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An Adaptive, On-line, Statistical Method for Detection of Broken Bars In Motors Using Stator Current and Torque Estimation

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Abstract ***In this paper, we propose an adaptive statistical time-frequency method to detect broken bars using digital torque estimation. The key idea in the proposed method is to transform motor current into a time-frequency spectrum to capture the time variation of the frequency components and to analyze the spectrum statistically to distinguish fault conditions from the normal operating conditions of the motor. Since each motor has a distinct geometry, we adapt a supervised approach in which the algorithm is trained to recognize the normal operating conditions of the motor prior to actual fault detection. To estimate the broken bar frequencies, we utilize the digital torque estimator.***

I. INTRODUCTION

In motor current based fault detection, there are two main issues:

- How to adapt the detection algorithm to the time varying normal operating conditions of the motor?
- How to estimate the fault frequencies in the absence of motor geometry information and variable speed?

The prior methods reported in the literature differ mainly in the way they address these issues. They can be categorized into two classes: Although the early methods recognized the nonstationary nature of he motor current, these methods employed Fourier analysis compromising the accuracy of the detection. In [1], the broken bar frequencies are estimated using the axial leakage flux data. In [3], the frequencies of interest are estimated directly from the current spectrum. With the recent advancement of new signal processing techniques, methods adaptable to time varying normal operating conditions have been proposed [4]-[5]. These methods utilize rule based expert systems and neural networks to achieve adaptive detection. However, these operations are performed in the Fourier transform domain which compromises the nonstationary nature of the data.

In this paper, we propose a statistical, time-frequency method which utilizes torque estimation to detect broken bars. The method consists of four stages: In the preprocessing stage, analog current data is low pass filtered to prevent aliasing and digitized. Next, the time-frequency spectrum of the data is computed and fed into the training stage. In the training stage, broken bar frequencies are estimated and a window of frequency components around the estimated fault frequencies are selected to form a feature vector. Next, feature vectors are segmented into homogenous normal operating modes along the time axis in time-frequency space using the digital torque estimation. The segmented feature vectors are used to determine a mode representative and threshold. After all possible normal operating modes of the motor are monitored, the testing stage starts. In this stage, the motor current data is periodically acquired and is subjected to the preprocessing and feature extraction methods described in the training stage. The distance of the test feature vector to the representatives of each mode are computed and the resulting distances are compared with the respective thresholds. If any of the distances is larger than the threshold, the test measurement is tagged as a potential fault signal. In the post processing stage, the testing process is repeated for a number of measurements to increase the accuracy of the final decision. A three dimensional illustration of the method is shown in Figure 1.

The proposed method has the following advantages:

- The method adapts itself to the varying operating conditions of the motor to be tested, thereby offering a more accurate detection of the fault than [2].
- By use of time-frequency spectrum in the analysis, difficult cases, such as coal crushers where speed varies instantly, may be efficiently handled.
- Unlike the prior art [2]-[3], the proposed method does not require axial flux leakage data or refined guesses to compute the broken bar frequencies. Instead, it utilizes the digital torque estimator [6].
- The proposed method does not require a high resolution frequency spectrum. The statistical measure adapted at the testing stage takes into account the spread or the resolution of each frequency component. This may reduce the memory required to compute a high resolution frequency spectrum.
- For the detection of broken bars only very limited frequency ranges are required, typically within a few slip frequencies around first few harmonics. Consequently the required computational load is substantially reduced for frequency ranges set by the torque based estimator.
- Restriction of the frequency range and the knowledge of speed help exclude extraneous components. Thus reducing the false alarms when load oscillations and other interference phenomena are present.
- By first identifying and isolating the broken bar and bearing frequency components, they may be excluded from further analysis. Thus reducing the computational load and simplifying the analysis of rest of the frequency components when looking for other type of faults.
- Finally, the proposed framework is applicable to any motor fault which causes rotor asymmetries.

