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Diagnosis of Induction Motor Stator Faults by using Motor Current Signature Analysis Method

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Abstract: This paper investigates fault frequencies of induction motors based on the motor current signature analysis and diagnosis of stator faults based on discrete wavelet transform, stationary wavelet transform and wavelet packet decomposition. The wavelet decomposition is used to pull out the information on a signal over a wide range of frequencies. This analysis is performed on both frequencies and time domain. The daubechies wavelet is selected for the analysis of the stator current. Wavelet component shows to be useful for detecting stator faults. In this paper we will study about the stator inter turn faults.

Keyword: Fault diagnosis, Induction motor, Inter-turn faults, IIR notch filter, Motor current signature analysis, Discrete wavelet transform, Stationary wavelet transform, Wavelet packet decomposition, Decomposition levels.

1. INTRODUCTION

The motors used in the industrial applications should have the following properties like low cost, low maintenance, variable speed control, compact in size, ruggedness and to be able to work under any operational circumstances. Induction motor is one of the motor which can full fill the above properties. Despite their relative high accuracy, induction motor when subjected to adverse stress during their running environment may build up some internal faults such as rotor and stator faults [1]. Of these stator faults are more ubiquitous and potentially vicious leading to the motor failures thus insulation break down can be as high as 30%-40% [1]-[2] is shown in Figure 1. In most of the situations these stator inter-turn insulation fault begins as a minor and often go hidden, which may ultimately grow and lead to major once [3]. Majorly this insulation degradation occurs under abnormal electrical, thermal, mechanical under different environmental stress [4]. The foremost intention is to extend schemes for reliable detection of faults at primary stage itself, which will allow a systematic and controlled maintains instead of rapid failure, thus dipping production losses outage time and injury to the instrumentation as per industrial surveys and supported alternative eventualities. Large percentages of failure in induction motors results from the stator failures which is ranking second after the baring failure [5]. In the time of yore whenever a machine experience some fault it can be detected by some simple techniques such as over current or over voltage detection of which these techniques required the machine to be in off line in order to clear the fault [6], but as of in the safety-critical applications, the shutdown of running motor is not an acceptable thing. This demands a better fault detection and remediation strategies [7]. Several approaches have been made for detection and diagnosis of inter turn faults. This paper presents analysis and summary of various online inter turn fault diagnosis methodologies for electrical machines by discussing their strengths and weaknesses in brief. This paper structured as follows section I, reviews about the fault frequencies identified by using MCSA technique for induction motor. Section II reviews infinite impulse response (IIR) notch filter and its advantages. Fault diagnoses to different types of wavelet method are reviewed in section III. Conclusion is exposed in section IV.

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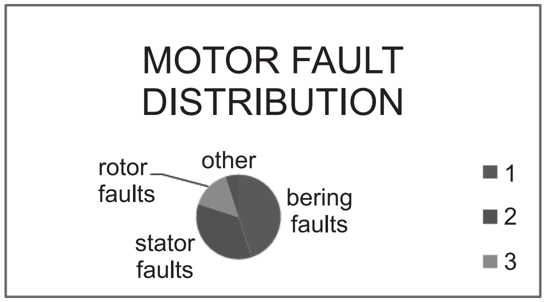

Figure 1: Distribution of faults in induction motor

2. MOTOR CURRENT SIGNATURE ANALYSIS (MCSA)

MCSA measures the most popular fault detection method [8]. MCSA is a technique used to identifying the working condition of induction motor without interrupting production. MCSA detect the fault at an early stage and keep away from the damage and total failure of the motor. MCSA is based on current monitoring of induction motor. So it is not very expensive. The MCSA used to current spectrum of the machine locate the fault frequencies [9]. Now a day's simple detect the normal faults in stator [10]. The example established in this paper includes many at the potential applications offered through execution of the motor diagnostic technologies. The basic principle behind unique expansion of MCSA technologies of the detection of stator faults [11].

