DETECTION OF BROKEN ROTOR BARS IN INDUCTION MOTORS USING WAVELET ANALYSIS

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***Abstract* - In this paper a new method for the detection of broken rotor bars in induction machines is introduced. The startup transient current of an induction machine is used as the medium for diagnoses. The fundamental component is extracted using an algorithm that predicts the instantaneous amplitude and frequency during startup. The residual current is then analyzed using wavelets and a comparison is made between a healthy and damaged machine. This method of machine condition monitoring is not load dependant and can be used for machines that are unloaded.**

I. INTRODUCTION

The most widely used methods of induction machine monitoring utilize the steady-state spectral components of the stator. These spectral components include voltage, current and power and are used to detect broken rotor bars, bearing failures and air gap eccentricity. These techniques are focused on the detection of faults using steady-state analysis. The accuracy of these techniques depends on the loading of the machine as well as the signal to noise ratio of the spectral components being examined.

A. The Fast Fourier Transform (FFT)

The stator current monitoring system contains the four processing sections shown in figure1.

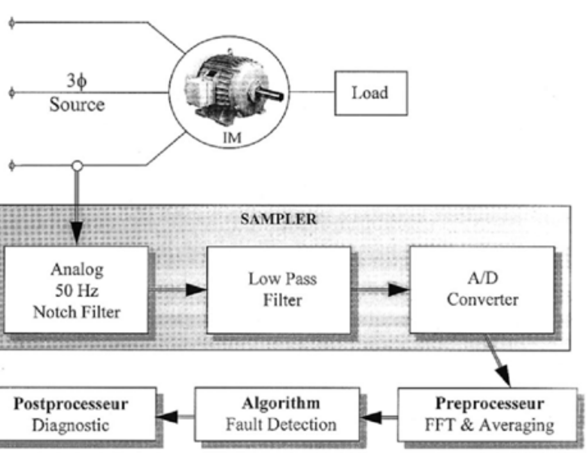

Fig 1. Single-phase stator current monitoring scheme. [1]

The phase current is sensed by a current transducer and sent to a 50-Hz notch filter where the fundamental component is reduced. The analog signal is then amplified and low-pass filtered. The A/D converter samples the filtered current signal at a predetermined sampling rate that is an integer multiple of the fundamental frequency. The preprocessor converts the sampled signal to the frequency domain using a FFT algorithm. The noise present in the signal is reduced by averaging a predetermined number of generated spectra. A large number of sampled points are analyzed to increase the accuracy of the FFT algorithm. An FFT length of 512 produces enough resolution to prevent the incorrect detection of frequencies. The Fault Detection Algorithm removes the spectral components that do not carry any useful information. The frequencies that are unaffected are those associated with motor faults. The Postprocessor classifies the machine's condition based on the detected frequency components.

B. Instantaneous Power FFT

The FFT of the instantaneous power is used as the medium for fault detection [2-4]. The amount of information described by the instantaneous power FFT is significantly more than that of the stator current FFT only. There are two sidebands around the power fundamental as well as a component that is a function of the modulation frequency. This is shown in equation (1).

$$p(t) = p_0(t) + \frac{MV_{LL}I_L}{2}\Big\{ Cos\left[(2\omega + \omega_{osc})t - \varphi - \frac{\pi}{6}\right] + Cos\left[(2\omega - \omega_{osc})t - \varphi - \frac{\pi}{6}\right] + 2Cos(\varphi + \frac{\pi}{2})\cos(\omega_{osct}) \Big\} \quad (1)$$

where

p	instantaneous power
M	modulation index
V_{LL}	rms value of the line-line current
I_L	rms of the line current
ω	supply radian frequency
φ	motor load angle
ω_{osc}	radian oscillation frequency

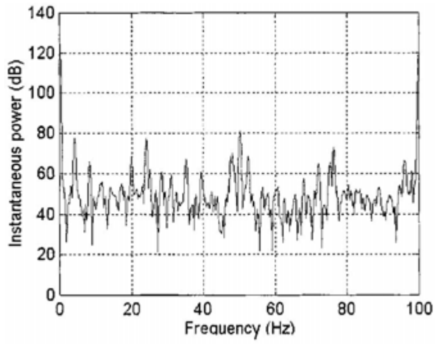

Fig. 2. Power spectrum of the instantaneous power [5].

Fig. 2 shows the instantaneous power FFT of a machine. It is shown that the spectral components are significantly contaminated by noise. For this reason it is more feasible to use only the stator current as a medium for condition monitoring.

