Detection and Diagnosis of Broken Rotor Bars and Eccentricity Faults in Induction Motors Using the Fuzzy Min-Max Neural Network

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Abstract—Fault detection and diagnosis of electrical machines is gaining importance in regards to machine downtimes, where an unpredicted shutdown of operations owing to unavailability of machines can be very costly. As such, an early warning system for incipient machine faults using condition monitoring is of significance in practical applications. In this paper, we propose a fault detection and diagnosis system to detect and classify broken rotor bars and eccentricity faults of induction motors using the Fuzzy Min-Max (FMM) neural network. A series of real experiments is conducted, where the acquired current signals under various motor conditions is used to build a database. The Power Spectral Density is then used to extract the discriminative input features for fault detection and classification with FMM. The results are comparable, if not better, than those from the Multi-Layer Perceptron neural network and other methods reported in the literature.

I. INTRODUCTION

Fault detection and diagnosis of motors has received considerable attention in industrial organizations, particularly when detection of potential faults at an early stage can be conducted [1]. This in turn not only reduces the maintenance and down time expenses, but also improves safe operations [1]. Motors are commonly used devices to convert electrical energy to mechanical energy. In order to improve motor efficiency, variable speed drives are commonly used, and this has led to increased motor overheating problems, harmonic problems, and shorter operational life of motors [2-3]. As a result, effective fault detection and diagnosis methods are needed in order to reduce the maintenance and downtime costs of motors. Various techniques for detection and diagnosis of induction motor faults have emerged rapidly, which are able to avoid unexpected failures of these motors [2].

Among different types of electric motors, induction motors contribute more than 60% of the electrical energy produced [4]. In general, fault detection and diagnosis methods for electric motors are normally provided by some combination of mechanical and electrical condition monitoring methods. This study aims to design and develop a low-cost and yet effective method to detect and classify broken rotor bars and eccentricity faults in induction motors. Failure surveys by Electric Power Research Institute [5] show that the typical failure percentages of induction motors are as follows: bearing related faults 40%, stator related faults 38%, rotor related faults 10%, and other faults 12%. The Motor Current Signature Analysis (MCSA), a low-cost and convenient method, for fault detection and diagnosis is used in this study. MCSA deploys the results of spectral analysis of the supply current to detect a particular motor failure in the drive system.

Recently, the demand for accurate fault detection and diagnosis methods has increased for complex industrial systems to be safer and more reliable, while minimizing the process downtime [6]. There have been a significant number of investigations on monitoring induction motor faults, with aim of reducing maintenance costs and preventing unscheduled downtimes [7]. Among various neural networks, backpropagation is a commonly used supervised learning method [8]. Current signals were transformed using fast Fourier transform and side-band frequency magnitudes were fed into a feedforward neural network trained with backpropagation to detect broken rotor bars. Wavelet packet decomposition was applied on current signals, which were fed into a Multi-Layer Perceptron for detection of broken rotor bars [9]. Park’s Vector modulus is used on the stator current of an induction motor, which was then fed into a fuzzy wavelet neural network for fault detection and classification of broken rotor bars [10]. A short-time Fourier transform was deployed to process the quasi-steady vibration signals, which was fed into a neural network trained with Levenberg-Marquardt for detection of eccentricity faults and broken rotor bars [11].

In this paper, the study is focused on fault detection and diagnosis of broken rotor bars and eccentricity problems in induction motors using the Fuzzy Min-Max (FMM) [12] neural network. MCSA is first applied to produce classification data sets based on the Power Spectrum Density (PSD) of real stator-current signals of induction motors. Based on the data sets, the broken rotor bars and eccentricity faults are classified using the FMM model. In this work, we focus on the FMM model because of its one-pass training with online learning capabilities, non-linear separability, and no overlapping between classes, as explained in [12].

The organization of this paper is as follows. In Section II, the FMM neural network is detailed. In Section III, the proposed method for fault detection and diagnosis is described. The experimental study and results are presented...
in Section IV. Finally, concluding remarks are given in Section V.