In the stator fault current is shown in Figure 2 in the region of the base frequencies, the inter turn short produces same frequencies in an induction motor are given by

$$f_{st_1} = f_s\left[\frac{m}{p}(1-s) \pm k\right] \tag{1}$$

Where f_s is that the base frequencies, $m = 0, 1, 2, 3$ and $k = 0, 1, 3, 5$, p is that the range of pole pairs and s is that the percentage unit slip the frequencies may be analyzed exploitation any frequencies domain signal process technique [12]. In order to remove the inter turn faults, this method employs frequencies analysis using different types of wavelet transforms for fault diagnosis in an induction motors frequencies

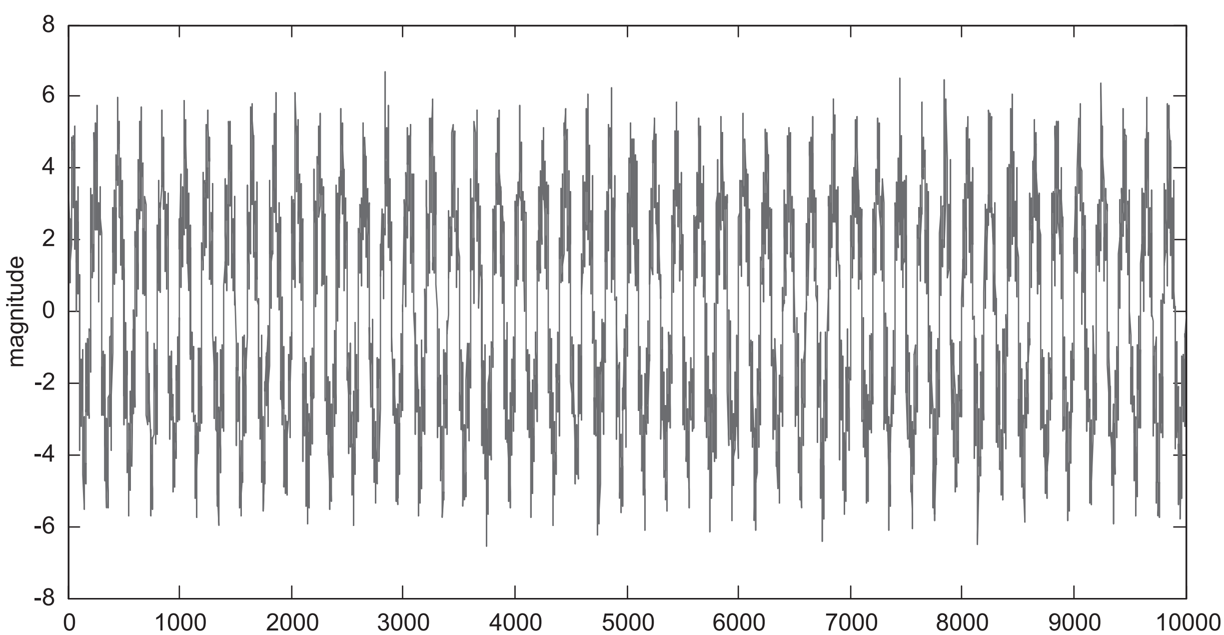

Figure 2: Faulted frequency current wave form

corresponding related to definite combinations of *k* & *m* in eqn (1) is used for brief circuit fault analysis as a result of the prevalence of voltage disturbs and different asymmetries

Table 1
Fault frequencies

	K = 0	K = 1	K = 3	K = 5
M = 0	0	+50, –50	+150, –150	+250, –250
M = 1	24.6	74.6, –25.4	174.6, –125.4	274.6, –225.4

3. PROPOSED METHOD

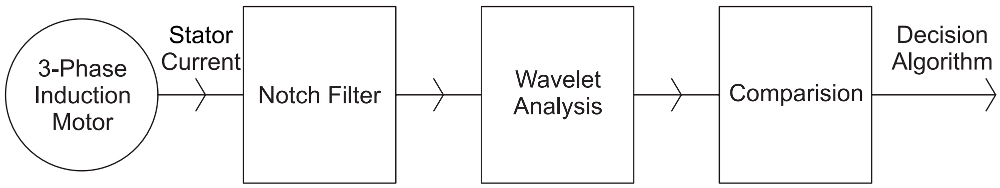

Figure 3: A Notch filter based wavelet analysis for a three phase induction motor

A. System Description

The configuration of notch filter based wavelet analysis for a three phase induction motor shown in Figure 3. The stator current from the three phase induction motor is fed to the notch filter. And the wavelet analysis is performed with and without notch filter in order to diagnose the faults and both of them are compared in the comparison block. This data is used for making the decision algorithm.

