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Broken Rotor Bar Fault Detection in No Load Condition Based on Wavelet Packet Signature Analysis

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ABSTRACT

This article presents condition monitoring of induction machine to detect the existence of broken rotor bar failure in it. Wavelet packet signature analysis is developed under no-load conditions. Signatures of fault are extracted through the combination of wavelet packet transform and FFT which is named wavelet packet signature analysis. Next step to extract the most relevant feature is the definition of mother wavelet function. To cover this aim, the standard deviation of wavelet packet coefficients is used. To alleviate the time-variant characteristics of the wavelet packet coefficients, statistical parameters in specified level and nodes are calculated as essential fault indices. The method is tested using fault-free and faulty induction motors. Applying the method presented, one, two, and three broken rotor bars are detected under no-load conditions.

Keywords: Wavelet Packet Signature Analysis, Broken Rotor Bar, Induction Motor, No-load, Statistical parameter,

1. INTRODUCTION

Electric motors have transformed the form of human living and shaped in the convenient lifestyle. In every item that we consume or utilize these days or in any facilities that we profit.It is for sure that there is an electric motor involved, or there is one that is used in some phase of the production process or service [1]. Therefore, electrical machine condition monitoring assumes a critical part in modern industries since induction machines are subjected to the unavoidable burdens in the practical applications. The rotor is subjected to different types of tensions that severely affect its normal condition and consequently create failures in it. In addition, localized rotor heating around the broken bars may progressively break the adjacent bars and the motor will be finally out of service. About 20% of failures that may happen in the induction motor are the rotor-related faults [2]. Generally to identify a broken rotor bar, any distorted harmonic in the stator current should be identified as a sign of the failure. For monitoring rotor bar fault, there are several fault detection and diagnosis methods in the literature, which predominantly involve motor current signature analysis [3][4], short time Fourier transform [5] and wavelet transform [6].

MCSA is extracting the spectral component of the stator current using signal processing method. Superimposed harmonics on the stator currents are used as signatures of broken rotor bar fault. MCSA is a

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technique that is easy to implement, as it only requires the current sensors to clamp the incoming power supply cables of the induction motors. However, if the signature cannot be extracted correctly, reliable detection cannot be achieved. Occurrence of rotor bar breakage introduces a distortion in the air-gap field which produces side band components in the current signal. This side band component is very close to the fundamental frequency, additionally, the fundamental frequency can cover the fault frequency component, called spectral leakage, and thus broken rotor bar cannot be recognized, especially under no load condition. As a result, experimental diagnostic via traditional spectral analysis (FFT) is not reliable for fault detection due to the subsequent reasons [7]:

- The precise measurement of slip and fundamental frequency,
- The simultaneous presence of numerous transitory and other various kinds of non-stationary characteristics such as noises, load torque fluctuations, voltage oscillations, and abrupt changes,
- Discrimination of several faults frequency span for different categories of faults may exist at the same time.

A straight forward solution for these difficulties is using Wavelet Transform (WT), because of its zooming and adaptive windowing capability. Frequency resolution and time localization nature of time-scale analysis have been used to extract and describe a more precise behavior of the stator current signal which is widely used for electrical machine diagnosis [8] [9] [10].

Although many researches have been devoted on the diagnosis of the rotor broken bars for many years using time frequency analysis.There are still some difficulties with regarding to the broken rotor bars diagnosis and determination of specific sub bands with narrow bandwidth without the attendance of other faults. To improve this inconvenience, wavelet packet transform (WPT), owning to the more detailed decomposition capability, has been employed for monitoring of machine operation condition in manufacturing, [11] [12] [13]. However, because wavelet transform is a time-scale domain technique, it does not provide frequency information on characteristic feature components. To tackle this issue, the fine time resolution of WPT integrated with the spectral resolution of Fourier transform is used to extract the most appropriate sub-band[14][15]. The procedure of finding the best mother wavelet is done simultaneously. The next section gives a brief development of the WPSA followed by a description of the experimental set-up. The third section is dedicated to the appropriate mother wavelet selection based on standard deviation of wavelet packet coefficient(WPC). The forth section develops feature extraction in order to characterize the wavelet packet coefficients in presence of broken rotor bar in the specified level and node. The last section ends with conclusions.

