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MUSIC-based Diagnosis Algorithm for Identifying Broken Rotor Bar Faults in Induction Motors Using Flux Signal

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Abstract – The diagnosis of motor failures using an on-line method has been the aim of many researchers and studies. Several spectral analysis techniques have been developed and are used to facilitate on-line diagnosis methods in industry. This paper discusses the first application of a motor flux spectral analysis to the identification of broken rotor bar (BRB) faults in induction motors using a multiple signal classification (MUSIC) technique as an on-line diagnosis method. The proposed method measures the leakage flux in the radial direction using a radial flux sensor which is designed as a search coil and is installed between stator slots. The MUSIC technique, which requires fewer number of data samples and has a higher detection accuracy than the traditional fast Fourier transform (FFT) method, then calculates the motor load condition and extracts any abnormal signals related to motor failures in order to identify BRB faults. Experimental results clearly demonstrate that the proposed method is a promising candidate for an on-line diagnosis method to detect motor failures.

Keywords: Broken rotor bar, Induction motor, Fault diagnosis, Spectral analysis, Flux signal

1. Introduction

Induction motors are widely used in industry as a major source of power due to the simplicity of their construction process and their reliability. However, they are subject to failures, which may be due to production processes or operating conditions. These unexpected failures can cause severe damage to the motors themselves, as well as motor related equipment and processes in industry. Therefore, the diagnosis of motor failures caused by stator, rotor, bearing, and other issues [1] is very important and needs to be highly accurate and the detection speed must be fast. Because of these requirements, on-line instead of off-line diagnosis methods are now being considered. For on-line methods to be feasible for use in industry, the following conditions must be met:

1) Low priced sensors and data acquisition system (DAS)
2) Easy installation of sensors
3) High accuracy in detecting motor failures

Many studies based on fast Fourier transforms (FFTs) have been conducted over the years to detect motor failures using current, vibration, and external flux signals [2-6]. However, FFT-based based diagnosis methods require a large number of data samples to improve the frequency resolution or the accuracy of detecting motor failures. However, the price of DASs increases with the number of data samples used.

A multiple signal classification (MUSIC) technique has been introduced in the motor failure diagnosis area to overcome the shortcomings of the FFT-based method [7], [8]. The MUSIC-based diagnosis method is a high-resolution technique that detects frequencies with a low signal-to-noise ratio (SNR) using a smaller number of data samples. The algorithm computes the autocorrelation matrix, and separates its eigenvalues into signal and noise subspaces. By using a smaller number of data samples, the MUSIC-based diagnosis method can improve the frequency resolution or the accuracy of motor failure detection, and reduce the influence of noise compared to the FFT-based diagnosis method.

In this paper, a MUSIC-based diagnosis algorithm, which can improve the feasibility of the on-line diagnosis method, is proposed to identify broken rotor bar (BRB) faults using a radial flux sensor. Using this approach, a low price sensor can be designed compared to commercial current or vibration sensors [12]. For the flux sensor installation, there is the additional cost of manufacturing associated with installing it. If the flux sensor is installed during motor production, however, there is no additional cost of the installation because the flux sensor can be designed as a search coil to be installed between stator slots easily [12]. Moreover, the diagnosis algorithm requires a smaller number of data samples to increase the accuracy of BRB fault detection. As demonstrated by experimental results, the proposed algorithm performs better than the traditional FFT-based diagnosis method and is therefore a good candidate for the on-line diagnosis method.

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2. Detection of Broken Rotor Bar

This section describes how to extract abnormal signals that are related to BRB faults in induction motors while they are operating. The BRB faults produce characteristic frequency components, which can be observed using spectrum analyses of the current and flux because the characteristic fault-related frequencies are the same in the current and flux spectrum.

2.1 Characteristic frequencies of broken rotor bar faults

When an induction motor operates with BRB faults, the current of the broken bar flows in the two bars that are adjacent to it. This causes an unbalanced air-gap local field. The field pulsates at the slip frequency and modulates the coil-induced voltage. This gives rise to harmonic components at frequencies given as follows [9]:

$$f_{BRB} = \left(1 \pm 2ks\right) f_0, \tag{1}$$

where f_0 is the electrical supply frequency, s is the per-unit slip, and $k = 1, 2, 3, \ldots$.

The characteristic frequency components of BRB faults are similar to the electrical supply frequency as in (1). To improve the performance of BRB fault detection, therefore, the frequency resolution must be increased.

