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Time Domain Signal Analysis to Detect Bearing Faults Using Motor Current Signature Analysis

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Abstract. Bearings are critical components in the rotating machinery. The need for an easy and effective fault diagnosis technique has led to increase the use of motor current signature analysis (MCSA). In this research, a fault detection system for bearings was developed and then different faults were simulated and investigated in the test rig. MCSA is utilized since it represents a reliable approach for fault recognition in rotating machinery, time domain signals analysis technique was utilized to extract some indicative features, such as such as root mean square, kurtosis and skewness. However, in addition to the machine healthy condition two fault types, which are inner race fault and outer race fault, were introduced in the test rig. Three current sensors, type SCT013, were interfaced to Arduino MEGA 2560 microcontroller and utilized together for the purpose of data acquisition, to record the motor current signals. Then, the captured signals were analyzed and different time domain features were extracted. The results showed the effectiveness of using MCSA based time domain signal analysis in detection and diagnosis different bearings faults.

INTRODUCTION

Bearings are one of the critical components in rotating machinery. The need of an easy and effective fault diagnosis technique has led to the increasing use of motor current signature analysis (MCSA). Bearing faults in the mechanical system run by an induction motor causes change in its stator current spectrum. The faults in the bearings cause variations of load irregularities in the magnetic field which in turn change the mutual and self inductance causing side bands across the line frequency.[1] sukhjet singh et.al discussed the outer race bearing fault detection in mechanical system using motor current signature analyses ., they cumbered between the healthy and faulty bearing using Fast Fourier Transform (FFT) for the first step and then used a six wavelet three of them are real , the other are complex valued Base wavelet has been selected on the basis of wavelet selection criteria - Maximum Relative wavelet energy. Then, 2D wavelet scalogram has been used for the detection and occurrence of outer race faults of various sizes in ball bearings outer race faults of the bearings of the load machine have been extracted from the time domain signals of the current signature. When an outer race fault is introduced into the system, the variations of the amplitude of running harmonics and their side bands have been noticed in the domain as well as in the 2D wavelet scalogram [1] , also Sulekha Shukla study the same subject but his study based on the mcsa with interval type-2 fuzzy logic , the results shows that mcsa with fuzzy logic can effectively detect abnormal operating conditions in induction motor applications The diagnosis of a broken rotor bar fault has been studied for stable, full load condition and has been carried out experimentally by analyzing the power spectrum density (PSD) of the motor stator current , [2] and Sumit Narwade , study the use of both vibration and (MCSA) to detect problem in mechanical system , he try to detect a various type of faults in mechanical system such as bearing damage and Electrical Fault and Electrical Fault etc , he used the fit to extract the features , and he collected the signals by using a daq card and analyzed it by the matlab program and compered the amplitude certain frequency components under fault and normal conditions. [3] ,then Randy R. Schoen study the application of motor current spectral analysis for the detection of rolling-

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element bearing damage in induction machines , Vibration monitoring of mechanical bearing frequencies is currently wed to detect the presence of a fault condition investigated the feasibility of detecting bearing faults using a spectrum of a single phase of the stator current of an induction machine. Air gap eccentricities cause variations in the air gap flux density that produce visible changes in the stator current spectrum at predictable frequencies. Since rolling-element bearings support the rotor, a bearing defect also produces variations is the air gap length of the machine. These variations generate noticeable changes in the stator current spectrum. The predictability of air gap eccentricities has been extended to include faults in rolling element bearings that excite mechanical vibrations at fractional values of the rotational speed. Measured current and vibration spectrums were presented to verify this relationship. While these changes are relatively small when compared to the rest of the current spectrum, they fall at locations that are different from the supply and slot harmonics of the machine. With sufficient spectral resolution, this discrimination makes the bearing harmonics sufficiently distinct for use as effective indicators of rolling-element bearing damage [4].

Test Rig Design and Development

The experimental work are consist of three phase, 1 H.P. (0.75 kW) AC motor, connected via flexible couplings with a mild steel shaft of 20 mm diameter mounted on two identical deep groove ball bearings fixed in two Plummer blocks attached with a cast iron frame as shown in TABLE 1.