B. IIR Notch Filter

IIR filter states to Infinite Impulsive Response. A notch filter may be a band-stop filter with a slim stop band (high alphabetic character factor), because of external disturbances in setting, system creates unwanted frequencies referred to as noise. Factors poignant Annoyance area unit as follows Primary Acoustic: Sound level, frequency and period Secondary Acoustic: Spectral complexness, fluctuations in frequency level, localization of noise supply. Non-acoustic: Adaptation and past expertise, listener's activity interference, certainty of noise, individual temperament [13]. Louder is that the noise the larger is that the annoyance. Detection of clanging curving signals and its adaptive frequency estimation area unit essential in communications, radar, sonar, controls, and medicine signal process systems, adaptive IIR notch filters are with success used for detection curving signals in wide-band noise. Generally, Associate in Nursing adaptive IIR notch filter) is most popular because of its less range of filter coefficients and therefore less procedure complexness [14]. The output of the fault signal by mistreatment the IIR notch filter is shown in figures 7, 9 &11. Notch filter take approach the interference at 50Hz and its harmonics alone, during this paper IIR notching filter eliminate F0 = fifty cycle per second frequency center frequency with quality issue Q = 5. BW = F0/Q. [15].

Different types of wavelet methods.

(i) Discrete wavelet transform (DWT).

(ii) Stationary wavelet transform (SWT).

(iii) Wavelet packet decomposition (WPD).

(i) Discrete Wavelet Transform (DWT)

It is a tool that varieties data into different frequency components, and then studies each component with resolution corresponding to its scale. DWT computes with a cascaded filtering followed by a factor two sub sampling [16]. In this paper, daubechies is a mother wavelet. This wavelet is compared with the fault signal in order to identify the fault location of the signal. To evaluate the frequency components of the signal, the Fourier transform is one of the useful tool. But the main drawback is over the whole time axis we cannot notify at what instant an exact frequency rises [17]. Wavelet transform is based on varying frequency of the small wavelets in a limited duration. In this paper, scaled version wavelet transform has been investigated. In this DWT method we have two types of coefficients is shone in Figure 4. One is approximation coefficient and the other is detailed coefficient. Of these detailed coefficient is considered in this paper, where it can decompose 8 levels of the fault signal. Among these 8 levels the two levels 5 & 7 indicates exact fault location of the faults in with and without notch filter results is shown in Figure 7 & 8 respectively.

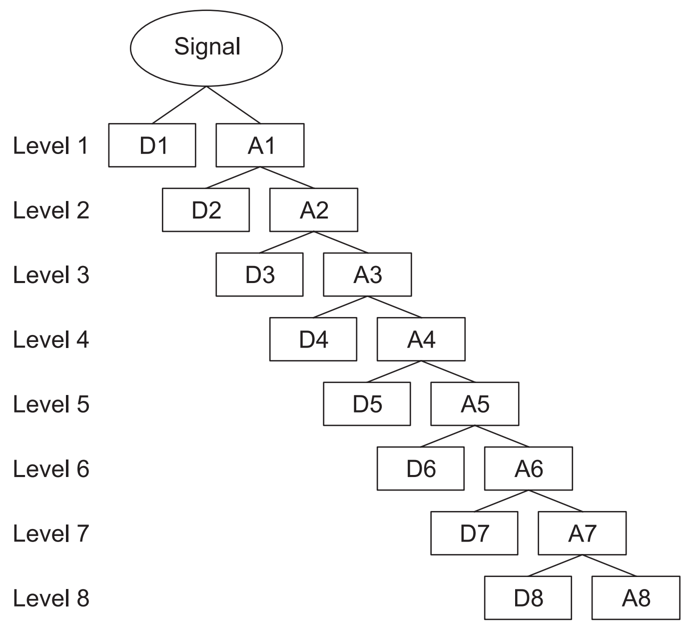

Figure 4: Decomposing levels of DWT

Signal and other levels 4, 6 & 8 indicates the average location of the fault signal, whereas the levels 1, 2 & 3 fails to indicate the fault location of the fault signal.

