Non-Invasive Vibration Measurement for Diagnosis of Bearing Faults in 3-Phase Squirrel Cage Induction Motor Using Microwave Sensor

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Abstract—The vibration is an important feature of the motor to diagnose the different faults. The existing invasive and non-invasive methods to capture and analyze vibration signals have many limitations. Thus, this work proposes a technique to capture and process the motor vibrations non-invasively to diagnose the multiple bearing faults using a microwave signal and software low pass filter respectively. The proposed method uses a high-frequency signal from microwave sensor (handheld Ultra-Wide Band (UWB) radar) projected on the Squirrel Cage Induction Motor (SCIM) and the reflected signal captured. The signal obtained is filtered with Software Phase Locked Loop (Low pass filter (SPLL)) and analyzed with a signal processing algorithm like Wavelet Transform to identify the faults in the motor. In this paper multiple bearing faults under no-load and full-load and a combination of bearing and rotor bar faults are diagnosed with the proposed method using Rational Dilation Wavelet Transforms (RDWT). The various bearing fault signal’s energy at the sub-band-7 compared under normal and fault conditions. The signal energy at the fault frequency sub-band under no-load increases by 2.11%, 23.5% and 42.5% compared with the no-fault condition with the increase in the number of bearing faults from 1 to 3. The signal energy variation indicates the severity of the defects and the accuracy of the proposed method is verified with the contact method using a vibration sensor (accelerometer). The other faults analyzed are the combination of the bearing and rotor bar faults with the variation of the signal energy at sub-band 7 & 6. The variation of the signal energy for bearing and rotor bar faults are verified with the theoretical calculation and the proposed method detects the faults with the accuracy of approximately 93%. On the other hand, the proposed method is simple and cost-effective compared with the existing methods.

Index Terms—Bearing faults, three-phase squirrel cage induction motor (SCIM), handheld UWB radar, Rational Dilation Wavelet Transforms (RDWT).

I. INTRODUCTION

Bearings and rotor bar are crucial components of the induction motors (IMs), which play a vital role in the operation. According to EPRI (Electric Power Research Institute) studies, 41% of the SCIM fail due to the bearing defects, 9% fail with rotor faults and stator faults causes 36% motors to fail [1]. With the use of improved technology to design high quality winding, stator faults are reduced and rotor bar faults are least affecting. Hence, the bearing fault diagnosis is important for industrial motors [2] to reduce revenue loss and maintenance. The SCIM’s bearings fail due to various factors like misalignment, contamination, improper installation, no lubrication, and corrosion [3]. The parameters of the motor like vibration [4]–[6], current [7], flux [8] around the machine are monitored to identify the faults in the early stage. A non-convex sparse regularization method measures the vibration [9] of the machine to determine the bearing faults. The method works based on the generalized minimax concave (GMC)
[9] penalty, which requires a dual loop algorithm, results in increased processing time and complexity analysis. The stator current, stray flux and impulsive feature analyzed with the spectral kurtosis and envelope analysis [10], average kurtosis [11] and sparse representation [12] respectively to diagnose the localized bearing fault. The sensitivity, position and distance of flux sensor affects the accuracy of fault identification. The vibration, current and acoustic emission are measured with wireless sensor network to diagnose the inner and outer race defects of the bearings [13] [14]. The technique has less accuracy due to the low data delivery and data loss due to other machines disturbance, improper mounting of sensors and high cost. The outer race and inner race faults identified by measuring motor parameters with the different techniques of wireless sensor network such as amplitude modulation [11], the inductive coupling principle [15] and a tri-axial accelerometer [16], [17]. However, these techniques have drawbacks like long processing time, complex analysis and a special temperature compensation circuit require for continuous operation of the piezoelectric accelerometers, which cause overheating of sensors.

The hardware techniques for identifying the bearing fault and rotor bar faults have disadvantages like difficult to implement and expensive. The soft-computing methods overcome the above drawbacks. The soft-computing techniques such as an artificial neural network (ANN) [18]–[21] neural-fuzzy logic [22], pattern recognition and fuzzy logic [23] have been employed to determine the bearing faults, which analyzes the vibration [9] [24] and current [25], [26] signal of the motor. The various algorithms such as Park’s vector algorithm, back-propagation and feed-forward network algorithm used for training the ANNs to analyze the current signal from the SCIM to diagnosis the bearing faults. However, ANNs require rigorous training and the same level of fault all the time. Only by adding new fuzzy rules for the optimization process, new faults can be identified. The vibration signals are also analyzed with the Convolutional Neural Network (CNN) [27], [28] and Hilbert transform [5], High-Order Differential Mathematical Morphology Gradient Spectrum Entropy [29] and Improved Quantum-Inspired Differential Evolution Algorithm [30] to identify the bearing faults and rotor bar faults occurrence in the SCIM. Soft-computing methods suffer from computational complexity, large computer memory, high processing time, professional required to analyze the signal to identify the fault severity and location [31]. So, the condition monitoring of the SCIM needs more precise, accurate fault detection and fault location. The objective of this paper is to propose a cost-effective, a non-invasive and simple method to diagnose the bearing faults of the SCIM by UWB radar signal analysis using signal processing technique. The outer race bearing fault diagnosis is explained in our previous work [32] and now, other bearing faults such as ball fault, combination of outer race and ball faults, outer race, inner race and ball faults are diagnosed in this paper. Also, the effectiveness of proposed method successfully demonstrated to diagnosis the bearing faults with load variation, the rotor bar and bearing faults simultaneously.

