A Study of FPGA-Based Detection Method for Induction Motors under Different Loads

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Abstract -- **Detection of vibration in rotating system is important due to the fact that the failure is silent and as a consequence it increases power consumption. Vibration introduces spurious frequencies in the electric line, which can be catastrophic. In this paper, the use of motor current signature analysis and mathematical morphology is used to detect broken bars on induction motors under different mechanical load conditions. The proposed method has been implemented in a field programmable gate array (FPGA), to be used in real-time online applications. The algorithm obtained on an average gives a 95% accuracy of failure detection.**

Keywords: Broken bars, fault diagnosis, field programmable gate array (FPGA), mathematical morphology, MCSA.

I. INTRODUCTION

ONLINE monitoring systems for early failure detection are a current demand in many industrial areas. In the vast field of rotating machines, induction motors are extensively used for a variety of industrial applications, representing around 85% of worldwide power consumption. Among several faults that can occur in induction machines, broken bars may cause excessive vibrations and higher thermal stress with catastrophic consequences if the situation is not corrected in early stages. As a consequence, broken bars detection must be carried out in early stages and under different load conditions [1]. Induction motor analysis can be performed on and off line. Online analysis is of great interest because it avoids the shutdown of production lines.

Motor current signature analysis (MCSA) is one of the most effective techniques for induction motor failure detection [2]. Several methodologies for broken bar detection using MCSA have been proposed. For example, Garcia-Perez *et al*. [6] developed an experimental study for partially broken rotor bar detection using high-resolution spectral analysis. Rangel-Magdaleno *et al*. [8] proposed the use of mathematical morphology (MM) to improve MCSA, where the advantages of using this transformation are presented. Their methodology was applied to a healthy motor and a motor with two broken bars under full-load conditions [8].

MCSA allows the observation of those spurious spectral components with amplitude proportional to the severity of the failure. However, for early stage and low-load condition, the detection by an automatic system is difficult.

In this paper, a field programmable gate array (FPGA) based methodology for broken rotor bar detection under different load condition using MCSA and MM is presented.

The proposed methodology is an extension of the algorithm presented in [8], with an improvement on detect ability through the addition of a load condition detection module based on a segmentation of the analysis area.

To demonstrate the efficiency of the proposed methodology, several tests were performed. At 50%, 75% and 100% load level besides three motor conditions, namely healthy motors, motors with one broken bar, and motors with two broken bars.

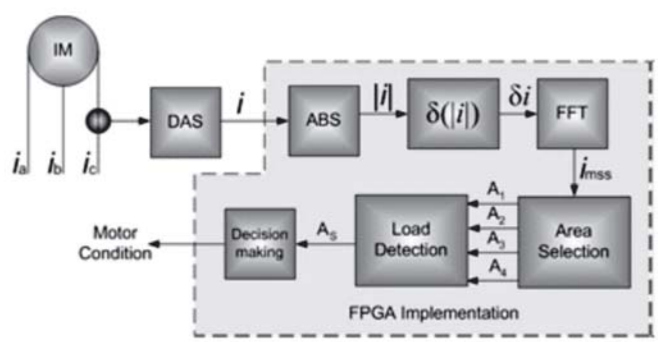


Figure 1. Proposed methodology.

The FPGA implementation reconfigurability provides constant updating to accomplish new requirements, an open architecture for future module integration or improvements in the methodology, and a parallel structure for a fast and efficient processing that permits continuous online monitoring.

Figure 1 shows the proposed methodology, where the FPGA implementation is bounded by a dotted line. The current signal of one motor phase is obtained using a standard AC current clamp i200s Fluke. The analog signal from clamp is ampliûed and then converted into a digital signal using a 16-bit analog to digital converter with sampling rate of 100 kHz conûgured to work at 1500 Hz.

The data acquisition system is controlled by an FPGA, which receives and stores the digital signal to be processed. Next is a description of each step.

1) Acquisition and storage of the current signal.
2) Calculation of the absolute of the signal (|i|). This is recommended by [12], to apply a MM operation.
3) A dilation transformation is applied to the absolute value of the signal using a structural element equal to five in this process the dilation of the current äi is obtained.
4) The power spectral density called i_{mss} of the signal is obtained using a 1024-point FFT.
5) The absolute of the power spectral signal i_{mss} is calculated by the block FFT.