2.2 Calculation of load condition

Most induction motors used in industry operate at variable load conditions and the characteristic frequency components of BRB faults are functions of the slip. Therefore, a calculation of the load condition is necessary in order to diagnose BRB faults on-line. One of the best ways to obtain load condition or slip information is to use rotor slot harmonics (RSHs) [10]. The slip frequency can be obtained as follows:

$$f_{slip} = \frac{p}{R}\left[\left(\frac{R}{p} + \alpha\right) f_0 - f_{RSH}\right], \tag{2}$$

where p is the number of pole pairs, R is the number of rotor slots, $\alpha = \pm k$ (k is positive integer) is the time harmonic order, and f_{RSH} is the RSH frequency given as follows:

$$f_{RSH} = \frac{R}{p} f_{rotor} \pm \alpha f_0 = \left(\frac{R}{p} \pm \alpha\right) f_0 - \frac{R}{p} f_{slip}, \tag{3}$$

where the rotor speed is represented by f_{rotor}.

3. Diagnosis Algorithm

In this section, the basic theory of the MUSIC technique is described briefly and a diagnosis algorithm is proposed for BRB fault detection. The proposed algorithm calculates the motor load condition and extracts any abnormal signals related to BRB faults using the MUSIC technique.

3.1 MUSIC technique

The MUSIC algorithm is a subspace method that can be used to estimate the frequencies of complex sinusoids with a low SNR using eigen-based decomposition methods [11]. Subspace methods assume that the discrete-time signal $x[n]$ is a sum of M complex sinusoids and white noise and is given as follows:

$$x[n] = \sum_{i=1}^{M} \overline{A}_i e^{j2\pi f_i n} + w[n], \tag{4}$$

where $\overline{A}_i = |A_i| e^{j\phi_i}$. In (4), $|A_i|$, ϕ_i, and f_i are the amplitude, the phase, and the frequency of the i th complex sinusoid, respectively, and $w[n]$ represents white noise with a mean of zero and a variance of σ^2. We can rewrite (4) as a compact matrix format as follows:

$$x(n) = F\overline{A} + w(n), \tag{5}$$

Where

$$x(n) = \left[x[n]\ x[n+1]\ \cdots\ x[n+L-1]\right]^T,$$
$$F = \left[f(f_1)\, f(f_2)\ \cdots f(f_M)\right],$$
$$f(f_i) = \left[1\ e^{j2\pi f_i}\ \cdots\ e^{j2\pi f_i (L-1)}\right]^T,\ i = 1, 2, \cdots, M,$$
$$\overline{A} = \left[\overline{A}_1 e^{j2\pi f_1 n}\ \overline{A}_2 e^{j2\pi f_2 n}\ \cdots\ \overline{A}_M e^{j2\pi f_M n}\right]^T,$$

and

$$w(n) = \left[w[n]\ w[n+1]\ \cdots\ w[n+L-1]\right]^T.$$

Here, $F = \left[f(f_1)\, f(f_2)\ \cdots f(f_M)\right]$ is a $L \times M$ Vardermonde matrix of rank M and $f(f_i)$ is a mode vector with frequency f_i, where $i = 1,\ 2,\ \cdots,\ M$.

The MUSIC algorithm uses the eigen-based decomposition of x to obtain the signal and noise subspaces. The autocorrelation matrix of x can be expressed as follows:

$$R = \sum_{i=1}^{M} |A_i|^2 f(f_i) f^H(f_i) + \sigma^2 I_L, \tag{6}$$

where I_L denotes a $L \times L$ identity matrix. Using the eigen-based decomposition, the eigenvalues and the corresponding eigenvectors of R can be obtained and we denote these as $\{\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_L\}$ and $\{v_1, v_2, \cdots, v_L\}$, respectively. The eigenvectors can be divided into the signal subspace eigenvectors, i.e., $\{v_1, v_2, \cdots, v_M\}$, associated with the M largest eigenvalues and the noise subspace eigenvectors, i.e., $\{v_{M+1}, v_{M+2}, \cdots, v_L\}$, which have an eigenvalue of σ^2. From (6), the sinusoidal signal vectors can be expressed as a linear combination of eigenvectors of the signal subspace. They are therefore orthogonal to the eigenvectors of the noise subspace, and this can be expressed as follows:

$$f^H(f_i)v_k = 0, \tag{7}$$

where $i = 1, 2, \cdots, M$ and $k = M+1, M+2, \cdots, L$.