The proposed method works based on the principle of international patent that a mechanically oscillating object modulates amplitude of a microwave signal if kept between a transmitter and a receiver [33]. Thus, the analysis of the modulated signal for fault frequency provides the information of the different faults in the motor, but the patent is not hinting about fault diagnosis in electrical machines and also the patent is not targeting any specific application. In the proposed method a microwave sine signal is projected on to the faulty motor with radar. The characteristic vibration frequency of the motor depends on the fault and the amplitude of the modulated signal increases with the severity of the faults. The reflected signal, which is amplitude modulated according to the characteristic frequency is received. The acquired signal is analyzed with Software Phase Locked Loop (SPLL) and Wavelet transforms to classify the faults in the proposed method. The proposed method is a cost-effective, a simple and non-invasive method for diagnosing the rotor bar faults and bearing faults with handheld UWB radar. In existing methods, accuracy is affected due to low resolution and sensitivity, drift, linearity, low accuracy and repeatability of the sensors. The proposed system uses only UWB radar with SPLL and signal processing algorithm to analyze the signal. Therefore, the system is simple and faster in analyzing the signal and the UWB radar has better resolution and sensitivity toward least change in vibration and flux. Also, due to placing the UWB device near to the SCIM, microwave signal is least affected by external noise and temperature.

The rest of the paper is organized as follows: In section II, Induction motor faults and characteristic frequencies are explained. Section III describes the fault identification techniques and section IV shows details of signal processing algorithms. Section V describes the experimental results and section VI provides the comparison of the proposed method with existing methods. Finally, section VII concludes our work.

II. INDUCTION MOTOR FAULTS AND CHARACTERISTIC FREQUENCIES

The device under test in the proposed method is Kirloskar Indus-3, a 3-phase SCIM of 2HP capacity. The SCIM fails due to bearing and rotor bar faults, during fault condition motor vibrates with a specific frequency.

A. Bearing Faults and Characteristic Frequencies

The SCIM vibrates with a specific frequency for each fault and the fundamental motions describe the dynamics of the bearings [5], [34]. The different fundamental frequencies of bearings are the ball rotational frequency \( (F_{RB}) \), the ball pass outer raceway frequency \( (F_{BPO}) \), the ball pass inner raceway frequency \( (F_{BPI}) \), the shaft rotational frequency \( (F_{SR}) \) and the fundamental cage frequency \( (F_{FC}) \). According the fault location on the bearings, motor vibrates with a specific frequency. So, signal processing techniques such as Fast Fourier Transforms (FFT), Short Time Fourier Transform (STFT) [35] and Wavelets [36], [37] analyzes the signals and provide a frequency spectrum to obtain fault frequencies.

1) Shaft Rotational Frequency \( (F_{SR}) \): The rotating system of the motor consists of bearing, rotor or shaft. Thus, all
components of rotating system rotate with the same speed \( F_{SRf} \) and other fundamental frequencies are functions of \( F_{SRf} \).

2) Fundamental Cage Frequency (\( F_{FCf} \)): The fundamental cage frequency \( F_{FCf} \) of the bearing is the ratio of the mean of the inner and outer raceway linear velocities to the radius of a bearing is described by (1) and (2) [38], [39].

\[
v_{erf} = \frac{(v_{irf} + v_{orf})}{2}
\]

\[
F_{FCf} = \frac{v_{erf}}{D_{cbf}} = \frac{(v_{irf} + v_{orf})}{2} \times \frac{D_{cbf}}{D_{cbf}}
\]

where

- \( v_{irf} \) - linear velocity of the inner raceway
- \( v_{orf} \) - linear velocity of the outer raceway
- \( v_{erf} \) - mean of linear velocities
- \( D_{cbf} \) - the bearing cage diameter
- \( r_{ef} \) - radius of the cage = \( D_{cbf}/2 \).

The linear velocities \( v_{irf} \) and \( v_{orf} \) represented with their respective rotational frequencies, i.e., inner rotational frequency \( F_{irf} \) and outer rotational frequency \( F_{orf} \) multiplied by their corresponding inner radii \( r_{irf} = r_{ef} - (D_{bbf} \cos \theta/2) \) and outer radii \( r_{orf} = r_{ef} + (D_{bbf} \cos \theta)/2 \). \( D_{bbf} \) is the ball diameter and \( \theta \) is the contact angle of the bearing. Thus, \( F_{FCf} \) can be further expressed by (3) [38], [39].

\[
F_{FCf} = \frac{v_{erf}}{D_{cbf}} = \frac{F_{irf} r_{irf} + F_{orf} r_{orf}}{D_{cbf}}
\]

\[
= \frac{1}{D_{cbf}} \left( F_{irf} \left( D_{cbf} - D_{bbf} \cos \theta \right)/2 + F_{orf} \left( D_{cbf} + D_{bbf} \cos \theta \right)/2 \right)
\]

3) Ball Pass Outer Raceway Frequency (\( F_{BPOrf} \)): Ball Pass Outer Raceway Frequency \( F_{BPOrf} \) is the rate at which bearing’s ball pass a point on outer raceway track and is calculated as the product of a number of bearing balls \( N_B \) and the difference of fundamental cage frequency \( F_{FCf} \) and outer rotational frequency \( F_{orf} \) given by (4) [38], [39].

