Research on Feature Extraction and Recognition of Inverter Fault Data Based on Neural Networks

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Abstract. This article proposes a fault detection method for cascaded inverters that combines digital signal processing technology and neural networks. This method determines the location and type of faults by detecting and analyzing the output voltage of the inverter. Fast Fourier transform (FFT) is used to analyze the frequency spectrum of output voltage signal to extract fault characteristics. By simplifying input data through Principal Component Analysis (PCA), the structure of neural networks can be improved. The feature recognition technology of inverter fault data based on neural networks can timely and effectively improve training speed and generalization accuracy.

Keywords: Neural network · Inverter failure · Data feature recognition

1 Introduction

High power cascaded multi-level converters without power frequency transformers belong to complex power electronic systems [1]. High reliability and ease of maintenance are the key factors for the practical application of such a complex power electronic system in industry. One of the effective methods to improve system reliability is to use fault-tolerant technology and redundancy technology [2]. However, the core of such technology is the timely and accurate detection of faults, Timely and accurate detection and diagnosis of faults [3].

2 Inverter Output Voltage Waveform and Fault Status

The above method is explained in detail through an example of an open circuit fault in a three-phase cascaded five level inverter modulated by the POD (Phase Opposition Disposition) strategy [4]. Figure 1(a) shows the structural diagram of an asynchronous motor system powered by a three-phase cascaded inverter, and Fig. 1(b) shows the schematic diagram of each phase of the three-phase cascaded inverter. Figure 2 shows the carrier wave, modulation wave, and corresponding output voltage waveform of the inverter using POD modulation [5].

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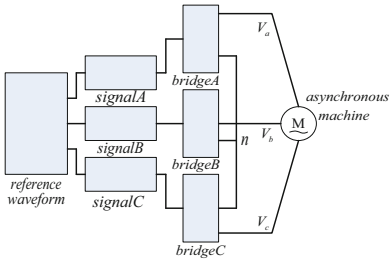
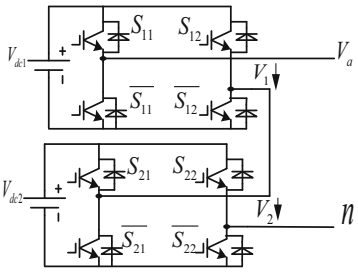


(a) Block diagram of induction motor drive system with inverter



(b) A phase schematic of inverter

Fig. 1. Induction motor system drive by five levels three phases cascaded H bridge inverter

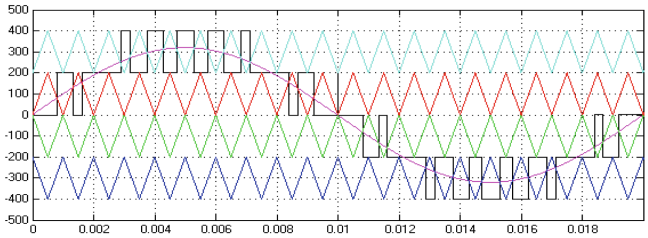


Fig. 2. The distribution of carrier wave and modulation wave and its output voltage when M = 0.8

Due to the three-phase symmetry of the inverter, the following analysis will take phase A as an example. To accurately diagnose faults, it is necessary to study the output characteristics of inverters under different faults. When any switch tube of the actual higher-level connected inverter malfunctions, it will affect the output voltage of the inverter. Figure 3 and Fig. 4 respectively show the corresponding output voltage waveforms for different switch tube open circuit and short circuit faults in phase A H Bridge1 [6].

By analyzing the output voltage in Fig. 3 and Fig. 4, it can be seen from the time domain that different fault states correspond to different output voltage waveforms.

3 FFT Analysis of 3 Fault Voltage Waveforms

In order to enable computers to accurately identify fault states by outputting voltage waveforms, this paper studies the application of artificial neural networks to analyze, classify, and distinguish fault waveforms. In the training of neural networks, it is necessary to provide characteristic training data [7, 8]. However, the output voltages in Fig. 3 and Fig. 4 are not suitable as training data directly, as there is a high similarity between the output voltage data and the feature is not obvious [9]. Therefore, this paper first carried out Fourier analysis on the output voltage, as shown in Fig. 5 and Fig. 6, and extracted the spectrum amplitude representing the first 30 harmonic components of the fault waveform as the training data of the neural network.

