On the Comparison of Multiple Signature LDA and Neural Network Based Broken Rotor Bar Detection Schemes in Induction Motors

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Abstract – Broken rotor bars in induction motors can be detected by monitoring any abnormality of the spectrum amplitudes at certain frequencies in the motor current spectrum. Broken rotor bar fault detection schemes should rely on multiple signatures in order to overcome or reduce the effect of any misinterpretation of the signatures that are obscured by factors such as measurement noises and different load conditions. Multiple Discriminant Analysis (MDA) and Artificial Neural Networks (ANN) provide appropriate environments to develop such fault detection schemes because of their multi-input processing capabilities. This paper describes two fault detection schemes for broken rotor bar fault detection with multiple signature processing and demonstrates that multiple signature processing is more efficient than single signature processing.

I. INTRODUCTION

Induction motors have dominated the field of electromechanical energy conversion, being 80% of the motors in use [1], [2]. The failure of induction motors can result in a total loss of the machine itself, in addition to a likely costly downtime of the whole plant. More importantly, these failures may even result in the loss of lives, which cannot be tolerated. Thus, health monitoring techniques to prevent induction motor failures are of great concern in industry and are gaining increasing attention [3]-[4].

Rotor failures are among these failures, and they now account for 5-10% of total induction motor failures [5]. Since 1980, the broken rotor bar fault detection problem has created substantial interest among researchers [6], [7]. Several monitoring techniques have been developed, most of which are based on motor current signature analysis (MCSA) [8].

Broken rotor bar fault in induction motors can be detected by monitoring any abnormality of the motor current power spectrum amplitudes at several certain frequency components. These frequency components are located around the main frequency line and are determined according to the number of poles and mechanical speed of the motor. However, there are other effects that may obscure the detection of the broken rotor bar fault or cause false alarms. For example, these effects can be intrinsic manufacturing dissymmetry [9], or load torque oscillation that can produce stator currents with the frequency values the same as the monitored frequencies. A broken rotor bar fault detection scheme based on multiple frequency signatures thus should be more reliable in overcoming or reducing the effect of misinterpreted signatures, which are caused by the effects discussed formerly or some other unknown reasons. Multiple Discriminant Analysis (MDA) and Artificial Neural Networks (ANN) provide appropriate environments to develop such fault detection schemes because of their multi-input processing capabilities.

This paper presents two fault detection schemes for broken rotor bar fault detection with multiple signature processing and demonstrates that multiple signature processing is more effective than single signature processing. The first scheme will be named the “monolith scheme,’’ and it is based on a single MDA or a single ANN unit representing the complete motor operating load torque region. The second scheme will be named the “partition scheme,’’ and it consists of several small LDA or ANN units, each of which represents a particular load torque operating region. The two detection schemes have been investigated using experimental data with LDA and ANN detection units, respectively.

This paper is organized as follows: Section II discusses the frequencies of interest to the broken rotor bar problem and outlines the frequencies to be used in the MDA and ANN units. Section III presents the experiment setup and motor data specifications. Section IV outlines the fault detection schemes together with experimental results and analysis. Section V concludes the findings of this paper.

II. MOTOR CURRENT SPECTRAL COMPONENTS FOR BROKEN ROTOR BAR

Kliman, Thomson, Filipetti, Elkasabgy [10] used motor current signature analysis (MCSA) methods to detect broken rotor bar faults by investigating the sideband components of the four main supply spectral components caused by the effects discussed formerly or some other reasons. Multiple Discriminant Analysis (MDA) and Artificial Neural Networks (ANN) provide appropriate environments to the broken rotor bar problem and are determined according to the number of poles of the motor and constant ‘120’ is used to express the motor synchronous speed, $n_s$, in revolutions per minute (rpm) unit.

The motor synchronous speed, $n_s$, is related to the line frequency $f_o$ as:

$$n_s = \frac{120 \cdot f_o}{P},$$

where $P$ is the number of poles of the motor and constant ‘120’ is used to express the motor synchronous speed, $n_s$, in revolutions per minute (rpm) unit.

The broken bars also give rise to a sequence of other sidebands given by [11]:

$$f_k = (1 \pm 2k) \cdot f_o, \quad k = 1,2,\ldots,k_n$$

where $f_k > 0 \forall k$. There are other spectral components that can be observed in the stator line current due to broken rotor bar fault [10]:

$$f_b = \left[ \frac{k}{p} (1 - s) \pm s \right] f_o, \text{ where } k/p=1,3,5,\ldots.$$
The induction motor was fed through a 3 phase ABB, ACS 501 inverter. A Tektronix TM 5003 current amplifier amplifies the induction motor stator currents before being sent to the interfacing Pentium PC through the oscilloscope. The needed load condition of the induction motor was established by connecting the test motor to a DC Motor, which is used as a generator and is capable of simulating any desired load condition. The speed of the induction motor was measured by a digital stroboscope.

The conceptual diagram of the partition scheme is presented in Fig. 4. The mapping units in the partition scheme provide partitioning of the complete motor operating load region into subregions, each subregion corresponding to a constant load condition. This procedure thus transforms the nonlinear mapping problem into linear mapping problems or mapping problems with a lower order of nonlinearities. The partition scheme needs motor load condition information as a prerequisite for the preparation of the corresponding mapping units.

