Fault Diagnosis System for a Multilevel Inverter Using a Neural Network

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Abstract **– In this paper, a fault diagnosis system in a multilevel-inverter using a neural network is developed. It is difficult to diagnose a multilevel-inverter drive (MLID) system using a mathematical model because MLID systems consist of many switching devices and their system complexity has a nonlinear factor. Therefore, a neural network classification is applied to the fault diagnosis of a MLID system. Five multilayer perceptron (MLP) networks are used to identify the type and location of occurring faults. The neural network design process is clearly described. The classification performance of the proposed network between normal and abnormal condition is about 90 %, and the classification performance among fault features is about 85 %. Thus, by utilizing the proposed neural network fault diagnosis system, a better understanding about fault behaviors, diagnostics, and detections of a multilevel inverter drive system can be accomplished. The results of this analysis are identified in percentage tabular form of faults and switch locations.**

Index Terms–**Multilevel inverter, neural network, fault diagnosis**

I. INTRODUCTION

In recent years, industry has begun to demand higher power ratings, and MLID systems have become a solution for high power applications. A multilevel inverter not only achieves high power ratings, but also enables the use of renewable energy sources. Renewable energy sources such as photovoltaic, wind, and fuel cells can be easily interfaced to the multilevel inverter system for a high power application [1].

A schematic of a single phase multilevel inverter system is illustrated in Fig. 1. Because multilevel inverter systems are utilized in high power applications, the reliability of the power electronics equipment is very important. For example, industrial applications such as industrial manufacturing are dependent upon induction motors and their inverter systems for process control. Generally, the conventional protection systems are passive devices such as fuses, overload relays, and circuit breakers to protect the inverter systems and the induction motors. The protection devices will disconnect the power sources from the multilevel inverter system whenever a fault occurs, stopping the operated process. Downtime of manufacturing equipment can add up to be thousands or hundreds of thousands of dollars per hour, therefore fault detection and diagnosis is vital to a company's bottom line.

Many engineers and researchers have focused on incipient fault detection and preventive maintenance to prevent inverter and motor faults from happening. The most important factor, however, is how the system could operate continuously while there is an abnormal condition.

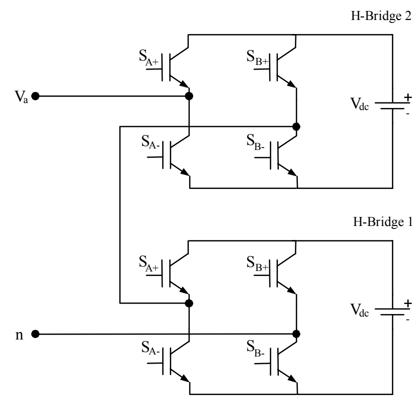


Fig. 1. Single-phase multilevel-inverter system.

In order to maintain continuous operation for a multilevel inverter system, knowledge of fault behaviors, fault prediction, and fault diagnosis are necessary. Faults should be detected as soon as possible after they occur, because if a motor drive runs continuously under abnormal conditions, the drive or motor may quickly fail.

The various fault modes of a conventional PWM voltage source inverter (VSI) system for an induction motor are investigated in [2]. Then, the integration of a fault diagnosis system into VSI drives is described in [3]. This integration system introduced remedial control strategies soon after failure occurrences; therefore, system reliability and fault tolerant capability are improved.

A noninvasive technique for diagnosing VSI drive failures based on the identification of unique signature patterns corresponding to the motor supply current Park's Vector is proposed in [4]. A study of a machine fault diagnosis system by using FFT and neural networks is clearly explained in [5]. Also, a fault diagnosis system for rotary machines based on fuzzy neural networks is developed in [6]. Furthermore, a new topology with fault-tolerant ability that improves the reliability of multilevel converters is proposed in [7]. The knowledge and information of fault behaviors in the system is important to improve system design, protection, and fault tolerant control. Thus far, limited research has focused on MLID fault diagnosis. Therefore, a MLID fault diagnosis system is proposed in this paper.

