Fault Diagnosis System for a Multilevel Inverter Using a Principal Component Neural Network

Surin Khomfoi
The University of Tennessee
Electrical and Computer Engineering
414 Ferris Hall, Knoxville, TN 37996-2100, USA
Email: surin@utk.edu

Leon M. Tolbert
The University of Tennessee
Electrical and Computer Engineering
414 Ferris Hall, Knoxville, TN 37996-2100, USA
Email: tolbert@utk.edu

Abstract— A **fault diagnosis system in a multilevel-inverter using a compact neural network is proposed in this paper. 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. Multilayer perceptron (MLP) networks are used to identify the type and location of occurring faults from inverter output voltage measurement. The neural network design process is clearly described. The principal component analysis (PCA) is utilized to reduce the neural network input size. A lower dimensional input space will also usually reduce the time necessary to train a neural network, and the reduced noise may improve the mapping performance. The comparison between MLP neural network (NN) and PC neural network (PC-NN) are performed. Both proposed networks are evaluated with simulation test set and experimental test set. The PC-NN has improved overall classification performance from NN by about 5% points. The overall classification performance of the proposed networks is more than 90%. 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 — **Fault diagnosis, multilevel inverter, principal component, neural network**.

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. Two topologies of multilevel inverters for electric drive application have been discussed in [1]. The cascade MLID is a general fit for large automotive all-electric drives because of the high VA rating possible and because it uses several level dc voltage sources which would be available from batteries or fuel cells [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.

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]. The possibilities offered by a neural network for fault diagnosis and system identification are investigated in [7]. Furthermore, a new topology with fault-tolerant ability that improves the reliability of multilevel converters is proposed in [8]. A method for operating cascaded multilevel inverters when one or more power H-bridge cells are damaged has been proposed in [9]. The method is based on the use of additional magnetic contactors in each power H-bridge cell to bypass the faulty cell. One can see from the literature survey that 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 that only requires measurement of the MLID's voltage waveforms.

An example of a MLID 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 in this state 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 a balanced condition at reduced power after the fault occurs until the operator identifies and replaces the failed 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 a 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 [10]. Then, the PCA is performed to reduce the input neural size [11-12]. The signal feature extraction is discussed, and the process of neural network design is fully described.

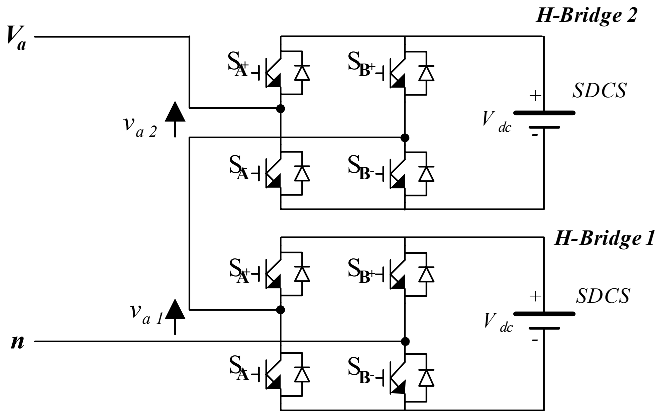


Fig. 1. Single-phase multilevel-inverter system

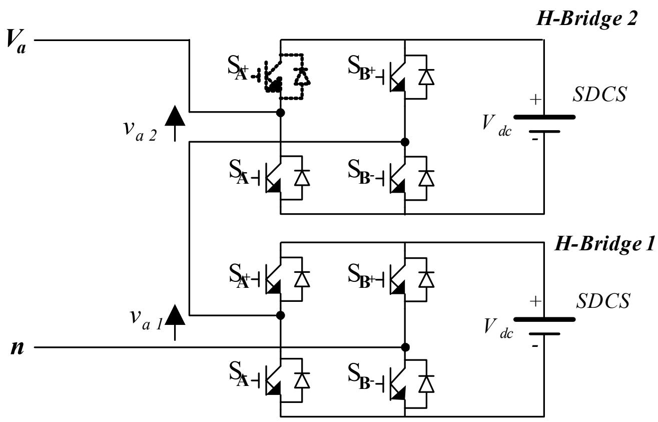


Fig. 2. H-Bridge 2, Switch S_{A+} open circuit fault at second level of single-phase multilevel-inverter.