In our case, we partition the motor’s load operating region into four subregions, depicted as $T_L = \{T_{L_{100\%}}, T_{L_{75\%}}, T_{L_{50\%}}, T_{L_{25\%}}\}$. We then form MDA and ANN units for each particular load subregion using the corresponding motor current signatures. For analyses and performance comparisons of the fault

<table>
<thead>
<tr>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power</td>
<td>0.75 kW (1Hp)</td>
</tr>
<tr>
<td>Input Voltage</td>
<td>380 V</td>
</tr>
<tr>
<td>Full Load Current</td>
<td>2.2 A</td>
</tr>
<tr>
<td>Supply Frequency</td>
<td>60 Hz</td>
</tr>
<tr>
<td>Number of Poles</td>
<td>4</td>
</tr>
<tr>
<td>Number of Rotor Slots</td>
<td>44</td>
</tr>
<tr>
<td>Number of Stator Slots</td>
<td>36</td>
</tr>
<tr>
<td>Full Load Torque</td>
<td>0.43 kg-m</td>
</tr>
<tr>
<td>Full Load Speed</td>
<td>1690 rpm</td>
</tr>
</tbody>
</table>

In our case, we partition the motor’s load operating region into four subregions, depicted as $T_L = \{T_{L_{100\%}}, T_{L_{75\%}}, T_{L_{50\%}}, T_{L_{25\%}}\}$. We then form MDA and ANN units for each particular load subregion using the corresponding motor current signatures. For analyses and performance comparisons of the fault
In analyzing fault detection performances, we use statistical hypothesis testing, Type I error, \( \alpha \), and Type II error, \( \beta \), which is expressed in Table II. Our null hypothesis, \( H_0 \):

\( \)Incoming motor signature test data correspond to healthy state of the motor.

Type I error, \( \alpha \), will then correspond to the ratio of the healthy motor data, which are classified as faulty, to the total number of motor data. Likewise, Type II error, \( \beta \), will correspond to the ratio of the faulty motor data, which are classified as healthy, to the total number of motor data. We will use the term ‘Correct Detection Rate’, \( \text{CDR} \), in our analyses, which is mathematically expressed in (9):

\[
\text{CDR} = (1 - \alpha - \beta).
\] (9)

In order to compare the fault detection performances of single signature and multiple signature processing, we have applied LDA to each of the four signatures individually for both Case 1 and Case 2. Tables III and IV depict the CDRs of each single signature under Case 1 and Case 2 together with Type I and Type II error measures. These tables indicate that CDRs change significantly according to each individual signature. Among these signatures, \( (1-4)s_1 \) has the highest CDR, while the other three signatures have lower CDRs. The seventh to ninth rows of Table IV simply sums CDRs and Type I-II errors of training and test data sets. We have then considered four of the signatures together and applied the monolith and partition schemes.

Table V depicts the CDR of LDA and ANN for the two schemes under Case 1 together with Type I and Type II error measures. Note that LDA’s correct detection performance improves with the partition scheme. It is also observed that CDRs in both schemes are higher than any of the single signature’s CDRs given in Tables III and IV.

The bar chart depicted in Fig. 5 presents the CDRs of both single signature processing and multiple signature processing for the two schemes under Case 1. This bar chart affirms that multiple signature processing is more efficient in broken rotor bar fault.

![Diagram](image-url)

**Fig. 4. The partition scheme.**
Similarly, Table VI depicts the CDRs and Type I-II errors of LDA and ANN under Case 2. In Case 2, since we have separated the data into training and test sets, we have included the sum of training and test data sets’ CDRs, in addition to each set’s separate CDR. There is a considerable improvement examined in the CDR with the partition scheme. In addition, these CDRs are higher than any of the single signature’s CDRs that are depicted in Tables III and IV with the exception of one equal case.

**TABLE V. CDRS WITH MONOLITH AND PARTITION SCHEMES UNDER CASE 1**

<table>
<thead>
<tr>
<th></th>
<th>Correct Detection Rate (CDR)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Monolith Scheme</td>
</tr>
<tr>
<td>CDR (LDA)</td>
<td>153/160=95.63 %</td>
</tr>
<tr>
<td>Type I Error (LDA)</td>
<td>1/160=0.63%</td>
</tr>
<tr>
<td>Type II Error (LDA)</td>
<td>6/160=3.75%</td>
</tr>
<tr>
<td>CDR (ANN)</td>
<td>160/160=100.0 %</td>
</tr>
<tr>
<td>Type I Error (ANN)</td>
<td>0/160=0.0%</td>
</tr>
<tr>
<td>Type II Error (ANN)</td>
<td>0/160=0.0%</td>
</tr>
</tbody>
</table>

The partition scheme has provided a way to cope with the nonlinearities in the mapping process and demonstrates an improved correct detection performance with LDA and ANN. Partitioning the initial mapping space of the fault detection problem with respect to one of its input variables into smaller disjoint subregions and introducing sub-mapping units, for each of these small subregions provide an increase in the correct detection performance.

**VI. REFERENCES**


