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A Survey Paper on FPGA-Based Broken Bar Detection of Induction Motor Using Motor Current Signature Analysis

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Abstract—**Preventive maintenance is one of the major concerns in modern industry where failure detection on motors increases the useful life cycle on the machinery. Broken rotor bars are among the most common failures in induction motors. Different methodologies based on current and vibration monitoring have been proposed using FFT and wavelet analysis for preventive monitoring of induction motors resulting in countless techniques for diagnosing specific faults, arising the necessity for a generalized technique that allows multiple fault detection. The paper is focused on the so-called motor current signature analysis (MCSA) which utilizes the results of spectral analysis of the stator current. MCSA techniques include parametric and nonparametric spectrum analysis methods of motor current in general. The novelty of this paper is the tutorial overview of an automatic online diagnosis algorithm for broken-rotor-bar detection, optimized for single low-cost field-programmable gate-array (FPGA) implementation, which guarantees the development of economical self-operated equipment.**

Index Terms- **Induction motor, motor current signature analysis, fast fourier transform.**

I. INTRODUCTION

Induction motors are key elements in every industrial process; their robustness, low cost, easy maintenance and versatility make them popular in many applications from home appliances to sophisticated industrial equipments. As an essential component in the industrial process, damage assessment & condition monitoring of induction motors has received considerable attention in recent years [1]. One of the most commonly seen motor faults is the broken rotor bar, which can cause serious motor damage if not detected in time [2]. Various techniques have been developed for broken rotor bar fault diagnosis, including vibrations [3], rotor speed [4], motor axial flux [5], Park's Vector current monitoring [6], and stator current analysis [7]. Among these methods, motor current signature analysis (MCSA) is the most widely used method, due to its low cost and non-invasive nature [8]. The bulk of fault detection and monitoring investigations can largely be distributed into mainly three categories.

The first category comprises work that centered on traditional lumped-parameter modelling and analysis of faulty motor performance, and case-history studies of actual motor faults in stators, rotors and bearings, as well as field experience and practical engineering insights into the causes and effects of these faults [9, 10].

The second category comprises investigations that centered upon "online" motor condition monitoring and fault diagnostics using the motor terminal current and voltage waveforms, while applying traditional Fourier transform spectral analysis techniques to these waveforms in actual case-study field experience. Some of these works included applications of neural network and other artificial intelligence (AI) methods to these spectral analyses results [11].

The third category consists of a small number of investigations in which the method of finite-element analysis of electric motor performance was enlisted in fault diagnostic studies; these works were rather limited in scope [12].

To improve the performance of the spectrum analyzers proposed up to now, several works have been carried out to introduce new characteristics to the previous designs. MCSA techniques include parametric and nonparametric spectrum analysis methods of motor current in general. In the parametric methods, autoregressive models have been fitted with time series of the signal, and model parameters have been used in order to compute the frequency spectrum. Nonparametric methods, on the other hand, are based on Fourier transform and search for periodicities of the signal. Power spectral density (PSD) analysis of motor current is one of the widely used MCSA techniques. There are several approaches to calculate PSD. The periodogram method and Welch's periodogram methods are two of the nonparametric spectrum methods.

Broken rotor bar fault in induction motors can be detected by monitoring any abnormality of the motor current power spectrum amplitudes at several certain frequency components. These frequency components are located around the main frequency line and are determined according to the number of poles and mechanical speed of the motor. However, there are other effects that may obscure the detection of the broken rotor bar fault or cause false alarms. For example, these effects can be intrinsic manufacturing dissymmetry, or load torque oscillation that can produce stator currents with the frequency values that are the same as the monitored frequencies. In monitoring these frequency components, it is assumed that the load torque is constant. Any variation of the load torque with the rotational speed can produce frequency harmonics, which may overlap the harmonics caused by broken rotor bar fault [13]. A broken rotor bar fault detection scheme based on multiple frequency signatures thus should be more reliable in overcoming or reducing the effect of misinterpreted signatures, which are caused by the effects discussed formerly or some other unknown reasons. According to cited works, the development of new processing algorithms using MCSA is currently a continuous topic of interest.

