

Fault Diagnosis of Auxiliary Inverter Based on GA Neural Network

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Abstract

In this article, an efficient method is proposed to diagnose urban rail vehicle auxiliary inverter faults based on wavelet packet neural network and genetic algorithm. Firstly, the original signals are decomposed into different frequency subbands by wavelet packet. Secondly, the wavelet packet energy eigenvector is constructed. Finally, those wavelet packet energy eigenvectors are taken as fault samples to train neural network. In order to improve the function approximation accuracy and general capability of the neural network system, an efficient genetic algorithm approach is used to adjust the parameters of translation and weights functions. The experiment shows that the GA-ANN model gives superior result than BP neural network. This approach can be used as a useful tool for the auxiliary inverter fault diagnosis.

Keywords: rail vehicle auxiliary inverter, wavelet packet, neural network, genetic algorithm, fault diagnosis

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1. Introduction

Auxiliary inverters are widely used in urban rail vehicle applications. The quality and reliability of the vehicle auxiliary inverter directly affects the running safety and passenger's comfort. It is estimated that many faults in urban railway are due to failures of auxiliary inverters. Therefore, the condition monitoring and fault diagnosis of the auxiliary inverters are extremely important for the safety and reliability of the urban rail vehicle.

Many methods have been proposed for diagnosis of inverters, such as FFT, STFT and BP, etc. However, as Lee et al. [1] pointed out, many of the above techniques are often unreliable and have other limitations. FFT method is widely used in the spectrum analysis of envelope signals [2]; however, it could only give the global energy-frequency distributions and fail to reflect the details of a signal. STFT is widely used in power quality analysis [3], which has a better frequency resolution, but has very limited analysis of transient signals. BP neural network has superior learning and noise suppression abilities and does not require process knowledge [4]. However, it is prone to getting into local optimum and convergence is slow [5]. To overcome these drawbacks, this study attempts to combine GA (genetic algorithm), avoiding local minima and achieving global convergence quickly and correctly by searching in several regions simultaneously.

The paper hereafter is organized as follows. First, in Section 2, we introduce the wavelet packet transform and the wavelet packet energy vector algorithm. Section 3 defines the BP neural network and GA-ANN model. In Section 4, Experiment results are provided to demonstrate the effectiveness and potential of the proposed hybrid algorithm for faults diagnosis of urban rail vehicle auxiliary inverter compared with BP neural network using the same observed data. Finally, the conclusions are drawn in Section 5.

2. Wavelet Packet Analysis and Wavelet Packet Energy Vector Algorithm

2.1. Wavelet Packet Transform

If $\psi(t) \in L^2(R)$ and its Fourier transform, $\hat{\psi}(f)$, satisfy the admissibility condition [6]

$$C_\psi = \int_{-\infty}^{\infty} \frac{|\hat{\psi}(f)|^2}{|f|} < \infty \quad (1)$$

A wavelet $\psi(t)$ is a function of zero average

$$\int_{-\infty}^{\infty} \psi(t) dt = 0 \quad (2)$$

$\psi(t)$ is a wavelet function and $L^2(\mathbb{R})$ is the space of square integrable complex functions. The corresponding family of wavelets consists of a series of son wavelets, which are generated by dilation and translation from the mother wavelet $\psi(t)$, is shown as follows:

$$\psi_{a,b} = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) \quad a, b \in \mathbb{R}, a \neq 0 \quad (3)$$

where a and b are the dilation and translation parameters, respectively. The continuous wavelet transform is then defined as follows [7]:

$$CWT(x(t); a, b) = \int x(t) \psi_{a,b}^*(t) dt \quad (4)$$

where "*" denotes the complex conjugation, When $a = 2^j$, $b = k2^j$, $j, k \in \mathbb{Z}(2)$ can be written as:

$$\psi_{j,k} = 2^{-j/2} \psi(2^{-j}t - k) \quad (5)$$

Wavelet packet, which is extension from wavelet theory, has several particular advantages in comparison with scalar wavelet on image fusion. Wavelet transform only decomposes low frequency band of the source images, so it omits some useful details of the images, but the wavelet packet transform decomposes every frequency band of the source images, either to low frequency or to high frequency. Obviously, this detailed decomposition provides possibility to utilize much more flexible fusion rules to acquire fused results with better quality. It can preserve more details of the source images.

