Wireless Sensors System for Broken Rotor bar Fault Monitoring using Wavelet Analysis

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Abstract. Accurate condition monitoring prevents unexpected failures in electrical systems including induction machines, and hence improves their performance significantly. To enhance the reliability of condition monitoring systems, wireless sensor systems are developed. In the recent years, researchers have placed considerable emphasis on developing cost-effective scheme using wireless sensor systems for fault diagnosis of equipments in industry. As broken rotor bar is one of the main causes of malfunction in electrical motors, this paper proposes a method for early detection of this failure in induction machines using wireless sensor system. In this respect, a test bed is developed where a sensor measures the motor current and then a microcontroller connected to this current sensor read and send the data to wireless sensor for remote real time data analysis. In the receiver unit, a Lab VIEW based program is developed to store data in a database and MATLAB is used for signal processing and fault.

1. Introduction

Induction machines (IMs), usually referred as the heart of industrial plants, are ubiquitous in industries. They facilitate production processes, operations and related services in various plants. However, during their operation, they are under inevitable stresses (electrical, mechanical, environmental, and thermal stresses) in the workplaces. These stresses create several Faults in different parts of IMs. These faults are one of the major reasons for poor performance of the industrial plants as they perturb the secure operation of the motor, imperil the standard manufacturing, and thus bring about the substantial expenditure [2]. An effective maintenance technique can avoid generation of sever failures that leads to malfunction of these devices, and therefore decrease unwanted expenses by preventing unscheduled downtimes. Fault diagnosis of IM is a common maintenance problem and industries are seeking for reliable maintenance systems that offer improved performance of the electrical motor through minimizing the risk of catastrophic failures and thus decrease both operational and maintenance costs. Such maintenance systems include precise assessment of machine performance through suitable condition monitoring and fault prediction techniques. Accurate monitoring of IMs parameters like current, vibration and torque, is thus a key for reliable maintenance schemes.

There are two common strategies applied for managing the equipment maintenance in industries, which are preventive and reactive maintenance [3]. In the reactive maintenance strategy, device is let to run until it fails, and then it is repaired if it is repairable. Preventive maintenance is a scheduled-
based strategy that assesses the lifetime of any device using failure statistics obtained from the similar system. Both these traditional maintenance strategies may result undesired outcomes including unnecessary downtime, offensive risk, high maintenance costs and inefficient usage of resource. The conventional maintenance methods for electrical motors are typically based on using portable or handheld data collection equipments [3]. Performance of electrical motor is checked manually by sending labor to the area where these devices are installed. This method is then time consuming and cumbersome and more importantly cannot provide precise condition monitoring of the equipment, which in turn results in inaccurate assessment of the site. This approach also impedes frequent monitoring of the device, where unexpected failures can threat safe performance of the motor. On-line condition monitoring of electrical motors based on predictive maintenance can offer accurate fault detection in the device and thus avoid unforeseen failures in them. Due to availability of data achieved through on-line monitoring, the reliability of the maintenance program is also improved [4]. Online predictive maintenance for IMs can be integrated, through wireless data collection technologies [3,5]. Wireless sensing can enhance the availability of system by connecting it to the selected equipment. This capability make them appropriate for different applications, particularly where there is difficulty in access to the device or cabling to it [6,7]. Another advantage of wireless sensing is a number of different locations can be monitored through one station. Accordingly, using wireless sensor will minimize both fixed investments and operational costs of the plants by reducing the amount of cables installed and the number of labors needed to manually check the devices and accessories in the (working place) sites. Wireless sensors are reliable, smart, cost-effective, energy-saving and easy-to-install sensors with capability of fast data acquisition [5].

To design a good maintenance scheme, the first step includes identifying the type of equipment, its operational characteristics and type of failures may occur. Based on this information, one or more suitable condition monitoring techniques using wireless sensors are then selected. The final step involves applying precise and reliable signal processing for the data achieved through sensors. With the aim of developing a cost-effective system for maintenance, this article presents a research using wireless sensor for detection of rotor bar breakage in squirrel cage IM. Current signals from IMs are acquired and then, wavelet analysis of signal is employed for fault diagnosis. In this research, a wireless sensor will play a critical role in monitoring and supervising electrical motor in remote areas by reporting the measured data to find the fault in IMs. This system has also feasibility to apply for intelligent fault diagnosis.

