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THE FAULT DIAGNOSIS SYSTEM DESIGN OF TRAIN AUXILIARY INVERTER BASED ON LMD AND RBFNN

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Abstract. *Focusing on the non-stationary characteristic of the fault signal of train auxiliary inverter, this paper designs a new system of fault diagnosis which combines local mean decomposition (LMD) with radial basis function neural network (RBFNN). Firstly, the new fault diagnosis system decomposes the non-stationary original signal into several product function (PF) components by LMD. Then the feature vectors of these components are extracted. In this way, the detection and classification of the fault signal in train auxiliary inverter can be realized. According to the analysis results of fault signal of train auxiliary inverter in simulation experiment, it has proved that the system based on LMD and RBFNN can identify these faults accurately and efficiently.*
Keywords: Train auxiliary inverter, LMD, RBFNN, Fault diagnosis

1. **Introduction.** Train auxiliary inverter has always been the core of the power supply system in train [1]. Meanwhile, the fault rate of auxiliary inverter is much higher than other electrical equipment, such as air conditioning; if the fault gets serious, it may affect the normal operation of train [2]. Therefore, it is of great significance to design a fault diagnosis system of auxiliary inverter that can be widely applied and identify fault quickly.

With the development of signal processing technology, how to extract and analyze the valuable information from a large number of irregular complex signals is always the hot topic of modern research. However, the traditional methods are not suitable for dealing with non-stationary and non-linear cases [3], such as Fourier transform and the Wavelet transform. To solve this, Huang et al. provided the empirical mode decomposition (EMD) method in 1998, which is the core of the Hilbert-Huang transform analysis technique [4]. EMD method is quite superior for screening, but there are still some problems, such as envelope, and mode mix. After that, Smith put forward local mean decomposition (LMD) which is a new adaptive time-frequency approach; LMD not only restrains the shortcomings like envelope, but also avoids the situation of negative frequency [5]. Nowadays, LMD is a kind of inevitable trends and has been widely applied in many fields like mechanic fault diagnosis [6,7]. Therefore, on the basis of the seniors' research, we take advantage of LMD and combine it with diagnosis model RBFNN for train auxiliary inverter, which not only overcomes the disadvantages of EMD and the local optimum problem which is common in normal fault diagnosis mode [8], but also obtains the optimal structure and high precision of fault diagnosis.

Focusing on the non-stationary and non-linear characteristics of the fault signal [9], this paper mainly consists of four parts, and the first part introduces the overall design of fault diagnosis system. Then it describes briefly the EMD and details the signal processing with LMD in the second part. The third part presents the feature extracting and fault diagnosis with RBFNN. The last part shows that new fault diagnosis system based on LMD and RBFNN achieves optimal results in simulation experiment.

2. **Overall Design of Fault Diagnosis System for Train Auxiliary Inverter.** The overall design of fault diagnosis system for train auxiliary inverter is shown in Figure 1.

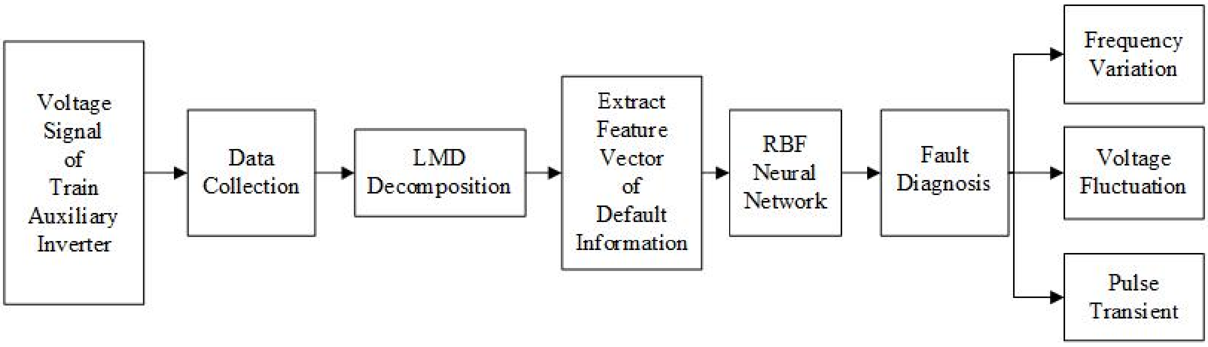


FIGURE 1. The overall design of fault diagnosis system

The collected non-stationary voltage signals of train auxiliary inverter with three different default states (frequency variation, pulse transient and voltage fluctuation) are sampled for many times with a certain frequency. Then the different PF components are represented by decomposing original signal with LMD. To analyze these components better, the fault feature vectors are extracted by using energy moment feature vector method. Finally, when the normalized feature vectors of PF components are used as the input of RBF neural network, the categories of faults can be classified with RBF neural network.