\[
F_{BPOrf} = N_B \left| F_{FCf} - F_{orf} \right|
\]

\[
= N_B \left| F_{irf} \left( C_{cf} - \frac{D_{bbf} \cos \theta}{2} \right) + F_{orf} \left( C_{cf} + \frac{D_{bbf} \cos \theta}{2} \right) \right| - F_{orf}
\]

\[
= \frac{N_B}{2} \left| F_{irf} - F_{orf} \right| \left( 1 - \frac{D_{bbf} \cos \theta}{D_{cbf}} \right)
\]

4) Ball Pass Inner Raceway Frequency (\( F_{BPIrf} \)): Ball Pass Inner Raceway Frequency \( F_{BPIrf} \) is the rate at which bearing’s ball pass a point on inner raceway track and is calculated as the product of a number of bearing balls \( N_B \) and the difference of fundamental cage frequency \( F_{FCf} \) and inner rotational frequency \( F_{irf} \) given by (5) [7].

\[
F_{BPIrf} = N_B \left| F_{FCf} - F_{irf} \right|
\]

\[
= N_B \left| F_{irf} \left( C_{cf} - \frac{D_{bbf} \cos \theta}{2} \right) + F_{orf} \left( C_{cf} + \frac{D_{bbf} \cos \theta}{2} \right) \right| - F_{irf}
\]

\[
= \frac{N_B}{2} \left| F_{irf} - F_{orf} \right| \left( 1 + \frac{D_{bbf} \cos \theta}{D_{cbf}} \right)
\]

5) Ball Rotational Frequency (\( F_{BRF} \)): The ball rotational frequency \( F_{BRF} \) is the speed of the ball rotating on its own axis. This frequency can be calculated given by (6) [38], [39].

\[
F_{BRF} = \frac{D_{cbf}}{D_{bbf}} \left| F_{irf} - F_{orf} \right| \left( 1 - \frac{D_{bbf}^2 \cos^2 \theta}{D_{cbf}^2} \right)
\]

where \( r_{bf} \) is the ball radius.

In a motor, the outer and inner raceway of the bearing rotates at a speed of ‘0’ and shaft speed respectively as the outer race locked by an external casing, i.e., \( F_{orf} = 0 \) and \( F_{irf} = F_{SRf} \). Therefore, the motor system frequencies described by (7)-(10) [38].

\[
F_{FCf} = \frac{1}{2} F_{SRf} \left( 1 - \frac{D_{bbf} \cos \theta}{D_{cbf}} \right)
\]

\[
F_{BPOrf} = \frac{N_B}{2} F_{SRf} \left( 1 - \frac{D_{bbf} \cos \theta}{D_{cbf}} \right)
\]

\[
F_{BPIrf} = \frac{N_B}{2} F_{SRf} \left( 1 + \frac{D_{bbf} \cos \theta}{D_{cbf}} \right)
\]

\[
F_{BRF} = \frac{D_{cbf}}{2 D_{bbf}} F_{SRf} \left( 1 - \frac{D_{bbf}^2 \cos^2 \theta}{D_{cbf}^2} \right)
\]

The bearings in the SCIM with defects will produce vibrations with any one of the frequencies among above described frequencies, these analyses help to diagnose the faults.

B. Rotor Bar Fault and Characteristic Frequency

The SCIM consists of a stator and a rotor with two bearings. The rotor is made of Diecast pressured Aluminium and rotor shaft with C45 carbon steel. The frequency associated with rotor bar fault \( f_{nbf} \) is given as (11) [40]

\[
f_{nbf} = f_{smf} \left[ \frac{l_{mf}}{p_{mf}} \left( 1 \pm s_{rbf} \right) \right]
\]

where \( l_{mf} / p_{mf} = 1, 5, 7, 11, 13, \ldots \). These are the characteristic values of the SCIM, \( f_{smf} \) is the electric supply frequency, \( p_{mf} \) is the number of poles and \( s_{rbf} \) is the per unit slip.

III. FAULT IDENTIFICATION TECHNIQUES

The SCIM experiences various internal and external faults like bearing faults, rotor bar faults, voltage fluctuation, load variation, unbalance supply and frequency variation. These faults are diagnosed with acquired current, voltage, temperature and vibration signal analysis with conventional methods. The signals are analyzed with algorithms like FFT,
STFT and Wavelet transform. The analysis of the signal provides information about the fault in the motor. However, these methods are expensive and require complex experimental setup. Hence, a new method with UWB radar is proposed. The proposed method uses a high-frequency signal from the UWB radar and the captured signal is analyzed with Wavelet transform like Rational Dilation Wavelet Transforms (RDWT).

In this paper, the bearing faults in the SCIM are identified with a non-invasive method (Proposed method) and verified the results with a vibration sensor (or) accelerometer (ADXL-335) based contact method (Existing method). The basic framework of all the methods is explained below

A. Proposed Method Based on UWB Radar

The framework of the proposed non-invasive method for the bearing fault identification in SCIM is shown in Fig.1. In the proposed SPLL based method, a microwave sensor used to focus on the SCIM and reflected signal is captured. The data acquisition system (SIGVIEW software) records the signal with a sampling frequency of 10kHz. The recorded signal is given to the SPLL, where SPLL acts as a low pass filter to remove unwanted high-frequency noise and provides an error output signal. The output of the SPLL is analyzed with the various signal processing algorithms and the fault is identified.