An example of a MILD open circuit fault at switch S_{A+} is represented in Fig. 2. S_{A+} fault will cause unbalanced voltage and current output, while the induction motor is operating. The unbalanced voltage and current may result in vital damage to the induction motor if the induction motor is run like this for a long time. The unbalanced condition from fault

S_{A+} can be solved if the fault location is correctly identified. Switching patterns and the modulation index of other active switches in the MLID can be adjusted to maintain output voltage and current in a balanced condition. Although the MLID can continuously operate in a balanced condition, the MLID will not be able to operate at its rated power. Therefore, the MLID can operate in balanced condition at reduced power while the fault occurs until the operator knows and repairs the inactive switch.

In this research, we will attempt to diagnose the fault location in a MLID from its output voltage waveform. MLID open circuit faults at each switch are considered. Although the MLID system usually consists of three phases of H-bridge inverters and also can have short circuit faults, the fault diagnosis system will be the same topology as a single phase and open circuit case. Moreover, one level of multilevel inverter is focused in this research; however, other inverter levels can be extended by using this proposed topology with more training data. The proposed network utilizes output voltage signals of the MLID to train the neural networks. The acquired data is transformed by using Fast Fourier Transform technique to rate a signal value as an important characteristic. The signal feature extraction is discussed, and the process of neural network design is clearly described in the following section.

II. General Notion of Fault Diagnosis System

A. Structure of fault diagnosis system

The structure for a fault diagnosis system is illustrated in Fig. 3. The system is composed of four major states: feature extraction, neural network classification, fault diagnosis, and switching pattern calculation with gate signal output. The feature extraction, neural classification, and fault diagnosis are the focus of this research. The feature extraction performs the voltage input signal transformation, with rated signal values as important features, and the output of the transformed signal is transferred to the neural network classification. The networks are trained with both normal and abnormal data for the MLID; thus, the output of this network is nearly 0 and 1 as binary code. The binary code is sent to the fault diagnosis to decode the fault type and its location. Then, the switching pattern is calculated.

B. Feature extraction system

The Simpower Matlab toolbox in Simulink is used to simulate data of fault features with 0.8 modulation index (m_a) out of 1.0 and as illustrated in Fig. 4. Also the output voltages are measured from the MLID prototype in no-load condition as shown in Fig. 5. As can be seen, the signals are difficult to rate as an important characteristic for classifying a fault hypothesis. Therefore, a signal transformation technique is needed. An appropriate selection of the feature extractor is to provide the neural network with adequate significant details in the pattern set so that the highest degree of accuracy in the neural network performance can be obtained. One possible technique for implementation with a digital

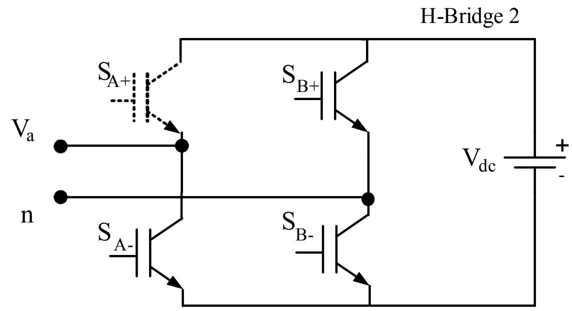


Fig. 2. H-Bridge 2 Switch S_{A+} open circuit fault at second level of single-phase multilevel-inverter.

