674. A neuro-detector based on the cybernetic concepts for fault detection in electric motors

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Abstract. In this study, an auto-associative neural network (AANN) is designed as a fault detector using the cybernetic concepts. In this sense, an artificial neural network structure is connected with a finite state system or a finite automata and an AANN topology is described as a virtual detector. In terms of the practical application, vibration signals, which are taken from an induction motor of 5 HP for both the healthy and faulty motor cases, are considered in the spectral domain. The vibration signal presented in the healthy motor case is separated into 4 blocks and the spectral set of these blocks is used as input and target pattern sets during the training of the AANN. After the training process, a new vibration spectrum, which is defined in the faulty motor case is applied to this trained network and the faulty case is determined by the error variation at output nodes of the AANN. In this application, the error signal shows huge amplitudes between 2 and 4 kHz as an indicator of the bearing damage.

Keywords: neuro-detector, cybernetic, fault detection, vibration, electrical motors.

1. INTRODUCTION

Early detection methods used in induction motors play a very important role in terms of the reliable operation of the industrial processes because their usage is very wide in various industrial fields. Fault types for the induction motors are of the electrical and mechanical character and majority of the detection methods are based upon signal processing techniques [1]. In this manner, one of the popular approaches is spectral analysis methods based on the Fourier transform. Hence, spectra of the electrical and mechanical signals related to the stator and rotor faults can be considered to get the signature analysis [2-4]. And also, there are so many different approaches applied in this area like fuzzy logic, artificial neural networks and various pattern recognition methods [5]. Nowadays, wavelet transform and its application to the rotating machinery are very popular as an alternative method to the Fourier transforms [6]. In this study, an induction motor of 5 HP is aged under the accelerated aging processes and data are gradually collected from the initial to aged case during the aging process [7]. In this sense vibration signals, which are taken from the healthy and faulty (aged) motor case are used to extract the damage characteristics. For this purpose, the spectra of the vibration signals are used for training process of an auto-associative neural network (AANN) and its topology is trained for the healthy motor case. Hence, faulty case is also easily determined by considering the error variation observed in spectral domain at the output nodes of the AANN. This AANN structure that is used in this study can be considered as a cybernetic system because it can be defined as an automaton. In the related literature, the automata or finite state system is described with finite sets like neural networks [8]. From this viewpoint, a neural system can also be defined as a cybernetic system in the manner of an automaton.

In terms of current applications, many automata are coupled to the man, machines and society. And also, the advanced techniques in computer technology, system and control theory and their applications as well as advanced signal processing techniques and learning systems are successfully applied to so many fields of the natural science like molecular biology, neurophysiology, and genetics and so on. For this reason, general system theory approaches related to the cybernetics can be interpreted as natural since deals with a particular kind of interaction between the subject and object, then artificial neural network approaches can also be evaluated and defined in this sense [8]. In this study we wanted to emphasize this aspect and therefore designed a virtual fault detector based upon the artificial neural network like a finite state system.

2. MATHEMATICAL METHODS

There are three different approaches of the mathematical methods used in this study. These are finite automata, neural network approach as a learning system and the spectral analysis technique.

2.1. Finite automata and its neural network interpretation

Finite automata can be described by five quantities. These are input, output, internal states end state functions. In this manner architecture of the finite automata can be given by the following equation (1) [9].

$$A = \left(I, O, W, \Omega, \Psi\right) \tag{1}$$

where, I: a finite input set; O: a finite output set; W: a finite set of the internal states.

And also, functions Ω and Ψ are next state function and next output function respectively.

Using the quintuple definition of the automata, it can be expanded to the neural network concept by the following theorem.

And also state functions Ω and ψ are defined by the mathematical operation which are shown as below.

$$\Omega : W \times I \to W \tag{2}$$
$$\Psi : W \times I \to O$$

Let $A = (I, O, W, \Omega, \Psi)$ be a finite automata. If its finite input, output and internal state sets can be given as $I = \left\{i_0, i_1, ..., i_{m-1}\right\}$, $O = \left\{o_0, o_1, ..., o_{r-1}\right\}$ and $W = \left\{w_0, w_1, ..., w_{q-1}\right\}$ respectively, then there exists a neural net N, subsets $\left\{\overset{*}{i}_0, \overset{*}{i}_1, ..., \overset{*}{i}_{m-1}\right\}$ of its input, $\left\{\overset{*}{o}_o, \overset{*}{o}_1, ..., \overset{*}{o}_{r-1}\right\}$ of its output and $\left\{\overset{*}{w}_0, \overset{*}{w}_1, ..., \overset{*}{w}_{q-1}\right\}$ of its states such that if input $i_{j_1}, i_{j_2}, ...i_{j_n}$ to A initially in state w_j yields output $o_{k_1}, o_{k_2}, ..., o_{k_n}$ then input $\overset{*}{i}_{j_1}, \overset{*}{i}_{j_2}, ..., \overset{*}{i}_{j_n}$ to N initially in state $\overset{*}{w}_j$ yields output $o_{k_1}, o_{k_2}, ..., o_{k_n}$.

