Neural Network Based Expert System for Induction Motor Faults Detection

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Early detection and diagnosis of incipient induction machine faults increases machinery availability, reduces consequential damage, and improves operational efficiency. However, fault detection using analytical methods is not always possible because it requires perfect knowledge of a process model. This paper proposes a neural network based expert system for diagnosing problems with induction motors using vibration analysis. The short-time Fourier transform (STFT) is used to process the quasi-steady vibration signals, and the neural network is trained and tested using the vibration spectra. The efficiency of the developed neural network expert system is evaluated. The results show that a neural network expert system can be developed based on vibration measurements acquired on-line from the machine.

Key Words : Vibration Signal, Neural Network, Fault Detection, Expert System

1. Introduction

Induction machines make up the majority of industrial prime movers and are popular for their reliability and simplicity of construction. However, many electrical machine components are susceptible to failure. In general, fault detection in induction motors has concentrated on sensing failures in one of the three major components : the stator, rotor, and bearings (Tavner and Penman, 1987). Long-term disruption of the operation of industrial plants causes large economic losses. Therefore, for both safety and economic considerations, it is necessary to monitor the behavior of motors working in critical production processes. Detection of incipient faults allows preventative maintenance to be scheduled for machines that might not ordinarily be due for service and can prevent an extended period of downtime caused by extensive motor failure. For this reason, rapid fault detection and location are very significant in industrial practice (Eisenmann and Eisenmann, 1997 ; Vas, 1999).

Practical condition monitoring techniques for three-phase induction motors generally involve some combination of mechanical and electrical monitoring. Although electrical sensing with an emphasis on analyzing the motor stator current is used widely, vibration-based condition monitoring has attracted the attention of many researchers working on induction machines and has gained industrial acceptance, as vibration analysis techniques are quite effective in assessing the health of a machine (Riley et al., 1998 ; Ob et al., 2004). It has been claimed that vibration monitoring is the most reliable method of assessing the overall health of a rotor system (Lagan, 1999).

Fault detection systems use different procedures

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in the diagnostic process, starting from heuristic knowledge, and include mathematical models and artificial intelligence methods (Oh et al., 2004). Motor operations can be diagnosed using different elements of the knowledge base, including analytical methods, support vector machines (Yang et al., 2004), expert systems (Yoon et al., 1995), and neural networks or fuzzy logic reasoning. Fault detection using analytical methods is not always possible because it requires perfect knowledge of a process model. With an insufficient or imprecise model, false alarms can occur due to errors estimating the state variables or process parameters of the system (Vas, 1993, 1999). Human knowledge and experience are much easier to apply ; automatic realization is difficult.

The recent success of neural networks for modeling highly complex systems implies their potential in the development of an automatic expert system for diagnosing induction machines (Choi, 1996 ; Atiya and Palos, 2000). A neural network can represent any nonlinear system without knowledge of its actual structure and can provide results quickly during the recall phase. This paper presents a neural network based expert system that uses vibration sensors to diagnose problems with induction motors. The short-time Fourier transform (STFT) is used to process the quasi-steady vibration signals, and the neural network is trained and tested using the vibration spectra. The effectiveness of the developed neural network expert system was evaluated. The results demonstrate that it is a practical on-line fault detection system.

Following this introduction, Section 2 briefly describes the basic principles of neural network applications in fault detection. Section 3 presents the detailed procedures used to develop a neural network based expert system and Section 4 presents the experimental results obtained when an induction motor was tested. Finally, Section 5 presents a summary and the conclusions drawn from this study.

2. Neural Network Applications in a Fault Detection System

During the operation of induction motors, different faults can arise in the electrical and mechanical parts of the stator and rotor, as well as in the loading machine and coupled devices. The possibility of detecting incipient faults in electrical, magnetic, and mechanical motor parts has recently become one of the most important problems in induction motor research (Eisenmann and Eisenmann, 1997 ; Vas, 1999).

