Fault Diagnosis System for NPC Inverter based on Multi-Layer Principal Component Neural Network

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***Abstract*—This paper presents a fault diagnosis method for a neutral point clamped (NPC) inverter using a multi-layer artificial neural network (MANN). The considered possible faults of NPC inverter include the open-circuit fault occurring in one single device or more devices. The upper, middle and down bridge voltages are adopted the test signals because of the difficulties in isolating some fault modes. A novel multi-layer neural network is proposed to diagnose all possible open-circuit faults. Furthermore, the principal component analysis (PCA) is utilized to reduce the input size of neural network. The comparison between neural network with and without PCA is performed. The simulation and experimental results prove the feasibility of the diagnostic method and show that the proposed method has the advantages of good classification performance and high reliability.**

***Index Terms*—three level inverter, fault diagnosis, MANN, PCA**

I. INTRODUCTION

The multilevel inverter could achieve more levels, lower harmonic distortion in the voltage output in addition to lowering the voltage stress of the power devices, as compared with the conventional two-level inverters [1-5]. Due to these advantages, NPC inverter has been widely used in high-power industrial applications. However, the NPC inverter system is composed of many switching devices which would reduce the reliability of a multilevel inverter, as a break in any one of these devices will inevitably make the entire inverter fail to work and produce the economic losses [6]. Therefore the fault diagnosis methods would be necessary to ensure the reliability of the multilevel inverter.

Some efforts have been made in the problem mentioned above. For example, the voltage output in faulty situation could be analyzed in real time mode and compared with the voltage output in normal situation in order to find out the faulty device, see [7]-[10]. Furthermore, it has been shown that the diagnostic performance could be enhanced if the intelligent methods like neural network, support vector machine etc. are introduced in recognizing different fault modes, see [11]-[14], though only simple applications of the neural network in NPC inverter have been proposed[15].

Investigating the current research works reveals that only the simplest fault mode, i.e. the open-circuit occurring in a single device has been taken into account. In order to improve the reliability of NPC inverter, this paper will focus on a more complicated fault mode, i.e. the open-circuit fault occurring in two devices simultaneously, in addition to diagnosing the open-circuit fault mode. Fault features will be extracted from three bridge voltages by the discrete Fourier transform (DFT) and a multi-layer artificial neural network (ANN) will be proposed to accomplish diagnosing all fault modes under consideration. In additional, the PCA is performed in this paper to reduce the input neural size [16-17]. Figure 1 shows a three level NPC inverter.

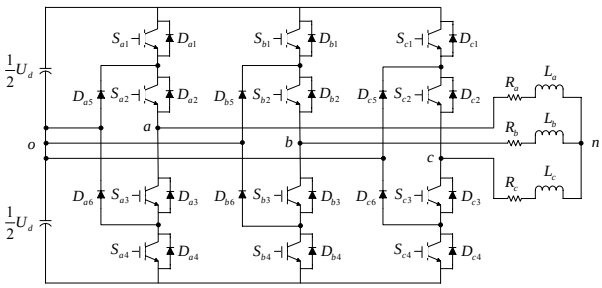

Figure 1. Main circuit of a three level NPC inverter

II. ANALYSIS OF POSSIBLE FAULT MODE

One single bridge leg of NPC inverter could be derived from Figure 1, e.g., as shown in Figure 2 for phase *a*.

There are three bridge voltages in Figure 2. The voltage between points a_u and o V_{ao} is named as 'middle bridge voltage', or 'bridge voltage' for simplicity. The voltage between points a_u and o V_{auo} is named as 'upper

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bridge voltage', while V_{ado} between points a_d and o is 'down bridge voltage'.