3. **Decomposition of Signal with LMD.**

3.1. **The theory of EMD and LMD.** EMD method of Huang can decompose the wave and trend of signals step by step and produce series of data sequences with different scales which are called intrinsic mode function components (IMF) [10]. So within the time range of function, the number of local extreme value point and zero point are equal, and the average value of upper and lower envelope is null. On the basis of EMD algorithm, LMD method has been successfully proposed to optimize the processing of non-stationary and non-linear signals, when the EMD determines the IMF components by using cubic spline interpolation, and LMD provides the product function (PF) in moving average way [11].

3.2. **LMD decomposition of system.** Many sets of non-stationary voltage signals are decomposed adaptively into the sum of several PF components by LMD and each PF component can keep a good amplitude and frequency transformation.

The decomposition process of inverter signal by LMD is as follows [12].

1) Find all local extremums of auxiliary inverter signal $X(t)$.

2) Compute the average value m_i and envelope estimate value a_i of two adjacent extreme value n_i and n_{i+1}.

$$m_i = \frac{n_i + n_{i+1}}{2} \tag{1}$$

$$a_i = \frac{|n_i - n_{i+1}|}{2} \tag{2}$$

$i = 1, 2, \ldots, n$; on the one hand, connect all the average value m_i of two adjacent extreme values with straight line, and then find the local mean value function $m_{11}(t)$ after smoothing in moving average method. On the other hand, connect the adjacent envelope estimate value a_i with straight line in the same way to get envelope estimate function

$a_{11}(t)$, but moving average span of moving average method is an odd number and is 1/3 of local average.

3) According to local average $m_{11}(t)$ and envelope estimate value $a_{11}(t)$ that are computed from local extreme value points, Formula (3) shows that $m_{11}(t)$ is separate from voltage signal $X(t)$, so:

$$h_{11}(t) = x(t) - m_{11}(t) \tag{3}$$

4) Divide $h_{11}(t)$ by envelope estimate function to get the demodulated signal.

$$s_{11}(t) = h_{11}(t) / a_{11}(t) \tag{4}$$

where $s_{11}(t)$ ideally is a pure frequency-modulated signal while the envelope estimate function $a_{12}(t)$ of $s_{11}(t)$ satisfies condition $a_{12}(t) = 1$. However, if not, system will let $s_{11}(t)$ be as original data and repeat the above iterative process until that system gets a pure frequency-modulated signal $s_{1n}(t)$, $-1 \le s_{1n}(t) \le 1$, and its envelope estimate function $a_{1(n+1)}(t)$ satisfies the requirement $a_{1(n+1)}(t) = 1$.

$$\begin{cases} h_{11}(t) = x(t) - m_{11}(t) \\ h_{12}(t) = s_{11}(t) - m_{12}(t) \\ \vdots \\ h_{1n}(t) = s_{1(n-1)}(t) - m_{1n}(t) \end{cases} \tag{5}$$

In the formula

$$\begin{cases} s_{11}(t) = h_{11}(t)/a_{11}(t) \\ s_{12}(t) = h_{12}(t)/a_{12}(t) \\ \vdots \\ s_{1n}(t) = h_{1n}(t)/a_{1n}(t) \end{cases} \tag{6}$$

The terminal condition of iteration is $1-\Delta \le a_{1n}(t) \le 1+\Delta$. In this paper, in order that PF components can keep a good amplitude and frequency transformation, set $\Delta = 10^{-4}$.