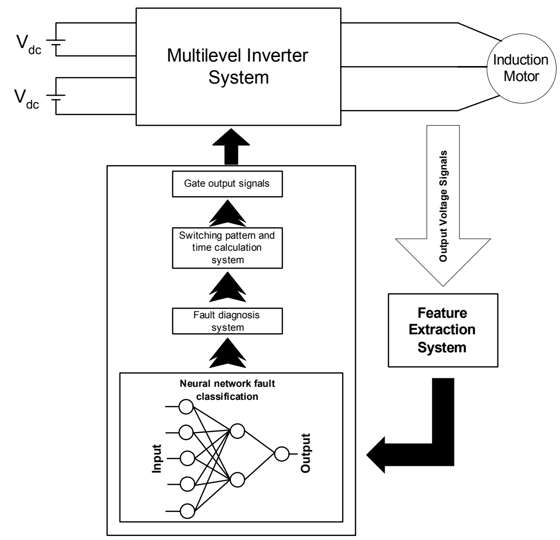


Fig. 3. Structure of fault diagnosis system.

signal processing microchip is Fast Fourier Transform [8]. Beginning with the discrete Fourier Transform in (1), then the FFT using the decimation in time decomposition algorithm is illustrated in (2).

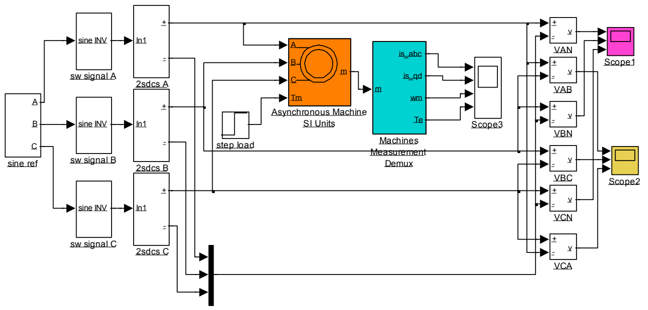
$$F_k = \sum_{n=0}^{N-1} f_n W_N^{nk} \qquad for\; k = 0, \ldots, N-1 \tag{1}$$

where $W_N = e^{-j\frac{2\pi}{N}}$

$$\begin{aligned} F_k &= G_k + W_N^k H_k & for\; k = 0, \ldots, \frac{N}{2}-1 \\ F_{k+\frac{N}{2}} &= G_k - W_N^k H_k & for\; k = 0, \ldots, \frac{N}{2}-1 \end{aligned} \tag{2}$$

G_k is for even-numbered elements of f_n, whereas H_k is for odd-number elements of f_n. G_k and H_k can be computed as shown in (3) and (4).

$$G_k = \sum_{n=0}^{\left(\frac{N}{2}\right)-1} f_{2n} W_{\frac{N}{2}}^{nk} \tag{3}$$



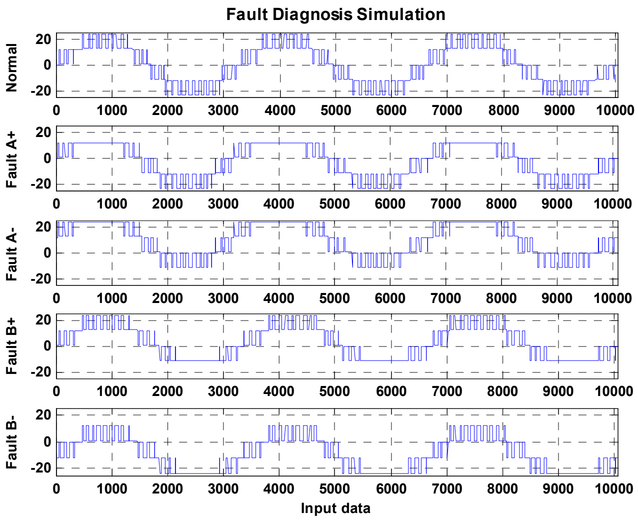


Fig. 4. Simulation of fault features at S_{A+}, S_{A-}, S_{B+}, and S_{B-} of H-bridge 2 with modulation index = 0.8 out of 1.0.