TABLE 1. Specification of 6304D Ball Bearing.

Bearing's Pare	Unit
Number of balls (Nb)	7
Max speed	14000 (rpm)
Bore diameter	20 (mm)
Outside diameter	52(mm)
Contact angle of bearing	0

For measuring the input current waveform of the three phases of the induction motor we used , three current sensors sct013. Vibration monitoring was done with an accelerometer, axdl345 (sensitivity of 300 mV/g), mounted on a Plummer block, To control the speed the N700E Inverter from Hyundai were used ,The load is applied on the two bearing in the middle of the shaft as shown FIGURE 1.

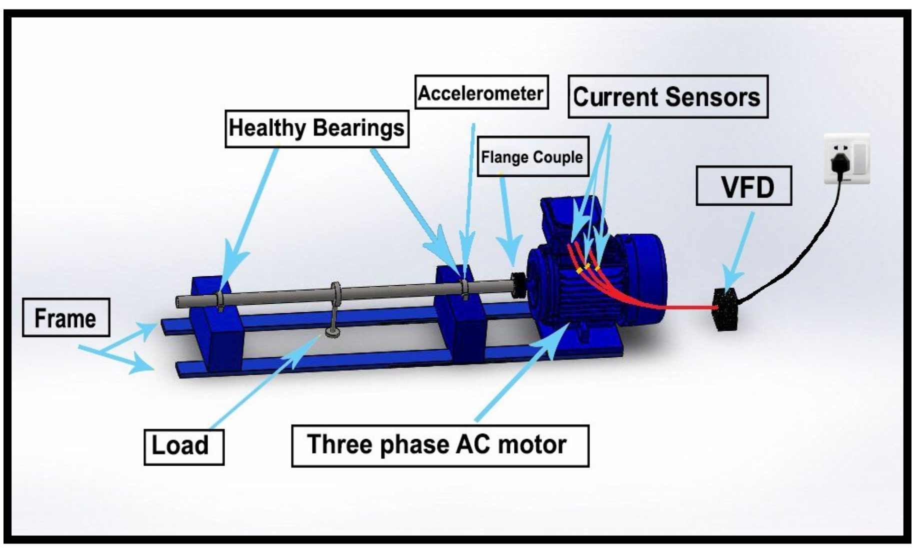


FIGURE 1. Test Rig Design and Development.

The three sct013 current sensors was calibrated instantaneously by a digital clam meter with (30 ampere) range with a screen monitor , the calibration was done by changing the sensitivity equation of the sensor in the programing cod of arduino until the read of sensors be equal to the read of clam meter, the speed of rotating shaft was measured using a contact tachometer as shown in FIGURE 2.

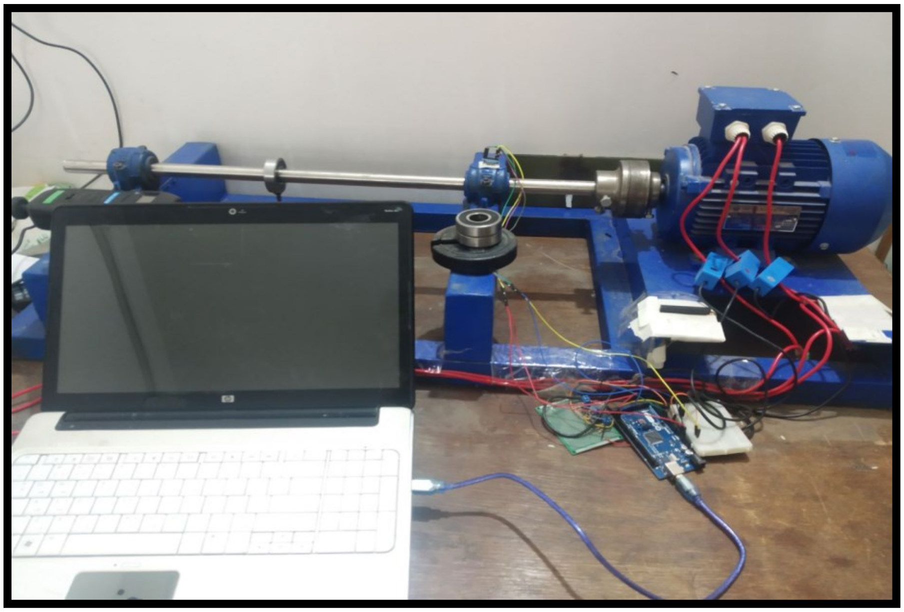


FIGURE 2. Test Rig.