Figure 2 shows the power spectral density of the signal i_{mss} for three different motor conditions: healthy [Figure 2(a)], one broken bar [Figure 2(b)] and two broken bars [Figure 2(c)]. In this figure the analysis area is marked by a rectangle; the broken bar frequency is named fb. In Figure 2, it can be seen how the amplitude of the frequency (fb) increases with the damage.

A comparison with typical area of analysis, speciûcally frequency (fb) with frequency (fbb), shows bigger amplitude of fb allowing better detection by an automatic system.

6. Figure 3 shows how the area selection unit selects the low frequencies from Analysis area (1–10 Hz), then divides the selection in four areas, A1, A2, A3, and A4 whose amplitudes are calculated as

$$A_1 = \sum_{j=3}^{5} i_{\mathrm{mss}}(k) \quad A_2 = \sum_{j=5}^{7} i_{\mathrm{mss}}(k)$$

$$A_3 = \sum_{j=7}^{8} i_{\mathrm{mss}}(k) \quad A_4 = \sum_{j=8}^{10} i_{\mathrm{mss}}(k)$$

where i_{mss} is the power spectral density of the current and k is an index which indicates the points of the power spectral density vector i_{mss} to be analyzed within each area.

7) To determine a load condition, a comparison of the resultant magnitude of the sum of components of these four areas is carried out. The selected segment As is obtained as

As = max (A1, A2, A3, A4).

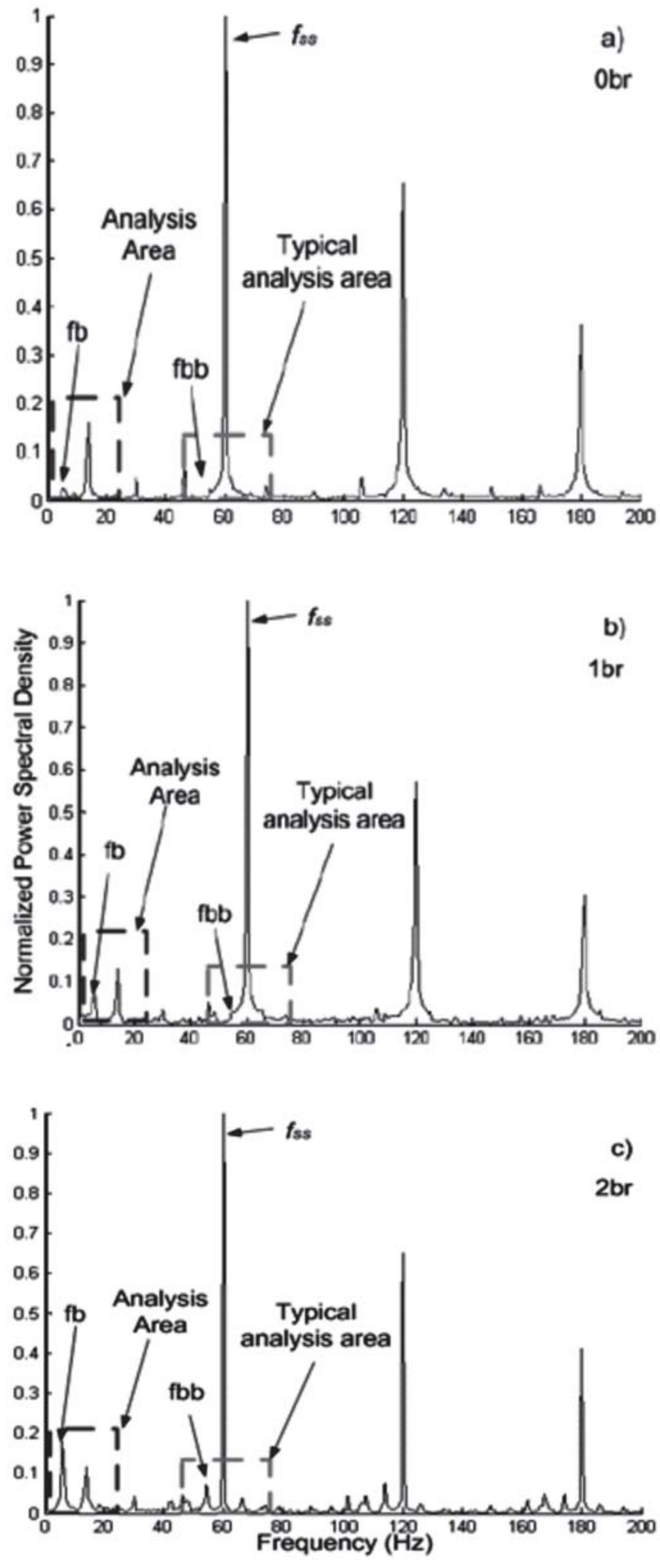


Figure 2. Power spectral density for current signal under different conditions (a) Healthy motor (b) One broken bar (c) Two broken bars.

