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FPGA Based Embedded System Development for Rolling Bearings Fault Detection of Induction Motor

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ABSTRACT

Bearing fault diagnosis is crucial in condition monitoring of any rotating machine. Early fault detection in machines can save millions of dollars in maintenance cost. Different methods are used for fault analysis such as short time Fourier transforms (STFT), Wavelet analysis (WA), Model based analysis, cepstrum analysis etc. Recently, there have been outstanding technological developments related to digital systems, in both hardware and software. These innovations enable the development of new designing methodologies that aim to the ease the future modifications, upgrades and expansions of the system. This paper presents a study of rolling bearing fault diagnosis of induction motor based on reconfigurable logic. A case study using FPGA, its design, as well as its implementation and testing, are presented.

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1. INTRODUCTION

Induction motors are workhorses of industrial processes and are frequently integrated in commercially available equipment and industrial processes. There are many published methods and numerous commercially available tools to monitor induction motors to ascertain a high degree of dependability uptime. Despite these tools, many companies are still faced with unforeseen system failures and decreased motor lifetime. The analysis of induction motor behavior during abnormalities and the possibility to diagnose these circumstances have been a challenging issue for many electrical machine researchers.

The literature indicate that majority of the failures in the three-phase induction motors are mechanical in nature such as bearing faults, eccentricity or misalignment faults and balance associated faults [1], [8].

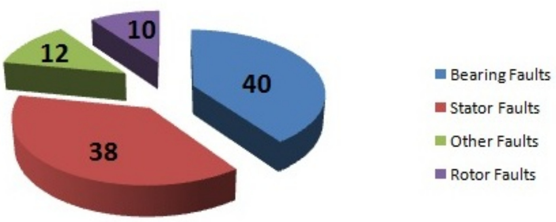

Figure 1. Fault Percentages in Induction Motor

The faults occurring in motor bearing is commonly due to the excessive load, rise of temperature within the bearing, employment of defective lubricant and so on. The bearing consists of primarily of the outer race, the inner race way, the balls and cage which ensures equidistance between the balls. The different faults that may occur in a bearing can be categorized according to the affected component [3], [7]:

a) Outer raceway defect
b) Inner raceway defect
c) Cage defect
d) Ball defect

Machine vibration analysis is commonly used for rolling bearing faults diagnosis. In numerous situations, vibration monitoring methods are exploited to detect the presence of incipient failures in electrical motors using sensors [8]-[10].

This paper presents the design of a vibration monitoring embedded system based on reconfigurable logic, for real time vibration measurement and analysis. Digital signal processing procedures, employed into a field programmable gate array (FPGA) were developed to provide on-line detection for rolling bear.

2. BEARING FAULTS

There are four major types of bearing faults [3]. They are material deterioration in inner race, outer race, cage, and ball defects. The bearing faults can be grouped into cyclic faults and non-cyclic faults. Cyclic faults emerge when the rolling component and the rolling element cage of the bearing passes through the point of defect. The deep scratches in a rolling element are a case of cyclic fault. The material abrasion, quality degradation of the lubricant due to contaminants, slither, insufficient lubrication and skid amongst the movable bearing components induce mutilation of the contact areas, which is a non-cyclic fault family. The bearing defects cause non-stationary and fault specific frequency constituents in the stator current and the generated vibrations.

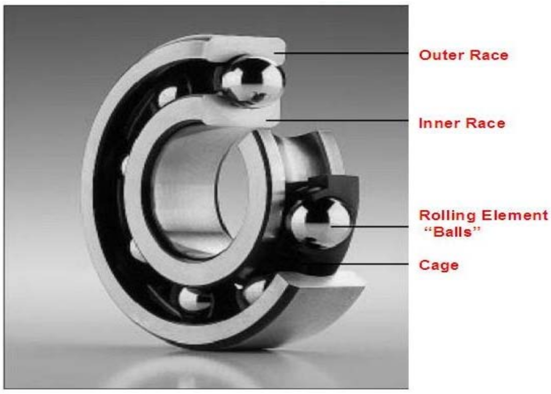

Figure 2. Bearing

2.1. Cage and Ball Defect:

The bearing cage in a ball bearing bears on the balls at evenly balanced berths and aids the confined rolling of the balls along the racetracks. While the motor shaft is rotating, the bearing cage rotates at a steady angular velocity that is average of the inner and outer race angular velocities. The cage angular velocity can be exploited to work out the value of dominant fault frequency due to cage defect, f_{CD} as given below:

$$f_{CD} = \frac{\omega_i r_i + \omega_o r_o}{60(D)} = \frac{1}{60D}\left[\omega_i \frac{D - d\cos\emptyset}{2} + \omega_o \frac{D + d\cos\emptyset}{2}\right] \quad (1)$$

Where ω_i = Angular speed of the inner race in RPM
ω_o = Angular speed of the outer race in RPM
D = Pitch Diameter
d = Ball Diameter
Φ = Ball contact angle
r_i = Inner race radius, r_o = Outer race radius

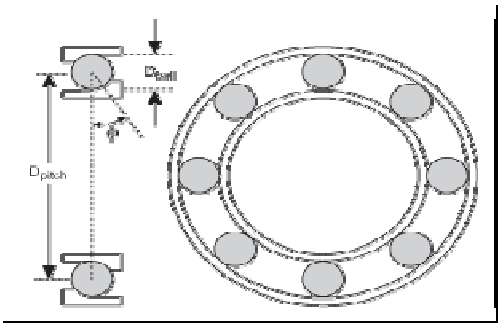

Figure 3. Roller Bearing geometry

The outer race is attached to the casing that is stationary. The shaft and inner race are mounted together and both revolve at the same angular speed. Consequently, it can be assumed that:

$$\omega_o = 0 \text{ and } \quad \omega_i = \omega_r \tag{2}$$

Where ω_r = Rotor angular speed in RPM

Incorporating the above mentioned assumption as shown in Equation (5) brings Equation (6) as given below:

$$F_{CD}=\frac{\omega r}{120}[1-\frac{d\cos\emptyset}{D}] \tag{3}$$

Empirically, the fundamental frequency due to cage defect for a ball bearing with six to twelve balls in it is given as:

$$f_{CD}=0.4\omega_{rs} \tag{4}$$

Where,

$$\omega_{rs}=\frac{Rotor\ angular\ speed\ in\ rpm}{60}$$

2.2. Inner Race Defect

The inner-race defect frequency, f_{IRD}, depends on the rate at which bearing balls pass over the point of flaw on the inner race. Each ball go across the flaw point at a pace that is proportional to the difference of angular speed of the cage and inner race. The characteristic fault frequency of the inner race defect is also related to the number of balls in the bearing. The fundamental fault frequency due to the inner race defect (for conditions $\omega o = 0$ and $\omega i = \omega r$) is given as:

$$f_{IDR}=\frac{n\omega_r}{120}\ [1+\frac{d\cos(\emptyset)}{D}] \tag{5}$$

Where the used variables have definition as given with Equation (1)

The empirical formula for f_{IDR} of a ball bearing consisting of six to twelve balls in it, is given as:

$$f_{IDR}=0.6n\omega_s \tag{6}$$

Where ω_{rs} is as mentioned along with Equation (4)

2.3. Outer Race Defect

The outer race defect frequency, f_{ORD}, depends upon the rate at which bearing balls cover the point of defect on the outer race. Each ball go across the point of defect at a rate that is relative to the difference of angular speed of the cage and outer race. The fault frequency due to the outer race defect is also related to the number of balls in the bearing. The fundamental fault frequency related to the inner race defect is given as:

$$f_{ODR}=\frac{n}{60}\ [\frac{\omega_i r_i+\omega_o r_o}{D}\ -\omega_o] \tag{7}$$

Where the used variables have definition, given along with Equation (1)

Using Equation (3), i.e. $\omega_o = 0$ and $\omega_{i.}$

$$f_{ODR} = (0.4).n.\omega_{rs} \tag{8}$$

Where ω_{rs} is as mentioned in Equation (4)

3. FAULT DETECTION STRATEGIES

There are two types of analysis for bearing faults identification: time domain and frequency domain. The frequency domain analysis is more attractive because it can give more elaborate information about the status of the motor. Time domain analysis can give qualitative information about the machine condition.