Fault Simulation

The most common bearings faults is (inner race fault , outer race fault , cage fault) in the present study we simulate a (3mm inner race defect and 3mm outer race defect) as shown in FIGURE 3.

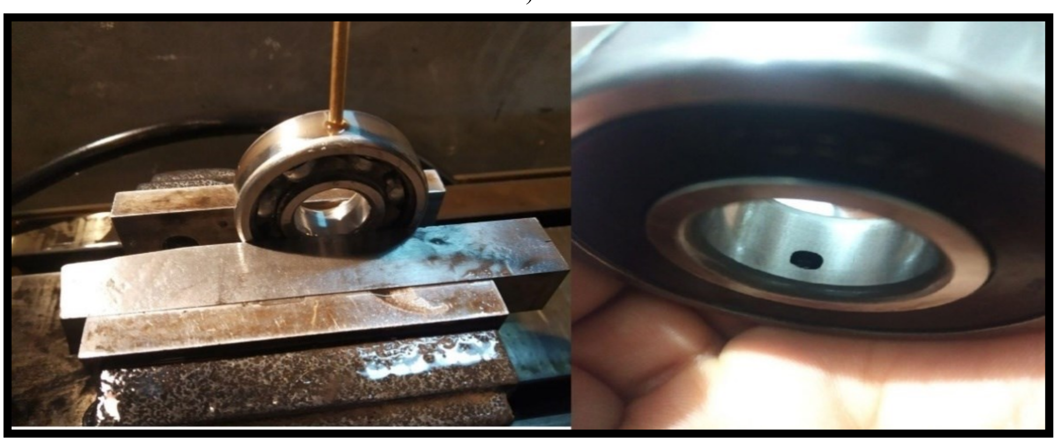


FIGURE 3. Inner Race and Outer Race Fault.

This faults was mad by EDM (cm323C) spark machine connecting to a rood of copper with 3 mm diameter , the machine was sitting to a (o.4 mm) a feed work with a flouting voltage (0 to 100) volte ,as shown in FIGURE 4.

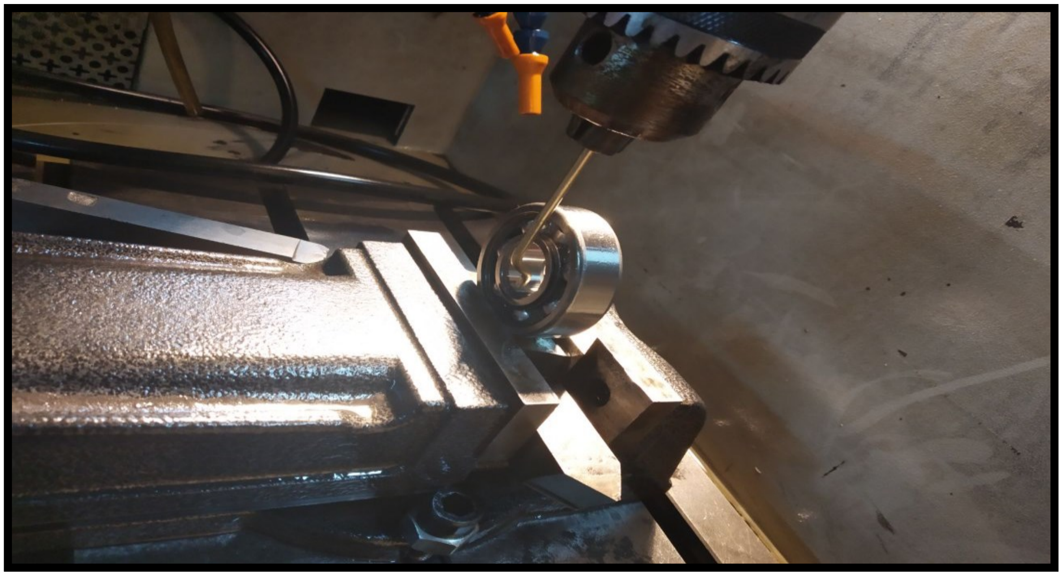


FIGURE 4. 3 mm Inner Race Fault Making.