As a special case, for $n=k$, the dimensions of the input and output sets are equal to each other and hence, the neural net N can be called as an auto-associative neural net (AANN). The AANN can be represented by the following structure:

$$\text{AANN} = (\text{ARC, LR}) \tag{3}$$

where ARC denotes the architecture and LR is also the learning rule. In terms of the feed-forward neural networks, one of the most popular learning algorithms is the back-propagation algorithm.

2.2. Neural networks and back-propagation algorithm

Neural networks are parallel distributed information processing systems. One of the most important models is the feed-forward neural network. In this sense, the information flows from the input layer to the output one. Hidden layers, which take place between the input and output layers, play an important role related to the knowledge extraction in the network topology. There are two important aspects of the neural nets. These are learning and recalling procedures. In the learning procedure, the neural net learns under the input-output relationships and this type of the learning procedure is named as learning with target. After the learning procedure, the information is stored in the weight factors of each processing elements of the network topology by the nonlinearity. In the recalling, the unknown data is applied to the neural network and then it produces a suitable response. In terms of the learning procedure, the most popular one is the back-propagation algorithm [10-15].

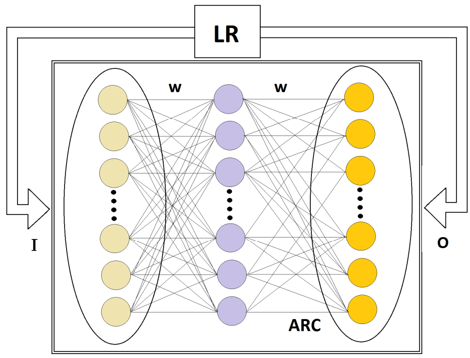

Fig. 1. An auto-associative neural network representation of the finite automata

The classical back-propagation algorithm

The back-propagation algorithm, which is considered for a multilayered feed-forward neural topology, can be described by the following calculation steps [10]:

Step 1: Initialize the weight factors w_{ik} with small random numbers.

Step 2: Determine the learning rate η.

Step 3: Apply the input pattern x^q.

Step 4: Propagate the input pattern from the input layer to the output layer using the following computation

$$o_i = f_i\left(\sum_{k=0}^{p} w_{ik} o_k\right) \tag{4}$$

Here the function $f(.)$ is a nonlinear activation function.

Step 5: Calculate the error term at the q^{th} output node,

$$E^q(w) = \frac{1}{2}\sum_{i=1}^{p}(o_i^q - y_i^q)^2 \tag{5}$$

Step 6: Calculate the delta term for the output layer

$$\delta_i^q = f_i'(\sum_{k=1}^{n} v_{ik} z_k)(o_i^q - y_i^q)\,, \tag{6}$$

where, the function f' indicates the derivative of the nonlinear activation function.

Step 7: Calculate the delta term for the hidden layer by propagating the delta term of the output layer

$$\delta_i^q = f_i'(\sum_{k=1}^{n} w_{ik} x_k^q)\sum_{j=1}^{p} v_{ij}\delta_j^q \tag{7}$$

Step 8: Calculate the difference in the weight factors

$$\Delta^q w_{ik} = -\eta \delta_i^q o_k^q \,. \tag{8}$$

and then update them.

Step 9: Change the state from q to q+1, and go to the step 3.

The algorithm leads to the optimal weight factors w^* when the difference in the error approximately becomes zero.

2.3. Spectral analysis

A common approach for extracting the information about the frequency features of a random signal is to transform the signal to the frequency domain by computing the discrete Fourier transform [16-19]. For a block of data of length N samples, the transform at frequency $m\Delta f$ is given by:

$$X(m\Delta f) = \sum_{k=0}^{N-1} x(k\Delta t)\,\exp\left[-j2\pi km/N\right]. \tag{9}$$

where Δf is the frequency resolution and Δt is the data-sampling interval. The auto-power spectral density (APSD) of $x(t)$ is estimated as:

$$S_{xx}(f) = \frac{1}{N}\left|X(m\Delta f)\right|^2, \; f = m\Delta f. \tag{10}$$

3. EXPERIMENTAL STUDY AND VIBRATION MEASUREMENTS

The experimental study is focused on the electrical discharge from the shaft to the bearing. Figure 2 shows this experimental setup to simulate the electrical discharge machining (EDM) for the motor bearing elements. At each aging cycle, the motor is run at no load for 30 minutes with externally applied shaft current of 27 A at 30 V-AC. The EDM aging is followed by thermal and chemical aging in order to accelerate the aging process [20]. After each cycle of accelerated aging, the test motor is put on a motor performance test platform and data with a sampling frequency of 12 kHz is acquired for the motor currents and voltages, rotor speed, torque and six vibration measurements. During this test procedure, there are eight measurement sets so that one healthy (initial) and seven aged cases are obtained. In this study, we consider only one vibration measurement represented by sensor #9 as indicated in Figure 3.