There are several methods for detecting, classifying, and locating induction motor faults. Analytical methods use deterministic and stochastic mathematical models for particular faults, heuristic reasoning based on expert knowledge and experience, and new techniques such as artificial intelligence, especially neural networks. Fault detection systems based on mathematical models usually require good knowledge of the physical phenomena of the plant and lead to very complicated software. The main principal of methods based on mathematical models lies in fault determination based on a comparison of the mathematical model and expert knowledge of the operation states of the plant. Heuristic reasoning requires an expert presence to perform any diagnostic task. Therefore, these two methods are very dependent on the adequacy of the mathematical model, measurement errors, and expert knowledge. Connecting knowledge based on analytical mathematical models and heuristic knowledge, which is realized in expert systems, enables significantly greater diagnostic efficiency. However, the need for a human expert is the main disadvantage of these methods. The shortage of skilled personnel has prompted research into automated on-site processing and the diagnosis of vibration measurements (Harris, 1991).

The introduction of artificial intelligence methods, especially the neural network approach, has eliminated these disadvantages. A neural network can represent any nonlinear system without knowledge of its actual structure. Intensive research has recently examined the application of neural networks to motor system diagnosis (Tahk and Shin, 2002) ; they are used as neural fault detectors and classifiers for electrical machines.

The strategy of a neural network based expert system involves identifying fault conditions based

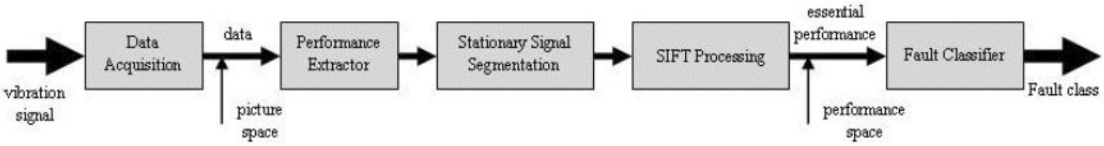

Fig. 1 Neural network based expert system

on vibration analysis and incorporating neural networks to model the status of fault conditions. The proposed neural network based expert system for monitoring technical plant involves designing a neural classifier for the states of the plant based on recorded and current measurement data. Since the state of the plant can be treated as a specific picture of the plant, characterized by a set of input/output signals, the diagnosis problem involves recognizing and classifying patterns. Neural network classifiers, with nonlinear feature mapping using sigmoidal basis functions, can identify multiple faults in vibration signal analysis (Chow, 1997). The main aim of such classifiers is to allocate the state of the motor to a previously determined fault category. Figure 1 is a schematic diagram of the neural network based expert system.

The data-acquisition system samples vibration signals and changes the recognized motor pictures into useful signals for conversion by a performance extractor, segmentation, and STFT processing modules. The main task of the extractor is filtering and scaling. In general, the measured motor vibration signals are highly non-stationary. A quasi-steady signal can be obtained using segmentation. Then, STFT is used to process the quasi-steady signals by windowing the signal using a shifted-window function (Mohanti, 1987). The converted vibration spectra are treated as specific motor pictures for the neural network classifier to decide the status of the motor, as vibration spectra provide a useful feature set for machine diagnostics (Harris, 1991). The design of a neural network classifier for an expert system is connected to the choice of neural network and the structure and determination of its weight coefficients in a suitable training procedure. The following section presents the design procedure for a neural network based expert system for detecting induction motor faults, and its training procedure.

3. Design Procedure for the Proposed Expert System

3.1 Quasi-steady segmentation and spectra conversion

Most features used in fault detection assume the presence of a stationary signal from which fault features are extracted, such as the mean, variance, or spectral estimates (Kim and Parlos, 2003a). However, the vibration signals of a motor are highly non-stationary, and contain both transient signals, resulting from start up conditions and varying loads, and steady-state signals.

Therefore, to obtain high-performance motor features that are not influenced by fast time-varying machine characteristics, the motor signature must be extracted from non-stationary vibration signals. In a recent paper (Kim and Parlos, 2003b), the authors derived a segmentation algorithm that could be applied to current measurements for the stator. The idea underlying signal segmentation is that for a signal to be considered stationary, it's fundamental and harmonics must remain constant over time. Since transient signals result in changes in the motor vibration signal harmonics, which are significantly smaller than the fundamental, a statistical method is used to process the vibration signal in the time domain. The RMS values for the vibration signals are calculated over the window defined by the STFT. If the RMS value at successive windows does not vary, then the signal is considered stationary. The equations are as follows :