To study the effect of these faults with mcsa we get a results from 15 cases of a bearing faults, as shown in TABLE 2.

TABLE 2. Sets of Experimental Setup.

Healthy		**Inner race**		**Outer race**	
Free load	15 HZ 25 HZ	Free load	15 HZ 25 HZ	Free load	15 HZ 25 HZ
25 Hz	1 kg 1.5 kg 2.5 kg	25 Hz	1 kg 1.5 kg 2.5 kg	25 Hz	1 kg 1.5 kg 2.5 kg

Data Acquisition System

The data acquisition system (DAS) was a general system designed to interface any test rig to any PC in order to measure and monitor variables such as temperature and vibration. The DAS consists of hardware and software [5]. The hardware is a three Non-invasive AC current sensor (30A max) with a (5 v) input and the 3 axis adxl (345) Digital Accelerometer (2.5 v) with 10-bit resolution . as shown in FIGURE 5.

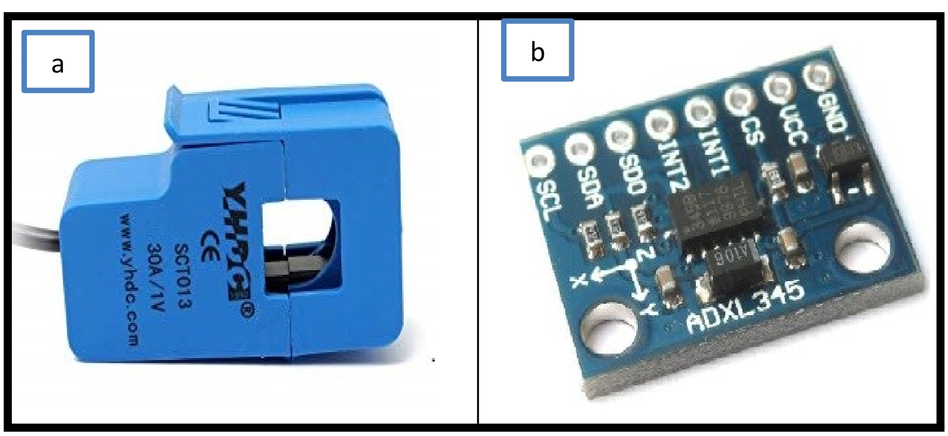


FIGURE 5. (a): Sct013 Sensor, (b): Adxl 345 Accelerometer.

The outputs signals from the accelerometer and current sensors were recorded by arduino Mega 2560 with a54 digital input/output pins (of which 15 can be used as PWM outputs), 16 analog inputs, 4 UARTs (hardware serial ports), a 16 MHz crystal oscillator, a USB connection, a power jack, an ICSP header, and a reset button.

It contains everything needed to support the microcontroller; simply connect it to a computer with a USB cable or power it with a AC-to-DC adapter or battery to get started as shown in FIGURE 6.