Wavelet packet decomposition is based on wavelet transform and decomposes a signal with the same widths in all frequency bands [8]. Orthogonal wavelet packet is defined as [9]:

$$\begin{cases} u_{2n}(t) = 2^{1/2} \sum_{k \in \mathbb{Z}} h_k u_n(2t - k) \\ u_{2n+1}(t) = 2^{1/2} \sum_{k \in \mathbb{Z}} g_k u_n(2t - k) \end{cases} \quad (6)$$

The main difference between wavelet transform (WT) and wavelet packet transform (WPT) is that WPT splits not only approximations but also details. The top level of the WPT is the time representation of the signal, whereas, the bottom level has better frequency resolution. Thus, with the use of WPT, a better frequency resolution can be obtained for the decomposed signal. In addition, the use of WPT extracts much more features about the signal. As shown in Figure 1, it is the diagram of wavelet packet decomposition.

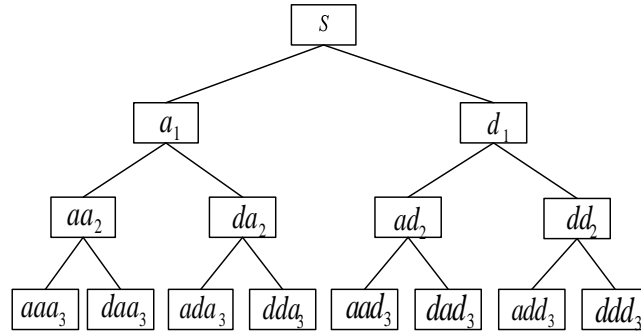


Figure 1. Signal diagram of wavelet packet decomposition

2.2. Wavelet Packet Energy Vector Algorithm

(1) The wavelet packet is adopted to decompose the signal of urban rail vehicle auxiliary inverter. In Figure 1, S represents original signal, a_1 represents the 1st low frequency coefficient X_{10} , which decomposed by wavelet packet, d_1 represents the 1st low frequency coefficient X_{11} , others is so on.

(2) We construct the wavelet packet Coefficient, then take the signal characteristics of each band. S_{30} represents the reconstructed signal of X_{30} , S_{31} represents the reconstructed signal of X_{31} , so the original signal S can be expressed:

$$S = S_{30} + S_{31} + \dots + S_{37} \tag{7}$$

(3) The total energy of each band

$$E_{3j} = \int |S_{3j}(t)|^2 dt = \sum_1^n |x_{jk}|^2 \tag{8}$$

Where, $x_{jk} (j = 0,1,K,7; k = 1,2K, n)$ represents Amplitude of the reconstructed signal.

(4) The wavelet packet energy eigenvector
The definition of all the energy of signal:

$$E = \sum_{j=0}^7 E_{3j} \tag{9}$$

A band of relative wavelet packet energy:

$$p_{3j} = \frac{E_{3j}}{E} \tag{10}$$

The definition of relative wavelet packet energy feature vector [10]:

$$K_i = (p_{30}, p_{31}, \dots, p_{37}) \tag{11}$$

3. The BP Neural Network and GA-ANN Model

3.1. BP Neural Network Model

The structure of the BPNN is shown as Figure 2, the node represents the neuron and the network consists of input layer nodes, hidden layer nodes and output layer nodes. The hidden layer can be single layer and also can be multilayer (The hidden layer in Figure 2 is single layer). Different layer nodes connect through arrows with weight. The essential idea is the learning process includes two sub-processes: forward propagating and backward propagating [11]. The forward propagating can be described as: the input signal spread from the input layer through hidden layer and then to the output layer, if the expected output is obtained, the learning algorithm is over, else turn to backward propagating. The backward propagating can be described as: calculating the error along the forward passage, and adjusting the weight and threshold between each layer nodes according to gradient descent method to reduce the error [12].