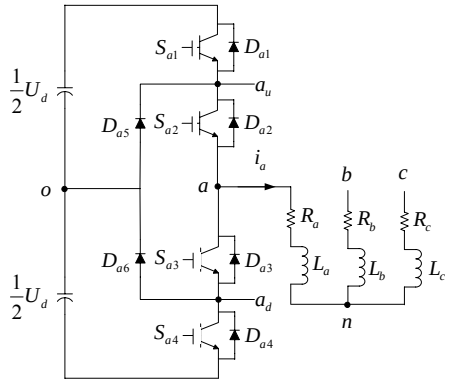
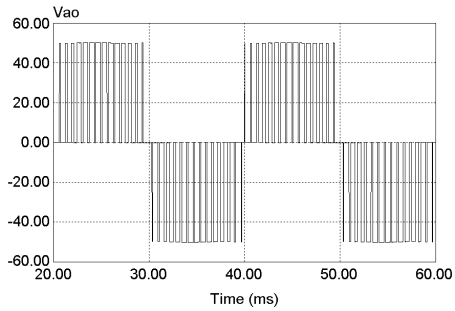


Figure 2. Single bridge leg of NPC inverter

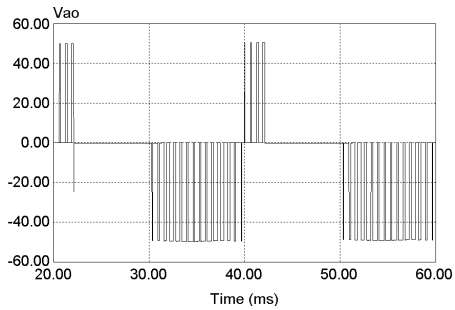
A. Open-circuit Fault of Single Device

Consider the circuit shown in Figure 2 which consists of six devices, namely S_{a1}, S_{a2}, S_{a3}, S_{a4}, D_{a5} and D_{a6}. Correspondingly, there are six possible fault modes for the open-circuit fault of single device, with each mode being denoted by the same symbol of each device. As the circuit is symmetric in configuration, those fault modes of S_{a1}, S_{a2} and D_{a5} need to be analyzed in detail, and the results apply for the other three fault modes.

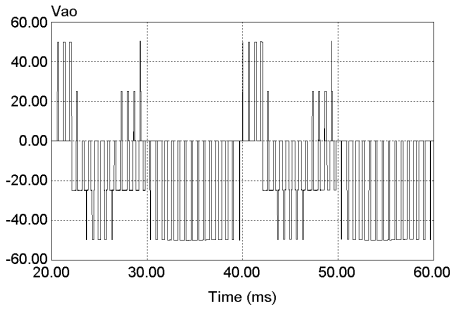
Performing simulation for the NPC inverter by the software PSIM, with the input DC voltage U_d being 100V, the load of each phase being resistance 8Ω and inductance 20mH in series, under the normal (fault free) condition and each single device open-circuit fault mode, the simulation waveforms of bridge voltage could be obtained as shown in Figure 3.



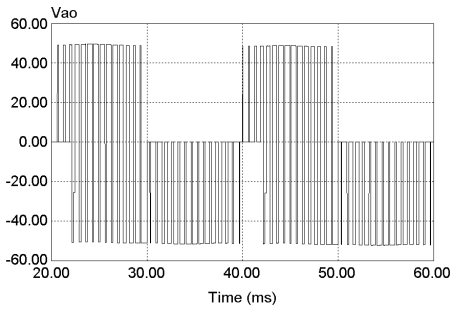
(a) Fault free mode



(b) S_{a1} open-circuit



(c) S_{a2} open-circuit



(d) D_{a5} open-circuit

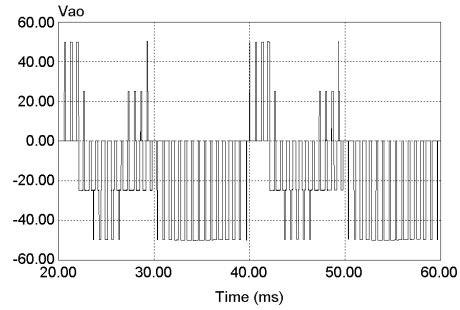
Figure 3. Simulation waveforms of bridge voltage for open-circuit fault of single device

It could be seen obviously from Figure 3 that the waveform of the bridge voltage is different from one another and has specific features. By theory of spectrum analysis [18], each waveform of bridge voltage in Figure 3 consists of specific harmonics differing from the other's. Therefore the 'fault features' could be extracted from the bridge voltages. Based on such fault features, it is possible to isolate the open-circuit fault of single device in some proper ways.