1.1. Rotor fault

Different parts of IM operating in industrial plants are subjected to inevitable stresses that damage the component and may cause further malfunctions. Rotor faults have attracted a great consideration since these failures result in serious subsequent failures in other parts of motor. Bonnett and Soukup, in their comprehensive study, addressed various stresses that create failures in rotor and identified the causes [1]. There are three common faults in the rotor including breakage or cracking of bars or end-rings, rotor eccentricity and rotor bow [8].

Among these failures, it is fair to note that breakage of rotor cage bars is the main one. Any rotor bar, during operation of motor, can be partially or completely broken because of improper geometry design and/or stresses of rotor. Presence of broken rotor bar, like any other failures, causes a decrease in efficiency of motor and that increase operational cost. Breakage of rotor bar also deteriorates the state of neighboring bars progressively and brings other secondary faults that developed serious malfunctions in the motor [8]. Once a bar breaks, the current flow in the neighboring bars boarding the broken bar rises up to 50% of rated current [9] and thus these bars are overheated [10]. Such extra heating in the bars causes the rotor bow and the eccentricity [11], and hence unbalanced currents and torque pulsation that consequently decrease average torque of motor [12]. Accordingly, early detection of breakage in rotor bar is crucial not only for protection of rotor but also for impede secondary faults in the motor.
1.2. Motor Current Analysis

The key for successful failure diagnosis of electrical motor relies on the availability of information that allows diagnosis of a motor condition. Condition monitoring techniques have been continuously developed over the years, which resulting a range of available methods for diagnosis of failures in IMs. Various techniques have been explored by using acoustic analysis, electromagnetic field monitoring, motor current signature analysis, induced voltage, instantaneous power, vibration and etc. The most common technologies used in the condition monitoring of rotor fault are presented in [8,13]. Among all condition monitoring techniques addressed, stator current analysis is the most popular one due to its simplicity in measurement, high reliability and accuracy. Besides that, this method is cost-effective as current sensors are easy to be implemented and do not require costly additional transducers.

When a failure is generated in the electrical motor, depends on the severity of this fault, some parameters of the machine change. For instance, any irregularity in the rotor causes an uneven distributed current in it. An ideal IM contains a single component corresponding to the supply frequency in current spectrum. Any asymmetry in IM causes other components to be appeared in spectrum of stator current. Current does not flow through broken rotor bar, and hence no magnetic flux creates around the breakage bar. Consequently, a non-zero backward rotating field that rotates at the slip frequency speed with respect to the rotor is generated. Any variation in the magnetic field of rotor induces a specific harmonic in the currents spectrum, which is added on the stator current. These harmonics have frequencies as \((1\pm2ks)f_s\), where \(k=1,2,3\ldots\) is an integer number, and \(s\) and \(f_s\) are slip and fundamental frequency, respectively [14].

1.3. Signal Processing Technique

A raw signal is normally presented as time domain graphs that specify how parameters vary over time. For extracting the information from raw signal, suitable signal processing technique needs to be applied. Signal processing provides necessary information extracted from a raw signal by applying a mathematical correlation. Signal processing techniques can provide principal information about the specific failure in the motor that makes the detection of the failure feasible. Basically, signal processing can be accomplished either in time analysis, frequency analysis or time-frequency analysis.

Frequency analysis based on fast Fourier transform is the most usual signal analysis technique utilized for fault detection in IMs [8]. However, there are some inconsistencies in ability of using Fourier analysis for fault detection [15,16] and thus advanced signal processing techniques are proposed for more accurate and reliable fault detection. These advanced techniques, like Short-time Fourier transform and wavelet transform are dependent upon time-frequency domain analysis of signal that provides simultaneous time and frequency analysis.