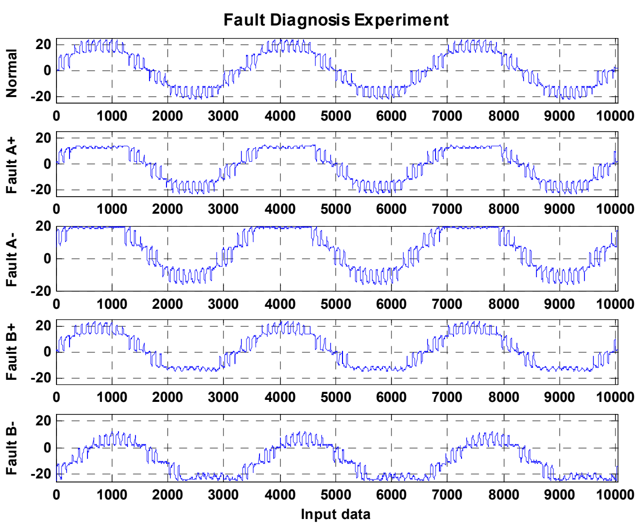


Fig. 5. Experiment of fault features at S_{A+}, S_{A-}, S_{B+}, and S_{B-} of H-bridge 2 with modulation index = 0.8 out of 1.0.

$$H_k = \sum_{n=0}^{\left(\frac{N}{2}\right)-1} f_{2n+1} W_{\frac{N}{2}}^{nk} \qquad (4)$$

Together, the computational savings of the FFT becomes $Nlog_2N$ compared to N^2 for the DFT [8]. Other popular signal transformation techniques such as Hartley and Wavelet are explained in [8].

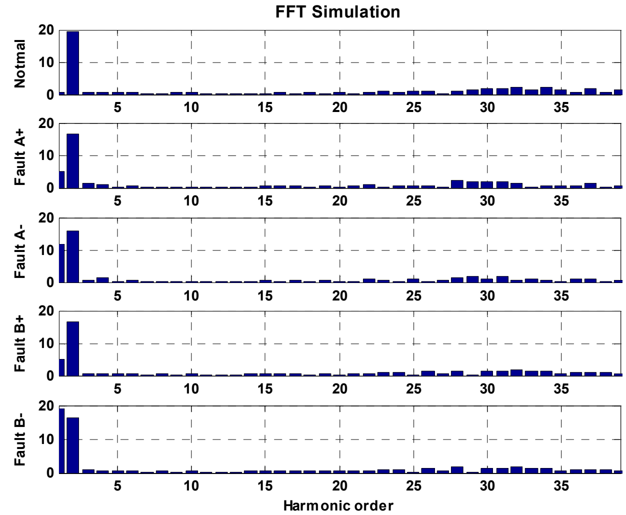


Fig. 6. Signal transformation of simulation output voltages by using FFT with modulation index = 0.8 out of 1.0.

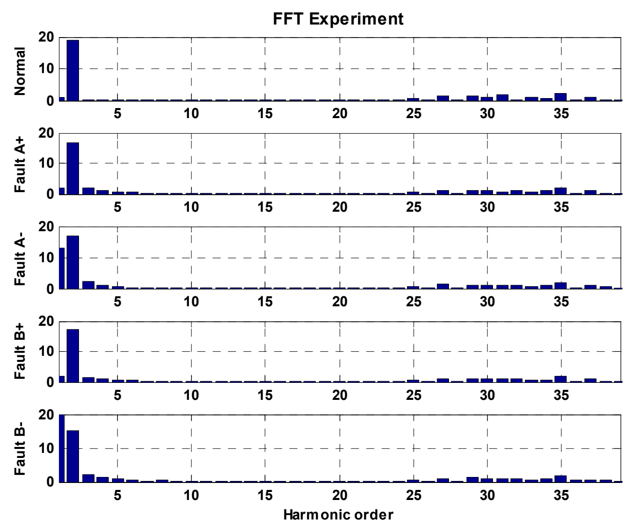


Fig. 7. Signal transformation of experimental output voltages by using FFT with modulation index = 0.8 out of 1.0.