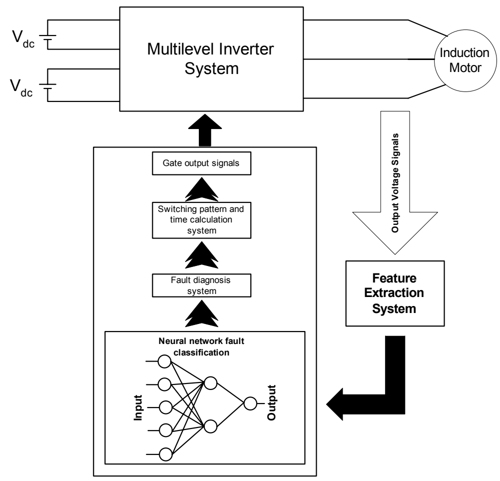


Fig. 3. Structure of fault diagnosis system.

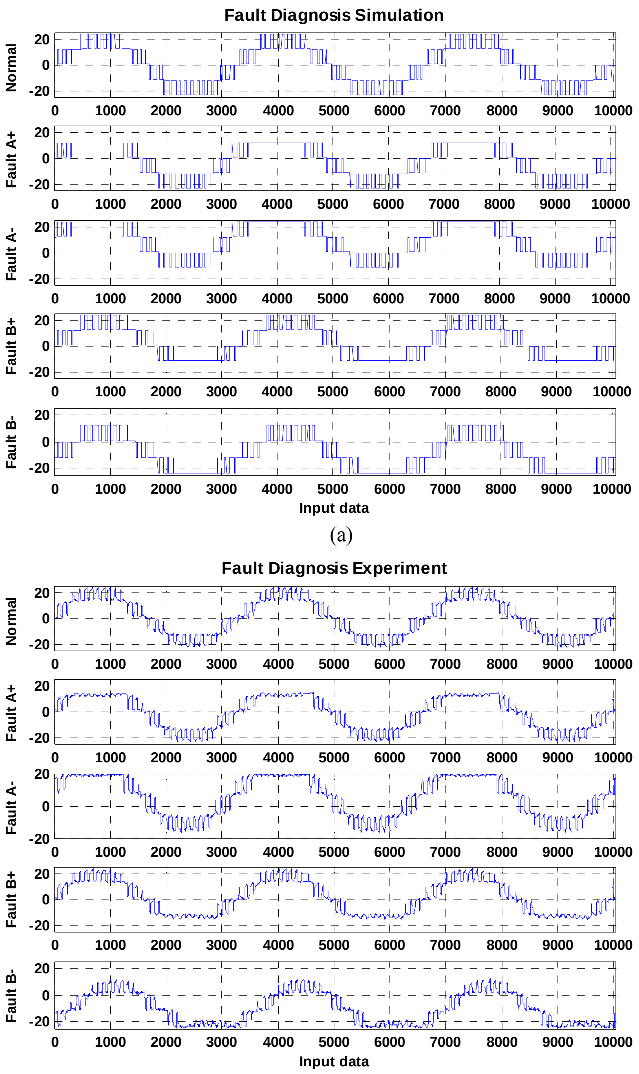
II. Fault Diagnosis System

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 to reconfigure the MLID to bypass the failed level.

