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# Wavelet-Based Analysis of MCSA for Fault Detection in Electrical Machine

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## Abstract

Early detection of irregularity in electrical machines is important because of their diversity of use in different fields. A proper fault detection scheme helps to stop the propagation of failure or limits its escalation to severe degrees, and thus it prevents unscheduled downtimes that cause loss of production and financial income. Among different modes of failures that may occur in the electrical machines, the rotor-related faults are around 20%. Successful detection of any failure in electrical machines is achieved by using a suitable condition monitoring followed by accurate signal processing techniques to extract the fault features. This article aims to present the extraction of features appearing in current signals using wavelet analysis when there is a rotor fault of eccentricity and broken rotor bar. In this respect, a brief explanation on rotor failures and different methods of condition monitoring with the purpose of rotor fault detection is provided. Then, motor current signature analysis, the fault-related features appeared in the current spectrum and wavelet transform analyses of the signal to extract these features are explained. Finally, two case studies involving the wavelet analysis of the current signal for the detection of rotor eccentricity and broken rotor bar are presented.

**Keywords:** Wavelet transform, Line start permanent magnet motor, Induction motor, Eccentricity, Broken rotor bar

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## 1. Introduction

Electrical machines are widely used for many industrial processes and play a non-substitutable role in a variety of industries [1–2]. In spite of their reliability and robustness, electrical

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machines are still prone to failures due to the exposure to a wide diversity of strict conditions and environments, incorrect operations, or even manufacturing defects [3]. These faults, gradual deterioration, and failures can lead to motor interruption, if left undetected, and their resulting unplanned downtime is very expensive. Early detection of irregularity in electrical machines with proper fault diagnosis schemes will help prevent high-cost failures, thereby decreasing the cost of maintenance and preventing unscheduled downtimes. However, stopping the propagation of the fault limits its escalation to severe degrees, which results in loss of production and financial income.

The fault identification schemes are basically based on data collection of electrical machines followed by signal processing. The condition of an electrical machine is examined from data that are acquired through sensors and supportive equipment methods. By using a suitable signal processing technique, each fault can be then detected via a specific feature present in the measured signal of a faulty motor when compared to a fault-free one. Hitherto, a number of data acquisition techniques, which display a certain parameter of the electrical machine, have been established. Essentially, the efficiency of a data acquisition method is characterized by its accuracy, cost, and importantly its capability to quantify the fault. On the contrary, condition monitoring based on data acquisition techniques requires the user to have adequate knowledge and proficiency to differentiate a normal operating condition from a potential failure state. The key step, but a difficult task, in the fault detection of electrical machines is to extract the fault-related features from the acquired signal and identify the condition of motor. Fault-related features are parameters derived from the acquired data that specify the existence of failure in device. The current signal of electrical machine is non-linear and non-stationary with strong noise interference; hence, the energy of early signal is too low to extract fault-related features in time domain [4]. Advanced signal processing methods based on analysis of time–frequency domain have been proposed as effective approaches for fault detection in electrical machines [5].

The focus of this chapter is on the extraction of features present in the current spectrum of electrical machine when one of two important rotor faults, eccentricity and broken rotor bar, exists. To extract features from the current spectrum in the presence of these faults, an advanced signal processing method, wavelet packet analysis, is used. In this regard, the fundamentals related to the detection of these two faults using wavelet packet analysis of current signal are explained in the following sections.

## **2. Rotor faults**

From the investigations on different failure modes in electrical machines, the rotor-related faults are around 20% of failures may happen in the motor [6]. The rotor is exposed to different types of stresses that seriously affect its normal condition and subsequently create faults in it. Bonnett and Soukup explained the stresses that motors are subjected to and their unfavourable causes [7]. Failures in rotor are classified into eccentricity of rotor, crack and/or breakage of rotor cage bars, and crack and/or breakage of end rings and rotor bow [8]. These irregularities

bring specific secondary failures that cause serious faults in electrical machines. Moreover, these types of faults may not show any symptoms during early stage until propagating to the next step and leading to the sudden collapse [9–11]. In recent years, rotor faults have been increasingly studied for developing advanced techniques that permit online early detection and diagnosis of motor faults to avoid any negative consequences of unexpected shutdowns, but this area still needs more research because of the complexity of the motor during the runtime. In this section, a brief description of different rotor faults is provided.

### 2.1. Rotor eccentricity

In a fault-free machine, the rotor is centre aligned in the stator bore that results in uniform air gap between the stator and rotor. In fault-free electrical machines, the rotation centre of the rotor is the same as the geometric centre of the stator bore. As a result, the rotor symmetrical axis ( $C_r$ ), stator symmetrical axis ( $C_s$ ), and rotor rotational axis ( $C_g$ ) coincide with each other, and thus the magnetic forces are balanced in opposite directions. Rotor eccentricity, displacement of the rotor from its centred position in the stator bore, generates an asymmetric air gap between the stator and rotor [12]. The rotor eccentricity also produces unbalanced magnetic pull (UMP), which is a radial magnetic force on the rotor shaft. The UMP also pulls away the rotor from the stator bore centre, thus causing excessive stress on the electrical machine [13, 14]. Eccentricity commonly presents in rotating electrical machines, and the maximum permissible level of eccentricity is defined, which is 5 or 10% of the air-gap length [15]. If eccentricity exceeds the permissible level, it will increasingly damage the winding, stator core and rotor core in the motor due to rubbing of the stator with the rotor [12, 14]. Three different types of eccentricity occur in an electrical machine: static eccentricity, dynamic eccentricity, and mix eccentricity. As an example, static eccentricity is explained next.

Static eccentricity in electrical machines occurs when the rotor symmetrical axis is concentric with the rotor rotational axis; however, they are dislocated with respect to the stator symmetrical axis; hence, the position of minimum radial air-gap length is fixed. In this state, the mutual inductances across the stator and rotor as well as the self- and mutual inductances among the rotor phases are related to the angular position of the rotor [16]. The implication of static eccentricity fault in motor is depicted in Figure 1.

Static eccentricity can be due to numerous motives such as elliptical stator core, wrong placement of the rotor or stator at the setup or subsequent of maintenance, incorrect bearing positioning, bearing deterioration, shaft deflection, housing imperfection, end-shield misalignment, excessive tolerance, and rotor weight or pressure of interlocking ribbon [17–19]. Static eccentricity leads to second failures which cause drastic harm to the rotor, stator core and windings. The radial forces in the static eccentricity condition produce a steady UMP in the radial route across the motor because the reluctance of the magnetic flux path decreases with the transmission of flux on the side of tiny air gap [20]. Albeit, the winding current induces more magnetic flux that causes a stronger pull and leads to the expansion of the air gap on the opposite side where the reluctance increases, thereby decreasing the flux and magnetic side pull. Therefore, the UMP compels the rotor to move toward the area of the narrowest air-gap length. During abrasion, the stator core subsequently generates abnormal vibration and

severely damages the rotor, windings and the stator [7]. Consequently, the static eccentricity causes acoustic noise, premature failure in the bearing, rotor deflection and bent rotor shaft.