II. TRAINING

The first step in the training stage is the estimation of the broken bar frequencies in the current spectrum. In motor theory, it is well known that broken bar faults show up as side band frequencies of the first, fifth, seventh and higher order harmonics [1]-[4]-[7]. These frequencies are given by the following formula:

$$f_{brk} = f_s\left[k\left(\frac{1-s}{p/2}\right) \pm s\right], \qquad k = 1,2,3,\ldots \tag{2.1}$$

where f_s is the electrical supply frequency, s is per unit slip and p is the number of poles. Note that due to the normal winding conditions only those frequencies for which $2k/p = 1,5,7,11,13,\ldots$ appears in the stator current with significant amplitude.

From the name plate of the motor, one can determine the number of poles. However, the slip s changes with the mechanical speed of the motor which is not readily available. The relationship between the mechanical speed and the slip is given by the following equations:

$$s = 1 - \frac{f_m}{f_{sy}}, \qquad f_{sy} = \frac{2f_s}{p} \tag{2.2}$$

where f_m is the mechanical speed, and f_{sy} is the synchronous speed.

The digital torque estimator provides a simple solution for the estimation of the mechanical speed and the slip [4]-[8]. The technique is illustrated in Figure 2. The number of poles provides the means to estimate the synchronous speed from torque-speed curve. This estimate is given by point #1 in Figure 2. Also the rated torque and the rated speed of the motor can be obtained from the name plate as shown by point #2. A straight line connecting points 1 and 2 is a sufficient approximation to the motor torque-speed curve in the normal range of loads. The torque estimator finds the actual steady state motor torque within 2% error which is shown by point #3. The mechanical speed of the motor then can be estimated by

$$f_m \cong \frac{T_{est}}{T_{rt}}\left(1 - \frac{f_{rt}}{f_{sy}}\right) f_s \tag{2.3}$$

where T_{est} is the estimated torque, T_{rt} is the rated torque, and f_{rt} is the rated speed. This is now sufficient to establish the slip frequency within 2% error.

In the absence of torque estimator, the broken bar frequencies can be estimated as in [7] which are given by the following formula:

$$f_{brk} \cong f_s \pm k \cdot f_m, \qquad k = 1,2,3,\ldots \tag{2.4}$$

Rotor asymmetry, resulting from rotor ellipticity, misalignment of the shaft with the cage, magnetic anisotropy, etc. show up at the same frequency components as the broken bars and must be distinguished from the broken bar frequencies. This can be achieved by examining the sidebands of the higher harmonics. An asymmetry results in low high frequency anisotropy, etc. show up at the same frequency components as the broken bars and must be distinguished from the broken bar frequencies. This can be achieved by examining the sidebands of the higher harmonics. An asymmetry results in low high frequency content. In contrast, localized effects, such as a broken bar, result in large high frequency content.

After estimating the broken bar frequencies, a window of frequency components around the estimates is selected to form the broken bar feature vector. Typically, the window is chosen such that at least 0.25 Hz on each side of the estimate are included into the feature vector. Explicitly, the broken bar feature vector $F_{brk}(n)$ at time instant n can be written as

$$F_{brk}(n)=\left[F_{brk}^{1}(n),F_{brk}^{5}(n),\ldots\right] \quad (2.5a)$$

$$F_{brk}^{n}(n)=\left[S\left(f_{brk}^{n}-w,n\right),\ldots,S\left(f_{brk}^{n},n\right),\ldots,S\left(f_{brk}^{n}+w,n\right)\right],$$

$$n=1,5,7,11,\ldots \quad (2.5b)$$

where S is the magnitude of the time-frequency transformation, i.e., $S(f,n)=|F(f,n)|^2$, and w is the length of the window around the estimates f_{brk}^{n}, $n=1,5,7,11,\ldots$ in Hz/bin. Note that for $n=1$, the slip frequency components are on both sides of the supply frequency due to the side band oscillations, but for higher harmonics, they are only on the lower side of the supply frequency.