In overcoming the problem of resolution in Short-time Fourier transform, wavelet transform was introduced, this technique has been widely selected in different areas of signal processing. Wavelet analysis provides both the frequency and time information of a signal by expressing original signal in an oscillatory functions series. These functions are defined with respect to both frequency and time. In wavelet transform, the signal is divided into time-scale space where the dimension of window in both time and frequency (scale) are flexible [17]. The Wavelet transform localizes the information of signal in the time–scale plane which makes it suitable for non-stationary analysis signals. A practical version of discrete wavelet transform, called wavelet multi-resolution analysis, was introduced by Mallat [18]. In this algorithm, original signal is disintegrated into a series of minor waves which is a member of wavelet family. The energies associated to the disintegrated signal for each detail and approximation coefficient can be calculated and refer in [19].

The multi-resolution analysis makes use of discrete dyadic wavelet and excerpts the approximations of the raw signal at various levels of resolution. The low-resolution and high resolution part of the raw signal represents approximation and detail respectively. The approximations and details can be
determined by applying the low and high pass filters. In the multi-resolution analysis, decomposition procedure is repeated as the approximations are divided consecutively, while the analyses in details never proceed further. Accordingly, in wavelet analysis, a signal is decomposed into many lower resolution components through successive decomposition of approximations. This procedure is called "wavelet decomposition tree" and the corresponding algorithm is shown in Figure 1 [20].

Wavelet analysis is a developed and enhanced technique for fault diagnosis in many devices including IM. However, its performance strongly depends on some parameters that need to be considered. For instance, type of wavelet function applied determines the result of signal decomposition. Different wavelet functions (such as Daubechies 8 [21,22], Daubechies10 [23], Daubechies12 [24], Daubechies 23 [25], Coiflet [26,27], Coiflet4 [28,29] and Meyer [16]) have been used for decomposition of current signal with purpose of rotor bar breakage diagnosis. Besides the effect of mother wavelet on the results of signal decomposition, various features, like energy of decomposed signal can be extracted from decomposed signal and used as fault characteristic feature [30,31,32]. Despite the multiple existing references, the scattering and the diversity of wavelet functions and features used in signal processing procedures makes a reliable comparison of the results difficult. Therefore, a comparative study that concentrates on the outcomes of different wavelet functions for early fault detection is essential. This study then intends to investigate the effects of the wavelet function for early broken rotor bar detection using energy feature of stator current signal in different load.

2. Experimental Section

2.1. Setup Configuration
In order to examine the capability of wireless system for early broken rotor bar detection, IMs under healthy and faulty situation were observed under different levels of load. The IM was joined to a generator, which works as a load simulation. Experimental data including stator current was acquired through a current sensor. The architecture of experimental setup used in this study is shown in Figure 2.
The characteristics of IM used in this study are: rated power 1hp, star connection, rated voltage 415 V, rated current 2.2 A, 6 poles, speed 1000 rpm. The stator slots and rotor bars number are 36 and 28 respectively. The bar breakage was done artificially in the workshop by drilling the bar. The stator current signal of one phase was measured under a fixed condition using a sensor (ACS756) that provides precise and economical solutions for AC or DC current measurement in industrial systems. The instruments for checking the condition of data collection in each test are torque and speed sensor. An 8 bit processor of ATmega328 was employed to control 16 bit analog digital conversion and wireless system. A wireless sensor checked the status of system in real-time. Base-station includes server and fault diagnosis system. The server was used for receiving data and feeding it into the data analysis part. In this program, the incoming data was considered and read as string. Therefore, the data was converted to decimal value before it was sent to a database. In this database portion, the connectivity between LabVIEW and database was prior to be established. Once the connection was ensured, the incoming data would be fed in to the database table. The specification of wireless sensor system is exhibited in Table 1. Figure3 demonstrates the experimental setup used in this study.