In the proposed method, the main components are SCIM, microwave sensor (handheld UWB radar) and SIGVIEW software with SPLL algorithm.

1) Induction Motor and Microwave Sensor: The device under test is a 2HP three-phase SCIM, operates with 415V, 50Hz supply. The main component of the proposed system is the microwave sensor (handheld UWB radar). Microwave sensor is a source of the high-frequency signal and the basic sensor module consists of transmitter and receiver antenna, mixer and Dielectric Resonant Oscillator (DRO). In the proposed technique, a microwave sensor module (HB-100) is used (Fig.2) [41], [42], which operates with 5V of DC supply and generates a high-frequency signal (10.525GHz frequency). The transmitter (Tx) and receiver (Rx) patch antennas focuses and receives a high frequency signal respectively. The mixer feed with received and transmitted signal, which outputs a signal with a frequency equal to the difference and sum of those two.

In the proposed method, the fault frequencies are identified based on the international patent application [33]. The transmitted microwave signal from UWB radar on to vibrating motor gets modulated according to the characteristic frequency of SCIM vibration. The handheld UWB radar emits a signal $ax(t)$ of sinusoidal with a frequency $f_{Ux} = 10.525GHz$ and amplitude of ‘X’, which is considered as carrier signal with a frequency $f_{Ux}$ represented as (12)

$$ax(t) = X \cos(2\pi f_{Ux}t)$$ (12)

The modulating signal $bx(t)$ is a vibration signal of the motor with a specific characteristic frequency $f_{fx}$ and amplitude of ‘Y’ represented as (13)

$$bx(t) = Y \cos(2\pi f_{fx}t)$$ (13)

As per the patent description, the microwave transmits a signal $ax(t)$, is amplitude modulated according to the machine vibration signal $bx(t)$ and modulated signal $cx(t)$ is given by (14) [33]

$$cx(t) = [1 + bx(t)] * ax(t) = ax(t) + ax(t) * bx(t)$$ (14)

Using mathematical identities [43], [44], $cx(t)$ can be shown as the sum of three sine waves given in (15)

$$cx(t) = X \cos(2\pi f_{Ux}t) + \frac{XY}{2} \left[ \cos2\pi \left( f_{Ux} + f_{fx} \right) t + \cos2\pi \left( f_{Ux} - f_{fx} \right) t \right]$$ (15)

Equation (15) gives the amplitude modulated signal, which contains an unchanged transmitted signal $ax(t)$ and two sideband pure sine waves with frequencies of $f_{Ux} + f_{fx}$ and $f_{Ux} - f_{fx}$. Furthermore, the UWB radar acquires the reflected signal from the motor vibration and flux, demodulate the signal with sidebands. The sideband signals are analysed with signal processing algorithms like FFT, STFT and Wavelet transforms for classification of various internal and external faults. This method is useful for identifying a number of frequency components in the same vibration and flux signals. The amplitude of the received modulated signal frequency component is exponentially proportional to the number of the faults as described below [45]. The radial component of the stress ($\sigma_{ra}$) due to the radial magnetic flux ($H_{ra}$) and radial flux density component ($B_{ra}$) in the motor is given in (16) [45].

$$\sigma_{ra} = \frac{B_{ra}^2}{2\pi_0} = \frac{\pi_0}{2} H_{ra} \cdot B_{ra}$$ (16)
The EMI noises in the motor exerts radial force and causes to change the vibration amplitude. The change in the vibration magnitude with EMI noises in the motor are only 1% to 5% of actual displacement [46]. Thus the EMI noises are neglected in this work. Based on (16) and analysis of the magnetic field, a fault index is defined, which gives the relation between the magnitude of vibration with a number of faults. The fault index is the ratio of the change in the vibration magnitude with \( n \) number of faults (\( u_0(n) \)) to 1-fault condition (\( u_0(1) \)) as (17) – (18) [45]

\[
\text{Fault}_{-}\text{Index}(n) = 10 \log \left( \frac{u_0(n)}{u_0(1)} \right) \quad (17)
\]

\[
\text{Fault}_{-}\text{Index}(n) = 10 \log \left( n^2 \right) \quad (18)
\]

The captured signal is given to the mixer in the radar, whose output signal frequency i.e., difference of the two signals considered, so, only sideband and low-frequency components come as output. Further, the output of the UWB radar signal is analyzed and frequency components are obtained. They indicate the fault condition in SCIM.

2) Data Acquisition System With SPLL: The software part of the proposed SPLL method consists of a data acquisition system and SPLL (Software filter). The signals captured by UWB radar after removing high frequency transmitted signal are given to a SIGVIEW software and recorded with a sampling frequency of 10 kHz. The recorded signal filtered with SPLL and high frequency noise is removed. SPLL is a software algorithm with all the functions are realized with a program and have advantages such as faster, immune to ambient conditions, accurate and reconfigurable capability [47]. The algorithm of SPLL is given below

Algorithm of Software Phase Locked Loop (SPLL)

1. Set sampling frequency, supply frequency, time of simulation
2. Provide an input reference signal obtained from the faulty motor to the phase detector.
3. Provide output of the phase detector to the loop filter.
4. Give the output of the filter to Digitally Controlled Oscillator (DCO) & calculate sine and cosine using the integration process.
5. Feedback the DCO output to the phase detector and obtain the error signal to analyses the fault in SCIM.