Utilizing the orthogonality of the signal vectors and the noise eigenvectors, the MUSIC pseudospectrum can be defined as follows:

$$P^{MUSIC}(f) = \frac{1}{\sum_{k=M+1}^{N} \left| f^H(f)v_k \right|^2}. \tag{8}$$

The M characteristic frequencies can be found by searching for the peaks in the MUSIC pseudospectrum.

For a practical application of the algorithm, we need to estimate $\hat{R}$ of R in (6). Using L_T serial discrete-time signals $x[n]$ in (4), a spatial smoothing (SS) method is applied to calculate $\hat{R}$ as follows [13]:

$$\hat{R} = \frac{1}{P_s}\sum_{n=1}^{P_s} x(n)x^H(n), \tag{9}$$

where $P_s = L_T - L + 1$ and $L_T > L$.

3.2 Proposed diagnosis algorithm

A block diagram of the proposed diagnosis algorithm for identifying BRB faults is shown in Fig. 1. The flux signal measured by the DAS is first used to calculate the motor load condition or slip using the MUSIC algorithm. Then, using the calculated slip, the MUSIC algorithm extracts the abnormal signals that are related to BRB faults at the frequency specified in (1). The last step of the proposed algorithm is to monitor for any changes to the abnormal signals. The method is designed based on the fact that specific changes appear at the characteristic frequencies when BRB faults occur.

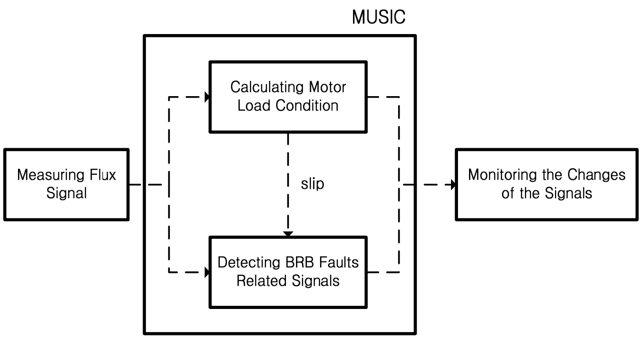


Fig. 1. Block diagram of the proposed algorithm

4. Experimental Setup

In this section, we present an experimental setup including a radial flux sensor and an induction motor test system to evaluate the performance of the proposed algorithm.

4.1 Radial flux sensor

The radial flux sensor developed by the authors is shown in Fig. 2 [12]. It can be made at a low price compared to commercial current or vibration sensors and is designed as a search coil and each search coil is made up of 20 turns (18 Ω). The induced voltage at the search coil can be simply expressed by Faraday's law as follows:

$$e = -N\frac{d\Phi}{dt}, \tag{10}$$

where N is the number of coil turns and Φ is the magnetic flux.

Fig. 2. Radial flux sensor designed by the authors

To achieve easy installation of the sensor, the radial flux sensor is installed between stator slots in the test motors during motor production as shown in Fig. 3.

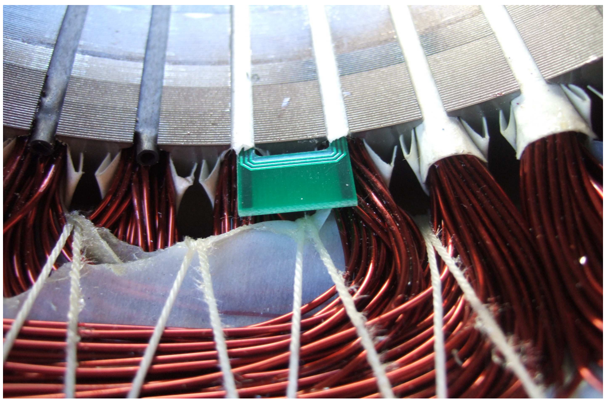


Fig. 3. Installation of radial flux sensor

4.2 Induction motor test system

Fig. 4 shows an induction motor test system, which consists of a test motor, a load motor, a DAS, and an inverter. The inverter operates load motor using vector control and the load motor rotates opposite direction of the test motor. This applies the load to the test motor. The specifications of the test motor and the load motor are given in Table 1. Three types of test motors were used in the experiment: a healthy motor, a motor with two BRBs, and a motor with four BRBs. The motors with BRBs are simulated by holes drilled in the motor as shown in Fig. 5.