II. THE FUZZY MIN-MAX NEURAL NETWORK

The FMM classification model is formed using hyperbox fuzzy sets. The size of a hyperbox is controlled by $\theta$, which varies between 0 and 1. When $\theta$ increases from a small to a large value, the number of hyperboxes created is reduced. The membership function is set with respect to the minimum and maximum points of a hyperbox, and to the extent to which a pattern fits in the hyperbox. For an input pattern of $n$-dimensions, a unit cube, $I^m$, is defined, and the membership value ranges between 0 and 1. The definition of each hyperbox fuzzy set $B_j$ is:

$$B_j = \{X, V_j, W_j, f(X, V_j, W_j)\} \forall X \in I^n,$$

(1)

where $V_j$ is the minimum and $W_j$ is the maximum points. Fig. 1 illustrates the minimum and maximum points of a three dimensional box. The combined fuzzy set that classifies the $k$-th pattern class, $C_k$, with the definition of a hyperbox fuzzy set, is:

$$C_k = \bigcup_{j \in K} B_j,$$

(2)

where $K$ is the set of hyperboxes associated with class $k$. The training process is concerned with finding and fine-tuning the boundaries of the classes.

![Fig. 1. A min-max hyperbox $B_j = \{V_j, W_j\}$ in $I^d$](image)

In FMM, the learning algorithm allows hyperboxes of the same class to overlap, while overlaps among different classes need to be eliminated. The membership function for the $j$th hyperbox, $b_j(A_k)$, $0 \leq b_j(A_k) \leq 1$, is used to measure the extent to which the $h$th input pattern, $A_h$, falls outside hyperbox $B_j$. In other words, the membership function serves as a measurement to the extent each component is greater (or lesser) than the maximum (or minimum) point along each dimension that falls outside the minimum and maximum boundary of the hyperbox. As $b_j(A_k)$ approaches 1, the point should be contained “more” by the hyperbox. The function that meets the membership function criteria is the sum of two complements, viz. average of the maximum point violation and average of the minimum point violation. The resulting membership function is:

$$B_j(A_k) = \frac{1}{2n} \sum_{i=1}^{n} \left( \max(0, 1 - \max(0, \gamma \min(1, A_h - W_j))) + \max(0, 1 - \max(0, \gamma \min(1, V_j - A_h))) \right),$$

(3)

where $A_h = (a_{h1}, a_{h2}, \ldots, a_{hn}) \in I^d$ is the $h$th input pattern, $V_j = (v_{j1}, v_{j2}, \ldots, v_{jn})$ is the minimum point for $B_j$, $W_j = (w_{j1}, w_{j2}, \ldots, w_{jn})$ is the maximum point for $B_j$, and $\gamma$ is the sensitivity parameter that controls how quickly the membership values decrease when the distance between $A_h$ and $B_j$ increases.

FMM is a three layer network, where the input layer contains input nodes equal in number to the number of dimensions of the input pattern while the output layer contains nodes equal in number to the number of classes. The hidden layer is called the hyperbox layer $F_B$. Each $F_B$ node represents a hyperbox fuzzy set, and its transfer function is the hyperbox membership function defined by (3). $F_A$ to $F_B$ connections are the minimum and maximum points, denoted by matrices $V$ and $W$ respectively. The connections between the $F_B$ and $F_C$ nodes are binary-valued and are stored in matrix $U$. The equation for assigning the values from $F_B$ to $F_C$ connections is:

$$u_{j_k} = \begin{cases} 1 & \text{if } b_j \text{ is a hyperbox for class } C_k \\ 0 & \text{otherwise} \end{cases},$$

(4)

where $b_j$ is the $j$th node and $C_k$ is the $k$-th node. Each $F_C$ node represents a class. The output of the $F_C$ node represents the degree to which input pattern $A_k$ fits within class $k$. The transfer function for each $F_C$ nodes performs the fuzzy union of the appropriate hyperbox fuzzy set values, and is defined as:

$$c_k = \max_{j=1}^{m} b_j u_{j_k},$$

(5)

The output of the $F_C$ class nodes can be utilized in two ways. When a soft decision is required, the outputs are utilized directly. When a hard decision is required, the $F_C$ node with the highest value is located, and its node value is set to 1 to indicate that it is the closest pattern class, while the remaining $F_C$ node values are set to 0, i.e. the principle of where winner-takes-all [13].