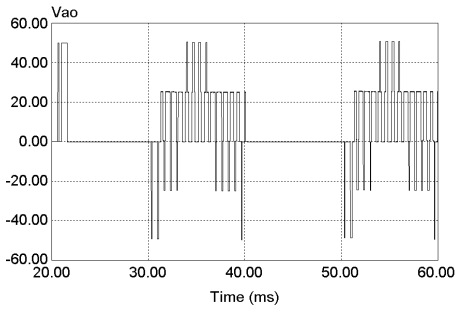
B. Open-circuit Fault of Two Devices

Two different situations arise while the case that two devices malfunction by open-circuit during certain period is taken into account. The first situation arises when two faulty devices lie in the same phase, e.g. S_{a1} and S_{a3}, and the second one arises when two faulty devices lie in different phases, e.g. S_{a1} in phase *a* and S_{b1} in phase *b*. Only the first situation needs to be investigated because the second situation could be reduced to the open-circuit fault of single device in two phases and then be treated by the way mentioned above.

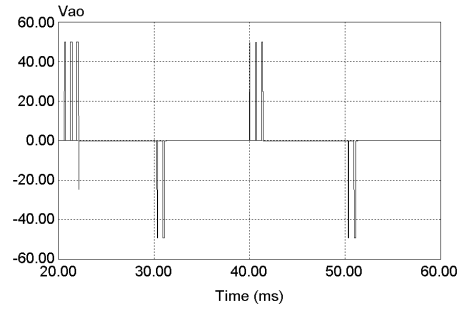
Considering the phase *a* without loss of generality, possibly there are six different fault modes as $\{S_{a1}, S_{a2}\}$, $\{S_{a1}, S_{a3}\}$, $\{S_{a1}, S_{a4}\}$, $\{S_{a2}, S_{a3}\}$, $\{S_{a2}, S_{a4}\}$ and $\{S_{a3}, S_{a4}\}$. Due to the symmetry in the configuration of NPC inverter, for the fault modes $\{S_{a2}, S_{a4}\}$ and $\{S_{a3}, S_{a4}\}$, the bridge voltage would be the same as one for $\{S_{a1}, S_{a3}\}$ and $\{S_{a1}, S_{a2}\}$ respectively, while the phase is just opposite. Therefore only the other four fault modes should be analyzed. The bridge voltages' simulation for these four faulty modes is given out in Figure 4.