II. MOTOR CURRENT SIGNATURE ANALYSIS

There are many techniques that have been developed to detect motor failures as aforementioned, where the most popular are MCSA and vibration analysis. The MCSA technique is based on the monitoring of the stator current at the motor to further correlate the measured signal with the specific failure under analysis. This technique employs two variations for signal analysis: 1) based on steady state analysis and 2) based on start-up transient analysis. Steady state analysis is used in [14], where the authors focus their work to detect broken rotor bars in induction motors using the sideband frequencies that appear in the current spectrum when the motor is damaged; steady-state current monitoring can also be used to detect another kind of failure, i.e., airgap eccentricity, bearing damage, load effects, among others, as shown in [15]. Another example of steady-state MCSA analysis is presented in [16], where they detect electrical motor failures such as open phase or short circuits by using the discrete wavelet transform (DWT). Startup transient analysis is also used by the MCSA technique to detect motor failures, as shown in [17]. In this, discrete wavelet analysis is applied to detect broken rotor bars by evaluating a weighting parameter. The MCSA technique provides good results on motor failure detection; yet, every failure needs an especially devoted instrumentation system and algorithm for automatic failure detection. As with other wavelet transforms, a main advantage of this transform has over Fourier transforms is temporal resolution: it captures both location information and frequency.

Kliman and Filipetti [18], [19] used MCSA methods to detect broken rotor bar faults by investigating the sideband components around the supplied current fundamental frequency (i.e., the line frequency) f_o

$$f_b = (1 \pm 2s)\, f_o \qquad (1)$$

where f_b are the sideband frequencies associated with the broken rotor bar, and is the per-unit motor slip. The slip s is defined as the relative mechanical speed of the motor n_m with respect to the motor synchronous speed n_s as

$$s = (n_s - n_m) / n_s \qquad (2)$$

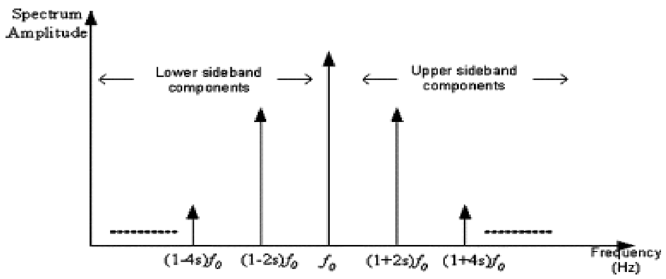

Fig.1. Sideband frequencies around the fundamental line frequency.

The motor synchronous speed n_s is related to the line frequency f_o as

$$n_s = (120\, f_o) / P \qquad (3)$$

where, P is the number of poles of the motor and the constant "120" is used to express the motor synchronous speed n_s in revolutions per minute (r/min) unit.

The broken bars also give rise to a sequence of other sidebands given by

$$f_b = (1 \pm 2ks)\, f_o\ ,\ k=1, 2, \ldots K_n, \text{ where, } f_b > 0\ ¥\ k \qquad (4)$$

and are depicted conceptually in Fig. 1.

Some of the benefits of MCSA include:

a) Non-intrusive detection techniques: With the technological advances in current-measuring devices, inexpensive and easy-to-use clamp-on probes are more affordable & convenient to use for sampling current without having to disconnect the electrical circuit or to disassemble the equipment.
b) Remote sensing capability: Current sensors can be placed anywhere on the electrical supply line without jeopardizing the signal strength and performance.
c) Safe to operate: Since there is no physical contact between the current sensor and the motor-driven equipment, this type of monitoring technique is partially attractive to application where safety is major concern.