B. Feature Extraction System and Principal Component Analysis

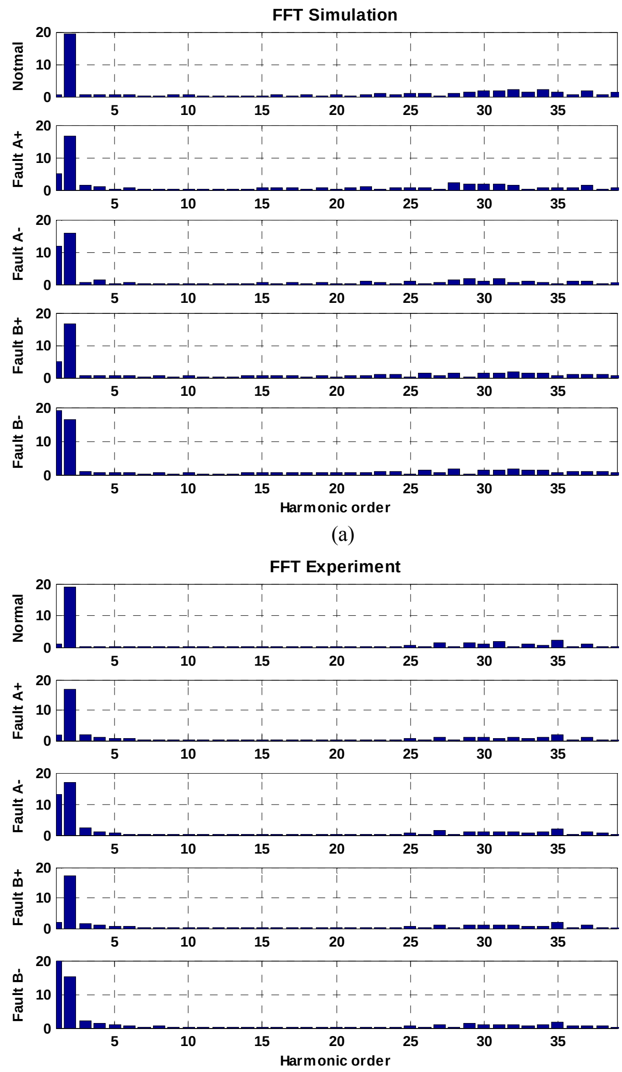
Simulated and experimental output voltages are illustrated in Fig. 4. As can be seen, the signals are difficult to rate as an important characteristic for classifying a fault hypothesis, and they have high correlation with each other. Therefore, a signal transformation technique is needed. The transformed signals using FFT of both simulation and experiment are represented in Fig. 5. Obviously, the results are satisfactory for identifying fault features. The FFT technique has a good identity feature to classify normal and abnormal features. However, many neurons are used to train the network (i.e. one neuron for each harmonic); therefore, PCA is used to reduce the number of input neurons as illustrated in Fig. 6. PCA is a method used to reduce the dimensionality of an input space without losing a significant amount of information (variability) [13]. The method also makes the transformed vectors orthogonal and uncorrelated. A lower dimensional input space will also usually reduce the time necessary to train a neural network, and the reduced noise (by keeping only valuable PCs) may improve the mapping performance. The detail of PCA and neural network design will be discussed in the next section.



(a)

(b)

Fig. 4. (a) Simulation and (b) experimental results 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.



(a)

(b)

Fig. 5. Signal transformation of (a) simulation and (b) experiment of output voltages by using FFT with modulation index = 0.8 out of 1.0.

C. Experimental Setup

The experiment setup is represented in Fig. 7. A three-phase wye-connected cascaded multilevel inverter using 100 V, 70 A MOSFETs as the switching devices was used to produce the output voltage signals. The Opal RT-Lab system 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 separated individual 12-volt dc power supply is supplied to each H-Bridge inverter in both simulation and experiment.

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. The voltage spectrum is calculated and transferred to the neural network fault classification system.