(ii) Stationary Wavelet Transform (SWT)

In this section, explains how the basic DWT algorithm can be adapted to give a stationary wavelet transform. The Stationary wavelet transform may be a time invariant transform, is analogous to discrete wavelet transform (DWT) however the sole process of down-sampling is suppressed, instead up-sampling the filters by inserting zeros between the filter coefficients [18]. SWT have other names like the un decimated wavelet transform, the invariant wavelet transform and the redundant wavelet transform. SWT provides redundant, linear and shift invariant transformation in this SWT method we have two types of coefficients is shown in figure5 one is approximation coefficient and the other is detailed coefficient [19]. Of these detailed coefficient is measured in this paper, where it can decompose 8 levels of the fault signal. Using SWT we can identify the fault coefficients. The eight levels of decompose the signal the levels 3, 6, 7 and 8 having good indication for without and with notch filer results is shown in Figure 9, 10 respectively by decomposing the eight levels, the four signal levels shows good indication i,e., 3, 6, 7 and 8. We compare to DWT the SWT is good indication for the fault.

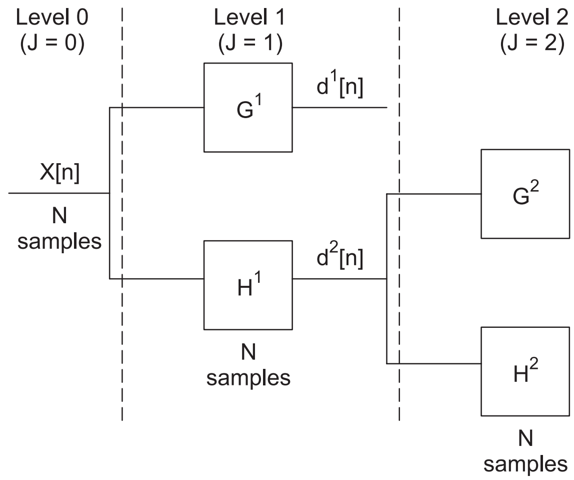

Figure 5: Decomposing levels of SWT

G^i = high pass filter at level, H^i = low pass filter at level I, n = sample number

The Figure shown above will decompose up to n levels. This decomposition has no down samplings.

(iii) Wavelet Packet Decomposition (WPD)

Wavelet packet decomposition is a method in wavelet transform where the signal is passed through more filters. They type bases that retain several of the orthogonally, smoothness, and localization properties of their mother wavelets [20].The algorithm of discrete wavelet packet transform is executed by two-channel filter banks having a half-band low pass filter and high pass filter pair. The study of a signal is processed out by first decomposing the signal in to a low pass and then high pass filtering repeatedly as shown in Figure 6. In the dwt, each level is calculated by passing the previous approximation coefficients through a high and low pass filters[21]. Based on ranking, the signal to be programmed is successively split into high and low frequency modules. The number of progressions is usually limited by the desired level of frequency resolution and available computational power.

The frequency ordering of the wavelet packet coefficients are quite in binary gray code sequence. The output of any two channels analysis is the result of low and high pass filtering followed by down sampling which in turn reduced by an order of two [22]. In this paper, the fault frequencies of the signal nodes is 8^{th} level 1^{st} node and 8^{th} level 6^{th} node of the without and with notch filer decomposition is shown in Figure 11 & 12 respectively. Exact fault location is deducted by using this method.