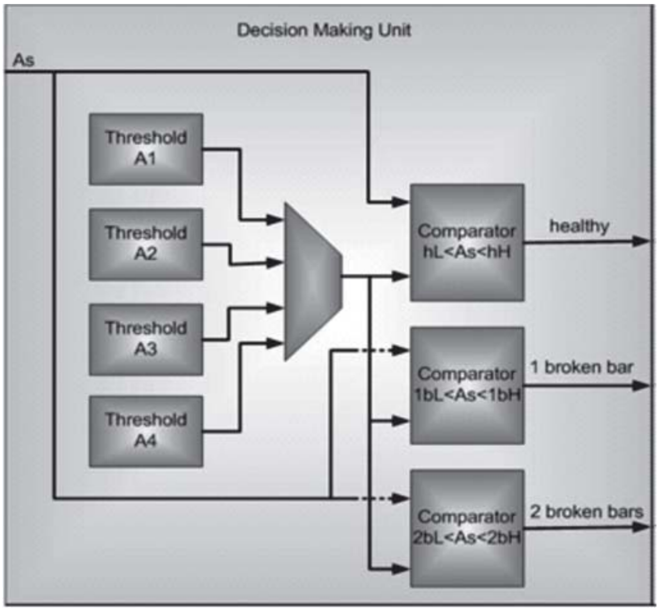


Figure 3. Decision Making Unit.

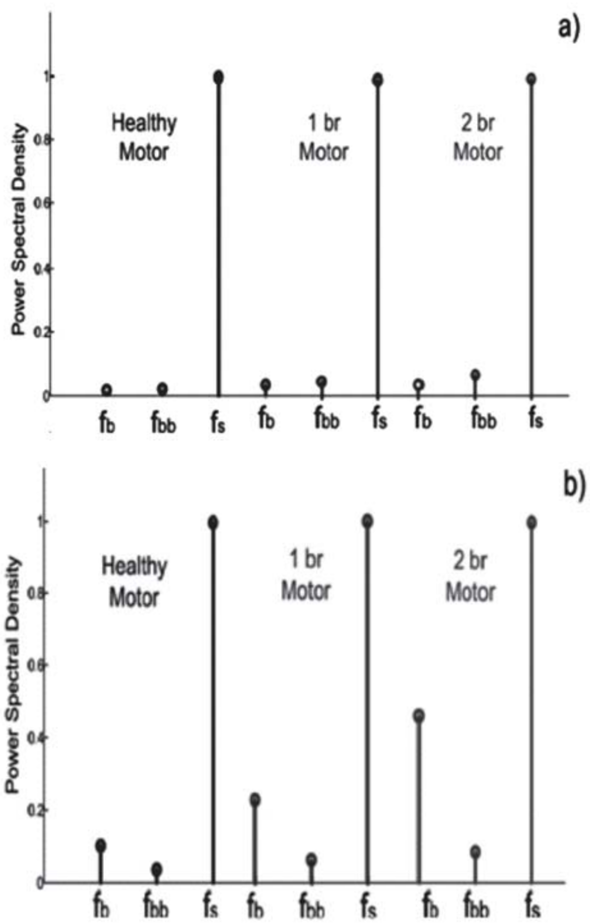
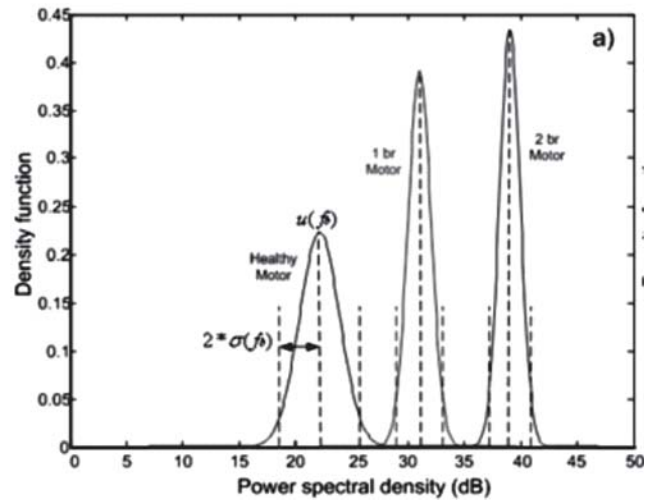


Figure 4. Frequency amplitudes for healthy motor, motor with one broken bar and motor with two broken bars (a) MCSA and (b) proposed methodology.