1.1. Wavelet Packet Signature Analysis (WPSA)

To obtain frequency characteristic associated with broken rotor bar and develop data analysis of wavelet transform, further FFT analysis can enhance the overall effectiveness of feature extraction. In general, spectral analysis like FFT and WPT represent a signal from different perspectives. The aim of this paper is to focus on the application of an effective signal processing through linking the strong points of both the time-scale and frequency domain analysis (WPSA). This technique is employed to pinpoint the fault signature in a reliable specific frequency bands with suitable sensitivity and a great concern of no load cases.

In order to accurately differentiate between healthy and faulty machines in more concentrated fault-related depths and nodes and to find the most reliable construction of wavelet packet tree, we adopt simple simulation signals with frequency of 50Hz to illustrate the merits of taking FFT to follow the bands including fundamental-oriented frequency as well as the fault-related band frequency. In the first step the current signal is decomposed into several signals containing some approximations and details using wavelet packet decomposition (WPD) in MATLAB® environment. The decomposition is implemented to track level 0 which is the original signal till level 10(2^{10} = 1024 ~ 2000 = Ns). In every level, all nodes (from 0 to 2^{Level}) are evaluated one by one. Then, for every selected node in proceeding level, the reconstructed signals are transformed to frequency domain using FFT to find the sub band with maximum value. In next step, when the maximum value is defined, the next level comes into theloop. This trend is continued for all available levels according to flow chart of WPSA in Fig 1.

Consequently, regarding to closeness of broken bar fault frequency to fundamental frequency, especially in no load condition, the exact fault-related sub band with high reliability is highlighted. The