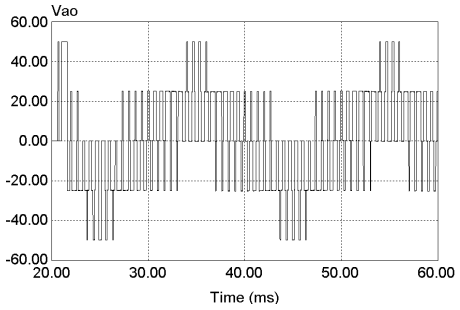
(a) { S_{a1} , S_{a2} }



(b) { S_{a1} , S_{a3} }



(c) { S_{a1} , S_{a4} }

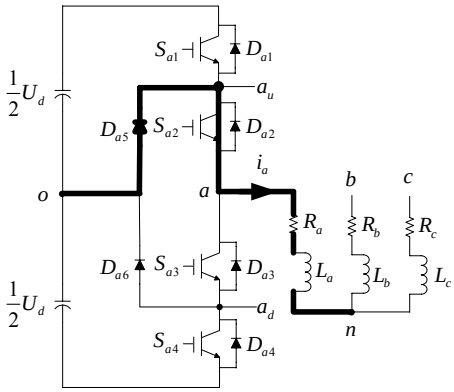


(d) { S_{a2} , S_{a3} }

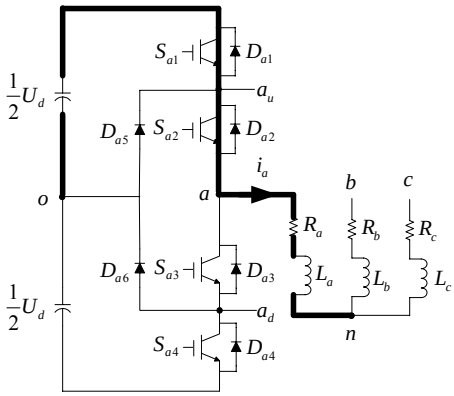
Figure 4. Bridge voltage when two devices malfunction

From Figure 3 and Figure 4 it could be found that the circuit would have the same bridge voltage for the fault modes { S_{a2} } (see Figure 3 (c)) and { S_{a1} , S_{a2} } (see Figure 4 (a)). This will be also the case for the fault modes { S_{a3} } and { S_{a3} , S_{a4} }.

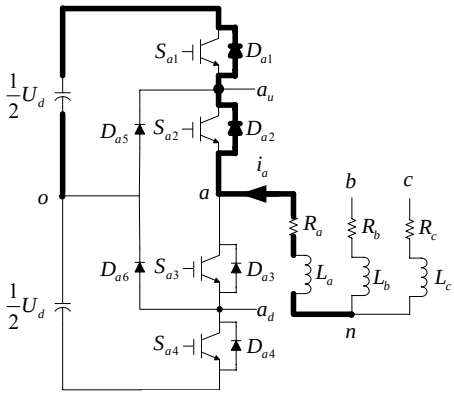
Consider the current path in Figure 2 from a to o through the upper half bridge where S_{a1} , S_{a2} , D_{a5} , D_{a1} and D_{a2} are involved, and denote the current of phase a as i_a . If $i_a > 0$, the current has two possible paths as shown in Figure 5 (a-b), but if $i_a < 0$, the current has only one path through D_{a1} and D_{a2} as shown in Figure 5 (c). When the fault { S_{a2} } occurs, current flow (3) is possible while current flow (1) or (2) is impossible. When the fault { S_{a1} , S_{a2} } occurs, only current flow (3) is possible. Hence, no difference exists in current flow and the bridge voltages for the cases { S_{a2} } and { S_{a1} , S_{a2} }. This reveals that the fault modes { S_{a2} } and { S_{a1} , S_{a2} } cannot be isolated if only the bridge voltage is used.



(a) Current flow (1)



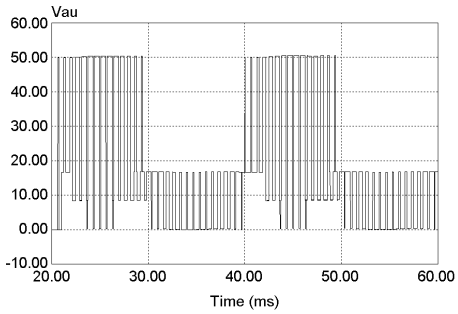
(b) Current flow (2)



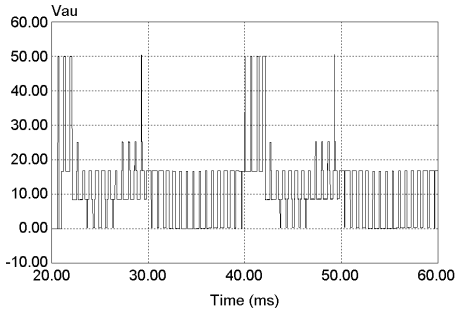
(c) Current flow (3)

Figure 5. Diagram of NPC inverter work states

In order to isolate all possible fault modes, the voltages of both the upper bridge and the down bridge as defined before are introduced. Figure 6 shows the waveform of the upper bridge voltage for { S_{a2} } and { S_{a1} , S_{a2} }. Obviously the waveform is different from each other.