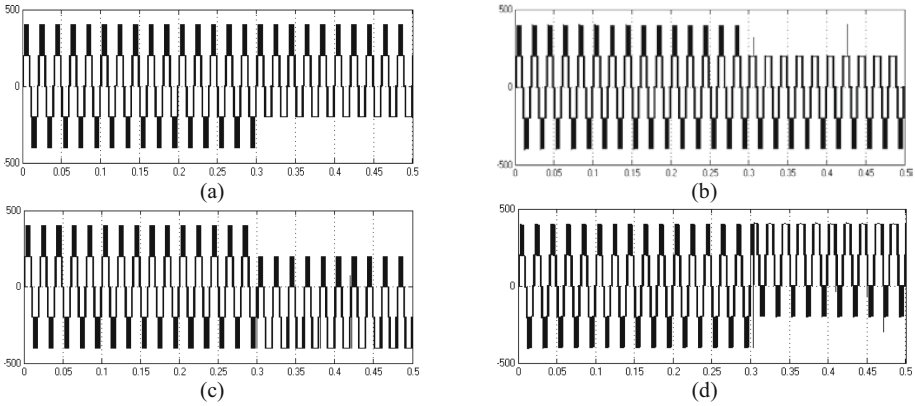


Fig. 3. Output voltage of different switching off circuits in A phase H Bridge1 (a) S_{12} S_{11} (b) $\overline{S_{11}}$ (c) (d) $\overline{S_{12}}$

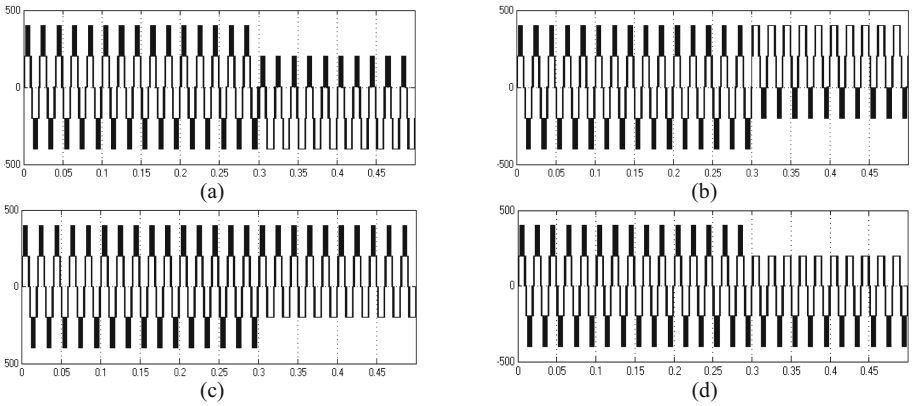


Fig. 4. Output voltage of short circuit with different switching tubes in A phase H Bridge1 (a) S_{11} (b) S_{12} (c) $\overline{S_{11}}$ (d) $\overline{S_{12}}$

4 Fault State Recognition Based on Feedforward Artificial Neural Network

In order to achieve fault diagnosis of cascaded inverters by applying the spectra shown in Fig. 5 and Fig. 6, this paper constructs a BP feedforward artificial neural network as shown in Fig. 7, which includes a hidden layer, 30 input nodes corresponding to the harmonic order, and an output node. The Activation function used by the neural network is sigmod function [9, 10]: tansig is used for the hidden layer, and log sig is used for the output layer. The output of the neural network is 0 or 1. The proposed fault diagnosis system is shown in Fig. 8, which consists of five neural networks with the same structure. The output of the system is a 5-bit binary code, which corresponds to different faults [5, 7].

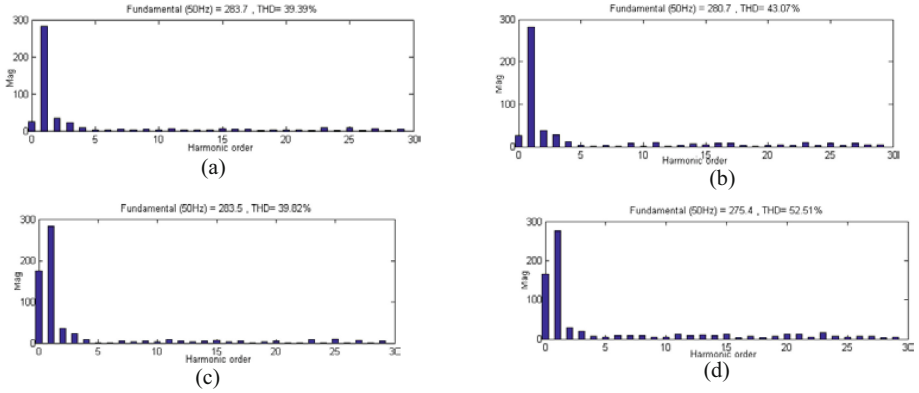


Fig. 5. The FFT of the output voltage signal under single circuit disconnection (a) S_{11} (b) S_{12} (c) $\overline{S_{11}}$ (d) $\overline{S_{12}}$