The FMM learning methodology comprises an expansion/contraction process. The training set, $D$, consists of a set of $M$ ordered pairs $\{X_h, d_i\}$, where $X_h = (x_{h1}, x_{h2}, \ldots, x_{hn}) \in I^d$ is the input pattern and $d_i \in \{1, 2, \ldots, m\}$ is the index of one of the $m$ classes. The learning process starts by selecting an ordered pair from $D$ and finding a hyperbox of the same class that can be expanded. The expansion criterion has a constraint to meet, and is defined as:

$$n\theta \geq \sum_{i=1}^{n} \left( \max(w_{ji}, x_{hi}) - \min(w_{ji}, x_{hi}) \right),$$

(6)

where $0 \leq \theta \leq 1$ is the hyperbox size. If the expansion constraint is met, the minimum and maximum points of the hyperbox are adjusted, as follows. 

$$w^{new}_{ji} = \min(w^{old}_{ji}, x_{hi}) \quad \forall \ i = 1, 2, \ldots, n$$

(7)

$$w^{new}_{ji} = \max(w^{old}_{ji}, x_{hi}) \quad \forall \ i = 1, 2, \ldots, n$$

(8)

When the hyperboxes expand, there is a possibility of overlaps among the existing hyperboxes. An overlap test is introduced to check if the overlap is among the same or different classes. In all dimensions, as long as one of the following cases is satisfied, then overlapping between the two hyperbox exists. During the search process, if an overlap is found, the index of the dimension and the smallest overlap value are used in the contraction process. Further details of FMM can be found in [12].

III. THE PROPOSED METHOD FOR FAULT DETECTION AND DIAGNOSIS

In this section, the procedure from acquiring motor current signals to arriving at a decision on the potential
motor faults is explained. A database comprising motor current signals from a series of real experiments of fault detection and diagnosis of induction motors is established, as follows. The three-phase stator currents from an induction motor are measured using three current probes connected to an oscilloscope as a data acquisition unit. Data from the oscilloscope are acquired using a network connection and are stored in a computer. A total of 10 cycles, equivalent to 0.2 seconds of the unfiltered three-phase stator currents, i.e. phase A, phase B, and phase C, are transformed using the Fast Fourier transform (FFT) to the respective Power Spectral Density (PSD) for feature extraction.

PSD is the Fourier transform of the auto-correlation function of a signal when the signal is stationary [14]. PSD is not restricted to using one specific harmonic for fault detection and diagnosis. On the other hand, in classical Fourier analysis, the power of a signal can be obtained by integrating PSD, i.e., the square of the absolute value of the Fourier-transform coefficients [14]. In this study, PSD is calculated by multiplying the FFT with its complex conjugates. It is then normalized by dividing it with the series length. The three-phase current signals are used to produce PSD for further analysis. PSD displays a 1,000 Hz frequency spectrum which contains odd numbers of harmonics, ranging from the 1st to the 19th harmonic. These harmonics, which contain unique values for each condition, are fed to FMM for fault detection and diagnosis.

During feature extraction, selected pairs of harmonic magnitudes from the frequency spectrum are used as the input features of FMM. The output of FMM is a prediction of motor conditions. A series of experiments has been conducted using a laboratory-scale test rig. As shown in Fig. 2, the test rig consists of an oscilloscope (1), three current probes (2), an induction motor (3), a belt, shaft, a load inducer (4), and a load controller (5).