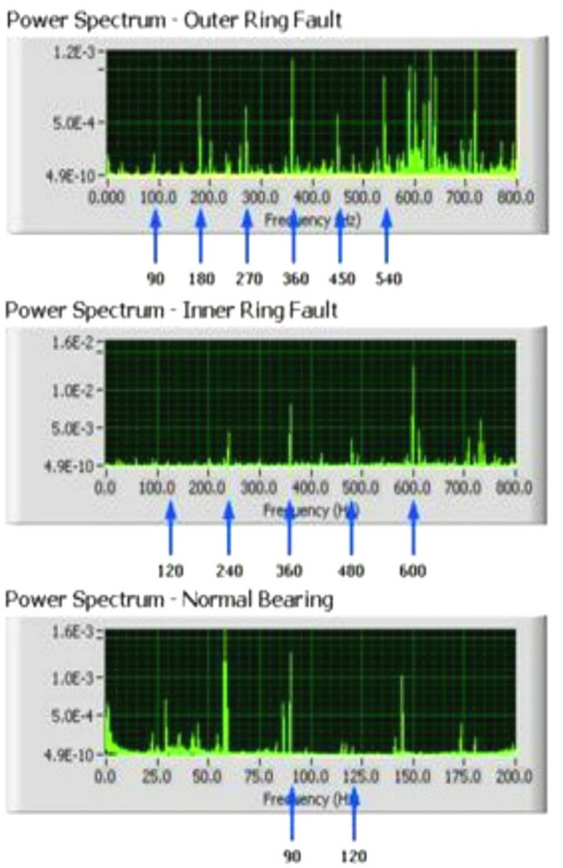

Figure 4. Illustration of vibration signature frequencies

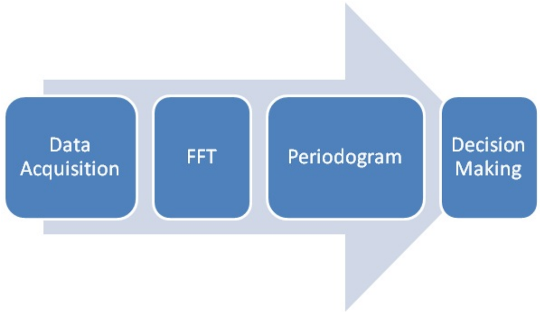

Figure 5. Schematic flow-diagram of the fault diagnosis system

Generally a fast Fourier transform (FFT) is used to perform machine vibration analysis. If the degree of random vibrations and the noise are high, inexact information about the machine condition is obtained. Noise and random vibrations may be inhibited from the vibration signal using signal processing tools such FIR filters, averaging, correlation and convolution [14].

In this case study, a diagnostic system for detection of bearing faults was developed. The virtual instrument system was developed using LabVIEW and this model was embedded on FPGA using RIO Kit.

3.1. LabVIEW RIO Kit

The LabVIEW RIO Architecture includes a standard hardware architecture that includes a floating point processor running a Real-Time Operating System (RTOS), an FPGA target, and I/O which can be programmed using a single development tool chain, LabVIEW.

4. LABORATORY TEST SETUP

A laboratory test setup was prepared to examine theoretical results, which has been focused on the development and testing of algorithms and methods suitable for real-time detection of rolling bearing faults identification. A test bench was created to provide a representative model of a real situation where the bearing could be mounted in its housing and the active forces and velocities were similar to those found in actual situations of the industrial environment. The vibration sensor is an accelerometer, with a bandwidth of more than 10kHz.