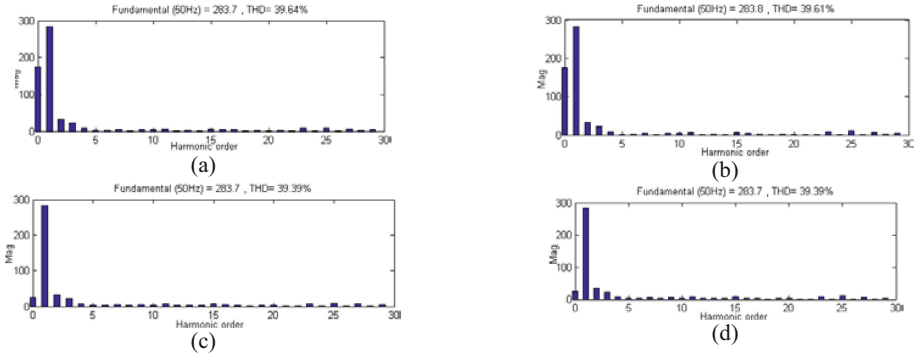


Fig. 6. The FFT of the output voltage signal under the condition of single tube short circuit (a) S_{11} (b) S_{12} (c) $\overline{S_{11}}$ (d) $\overline{S_{12}}$

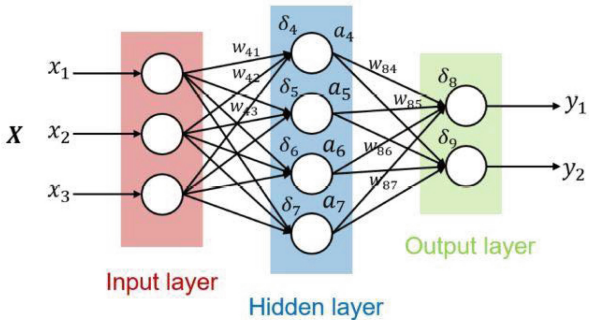


Fig. 7. The structure of artificial neural network

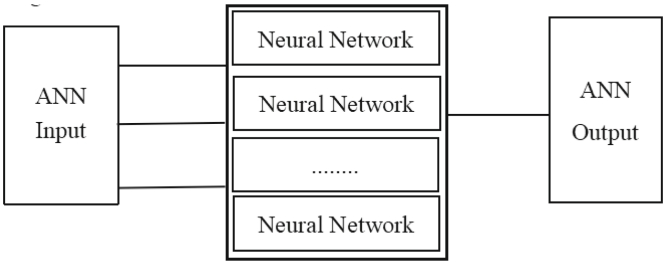


Fig. 8. Fault diagnosis system based on artificial neural network

The first 30 frequency component amplitudes of the fault voltage waveform corresponding to different modulation ratios are used as input data for the artificial neural network. The meanings of the 5 output data of the artificial neural network are shown in Table 1.

Table 1. Means of network output binary code

fault type	Network output				
	Network 1	Network 2	Network 3	Network 4	Network 5
System is normal	One	0	0	0	0
S_{11} open circuit	0	One	0	0	0
S_{12} open circuit	0	0	One	0	0
$\overline{S_{11}}$ open circuit	0	0	0	One	0
$\overline{S_{12}}$ open circuit	0s	0	0s	0s	One

The neural network is trained using the Levenberg Marquardt paradigm trainlm. Input the test data (corresponding harmonic amplitudes of the fault voltage at modulation ratios M = 0.65, 0.75, 0.85, and 0.95) into the trained neural network for prediction, and obtain the prediction results shown in Table 2. It can be seen from the table that the S_{12} accuracy of the fault discrimination network in judging whether the whole system operates normally, S_{11} faults, $\overline{S_{11}}$ faults and $\overline{S_{12}}$ faults is 100%, the accuracy in judging faults is 50%, and the overall accuracy of the system can reach 90%.

5 Artificial Neural Network Fault Diagnosis Using Principal Component Analysis

Although the data in Fig. 5 and Fig. 6 can be directly used to train neural networks for fault classification, these data still have high correlation and similarity. Therefore, this paper adopts a statistical method - Principal Component Analysis (PCA) to first simplify the input data, thereby improving the training speed and generalization accuracy of the neural network.