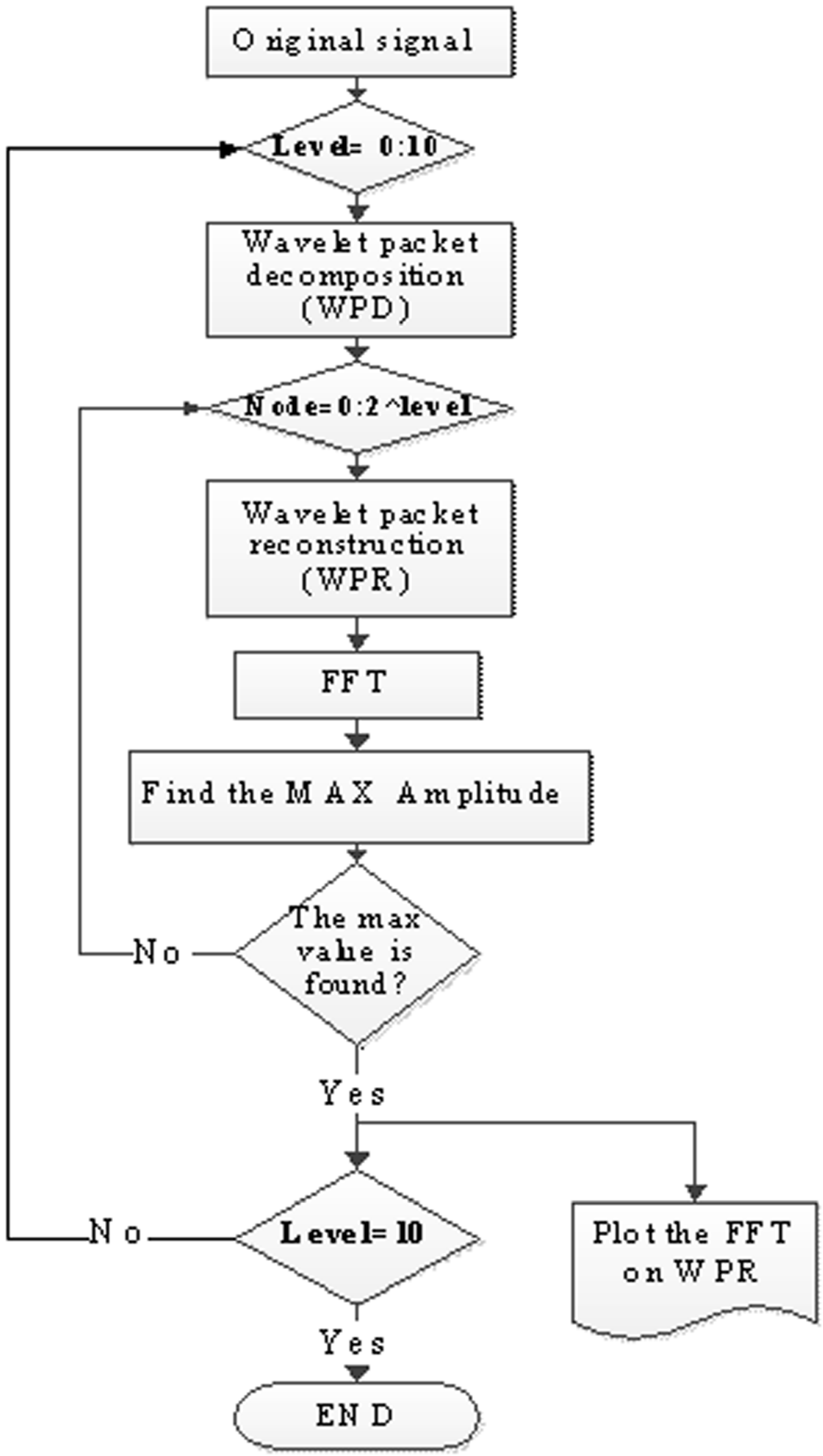

Figure 1: Flow Chart of WPSA

machine test stand consists of a three-phase power supply, a test machine and an AC generator under both healthy and faulty conditions to study the effects of putting no load in fault identification procedure. The motor supply line current signal as well as speed and torque values were recorded during the test. The fundamental frequency (f_s) is 50HZ and the stator current has been collected during 4s and was sampled at 2 KHz before and after defects with a sampling number of N = 2000 during the steady-state operating condition of the motor.

2. MOTHER WAVELET (MW)

For the orthogonal wavelet transform, an appropriate wavelet packet base which preserves global energy, and reconstructs exact features the signal behavior needs to be considered. Otherwise, an ill-selected base may return false diagnosis results. For that reason, the selection of mother waveletsare essential in wavelet analysis such like that the compatibility between mother wavelet and signal is computed as wavelet coefficients. Consequently, the standard deviation of wavelet coefficients is an extremely appropriate spotlight to exhibit the highest level of similarity between the pattern of MW mother wavelet and signal. This research concentrates at 82 candidates' mother functions from different families to understand their behaviors for broken rotor bar fault diagnosis according to MATLAB® Software based on the following steps:

- Recorded stator current signals were subdivided into ten segmented signals for each mode of rotor fault (e.g. healthy motor and faulty motor with 1,2 and 3 broken rotor bars,
- The standard deviation (StD) of wavelet packet coefficients of synchronized current signals was calculated in the fifth level of decomposition for each of 10 segmented signals by 82 different mother wavelets in each motor requirement.
- The mean of the StD vector in the 10 segmented signals were computed.
- Finally the mean of the StD compared for all candidate mother wavelets. The one that had the highest value in all motor conditions was named as the most analogous function to our current signals because the more StD we have, the greater the ability to properly classify failures.

Fig. 2 shows the decision-making flow chart for selecting the most suitable mother wavelet. The StD of Daubechies 44 was the maximum in the class of 82 mother wavelets. The point is to determine which mother wavelet has more distinctive wavelet coefficients for different conditions in fault identification.82 wavelet packet candidate mother wavelet functions from selected families is tabulated in Table 1. The practically identical mother wavelet for interpreting the stator current signal was selected based on standard deviation of wavelet packet coefficients in first node of fifth depth, (5,1), with [31.25-62.5] frequency range.