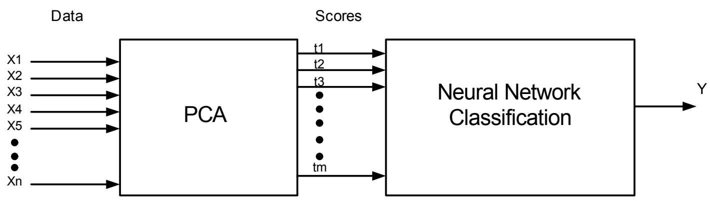


Fig. 6. Principle Component Neural Network

III. Principal Component Analysis (PCA)

Basically, 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. A distinguished introduction and application of PCA has been provided by [14]. Also, PCA technique is possible to implement on floating point DSP for real-time applications as proposed in [15].

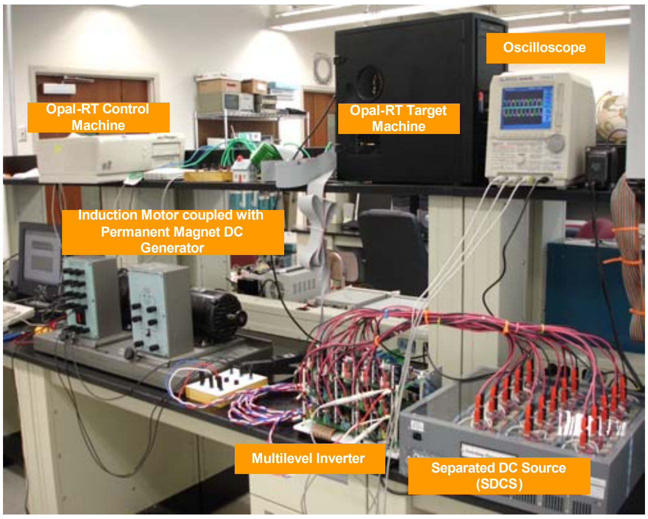


Fig. 7. Experiment setup.

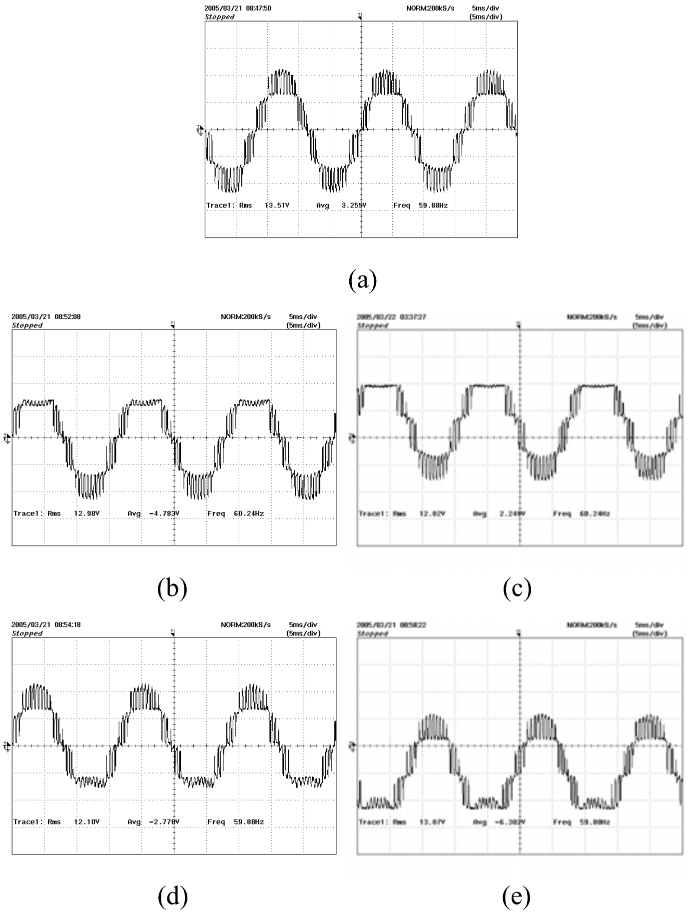


Fig. 8. Experiment of fault features at (a) normal, (b) S_{A+} fault, (c) S_{A-} fault, (d) S_{B+} fault, and (e) S_{B-} fault of H-bridge 2 with modulation index = 0.8 out of 1.0.