Figure 6 shows the laboratory test setup that illustrates the test environment used for the development of virtual instrumentation and reconfigurable system proposed. Basically, it consists of a RIO kit, an amplifier, a signal conditioner, an accelerometer and a three-phase induction motor.

4.1. Diagnostic System

The diagnostic system has two primary blocks, the virtual instrumentation system and the RIO based FPGA embedded system. The VI system comprises of an accelerometer interfaced with the DAS. The system includes an anti-aliasing filter, which is integrated with the accelerometer. This filter confines the acceleration signal to a bandwidth of 750Hz, allowing for a sampling frequency of 1500Hz. The FFT comprises of 1024 points, rendering a frequency resolution of 1.46Hz. The frequency range and the number of periodograms are selected depending on the type of failure to be analyzed.

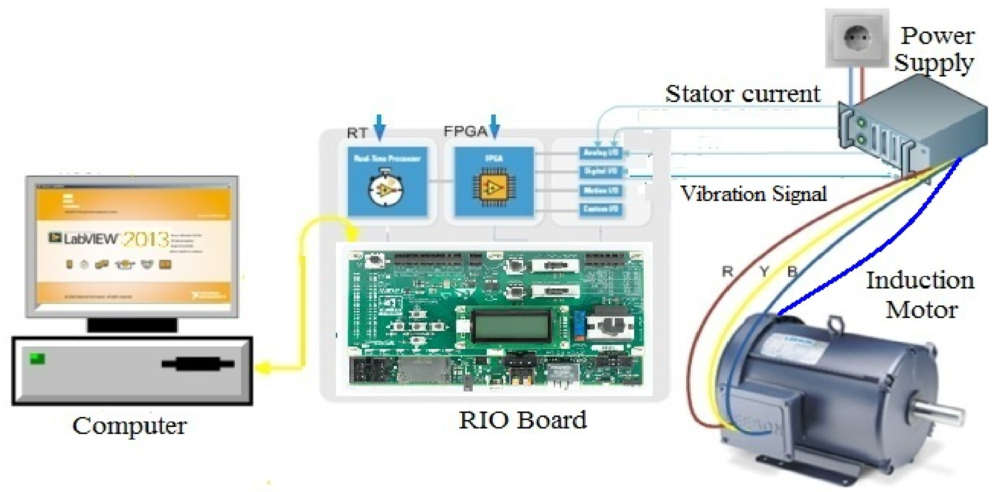

Figure 6. Test environment used for the development reconfigurable system

The FPGA embedded system holds different blocks: DAS drivers for controlling the communication between the sensor and the FPGA, FFT and periodogram blocks for obtaining the spectrum of the signals and a decision making unit for postprocessing of the resulting spectra and furnishing an automatic diagnosis of the motor state. The FFT in the FPGA has 1024-point resolution. The user can select from a range of averaged periodograms, which is a feature of the FPGA reconfigurability. The periodogram is an estimate of the spectral density of a signal. A reconfigurable algorithm was developed for postprocessing using RIO. This decision making unit selects the limited spectrum array dependent on the examined failure, and then, it gets the weighting parameter to be compared with the calibrated threshold in the decision making unit to give the motor condition as a result.

5. EXPERIMENTAL RESULTS

The proposed method has been applied to a 1.1KW, 50Hz, 4-pole, three-phase, SCIM. Table 3 shows the fault frequencies and harmonics calculated by the virtual instrumentation system, considering the rotation axis as 24.75Hz (1485rpm No-load speed) and the geometric parameters of the SKF 6205 bearing.

Figure 8 shows a spectrum of vibration signal demodulated with the detection of the characteristic frequency of outer-race fault. It can be observed that the desired frequency constituents can be distinguished easily. If the time interval between periodically happening peaks in the envelope curvature match one among the critical frequency characteristics of bearing damage, then the matching bearing component will be indicated as damaged. The Trending of characteristic overall value measurements of machine condition over time are monitored by the developed system. The trend readings are plotted as shown in Figure 8 and compared with appropriate warning and alarm thresholds. When thresholds are exceeded, a message and alarm are given by the system.