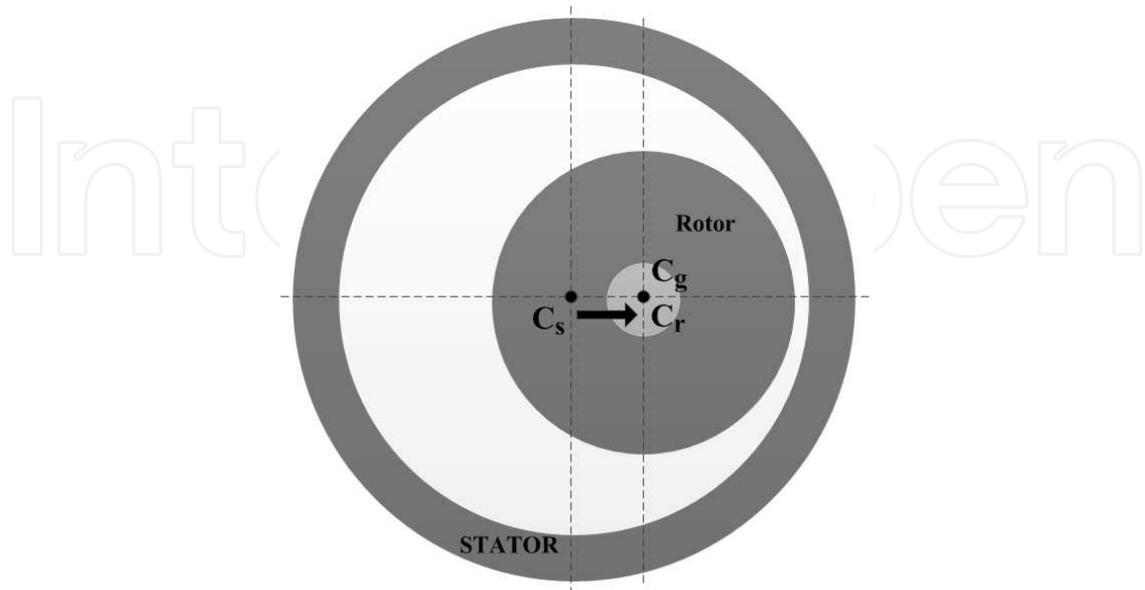


Figure 1. Cross section of motor under static eccentricity fault

The degree of static eccentricity is calculated by the equation based on Figure 2 [16]:

$$D_{SE} = \frac{|C_s C_g|}{g} \tag{1}$$

where  $\vec{C_s C_g}$  is the vector of static transfer which is invariant for rotor angular positions and  $g$  is the uniform air-gap length.

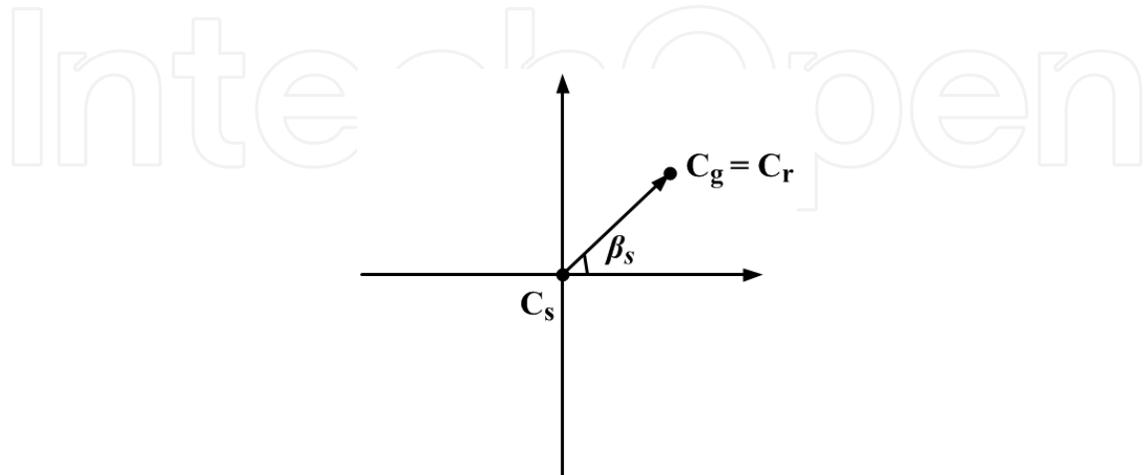


Figure 2. Location of stator and rotor under static eccentricity condition

## 2.2. Rotor bar breakage

The breakage of rotor bars is one of the important failures in the rotor cage of electrical machines. During the operation of electrical machines, rotor bars may be broken partially or completely. The main reasons for bar breakage include electrical, mechanical, and environmental stresses during the operation of electrical machines and/or improper design of rotor geometry. Once a bar breaks, the stress increases and deteriorates the condition of the neighbouring bars progressively. Such a destructive process can be prevented, if any crack in the bar is detected early [21]. Typical causes of rotor bar breakage are referred as follows [22]: high thermal and mechanical stresses, direct online starting duty cycles for which the rotor cage was not well designed to endure against the stresses, imperfections in design and fabrication process of the rotor cage bars. Any failure in rotor bars itself causes unbalanced currents and torque pulsation and, therefore, decreases the average torque [23].

The rotor bars are short-circuited on both sides of the rotor by end rings. Depending on the type of squirrel cage in the motor, the source of failures in the end ring differs, in die-cast aluminium rotors caused by porosity of casting and in fabricated rotor cages caused by poor end-ring joints during manufacturing. Once the preliminary failure occurs, localized heat may extend to the rotor cage excessively. Therefore, the fault propagation is continued by multiple start-ups similar to load variations, which create high centrifugal forces. Accordingly, end-ring faults cause a drastic increase in the current and speed fluctuation [21].

## 2.3. Rotor bow

Any irregular thermal variation (heating or cooling) and unfavourable thermal distribution of the rotor during operation of electrical machines may bow the rotor [24]. The bow created in the rotor prevents sufficient alignment in the motor and generally produces a preload on the bearings. Bend locations in the rotor cause major failures in other parts of the motor [25]. The bow in the rotor is classified as local and extended [24]. When an asymmetrical heating is confined to a part of the rotor, a local bow is generated. For example, rotor-to-stator rubbing can generate a local asymmetric thermal distribution, which causes the local bow. When an asymmetrical heating extends along the rotor, an extended bow is generated. Long-lasting gravity effects on off-line machines generate rotor bow classified as an extended bow, when unsuitable rotor straightening turning system is not used [24]. Since the rotor is limited by two bearings, extended bow commonly causes a shaft bow [24].

## 3. Condition monitoring techniques for rotor fault detection

Condition monitoring programme which can predict a failure in electrical machines has received considerable attention for many years [2, 8]. Successful detection of any failure in electrical machines is achieved by using suitable condition monitoring. When a failure occurs, some machine parameters are exposed to changes that depend upon the fault degree. Any irregularity in the rotor of electrical machines presents with variation distributed in the rotor currents. The feedback of these currents to the air-gap field produces specific signatures of fault in the spectrum of speed, torque, current, and power. Reliable condition monitoring

techniques depend on the best understanding of the mechanical and electrical characteristics of the electrical machines in both fault-free and faulty situations. Researchers have used different condition monitoring techniques that can be categorized as follows [8]:

- Acoustic emission
- Air-gap torque
- Current
- Electromagnetic field monitoring
- Induced voltage
- Instantaneous angular speed
- Motor circuit analysis
- Power
- Surge testing
- Vibration
- Voltage

### 3.1. Motor current signature analysis

The drowned current signal by an electrical machine contains a single component. Any magnetic or mechanical asymmetries in the machine generate other frequency components in the stator current spectrum. These frequency components are diverse according to each specific fault in the machine.

Motor current signature analysis (MCSA) analyses the stator current signal to identify the presence of any failure in electrical machines. This analysis method has been introduced as an effective way for monitoring electrical machines for many years [8]. From all these methods suggested in the literature, MCSA is a forerunner because of its advantages [10, 13, 26–28]:

- Online monitoring characteristics
- Remote monitoring ability
- Non-invasive feature
- Inexpensive equipment and easy measurement
- Different fault detection capability (such as broken rotor bars, air-gap eccentricity, stator faults, etc.)
- Early-stage fault detection
- Highly sensitive
- Selective

When a failure is generated in the electrical machine, depending on the severity of this fault, some of the machine parameters change. For instance, the current spectrum of an ideal electrical machine contains a single component corresponding to the supply frequency. Any asymmetry in electrical machine causes other components to appear in a spectrum of stator current. When a rotor bar breaks, current does not flow through it, and hence no magnetic flux is created around the breakage bar. Therefore, there is no non-zero backward rotating field that rotates at the slip frequency speed with respect to the rotor. This asymmetry in the magnetic field of rotor induces harmonics in stator windings, which are superimposed on it. These superimposed harmonics appear at frequency spectrums as described in

$$f_{\text{BRB}} = [1 \pm 2KS] f_s \quad (2)$$

where  $f_{\text{BRB}}$  is the harmonic component due to broken rotor bar,  $S$  is the slip,  $f_s$  is the fundamental frequency, and  $k = 1, 2, \dots$  [29].