$$V_{rms}(i) = \sqrt{\frac{1}{N_W}\sum_{j=1}^{N_W} V^2(j)} \tag{1}$$

$$|V_{rms}(i+1) - V_{rms}(i)| < \beta \quad i=1, 2, \cdots, n \tag{2}$$

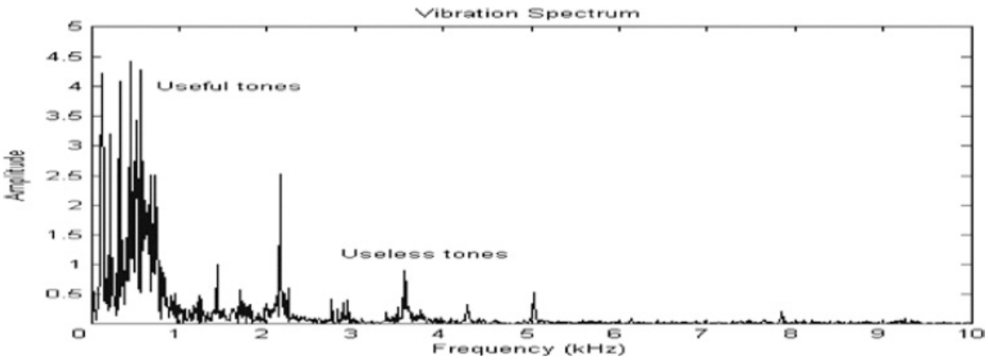

Fig. 2 Vibration spectrum in normal condition

where $V_{rms}(i)$ is the RMS value of the vibration signal in each window, N_W is the window size, β is a user-defined threshold, and n is the total number of windows in the signal. The comparison is made throughout the signal. If this algorithm does not result in the selection of quasi-steady segments, then the threshold can be increased.

The measured spectrum, shown in Fig. 2, has tones up to 10 kHz. A reported theoretical analysis applied to the motor under test suggests that the faults considered give rise to additional meaningful tones not higher than 1 kHz (Betta et al., 2002). Therefore, to improve the computational speed and reduce the network size, the quasi-steady signal is filtered through the performance extractor module.

3.2 Neural network classifier development

Due to the random nature of the vibration signal, explicit fault classifiers cannot be developed using conventional methods. It is difficult to establish an exact mathematical formulation that describes the relationships between machine faults and the vibration harmonics generated. Therefore, a neural network classifier can be achieved more efficiently, since a neural network is a nonlinear empirical model that can capture the nonlinear system dynamics and does not require knowledge of specific system parameters (Gao and Ovaska, 2000).

The application of neural network techniques to modeling or classification problems generally proceeds systematically. First, we start with a reduced classification problem, with each class representing a well-defined fault condition, and then increase the number of classes as additional data become available. Second, we indicate class membership using an associated output value for the corresponding neural network classifier output, and these outputs can be used to indicate the severity of the presence of a condition, on a continuous scale. In this study, the neural network classifier was trained to distinguish between three classes: normal, an air-gap eccentricity fault, and a broken rotor bar fault.

3.2.1 Neural network classifier formulation

In this study, we use a multi-layer perceptron neural network that undergoes supervised learning to classify motor conditions. The structure of the neural network classifier is shown in Fig. 3; it consists of an input layer, a hidden layer, and an output layer. Each of the processing elements of a neural network is governed by the following equation:

$$x_{[l,i]}=\sigma_{[l,i]}\left(\sum_{j=1}^{N_{[l-1]}}\omega_{[l-1,j][l,i]}x_{[l-1,j]}+b_{[l,i]}\right) \quad (3)$$

for $i=l, \cdots, N_{[l]}$ (the node index), and $l=1, \cdots, L$ (the layer index), where $x_{[l,i]}$ is the i^{th} node output of the l^{th} layer for sample t, $\omega_{[l-1,j][l,i]}$ is the weight, the adjustable parameter, connecting the j^{th} node of the $(l-1)^{th}$ layer to the i^{th} node of the l^{th} layer, $b_{[l,i]}$ is the bias, which is also an adjustable parameter, of the i^{th} node in the l^{th} layer, and $\sigma_{[l,i]}(\cdot)$ is the discriminatory function of the i^{th} node in the l^{th} layer.