The SPLL acts as a low pass filter, which removes unwanted high-frequency noise and gives the output error signal [32], which is analyzed with various signal processing algorithms to identify the faults. The proposed method detects various faults. The accuracy of fault detection is compared with existing method like vibration sensor-based analysis explained below.

B. Vibration Sensor-Based Contact Method

The framework of the contact method for the bearing fault identification in SCIM is shown in Fig.3. In the contact method, 3-axis accelerometer [ADXL-335], which is a vibration sensor, is attached to the SCIM to collect the vibration signal from the motor. The vibration sensor senses the vibration of SCIM and that signal is recorded by the data acquisition system (SIGVIEW software). The acquired signal is fed to SPLL and an error signal is obtained. The received signal is processed with the signal processing algorithms and the fault is identified.

The device under test is a 2HP three-phase SCIM. The critical component of the contact method is 3-axis accelerometer to sense vibration (ADXL-335). Fig.4 shows the basic structure of ADXL335 [48], which is a small, thin, low power sensor for sensing motion and tilt of the machine.

The sensor measures the static and dynamic acceleration in tilt sensing, motion, shock and vibration application. The sensor will work with a supply voltage of +3V. The ADXL335 is made on the silicon wafer with the micromachined polysilicon surface. The sensor measures acceleration with signal conditioning circuit and an output voltage proportional to the acceleration in the analog form. The differential capacitor measures the deflection, polysilicon springs act as a restraining force for acceleration and provides an output proportional to acceleration.

IV. SIGNAL PROCESSING ALGORITHMS

The SCIM develop a vibration of the specific frequency for different faults. The fault frequencies may be identified with signal analysis algorithms like FFT, STFT and Wavelet transform. All the signals are classified as stationary signals and non-stationary signals. The stationary signals are analyzed by Fourier analysis [49]. The FFT is not appropriate to analyze a non-stationary signal and required long acquisition time, results in the change of fault spectrum [32], [40], [50]. The non-stationary signals have transitory characteristics
[1], therefore the non-stationary signals can be analyzed by considering the small portions of the signals. The technique of analyzing small portions of the signal is known as STFT. The STFT of an input signal $x(t_1)$ with frequency $f_1$ as (19) [51]

$$STFT_{x_1}^{(o)}(t_1', f_1) = \int \left[ x(t_1) \cdot w^*(t_1 - t_1') \right] e^{-j2\pi f_1 t} dt$$

where $w^*(t_1 - t_1')$ = window function centered at time $t_1 - t_1'$

The size of the window decides the precision of the STFT, whereas STFT not allow the dynamic change of the window. Wavelet transforms overcomes the difficulties mentioned above with the variable-size window. In this paper, Rational Dilation Wavelet Transforms (RDWT) utilized for bearing fault identification. In the RDWT, the energy of the fault frequency is compared under normal and fault conditions to identify the severity of the fault of SCIM. There are a number of Wavelets transforms available for vibration signal analysis like cosine modulated filter banks, Wavelet packets and dyadic Wavelet [52]. The cosine modulated filter banks and Wavelet packets, are often used for vibration signals instead of the dyadic Wavelet Transforms (dyadic WT) as the dyadic WT is less efficient, low-Q factor and poor frequency resolution. But these transforms do not have a constant-Q. WT can be implemented as critically sampled and overcomplete. The over complete WT has advantages like minimal-length perfect reconstruction filters, shift-invariant and smooth analysis/synthesis function [53]–[55] over the critically sampled WT. The various over complete WT are double density Wavelet transform [56], higher density Wavelet transform [57]–[59], dense framelets [60], M-band flexible Wavelet transform [61] and the RDWT. Some over-complete algorithms for feature extraction, such as K-Singular Value-Deomposition (K-SVD algorithm) [62] are used for fault diagnosis. However, these over complete techniques have disadvantages such as M-band flexible Wavelets need complex filter design and the K-SVD algorithm’s accuracy depends on the value of K. Thus, RDWT used in this paper and also the RDWT have advantages such as better time-frequency lattice and have well matched analysis/synthesis functions.

The output plot of Wavelet transforms consists of 12 sub-bands along with actual signal recorded [32]. Each sub-band carries information about a particular band frequency. In the plots, a sub-band signal power is displayed as a percentage of the total power, as the total power of the signal is considered 100%. The percentage energy of each sub-band gives the percentage of frequency content in the total signal [63]. In general, the energy ($e$) concentrated in the signal $x(n)$ can be calculated by using (20) [52], [53], [64]

$$e = \sum_{n=1}^{N} |x(n)|^2$$

The RDWT implements a filter bank a low pass component $H_L(\omega_L)$ and high pass component $G_H(\omega_L)$ as given in (21) and (22) respectively [52], [53].

where $p_1, q_1, s_1$ are rational sampling factors.