Any asymmetry caused by static eccentricity produced other components that appear in the spectrum of stator current. The characteristic frequency component associated with static eccentricity is located according to Eq. (3) [16]:

$$f_{\text{static}} = \left[ 1 \pm \frac{m}{p} \right] f \quad (3)$$

where  $f_{\text{static}}$  is the harmonic component due to static eccentricity in line start permanent magnet synchronous motor (LSPMSM),  $m$  is an odd integer value,  $p$  is the number of pole pair, and  $f$  is the line frequency.

#### 4. Wavelet

Frequency domain analysis is not reliable for fault detection because some outside parameters can affect the location and amplitude of fault-related feature. This parameter can be classified as follows: first, the fault frequency components depend on the slip of the motor; second, the fault feature amplitude is load dependent; third, the frequencies of the fault components are affected by voltage fluctuations; and fourth, long sampling interval is needed for a high-resolution frequency. Therefore, in general, frequency domain analyses are suitable for the steady-state situation. The problem involved in the analysis of non-stationary signals can be shunned by time–frequency analysis of the signal, which illustrates the signal in three-dimensional axis as time, frequency, and amplitude. The most popular time–frequency representations include Wigner–Ville distribution, short-time Fourier transform, and wavelet transform.

Wavelet transform expresses a signal in oscillatory function series at different frequencies and time. Wavelet transform divides the original signal into time-scale space, where the dimension of windows at time and scale (frequency) is not rigid [30]. Therefore, in fault diagnostics domain, wavelet transform has been used to extract the dominant features from original signals [31]. Various types of wavelet transforms have been widely used in the condition monitoring of electrical machine. Among all these techniques, discrete wavelet transform and wavelet packet transform (WPT) are the most common ones, explained in the following.

#### 4.1. The principle of discrete wavelet decomposition

Discrete wavelet transform is based on signal analyses using a minor set of scales and specific number of translations at each scale. Mallat (1989) introduced a practical version of discrete wavelet transform called wavelet multi-resolution analysis [32]. This algorithm is based on the fact that one signal is disintegrated into a series of minor waves belonging to a wavelet family.

A discrete signal  $f[t]$  could be decomposed as

$$f[t] = \sum_k A_{m0,n} \phi_{m0,n}[t] + \sum_{m=0}^{m-1} \sum_n D_{m,n} \psi_{m,n}[t] \quad (4)$$

where  $\phi$  is the scaling function (father wavelet) and  $\psi$  is the wavelet function (mother wavelet),  $A$  is the approximate coefficient and  $D$  is the detail coefficient.

The multi-resolution analysis commonly uses discrete dyadic wavelet, in which positions and scales are based on powers of two. In this approach, the scaling function is depicted by the following equation:

$$\phi_{m0,n}[t] = 2^{m0/2} \phi(2^{m0}t - n) \quad (5)$$

that is,  $\phi_{m0,n}$  is the scaling function at a scale of  $2^{m0}$  shifted by  $n$ . Wavelet function is also defined as

$$\psi_{m,n}[t] = 2^{m/2} \psi(2^m t - n) \quad (6)$$

that is,  $\psi_{m,n}$  is the mother wavelet at a scale of  $2^m$  shifted by  $n$ .

Generally, approximate coefficients  $A_{m0,n}$  are obtained through the inner product of the original signal and the scaling function

$$A_{m0,n} = \int_{-\infty}^{\infty} f(t) \phi_{m0,n}(t) dt \quad (7)$$

The approximate coefficients decomposed from a discretized signal can be expressed as

$$A_{(m+1),n} = \sum_{n=0}^N A_{m,n} \int \phi_{m,n}(t) \phi_{m+1,n}(t) dt = \sum A_{m,n} \cdot g[n] \quad (8)$$

In the dyadic approach, the approximation coefficients  $A_{m0,n}$  are at a scale of  $2^{m0}$ . The filter,  $g[n]$ , is a low-pass filter. Similarly, the detail coefficients  $D_{m,n}$  can be generally obtained through the inner product of the signal and the complex conjugate of the wavelet function:

$$D_{m,n} = \int_{-\infty}^{\infty} f(t) \cdot \psi_{m,n}^*(t) dt \quad (9)$$

The detail coefficients decomposed from a discretized signal can be expressed as

$$D_{(m+1),n} = \sum_{n=0}^N A_{m,n} \int \phi_{m,n}(t) \cdot \psi_{m+1,n}(t) dt = \sum A_{m,n} \cdot h[n] \quad (10)$$

In the dyadic approach,  $D_{m,n}$  are the detail coefficients at a scale of  $2^{m0}$ . The filter,  $h[n]$  is a high-pass filter.

The multi-resolution analysis utilizes discrete dyadic wavelet and extract approximations of the original signal at different levels of resolution. An approximation is a low-resolution representation of the original signal. The approximation at a resolution  $2^{-m}$  can be split into an approximation at a coarser resolution  $2^{-m-1}$  and the detail. The detail represents the high-frequency contents of the signal. The approximations and details can be determined using low- and high-pass filters. In the multi-resolution analysis, the approximations are split successively, while the details are never analysed further. The decomposition process can be iterated, with successive approximations being decomposed in turn; hence one signal is broken down into many lower-resolution components. This process is called the wavelet decomposition tree as shown in Figure 3. It illustrates the dyadic wavelet decomposition algorithm regarding the coefficients of the transform at different levels according to the description by Polikar et al. (1998) [33].

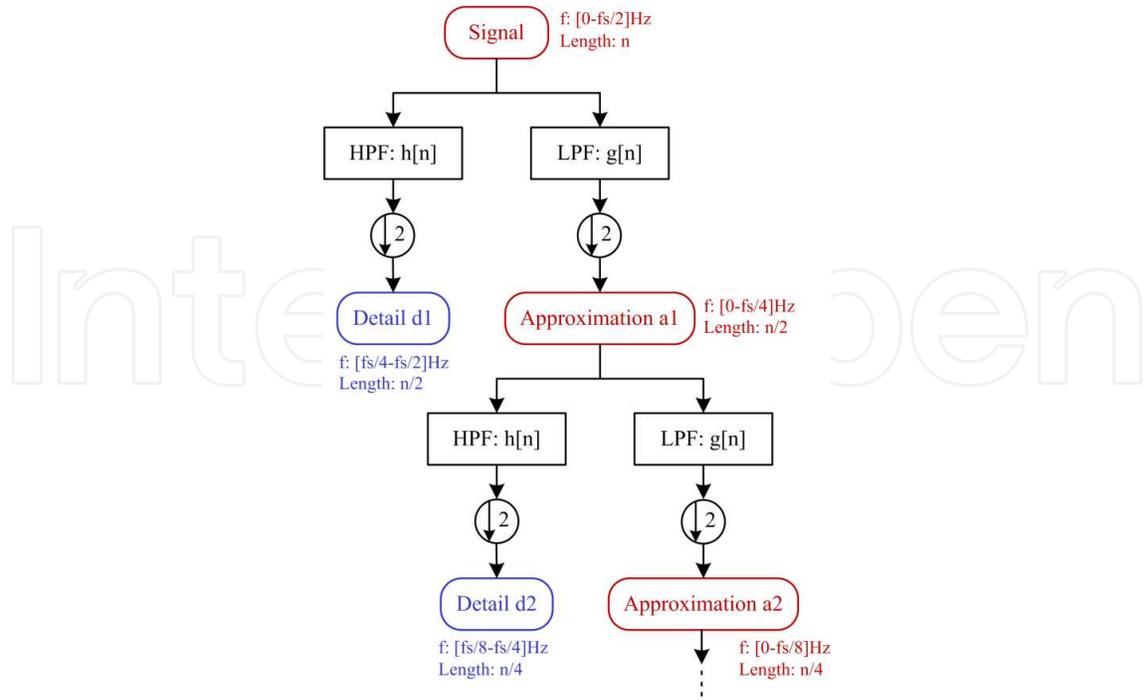


Figure 3. Dyadic wavelet decomposition algorithm [34].

### 4.2. The principle of wavelet packet decomposition

The wavelet packet transform is a direct expansion of discrete wavelet transform, where the details as well as approximation are split up. Therefore, this tree algorithm is a full binary tree that offers rich possibilities for signal processing and better signal representation in comparison to a discrete one.