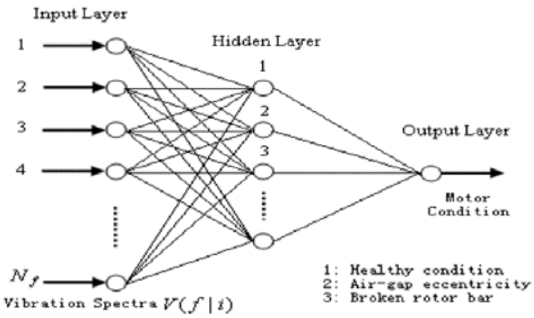

Fig. 3 Structure of neural network classifier

The relation between input and output in a multi-layer neural network can be expressed using general nonlinear input-output models, as follows:

$$\hat{y}(W) = f(u(k);\ W) \tag{4}$$

where W is a weight matrix that is determined by the learning algorithm, and f represents the nonlinear transformation of the input approximated by a neural network; a hyperbolic tangent function is used here. The input vector $u(k)$ is defined as:

$$u(k) = [V(k_1),\ \cdots,\ V(k_n)] \tag{5}$$

where $V(k_i)$ is the magnitude of the vibration spectrum for each window. The process that defines the weights using the training data is referred to as training the neural network.

3.2.2 Learning algorithms

Using the structure of Eq. (4), the neural network model is trained using the Levenberg-Marquardt (LM) algorithm. LM algorithm, which is based on the Gauss-Newton method, can solve the problems presented by the Steepest Descent and Newton methods dynamically. In this training phase, the error function to be minimized is given by,

$$\varepsilon = \sum_{t=0}^{NP-1} \sum_{k=1}^{n} [\hat{y}_k(t) - y_k(t)]^2 \tag{6}$$

where n is the number of outputs included in training, and NP is the number of training samples. The LM algorithm is designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares, then the Hessian matrix can be approximated as,

$$H = J^T J \tag{7}$$

and the gradient can be computed as,

$$g = J^T \varepsilon \tag{8}$$

where J is the Jacobian matrix that contains the first derivatives of the network errors with respect to the weights and biases, and ε is the network error. Then, the processing element is updated using,

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T \varepsilon \tag{9}$$

When the scalar μ is zero, this is simply Newton's method, using the approximate Hessian matrix. When μ is large, it becomes a gradient descent with a small step size. The detailed computation of the gradients involved in the LM learning algorithm can be found in many neural network references, such as Norgaard et al. (2000).

3.2.3 Model training and validation

The vibration signals form a multivariate feature space. The required number of training samples for a classifier generally increases exponentially with the number of features, assuming uncorrelated data (Chow et al., 1996). The frequency domain of the vibration signal provides a useful feature set for machine diagnostics. Most defects are related to specific frequency domain features (Harris, 1991; Taylor, 1994). For this paper, vibration spectra ranging from 0-1 kHz were used as features for the neural network classifier input, as shown in Fig. 4. The vibration signals were acquired continuously and converted. The vibration spectra for the healthy condition, air-gap eccentricity condition, and broken rotor bar condition are used for neural network classifier training and validation. The vibration spectrum after STFT processing is expressed as $V(f\,|\,i)$. where i is the index of windows in the training set. The designed multi-layer neural network is based on the multi-layer perceptron structure shown in Fig. 3, and consists of one hidden layer, one input layer, and one output

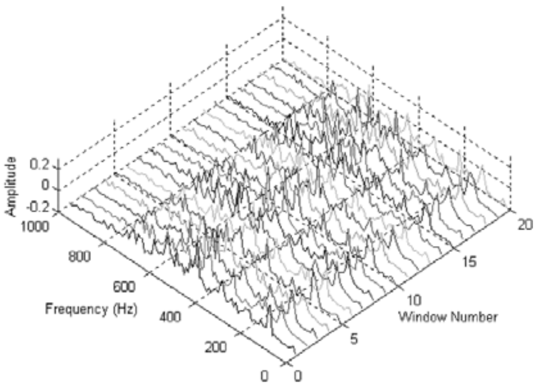

Fig. 4 Vibration spectra for neural network classifier input

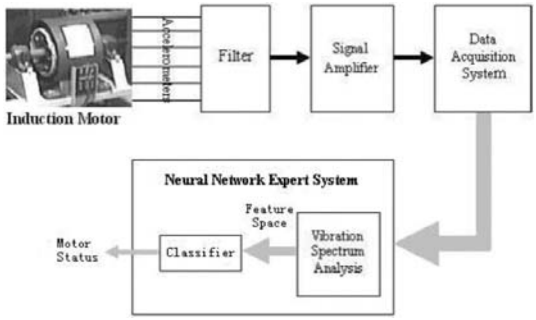

Fig. 5 Schematic of the experiment system

layer, both with N_f nodes, which are equal to the amplitude in the vibration spectrum. The classifier structure of the neural network was decided after various experiments, and the pruning method is also used.

