electrical Engineering, Xi’an Jiaotong University, Xi’an China in 1998 and 2001, respectively. His research fields of interest included the design of intelligent apparatus and electronic circuits, high power test technology, and on-line condition monitoring for power equipments. He has been working for his Ph.D. degree in Department of Electrical Engineering, Xi’an Jiaotong University since 2001. His Ph.D. work is mainly concerned with on-line condition monitoring and fault identification of high-voltage circuit breakers.

Shenli Jia received the B.S., M.SC., and Ph.D. degrees in the Dept. of Electrical Engineering from Xi’an Jiaotong University, Xi’an, China, in 1989, 1993, and 1997, respectively. From July 1989 to September 1990, he worked in the High Power Laboratory at Xi’an High Voltage Apparatus Research Institute, the certification test laboratory in China, as testing engineer. Dr. Jia is currently a professor at Xi’an Jiaotong University, a member of Chinese Society for High Power Test Technology and Director of High Power Laboratory of Xi’an Jiaotong University. His special fields of interest included vacuum arc and vacuum switches, high power test technology, and on-line condition monitoring for power equipment.

Mingzhe Rong received the B.SC. and Ph.D. degrees from Department of Electrical Engineering of Xi’an Jiaotong University in 1984 and 1990, respectively. He is currently a professor with the same university. His research interests include arc physics and electrical contact theory. Since 1984 he has published over 50 papers. He is a member of IEEE and that of China Electrotechnology Society (CES).