A wavelet packet function has three naturally interpreted indices in time–frequency functions:

$$\psi_{j,k}^i = 2^{\frac{j}{2}} \psi^i(2^j t - k), \quad i = 1, 2, 3, \dots \tag{11}$$

where integers  $j$ ,  $k$ , and  $i$  are called the scale, translation, and simulation parameters, respectively. Scaled filter  $h(n)$  and the wavelet filter  $g(n)$  are quadrature mirror filters associated with the scaling function  $\Phi(t)$  and the wavelet function  $\psi(t)$  [32]. The conjugate mirror filters  $h$  and  $g$  with finite impulse responses (FIRs) of size  $k$  can define the fast binary wavelet packet decomposition (WPD) algorithm of the signal  $f(t)$ :

$$\begin{cases} d_0^0(t) = f(t) \\ d_{j+1}^{2^n}(t) = \sum_k h(k-2t) d_j^i, \quad i = 0, 1, \dots, 2^j - 1 \\ d_{j+1}^{2^{n+1}}(t) = \sum_k g(k-2t) d_j^i \end{cases} \tag{12}$$

The wavelet packet component signals  $f_j^i(t)$  are produced by a combination of wavelet packet function  $\psi_{j,k}^n(t)$  as follows:

$$f_j^i(t) = \sum_{i=1}^{2j} C_{j,k}^i(t) \psi_{j,k}^i(t) \tag{13}$$

where the wavelet packet coefficients  $C_{j,k}^i(t)$  are calculated by

$$C_{j,k}^i(t) = \int_{-\infty}^{\infty} f(t) \psi_{j,k}^i(t) dt \tag{14}$$

Provided the wavelet packet functions are orthogonal

$$\psi_{j,k}^m(t) \psi_{j,k}^n(t) = 0 \text{ if } m \neq n \tag{15}$$

As data sets of wavelet packet coefficients increase in size, the energy principle is applied to current signals after WPT for fault location estimation [35].

### 4.3. A review of wavelet decomposition for fault detection

Different types of wavelet transform techniques have been widely used in algorithms designed for fault detection in electrical machines. Table 1 presents the common types of these techniques.

Ref	Year	Diagnostic Monitoring Techniques (MTs)	Signal Processing	Classifier and Decision-making Tool	Purpose	Achievement and Limitation
[5]	1996	Current (start-up)	short time fourier transform(STFT), continuous wavelet - transform(CWT), Wigner distribution		To compare individual signal processing techniques using both test and actual data	The CWT has been proven to be the most efficient technique for the extraction of the frequency component of interest. Limitation: available. The technique would be of particular use to industrial applications where motors are frequently started on no load, or have been moved to a workshop environment where

Ref	Year	Diagnostic Monitoring Techniques (MTs)	Signal Processing	Classifier and Decision-making Tool	Purpose	Achievement and Limitation
						fully loaded conditions are neither practical nor achievable
[36]	2001	Motor current signature analysis (MCSA)	Discrete wavelet transform (DWT)	-	To develop current monitoring procedure for BRB detection	A new approach in detection of BRB having only stator current signal
[37]	2002	MCSA	WT, park transform(PT)	-	To compare model-based and signal-based approaches based on Park transform for BRB detection	The spectral decomposition obtained by the wavelet transform may be used to isolate different kinds of faults
[38]	2002	MCSA, voltage, speed	Wavelet packet decomposition (WPD)	Artificial neural network	To develop a model-based diagnosis system for detection of various faults including BRB	The proposed system was shown effective in detecting early stages of different IM faults
[39]	2003	MCSA	WPD	Artificial neural network	To improve MCSA monitoring procedure for BRB and air-gap eccentricity detection	It provides feature representations of multiple frequency resolutions for faulty modes
[40]	2004	Current (start-up)	DWT	-	To improve the start-up current monitoring procedure for BRB detection using a filter that actively tracks the changing amplitude, phase and frequency to extract the fundamental mode from the transient	This method does not require parameters such as speed or number of rotor bars. It is not load dependent and can be applied to IMs that operate continuously in the transient mode
[41]	2005	MCSA	fast fourier transform (FFT), WPD	-	To improve MCSA monitoring procedure for the detection of various faults including BRB	The features of BRB and static eccentricity yield similar results in the wavelet analysis, but are different in Fourier analysis. Therefore the use of both types of analysis together can distinguish the faults

Ref	Year	Diagnostic Monitoring Techniques (MTs)	Signal Processing	Classifier and Decision-making Tool	Purpose	Achievement and Limitation
[42]	2005	Current (start-up)	DWT	-	To develop start-up current monitoring procedure for BRB detection	The method is not load dependent and can be effective on small lightly loaded machines
[43]	2005	Current (envelope, start-up)	CWT	-	To develop start-up current monitoring procedure using envelope extraction of current spectrum for BRB detection	The procedure is not affected by other factors such as initial rotor position, phase of the supply and supply imbalance. It is able to classify the different degrees of BRB. Limitation: A partial BRB could not be indicated
[44]	2006	MCSA	WPD	Adaptive neuro-fuzzy	To present a novel online diagnostic algorithm for BRB and air-gap eccentricity detection in variable speed drive systems	Although the algorithm is able to detect the fault with high accuracy, the number of training iterations and the CPU processing time were reduced
[45]	2006	Instantaneous power	DWT	-	To improve IP monitoring for BRB detection under various load levels	Wavelet approach applied to IP showed superior ability for BRB detection compared to the frequency domain analysis
[46]	2006	MCSA	FFT, WPD	Fuzzy entropy-artificial neural network	To improve MCSA monitoring procedure for the detection of various faults including BRB	An approach was proposed based on Fourier transformation and wavelet transform and neural network system to classify the faults
[47]	2006	Current (start-up)	DWT	-	To develop start-up current monitoring procedure for BRB detection. To compare the influence of the discrete wavelet transform parameters (type of mother wavelet, order of the mother wavelet, sampling rate	The tests show that if the start-up transient is not very short, the reliability of the proposed method for BRB detection is similar to that of the classical approach, based on the Fourier transform, in the case of loaded motors. In addition, the method can detect faults in an unloaded condition, and it

Ref	Year	Diagnostic Monitoring Techniques (MTs)	Signal Processing	Classifier and Decision-making Tool	Purpose	Achievement and Limitation
					or number of levels of the decomposition) over the diagnosis	allows a correct diagnosis of a fault-free machine in some particular cases where Fourier analysis leads to an incorrect fault diagnosis
[48]	2007	Induced voltage	FFT, WT	-	To investigate the limitations and harmonics of the induced voltage after supply disconnection harmonics for BRB detection	Fourier transform did not provide information about fault severity and load variations. A method based on wavelet analysis of induced voltage spectrum was developed for BRB detection Limitation: Tests need to be carried out for fault-free motor to develop a baseline response. It is sensitive to changes in load, system inertia, rotor temperature and supply voltage
[49]	2007	MCSA	WPD	-	To detect incipient bearing fault via stator current analysis	Cover better analysis under various conditions and more tolerant frequency bands with WPD method
[50]	2007	MCSA	WPD	-	To detect real-time fault for various disturbances in three-phase IM	Selecting the optimal levels of decomposition and optimum mother wavelet
[51]	2008	MCSA	STFT, WT	-	To improve MCSA monitoring procedure for BRB and stator shorted turns detection	Wavelet decomposition is superior to STFT. Power spectral density for wavelet details was introduced as a merit factor for fault diagnosis. The proposed method can diagnose shorted turns and BRB in non-constant load-torque IM applications
[52]	2008	Current (start-up)	DWT	Principle component	To develop transient current monitoring	Feature reduction and extraction using component