Initially, in this study, the neural network classifier was developed for a 597-kW Allis Chalmers (AC) machine with training data representing several conditions, such as air-gap eccentricity and a broken rotor bar. After developing this baseline classifier, additional classes representing different motor faults can be added when additional data become available. The training dataset consists of 8,400 samples for estimation, and 1,200 samples for validation. The validation dataset is used to determine the best time to stop predictor training to prevent over training, and to select the neural network structure. In testing the performance of the developed neural network classifier, the classifier is evaluated in terms of its performance with test datasets.

4. Experimental Evaluation of the System

4.1 Experimental settings and data acquisition

To test the effectiveness of a neural network based expert system for detecting induction motor faults, it is necessary to investigate its performance under actual operating conditions. An experimental system was set up to collect the data needed for these experiments. To acquire the necessary digital data, various anomalies were introduced to a 3-ϕ, eight pole, 597 kW Allis Chalmers motor, and motor faults were staged.

The staged incipient faults included several mechanical faults, such as air-gap eccentricity and broken rotor bars, which are the most common motor faults (Albrecht et al., 1986; IAS, 1985). The results of a few of these anomalies and staged faults are presented here. The motor was run from the mains power supply directly. The motor was connected to dynamometers that were used to load it. A simplified schematic of the experimental system is shown in Fig. 5.

During the tests, accelerometers were placed both horizontally and vertically on the motor and used to acquire vibration signals. An IOTech data-acquisition system was used to record the vibration signals and the encoder speed signal at a 40-kHz sampling frequency. The vibration signals were filtered and down-sampled to 1,000 Hz for further processing. A wide range of case studies was collected for the motor, including healthy cases and cases with operational anomalies.

4.2 Results and analysis of the experiment

In this study, the vibration measured from the 597 kW Allis Chalmers motor represented three conditions: a healthy motor, an air-gap eccentricity, and a broken rotor bar. The first 10,000 samples for these three conditions are illustrated in Figs. 6~8, respectively. Figure 9 shows the magnitude of the RMS value for quasi-steady segmentation, which shows that quasi-steady vibra-