5) Envelope signal, also called instant amplitude function is generated from multiplying all of envelope estimate function in the process of iteration.

$$a_1(t) = a_{11}(t)a_{12}(t)\cdots a_{1n}(t) = \prod_{q=1}^{n} a_{1q}(t) \tag{7}$$

6) Then multiply envelope signal with frequency-modulated signal to obtain the first PF component of the original auxiliary inverter signal.

$$PF_1(t) = a_1(t)s_{1n}(t) \tag{8}$$

It is the single amplitude and frequency-modulated signal which contain the highest frequency component in original signal of train auxiliary inverter.

7) Repeat the above steps K times while PF_1 is as original data until the last separated component is a monotonic function. Now the original auxiliary inverter signal is segregated into the sum of K numbers of PF components and a monotonic function.

$$x(t) = \sum_{p=1}^{k} PF_1(t) + u_k(t) \tag{9}$$

4. **Fault Diagnosis of System.**

4.1. Extracting fault feature by energy moment normalization. After processing the fault signals with the above LMD method, the fault feature vector from PF components of each set of original data will be extracted by energy moment normalization [13].

$$E_i = \int_{-\infty}^{+\infty} |PF_i(t)|^2 dt \tag{10}$$

E_i is the energy of the i-th PF component, so the total energy of signal E is the sum of energy from m components. Therefore, the feature vector T from normalization of energy is wanted.

$$E = \sum_{i=0}^{m} E_i \tag{11}$$

$$T = (E_1/E, E_2/E, \ldots, E_m/E) \tag{12}$$

4.2. Fault diagnosis with the model of RBF. The new fault diagnosis system selects the radial basis function neural network (RBFNN) to optimize the results, which is a three-layer feed-forward network with single hidden layer [14]. The structure of the model is shown in Figure 2. Divide many sets of auxiliary inverter signals with different fault states into two groups which include training sample T_1 and test sample T_2, and the fault diagnosis process of system by RBFNN is as follows [15].

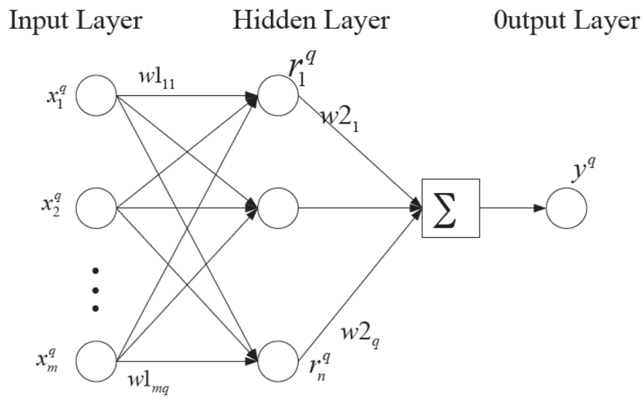


Figure 2. The structure of RBFNN

1) Initiate the parameters of model, such as diagnosis error e, and the number of hidden neuron R.

2) Start to train the model of RBFNN. Let extracted feature vectors of training sample T_1 be as the input X^q of the RBFNN and the fault state Y of T_1 be as the output of RBFNN.

3) Compute the input value of neuron i in hidden layer in Formula (13), and the distance between the weight vector $W1_i$ and input layer X^q is multiplied with threshold value $b1_i$.

$$k_i^q = \sqrt{\sum_{j=1}^{m} \left(w1_{ji} - x_j^q\right)^2} \times b1_i \tag{13}$$

4) Find the corresponding output expression of hidden layer. Hidden layer adopts radial basis function as excitation function. In this paper, hidden layer adopts Gaussian basis function as radial basis function [16]. So:

$$r_i^q = \exp\left(-(k_i^q)^2\right) = \exp\left(-\left(\| w1_i - X^q \| \times b1_i\right)^2\right) \tag{14}$$

Because threshold value $b1$ is capable of adjusting the sensitivity of function, it is always replaced by a spread constant C:

$$g_i^q = \exp\left(-0.8326^2 \times \left(\frac{\|w1_i - X^q\|}{C_i} \times b1_i\right)^2\right) \tag{15}$$

It is easier to see that the choice for C output has effect on the corresponding range of input, that is to say, the bigger C value is, the lager range of response hidden layer has to input vector, and the better the smoothness among neurons is [17].