C. Simulation and experiment comparison

The transformed signals of both simulation and experiment are represented in Fig. 6 and Fig. 7, respectively. Obviously, the results are nearly identical fault features. The FFT technique has a good identical feature to classify normal and abnormal features; therefore, FFT is used to transform voltage output signals in this research in order to rate signal value for important features so that the features for a fault hypothesis can be classified.

In the experiment, a three-phase wye-connected cascaded multilevel inverter using 100V, 70 A MOSFET as the switching devices was used to carry out the output voltage signals. A FPGA chip with 8 µsec time step is utilized to generate gate drive signals and interfaces with the gate drive board. The switching angles are calculated by using Simulink based on sinusoidal PWM. A 12-volt battery is supplied to each H-Bridge inverter in both simulation and experiment.

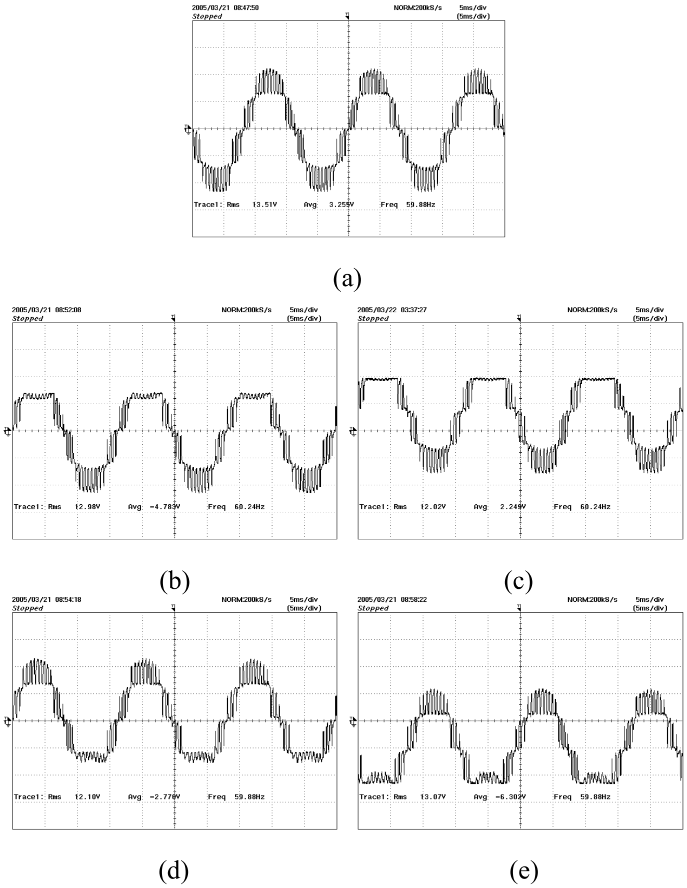


Fig. 8. Experiment of fault features at (a) normal, (b) S_{A+} fault, (c) S_{A-} fault, (d) S_{B+} fault, and (e) S_{B-} fault of H-bridge 2 with modulation index = 0.8 out of 1.0.

Fault occurrence is created by physically removing the switch in the desired position. A Yokogawa DL 1540c is used to measure output voltage signals shown in Fig. 8 as ASCII files. The measured signals are set to N =10032; sampling frequency is 200 kHz. Voltage spectrum is calculated and transferred to the neural network fault classification.