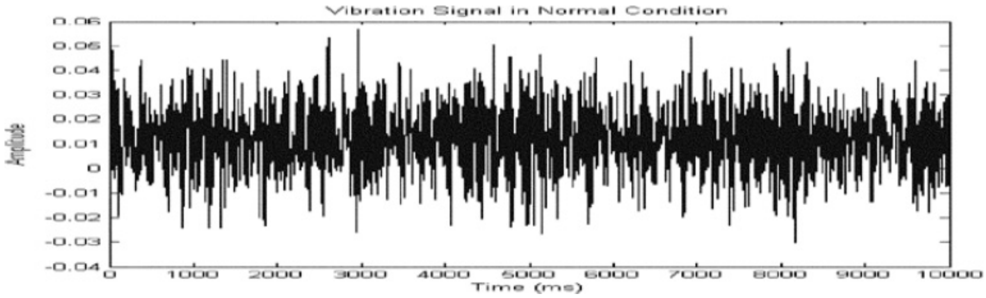

Fig. 6 Vibration signal under healthy condition

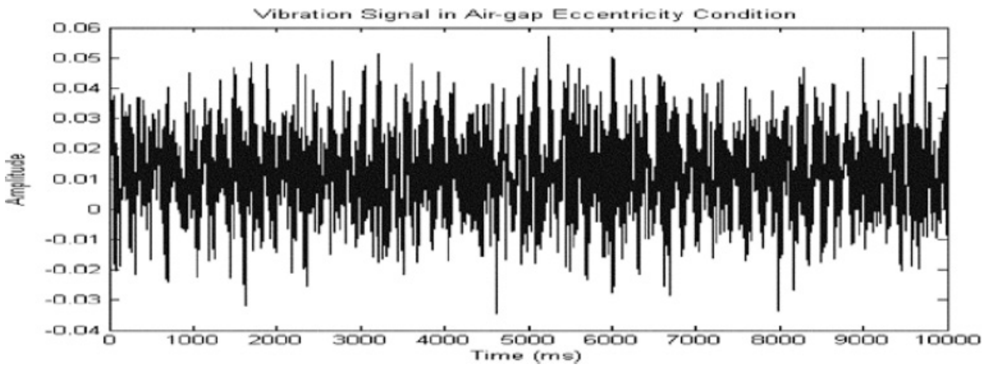

Fig. 7 Vibration signal under air-gap eccentricity condition

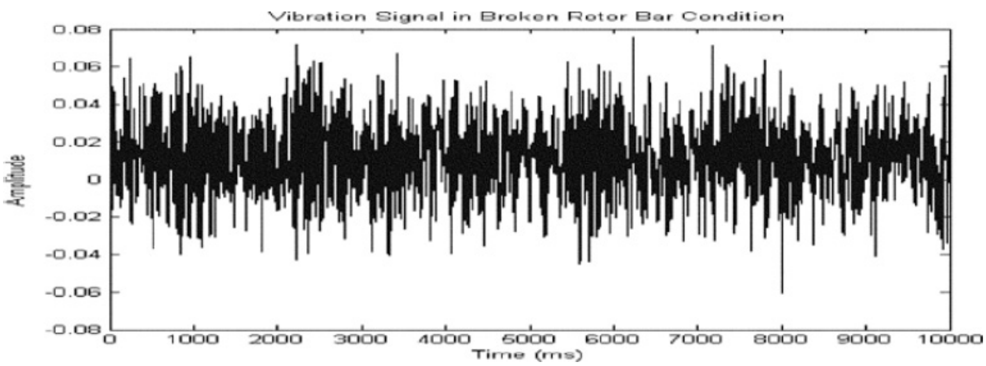

Fig. 8 Vibration signal under broken rotor bar condition

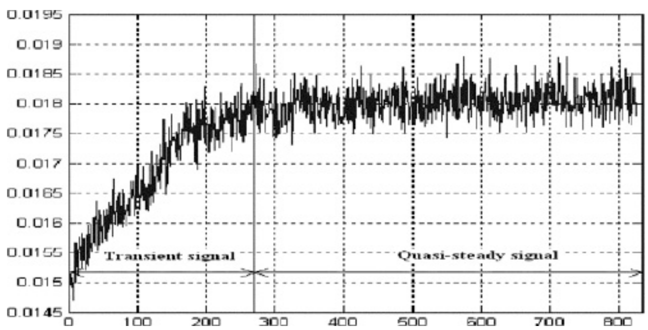

Fig. 9 RMS value of quasi-steady segmentation

Table 1 Training and test data sets

Training Data Set (Healthy)			Test Data Set (Healthy)		
Update	Condition	Samples	Update	Condition	Samples
Yes	Healthy	1200	No	Healthy	800
Yes	Air-gap eccentricity 1	1200	No	Air-gap eccentricity	800
Yes	Air-gap eccentricity 2	1200	No	Broken rotor bar	800
Yes	1/2 Broken rotor bar	1200	No	Multiple	800
Yes	One Broken rotor bar	1200	No	Multiple	800
Yes	Two Broken rotor bars	1200	No	Multiple	800
Yes	Four Broken rotor bars	1200	No	Multiple	800
No	Multiple	1200	No	Multiple	800

tion signals can be extracted from the start-up condition efficiently with the proper threshold. The training dataset used to develop the neural network classifier was divided into two separate datasets. The first dataset, containing 8,400 samples, was used for estimation, and the second set, containing 1,200 samples, was used for validation. Several additional datasets, each with 800 samples, were used to test the performance of the developed neural network classifier. The training and testing datasets used in the development of the neural network classifier are presented in Table 1.

Our neural network classifier has 15 hidden nodes and 1 output node. The number of hidden layer nodes was determined by trial and error. The mean-squared error (MSE) of neural networks with different numbers of hidden layer nodes after 400 iteration steps of training is compared in Table 2. The simplicity of the neural network is the main condition for the practical realization of such a neural network classifier using a digital signal processor. The training procedure for a neural network classifier with zero initial context node outputs using the LM algorithm is shown in Fig. 10. The vibration spectra were scaled in the range $[-0.5, 0.5]$ to avoid saturating the neural network nodes. To evaluate the accuracy of the developed neural network classifier, the maximum and mean model errors were used. In addition, the normalized mean-squared error (MSE) was also used. The test dataset comprised different measurements than those used in the training dataset. The performance evaluation for the test set is summarized in Table 3.