The discussion of PCA presented in this section will be brief, providing only indispensable equations to elucidate the fundamental PCA approach applied to a fault diagnosis system in MLID. The fundamental PCA used in a linear transformation is illustrated in (1). The original data matrix, $\boldsymbol{X}$ of n variables (harmonic orders) and m observations (different modulation indices of output voltage of MLID) is transformed to a new set of orthogonal principal components (PC), $\boldsymbol{T}$, of equivalent dimension $(m \times k)$ as represented in (2). The transformation is performed such that the direction of first PC is identified to capture the maximum variation of the original data set. The subsequent PCs are associated with the variance of original data set in order; for instance, second PC indicates the second highest variance of the original data set, and likewise.

$$T = XP \tag{1}$$

where:

$\boldsymbol{T}$ is the $m \times k$ score matrix (transformed data)
m = the number of observations
k = dimensionality of the PC space
$\boldsymbol{X}$ is the $m \times n$ data matrix.
m = the number of observations
n = dimensionality of original space
$\boldsymbol{P}$ is the $n \times k$ loadings matrix (PC coordinates)
n = dimensionality of original space
k = number of the PCs kept in the model

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

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

Selecting a reduced subset (PCs kept in the model) of PC space results in a reduced dimension structure with respect to the important information available as shown in (3). The objective of PC selection is not only to reduce the dimension structure, but also to keep the valuable components. Normally, high variance components could contain related information, whereas small variance components that are not retained are expected to contain unrelated information; for instance, measurement noise. It should be noted that the high variance components may not contain the useful information for a classification problem.

IV. Principal Component Neural Network Methodology

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. 4, 5, and 8. As mentioned before, a systematic mathematical technique may be complicated to implement in the practical real time control system; therefore, a feed forward neural network technique permitting input/output mapping with a nonlinear relationship between nodes will be utilized [11]. 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 [7]. The fault diagnosis of MLID using a neural network has been proposed in [16]. The proposed network in [16] has many input neurons, which could consume significant time to train the network. Therefore, principle component analysis (PCA) is used to reduce the dimension of input space. The stages of principle component neural network fault classification are explained in the following.

A. Data Analysis

The data from the FFT are transformed to principle component space by using MATLAB statistic toolbox function, *[PC, Latent, Explained]=PCACOV(XC)*; *PC* is the principal component loading matrix, *Latent* is the eigenvalues of the covariance matrix of the original input data (*XC*), and *Explained* is the vector of variance in each PC. The relationship of principal components and their cumulative percentage variance explained are illustrated in Fig. 9. As can be seen, the summation of the first 15 PCs contains about 90% of the data. However, the eigenvalues of the 14th, 15th and other PCs are less than 1; this means the PCs have less variance than the original data which might contain measurement noise or uncorrelated information. We can see from the plot in Fig. 9 that the break is between 5 and 8 PCs; therefore, a study suggests that 5 or 8 PCs should be the optimum model.

The collected data from both simulation and experiment are analyzed to select valuable PCs for fault classification. The transformation matrix (Loading) for important PCs and the scores of samples of PCs are shown in Fig. 10. The first 5 samples are normal condition, the next 5 samples are Fault A+, the next 5 samples are Fault A-, the next 5 samples are Fault B+, and the next 5 samples are Fault B-. The next 25 samples are unknown samples for testing the proposed neural networks. Clearly, the first PC can be used to distinguish between normal and fault conditions. We can see that the first 5 samples have positive scores, whereas the next 15 samples have mostly negative scores. We also see that the first PCs are weighted negatively toward most of the samples.