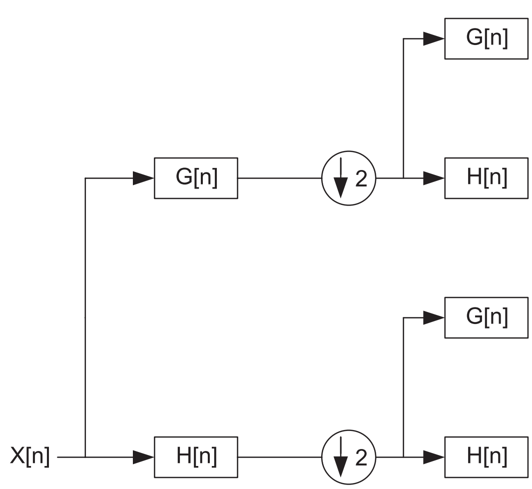

Figure 6: Decomposing levels of WPD

Table 2
Standard deviation values of DWT

Without Notch Filter				
Level	*Healthy*	*Faulty 1*	*Faulty 2*	*Faulty 3*
Level 1	0.1797	0.183	0.184	0.1824
Level 2	0.1821	0.1805	0.1818	0.1854
Level 3	0.1941	0.2036	0.2059	0.2057
Level 4	0.4862	04761	0.4844	0.5286
Level 5	0.789	0.8018	0.8021	0.8088
Level 6	0.6305	0.606	0.6108	0.0622
Level 7	7.1139	7.1167	7.1174	7.1477
Level 8	2.4082	2.3769	2.3363	2.366

Table 3
Standard deviation values of DWT

With Notch Filter				
Level	*Healthy*	*Faulty 1*	*Faulty 2*	*Faulty 3*
Level 1	0.1854	0.1826	0.1816	0.1798
Level 2	0.1828	0.1812	0.1875	0.1812
Level 3	0.1726	0.1778	0.1757	0.1677
Level 4	0.1258	0.1296	0.1305	0.1304
Level 5	0.1398	0.1411	0.1496	0.1692
Level 6	0.2585	0.2256	0.2253	0.2976
Level 7	0.6881	0.7617	0.7914	0.8363
Level 8	0.6388	0.64	0.6034	0.6933

Table 4
Standard deviation values of SWT

Without Notch Filter				
Level	*Healthy*	*Faulty 1*	*Faulty 2*	*Faulty 3*
Level 1	0.1772	0.1825	0.1823	0.1804
Level 2	0.1773	0.178	0.1806	0.1825
Level 3	0.1993	0.2009	0.1984	0.1969
Level 4	0.4383	0.4703	0.4755	0.4738
Level 5	0.7689	0.7921	0.7784	0.7842
Level 6	0.6154	0.612	0.6152	0.6112
Level 7	7.4339	7.3889	7.4205	7.4391
Level 8	2.2729	2.2536	2.2751	2.2706

Table 5
Standard deviation values of SWT

With Notch Filter				
Level	*Healthy*	*Faulty 1*	*Faulty 2*	*Faulty 3*
Level 1	0.1792	0.1796	0.18	0.1782
Level 2	0.1759	0.1848	0.1812	0.1788
Level 3	0.1716	0.1747	0.1761	0.1789
Level 4	0.121	0.1251	0.1208	0.1253

With Notch Filter				
Level	*Healthy*	*Faulty 1*	*Faulty 2*	*Faulty 3*
Level 5	0.1228	0.1363	0.1418	0.1642
Level 6	0.1999	0.2079	0.2181	0.2786
Level 7	0.8483	0.8511	0.8574	0.8887
Level 8	0.5952	0.5982	0.619	0.6329

Table 6
Standard deviation values of WPD

Without Notch Filter				
Level	*Healthy*	*Faulty 1*	*Faulty 2*	*Faulty 3*
Level 1	3.7401	3.4568	3.6469	4.2482
Level 2	2.3773	2.3802	2.4214	2.3742
Level 3	2.1369	2.0792	2.0801	2.1556
Level 4	9.5958	9.6465	9.6395	9.5637
Level 5	0.1973	0.2065	0.2089	0.2478
Level 6	0.3043	0.2961	0.2522	0.2947
Level 7	0.5337	0.4795	0.524	0.625
Level 8	0.9981	1.0307	1.0341	1.775

Table 7
Standard deviation values of WPD

Without Notch Filter				
Level	*Healthy*	*Faulty 1*	*Faulty 2*	*Faulty 3*
Level 1	1.9248	1.19311	1.9432	2.193
Level 2	0.6053	0.6004	0.6192	0.5992
Level 3	0.4905	0.5037	0.4575	0.6253
Level 4	0.8394	0.8322	0.8244	0.8091
Level 5	0.2143	0.1525	0.2062	0.1427
Level 6	0.1804	0.1922	0.1956	0.199
Level 7	0.3495	0.3758	0.3557	0.5
Level 8	0.2034	0.1981	0.1849	0.2096

$$\text{Fault current} = \frac{\text{Fault Standard deviation}}{\text{Healthy Standard Deviation}} \tag{2}$$

By using equation (2), the wavelet analysis is performed to the stator current based on the faulty and healthy standard deviation values in order to find out the fault current.