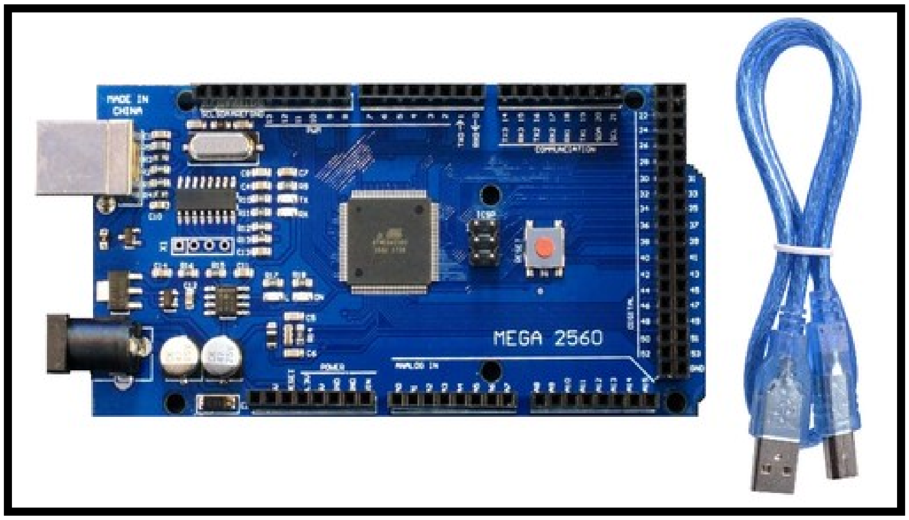
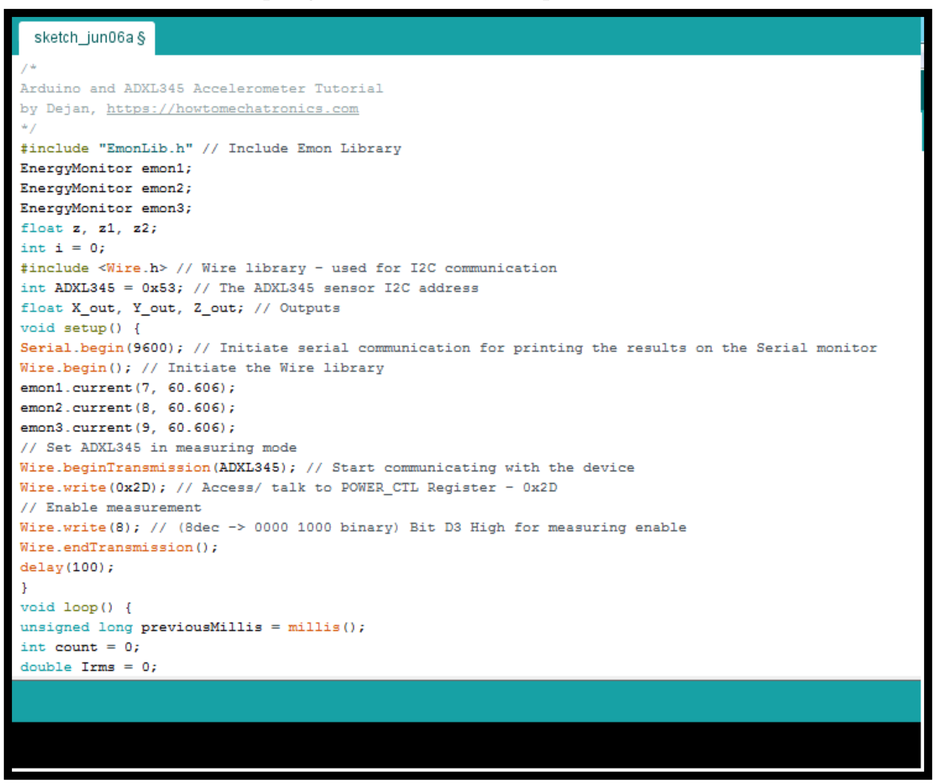


FIGURE 6. Arduino Mega 2560.

The software part of d Data Acquisition System is arduino cod with arduino program as the cod was programed to read the signals from the three current (A) sensors and three axis (g) of the accelerometer and print it on the serial port at the same time with a (100) sampling rat for a (5000) sample as shown in FIGURE 7.



```
sketch_jun06a §
/*
Arduino and ADXL345 Accelerometer Tutorial
by Dejan, https://howtomechatronics.com
*/
#include "EmonLib.h" // Include Emon Library
EnergyMonitor emon1;
EnergyMonitor emon2;
EnergyMonitor emon3;
float z, z1, z2;
int i = 0;
#include <Wire.h> // Wire library - used for I2C communication
int ADXL345 = 0x53; // The ADXL345 sensor I2C address
float X_out, Y_out, Z_out; // Outputs
void setup() {
Serial.begin(9600); // Initiate serial communication for printing the results on the Serial monitor
Wire.begin(); // Initiate the Wire library
emon1.current(7, 60.606);
emon2.current(8, 60.606);
emon3.current(9, 60.606);
// Set ADXL345 in measuring mode
Wire.beginTransmission(ADXL345); // Start communicating with the device
Wire.write(0x2D); // Access/ talk to POWER_CTL Register - 0x2D
// Enable measurement
Wire.write(8); // (8dec -> 0000 1000 binary) Bit D3 High for measuring enable
Wire.endTransmission();
delay(100);
}
void loop() {
unsigned long previousMillis = millis();
int count = 0;
double Irms = 0;
```

FIGURE 7. Arduino Cod.