After conducting principal component analysis on the original sample data in Fig. 5 and Fig. 6, the variance and cumulative contribution rate of each principal component can be obtained as shown in Fig. 9.

Table 2. Generalization results of neural networks.

test data	Target output	Actual output	Accuracy
M = 0.6, 0.7, 0.8, 0.9	1 0 0 0 0	1 0 0 0 0	100%
		1 0 0 0 0	
		1 0 0 0 0	
		1 0 0 0 0	
	0 1 0 0 0	0 1 0 0 0	100%
		0 1 0 0 0	
		0 1 0 0 0	
		0 1 0 0 0	
	0 0 1 0 0	0 1 0 0 0	50%
		0 0 1 0 0	
		0 1 0 0 0	
		0 0 1 0 0	
	0 0 0 1 0	0 0 0 1 0	100%
		0 0 0 1 0	
		0 0 0 1 0	
		0 0 0 1 0	
	0 0 0 0 1	0 0 0 0 1	100%
		0 0 0 0 1	
		0 0 0 0 1	
		0 0 0 0 1	

It can be seen from Fig. 9 that the cumulative contribution rate of the first seven principal components has reached 85%, including the main information of the original data. In this way, the first seven principal components can be used to replace the original data for neural network training. Reconstruct the fault diagnosis system of the artificial neural network shown in Fig. 8, simplifying the input from the original 30 to Fig. 7. The generalization test of the reconstructed fault discrimination neural network using test data can obtain the results shown in Table 3.

Comparing the generalization results of the neural network shown in Table 2 with the generalization results of the neural network with principal component analysis shown in Table 3, it can be concluded that both proposed neural network structures have good generalization accuracy, and both have an overall accuracy of 90%; However, neural networks with principal component analysis have a simple structure and fast training

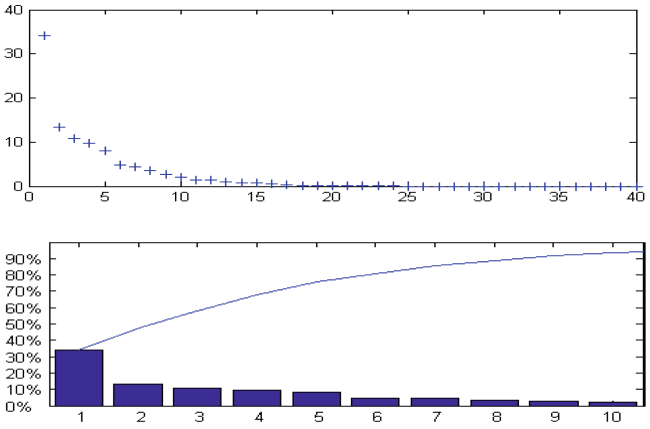


Fig. 9. Contribution rate and cumulative contribution rate of each principal component

Table 3. Generalization results of PCA neural networks.

test data	Target output	Actual output	Accuracy
M = 0.6, 0.7, 0.8, 0.9	1 0 0 0 0	1 0 0 0 0	100%
		1 0 0 0 0	
		1 0 0 0 0	
		1 0 0 0 0	
	0 1 0 0 0	0 1 0 0 0	100%
		0 1 0 0 0	
		0 1 0 0 0	
		0 1 0 0 0	
	0 0 1 0 0	0 1 0 0 0	100%
		0 0 1 0 0	
		0 1 0 0 0	
		0 0 1 0 0	
	0 0 0 1 0	0 0 0 1 0	100%
		0 0 0 1 0	
		0 0 0 1 0	
		0 0 0 1 0	
	0 0 0 0 1	0 0 0 0 1	100%
		0 0 0 0 1	
		0 0 0 0 1	

(*continued*)

Table 3. (*continued*)

test data	Target output	Actual output	Accuracy
		0 0 0 0 1	
Total accuracy			90%

speed, especially when the input data of the neural network is large, the advantages of neural networks with principal component analysis will be very obvious.

6 Conclusions

This article introduces a cascaded inverter fault detection method that integrates digital signal processing technology and neural networks. This method determines the location and type of faults by monitoring and analyzing the output voltage of the inverter. Fast Fourier transform (FFT) is used to analyze the frequency spectrum of output voltage signal and extract fault features. A fault diagnosis system based on feed forward artificial neural network has been established, using the amplitude values of each harmonic wave of the fault voltage as the training input data of the neural network, and using the fault type as the output of the neural network. Simplify input data through principal component analysis (PCA), improve neural network structure, and implement inverter fault data feature recognition technology based on neural network to improve training speed and generalization accuracy, as well as timeliness and effectiveness.

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