Table 2 Accuracy of the neural network with different numbers of hidden layer nodes

Node Number	3	5	9	13	15	17	20
MSE (%)	0.188	0.188	0.186	0.181	0.177	0.181	0.181

Table 3 Evaluation of neural network model accuracy

Test Set	MSE (%)	Max. Error (%)	Mean Error (%)
1	0.188	3.1	0.9
2	0.191	2.9	1.1
3	0.186	3.0	0.8
4	0.189	3.1	0.9

The motor condition is represented by the output states of a neuron in the output layer of the neural network classifier. For this expert system, these outputs are:

(1) for a healthy motor;
(2) for an air-gap eccentricity fault; and
(3) for a broken rotor bar.

Air-gap eccentricity is one of the main causes of induction motor failure, because eccentricities place excessive stress on the motor and greatly increase bearing wear. Here, two air-gap eccentricity tests were performed using the 597 kW motor. The first case involved moving the rotating center at the end of the inboard shaft 25% upward, and the second case involved moving the rotating center at the end of the outboard shaft 20% downward and 10% to the right. Following

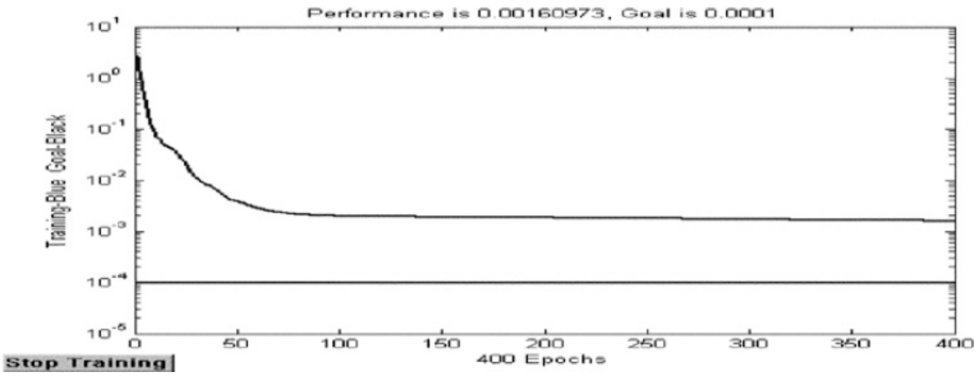

Fig. 10 Training procedure of neural network classifier using LM algorithm

Table 4 Test results for air-gap eccentricity faults

Healthy condition										
Motor status	1	1	1	1	1	1	1	1	1	1
NN output	1.029	0.97	0.956	1.052	0.935	1.137	1.012	1.023	1.033	0.895
Rounding output	1	1	1	1	1	1	1	1	1	1
Air-gap eccentricity fault condition 1										
Motor status	2	2	2	2	2	2	2	2	2	2
NN output	1.803	2.194	1.93	2.058	2.038	1.775	2.122	1.744	2.19	2.037
Rounding output	2	2	2	2	2	2	2	2	2	2
Air-gap eccentricity fault condition 2										
Motor status	2	2	2	2	2	2	2	2	2	2
NN output	2.108	2.311	1.922	2.102	2.105	2.034	2.752	2.098	2.124	1.94
Rounding output	2	2	2	2	2	2	3	2	2	2

data collection, down-sampling and scaling was performed. As the faults considered give rise to additional meaningful tones not higher than 1 kHz, the acquired signal was filtered (1 kHz cut-off) and down-sampled (decimation factor=4) to improve computation. The vibration signals were processed through the quasi-steady segmentation stage, revealing the quasi-steady motor operation signals. The test results of our expert system for detecting air-gap eccentricity faults are presented in Table 4. In this table, incorrect responses by the expert system are shown in bold numbers. The test results for both air-gap eccentricity cases indicate that the expert system can detect this type of fault almost without error.

Another major cause of motor problems is a broken rotor bar, which can cause asymmetry of the motor's magnetic field and lead to catastrophic failure. The effects of a broken rotor bar are very weak initially, and sensitive measurements are required to detect the damage. In this study, we tested four broken rotor bars of different severities. The four cases were one half-broken bar, one broken bar, two broken bars, and four broken bars. The measurements were further processed, as in the case of air-gap eccentricities, and the outputs of the neural network classifier were obtained. The test results of the expert system that was developed to detect broken rotor bar faults are presented in Table 5. The results show that the proposed expert system can effectively detect broken rotor bar faults of different levels of severity. As the number of broken bars increases, the fault condition becomes more severe, providing clearer features in the vibration spectrum for the neural network classifier, and making fault detection more accurate.