(a) { S_{a2} }



(b) { S_{a1} , S_{a2} }

Figure 6. Waveform of the upper bridge voltage

III. FAULT DIAGNOSIS

A. Structure of Fault Diagnosis System

The structure for a fault diagnosis system is shown in Figure 7. The system is composed of three major states: feature extraction, principal component analysis and multi-layer neural network. The output of the MNN is nearly 0 and 1 as binary code which can be related to different fault mode.

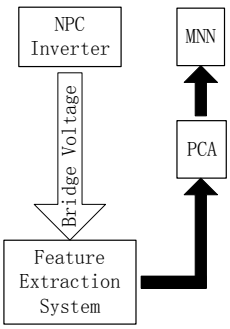


Figure 7. Structure of Fault Diagnosis System

B. Feature Extraction

An appropriate selection of the feature extractor is to provide the MNN with adequate significant details in original data so that the highest accuracy in the MNN performance can be obtained. In this paper the DFT technique is adopted to extract feature from the middle, upper and down bridge voltages. The transformed signals of Figure 3 and Figure 4, whose fundamental frequency is 50Hz and carrier frequency is 1.5kHz, are represented in Figure 8 and Figure 9 respectively.

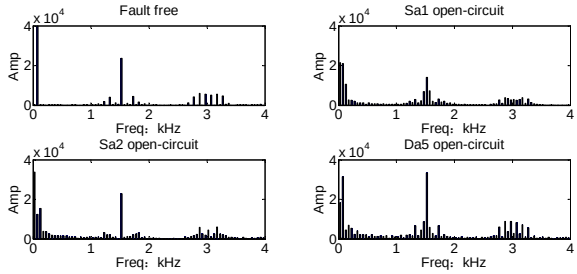


Figure 8. DFT result of figure 3

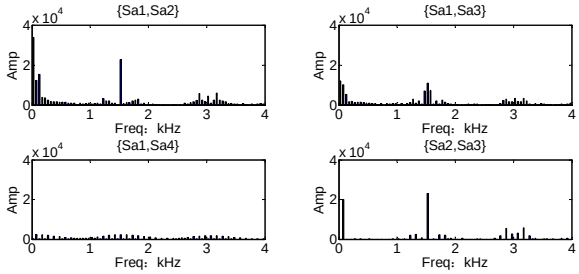


Figure 9. DFT result of figure 4

According to the spectrum characteristics of PWM inverters [19], and also could be seen from Figure 8 and Figure 9, obviously, main harmonics of the bridge voltage are distributed in the fundamental frequency, carrier frequency and their multiples. Hence, some components of these main harmonics are selected as the fault feature by feature extraction system in Figure 7.

The selection of input data for the main neural network include amplitude of DC component, fundamental, double fundamental, three times of fundamental, carrier frequency (1.5kHz), side frequency of carrier (1.4kHz and 1.6kHz) and double carrier frequency. The phase of DC component, fundamental and double fundamental are also selected as input data for the main neural network. It could be counted that the dimension of the input data for the main neural network is 11.

For both auxiliary neural networks, the amplitude of DC component, fundamental and double fundamental are selected as the input data with the dimension of three.