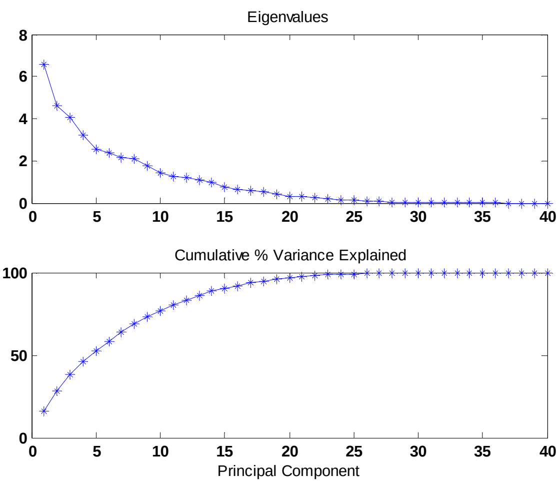


Fig. 9. The plot of principal components versus eigenvalues.

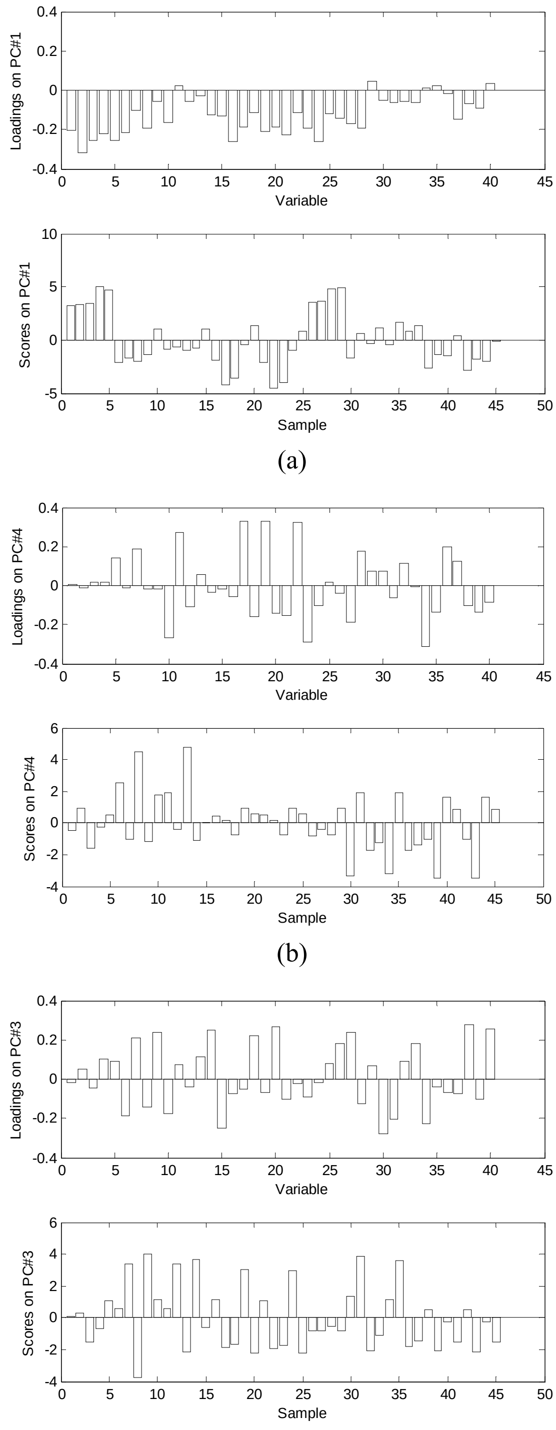


Fig. 10. The selected plot of principal components score and loading; (a) first PC, (b) fourth PC, and (c) third PC

Also, the 4th PC can be used to classify the different features between Fault A+ and A- and Fault B+ and B-. However, the 3rd PC may not be useful because the 3rd PC could not reveal any classification information as shown in Fig. 10 (c), although it contains more information and variance (Eigenvalue) than the 4th. Therefore, in this research, the combination of 1, 2, 4, 6 and 8 principal components are used to perform the neural network classifications. The 3-D plots of PC scores are shown in Fig. 11. We can see that the classification between normal and faults could be a linear problem, whereas the classification among faults is a nonlinear problem. That is why the neural network is applied to solve this problem. By using PCA, the size of input neurons can be reduced from 40 nodes to 5 nodes. (i.e. 5 harmonics instead of 40 harmonic components)