$\theta_1$ and $\theta_{cc}$ are the transition and complementary transition functions

$$H_L(\omega_L) = \begin{cases} \sqrt{p_1q_1} \omega_L - a_1 & \omega_L \in \left[0, \frac{1}{s_1} \right] \\ \omega_L & \omega_L \in \left(\frac{1}{s_1}, \frac{\pi}{p_1} \right) \\ \pi & \omega_L \in \left(\frac{\pi}{q_1}, \pi \right) \end{cases}$$

$$G_H(\omega_L) = \begin{cases} \sqrt{s_1} \theta_{cc} \frac{s_1}{p_1} \omega_L & \omega_L \in \left[0, \frac{1}{s_1} \right] \\ \omega_L & \omega_L \in \left(\frac{1}{s_1}, \frac{1}{s_1} \pi \right) \frac{p_1}{q_1} \\ \pi \frac{p_1}{q_1} & \omega_L \in \left(\frac{1}{s_1} \pi, \pi \right) \frac{p_1}{q_1} \end{cases}$$

where

$$a_1 = \left(1 - \frac{1}{s_1} \right) \frac{s_1}{p_1}, b_1 = \frac{1}{q_1} - \left(1 - \frac{1}{s_1} \right) \frac{1}{p_1}, \theta_{cc} = \sqrt{1 - \theta_1^2} (\omega_L), \omega \in [j] = G^* X, X = fft(x) \theta_1(\omega_L) = \frac{1}{2} (1 + cos(\omega_L)) \sqrt{2 - cos(\omega_L)}$$

The total energy $e_1(J)$ and percentage of the energy of the $k$th sub-band $e_k(k)$ calculation for the RDWT can be done as (23)-(24) [52], [53]

$$e_1(J) = \sum_{j=1}^{J+1} |w(j)|^2$$

where $J$ is the total no of sub-bands

$$\% = \frac{e_k(k)}{e_1(J)} \times 100$$

V. RESULTS AND DISCUSSION

The parameters of 3-Phase SCIM which is used for conducting experiments are tabulated Table 1. Fig.5 shows the experimental setup. The equipment required for the proposed method is

1) Three-phase Squirrel Cage 2-HP Induction Motor with brake drum loading setup;

2) High-frequency signal source (10.525GHz), i.e., handheld UWB radar

3) SIGVIEW software for recording radar signals and SPLL.

The high-frequency source is arranged at 30cm away from the SCIM and the transmitted signal is projected on SCIM. The receiver section of the radar receives the reflected signal and records with a sampling rate of 10 kHz (sampling period of 0.1ms). The first 2.5s of signal information is processed with SPLL, analyzed and plotted on a graph. The various faults occur in bearings and rotor bar of the SCIM are identified through the radar reflected signal with an experimental setup.

In the experiment conducted to diagnose the various faults in the SCIM, the bearing and rotor bar faults are created artificially and the corresponding signals are recorded. The faults are made by drilling the outer race, inner race, ball of...
the bearing and rotor bar of the SCIM. Fig. 5 shows the different bearing faults and rotor bar faults respectively. Five different bearings with no-fault, outer race fault, ball fault, outer race fault combination of ball fault and outer race fault combination of inner race and ball fault are tested to diagnose the faults. The bearing faults with rotor bar faults simultaneously verified with combinations like one rotor bar with outer race faults, two rotor bars and three rotor bars faults with three bearing faults. Based on the parameters of bearing and rotor bar, the characteristic vibration frequencies are listed in Table II [20].

The signal obtained with the proposed method analyzed with FFT [32]. FFT analysis is suitable for external electrical fault identification, but internal fault identification is challenging. Thus, the error signal is analyzed with STFT, which is having a better frequency resolution to identify the bearing faults. The STFT analysis indicates strong harmonics like rotor harmonics, but bearing fault harmonics (outer race and ball fault harmonics) and rotor bar fault harmonics with minimum power are not observable in the STFT analysis [32]. So, the error signal is analyzed with Wavelet transforms, i.e., RDWT and results are presented below.
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Table I

<table>
<thead>
<tr>
<th>S.No</th>
<th>Parameter</th>
<th>Rated Value</th>
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<tbody>
<tr>
<td>1</td>
<td>Power</td>
<td>21HP (1.5KW)</td>
</tr>
<tr>
<td>2</td>
<td>Current</td>
<td>3.5A</td>
</tr>
<tr>
<td>3</td>
<td>Synchronous Speed</td>
<td>1500 r/min</td>
</tr>
<tr>
<td>4</td>
<td>Speed</td>
<td>1410 r/min</td>
</tr>
<tr>
<td>5</td>
<td>Supply Voltage</td>
<td>3-Phase, 415V, 50Hz</td>
</tr>
</tbody>
</table>

Table II

<table>
<thead>
<tr>
<th>Sl.No.</th>
<th>Fault Location</th>
<th>Characteristic Defect Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Normal</td>
<td>24.96Hz</td>
</tr>
<tr>
<td>2</td>
<td>Outer race bearing fault</td>
<td>89.18Hz</td>
</tr>
<tr>
<td>3</td>
<td>Bearing ball fault</td>
<td>116Hz</td>
</tr>
<tr>
<td>4</td>
<td>Inner race bearing fault</td>
<td>135.5Hz</td>
</tr>
<tr>
<td>5</td>
<td>Rotor Bar Fault</td>
<td>240-260 Hz</td>
</tr>
</tbody>
</table>

Table III

<table>
<thead>
<tr>
<th>Machine Condition</th>
<th>Percentage of Signal Power at Sub-band-7 (%) in Total Power</th>
<th>Percentage Change of Power Compared with Normal Condition (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal condition</td>
<td>4.72</td>
<td>-</td>
</tr>
<tr>
<td>Single fault</td>
<td>4.82</td>
<td>2.11</td>
</tr>
<tr>
<td>Two faults</td>
<td>5.82</td>
<td>23</td>
</tr>
<tr>
<td>Three faults</td>
<td>6.73</td>
<td>42.5</td>
</tr>
</tbody>
</table>

Case 1: Diagnosis of the Bearing Faults With No-Load and Full-Load

A. Analysis of the Bearing Faults With the Proposed Method Under No-Load Condition

The bearing faults are analyzed with the constant-Q Wavelet transform called Rational Dilation Wavelet Transform (RDWT). Fig. 8a to 8e shows the RDWT outputs for various fault conditions of the SCIM and the plot consists of waveforms of 12 sub-bands of WT along with actual signal recorded and the percentage of the signal energy at different sub-bands. Each sub-band carries information about a particular band frequency.