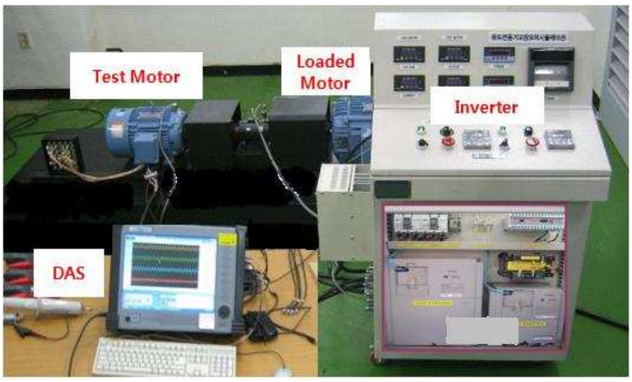


Fig. 4. Induction motor test system

Table 1. Specifications of the motors

	Test motor	Load motor
Power (kW)	7.5	22
Voltage (V)	220	220
Current (A)	28.2	76.8
Poles	4	4
Frequency (Hz)	60	60
Speed (rpm)	1760	1775

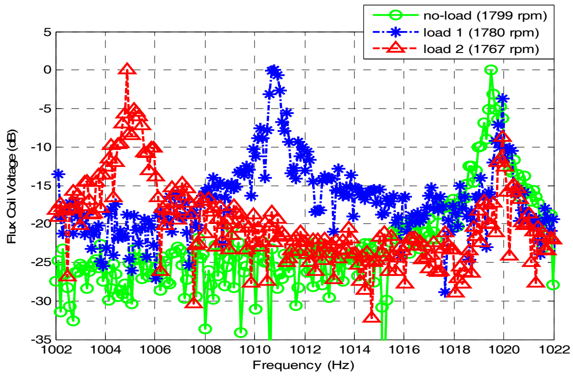
Fig. 5. Motors with simulated BRBs

5. Experimental Results

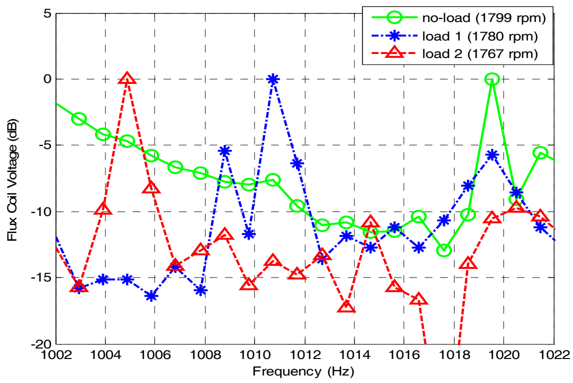
Experimental results are presented in this section to verify the performance of the proposed algorithm as a candidate for on-line BRB fault detection that is highly accurate when compared to the traditional FFT-based method.

5.1 Results of load condition

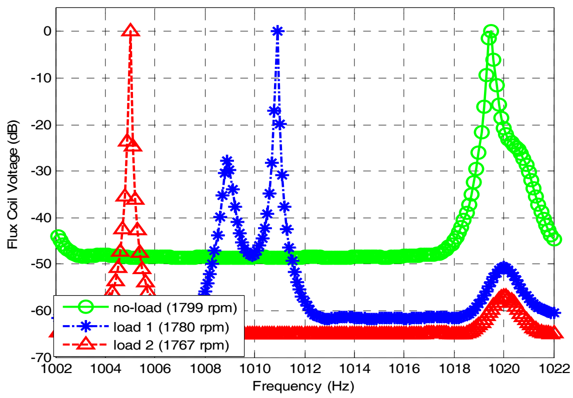
The spectral analyses displayed in Fig. 6 show the RSHs amplitudes for different motor load conditions of a healthy motor where $\alpha = -3$ and $R = 28$ in (3). For each experimental data point, a 4 kHz sampling rate with 4096 samples was used, which can be achieved by down sampling