### Table 1. Wireless sensor specification

| Processor (ATmega328) | Wireless Bridge |
|-----------------------|-----------------|
| Communication: UART  | Name: XBEE-PRO-S1 |
| Embedded: IST, JTAG   | Company: MaxStream |
| Memory: 32 K          | Networking: 802.15.4 |
| Clock: 16 MHz         | Standard: IEEE 802.15.4 |

#### 2.2. Fault detection algorithm

In order to examine the capability of wireless sensor for early broken rotor bar detection, IMs under healthy and faulty situation were observed at various levels of load. An IM with one broken rotor bar is considered as faulty one. Before data analysis, the raw current signal was re-sampled by synchronizing at phase 0. This preprocessing on the raw current signal is needed since the unsynchronized signal influences the results of diagnosis [16,30]. The total re-sampled cycles of the signals were five cycles. In the following step, all wavelet functions provided by wavelet tool box in MATLAB were examined to find the suitable Wavelet function. In multi-resolution analysis, a signal is disintegrate into various levels and each level enclosed by definite range of frequency. To determine the appropriate decomposition level, the original signal was first decomposed into 8 levels using wavelet decomposition technique. Each decomposition level has its own selected frequencies and detailed coefficients. Table 2 presents the frequency ranges corresponding to each detail. It is clear that the fundamental frequency as well as sidebands frequency is existed in the frequency band matching to level 8 of detail. These sidebands are commonly used to detect rotor bar breakage in IM. Three different levels of load, the nearest left and right sidebands, when k equals to one, were obtained and summarized in Table 3. The results indicate that when load increases, the sidebands frequency also changes. This change is attributed to the broken bar in the motor and then 8th level of decomposition can be chosen for wavelet analysis of current signal with purpose of broken rotor bar detection.
Table 2. Frequency bands for signal decomposition using wavelet.

| Level of Decomposition | Frequency Bands (Hz) |
|------------------------|----------------------|
| Detail 1               | 10000-5000           |
| Detail 2               | 5000-2500            |
| Detail 3               | 2500-1250            |
| Detail 4               | 1250-625             |
| Detail 5               | 625-312.5            |
| Detail 6               | 312.5-156.25         |
| Detail 7               | 156.25-78.12         |
| **Detail 8**           | **78.12-39.06**      |
| Approximation 8        | 39.06-0              |

Table 3. Broken rotor bar sidebands frequency at different load levels.

| Torque (Nm) | Speed (rpm) | Slip  | (1-2s)f<sub>s</sub> (Hz) | (1+2s)f<sub>s</sub> (Hz) |
|-------------|-------------|-------|--------------------------|--------------------------|
| 2.70        | 984         | 0.016 | 48.4                     | 51.6                     |
| 4.00        | 976         | 0.024 | 47.6                     | 52.4                     |
| 6.25        | 960         | 0.040 | 46.0                     | 54.0                     |
Measure the current signal from one phase of motor under 35%, 50% and 80% of full load

Preprocessing

Analyse the current signal with wavelet transform (Five wavelet functions are being examined: Biorthogonal 6.8, Coiflet 2,5 Daubechies 1,6 & 10 )

Extract the feature (Energy) from data calculated by wavelet analysis

Calculate the mean value of features for ten samples at each level of load for each type of wavelet function used

Compare the mean values and standard deviation of features obtained from using different mother wavelet to determine the reliable type of it for signal analysis

Calculate the standard deviation of features for ten samples at each level of load for each type of wavelet function used

Those wavelet functions that generate a decomposed signal with higher energy value in determined level of decomposition were selected for broken rotor bar detection. Energy coefficient, as characteristic feature, was extracted from wavelet decomposition of current signal. Each test was repeated 10 times and the average value of the features were calculated and used for further investigation. Figure 4 depicts the procedure used for wavelet analysis of current signal.

3. Results and Discussion

The energy value of current signal decomposed at 8th detail was determined and investigated as a fault characteristic feature for diagnosis of broken rotor bar. Tables 4 and 5 present the mean values for the characteristic features of the 8th detail decomposition for healthy and faulty machines under different types of mother wavelet when various levels of load were applied.