C. Bispectrum

The bispectrum is a periodic function that preserves both magnitude and phase information. The derivation for the bispectrum is shown in Fig 3. Since the bispectrum is a function of both magnitude and phase, it includes these dimensions and therefore contains significantly more information.

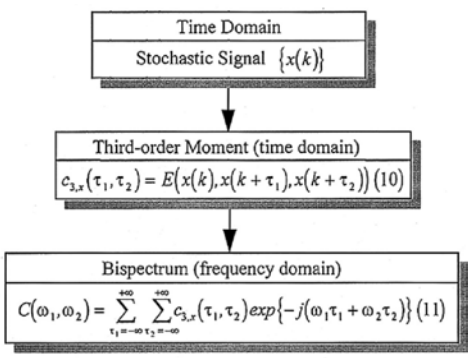

Figure 3 Bispectrum evaluation from the discrete time-domain signal

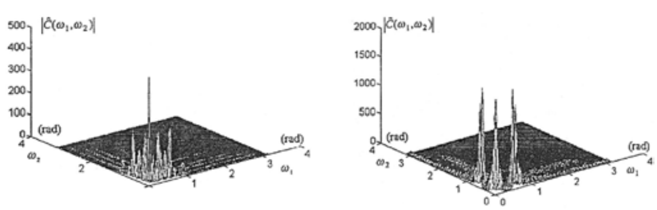

Fig. 4 Bispectrum [6] (a) Reference condition (healthy machine). (b) Stator winding faults condition.

D. High-Resolution Spectral Analysis

The classical spectral estimation techniques which have been used are among the most robust ones, allowing computationally efficient algorithms like the FFT. However, a main disadvantage of the classical spectral estimation is the impact of side lobe leakage due to the inherent windowing of finite data sets.

In order to improve the statistical stability of the spectral estimate, pseudo ensemble averaging by segmenting the data was introduced at the price of further decreasing the resolution. Therefore, tradeoffs among stability, resolution, and leakage suppression are necessary. A class of spectral techniques based on an eigenanalysis of the autocorrelation matrix has been promoted in the digital signal processing research literature. They may improve or maintain high resolution without sacrificing as much stability, allowing us to keep only the principal spectral components of the signal and to decrease noise influence [1].

E. Wavelet Analysis

The Fourier Transform produces detailed frequency information of a waveform. It produces excellent results when the waveforms examined are stationary or periodic. The Fourier transform is, however, not appropriate for a signal that has transitory characteristics such as drifts, abrupt changes, and frequency trends [7]. To overcome this problem, the Fourier Transform has been adapted to analyze small sections of the signal at a time. This technique is known as short-time Fourier transform (STFT), or windowing technique. The STFT represents a sort of compromise between time- and frequency-based views of a signal and it provides some information about both. This information produced by the STFT is obtained with limited precision because the window size is fixed. The wavelet transform was then introduced with the idea of overcoming the difficulties mentioned above. A windowing technique with variable-size region is then used to perform the signal analysis, which can be the stator current, the case that is considered here. Wavelet analysis allows the use of long time intervals where we want more precise low-frequency information, and shorter regions where we want high-frequency information.

II. CLASSICAL DETECTION OF BROKEN ROTOR BARS USING STEADY-STATE ANALYSIS

Broken rotor bars can be detected by monitoring the current spectral components [8]. These spectral components are illustrated by equation 2.

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

where k/p = 1,5,7,11,13,… .

The amplitude of the left sideband is proportional to the number of broken bars. The spectral component associated with broken rotor bars is found at the frequency, f_s(1-2s). This is shown in figures 5 an 6. If the machine is unloaded the slip will be approximately zero and the frequencies associated with broken bars overlap the frequency of the supply. In this case it is impossible to detect the presence of the frequencies associated with broken rotor bars. As a result the machine needs to be heavily loaded in order to separate these spectral components as well as increase the signal to noise ratio.