B. Neural Network Architecture Design

The multilayer feed forward networks, or MLP, are used in this research with two different neural networks (NN). The first NN architecture has one hidden layer with 40 input nodes, 4 hidden nodes, and 3 output nodes as proposed in [16]. The original data from the feature extraction system (FFT) is used in this network. The second NN architecture has one hidden layer with 5 input nodes, 3 hidden nodes, and 3 output nodes. The PCA is applied in this network to reduce the number of input neurons. The sigmoid activation function is used in both NNs: *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 [11, 16].

C. Input/Output Data

The set of original input data at each MLID operation contains 5 classes: a normal data (normal condition) and four abnormal data (Fault A+ A- B+ B-). The MLID operation will be changed with desired load, so modulation index must be changed. In this research, modulation indices are varied from 0.6 to 1 with 0.05 intervals. Therefore, the original data contains 45 observers covering all possible operations. The output target nodes are coded with a binary code as shown in the Table I. The *round ( )* function is used to make the binary code outputs for the test sets.

D. Neural Network Training

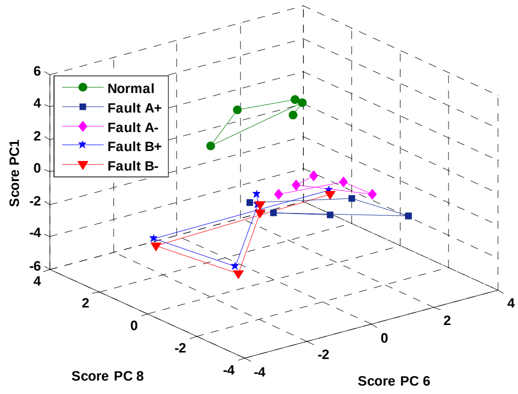
The Levenberg Marquardt training paradigm, *trainlm* is utilized in this research because *trainlm* not only performs very fast training time but also has inherent regularization properties [11]. Regularization is a technique which adds constraints so that the results are more consistent. The 1% misclassification and 1% input data error rate are chosen to calculate a sum of square error goal, SSE; therefore, a SSE < 0.025 goal is used to train the network by calculating from (4). The training process will be finished when the SSE goal is met.

$$SSE = \sum_{i=1}^{n} \left(y - \bar{y}_i \right)^2 \qquad (4)$$

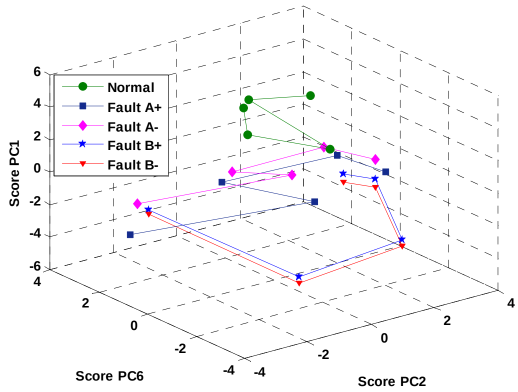
where y is the output target binary codes,
$\bar{y}_i$ is output of training data,
n is the number of training data,

E. Training and Testing Data Set Selection

The training data set should also cover the operating region, thus the training set is generated from simulation with various operation points (different modulation indices, 0.6, 0.7, 0.8, 0.9 and 1). The testing sets have two different sources: first, the test set is generated from simulation with modulation indices, 0.65, 0.75, 0.85, and 0.95.



(a)



(b)

Fig. 11. The 3-D plots of PC scores; (a) score on PC 6, 8, 1, (b) score on PC 2, 6, 1.