(a) FFT with 100 kHz and 1048576 samples

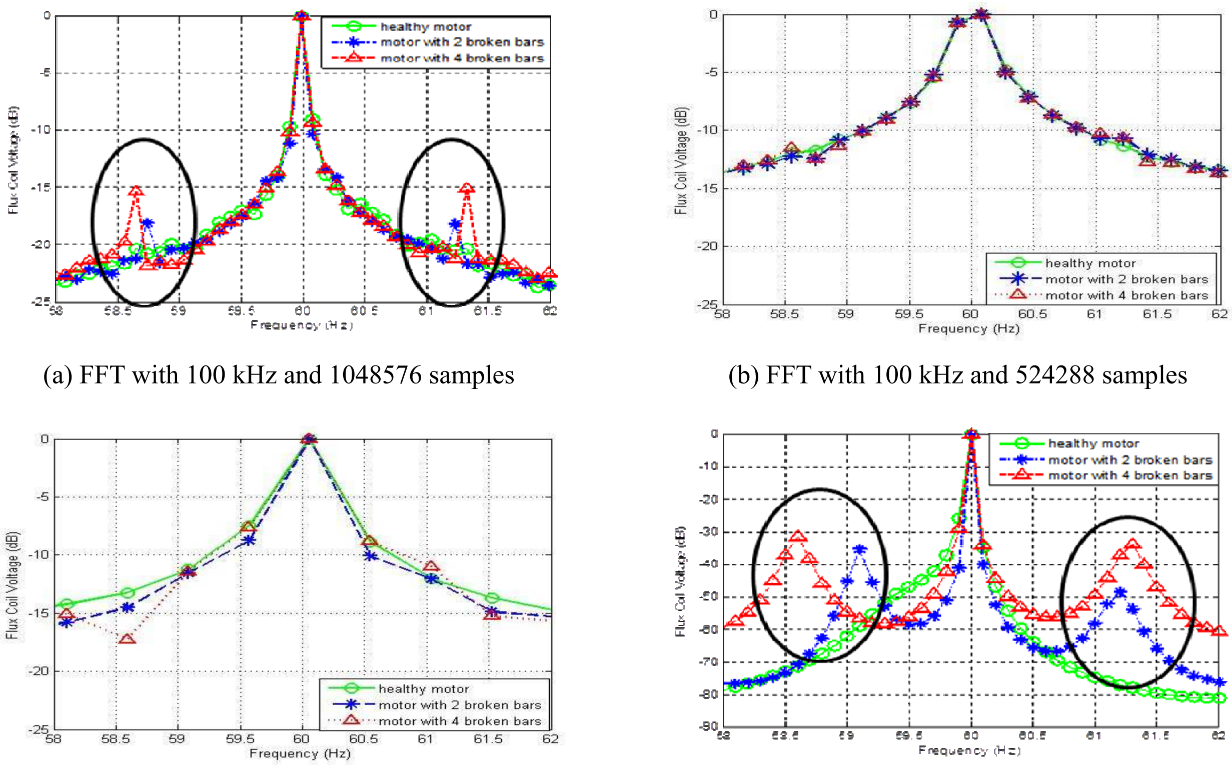


(b) FFT with 4 kHz and 4096 samples



(c) MUSIC with 4 kHz and 4096 samples

Fig. 6. Spectral Analyses for RSHs



(a) FFT with 100 kHz and 1048576 samples

(b) FFT with 100 kHz and 524288 samples

(c) FFT with 2 kHz and 4096 samples

(d) MUSIC with 2 kHz and 4096 samples

Fig. 7. Spectrum Analysis for BRB faults

from original data with a sampling rate of 100 kHz and 1048576 samples. As shown in Figs. 6(b) and 6(c), the RSHs are almost the same as the original data shown in Fig. 6(a). This means that the FFT-based method and the proposed method can calculate the load condition of the test motor if the motor maintains its load condition for 1.0240 seconds. In the case of the load condition 1, where the test motor operates at a speed of 1780 rpm, the RSH frequency is 1011 Hz as shown in Fig. 6(c). Using this RSH frequency, the slip is easily calculated to be 0.011.

5.2 Broken rotor bar frequency component results

Comparisons between the FFT-based method and the proposed method for identifying BRB faults are shown in Fig. 7. Three different motors are considered: a healthy motor, a motor with two broken bars, and a motor with four broken bars. For each experimental data point, a 2 kHz sampling rate with 4096 samples was used, which can be achieved by down sampling from original data with a sampling rate of 100 kHz and 1048576 samples. The induction motors used in this experiment operate at a speed of 1780 rpm, therefore, using (1) when $s = 0.011$ and $k = 1$, any abnormal signals will appear near the frequencies of 61.3 Hz and 58.6 Hz. Even though the FFT-based method can identify BRB faults as shown in Fig. 7(a), it cannot detect abnormal signals when the sampling rate and the number of samples decrease as in Fig. 7(b) and (c) because of the low frequency resolution and the high noise floor. As shown in Fig. 7(c) and 7(d), using 2 kHz sampling rate and 4096 samples, the proposed MUSIC method can detect broken rotor bar faults using the fault signatures, while the FFT method cannot detect broken rotor bar faults. As shown in Fig. 7(d), the left and right sidebands for the motor with 4 broken rotor bars appear at twice the slip frequency, 2sf, from the main frequency, while the left sideband result of the motor with 2 broken rotor bars is not away from the main frequency by 2sf. This is because the proposed MUSIC algorithm uses low sampling rate with small number of samples.