4. CONCLUSION

This paper described about the MCSA method in induction motor. This method is highly adaptable, reliable and more flexible for condition monitoring and fault frequencies levels. In order to find the magnitudes of fault levels different wavelets were implemented and for reducing the noise in the fault signal IIR notch filter used. One of the main advantage of this MCSA is it can detect the faults at an early stage and these helps in avoiding the inferior damage and complete failure of the motor. But this MCSA method should be done mathematically.

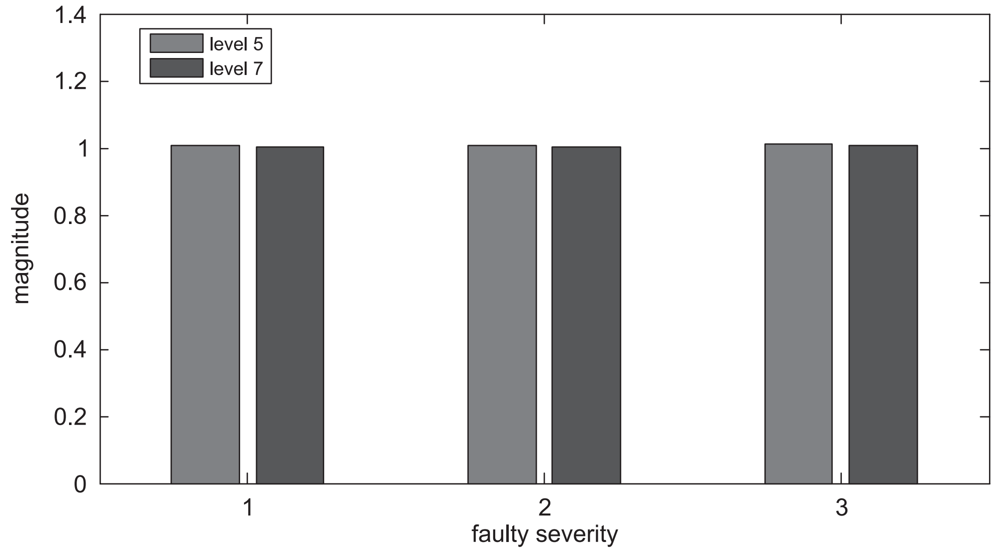

Figure 7: Standard deviation ratio of faulty stator currents from DWT analysis without notch filter.

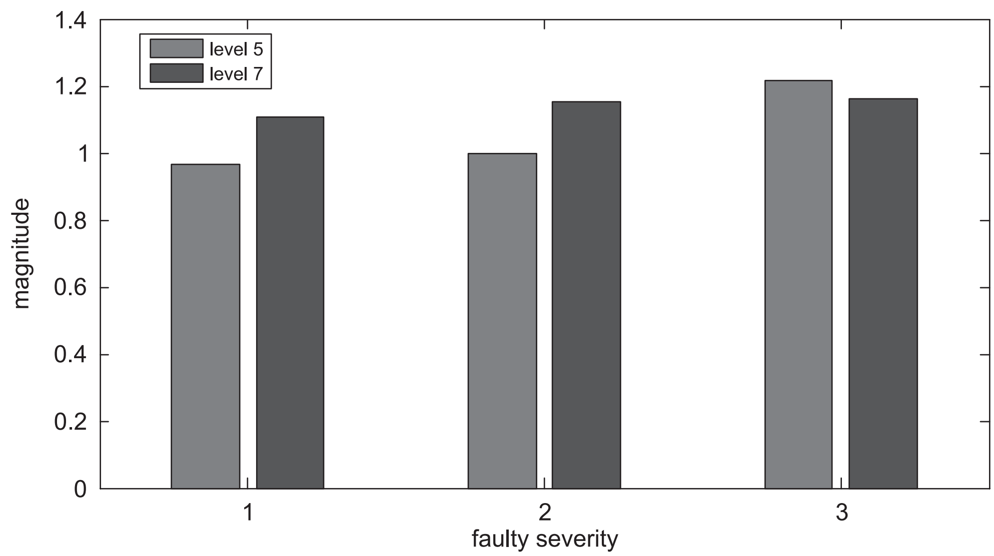

Figure 8: Standard deviation ratio of faulty stator currents from DWT analysis with notch filter.