III. Methodology of Neural Network Fault Classification

All fault features, as previously discussed, can be classified based upon their effects upon the output voltages. The transformation of output voltage signals is achieved by using FFT as shown by simulation and experimental results in Figs. 6 and 7. As mentioned before, the systematic mathematical technique may be complicated to implement in the practical real time control system; therefore, a feedforward neural network technique permitting input/output mapping with a nonlinear relationship between nodes will be utilized [9]. Neural networks provide the ability to recognize anomalous situations because of their intrinsic capacity to classify and generalize. Especially, the sensitivity and response time of the original procedure presented for the on-line analysis of fault set repetition enable on-line fault location techniques to be developed [10]. The stages of neural network fault classification are explained as follows:

A. Neural network architecture design

The architecture of the proposed fault diagnosis neural network, NN, is illustrated in Fig. 9. The five multilayer feedforward networks, or MLP, are used in this research because the input data contain continuous features. A network has one hidden layer with 40 input nodes corresponding to harmonic order and magnitude, 2 hidden nodes, and 1 output node. The sigmoid activation function is used: *tansig* for hidden nodes and *logsig* for an output node. A *logsig* activation function is used for an output node because the target output is between 0 and 1. The implementation of the proposed neural network classification system, consisting of five NNs is shown in Fig. 10. It should be noted that the number of nodes for the input and output layers depends on the specific application. The selection of number and dimension in the hidden layer is based on neural network accuracy in preliminary tests. Indeed, optimizing of network architecture selection is a significant topic in a study of artificial intelligence aspects [9, 10].

B. Input/output data

Each network is trained with one set of normal data and four sets of abnormal data, thus the size of the input matrix is 5 input data rows with 40 columns, $[5 \times 40]$. The size of the output target is $[5 \times 1]$. The target output corresponding with classification data is represented in Table I. A selection of training data and test data, from the original signal, is discussed in the next section.

C. Neural network training

The Levenberg Marquardt training paradigm, *trainlm* is utilized in this research because *trainlm* not only performs very fast training time but also has inherent regularization properties. Regularization is a technique which adds constraints so that the results are more consistent. The 1% misclassification and 1% input data error rate are chosen to calculate a sum of square error goal, SSE; therefore, a 0.0334 SSE goal is used to train the network by calculating from (5). The training process will be finished when the SSE goal is met.

$$SSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{L}\left(y_{ij} - d_{ij}\right)^2} \tag{5}$$

where y_{ij} is an output value of neural network,
d_{ij} is an output of training data,
N is the number of training data,
L is the number of units in the output layer.

1. Training and testing data set selection

The training data set should also cover the operating region; thus, the test data sets are generated from simulation with various operation points (different modulation indices). The testing sets are measured from experiment. Training and testing sets have 200 kHz sampling frequency. Both data sets are transformed by FFT from 0 to 39 harmonic orders. Zero harmonic order means the dc component of the signals.

TABLE I
TARGET AND CLASSIFICATION DATA

Number of NN	Classification	Target
1	Normal	$[\ 1;0;0;0;0\ ]_{5x1}$
2	Fault at S_{A+}	$[\ 0;1;0;0;0\ ]_{5x1}$
3	Fault at S_{A-}	$[\ 0;0;1;0;0\ ]_{5x1}$
4	Fault at S_{B+}	$[\ 0;0;0;1;0\ ]_{5x1}$
5	Fault at S_{B-}	$[\ 0;0;0;0;1\ ]_{5x1}$

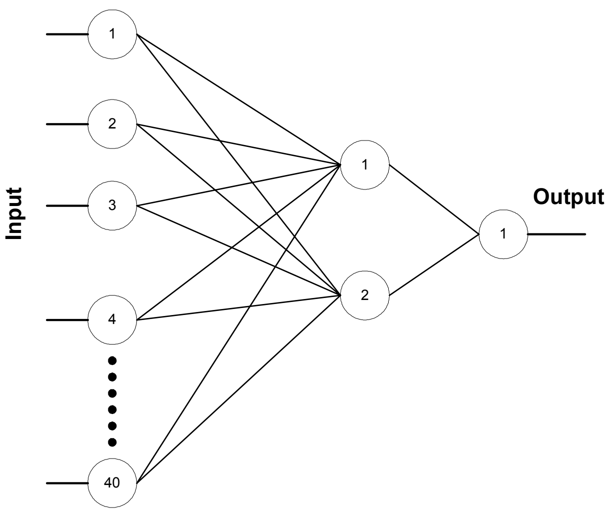


Fig. 9. Proposed neural network architecture.