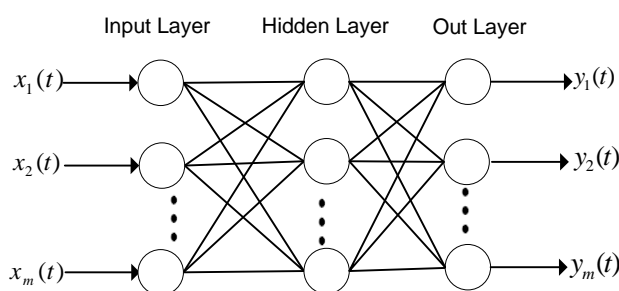


Figure 2. BP neural network model

3.2. GA-ANN Model

The artificial neural network learning process consists of two stages: firstly employing GA to search for optimal or approximate optimal connection weights and thresholds for the network, then using the BP learning rule and training algorithm to adjust the final weights. The combination of GA and ANN process is shown in Figure 3. At first, the initial population is done; then the fitness of each chromosome in the population is calculated. If it meets the termination criterion, the ANN weights and thresholds are outputted, if not, selection, crossover and mutation are implemented. In this way, the ANN weights and thresholds are initialized as chromosome of best fitness population member. This procedure is completed by applying a BP algorithm on the GA established initial connection weights and thresholds [13].

The optimized process includes initialization of population, determination of fitness function, selection, crossover and mutation operations, and initialization of BP neural network.

(1) Initialization of population.

Set the population scale and generate initial population including individuals with the number N . Set the range of data, select linear interpolation function [14] to generate real vectors as the individuals of GA. Each individual adopts real code and becomes a real string, which consists of the connection weight between input layer and hidden layer, threshold of hidden layer, connection weight between hidden layer and output layer, and threshold of output layer. When the BP neural network is established, the structure, weight and threshold will be ascertained according to each individual.

(2) Determination of fitness function

Fitness function is a good standard which will effectively evaluate the adaptability to environment of individuals in population.

The initial weight and threshold of BP neural network are assigned on the basis of individual. The network obtains forecasting output by training sample, calculates the training error between forecasting output and desired output, and adopts the sum of square training error as the fitness.

(3) Selection

The paper uses roulette wheel selection [15] to determine the probability by which the individual will be selected. The roulette wheel selection is a kind of selecting strategy for individual based on the fitness proportion. The formula of selection probability is show as follows:

$$P_i = f_i / \sum_{i=1}^N f_i, \quad i=1,2,\dots,N \quad (12)$$

Where N is the population scale, f_i is the reciprocal of individual fitness.

(4) Crossover and Mutation

To generate new population, GA takes the operations of crossover and mutation to deal with current population. As a consequence, probabilities of crossover and mutation are two important parameters which will have a great effect on the performance and property of convergence of GA. Different from traditional algorithm, this paper proposes the adaptive genetic algorithm [16], in which probabilities of crossover and mutation can change adaptively according to individual fitness. The adaptive change will maintain the diversity of population, improve the capability of global search and avoid individual being earlier mature.

$$P_c = \begin{cases} P_{c1} - \frac{(P_{c1} - P_{c2})(f' - f_{avg})}{f_{max} - f_{avg}}, & f' \geq f_{avg} \\ P_{c1} & f' < f_{avg} \end{cases} \quad (13)$$

$$P_m = \begin{cases} P_{m1} - \frac{(P_{m1} - P_{m2})(f - f_{avg})}{f_{max} - f_{avg}}, & f \geq f_{avg} \\ P_{m1} & f < f_{avg} \end{cases} \quad (14)$$

Where P_c is the crossover probability, P_m is the mutation probability, f_{max} is the maximum fitness of population, f_{avg} is the average fitness, f' is the larger fitness of two individuals in crossover, f is the fitness of individual in mutation. Based on repeated experiments and former experience, the paper chooses $P_{c1}=0.9$, $P_{c2}=0.7$, $P_{m1}=0.1$, $P_{m2}=0.002$.

(5) Initialization of BP neural network

After obtaining the optimal individual, decompose the individual into initial connection weight and threshold of BP neural network and train the new network to get desired forecasting output of time series.

4. Experiment and Analysis

4.1. The Process of Wavelet Packet

Three-layer wavelet packet is used as a feature extractor which gives distinguishable characteristic features about the signals. After wavelet packet decomposition, the wavelet packet energy eigenvector is constructed. The method is validated on two datasets, the parts of training data is listed in Table 1. The testing data is listed in Table 2.