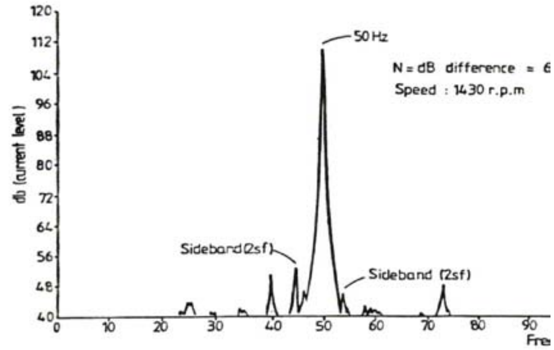

Figure 5. Current Spectrum of a healthy induction motor

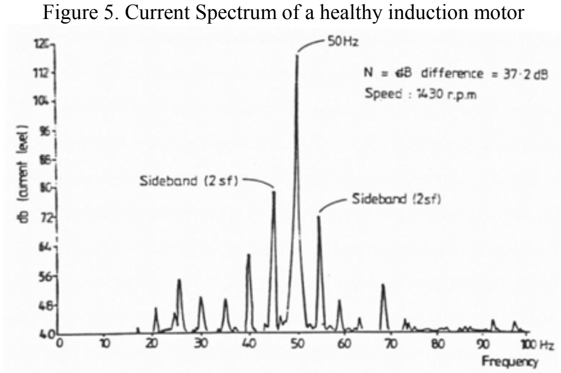

Figure 6. Current Spectrum of an induction motor with broken rotor bars

III. BROKEN ROTOR-BAR DETECTION USING TRANSIENT ANALYSIS

The advantages of using wavelet techniques for fault monitoring and diagnosis of induction motors is increasing because these techniques allow us to perform stator current signal analysis during transients. The wavelet technique can be used for a localized analysis in the time-frequency or time-scale domain.

Instead of examining the steady-state currents, the startup transient of the stator current is analyzed. The duration of the startup transient is only a few cycles depending on the load. All the information regarding the machine's condition is embedded within this transient. Because the Fourier Transform is an integration over infinity, all the information that exists during the startup transient will be lost. This poses the problem that the Fourier Transform cannot be used. The wavelet transform is therefore used to analyze the startup transient.

The frequencies associated with the broken rotor bars are a function of the rotor speed. These frequencies will increase during the transient startup time. The frequency of the supply current will drift from 50Hz.This is the result of the change in power factor from machine startup to steady-state running. It is desirable to separate the rotor bar frequencies from the supply frequencies. A notch filter cannot be used for this purpose since it introduces a phase shift during the transient state. For this reason an alternative algorithm for the extraction of the varying supply frequency is implemented [10]. Wavelet analysis is then applied to the residual current.

IV. EXPERIMENTAL RESULTS

Two identical rotors of a ½ horse power induction motor were used in this experiment except that one had a broken rotor bar. The same bearings and stator was used in order to minimize their influences on the startup transients. The machine was tested under loading conditions varying from 30% to 100% to determine if this method of detection could be successful and independent of the loading conditions. It was found that the motor had a very low inertia and detection could not be done below 30% loading because the transient times were too short.

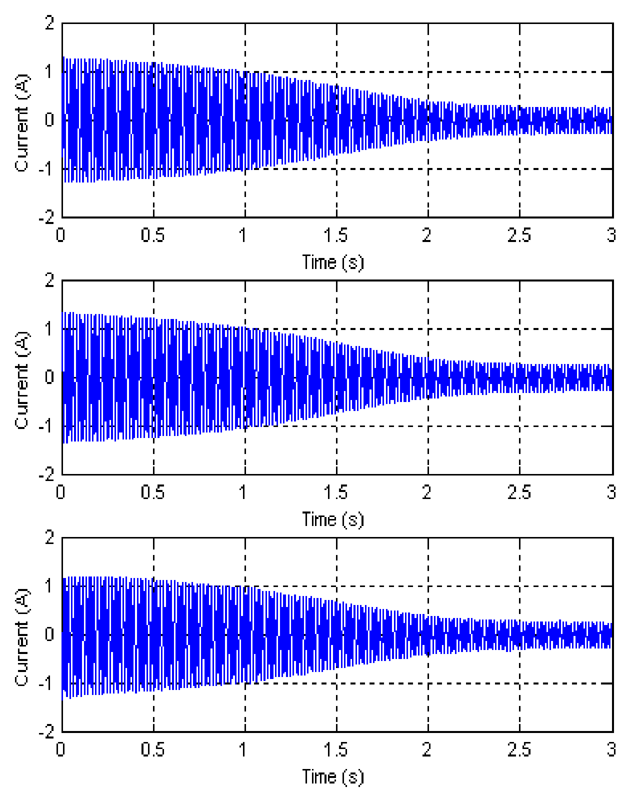

Figure 7. Startup current transients for phases A,B and C

The startup current transients of a ½ Hp induction motor is shown in figure 7. Before implementing the fundamental extraction algorithm[10], the individual line currents are transformed into a single rotating current vector as shown in figure 8. This vector is then transformed into the time domain and used as an input to the extraction algorithm. The algorithm estimates the frequency, amplitude and phase of the non stationary fundamental. The fundamental component is extracted with this algorithm. The resulting waveform shown in figure 9 has information relating to the health of the machine including bad bearings, broken rotor bars etc.