5) According to that exciting function of output is a pure linear function, so the output of train sample y^q satisfies Formula (16).

$$y^q = \sum_{i=1}^{n} r_i^q \times w2_i \tag{16}$$

6) If the training error satisfies: $|y^q - Y| \geq e$, the model will adjust the values of C and the neurons' number R in hidden layer, and then it turns to step (3); else stop the training and turn to step (7).

7) Put the data of test sample T_1 into the input of well-trained model of RBFNN, and then the diagnosis output of signal can be achieved.

5. **Result of Experiments.** Apply this system to fault diagnosis of train auxiliary inverter. The simulation process with tool MATLAB7.0 is presented as follows. Firstly, sample the original signal of auxiliary inverter which has 380V/220V voltage and frequency is 50Hz, and sample point is 4096. There are 20 groups sample data of three fault states. While 15 sets of data are as training sample for RBF neural network, there remains 5 sets as test sample. To classify the categories better, three fault states have been coded respectively according to fault reason in (1 0 0), (0 1 0), (0 0 1), which stands for frequency variation, pulse transient and voltage fluctuation. The LMD decomposition situation of voltage fluctuation as an example is shown in Figure 3. It is easy to see that the original signal is decomposed into 5 PF components and 1 remnant.

Among these 5 decomposed PF components, PF1 and PF2 have higher frequency, so this paper selects the first 5 PF components which contain obvious fault signal to extract feature vectors and let these vectors be as the input of RBF network. The identified result

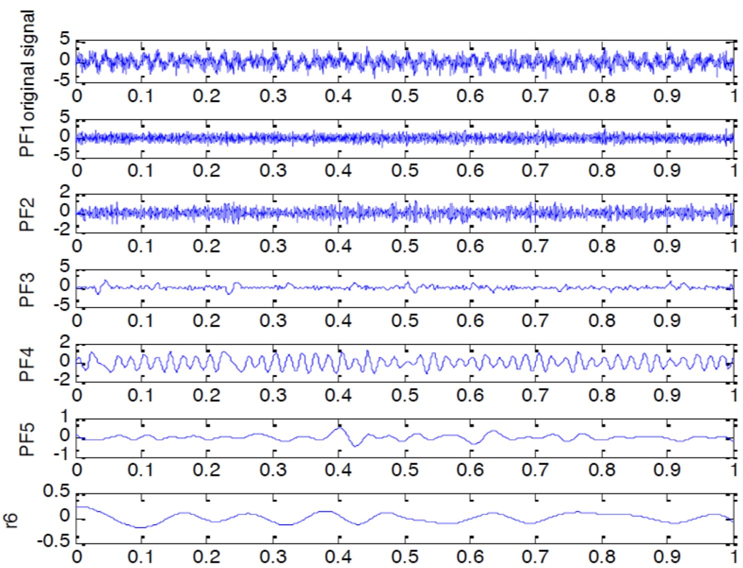
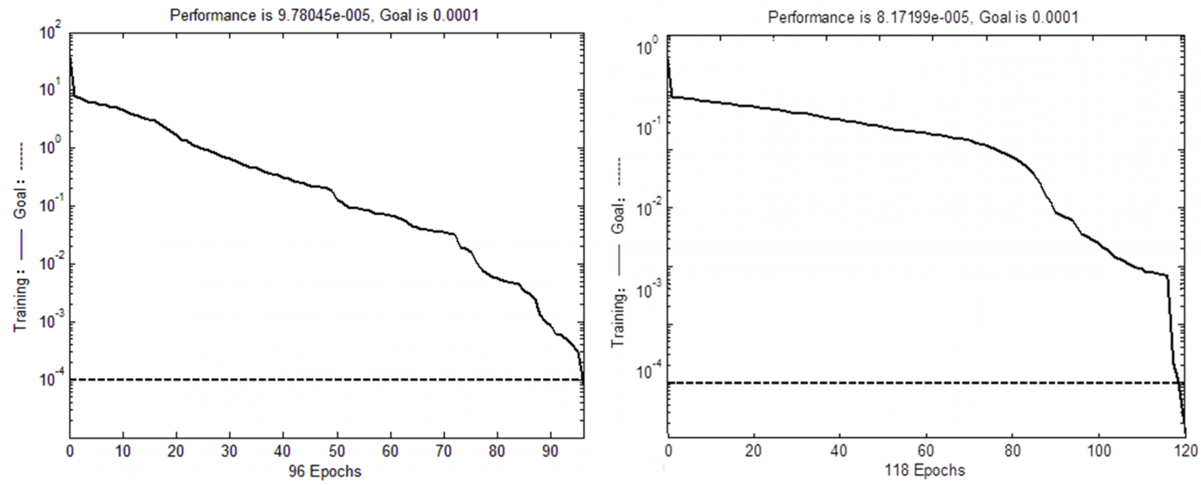