C. Principal Component Analysis

It could be seen that the input data of the main neural network has high dimension and we don't know whether these 11 dimension data are correlated or uncorrelated. PCA is a statistical technique used to transform a set of correlated variables to a new lower dimensional set of variables, which are uncorrelated or orthogonal with each other. The fundamental PCA used in a linear transformation is shown as follows:

$$T = X \cdot P \tag{1}$$

Where T is the $m \times k$ score matrix (transformed data), m is number of observations, k is dimensionality of the PC space; X is the $m \times n$ data matrix, m is number of observations, n is dimensionality of original space; and P is the $n \times k$ loadings matrix (PC coordinates), n is dimensionality of original space, k is number of the PCs kept in the model. The detail equation of Equation (1) is shown in the follow expression:

$$\begin{bmatrix} t_{11} & t_{12} & \cdots & t_{1k} \\ t_{21} & t_{22} & \cdots & t_{2k} \\ \vdots & \vdots & \vdots & \vdots \\ t_{m1} & t_{m2} & \cdots & t_{mk} \end{bmatrix} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \cdot \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1k} \\ p_{21} & p_{22} & \cdots & p_{2k} \\ \vdots & \vdots & \vdots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nk} \end{bmatrix} \tag{2}$$

Selecting a reduced subset of PC space results in a reduced dimension structure with respect to the important information available as shown in the following expression:

$$\begin{bmatrix} t_1 & t_2 & \cdots & t_k \end{bmatrix} = \begin{bmatrix} x_1 & x_2 & \cdots & x_n \end{bmatrix} \cdot \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1k} \\ p_{21} & p_{22} & \cdots & p_{2k} \\ \vdots & \vdots & \vdots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nk} \end{bmatrix} \tag{3}$$

D. Artificial Neural Network

ANN is a computer model whose architecture essentially mimics the knowledge acquisition and organizational skills of the human brain. Although there are a variety of ways to construct these models, Back-Propagated (BP) neural network has become one of the most widely used ANNs in practice. BP neural network with a single hidden layer is selected in this paper, which has been demonstrated to be sufficient to approximate any continuous function within the desired accuracy [20]. Figure 10 shows a diagram of neural network with a single hidden layer.

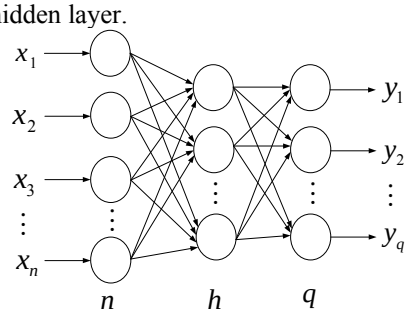


Figure 10. Neural network with a single hidden layer

The three layers are called the input layer, hidden layer and output layer, respectively. Each layer consists of logic units or neurons, as the basic information processing units in ANN. The relationship of the input value of the unit i in input layer and that of unit j in hidden layer is:

$$u_j = \sum_{i=1}^{n} \omega_{ji} x_i + b_j \tag{4}$$

Where x_i is an input value of the logic unit i in the input layer, u_j an initial output value of the logic unit j in the hidden layer, ω_{ji} connection weights between unit j and i, b_j input bias of the unit j, n the number of logic units in the input layer.

The initial output value u_j is further transformed with the common transfer function in a sigmoid form:

$$O_j = \frac{1}{1+e^{-u_j}} \tag{5}$$

Where O_j is the final output value of the logic unit j.

The goal of the training of ANN is to minimize the error between predicted and target values by adjusting the connection weights and biased. The error is given by Equation (6):

$$E = \sum_{p=1}^{p} \sum_{q=1}^{q} (a_{pq} - o_{pq})^2 \tag{6}$$

Where q is the number of logic units in output layer, and p is the number of training samples, a_{pq} and o_{pq} are the predicted and target values, respectively.

E. Multi-layer Neural Network

A new method named as multi-layer neural network is proposed to diagnose all open-circuit fault modes under consideration for the NPC inverter, as shown in Figure 11.