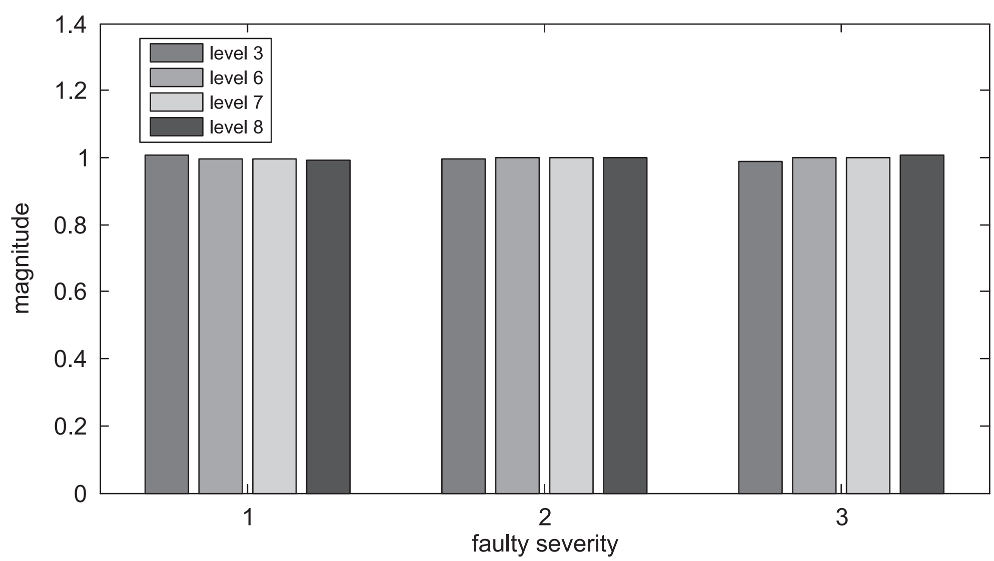

Figure 9: Standard deviation ratio of faulty stator currents from SWT analysis without notch filter

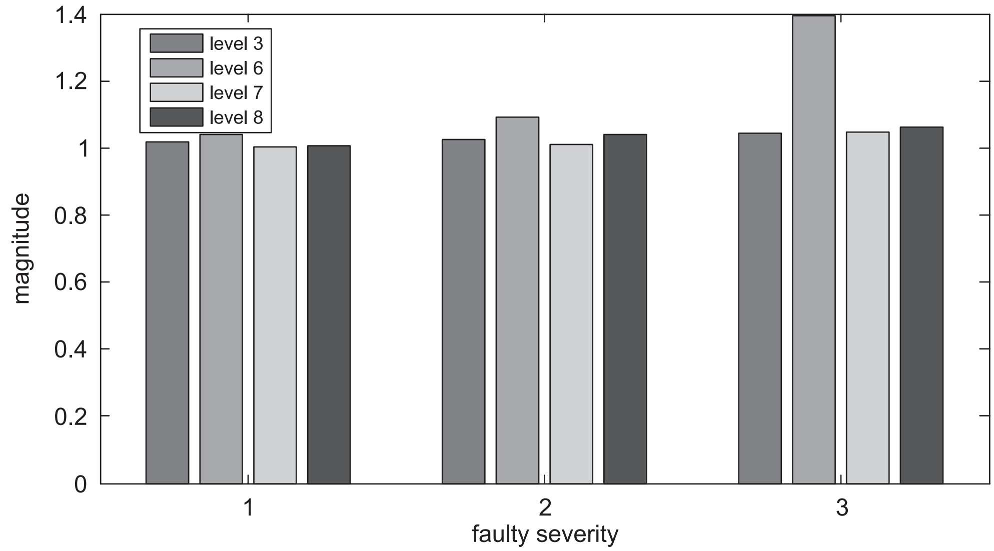

Figure 10: Standard deviation ratio of faulty stator currents from SWT analysis with notch filter.