3. FEATURE EXTRACTION

In order to diagnose any fault following a disturbance, it is necessary to build a feature extraction technique. For each operating condition, 20 sets of motor currents data are collected under sampling frequency,

Table 1
Wavelet Families

No.	*Family (short form)*	*Order*
1	Discrete Meyer (dmey)	′dmey′
2	Haar (db1)	′db1′
3-46	Daubechies (db)	′db2′ to ′db45′
47-77	Symlet (sym)	′sym1′ to ′sym30′
78-82	Coiflet (coif)	′coif1′ to ′coif5′

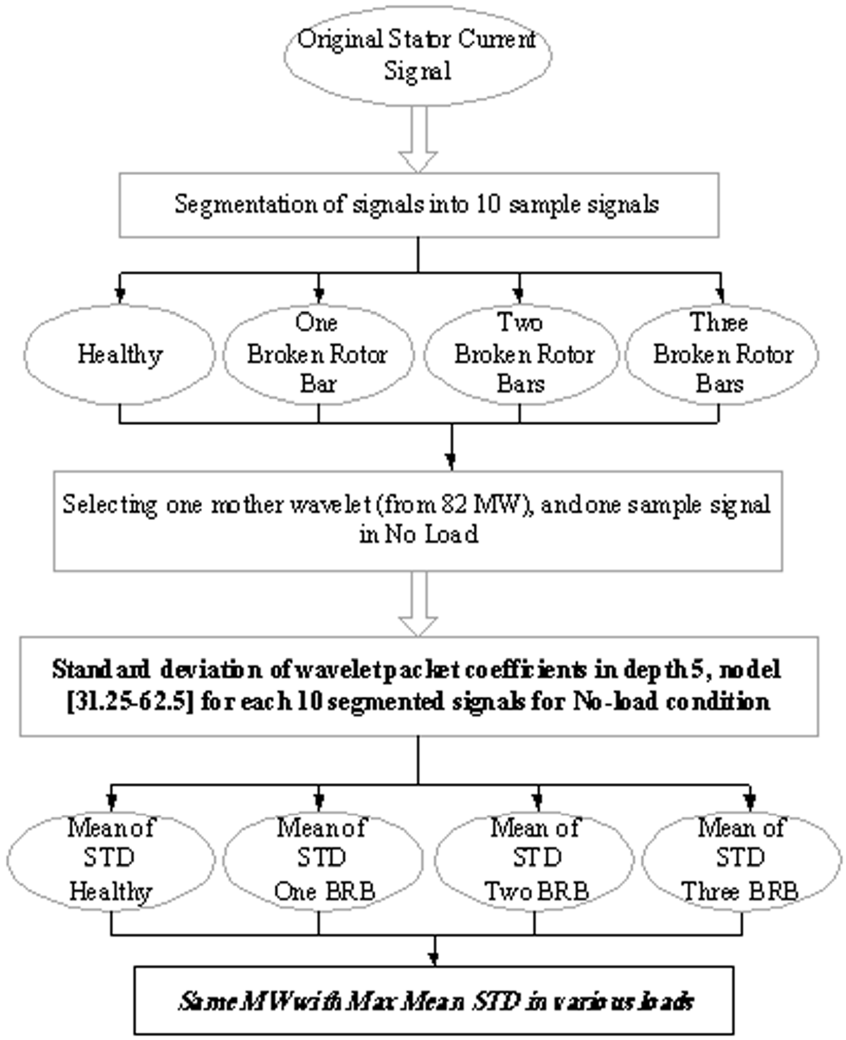

Figure 2: Flow Chart of Best Bases

f = 2000 Hz, and number of samples, Ns = 2000. WPSA is used for the feature extraction which gives distinguishable signatures from stator current signal in a reliable specific frequency band. In experimental setup, the left affected frequency is considered ($f_{brb} = (1 - 2s)f_s$) to discern the healthy and faulty condition as well as fault severity. The related depths and nodes of WP tree constitute of most appropriate frequency range is arranged to cover no load is (9, 21) which is consists of [48.83-50.78]. After wavelet packet decomposition to ten levels of resolution using the selected mother wavelet "db44", coefficients-related features are extracted and calculated by the fourteen wavelet statistical parameters in no- load condition.The mean value of these parameters are sorted in Table 2 and to name the parameters they include root-mean-square (RMS), root-sum-square (RSSQ), kurtosis, skewness, mean, peak to peak (P to P), peak to RMS (PeaktoRMS), log-detect, peak to average power-ratio, shape factor, impulse factor, energy, standard