Ref	Year	Diagnostic Monitoring Techniques (MTs)	Signal Processing	Classifier and Decision-making Tool	Purpose	Achievement and Limitation
						analysis via PCA and KPCA are highlighted. The performance of WSVM is validated by applying it to fault detection and classification of induction motor based on start-up transient current signal. Limitation: A proper pre-processing for the transient current signal is needed to improve the emerging salient differences between conditions in induction motors
[35]	2008	MCSA	WPD	Artificial neural network	To estimate transmission line fault	A powerful and reliable method by applying the energy criterion after wavelet packet transform (WPT) for reducing the data size
[53]	2009	MCSA	WPD	Artificial neural network	To propose a novel online diagnosis algorithm for BRB detection	The diagnosis can be performed with reduced load condition. An accurate measurement of the slip speed is not necessary
[54]	2009	Current (start-up)	DWT	-	To develop start-up current monitoring procedure for distinguishing various faults including BRB and other phenomena, such as load-torque oscillations	The proposed methodology showed promising ability for the reliable discrimination of simultaneous electromechanical faults and the diagnosis of faults combined with other phenomena
[55]	2009	Current (envelopes)	DWT	-	To propose a new technique, slip independent, for BRB detection under different load levels	The proposed method gives the same reliable results for BRB detection under different load levels when applying to the stator-current space-vector magnitude and the

Ref	Year	Diagnostic Monitoring Techniques (MTs)	Signal Processing	Classifier and Decision-making Tool	Purpose	Achievement and Limitation
						instantaneous magnitude of the stator-current signal
[56]	2009	Vibration	WPD	Artificial Neural Network	To optimize gear failure identification using GAs and ANNs	The technique determines the best values 'mother wavelet', 'decomposition level' and 'number of neurons in hidden layer'
[57]	2009	Vibration	WPD	Hybrid support machine	To propose an intelligent method to diagnose rotating machinery failures	An accurate and quick fault-type estimation method by applying hybrid SVM to the energy criterion after WPA
[58]	2009	MCSA	DWT	-	To compare a different wavelet family for BRB fault detection	The technique determines the best mother wavelet
[59]	2010	MCSA	WT,PSD	-	To develop BRB detection methods based on MCSA	The method has the ability to detect BRB for both constant torque and for variable load torque
[60]	2011	MCSA	FFT,WT	-	To propose a new method for early fault detection	The approach has been proved to be effective to detect failures in its very early stages
[4]	2012	Vibration	WPD,EMD	Artificial neural network	To integrate the fine resolution advantage of WPD with the self-adaptive filtering characteristics of empirical mode decomposition (EMD) to early fault diagnosis	Ability to extract weak signals and early fault detection of rotating machinery
[61]	2013	MCSA	Stationary WPD	Multiclass support vector machines	BRB feature extraction by SWPT under lower-sampling rate	Lower computation and cost without any effect on the performance of SWPT to detect BRB
[62]	2013	Vibration	WPD,FFT	Artificial neural network	To classify fault and predict remaining useful life	To deal with complex problems and non-linear

Ref	Year	Diagnostic Monitoring Techniques (MTs)	Signal Processing	Classifier and Decision-making Tool	Purpose	Achievement and Limitation
						systems and predict remaining useful life
[63]	2014	Vibration	WPD	-	To improve the accuracy and rectify the distortion of WPT coefficients	Magnifying the amplitude of the fault characteristic frequency
[34]	2014	MCSA	DWT	-	To investigate the ability of different types of wavelet functions for early BRB detection	The reliability of the fault detection depends on the type of wavelet function applied for decomposition of the signal
[64]	2014	Apparent power	DWT	-	To develop air-gap eccentricity fault detection methods based on apparent power	The energy evaluation of a known bandwidth permits to define a fault severity factor (FSF)
[65]	2014	MCSA	DWT	Fuzzy support vector machine, principal component analysis, kernel neural network	To develop eccentricity fault detection methods and degree precisely based on MCSA in PMSM	The novel index for eccentricity fault diagnosis is introduced based on energy, peak, head angle of the peak, the area below the peak, the gradient of the peak and coefficients of the autoregressive (AR) model

**Table 1.** Summary of published paper with the aim of using wavelet transform for broken rotor bar and eccentricity fault detection

## 5. Case study 1

The detection of static eccentricity in three-phase LSPMSM using motor current signature analysis is studied. A detailed description of experimental test rig used in this study and the method used for signal measurement and analysis is provided in the following.

### 5.1. Experimental set-up

The experimental test rig is shown in Figure 4. The tested motor for both fault-free and faulty (with static eccentricity) cases is a three-phase LSPMSM with the specification as mentioned in Table 2. The motor is directly fed by the grid power supply, while the stator windings are

Y connected, and the current nominal value is 1.28 A. The LSPMSM is coupled to torque/speed sensor in order to measure the torque value in different operation conditions. On the other side, a mechanical load is provided by a DC-excited magnetic powder brake (MPB) coupled to torque/speed sensor. The specific load torque level could be furnished to the motor shaft by controlling the input dc voltage of MPB. This system is used to sample the stator current non-invasively when the motor is operated in the steady-state condition. Notably, only one phase-current signal is required to be recorded for the detection process in this study. The recorded signals are analysed by a computer-based signal processing program.

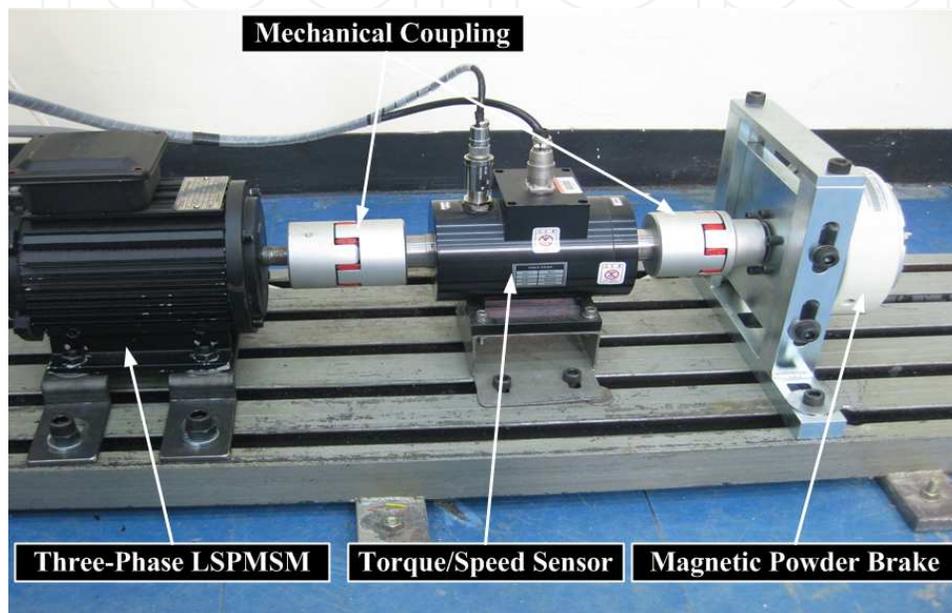


Figure 4. Experimental test rig

## 5.2. Method

The method proposed in this study for the creation of eccentricity fault in LSPMSM, by changing the original bearings of motor with a new set of bearing with larger inner diameter and smaller outer diameter, results in the creation of free space between the shaft and bearings and also between the bearings and the housing of end shields. Static eccentricity is created by fixing concentric inner rings between the new bearings and shaft on both ends of LSPMSM and non-concentric outer rings between the new bearings and housings of both end shields. The aforementioned strategy is used to create 33% and 50% static eccentricity in the motor discussed in the case study.

The current spectrum is stored with the sampling frequency ( $f_s$ ) of 5 kHz over a total sampling period of 6.5 s, which allows the analysis of the signals with a minimum frequency of 0.15 Hz. Daubechies-24 (db24) is used as the mother wavelet in discrete wavelet transform (DWT) analyses. Since the four-pole, three-phase LSPMSM is considered, the characteristic frequency component associated with static eccentricity is located at 25 Hz, according to Eq. (3) [16].

Rated output power (HP)	1
Rated voltage (V)	415
Rated frequency (Hz)	50
Number of poles	4
Rated speed (RPM)	1500
Connection	Y
Air-gap length (mm)	0.30

**Table 2.** Specification of three-phase LSPMSM

The number of decomposition levels ( $l_d$ ) can be determined using Eq. (16) which is  $l_d=7$  in this case.

$$l_d = \frac{\log(f_s / f_{static})}{\log(2)} \quad (16)$$

The frequency bands of wavelet signals are summarized in Table 3. Energies of the detail coefficient  $E(D_j)$  are calculated using the following formulas [45]:

$$E(D_j) = \sqrt{\frac{1}{N_1} \sum_{i=1}^{N_1} (D_j)^2 [i]} \quad (17)$$

where  $j=1, 2, \dots, l_d$  and  $N_1$  is the data length of the decomposition level.