2. Scaling data

The input training data are scaled by using the mean center and unit variance method (Z-score scaling). The scaling data will avoid premature saturation of sigmoidal units and also allow the use of a specific output neuron [9]. The scaling parameters: the mean value (X_M) and the standard deviation value (X_S) are saved with the same data file as weights and biases. The testing data set will be scaled with the same scaling parameters as the training data set when the network is examined.

D. Neural network testing

The networks are examined with the test data sets, as mentioned above, when the proposed networks have trained to the desired error goal. Testing the network involves presenting the test set to the network and calculating the error. If the error goal is met, the training is complete.

IV. FAULT CLASSIFICATION RESULTS

The performances of the proposed networks are tested in two categories. First, the networks are tested with the selected test set at the same operating point (m_a = 0.8) as previously mentioned. The tested results along with the testing data set are illustrated in Table II. As can be seen, the error between the actual and target output data after testing the network is less than the SSE goal (0.0334), thus the training process is complete.

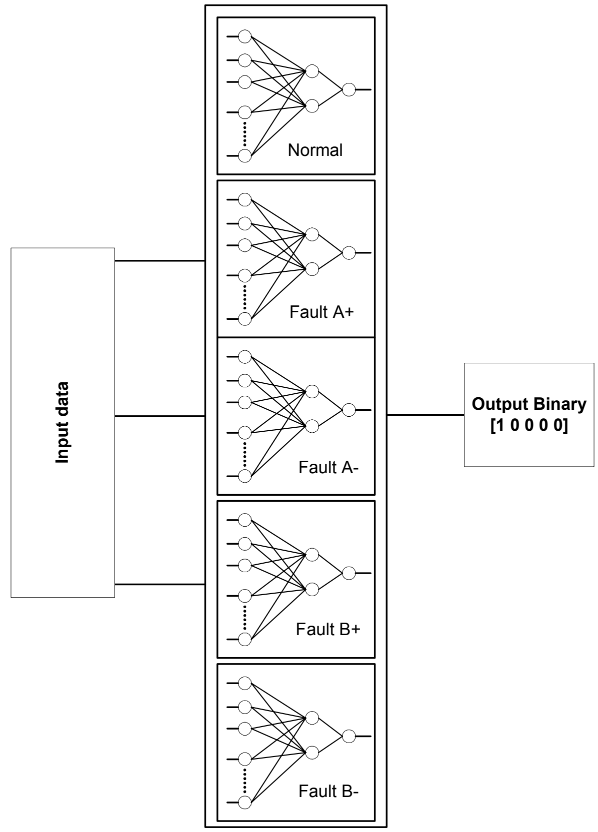


Fig. 10. Implementation of proposed neural network classification system.

TABLE II
CONFUSION TABLE FOR TESTING DATA SET (m_a = 0.8)

	Actual Data				
Classification Target	Normal	Fault A+	Fault A-	Fault B+	Fault B-
Normal [1 0 0 0 0]	$9.993x10^{-1}$ 99.93%	$6.425x10^{-4}$ 0.064%	$9.873x10^{-5}$ 0.0098%	$9.942x10^{-4}$ 0.0994%	$1.071x10^{-3}$ 0.1%
Fault A+ [0 1 0 0 0]	$8.854x10^{-4}$ 0.088%	$9.896x10^{-1}$ 98.96%	$1.271x10^{-3}$ 0.013%	$8.853x10^{-4}$ 0.088%	$1.214x10^{-3}$ 0.1214%
Fault A- [0 0 1 0 0]	$1.195x10^{-3}$ 0.019%	$2.289x10^{-4}$ 0.023%	$9.990x10^{-1}$ 99.99%	$1.064x10^{-3}$ 0.106%	$1.046x10^{-3}$ 0.105%
Fault B+ [0 0 0 1 0]	$9.288x10^{-4}$ 0.093%	$6.929x10^{-5}$ 0.00693%	$1.696x10^{-3}$ 0.169%	$9.989x10^{-1}$ 99.89%	$3.476x10^{-5}$ 0.0035%
Fault B- [0 0 0 0 1]	$6.631x10^{-4}$ 0.066%	$7.386x10^{-4}$ 0.074%	$1.518x10^{-3}$ 0.152%	$1.218x10^{-3}$ 0.122%	$9.997x10^{-1}$ 99.97%