Figure 4 (a)—Figure 6 (a) are the time domain of the signal, Figure 4 (b)—Figure 6(b) are the reconstructed waveform signal using db1.

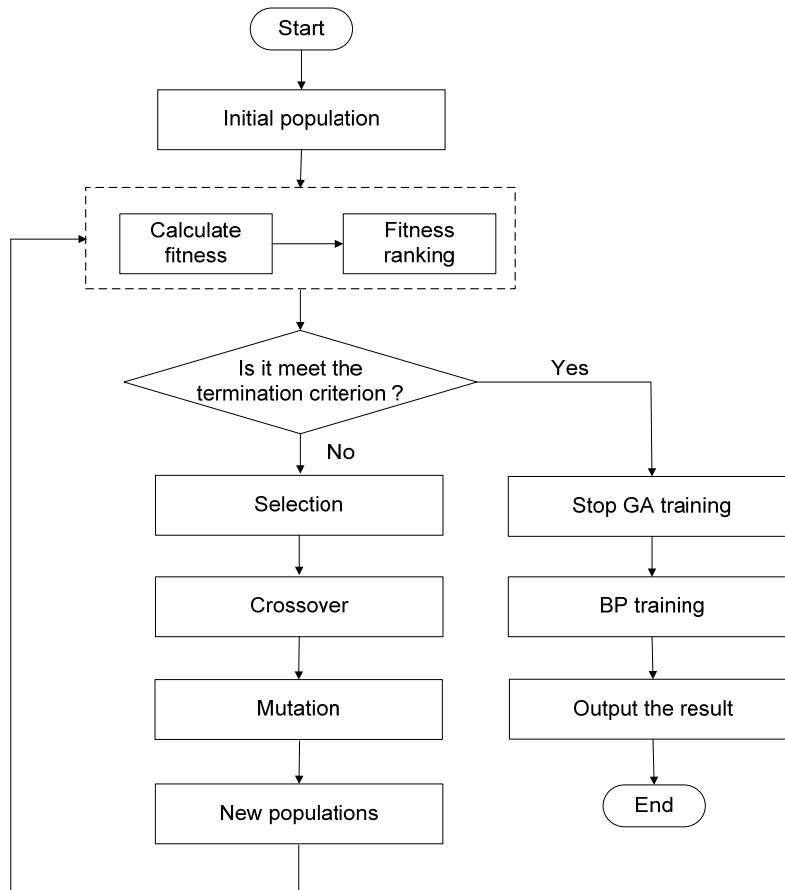


Figure 3. Framework of training neural network using GA–BP algorithm.