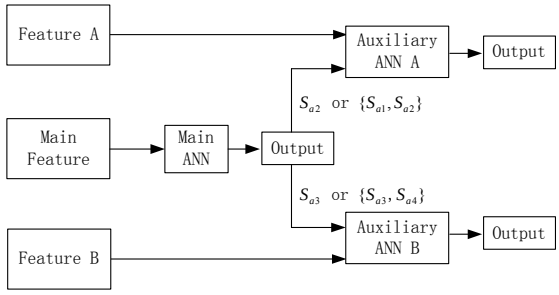


Figure 11. Multi-layer neural network

TABLE I.
FAULT MODES AND OUTPUT OF MAIN ANN

Fault modes (open-circuit)	Target output
Fault free	000000
S_{a1}	100000
S_{a2} or { S_{a1} , S_{a2} }	010000
S_{a3} or { S_{a3} , S_{a4} }	001000
S_{a4}	000100
D_{a5}	000010
D_{a6}	000001
{ S_{a1} , S_{a3} }	101000
{ S_{a1} , S_{a4} }	100100
{ S_{a2} , S_{a3} }	011000
{ S_{a2} , S_{a4} }	010100

TABLE II.
FAULT MODES AND OUTPUT OF AUXILIARY ANN A

Fault modes (open-circuit)	Target output
S_{a2}	0
{ S_{a1} , S_{a2} }	1

Main Feature extracted from the bridge voltage V_{ao} is used as input data for main ANN, which is used to diagnose eleven fault modes represented in Table I (including fault free mode). While *Feature A* and *Feature B* extracted from upper bridge voltage V_{auo} and down bridge voltage V_{ado} are used as the input data for auxiliary ANN A and B respectively. Table II and Table

III represent the fault modes diagnosed by two auxiliary ANNs and their target output.

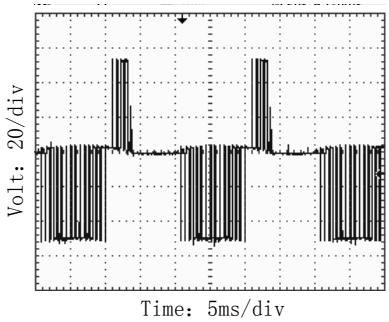
TABLE III.
FAULT MODES AND OUTPUT OF AUXILIARY ANN B

Fault modes (open-circuit)	Target output
S_{a3}	0
$\{S_{a3}, S_{a4}\}$	1

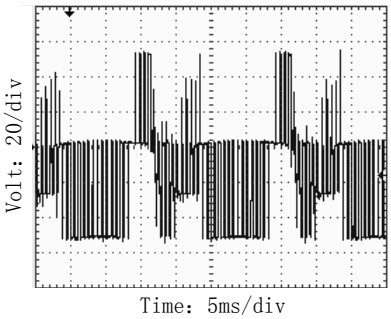
IV. DIAGNOSIS RESULT

To verify the proposed method, an NPC inverter using MOSFET IRF640 as the switching device is used to carry out the three bridge voltages. A DSP chip TMS320F2812 is utilized to generate gate drive signals. The input DC voltage is 90V to 110V and the three phase wye-connected load is 8Ω resistance series with 20mH inductance. Fault occurrence is created by physically removing switching signal in the desired position.

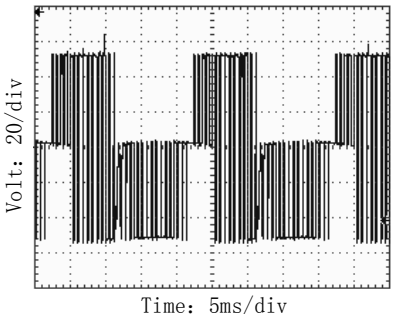
Figure 12 shows the experimental bridge voltage waveforms for open-circuit fault of single device. Figure 13 shows the experimental bridge voltage waveforms when open-circuit fault occurring in two devices simultaneously.