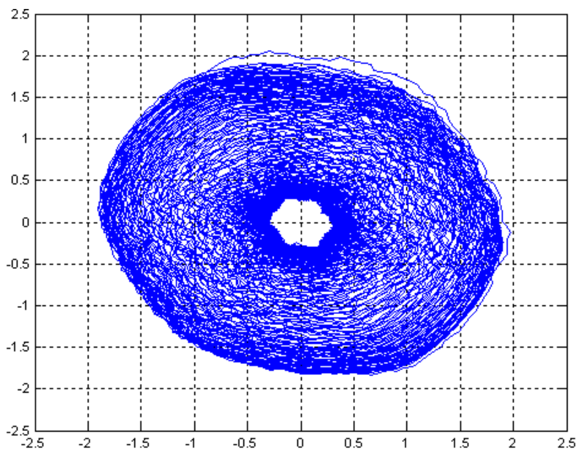

Figure 8. A plot of the current vector

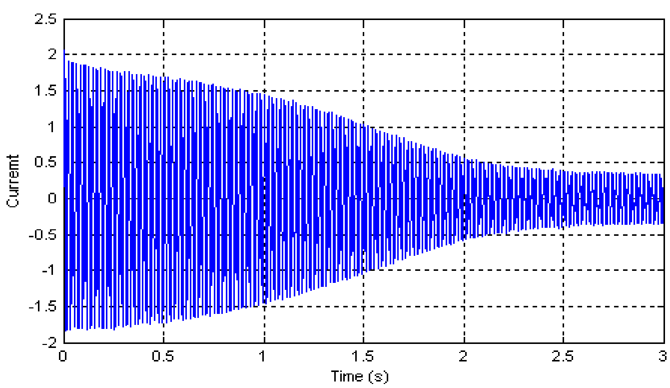

Figure 9. The time domain representation of the current vector

The extraction algorithm takes a few cycles to converge onto the amplitude and frequency of the fundamental. As a result when the estimated fundamental is subtracted from the original waveform, the algorithm's output between 0 and 0.2 seconds should be discarded to allow for algorithm convergence. The resulting truncated waveform is shown in figure 9.

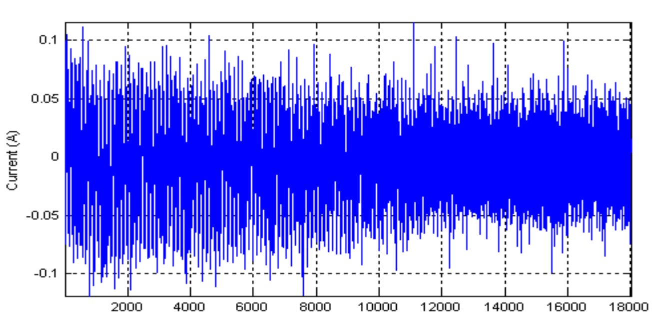

Figure 10. The startup current after extraction of the fundamental

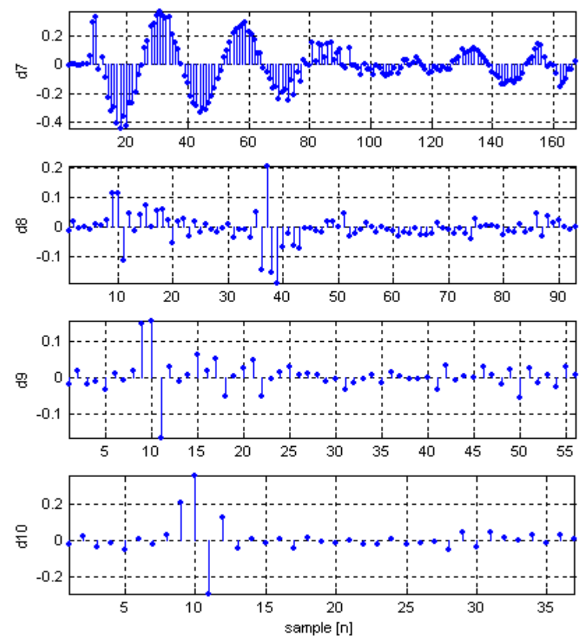

Figure 11. Wavelet decomposition levels D7-D10 of a fully loaded healthy machine

The residual current is then decomposed using the Discrete Wavelet Transform and Daubechies 8 wavelet By examining the first six detail scales of the discrete wavelet transform it was found that no distinction could be made between a healthy condition and the machine with the broken rotor bar. When examining scales 7-10 it is evident that there are differences in the wavelet coefficients as show in figures 11-14.