Signal	Frequency band (Hz)
$A_7$	0–19.53
$D_7$	19.53–39.06
$D_6$	39.06–78.13
$D_5$	78.13–156.25

**Table 3.** The frequency bands of wavelet signals

### 5.3. Results and discussion

Figure 5 shows the stator current signal (original signal) and  $D_5$ ,  $D_6$ , and  $D_7$  are the detail signals obtained by db24 at level 7 for fault-free LSPMSM. The fault-related components ( $f_{static}$ ) are visible at 25 Hz, which confirm the productivity of  $D_7$  signal for the detection of static eccen-

tricity. The original and detail signals of LSPMSM with 33% and 50% static eccentricity are indicated in Figures 6 and 7, respectively.

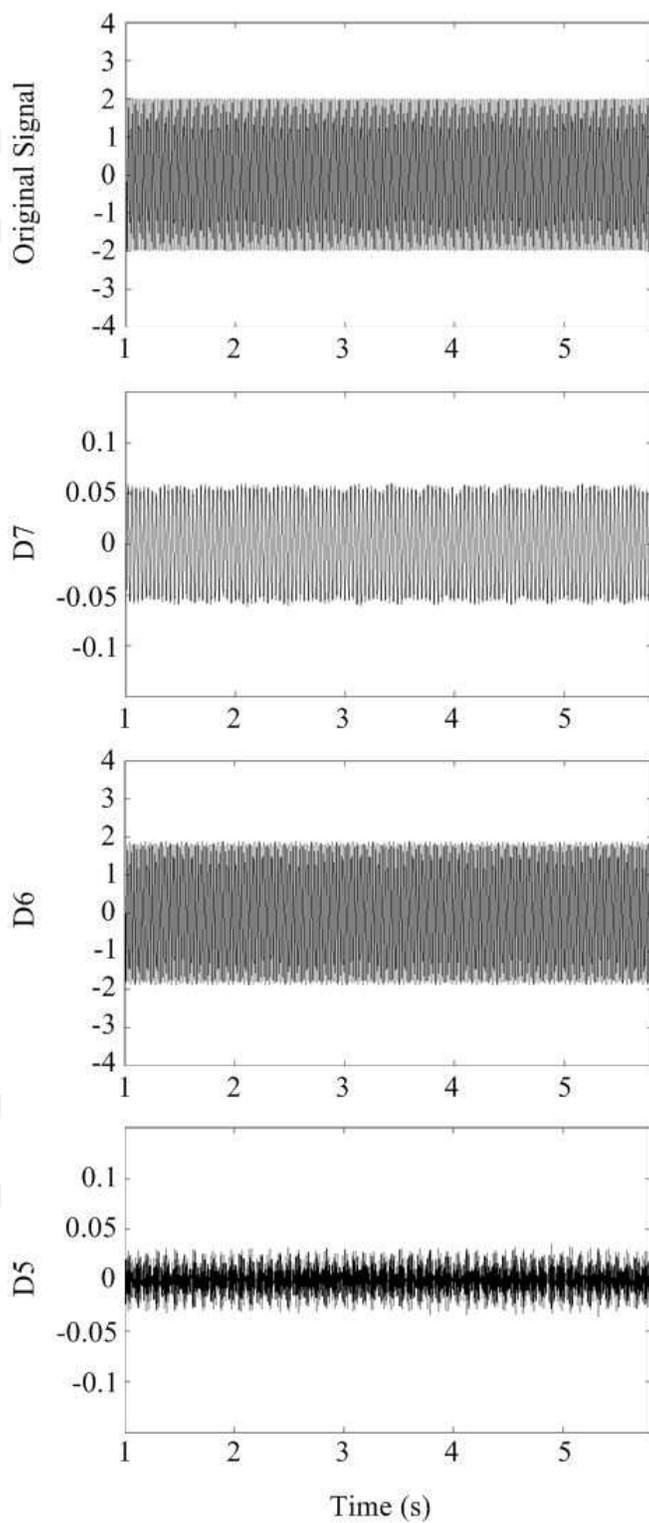
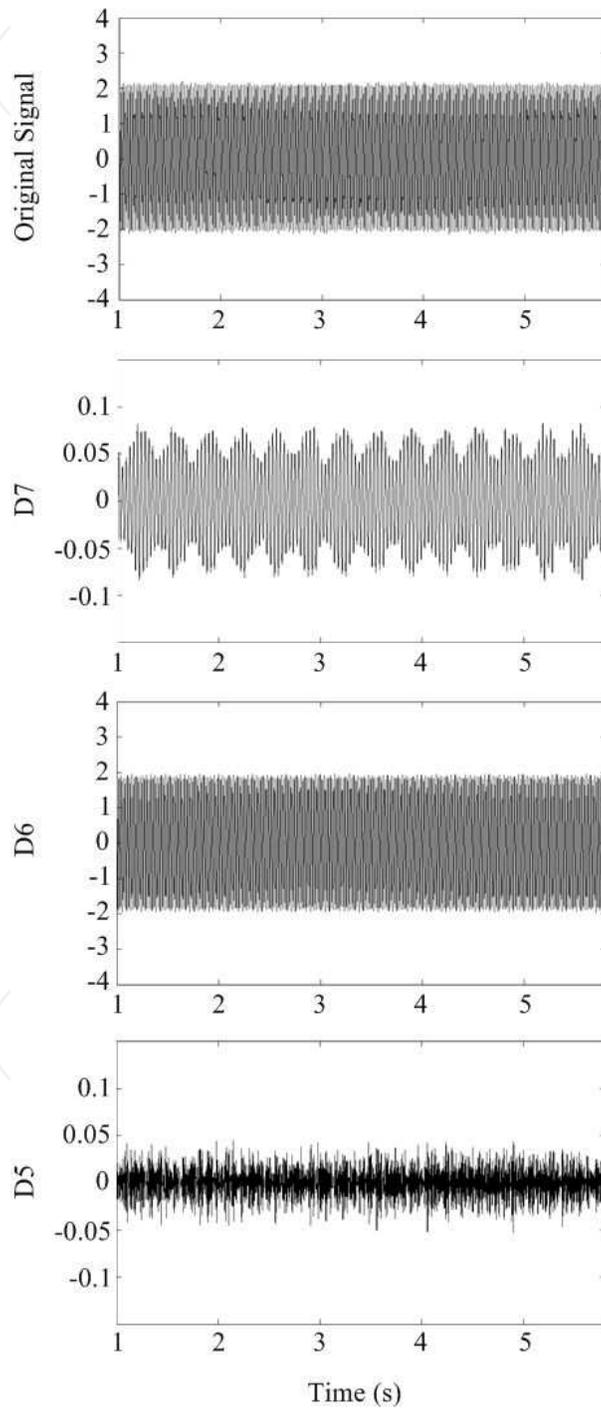
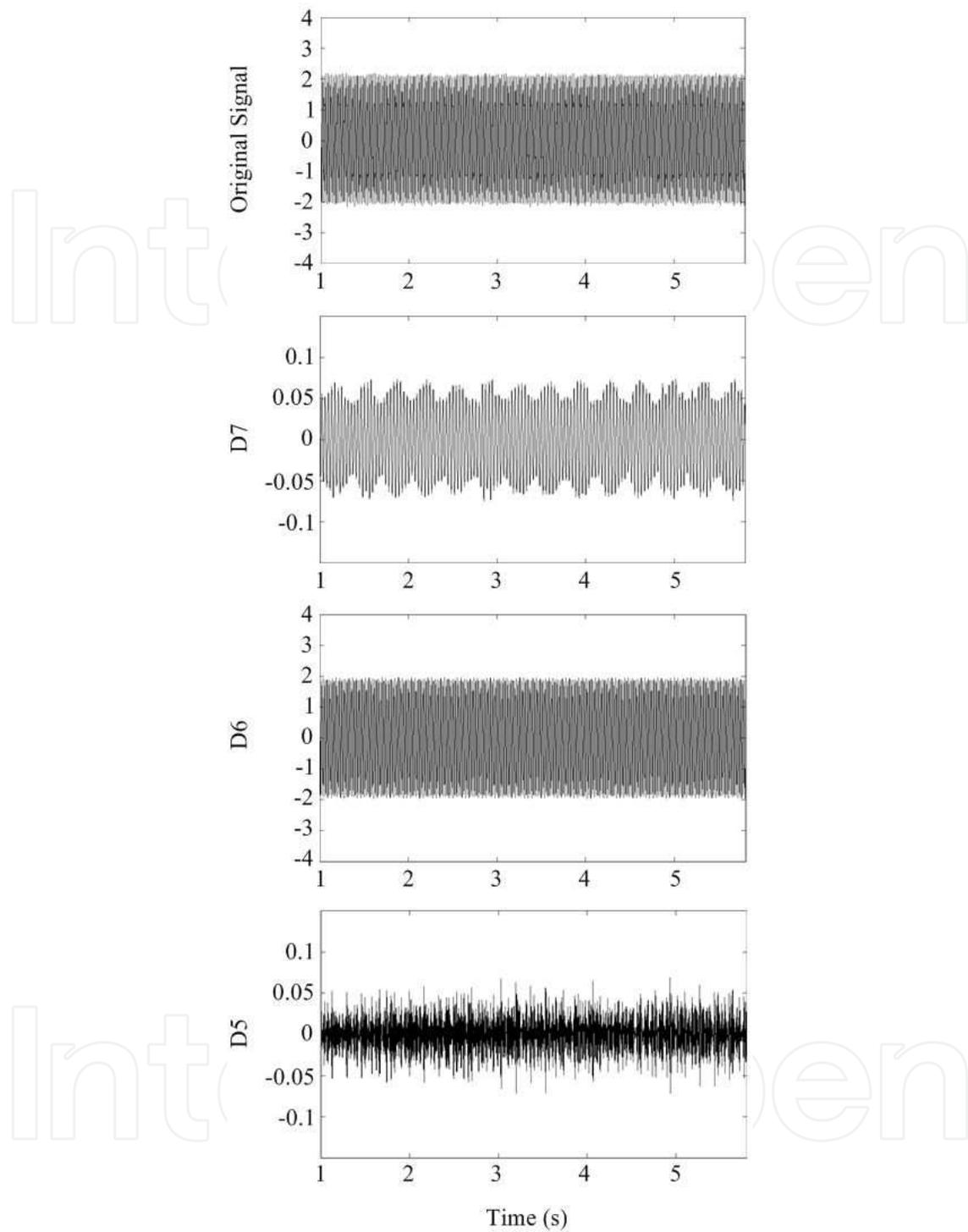