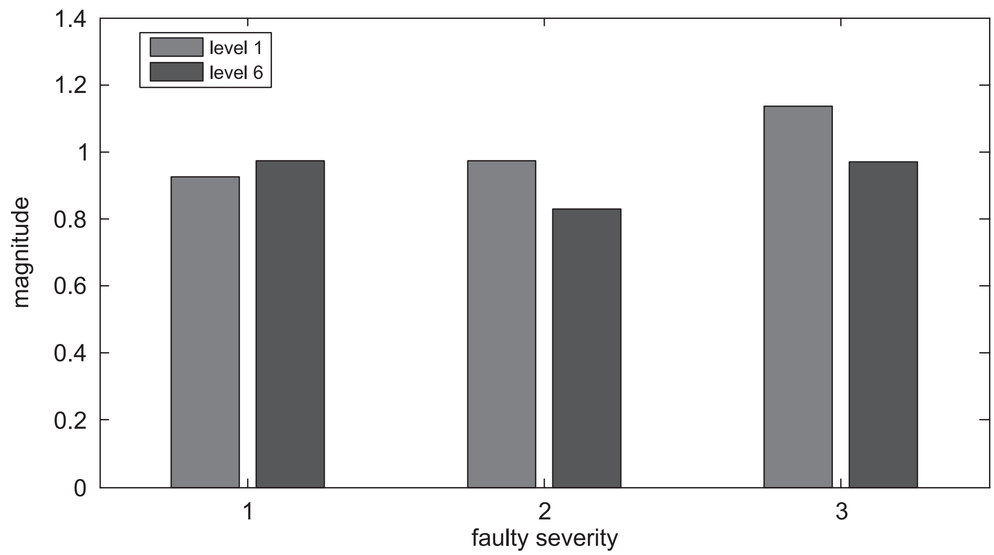

Figure 11: Standard deviation ratio of faulty stator currents from WPD analysis without notchfilter.

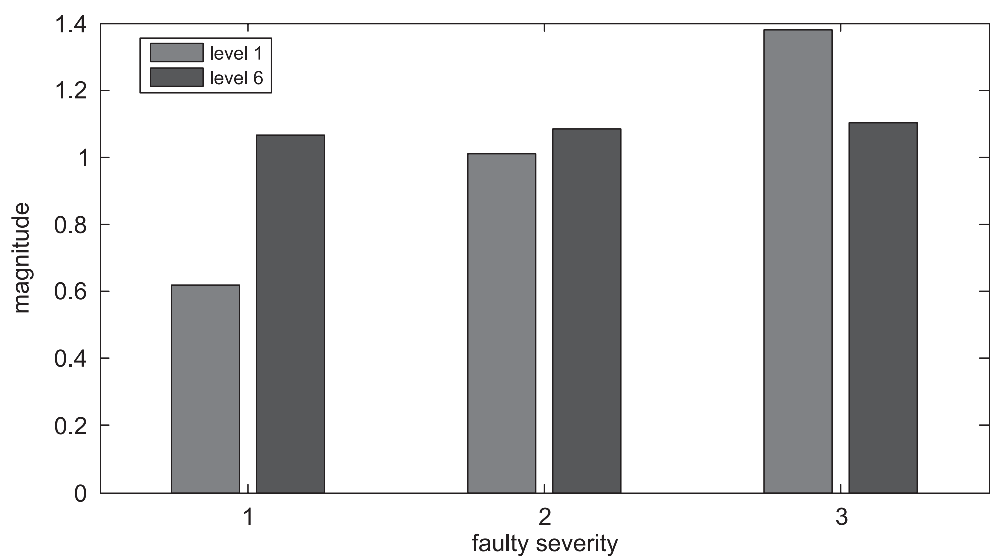

Figure 12: Standard deviation ratio of faulty stator currents from WPD analysis with notch filter.

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