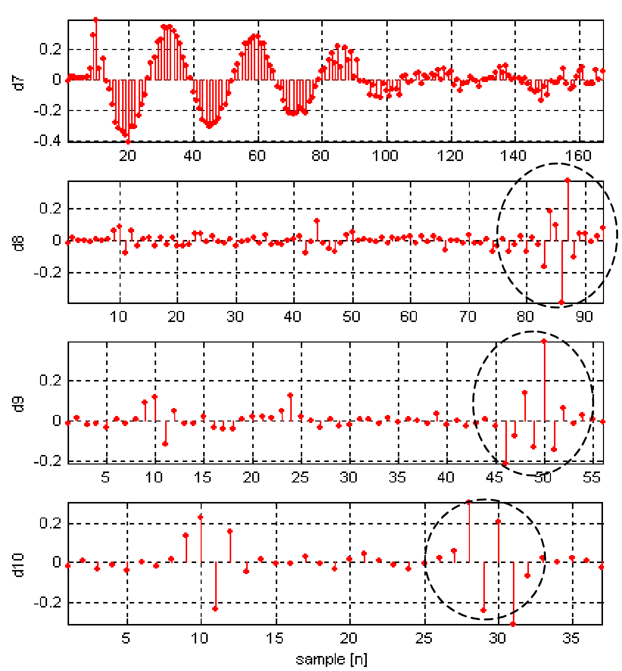

Figure 12. Wavelet decomposition levels D7-D10 of a fully loaded damaged machine

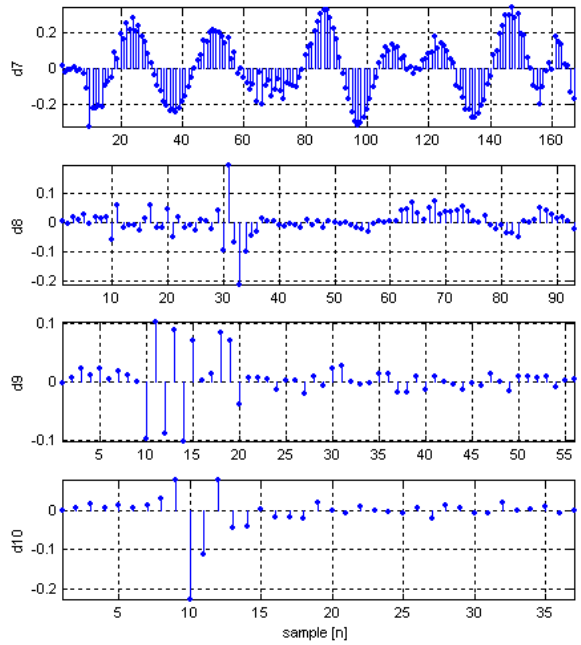

Figure 13. Wavelet decomposition levels D7-D10 of a 30% loaded healthy machine

Figures 11-12 and 13-14 show the differences and similarities between the decompositions of a 100% and 30% loaded machine. Two major features are obsrvered by examining the detail level, D9, of the decompositions. The first feature found between samples 8-13 is found in both healthy and damaged conditions. The second feature found between samples 45-55 is only visible in the decompositions of the damaged machine