6. Conclusion

This paper has described the initial step taken to develop an on-line diagnosis method for identifying BRB faults using flux signals. The use of a specially designed radial flux sensor that can be constructed at a low cost and easily installed has been described. Experimental results demonstrated that the proposed algorithm detects motor failures more accurately than the traditional FFT-based method. Moreover, it can detect BRB faults when the sampling rate is low and the number of samples is small. That means it can reduce the burden of the DAS because of its high-resolution properties.

The main advantages of the proposed scheme are that the radial sensor can be implemented with a low cost and the MUSIC scheme can be performed with small data samples. Therefore, it is expected that this method will be applied as an on-line diagnosis method to detect motor failures. The main drawback, which is also found in other subspace method with high resolution, is the need of computational complexity to perform the eigen-decomposition.

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References

[1] Motor Reliability Working Group, "Report of large motor reliability survey of industrial and commercial installation, Part II," *IEEE Trans. Ind. Appl.*, Vol. IA-21, No. 4, pp. 865-872, July/Aug. 1985.

[2] W. T. Thomson and M. Fenger, "Current signature analysis to detect induction motor faults," *IEEE Ind. Appl. Mag.*, Vol. 7, No. 4, pp. 26-34, July/Aug. 2001.

[3] J. R. Cameron, W. T. Thomson, and A. B. Dow, "Vibration and current monitoring for detecting airgap eccentricity in large induction motors," *Proc. IEE-Electric Power Appl.*, Vol. 133, No. 3, pp. 155-163, May 1986.

[4] R. R. Schoen, T. G. Habetler, F. Kamran, and R. G. Bartfield, "Motor bearing damage detection using stator current monitoring," *IEEE Ind. Appl.,* Vol. 31, No. 6, pp.1274-1279, Nov./Dec. 1995.

[5] M. J. Devaney, and L. Eren, "Detecting motor bearing faults," *IEEE Instrumentation and Measurement Mag.*, Vol. 7, No. 4, pp. 30-50, Dec. 2004.

[6] H. Henao, C. Demian, and G.-A. Capolino, "A frequency-domain detection of stator winding faults in induction machines using an external flux sensor," *IEEE Ind. Appl.* Vol. 39, No. 5, pp. 1272-1279, Sep./Oct. 2003.

[7] M. E. H. Benbouzid, M. Vieira, and C. Theys, "Induction motors' faults detection and localization using stator current advanced signal processing techniques," *IEEE Trans. Power Electron.,* Vol. 14, No. 1, pp. 14-22, Jan. 1999.

[8] S. H. Kia, H. Henao, and G.-A. Capolino, "A high-resolution frequency estimation method for three-phase induction machine fault detection," *IEEE Trans. Ind. Electron.,* Vol. 54, No. 4, pp. 2305-2314, Aug. 2007.

[9] I. Ahmed, and M. Ahmed, "Comparison of stator current, axial leakage flux and instantaneous power to detect broken rotor bar faults in induction machines," *in Proc. of Power Engineering Conference*, pp. 1-6, Dec. 2008.

[10] R. Blasco-Gimenez, G. M. Asher, M. Sumner, and K. J. Bradley, "Performance of FFT-rotor slot harmonic speed detector for sensorless induction motor drives," *Proc. IEE-Electric Power Appl.*, Vol. 143, No. 3, pp. 258-268, May 1996.

[11] M. H. Hayes, *Statistical digital signal processing and modeling*: John Wiley & Sons, Inc, 1996.

[12] Don-Ha Hwang et al., "Detection of air-gap eccentricity and broken-rotor bar conditions in a squirrel-cage induction motor using the radial flux sensor," *Journal of Applied Physics*, Vol. 103, No. 7, pp. 07F131-07F131-3, Apr. 2008.

[13] M. Kristensson, M. Jansson, and B. Ottersten, "Further results and insights on subspace based sinusoidal frequency estimation," *IEEE Trans. Signal Process.*, Vol. 49, No. 12, pp. 2962-2974, Dec. 2001.

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