Despite being a very easy and convenient method for detecting rotor failures, the industrial application of MCSA has practical limitations [20], mainly due to the following reasons.

a) Spectrum Leakage: This is the result of the use of a finite-time window. The energy of the mains frequency spreads over the other frequencies and can hide the sideband components.
b) Need for a High-Frequency Resolution: Frequency resolution (Δf) is the frequency separation between two adjacent bins in the spectrogram. It is inversely proportional to the time of measurement, T_m.
c) Varying Load Conditions: If the load varies during the sampling time, then the sideband frequencies, which depend on the motor slip, change with the speed. These changing frequencies can invalidate an MCSA based diagnosed process, either because they produce a typical smearing effect on the current spectrum, which hides the sideband components, or because they generate the same frequencies associated with broken rotor bars.
d) Confusing Mechanical Frequencies: A "two-test comparison" is needed that performs two MCSA tests at significantly different loads. Confusing mechanical frequencies induced by the load can be avoided with a no-load test, but, in this case, the sideband frequencies have a small magnitude and are very close to the main frequency; so, they may be buried by spectral leakage.

III. FAULTS DETECTION TECHNIQUES

Modern measurement techniques in combination with advanced computerized data processing and acquisition show new ways in the field of induction machines monitoring by the use of spectral analysis of operational process parameters. Below, some of the main stator-current-signature-based techniques are presented [21].

1. Classical Fast Fourier Transform (FFT):

For this method, the stator current monitoring system contains mainly four processing sections.

1) Sampler: Its purpose is to monitor a single-phase stator current. This is accomplished by removing the 50-Hz excitation component through low-pass filtering, and sampling the resultant signal.
2) Preprocessor: It converts the sampled signal to the frequency domain using an FFT algorithm.
3) Fault Detection Algorithm: The algorithm keeps only those components that are of particular interest because they specify characteristic frequencies in the current spectrum that are known to be coupled to particular motor faults.
4) Postprocessor: It diagnoses the frequency components and then classifies them.

2. Instantaneous Power FFT:

In this case instead of stator current, the instantaneous power is used as a medium for the motor signature analysis. Here, fault harmonics domain is well bounded but the power spectra are still noisy.

3. Bispectrum:

The bispectrum is defined in term of the two-dimensional Fourier transform of the third-order moment sequence of a process. The bispectrum is periodic with a period of 2π, and preserves both the magnitude and phase information. It is then capable of revealing both the amplitude and phase information of the signals. With these additional provided dimensions the fault detection and diagnostic process can be enriched.

4. Wavelet Analysis:

Wavelet analysis allows the use of long time intervals where we want high-frequency information, and shorter regions where we want high-frequency information. 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. It is then a powerful tool for condition monitoring and fault diagnosis.

IV. METHODOLGY

The proposed methodology is based on MCSA. This methodology was implemented into a low-cost FPGA from Altera (DE0 nano-development kit) with an operation frequency of 50 MHz [22]. The use of the FPGA allows a real-time low-cost implementation with the advantage of low-power consumption and rapid prototyping. 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.

Fig. 2 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 amplified and then converted into a digital signal using a 16-bit analog to digital converter (ADS7809) with sampling rate of 100 kHz configured to work at 1500 Hz. The data acquisition system is controlled by an FPGA, which receives and stores the digital signal to be processed.

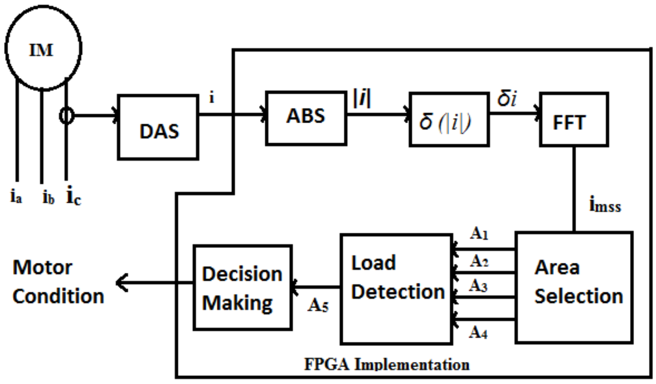

Fig. 2. Proposed Methodology.

Next is a description of each step.