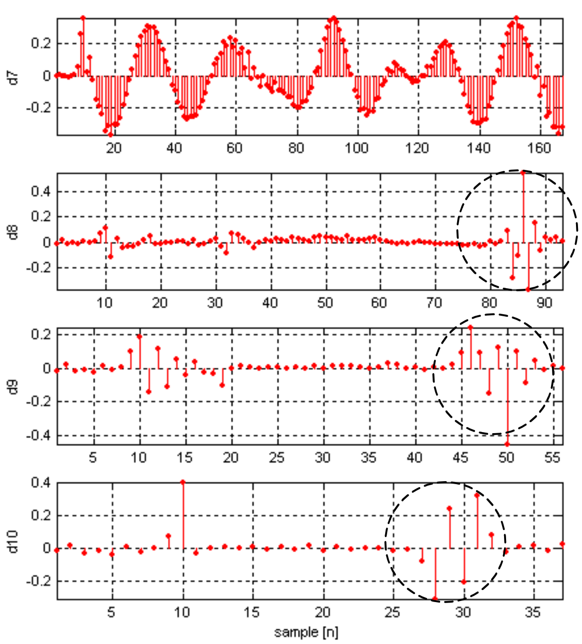

Figure 14. Wavelet decomposition levels D7-D10 of a 30% loaded damaged machine

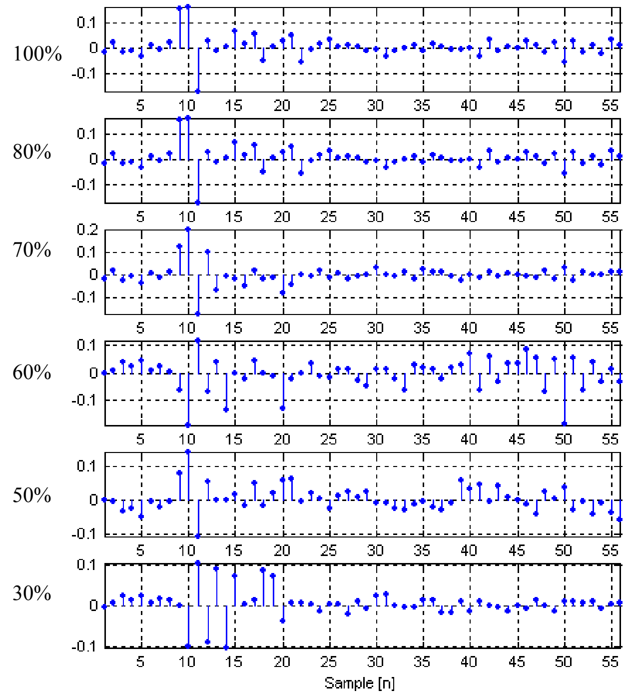

Figure 15. Wavelet decomposition levels D9 of a healthy machine loaded 30% to 100%

To investigate the effect of loading on the detection algorithm, the machine was loaded between 30%-100% and the level D9 of the decompositions were compared as shown in figures 15 and 16. It is evident that the same feature difference appears throughout the loading conditions.

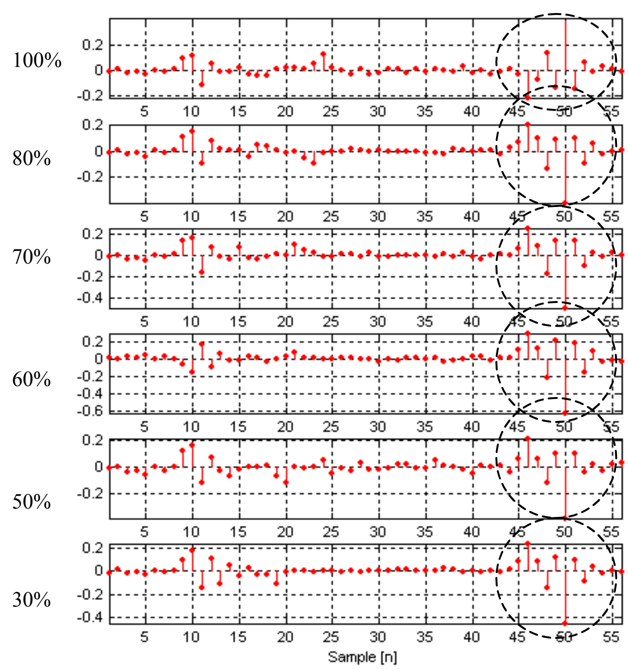

Figure 16. Wavelet decomposition levels D9 of a damaged machine loaded 30% to 100%

V. CONCLUSIONS

It has been shown that broken rotor bars can be detected by the decomposition of the startup current transient. This method has advantages over the traditional steady-state condition monitoring methods. It is not load dependant and can be effective on small lighly loaded machines. The machine does not have to be heavily loaded to make an accurate assessment of the machine's condition. There is no need for speed, torque or vibration measurement.

The analysis clearly shows that that the broken rotor bar can be can be detected using transient results only. Thus the method can be used for standard induction motors, but also for machines that operate predominantly in the transient like wind generators or motor operated valves.

VI. ACKNOWLEDGMENTS

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VII. REFERENCES

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