(a) S_{a1} open-circuit



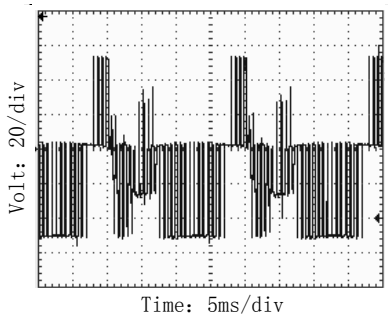
(b) S_{a2} open-circuit



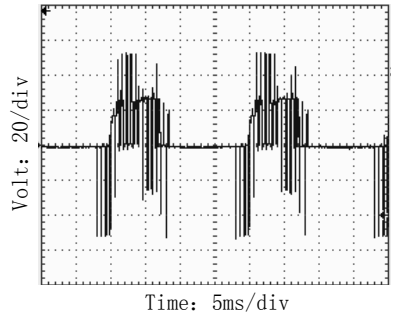
(c) D_{a5} open-circuit

Figure 12. Experimental bridge voltage waveforms for open-circuit of single device

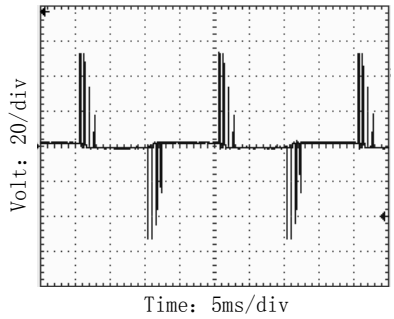
Each fault mode from Tab.1 to Tab.3 must cover the operating region. Thus, there are three degrees of input DC voltage in the experiment include 90V, 100V and 110V. Under each DC voltage, the modulation index is changed from 0.2 to 1 with step of 0.1. Therefore, 27 sets original data can be obtained for each fault mode. The data whose modulation index is 0.5, 0.7 and 0.9 are utilized as test sample and the rest data are utilized as train sample.



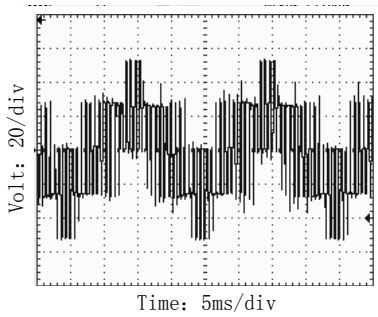
(a) $\{S_{a1}, S_{a2}\}$



(b) $\{S_{a1}, S_{a3}\}$



(c) $\{S_{a1}, S_{a4}\}$



(d) $\{S_{a2}, S_{a3}\}$

Figure 13. Experimental bridge voltage waveforms when two devices malfunction

TABLE IV.
DIAGNOSIS RESULT OF MULTI-LAYER ANN (WITHOUT PCA)

	Main SVM	Auxiliary SVM A	Auxiliary SVM B
No noise	98.84%	100%	100%
10% white nosie	96.31%	100%	100%

Table IV shows diagnosis result of the multi-layer ANN without PCA and the dimension of the input data of the main ANN is 11.

Table V shows diagnosis result of the multi-layer ANN with PCA. Here, only the input data of the main ANN is transformed by the technique of PCA and the dimension of the new input data of the main ANN is 8.

TABLE V.
DIAGNOSIS RESULT OF MAIN ANN (WITH PCA)

	Main SVM
No noise	99.24%
10% white nosie	98.43%

It could be seen from Table IV and Table V that the diagnosis precision of the main ANN with PCA is higher than that without PCA. It could be deduced that the ANN with PCA must be trained better than the ANN without PCA and has better generalization ability.

V. CONCLUSIONS

Additional signals are required in order to isolate more complicated faults of open-circuit occurring in two devices in NPC inverter during certain period. Note that this is not just a theoretical problem but a practical one because some failures have been reported recently, see [21]-[22]. In this paper, the voltages in all the upper, middle and down bridge are suggested to extract fault features. A scheme of multi-layer ANN is proposed to implement fault diagnosis of NPC inverter, involving the simple open-circuit of one device or more devices. Better precision could be achieved when the input data is transformed by PCA.

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