To identify the different normal operating modes of a motor, we segment the current into loadwise homogenous segments using the digital torque estimator. The time instants at which significant load changes occur are recorded and the time-frequency spectrum in each loadwise constant segment is computed. The sample mean and the covariance matrix of the feature vectors in each constant operating mode are chosen as the mode representatives. Also, the Bhattacharyya distance [9] between the distinct operating modes are calculated and stored in the database to be used in the postprocessing stage.

To determine a threshold for each mode, we first calculate an intra mode distance between the members of the mode and its representative using the Mahalanobis distance [11]. Next, the sample mean and standard deviation of the intra mode distances are calculated and α unit standard deviation away from the mean distance is chosen as the mode threshold. Note that in the case of normal distribution of the intra mode distances, α is typically chosen to be 2 to provide a 95% confidence interval.

III. TESTING AND POSTPROCESSING

After all the normal operating modes of the motor are learned, the algorithm switches to the testing stage and starts acquiring current data periodically. The data is subjected to the preprocessing and feature extraction operations discussed in the training stage. Next, the distance of the test feature to the representatives of each normal operating mode is calculated using the Mahalanobis distance. If the test feature is beyond the thresholds of all the normal operating modes, it is tagged as a potential fault signal. Otherwise, it is assigned to the mode for which its distance is minimum.

In the postprocessing stage, we check if the potential fault features form a distinct mode in the feature space. As the potential fault features are detected, the mean and covariance matrix of the test features are computed. The distance of the fault representatives and the normal operating modes is calculated using the Bhattacharyya distance to determine if the fault features form a distinct mode. If the shortest distance is larger than the distances between the normal operating modes of the motor, the fault mode is declared distinct and a final alarm is triggered for broken bars.

IV. EXPERIMENTAL RESULTS

For broken bar detection experiments, the archived data from a 35 HP inside out motor which was generated for the EPRI Broken Bar Project - EPRI RP2331-1 was used [2]. The analog current data was low pass filtered at 800 Hz, and digitized at 32 samples per power cycle. However, the algorithm does not require frequencies larger than 300 Hz, and sampling frequency can be as low as 6 samples per power cycle. Each data file in the experiments contains 8 channels which includes 3 phase currents, 3 phase voltages, 60 Hz notch filtered first phase current, and accelerometer data. Notch filtered data was collected in anticipation of improving the dynamic range of the A/D converter.

For the training stage, a 35 HP inside out motor operating in three different load and operating conditions was used. The specifications of these data sets are tabulated in Table 1. Note that for the healthy modes non zero label is used, the label 0 is reserved for the fault modes. The time-frequency spectrum of the training data is shown in Figure 3. The spectrum was computed so that the frequency resolution would be at least 0.2 Hz/bin. This yielded 6 strips of frequency spectra per data set. The broken bar feature vector was formed by a window of frequency components around the first, fifth and seventh harmonic sidebands as described in Section II. Figure 4 illustrates the representatives of each mode around the fifth harmonic.

In the testing stage, seven different sets of data three of which were from a non defective motor and four from motors with varying degree of broken bars, load conditions, and rotating asymmetries were used. The specifics of these data sets are tabulated in Table 2. Out of 42 tests performed, all were correctly classified resulting in 100% accuracy. The results are tabulated in detain in Table 3.

V. CONCLUSIONS

In this paper, we discussed an adaptive time-frequency method to detect broken bars. The method utilizes digital torque estimation to divide current into loadwise homogenous modes and to estimated broken bar frequencies. We showed that a window of frequency components around the estimated fault frequencies has to be monitored because the estimates, even in the case of exact knowledge of the motor geometry and the operating conditions, are never accurate. This approach also allows us to efficiently process frequency components which are spread due to low frequency resolution.