The characteristic frequency of the motor vibration under the no-fault and faulty conditions fall in sub-band 7 and 9 [32, 40]. The signal energy in the sub-band-7 under different fault conditions increases as the number of faults increases as shown in Table III indicate the vibration of the motor increases with a number of faults.

Under single fault, the energy variation is less, with two and three faults, the energy variation is severe with each fault addition. During a no-fault condition, the signal power is only 4.72% of the total power, with outer race fault alone, the signal power increases by 2.11% compared with no fault condition, indicates that the fault frequency is affected and with only ball fault, the signal power increases by 6.56% compared with no fault condition.
fault condition. Similarly, with the two faults (outer race and ball fault), the signal power increases by 23% and with three faults (the outer race, inner race and ball fault), the signal power increases by 42.5% from the normal condition, indicates that the fault frequencies, which are in the range of sub-band-7 are dominant and affecting Induction Motor (IM) more severely. The patent described in [65] explains with an increase of faults, the oscillating frequency components of vibrating-element increases, results in a proportional increase of the amplitude of the modulated signal. In the proposed method, the signal energy increases in the fault sub-band (Sub-band-7) with the number faults increases, which is correlated with the theory of the vibrating string.

B. Analysis of the Bearing Faults With the Proposed Method Under Full-Load Condition

To demonstrate the usefulness of the proposed method to diagnose the various bearing faults under load varying condition, a condition of full-load is considered and tested. The RDWT output results with full-load is presented in Fig. 9. The fault frequency energy for no-fault, one fault (ball fault) and two faults (outer race and ball fault) under full-load is 3.95%, 4.46% and 4.65% respectively. Whereas, under no-load, fault frequency energy for no-fault, one fault and two faults 4.72%, 5.03% and 5.85% respectively as shown in Fig. 8a, 8d, 8c. The results indicate that the proposed method is able to distinguish the different faults under varying load condition also.

C. Analysis of the Bearing Faults With Vibration Sensor-Based Contact Method

The sensor is attached to the motor and the received signal is processed with RDWT. The proposed non-invasive
method based on the UWB radar accuracy is verified with a contact method using an accelerometer sensor. Fig. 10a to 10d shows the RDWT outputs of the vibration sensor signals with various fault conditions of the SCIM like normal, single fault (outer race fault), two faults (outer race & ball fault) and three faults (outer race, inner race & ball fault). As the characteristic frequency of the motor vibration under the faulty conditions fall in sub-band 7, the signal energy is compared to diagnosis the faults.

The signal energy in the sub-band-7 increases (4.6% to 7.07%) as the vibration of the motor increased with the number of faults. During no-fault condition, the signal power is only 4.6% of the total power, with outer race fault alone, the signal power increases by 5% compared with no fault condition, indicates that the fault frequency is affecting. Similarly, with the two faults and three faults, the signal power increases by 26.7%, 53.7% from the normal condition respectively indicates that the fault frequencies are dominant and affecting IM more severely.

Table IV gives the comparison of the change in the fault sub-band energy in the proposed method and accelerometer (vibration sensor) based method, which indicates that the proposed method is able to identify the faults with the same accuracy of the contact method, so it is an alternate solution to the costly and complex contact methods. Table V provides the theoretical displacement of SCIM and signal energy change observed in the proposed method for two and three faults when compared with one fault occurred in the motor calculated based on (17,18) [45] in dB. The values of the displacement and energy change in dB are almost equal and the proposed method able to detect the displacement of the motor, which is proportional to the amplitude of the modulated signal with an

<table>
<thead>
<tr>
<th>S.no</th>
<th>Type of Fault</th>
<th>% of change in energy in Sub-band-7 under fault condition compared with normal</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>The proposed method</td>
<td>Vibration accelerometer (Existing Method)</td>
</tr>
<tr>
<td>1</td>
<td>Single Fault</td>
<td>2.11%</td>
</tr>
<tr>
<td>2</td>
<td>Two Faults</td>
<td>23%</td>
</tr>
<tr>
<td>3</td>
<td>Three Faults</td>
<td>42.5%</td>
</tr>
</tbody>
</table>

Table VI

<table>
<thead>
<tr>
<th>S.no</th>
<th>Type of Fault</th>
<th>% of the energy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Sub-band-6</td>
</tr>
<tr>
<td>1</td>
<td>No-fault</td>
<td>2.19%</td>
</tr>
<tr>
<td>2</td>
<td>One bar with bearing outer race fault.</td>
<td>2.25%</td>
</tr>
<tr>
<td>3</td>
<td>Two bars with three bearing faults.</td>
<td>5.03%</td>
</tr>
<tr>
<td>4</td>
<td>Three bars with three bearing faults.</td>
<td>5.54%</td>
</tr>
</tbody>
</table>
The accuracy of the proposed method increases with the number of faults increased.