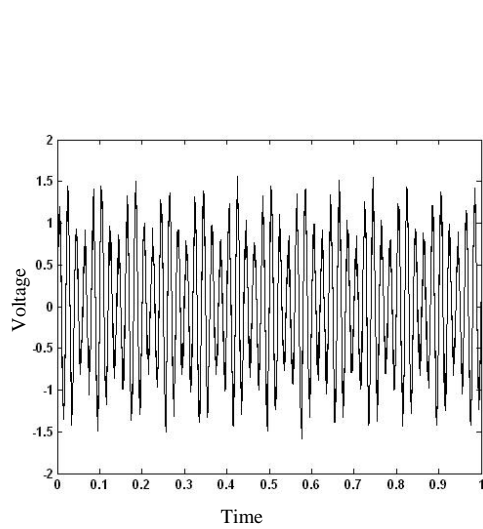


Figure 4(a). The time domain of voltage fluctuation signal

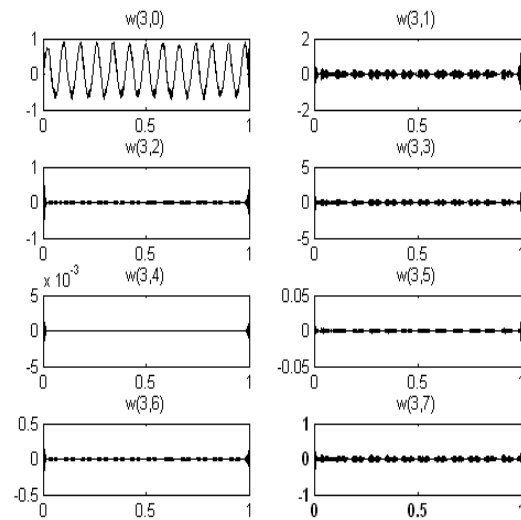


Figure 4(b). The reconstructed waveform of voltage fluctuation signal

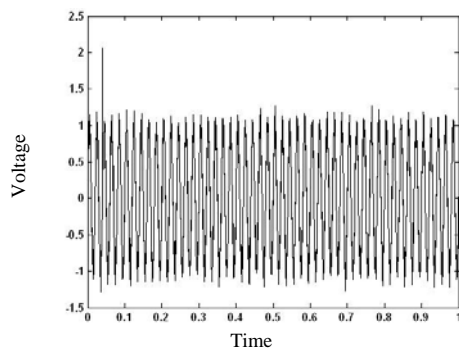


Figure 5(a). The time domain of impulsive transient signal

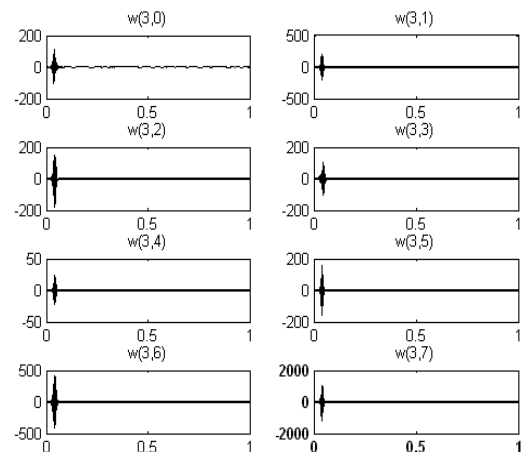


Figure 5(b). The reconstructed waveform of impulsive transient signal

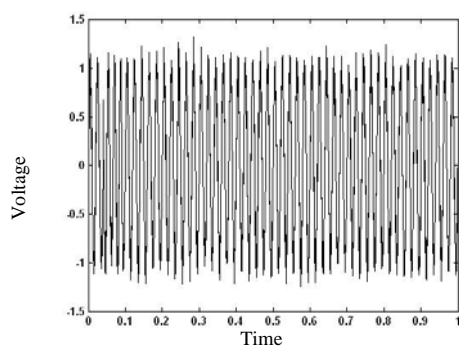


Figure 6(a). The time domain of Frequency variation signal

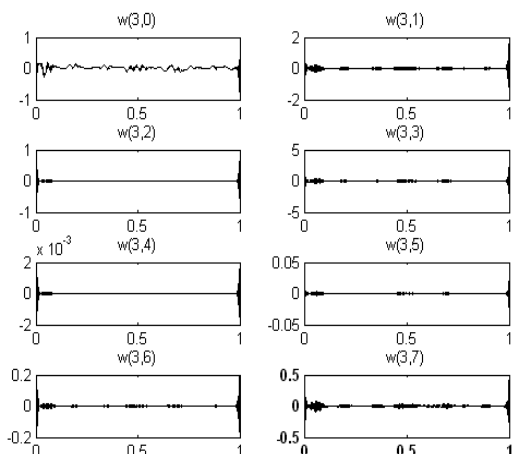


Figure 6(b). The reconstructed waveform of Frequency variation signal

4.2. The Process of Neural Network

(1) Getting the bearing sample data in order to training the network

The samples are divided into two groups: the training group and the testing group. The training group is used to train the BP neural network and GA-ANN. After trained the network, the testing group is used to examine the trained BP neural network and GA-ANN.

(2) Constructing BP neural network and GA-ANN using MATLAB

The BP neural network and GA-ANN architecture used for fault diagnosis consists of 8 inputs corresponding to the 8 different ranges of the frequency spectrum of a fault signal, 3 outputs corresponding to 3 respective signals, such as voltage fluctuation signal, impulsive transient signal and Frequency variation signal. The features obtained by wavelet packet energy vector algorithm are used as the inputs of BP neural network and GA-ANN.