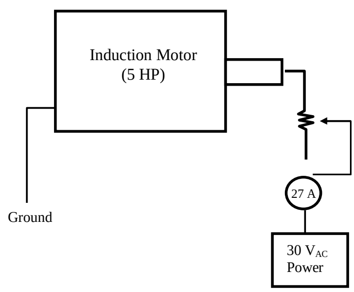

Fig. 2. Schematic of the electrical motor bearing EDM setup

Vibration measurements, which come from the sensor#9, can be shown by the Figure 4.

4. APPLICATION TO VIBRATION SPECTRA FOR FAULT DETECTION

In this section, the vibration signal, which is defined for the healthy case is represented by 4 blocks and hence, power spectral density (PSD) functions of these blocks are computed and their amplitudes are used to train the associative neural network by a pattern set. In this manner, the input-output (target) patterns are identical to each other. The PSD variations of the vibration blocks are shown as below in Fig. 5.

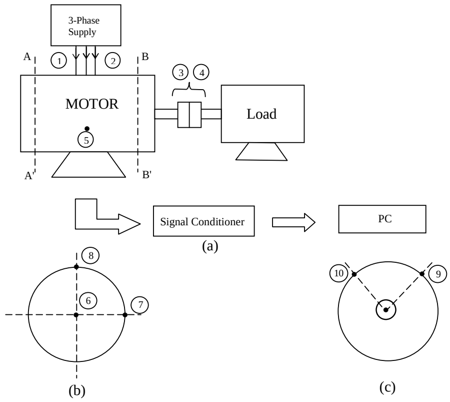

Fig. 3. Motor load testing and data acquisition system: a) Experimental set-up configuration; b) Cross section (A-A') at short end; c) Cross-section (B-B') at pulley end

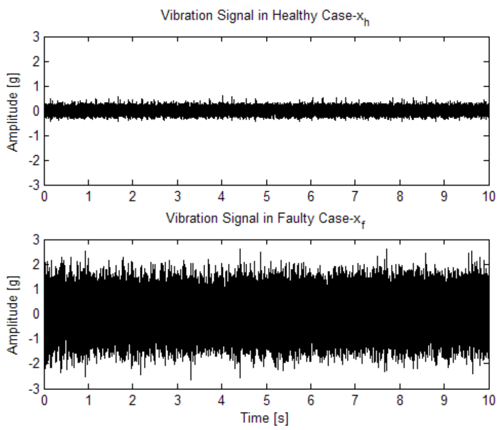

Fig. 4. Vibration signals for healthy and faulty bearing cases

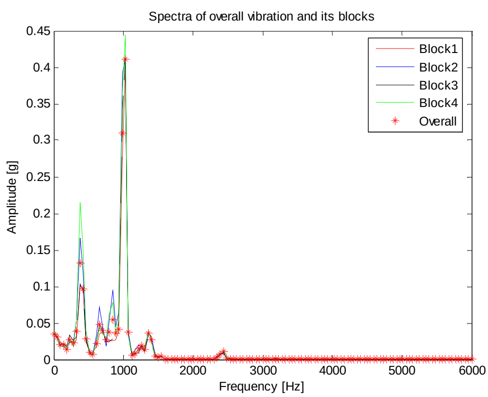

Fig. 5. PSDs of the blocks in the vibration signal defined for the healthy case

The PSD calculation is realized at 128 points and then, the number of input nodes of the neural network becomes 128. Hence the neural network topology is constructed by size of 128 x 60 x 128. Here the number of the hidden nodes is 60. Consequently, these PSD amplitudes are taught to neural topology, pattern by pattern, as an input-output pairs. This application is represented by Figure 6.

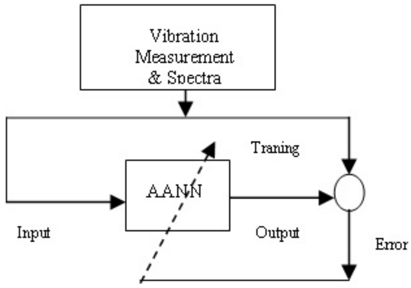

Fig. 6. Training of the AANN

For this procedure, the learning rate is selected as 0.1 and target error value is also 10^{-4}. The learning variation is represented as indicated in Figure 7.