A number of tests were performed at 25%, 50%, 75%, and 100% load conditions. A total of 10,000 data samples were captured at four different load conditions for each motor fault. Three-phase power was supplied to the induction motor, and three current probes were clamped individually onto the cables of each phase. The current probes were connected to an oscilloscope where the current signals were captured. Current signals from the oscilloscope were transferred from the oscilloscope to the computer using a network connection. The current signals were transformed into their associated PSD. The PSD outputs comprised a 1,000 Hz frequency spectrum, from the 1st to 19th harmonics. Note that in a balanced three-phase system, the triplen harmonic voltages should be absent. However, owing to machine supply and constructional unbalances, some of them may or may not be present in the motor supply currents [15]. To minimize the number of input features, the 3rd, 9th, and 15th harmonics were discarded in this study.

In addition to FMM, the Multilayer Perceptron (MLP) network with Levenberg-Marquardt training was implemented for performance comparison purposes. The trial-and-error method was often used to determine the number of hidden nodes in order to obtain the best accuracy rate [16]. The same method was adopted in this research. Using an Intel Core i5 2.5 GHz processor with 4GB RAM on MATLAB® R2010a, the computational time consumed by a single run of the cross-validation experiment was also recorded.

IV. THE EXPERIMENTAL STUDY AND RESULTS

A. Broken Rotor Bars

Two different types of cage rotors exist in induction motors, viz. cast and fabricated. Cast cage rotors are used in motors up to 3,000-kW rating while fabricated cages are found in motors of higher ratings, and are used in special machines. Cast rotors are almost impossible to get fixed once there are breakages or cracks in them, although they are more durable and rugged than fabricated cages [17]. During the broken rotor bars event, the sideband currents are given by [18]:

\[ f_b = (1 \pm 2ks)f, \]

where \( k = 1, 2, 3 \), \( s \) is the slip, and \( f \) the supply frequency. When there are broken rotor bars, other frequency spectrums besides the fundamental ones, which can be observed from the stator-current spectrum, are given by [18]:

\[ f_h = \left(\frac{k}{p}\right)(1 - s) \pm s \]

where \( f_h \) are detectable broken bars frequencies, \( p \) is the number of pole pairs, and \( k/p = 1, 2, 3 \).

![Fig. 2. Experimental study setup](image-url)
Broken rotor bars will not cause immediate failures of an induction motor. But, if there are many broken rotor bars, the motor may not be able to start once it is powered off. This is mainly due to insufficient accelerating torque during the start-up process.

In this study, to create the broken rotor bar fault, the rotor was first separated out from the motor. An electrical drill was used to drill a hole in order to break a single bar, as in Fig. 3 (a). The same procedure was used in [19], where a hole was drilled into the rotor bar of a three-phase induction motor to induce the broken rotor bar fault. Two sets of experiments were conducted, first with a single broken bar. Then, the same process was repeated to add another hole in the adjacent bar, as shown in Fig. 3 (b), for creating two broken bars.

The induction motor was operated with first one broken bar and then two broken bars. Table I shows the results. FMM produced the best results at 99.42% with 12 hyperboxes while MLP produced 94.47% with a more complex network structure, i.e. 25 hidden nodes. Besides, the computational time of FMM was only 0.12 seconds, while MLP consumed 2 seconds. A total of two papers, [9] and [20] are used for comparison. In [9], the Wavelet Packet Decomposition (WPD) method was used to extract different frequency resolutions while MLP with back-propagation was used for fault detection based on stator currents. Motors with one and two broken rotor bars were analyzed. In [20], Multiple Discriminant Analysis (MDA) was used to detect broken rotor bars too. The best results of WPD with MLP and MDA (extracted from [9] and [20]) are comparable with those of FMM, with 99% and 99.38% accuracy, respectively. Nevertheless, batch learning was used in WPD with MLP [9], while one-pass learning was realized in FMM. Thus, FMM enjoys the advantage of a single-pass training scheme over WPD with MLP in its operation.