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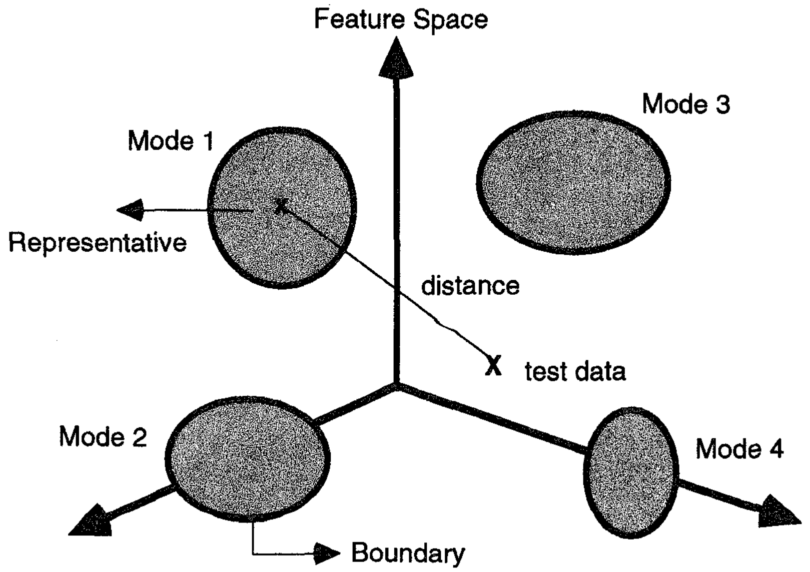