deviation and six central moment. The increasing trend of some features such as RMS, RSSQ, Energy, and StD and decreasing trend for kurtosis, PeaktoRMS, and PAPR for sub band (9, 21) in no-load condition are bolded in Table 2. Therefore, these indices are compared for (Level 9–Depth 21) under no load condition to define the most appropriate frequency band to represent the frequency components caused by the broken rotor bar malfunction in induction motor.

The distances between healthy and faulty conditions indicate the more efficiency of RMS, RSSQ, energy and StD features of wavelet packet coefficients. Root mean square of wavelet packet coefficients is depicted in Fig 3. The result are also shown regarding the increasing trend of RSSQ in Fig 4, energy in Fig 5, and standard deviation of wavelet packet coefficients in Fig 6.

Table 2
Mean Value of Statistical Features for Healthy and Faulty Motor in No Load

No Load (9,21)

Features	*Healthy*	*One BRB*	*Two BRB*	*Three BRB*
RMS	20.57171	21.24321	21.32636	21.68617
RSSQ	195.1604	201.5308	202.3196	205.7331
Kurtosis	3.326857	3.27325	3.182178	3.007614
Skewness	-0.05798	-0.0624	-0.06542	-0.06943
Mean	-0.83483	-0.8774	-0.77048	-1.05664
PtoP	111.702	114.2284	112.6958	112.2562
PeaktoRMS	2.871664	2.8379	2.72869	2.678631
LogDectect	10.06006	10.5937	10.40032	11.48413
PAPR	8.246556	8.053948	7.35466	7.188944
ShapeFactor	-24.9104	-24.8527	-29.1772	-20.7663
ImpulseFactor	-71.5184	-70.5556	-80.1088	-55.783
Energy	38129.89	40617.22	40938.41	42330.41
StD	20.66977	21.34352	21.43089	21.78155
6th-Moment	1.28E+09	1.47E+09	1.39E+09	1.4E+09