Figure 5. DWT analysis of current signal of fault-free LSPMSM

A comparison between Figures 5, 6, and 7 shows that the signals of  $D_7$  are clear from any distortion in a fault-free motor while the high distortions are manifested in  $D_7$  in the presence of static eccentricity that demonstrates the faulty condition of LSPMSM. The source of these distortions is due to the increase in the amplitudes of fault-related frequency components based on Eq. (3).



**Figure 6.** DWT analysis of current signal of LSPMSM under 33% static eccentricity



**Figure 7.** DWT analysis of current signal of LSPMSM under 50% static eccentricity

An effective static eccentricity detection index is introduced for three-phase LSPMSM based on the energy of  $D_7$  for the stator current signal. The proposed index is examined for fault-free and eccentric LSPMSM with 33% and 50% static eccentricity as shown in Figure 8. The energy variation of  $D_7$  (index) for stator current signal using db24 is provided in Table 4.

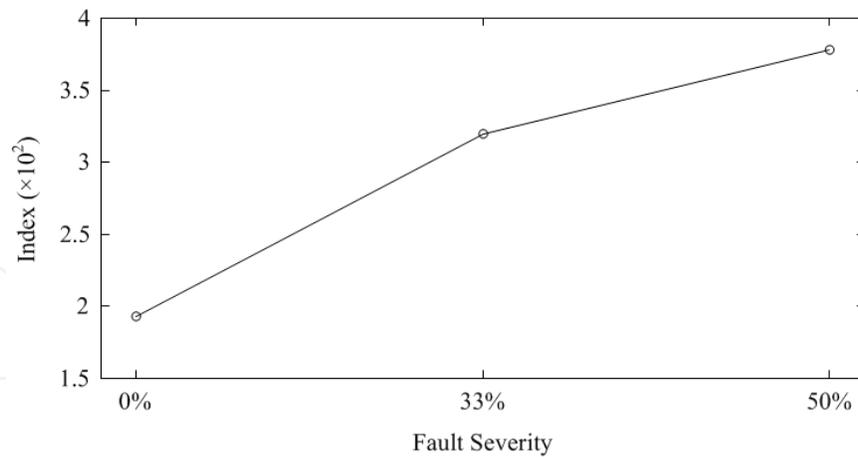


Figure 8. Static eccentricity severity versus proposed index (energy of  $D_7$ )

Index	Static eccentricity degree (%)		
	0	33	50
Energy of $D_7$	193	320	378

Table 4. Evaluation of proposed index due to fault degree

### 5.4. Conclusion

Discrete wavelet transform is employed to analyse the stator current signal of three-phase LSPMSM in order to propose an effective index for static eccentricity fault detection. The energy of detail signal ( $D_7$ ) is introduced as eccentricity index. The achieved results confirm the productivity of the proposed method for the motor discussed in the case study.

## 6. Case study 2

The detection of broken rotor bar in three-phase squirrel cage induction motor using motor current signature analysis is studied. A detailed description of experimental test rig used in this study and the method used for signal measurement and analysis is explained in the following.

### 6.1. Experimental set-up

Figure 9 illustrates the experimental test rig used in this study. Table 5 presents the parameters of the three-phase squirrel cage induction motor used for both fault-free and faulty motors. The faulty motor is with three broken rotor bars. The motor is directly fed by the grid power supply, while the stator windings are Y connected and the current nominal value is 2.2 A. In order to measure the torque and speed value of the squirrel cage induction motor in different

operation conditions, a torque/speed sensor is coupled to it. A generator is used as a load and the specific load torque level can be furnished to the motor shaft by controlling the resistor connected to the generator. Recall that only one phase current signal is required to be recorded for the detection process in this study. The recorded signals are then analysed by a computer-based signal processing program.

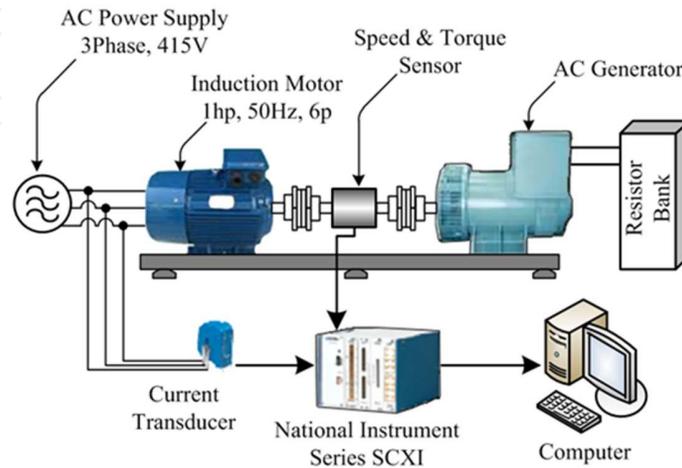


Figure 9. Experimental set-up

Rated output power (HP)	1
Rated voltage (V)	415
Rated frequency (Hz)	50
Number of poles	6
Rated speed (RPM)	1000
Connection	Y
Number of rotor bars	28

Table 5. Specification of a three-phase squirrel cage induction motor

## 6.2. Method

The architecture of the proposed system for broken rotor bar detection is shown in Figure 10, and the procedure used in this study is as follows: First, to force a real bar breakage in the rotor, a hole is drilled artificially in it. The original stator current was recorded from a three-phase induction motor. The stator current is sampled at 20 kHz lasting four seconds for both fault-free and faulty motors (three-rotor bar breakage) at 80% full load. The measured current signals are then decomposed using wavelet packet transform with two different purposes: One as a pre-processing of signal for FFT analysis and the frequency of  $((1-2s)f_s)$  obtained is used as a fault feature for broken rotor bar detection. The other purpose of using WPT is for feature

extraction, where some statistical features determined by wavelet packet coefficients are used for broken rotor bar detection. For both purposes, Daubechies-44 (db44) is applied as a mother wavelet in 12 levels of decomposition. To extract the fault-related feature, those nodes that involve fault frequency ( $f_{BRB}$ ). Figure 11 shows the process explained above, called the wavelet packet tree. In this work, the signal energy, root mean square (RMS), and kurtosis are obtained as selected features for the diagnosis of the broken rotor bar.