**Case 2: Combination of the Rotor Bar Fault and Bearing Faults Diagnosis**

The usefulness of the proposed method to detect the bearing faults and rotor bar faults at the same instant is tested and the results are presented in Fig.11. Fig.11(a) to 11(d) are Wavelet output for SCIM with a combination of bearing and rotor bar fault signal analyzed using RDWT. The rotor bar and bearing fault characteristic frequencies fall under sub-band-6 and sub-band 7 respectively, so, the signal energy of these two sub-bands are analyzed. Table VI shows the signal energy at sub-band-6 and sub-band-7 changes with the number of the faults increases. The sub-band-6 energy changes from 2.19% at the no-fault condition to 2.25%, 5.03%, 5.54% with one bar, two bar and three bar faults and sub-band-7 energy 4.72% to 14.48% with an increase of the bearing faults. The results indicate that with an increase of the faults, the SCIM vibration also increases, which reflects on the signal energy of a particular fault frequency. So, the proposed method detects the bearing faults, rotor bar faults and even a combination of both faults.

**VI. COMPARISON WITH RELATED WORK**

Table VII gives the comparison of the existing methods with the proposed method, used for bearing fault diagnosis in the SCIM regarding signals measured, analysis technique, unique components required, signal information required and approximate estimated cost of the system. Multi-sensor wireless system [14] needs various sensors and sensor network ($500) and suffers from data loss while transmitting. The temperature measurement and vibration measurement [15] for fault diagnosis is more expensive ($1000) due to the special wireless sensor network and lab with special arrangements. The stray flux measurement [8] is a non-contact method, which requires a unique stray flux measuring coil and data acquisition board ($100) results in the expensive setup. The accuracy of the flux measurement depends on the presence of other machines and quantity of flux measured. Also, the cost of the system is high and experimental setup is a complex.

The other type of methods for bearing fault diagnosis are contact methods, which measure motor current [7] and vibration [66]. The contact methods require periodical replacement of the sensors, which increases the maintenance and cost of the system. Also, these methods require expensive experimental components such as signal capturing and storage devices like DSO ($100). The Kurtosis and Envelope Analysis [10] and rotor speed based bearing fault diagnosis [66] methods not able to distinguish faults from the other sources of speed oscillation. All these methods are expensive, but the proposed SPLL based method uses only one microwave sensor, no expensive data acquisition boards, signal storage devices and special software.
for signal analysis. The SPLL based method able to identify the multiple faults in the bearing and cost effective.

The other parameters compared are the signals acquired and analysis method for identifying the faults. In the proposed method vibration signal alone analyzed, whereas, in other techniques, more than one signal (vibration, current, speed and acoustic signal) is required for fault identification. The signal analysis algorithms used in the other methods are FFT [10], Hilbert–Huang Transform (HHT) [14], DWT [49] and absolute value-based principal component analysis (AVB-PCA) [66], which suffer from unstable Q-factor, whereas, in the proposed method RDWT (constant Q-factor) is utilized for signal analysis.

The proposed method, experimental setup is simple as only one sensor is used, but the other methods with a set of sensors and specialized equipment for recording data signal increase complexity and cost. The signal length required for analyzing is small (2.5s) compared with the other method (50s, 60s and 100s), resulting the proposed method is faster in fault diagnosis. From all the above comparison, the proposed method have advantages like cost effective, low complexity of the experimental setup, tolerant to temperature change and the acoustic emission of other machines and not affected due to overheating of the motors during the fault condition. The proposed method also identifies simultaneously the multiple faults in the bearing and rotor bar.

### VII. Conclusion

In this paper, microwave sensor based non-invasive, cost-effective method proposed and implemented successfully to identify the various bearing faults and rotor faults. The signals obtained from UWB radar are analyzed with SPLL algorithm and Wavelet transforms. The faulty signal of first 2.5s is analyzed to classify the faults in the SCIM.

The bearing fault signals are analyzed with RDWT and by comparing the signal power at fault frequency sub-band, the faults in the bearing are identified. The signal power increases with the increase of the number of faults by 2.11%, 23% and 42.5% at the sub-band-7 as compared with no-fault condition signal power. Thus, observing the sub-band signal energy, particular motor fault identified. The usefulness of the proposed SPLL based non-invasive method for early stage bearing fault diagnosis verified with by performing many experiments. The obtained results also verified with the existing vibration sensor/accelerator [ADXL-335] based method and found that the proposed method is use full and better replacement for contact method.

In this paper, the proposed method is utilized for detecting the multiple bearing and rotor bar faults simultaneously. The signal energy at sub-band-7 and sub-band-6 is compared to identify both faults. The proposed method has identified the fault accurately and without disturbing the machine operation. The results obtained are compared with a theoretical value and proved that the proposed method is having more than 93% accuracy in the detecting the faults. The existing methods suffer from the constant replacement of sensor for better accuracy, affected by machine temperature, low sensor sensitivity, resolution, the influence of adjoining electrical machines, surrounding environmental changes and require human expertise to mount the sensors. The proposed SPLL based method overcomes drawbacks of existing methods and has advantages like immune to the surrounding temperature variation, other machine’s influence, works for the long duration without any performance variation and regular replacements.

The proposed method is cost-effective, non-invasive and simple. However, in this paper, the automation of the fault diagnosis in the industrial application is not verified. The UWB radar signal is least affected by noise, but, still the proposed method is not tested in industry application with real time noise.

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### REFERENCES


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