TABLE III
CONFUSION TABLE FOR DIFFERENT OPERATION DATA SET (m_a=1)

	Actual Data				
Classification	Normal	Fault A+	Fault A-	Fault B+	Fault B-
Normal	95.40%	4.05%	0.098%	1.094%	0.358%
Fault A+	2.28%	75.94%	0.41%	15.08%	1.81%
Fault A-	0.29%	3.03%	84.29%	2.16%	10.24%
Fault B+	2.28%	0.36%	2.69%	78.89%	0.76%
Fault B-	0.25%	16.74%	12.52%	2.77%	86.83%

Clearly, each network has classification performance of more than 98%; therefore, the classification performance of the network is quite satisfactory in the first category.

Second, the new testing data are simulated at different operating points by changing the modulation index (m_a) from 0.8 to 1.0. The new testing data set, at a unity modulation index, is transferred to the neural networks. In the MLID application, the modulation index is dependent on the operation point of the induction motor. Therefore, it would be better if the networks have good classification performance for a wide range of operation. The second category testing results are illustrated in Table III. Obviously, the classification performance between normal and abnormal conditions is about 90 %, which is very good performance, whereas the classification performance among fault features is about 85 % in Fault A- and B- and about 75% in Fault A+ and B+ (The proposed network misclassified only 1 out of 4 test sets). It should be noted that the future classification performance is important for the application. The classification performance among fault occurrences is acceptable. The neural network can be trained with a larger, more complete fault data set to get more accurate classification results.

As shown in Table III, the classification performance decreases when the operation point of MLID is changed. This suggests that an additional training set, or more training data, may be needed to train the fault classification neural network especially in Fault A+ and Fault B+ training set. Also, a better data transformation technique may be required; however, the time-consuming process for feature extraction should be considered in order to implement it in an on-line fault diagnosis system. On-line fault diagnosis with a wide range operation due to desired modulation index is important in MLID. Although the classification performance decreases when the operating point is changed, the classification performance of the proposed network is adequate to classify the fault's occurrence with its location.

V. Conclusions

A study of a fault diagnosis system in a multilevel inverter using neural networks has been proposed. The feature extraction system has been discussed. An FFT technique is utilized to transform output voltage signals in order to rate the signal value as an important characteristic for classifying a fault hypothesis. FFT has an advantage in that less time is needed to calculate this signal transformation process, and it is possible to implement with a digital signal processing microchip. The feature extraction system is an important process because bad transformation signals will lead to poor classification performance. A study suggests that the feature extraction is a challenging research topic.

The proposed networks perform very well with the selected testing data set. The classification performance is very high, more than 98%. Obviously, the classification performance between normal and abnormal condition is quite satisfactory in both testing categories; whereas, the classification performance among fault features is acceptable in the second category. The classification performance decreases when the operating point of the MLID is different from the training set. The results tell us that a new training set, or more training data, may be needed to accomplish a wide range of operation.

Although the classification performance decreases when the operating point is changed, the overall classification performance of the proposed fault diagnosis system is acceptable**.** The proposed networks have the ability to classify normal and abnormal conditions, including the fault location. Therefore, by utilizing the proposed neural network fault diagnosis system in this research, a better understanding of fault behaviors, diagnostics, and detections for multilevel inverter drive systems can be achieved.

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