(3) Testing network

After trained the network, the testing group is used to examine the trained BP neural network and GA-ANN. The test results of BP neural network are shown in Table 3 and GA-ANN are shown in Table 4.

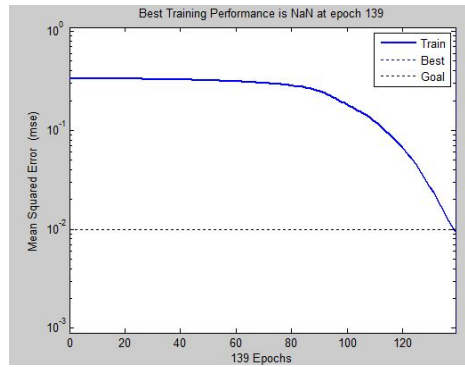


Figure 7. Training curves with ANN

Table 1. Sample data of urban rail vehicle auxiliary inverter operation

Number	Training sample								Fault status	Fault vector
1	0.9389	0.0174	0.0032	0.0384	0.0000	0.0000	0.0003	0.0018	voltage fluctuation	(1 0 0)
2	0.9348	0.0208	0.0031	0.0393	0.0000	0.0000	0.0003	0.0017	voltage fluctuation	(1 0 0)
3	0.8521	0.0395	0.0082	0.0946	0.0000	0.0000	0.0009	0.0047	voltage fluctuation	(1 0 0)
4	0.0063	0.0222	0.0209	0.0056	0.0004	0.0102	0.1262	0.8083	impulsive transient	(0 1 0)
5	0.0042	0.0643	0.0156	0.0677	0.0003	0.0083	0.1084	0.7312	impulsive transient	(0 1 0)
6	0.0027	0.0405	0.0153	0.0594	0.0001	0.0036	0.1806	0.6978	impulsive transient	(0 1 0)
7	0.1426	0.2836	0.0373	0.5116	0.0000	0.0000	0.0035	0.0214	Frequency variation	(0 0 1)
8	0.1939	0.2454	0.0351	0.4991	0.0000	0.0000	0.0036	0.0229	Frequency variation	(0 0 1)
9	0.2071	0.2216	0.0320	0.5111	0.0000	0.0000	0.0033	0.0249	Frequency variation	(0 0 1)

Table 2. Testing data

Number	Training sample								Fault status
1	0.7897	0.0579	0.0075	0.1367	0.0000	0.0000	0.0010	0.0072	voltage fluctuation
2	0.0031	0.0523	0.0351	0.2366	0.0000	0.0031	0.1323	0.5375	impulsive transient
3	0.3552	0.1641	0.0111	0.4450	0.0000	0.0000	0.0015	0.0231	Frequency variation

Table 3. Testing results of BP neural network

Fault status	Fault vector	Actual outputs			Testing results
voltage fluctuation	(1 0 0)	(0.9213	0.0179	0.0659)	voltage fluctuation
impulsive transient	(0 1 0)	(0.0301	0.8912	0.0358)	impulsive transient
Frequency variation	(0 0 1)	(0.0287	0.0231	0.8565)	Frequency variation

Table 4. Testing results of GA-ANN

Fault status	Fault vector	Actual outputs			Testing results
voltage fluctuation	(1 0 0)	(0.9838	0.0156	0.0130)	voltage fluctuation
impulsive transient	(0 1 0)	(0.0212	0.9520	0.0264)	impulsive transient
Frequency variation	(0 0 1)	(0.0265	0.0198	0.9582)	Frequency variation

By contrasted the outputs of the examination sample with the ideal outputs of the examination sample, the outputs of BP, genetic algorithm neural network are all closed to the corresponding ideal outputs of the examination sample, the outputs of genetic algorithm neural network are better than BP.

5. Conclusion

This paper presents evolving neural network using genetic algorithm for faults diagnosis of urban rail vehicle auxiliary inverter. Experimental investigations are carried out to evaluate the proposed system in urban rail vehicle auxiliary inverter fault diagnosis. The results show that

this method can extract the feature and classify the different faults of auxiliary inverter. The proposed technique gives an effective and attractive approach for the multi-concurrent fault diagnosis of the urban rail vehicle auxiliary inverter.

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