1) Acquisition and storage of the current signal.
2) Calculation of the absolute of the signal ($|i|$).
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 δi 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.
6) Area selection unit selects the low frequencies from analysis area (1–10 Hz), then divides the selection in four areas, A_1, A_2, A_3, and A_4 whose amplitudes are calculates as

$$A_1 = \sum_{j=3}^{5} i_{mss}(k) \qquad A_2 = \sum_{j=5}^{7} i_{mss}(k)$$
$$A_3 = \sum_{j=7}^{8} i_{mss}(k) \qquad A_4 = \sum_{j=8}^{10} i_{mss}(k) \qquad (5)$$

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 A_s is obtained as

$$A_s = \max(A_1, A_2, A_3, A_4) \quad (6)$$

This process is taken into consideration the slip of the motor. The selection is done as follows: if region A_4 has the biggest amplitude then motor has full load, if A_3 has the biggest amplitude then the motor has 75% and so on. This process is carried out in the load condition unit.

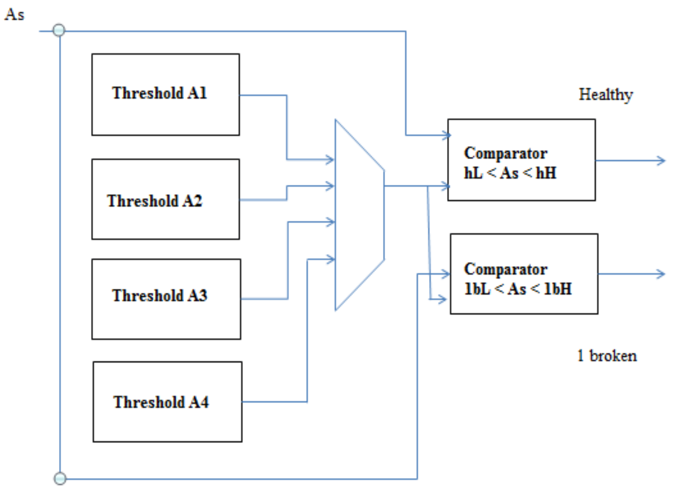

Fig. 3. Decision- making unit.

8) Once the load condition is determined, the resultant amplitude of the corresponding area is sent to the decision-making unit for threshold comparison. The decision-making unit is composed of a decision tree in which the thresholds obtained for each condition motor are compared with the resultant amplitude A_s to determine the motor condition. Fig. 3 shows the implementation of the decision-making unit, the threshold blocks contains the lower and upper limits for each condition, these limits are: *hL* is a lower limit and *hH* is an upper limit for healthy motor, *1bL* and *1bH* are the lower and upper limits for one broken bar, respectively.

The decision-making unit states the motor condition by indicating whether the motor is in good condition or in a broken bars condition.

V. Conclusion

This paper has attempted to review fundamentals, main results, and practical applications of the MCSA used for induction motors faults detection and its implementation on FPGA. MCSA provides a highly sensitive, selective, and cost-effective means for online monitoring of a wide variety of heavy industrial machinery. Additionally, the FPGA implementation results in an efficient and low-cost SoC.

References

1. Thorsen O and Dalva M," A survey of faults on induction-motors in offshore oil industry, pretrochemical industry, gas terminals, and oil refineries " IEEE Transaction on Industrial applications vol. 31 pp. 1186-1198, Oct.1995.
2. Benbouzid M and Kliman G,"What stator current processing-based technique to use for induction motor rotor faults diagnosis " IEEE Transactions on Energy Conversion vol.18 pp. 238-246, Jan. 2003.
3. Rodriguez P., Belahcen A., Arkkio A., "Signatures of electric faults in the force distribution and vibration pattern of induction motors", IEE Proceedings on Electric Power Applications vol. 153 pp. 523 Nov. 2006.
4. Filippetti F., Franceschini G., Gassoni C. ,Vas P., "AI techniques in induction machines diagnosis including the speed ripple effect" IEEE Transaction on Industry Applications vol. 34 pp. 98, Feb. 1998.
5. Penman J., Dey M., Tait A., Bryan W., "Condition monitoring of electrical drives", IEE Procedings on Electric Power Applications vol. 133 pp. 142, Dec. 1986.
6. Cabanas M., Pedrayes F., Gonzalez M., Melero M., Rojas C., Orcajo G., Cano J., Nuno F., "A new electronic instrument for the early detection of broken rotor bars in asynchronous motors working under arbitray load conditions", 5th IEEE International Symposium on Diagnostics for Electric Machines, Power Electronics and Drives p1 Mar. 2005.
7. Marques Cardoso A., Cruz S., Carvalho J., Saraiva E.," 1995 Rotor cage fault diagnosis in three-phase induction motors, by Park's vector approach", 13th IAS Annual Meeting vol. 1 pp 642-653, Nov. 2005.
8. Benbouzid M.,"A review of induction motors signature analysis as a medium for faults Detection",IEEE Transaction on Industrial Electronics vol. 47 pp. 984, Feb. 2000.
9. S. J. Manolas and J. A. Tegopoulos, "Analysis of squirrel cage induction motors with broken bars and rings," IEEE Trans. Energy Conversion, vol. 14, pp. 1300–1305, Dec. 1999.
10. D. G. Dorrell, W. T. Thomson, and S. Roach, "Analysis of airgap flux, current, and vibration signals as a function of the combination of static and dynamic airgap eccentricity in three-phase induction motors," IEEE Trans. Ind. Applicat., vol. 33, pp. 24–34, Jan./Feb. 1997.
11. R. F. Walliser and C. F. Landy, "Assessment of interbar currents in double-cage induction motors with broken bars," IEEE Trans. Energy Conversion, vol. 9, pp. 159–164, Mar. 1994.
12. W. T. Thomson and A. Barbour, "On-line current monitoring and application of a finite element method to predict the level of airgap eccentricity in