The proposed system was tested using 38 cases of staged fault data from the 597-kW Allis Chalmers motor. The analyzed cases included different mo-

Table 5 Test results for broken rotor bar faults

Healthy condition										
Motor status	1	1	1	1	1	1	1	1	1	1
NN output	1.194	0.974	1.173	1.206	0.953	0.926	0.913	1.126	1.007	1.19
Rounding output	1	1	1	1	1	1	1	1	1	1
1/2 Broken rotor bar condition										
Motor status	3	3	3	3	3	3	3	3	3	3
NN output	3.045	2.62	2.623	2.376	2.687	2.762	2.603	3.067	2.955	2.723
Rounding output	3	3	3	2	3	3	3	3	3	3
One Broken rotor bar condition										
Motor status	3	3	3	3	3	3	3	3	3	3
NN output	2.981	3.179	2.891	2.593	2.943	2.869	3.055	3.024	2.947	3.025
Rounding output	3	3	3	3	3	3	3	3	3	3
Two Broken rotor bars condition										
Motor status	3	3	3	3	3	3	3	3	3	3
NN output	2.989	2.991	3.041	2.962	3	3.002	3.052	3.101	3.159	3.032
Rounding output	3	3	3	3	3	3	3	3	3	3
Four Broken rotor bars condition										
Motor status	3	3	3	3	3	3	3	3	3	3
NN output	2.936	3.039	3.132	2.999	3.077	3.037	2.898	2.981	2.897	2.978
Rounding output	3	3	3	3	3	3	3	3	3	3

Table 6 Summary of analyzed staged fault experiments

Motor Condition	Number of Cases	Accuracy	Detailed Description
Healthy	12	98.86%	Balanced Supply
Air-Gap Eccentricity	9	97.43%	Offset of 25% Up Inboard, Offset of 20% Down 10% Right Outboard and 25% Up Inborad.
Broken Bars	17	97.75%	Half-broken Bar One Broken Bar Two Broken Bars Four Broken Bars
Number of Analyzed Faults	38	98.02%	

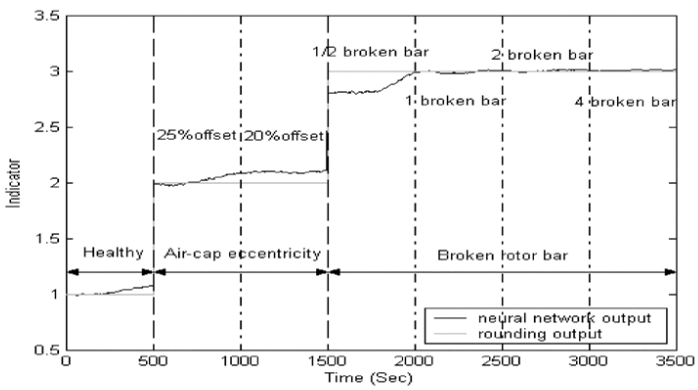

Fig. 11 Output of the neural network expert system under multiple conditions

tor operating conditions with an eccentric air-gap or broken rotor bars. Healthy motors were also considered. The indicator of the expert system under all of these test conditions is illustrated in Fig. 11 ; each condition was run for 500 seconds. Table 6 summarizes some of these test cases used to analyze the performance of the proposed system. Compared with other fault-detection methods (Taniguchi et al., 2000 ; Su and Chong, 2005), our scheme has a simpler structure and algorithm. In addition, it does not require on-line adaptation of any parameters in the neural network. This feature makes it well suited for time-critical applications.

5. Conclusions

This paper presents the development and testing of a neural network based expert system for diagnosing induction motor faults. The proposed system uses a multi-layer perception neural network that is trained using vibration spectra. The investigation was based on the notion that a neural network can capture nonlinear system dynamics and does not require knowledge of specific system parameters. The experimental results show that the neural network classifier can be used effectively for recognizing mechanical motor faults by appropriate measurements and interpretation of STFT analysis of vibration spectra. Since on-line frequency analysis can be carried out using this method, it is practical to apply the proposed method to monitoring motor conditions in real time.

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