Second, the test set is measured from experiment at different modulation indices of 0.7, 0.8, 0.9, and 1 as shown in Fig. 5(b) and 8. 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. Again, it should be noted that each modulation index has 5 classifications: normal, Fault A+, A-, B+ and B-. The test sets are used to examine the neural network classification performance. It should be noted that the input training and testing data are scaled by using the mean center and unit variance method as explained in [16].

V. Fault Classification Results

The performance of the proposed networks is tested in two categories. First, the networks are tested with the simulation test sets as previously mentioned. Second, the networks are evaluated with the experimental test set. The tested results along with the testing data sets are illustrated in Table I. Clearly, in the simulation test set, both NN and PC-NN have a good classification performance (about 95%); therefore, the classification performance of the networks is quite satisfactory. The misclassification samples are the same operation point and class which are 0.65 modulation index and fault B-. This result suggests that both networks have confusion between Fault A- and Fault B- at low modulation index.

TABLE I
CONFUSION TABLE FOR MLID H-BRIDGE

Testing set	Target	Actual Output		% Classification	
		NN	PC-NN	NN	PC-NN
Simulation test set	Normal [1 1 1]	1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1	100%	100%
	Fault A+ [0 0 1]	0 0 1 0 0 1 0 0 1 0 0 1	0 0 1 0 0 1 0 0 1 0 0 1	100%	100%
	Fault A- [0 1 0]	0 1 0 0 1 0 0 1 0 0 1 0	0 1 0 0 1 0 0 1 0 0 1 0	100%	100%
	Fault B+ [1 0 1]	1 0 1 1 0 1 1 0 1 1 0 1	1 0 1 1 0 1 1 0 1 1 0 1	100%	100%
	Fault B- [1 1 0]	1 1 0 1 1 0 1 1 0 0 1 0	1 1 0 1 1 0 1 1 0 0 1 0	75%	75%
% Classification performance in simulation test set				95%	95%
Experimental test set	Normal [1 1 1]	1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1	100%	100%
	Fault A+ [0 0 1]	0 1 1 0 1 1 0 1 1 0 1 0	0 0 1 0 0 1 0 0 1 0 0 1	75%	100%
	Fault A- [0 1 0]	0 1 0 0 1 0 0 1 0 0 0 1	0 1 0 0 1 0 0 1 0 0 1 0	75%	100%
	Fault B+ [1 0 1]	1 0 1 1 0 1 1 0 1 1 0 1	1 0 1 1 0 1 1 0 1 1 0 1	100%	100%
	Fault B- [1 1 0]	1 1 0 1 1 0 1 1 0 0 1 0	1 1 0 1 1 0 1 1 0 0 1 0	75%	75%
%Classification performance in experimental test set				85%	95%
Total %Classification performance				90%	95%

The second category of testing results is also illustrated in Table I. Obviously, the classification performance of PC-NN is better than NN by 10% points. The NN has 85 % classification performance, whereas the PC-NN has 95% classification performance. As expected, PCA conveys lower dimensional input space, reducing the time necessary to train a neural network. Also, the reduced noise could improve the mapping performance which leads to the improvement of total classification performance. Obviously, PC-NN has a better overall classification performance of about 5% points. Again, the misclassification samples are mainly at 0.65 modulation index. A study suggests that a new training set, or more training data, may be needed to accomplish a wide range of operation and also a better data transformation technique may be required. Although the classification performance decreases at the lower operating point, the classification performance of the proposed networks is acceptable.

VI. CONCLUSIONS

A fault diagnosis system in a multilevel inverter using neural networks has been proposed. The proposed networks perform very well with both simulation and experimental testing data set. It should be noted that the test sets are not the same as the training sets. The test sets should be data that the networks have not ever seen before. The classification performance is very good, more than 90%. Obviously, the results show that the PCA conveys lower dimensional input space and reduces the time necessary to train a neural network. Also, the reduced noise may improve the mapping performance which leads to the total classification performance. PC-NN has a better overall classification performance by about 5% points.

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