three-phase induction motors," IEEE Trans. Energy Conversion, vol. 13, pp. 347–357, Dec. 1998.

13. Jose de Jesus Rangel-Magdaleno and Rene de Jesus Romero-Troncoso,"Novel methodology for online half-broken-bar detection on industrial motors." IEEE Trans. on Instru. & Meas., Vol.58, pp. 1690-1698, May 2009.
14. B. Ayhan, M. Chow, and M. Song, "Multiple signature processing-based fault detection schemes for broken rotor bar in induction motors," IEEE Trans. Energy Convers., vol. 20, no. 2, pp. 336–343, Jun. 2005.
15. M. El Hachemi Benbouzid, "A review of induction motors signature analysis as medium for faults detection," IEEE Trans. Ind. Electron., vol. 47, no. 5, pp. 984–992, Oct. 2000.
16. F. Ponci, A. Monti, L. Cristaldi, and M. Lazzaroni, "Diagnostic of faulty induction motor drive via wavelet decomposition," IEEE Trans. Instrum. Meas., vol. 56, no. 6, pp. 2606–2615, Dec. 2007.
17. A. Ordaz-Moreno, R. J. Romero-Troncoso, J. A. Vite-Frias, J. R. Rivera-Guillen, and A. Garcia-Perez, "Automatic online diagnosis algorithm for broken-bar detection on induction motors based on discrete wavelet transform for FPGA implementation," IEEE Trans. Ind. Electron., vol. 55, no. 5, pp. 2193–2202, May 2008.
18. G. B. Kliman et al., "Non-invasive detection of broken rotor bars in operating induction motors," IEEE Trans. Energy Convers., vol. EC-3, no. 4, pp. 873–879, Dec. 1988.
19. F. Filipetti et al., "AI techniques in induction machines diagnosis include the speed rifle effect," in Proc. IEEE Industry Applications Society Annu. Meet. Conf., San Diego, CA, Oct. 6–10, pp. 655–662, Apr. 1996.
20. R. Puche-Panadero and M. Pineda-Sanchez,"Improved resolution of the MCSA method via Hilbert transform, enabling the diagnosis of rotor asymmetrics at very low slip", IEEE Trans. on Energy Conversion, vol. 24, pp.52-59, March 2009.
21. Mohamed EI Hachemi Benbouzid," A review of induction motors signature analysis as a mrdium for faults detection", IEEE Trans. on Industrial Electro., vol.47, pp. 984-993, Oct. 2000.
22. Jose de Jesus Rangel-Magdaleno and Hayde Peregrina-Barreto, "FPGA- based broken bar detection on induction motors under different load using motor current signature analysis and mathematical morphology", IEEE Trans. on Instru. And Meas. vol. 63, pp.1032-1040, May 2014.