Time Domain Signal Analysis

Signals are carrying the information and features about the monitored system. The extracted features of the signal can be classified as stationary or non-stationary, based on the nature of the feature, the stationary feature classified into deterministic and nondeterministic. Deterministic signals have specific frequency components [6].

The features are defined as follow [7].

Root mean square (RMS) : measures for all level of a signal.

$$\text{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} f_n^2} \qquad (1)$$

N is the number of separate point and refers to the signal from each sampled point.

Standard deviation: This parameter measures the desperation of signal about the mean and is given:

$$S = \left(\frac{1}{N-1}\sum_{n=1}^{N}(f_n - \bar{f})^2\right)^{\frac{1}{2}} \qquad (2)$$

Kurtosis: The forth moment, normalized with respect to the forth power of standard deviation is quite useful in fault diagnosis. This quantity is called kurtosis, which is compromise measure between the intensive lower moments and other sensitive higher moments.

$$\text{Kurtosis} = \frac{\frac{1}{N}\sum_{n=1}^{N}(f_n - \bar{f})^4}{\text{RMS}^4} \qquad (3)$$

Skewness: machined or ground surfaces in bearings show a random distribution of asperities that are commonly described with the normal distribution function. For this reason, various statistical moments can describe the shape of distribution curves therefore, assessing bearing surface damage level. Equation defines the third moment or skewness as:

$$\text{Skewness} = \frac{\frac{1}{N}\sum_{n=1}^{N}(f_n - \bar{f})^3}{\text{RMS}^3} \qquad (4)$$

Where f: is the mean value.

For normally distributed data sets the odd moments are zero, unless the time domain signal is rectified. Hence, skew can easily track for bearing condition [3].

RESULTS AND DISCUSSION

Features Extraction When Varing Loading Conditions

To further investigate varying the loading effect and also to calculate sets of statistical valuesfrom the time-domain signals, the root mean squar (RMS), standard deviation (STD), kurtosis (KU), skweness (SK) and crest factor (CF) values for each loading condition at different bearing health state was extracted and compared, as illustrated in the following figurer

FIGURE 8 show the values of RMS, for the captured current signal after being divided into sub-signals. Where the X-axis represents the number of data sets (data pattern) and Y-axis is the value of the calculated feature. However, an important observation can be noticed from these figures is that the computed time domain (statistical) features are altered as the fluctuation occurres in the captured random current signals. Generally, from the obave mentioned figures can be noticed that the values of RMS are higher when outer race fault is simulated, less in the case of inner race fault and normally lesser when the bearing is healthy. This is the same for all the three loading cases. Also, these features are clearly seperated based on the simulated health state.