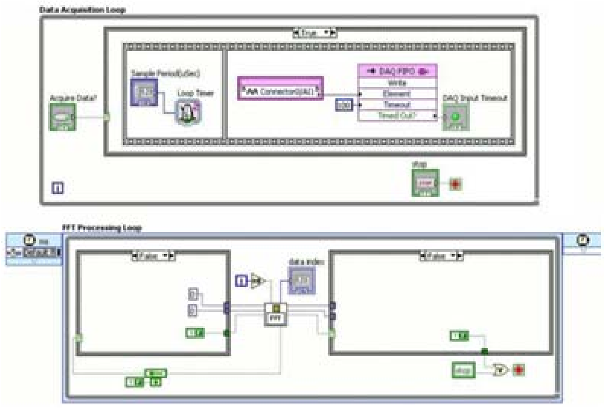

Figure 7. LabVIEW Virtual Instrumentation Panel

Table 1. Bearing Frequency Factors

Bearing ID	FTF	Ball spin frequency	Outer-race frequency	Inner-race frequency
FAG 6311	0.378	1.928	3.024	4.976
SKF 6311	0.382	2.003	3.057	4.943
NTN 6311	0.384	2.040	3.072	4.928

The bearing frequencies are determined by multiplying the numbers in Table 1 by the revolving speed of the shaft. If we consider the data for the SKF 6311 bearing, as an average, we will obtain the frequencies in Table 2.

Table 2. Bearing Frequencies for SKF 6311 Turning at 1485 rpm (24.75 rps) at No-load and at 1380 rpm (23 rps) at Full-load

Fault frequency type	At no-load	At full load
Fundamental train frequency(cage)	0.382 X 24.75 = 9.45 Hz	0.382 X 23 = 9.36 Hz
Ball spin frequency	2.003 X 24.75 = 49.07 Hz	46.07 Hz
Outer-race frequency	3.057 X 24.75 = 74.90 Hz	3. 70.31 Hz
Inner-race frequency	4.943 X 24.75 = 121.10 Hz	113.69 Hz

Table 3. Characteristic Frequencies of Bearing Faults

Fault Frequency	Harmonic	Harmonic	Harmonic
(Hz)	1X	2X	3X
Cage	9.45 Hz	18.99	28.35
Ball	49.07 Hz	98.14	147.21
Outer race	74.90 Hz	149.8	224.7
Inner race	121.10 Hz	242.2	726.6

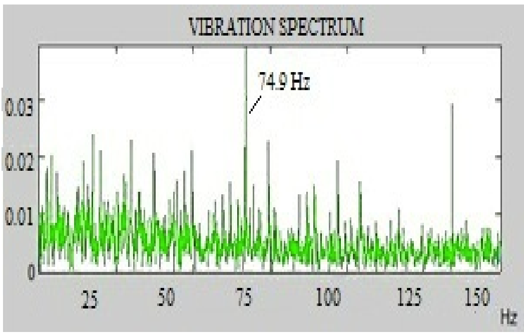

Figure 8. Vibration spectrum for outer race fault

6. ANALYSIS AND DISCUSSION

This paper discussed a comprehensive approach for modeling, simulation and development of an on-line reconfigurable vibration analysis tool based on FPGA device. FPGAs offer the maximal DSP performance available on a programmable platform, but optimizing a DSP algorithms in an FPGA could be challenging. Until recently, the algorithms necessitated to be ported to HDL and then RTL operational simulation would be asserted to employing the high-level simulation tests. The set of design tools used, NI RIO based design abstraction and productivity. This approach employs a high-level behavioral description of the DSP algorithm. The results obtained were consistent with the motor faults generated on a bearing, and consequently validate the proposed strategy. Thus, this implementation can be replicated and deployed on industrial plants.

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