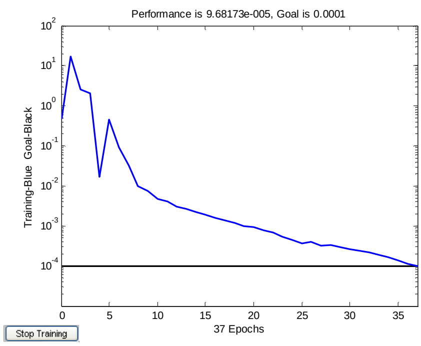

Fig. 7. Training procedure and variation of the error function

After the training procedure, the neural network produces training error variation defined between the vibration spectrum in the healthy case and the actual output of the neural net as indicated in Figure 8.

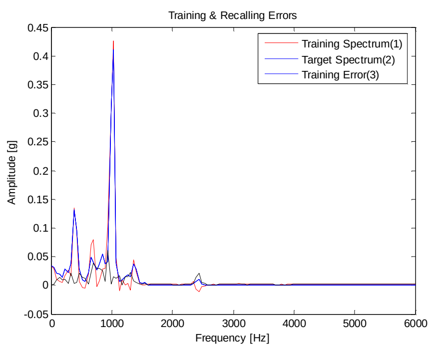

Fig. 8. Training spectra and their error variation

This variation of the training error is at approximate zero value. At the second stage, the vibration spectrum of the faulty case is applied to the neural topology as recalling procedure and then it produces huge error variation at its output nodes. Therefore, these huge amplitudes of the error variation can be interpreted as an indication of the faulty case as shown in Figure 9.

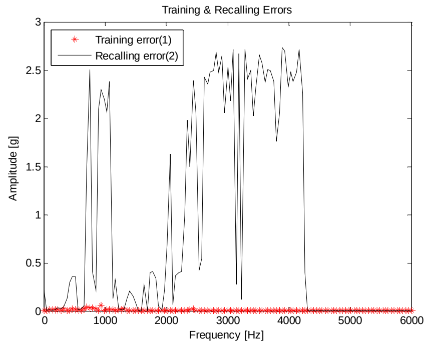

Fig. 9. Determination of the faulty case from the recalling error variation

As a result of this application, it can be said that the faulty case is represented by the huge amplitudes generated between 2 and 4 kHz, comparing with Figure 8.

5. CONCLUSIONS AND DISCUSSIONS

In this research, vibrations measurements, which are taken from an induction motor of 5 HP under the accelerated aging studies, are considered for the healthy and faulty motor cases. Hence vibration spectra are calculated and they are used for the training and recalling processes of an associative neural network. In this manner, amplitude values of the spectrum that defines the healthy case are thought to the network topology as an input-target pairs. Hence the neural net learns the normal case. After that, the faulty or unknown case is applied to this topology in order to get huge error variation. Consequently this error variation is connected with the faulty case in spectral domain and the faulty case related to the bearing damage is characterized by these huge amplitudes induced in the range of 2-4 kHz.

Under the general system theory approach, using the definition of the finite state machines, this neural network approach applied in this study as a fault-detector is interpreted as a finite automaton and hence, it is based upon the cybernetic concepts as well as classical usage of the neural nets [21]. Hence it can be called as a "*Neuro-Detector"* or "*Neuro-Cybernetic Detector"*, which will be used for condition monitoring.

In terms of the general interpretations of the cybernetic concepts, the following figure can be given (see Fig. 10).

According to the Figure 10, cybernetic systems is supported by the peripheral units like natural systems and artificial information processing/learning systems, from this point of view, it can be said that the neuro-detector defined in this study will be evaluated under the classification of nature inspired algorithm for the electrical machinery application.

As a future work, the concept of the "*Neuro-Cybernetic Detector*" will be developed.

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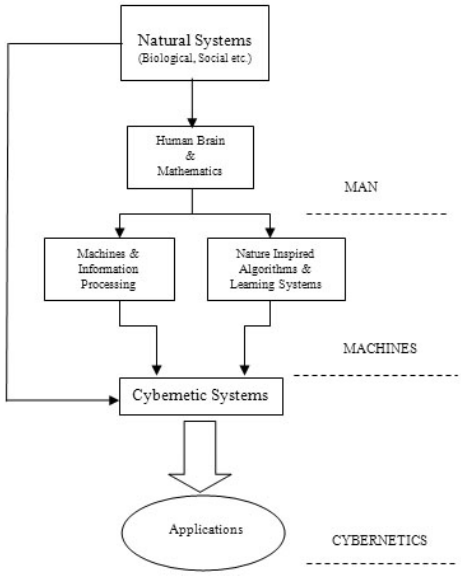

Fig. 10. Man, machine and cybernetic system interaction

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