Figure 3. LMD decomposition situation of voltage fluctuation

Table 1. Feature vector and diagnosis result of system

Fault	Nr.	PF1	PF2	PF3	PF4	PF5	Code	Output of network
Frequency variation	1	0.4462	0.1208	0.1881	0.2330	0.0118	(1 0 0)	(0.942 0.054 0.004)
	2	0.4220	0.1112	0.2413	0.2108	0.0148	(1 0 0)	(0.924 0.036 0.039)
	3	0.4415	0.1136	0.1661	0.2461	0.0327	(1 0 0)	(0.981 0.010 0.009)
Voltage fluctuation	1	0.3210	0.0817	0.3950	0.1822	0.0201	(0 1 0)	(0.595 0.572 −0.092)
	2	0.3279	0.0872	0.3912	0.1657	0.0280	(0 1 0)	(−0.050 1.142 −0.092)
	3	0.3115	0.0884	0.3563	0.2156	0.0281	(0 1 0)	(0.020 0.965 −0.014)
Pulse transient	1	0.3867	0.1004	0.0478	0.3853	0.0668	(0 0 1)	(−0.327 0.087 1.239)
	2	0.3975	0.1036	0.0437	0.3303	0.1149	(0 0 1)	(−0.047 −0.085 1.24)
	3	0.4009	0.1014	0.0491	0.3393	0.0854	(0 0 1)	(0.086 −0.046 0.960)



(a) Fault diagnosis of LMD-RBFNN (b) Fault diagnosis of EMD-RBFNN

Figure 4. The simulating result of fault diagnosis system

Table 2. Diagnosis results of LMD-RBFNN and EMD-RBFNN

Type	Frequency variation	Impulsive transient	Voltage fluctuation	Diagnosis accuracy
LMD-RBF	15/15	13/15	14/15	93.33%(42/45)
EMD-RBF	12/15	13/15	13/15	84.44%(38/45)

of diagnosis system is shown in Table 1. We take fault feature vectors and diagnosis results of 6 groups as an example.

This paper chooses 15 groups of feature vectors for each three fault states to train the network and another 5 groups remained as test data. Set the target error is null and distribution spread of radial basis function is 1.5, while the system satisfies the smoothness for fitting curve. As a result, the simulation error of train sample in network is 0.0188 while the neurons in hidden layer increase with display interval 5 from 0 to 30. After proceeding fault diagnosis with the rest of test data, the error of network output is reduced to 0.000081. At last, the system is able to identify the categories of 42 groups fault signal in 45 groups accurately, and a high accuracy rate is up to 93.3%. The simulating result is shown in Figure 4(a).

In this paper, we compare the diagnosis result of the new system with EMD-RBFNN. As is seen in Table 2 and Figure 4, the diagnosis accuracy of EMD-RBFNN is 84.44%, while LMD-RBFNN is 93.3%. At the same time, the convergence speed of this new system is faster. What is more, the system of LMD-RBFNN overcomes the problems of envelope and mode mix. So the fault diagnosis system of LMD-RBFNN is feasible and effective for train auxiliary inverter.

6. **Conclusions.** A new fault diagnosis system based on LMD and RBFNN for train auxiliary inverter is introduced here. The collected non-stationary signal is decomposed into several PF components by LMD and then is as input data of RBF neural network. The LMD method overcomes modal aliasing problem in EMD and improves the accuracy of extracting feature vector. Furthermore, local optimal problem that is common in normal faults diagnosis is solved because of the local approximation advantage in RBFNN. The simulation experiment results reveal the inner intrinsic information clearly, with high precision and good performance, and it lays the foundation of practice application of fault diagnosis in train auxiliary inverter.

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