Table 4. Characteristic features of the 8th detail decomposition for healthy motor under different levels of load when various types of wavelet function were used

| Feature     | Load (%) | Bior 6.8 | Coiflet 2 | Coiflet 5 | Daub 1 | Daub 10 |
|-------------|----------|----------|-----------|-----------|--------|---------|
| Energy      | 35       | 4658     | 4803      | 7029      | 2504   | 7898    |
| detail 8    |          |          |           |           |        |         |
|             | 50       | 4763     | 4911      | 7196      | 2570   | 8096    |
|             | 80       | 5242     | 5411      | 7929      | 2849   | 8939    |

| Feature     | Load (%) | Bior 6.8 | Coiflet 2 | Coiflet 5 | Daub 1 | Daub 10 |
|-------------|----------|----------|-----------|-----------|--------|---------|
| Energy      | 35       | 4713     | 4767      | 7057      | 2513   | 8006    |
| detail 8    |          |          |           |           |        |         |
|             | 50       | 4782     | 4900      | 7194      | 2585   | 8152    |
|             | 80       | 5729     | 5921      | 8637      | 3095   | 7854    |

It has been firmly confirmed that if any failure occurs in the machine, the faulty situation has higher characteristic features values than the healthy ones [24]. However, the data presented in Tables 4 and
5 indicates some inconsistencies. For instance, when wavelet function of Coiflet 2 and Daubechies 10 were used for signal analysis, the energy values of faulty conditions were smaller than healthy. No such inconsistencies were observed when Daubechies 1 and/or Biorthogonal 6.8 were applied for wavelet decomposition of the signal. These observations express that not only the type of wavelet function used for signal analysis influence the result but also the characteristic feature needs to be taken into account. As just two wavelet functions, Daubechies 1 and/or Orthogonal 6.8, showed reliable information, these two were further investigated. Therefore, the standard deviations of all features for these two wavelet functions were computed as presented in Table 6. Comparatively, Daubechies1 had smaller standard deviation that indicates the sampled data had smaller dispersion from the average. Therefore, the characteristic features obtained from decomposition of current signal using Daubechies 1 were more reliable to be used for early detection of fault in squirrel-cage IM than Biorthogonal 6.8. This study proved that there is a significant difference in ability of wavelet functions for accurate signal analysis and interpretation. Therefore, the arbitrary selection of wavelet function for wavelet analysis of signal cannot supply reliable information for fault diagnosis in machine. It is recommended that different characteristic features to be selected and observed for increasing the accuracy of condition monitoring.

Table 6. Statistical parameters computed for characteristic features obtained from wavelet analysis of the current signal using Biorthogonal 6.8 and Daubechies 1

| Feature       | Healthy | Biorthogonal 6.8 | Daubechies 1 | Faulty (one BRB) | Biorthogonal 6.8 | Daubechies 1 |
|---------------|---------|------------------|-------------|-----------------|------------------|-------------|
| Energy        | Torque (Nm) | Load (%)        | Mean | STD  | Mean | STD  | Mean | STD  | Mean | STD  |
| detail 8      | 2.70    | 35               | 4658 | 6.85 | 2505 | 4.93 | 2513 | 26.54 |
|               | 4.00    | 50               | 4763 | 9.55 | 2570 | 7.85 | 2585 | 59.89 |
|               | 6.25    | 80               | 5242 | 8.21 | 2850 | 6.45 | 3095 | 24.66 |

4. Conclusions
This article develops a method for diagnosis of broken rotor bar in squirrel-cage IM using a wireless sensors system. Different types of wavelet functions were applied to decompose the current signal. These functions were then compared in screening the feature in related to the present fault. The characteristic feature observed was the energy value of the decomposed signal. Wireless sensor used indicates a good performance in fault detection problem of IM. This study also proved that the types of mother wavelet used for signal processing considerably influence the reliability of the diagnostic method. Among different wavelet functions examined in this research for current signal decomposition, Daubechies 1 provided more reliable information for early diagnosis of rotor bar breakage in IM. An increase in the value of characteristic feature was observed for faulty situation as compared to the healthy situation that worked under the same level of the load.

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