Figure 2 shows an example of the spectra of dilation signals for a healthy motor (a), a motor with one broken bar (b), and a motor with two broken bars (c). A comparison among Figures 2(a), (b), and (c) shows that different spectral components may be used for fault condition monitoring. It is clear that frequency fb presents greater frequency amplitude than frequency fbb, improving detectability.

III. TESTING RESULTS AND ANALYSIS



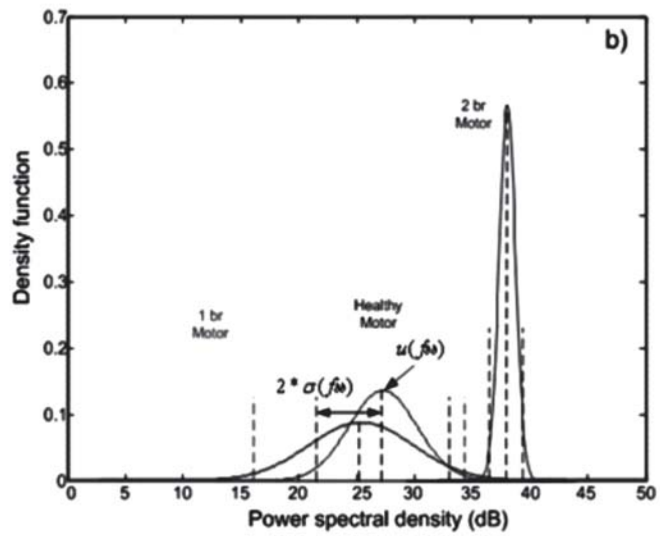


Figure 5. Statistical analysis for a mechanical load of 100% (a) Proposed methodology, *fb* and (b) analysis in *f*bb.

The results of the statistical analysis for a mechanical load of 100%, 75% and 50% are shown in figures (5–7) respectively, where $\mu(fb)$ is the mean of *fb*, $\sigma(fb)$ the standard deviation, $\mu(fbb)$ is then mean of the *f*bb and $\sigma(fbb)$ the standard deviation.

Figure 5(a) shows a plot of the Gaussian distribution of the 50 runs for each motor condition: healthy motor, one broken bar, and two broken bars, considering the area *A*4. Figure 5(b)

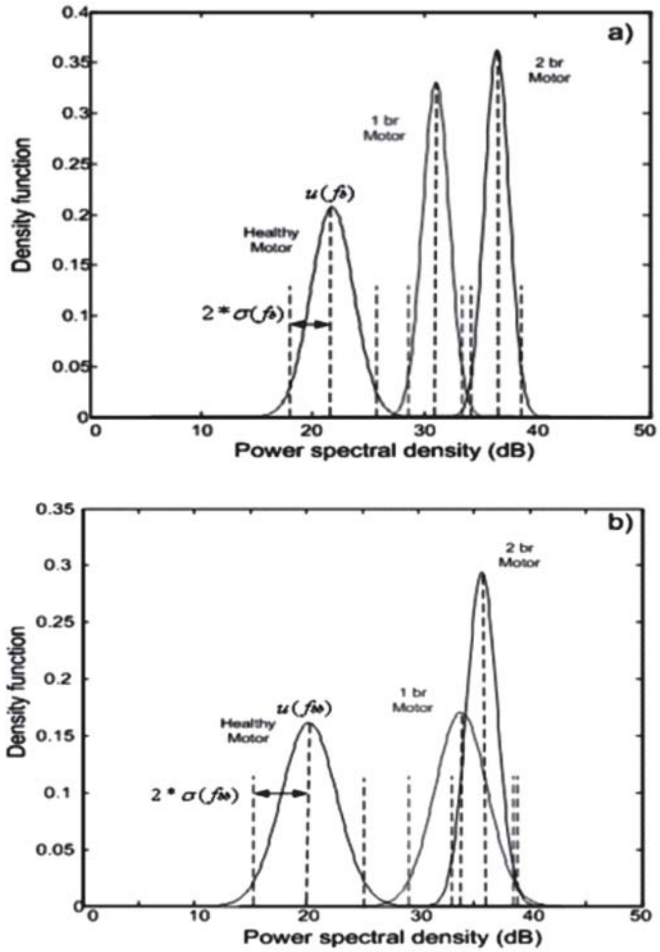
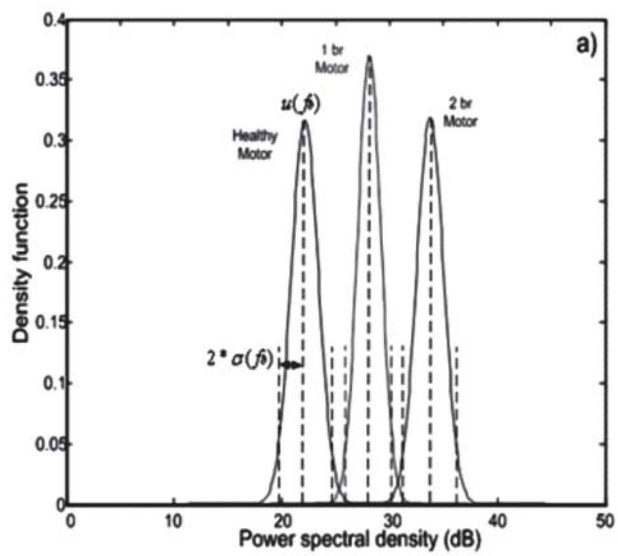