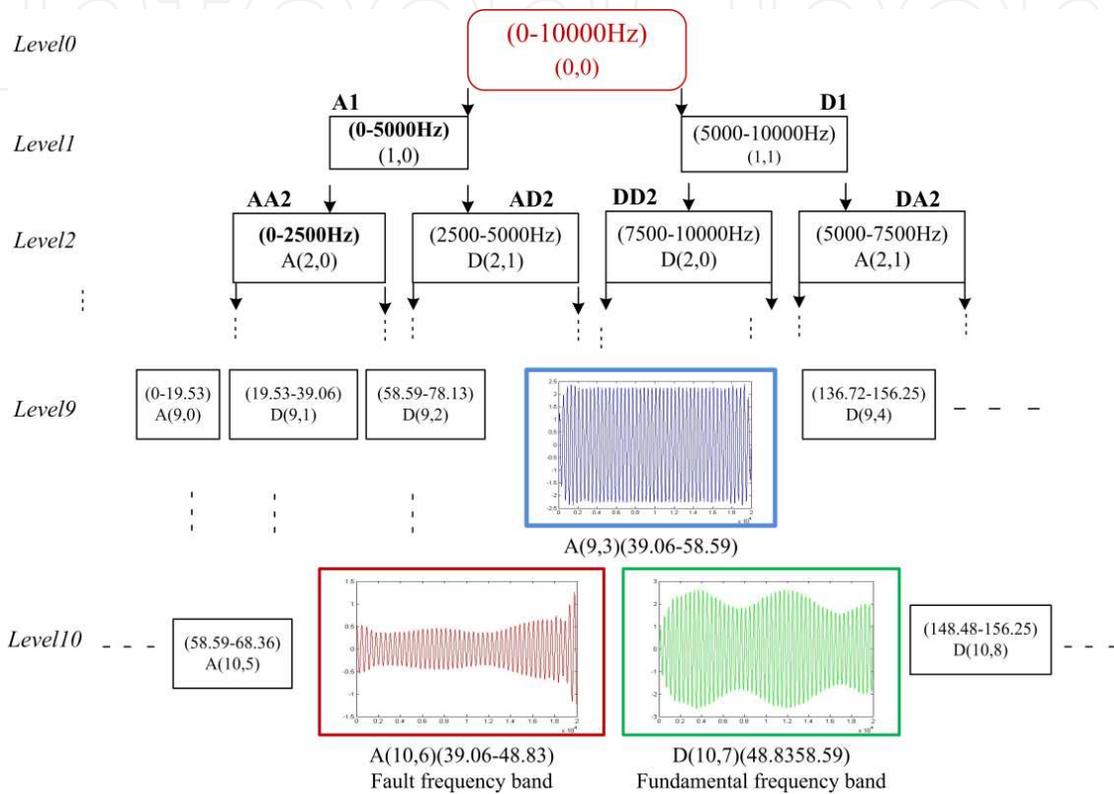


Figure 10. The architecture of the proposed system for broken rotor bar detection

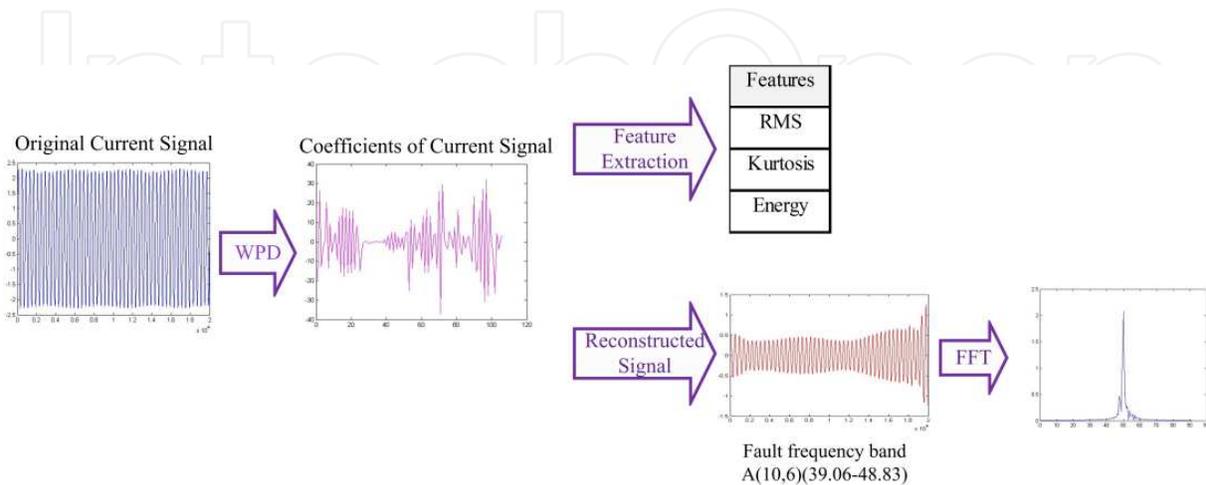


Figure 11. Approximations and details in wavelet packet decomposition

### 6.3. Results and discussion

In order to obtain the differences between fault-free and faulty conditions under 80% full-load conditions, WPD was used for the feature extraction. The WPD gives distinguishable signatures from stator current signal in a specific frequency band. After WPD of the current signal, two procedures for failure feature extraction using WPD are used (Figure 10). One procedure includes using FFT for the determination of amplitude of fault frequency and the other includes the statistical analysis of coefficients extracted by WPD.

The amplitude of fault frequency in the current spectrum for fault-free motors and for motors with three broken bars achieved in the first procedure is presented in Table 6. The results indicate that the amplitude of harmonic components  $((1-2s)f_s)$  in both nodes, presented in Table 6, increase the faulty condition. However, the degree of increase is not significant, and it cannot be used to differentiate the conditions.

Node	Frequency Band	Amplitude $(1-2s)f_s$	
		Fault-free	Faulty
[10, 6]	(39.06–48.83)	0.43	0.43
[11, 13]	(46.39–48.83)	0.42	0.42

$f_{BRB} = (1-2s)f_s = 47.604$  Hz

**Table 6.** Amplitudes of harmonic components for fault-free and faulty motors

In the second procedure, three statistical parameters including RMS, kurtosis and energy are calculated using the statistical analysis of coefficients determined by WPD of current signal. Table 7 presents these statistical parameters in three different nodes [10, 6], [11, 13] and [12, 26]. These parameters are compared to define the most appropriate frequency band that represents the frequency components from the broken rotor bar. According to Table 7, the nodes [11, 3] (46.39–48.83 Hz) in wavelet packet tree are the most dominant bands that can differentiate between fault-free and faulty motors under full load.

Feature	Condition	[10, 6]	[11, 13]	[12, 26]
RMS	Fault-free	11.82	15.93	40.36
	Faulty	12.96	17.78	22.06
Kurtosis	Fault-free	2.94	2.97	2.16
	Faulty	3.3	3.61	3.09
Energy	Fault-free	14,816	24,375	172,684
	Faulty	17,814	30,343	44,277

**Table 7.** Statistical features for fault-free and faulty motors

## 6.4. Conclusions

This case study proposes a feature extraction system for broken rotor bar detection using wavelet packet coefficients of the stator current. It is shown that in a faulty case, the amplitude in specific side bands increases and dominant features of signals can be extracted for fault diagnostics. The results of this study indicate that the energy, kurtosis and RMS value of WPD coefficients are the appropriate features for detecting broken rotor bar in particular bands.

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