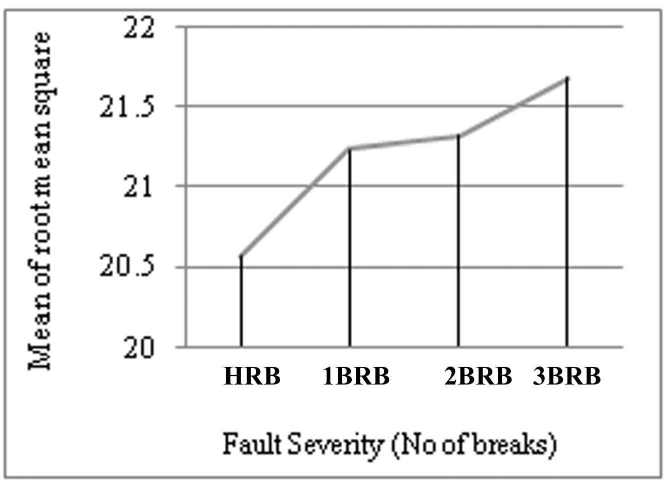

Figure 3: Mean value of Root mean square in no-load condition

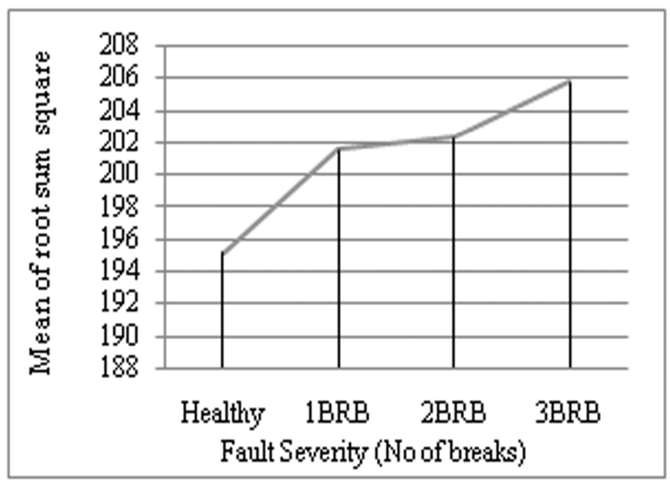

Figure 4: Mean value of Root sum square in no-load condition

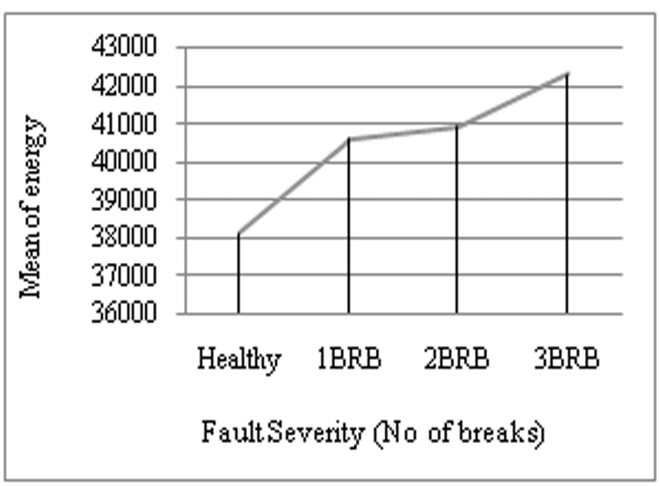

Figure 5: Mean value of energy in no-load condition

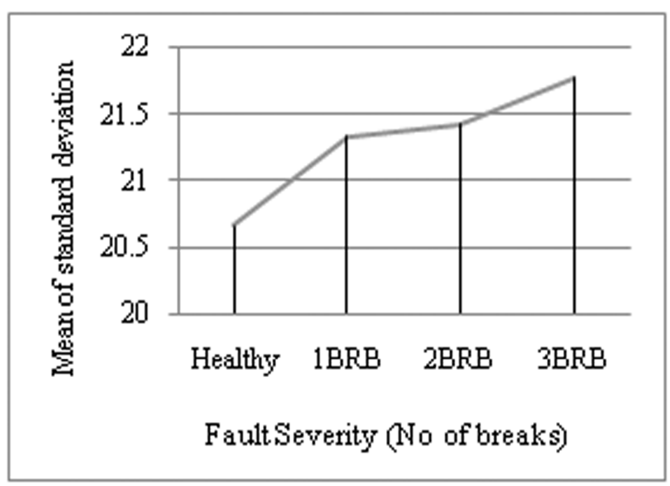

Figure 6: Mean value of Standard deviation in no-load condition

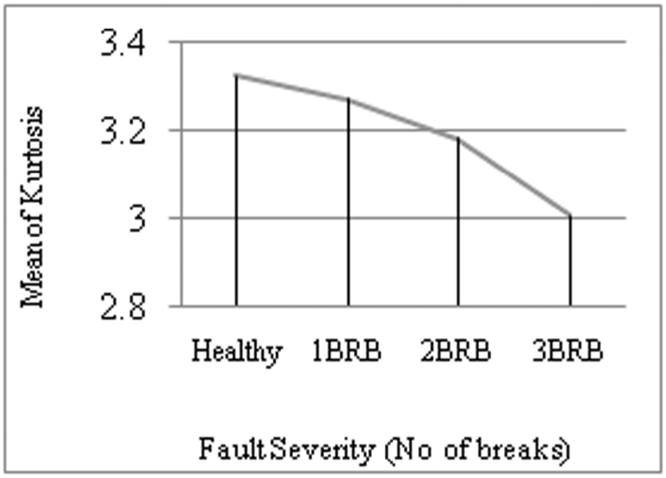

Figure 7: Mean value of Kurtosis in no-load condition

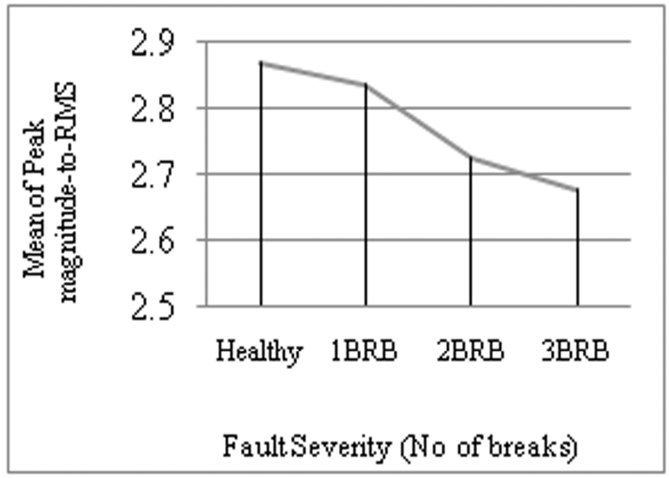

Figure 8: Mean value of Peak to RMS in no-load condition

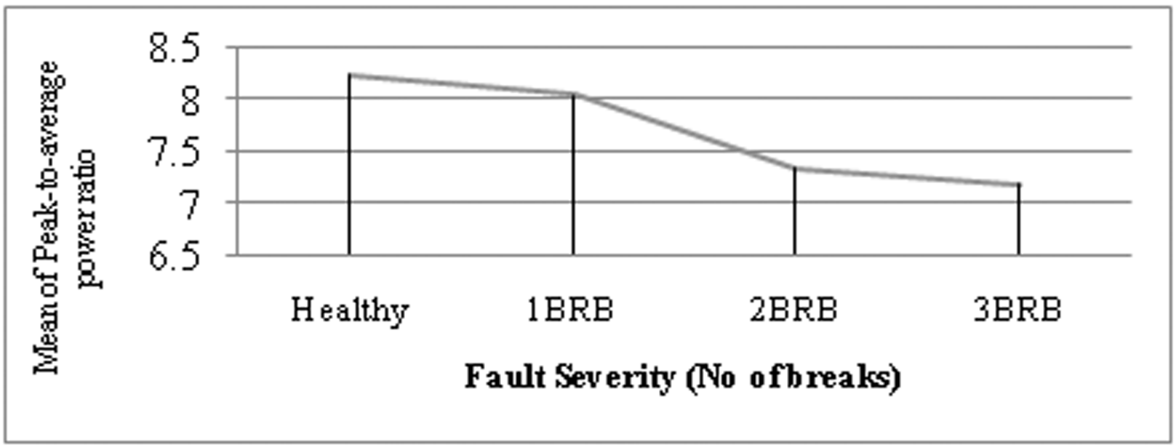

Figure 9: Mean value of Peak to average power ratio in no-load condition

The relationship between fault severity and some wavelet statistical parameters such as kurtosis, peak magnitude to RMS, and peak to average power ratio with decreasing trend is depicted in Fig. 7, Fig. 8, Fig. 9 respectively.

4. CONCLUSION

WPSA is used to extract the superimposed spectral harmonics of the wavelet packet reconstructed signal using FFT. As a result of WPSA, the overall effectiveness of extraction of defect-dependent feature is enhanced. The proposed signal processing presents exactly faulty sub band in more details. This research tends to focus on extraction of features that represent the broken rotor bars faults precisely in a SCIM. Therefore, the captured stator current of healthy motor, as well as motors with one, two, and three broken rotor bars are examined at low slip. Then db44 is determined as the best mother wavelet that calculates the wavelet coefficients of monitored signal. The most appropriate features are extracted by implementing wavelet statistical parameter. The WP-based statistical parameters are found to be fast, accurate, and easy to implement. It is shown that in faulty case, the amplitude in specific side bands increases and dominant features of signals can be extracted for fault diagnostics.

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