Figure 6. Statistical analysis for a mechanical load of 75%
(a) Proposed methodology, *fb* and (b) analysis in *f*bb.



shows the Gaussian distributions for the same conditions, but using MCSA and *f*bb. In this case, healthy motor, and one broken bar condition are overlapped impeding the detection.

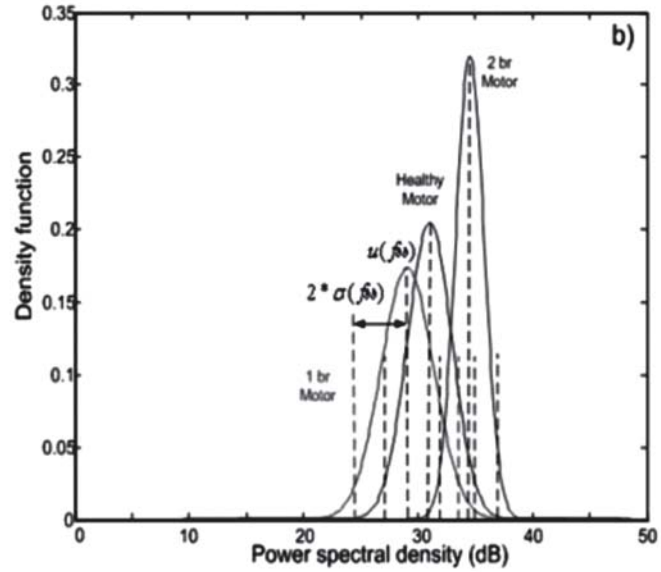


Figure 7. Statistical analysis for a mechanical load of 50%
(a) Proposed methodology, *fb* and (b) analysis in *f*bb.

Figure 6(a) shows the statistical analysis for data with 75% mechanical load. 50 runs for each motor condition were made, area *A*3 was used. The figure shows a good detectability, with at least two standard deviations separation among each Gaussian distribution Figure 6(b) shows the results using *f*bb as a detection frequency; notice that one broken bar and two broken bars condition are overlapped. For this load condition, the proposed methodology increases the detectability between one broken bar and two broken bar from 50% to 95%.

The statistical analysis for data with 50% mechanical load is shown in Figure 7. The results of the proposed methodology for this condition are similar to the case previously described. Gaussian distributions are separated by more of two standard deviations with an accuracy of 95%. For this condition area *A*2 was used. Figure 7(b) shows an overlapping on each condition inhibiting the detection.

IV. CONCLUSION

Mathematical morphology has been used to improve MCSA analysis to detect broken rotor bars in early stages. Spurious frequencies associated with broken bar conditions are emphasized through a morphologic dilation transform which improves the detection with an automatic system.

Figures show comparative statistics obtained with typical MCSA analysis and the proposed method. Gaussian distribution corresponding to both cases shows how the conditions severability is increased when the proposed method is applied the detection accuracy of the proposed methodology.

An FPGA-based methodology to enhance detectability for broken bar detection under different load condition using

MCSA and MM was presented. The current signal was obtained from a single phase by a standard clamp. The implementation was made into an FPGA from Altera to achieve online operation. Selected frequency *fb* for analysis shows better detection than frequency *f*bb when the signal is preprocessed by dilation transformation.

V. ACKNOWLEDGEMENT

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