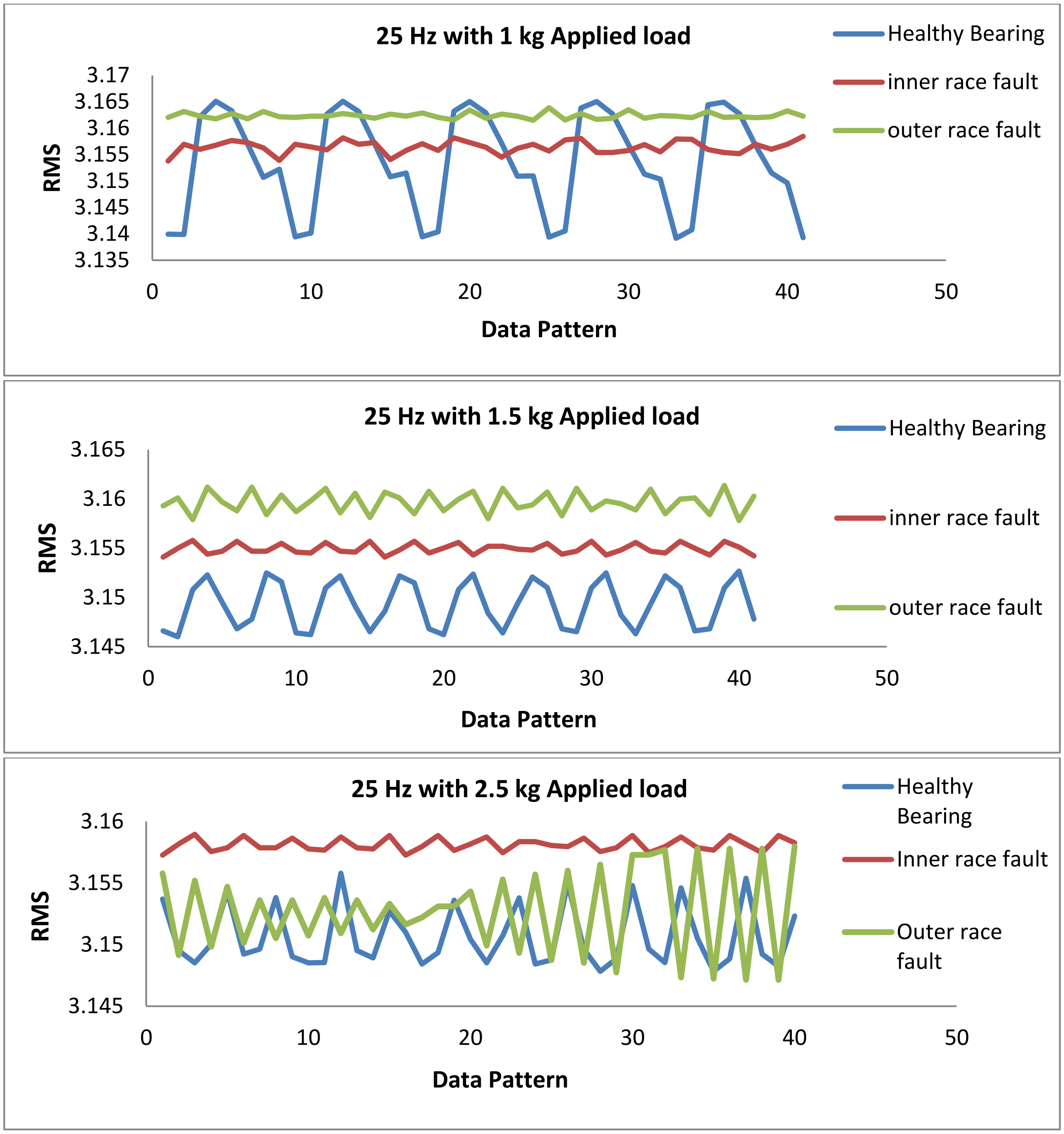


FIGURE 8. Variation of RMS with the applied load.

CONCLUSIONS

In this research a faults diagnosis system for rolling bearings has been developed using MCSA based on time domain features extraction. Tow deep grove ball bearings was attached to an AC Motor via mechanical coupling and rotating shaft. A low cost data acquisition system was constructed using three current sensors type SCT013 and Arduino MEGA 2560 microcontroller. Extracted features play a vital role in any health monitoring system so it gives a good indication about bearing health. Thus, time-domain signal analysis based feature extraction was conducted. Various features, such as kurtosis and skewedness, were computed. Extensive experimental investigation was carried out on the bearings fault simulation test rig. Firstly, current signals were acquired and then the features are extracted from the system when it is healthy. More signals and further features were acquired when two different faults were introduced. Three states of bearing health were studied in this investigation (healthy, inner race and outer race fault). The result showed that time domain features can give a preliminary indication about bearing health as they are varying as the fault severity is increased. For future work, further improvements are suggested to be made on the developed detection system. Training this features using the artificial neural network (ANN) and applying the ANN concurrently with feature extraction process will significantly help in automate the fault detection approach.

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