FIGURE 1.
THREE DIMENSIONAL ILLUSTRATION OF THE FAULT DETECTION METHOD

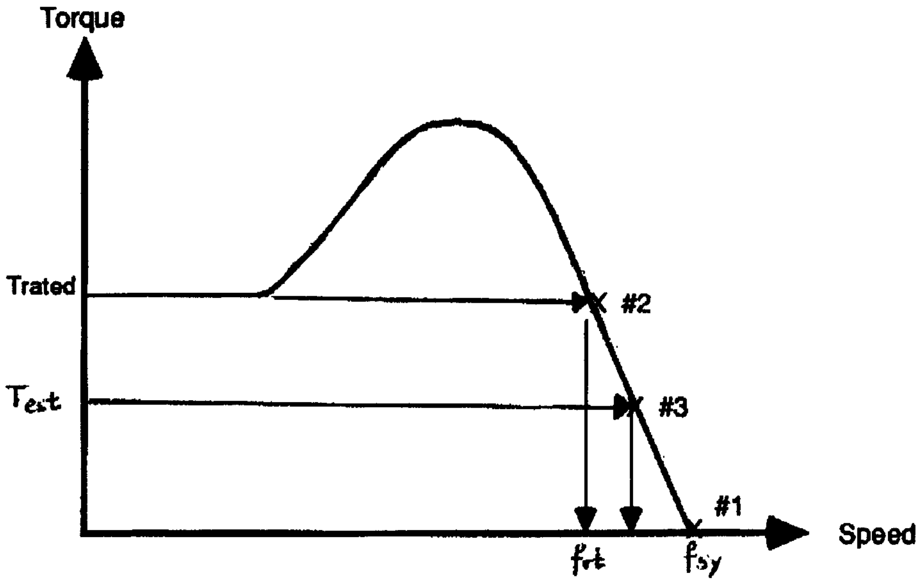

FIGURE 2.
TORQUE-SPEED CURVE FOR MECHANICAL SPEED ESTIMATION

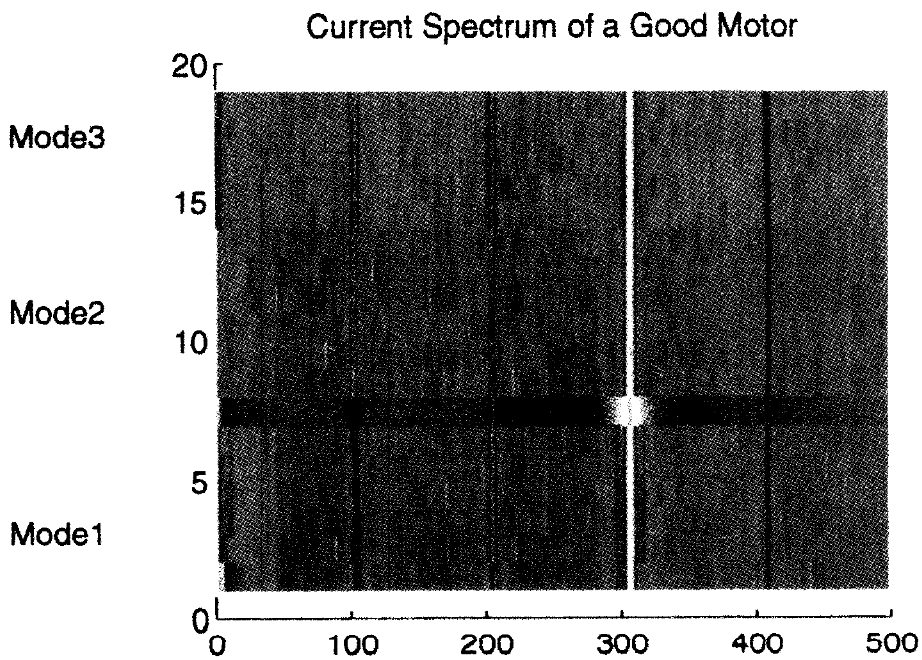

FIGURE 3.
TIME-FREQUENCY SPECTRUM OF THE NORMAL OPERATING MODES OF THE BROKEN BAR MOTOR.

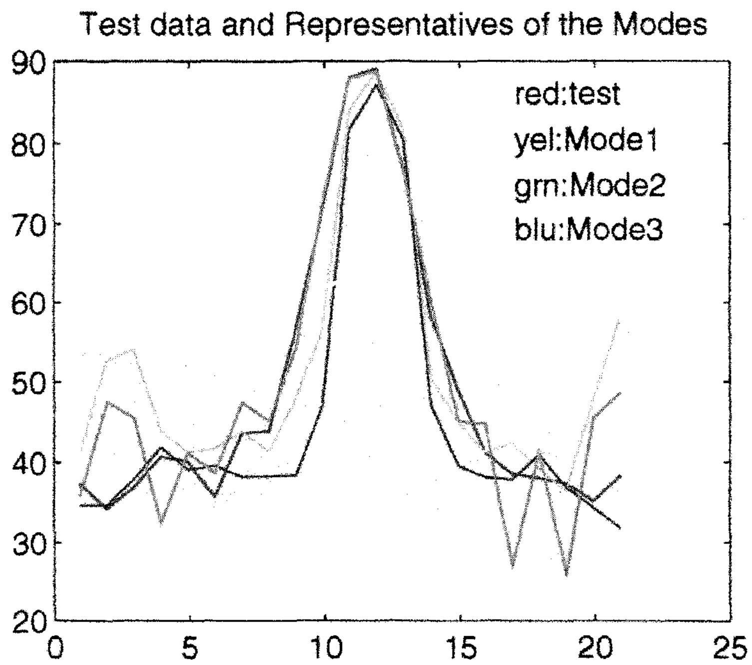

FIGURE 4.
THE REPRESENTATIVES OF THE NORMAL OPERATING MODES OF THE BROKEN BAR MOTOR AROUND THE FIFTH HARMONIC AND A TEST FEATURE FROM THE MOTOR WITH BROKEN BARS.

Mode	Torque	Alignment
1	Over load	10 mil offset
2	Full load	Aligned
3	No load	Aligned

TABLE 1
DATA FROM 35 HP MOTOR WITH NO BROKEN BARS

Mode	Torque	Alignment	Broken Bars
0	No load	Aligned	1 cut
0	Full load	Aligned	2 adjacent cuts
0	No load	Aligned	2 adjacent cuts

TABLE 2
DATA FROM 35 HP MOTOR WITH BROKEN BARS

Mode	1	2	3	0
1	6			
2		6		
3			6	
0				24

TABLE 3
RESULTS OF THE BROKEN BAR DETECTION TESTS FOR UNFILTERED DATA DIGITIZED AT 32 SAMPLES PER POWER CYCLE.