<table>
<thead>
<tr>
<th>Network</th>
<th>Accuracy (%)</th>
<th>StdDev</th>
<th>Complexity</th>
<th>Time (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLP</td>
<td>94.47</td>
<td>4.86</td>
<td>25 Hidden Nodes</td>
<td>2.03</td>
</tr>
<tr>
<td>FMM</td>
<td>99.42</td>
<td>1.68</td>
<td>12 Hyperboxes</td>
<td>0.12</td>
</tr>
</tbody>
</table>

**B. Eccentricity Faults**

Eccentricity-related faults commonly occur as a result of bearing faults, and can lead to a non-uniform air gap. Eccentricity faults are divided into two categories: static and dynamic [21]. In static eccentricity, the air gap has a fixed minimal position. This position rotates with the rotor in dynamic eccentricity. Due to imperfection in design and manufacturing procedures, up to 10% eccentricity is allowed [22]. Higher orders of eccentricity can cause rotor-to-stator rub, resulting in damage of rotor and/or stator windings or cores.

The presence of static and dynamic air gap eccentricity can be detected using MCSA. One of the equations describing the frequencies components is given by [23]:

$$f_{vec} = f_k \left( kR \pm n_d \left( 1 - s \right) \pm v \right) / p$$  \hspace{1cm} (11)

where $n_d = 0$ in the case of static eccentricity, and $n_d = 1, 2, 3$, in the case of dynamic eccentricity, $R$ is the number of rotor slots, $s$ is the slip, and $p$ is the number of pole pairs.

In this study, the induction motor was operated under the condition of both dynamic and static eccentricity. In accordance with [24], mixed dynamic and static eccentricity was obtained by fitting non-concentric support parts between the shaft and bearing, as in Fig. 4. In this study, 30% dynamic eccentricity and 10% static eccentricity were produced for evaluation.

![Fig. 4. Eccentricity fault creation in accordance with [24]](image)

Table II shows the results. FMM produced the best results at 98.79% with only 10 hyperboxes. MLP produced 92.76% with a more complex network structure, i.e. 20 hidden nodes. Besides, the computational time of FMM was only 0.10 seconds, while MLP consumed 2 seconds. Results from [11] are used for comparison purposes. In [11], vibration signals were used as inputs to Short-Time Fourier transform (STFT) for processing. The output of STFT, i.e., vibration spectra, was fed into an MLP network for detection of eccentricity faults. The result of MLP was at 92% accuracy. As such, FMM is able to yield better performance as compared with STFT-MLP.

![Fig. 3. (a) One broken rotor bar (b) Two broken rotor bars](image)
Table II. FMM and MLP Results for Eccentricity Faults

<table>
<thead>
<tr>
<th>Network</th>
<th>Accuracy (%)</th>
<th>StdDev</th>
<th>Complexity</th>
<th>Time (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLP</td>
<td>92.76</td>
<td>5.43</td>
<td>20 Hidden Nodes</td>
<td>2.06</td>
</tr>
<tr>
<td>FMM</td>
<td>98.79</td>
<td>1.96</td>
<td>10 Hyperboxes</td>
<td>0.10</td>
</tr>
</tbody>
</table>

V. SUMMARY

The proposed method to incipient fault detection and diagnosis uses MCSA for stator-current signal acquisition and PSD to transform them into their frequency spectra. Motor current harmonics from PSD has been employed to form the input features to FMM for detection and diagnosis of broken rotor bars and eccentricity fault conditions. The results of FMM are comparable, if not better, than those of MLP and other methods reported in the literature. This approach has been shown to be effective in making rapid and accurate predictions for induction motor fault detection and diagnosis. Further work will focus on the implementation of MCSA and FMM for real-time fault detection and diagnosis of induction motors.

REFERENCES