SECOND GENERATION WAVELET TRANSFORM FOR INCIPIENT FAULT DETECTION IN DOUBLE CAGE INDUCTION MOTORS

Firas Ben Abid   Ahmed Braham
MMA Laboratory, INSAT, TUNISIA
firas.bn.abid@gmail.com, ahmed.braham@insat.rnu.tn

Abstract: *An increasing demand of availability improvement of industrial processes has been expressed in the last decades. Therefore, the fault detection and diagnosis has become considered indispensable to ensure high performances of the plant operation. Induction motors have dominated among all industrial drives. Their Condition Monitoring (CM) has therefore become critical. Despite their recurrent use, the CM of double cage induction motors (DC-IM) has not received sufficient research focus. This paper is inspired from the advanced signal processing techniques in order to diagnose one of the critical and most hardly detected faults in DC-IM. Actually, the challenge in DC-IM is the detection of the outer cage's bar fault at an early stage. This study proposes a novel solution of this issue based on the Information Entropy of the Second Generation Wavelet Transform (SGWT). Using the Motor Current Signature Analysis, several rotor conditions including the incipient outer cage's bar fault are analyzed under different severities and variable load levels. The results concluded by the experiments demonstrate the competence of this approach.*

Key words: *Broken Rotor Bar; Condition Monitoring; Double Cage Induction Motor; Lifting Scheme, Motor Current Signature Analysis; Second Generation Wavelet Transform.*

1. Introduction

Because of its robustness and cost-effectiveness, Induction Motors (IM) lead all industrial rotating machines. Practically 85% of the electric energy is consumed by IM [1]. Nevertheless, several types of defects could affect them. The IM breakdown may lead to the production line's halt. Their Condition Monitoring (CM) has therefore become a key issue. Most of CM works concentrate on the detection of air gap eccentricities, bearing defects, rotor defects, and short-circuits in stator in single cage IM [2]-[6]. The rotor faults, specifically the broken rotor bar (BRB) fault, are classified as the less occurring defects [5], [6]. However, the destructive consequences on the other parts of the IM make the detection of BRB very important, especially at an incipient stage. Different CM approaches such as vibration analysis, acoustic emission and infrared thermography were applied. However, the installation of these techniques is both difficult and expensive since the placement of sensors such as accelerometers and acoustic sensors is indispensable. MCSA is both a cost-effective alternative and a more sensitive technique to BRB fault. In fact, it does not need devices excepting those already employed to measure the principal electrical quantities. Besides, the BRB fault is an electrical fault, which is directly correlated to current variations. According to the ISO standard 20958:2013, the MCSA essentially consists in a spectral analysis performed on the motor line current in order to determine if there are signatures at specific frequencies that can indicate the presence of faulty components. However, the signatures related to the incipient faults such as incipient BRB are fundamentally weak and can therefore be buried in noise when using spectral techniques [6]. Spectro-temporal techniques were efficiently introduced to extract weak signatures. Recently, many research works have focused on the incipient BRB fault detection at an early stage using MCSA [6]-[18].

Many works carried out the half BRB detection [7]-[9]. Several frequency and time-frequency based techniques were successfully applied. Further works enhanced these techniques to be able to detect BRB faults with lesser severity levels [10]-[18]. The spectral analysis such as Fast Fourier Transform, Hilbert transform and High-Resolution Spectral Analysis was previously investigated for this purpose [14]-[16]. Although these techniques succeeded to detect incipient broken rotor bar faults, they are still suffering from the requirement of big data acquisition and they are still inappropriate for non-stationary conditions. To overcome the frequency analysis drawbacks, the time-frequency based techniques were introduced [18]. In single cage IM, the startup current was also used to extract faulty feature related to the incipient BRB fault in [16]-[18]. However, the startup current cannot be suitable for online condition monitoring. Although several techniques were successfully applied for incipient BRB in single cage IM, a lack of focus is reported when dealing with double cage IM (DC-IM) case. In several industrial applications, the DC-IM is used, especially when a high startup torque is required [19], [20]. In fact, MCSA is 10 times less sensitive to the outer cage's bar fault compared to the BRB fault in a single cage IM [19]. The wavelet transforms have shown high performances in the detection of the fault of the outer cage's bars in DC-IM [6], [18] and [19]. Daviu *et al.* [18] applied the DWT to detect the breakage of the entire outer cage's bar. Nevertheless, the proposed approach used 30.000 Samples, which is a big number of data. Another drawback is that this approach is not suitable for steady state condition. To overcome these drawbaks, Gritli *et al.* [19] applied the DWT using 9.600 Samples to detect three broken outer cage's bars of a DC-IM even in steady state. Despite the success of the detection of the outer cage's bar fault in the aforementioned works, the incipient BRB fault can relatively be considered in an advanced stage. An earlier detection should be performed. Hmida et al. [6] have recently performed another work for incipient outer cage's bar detection. The authors also used another variant of the traditional wavelet transform, namely the recursive stationary wavelet packet transform. Although the success of the wavelet-derived techniques, they are still suffering from computational intensity [21]. To overcome this drawback, the second-generation wavelet transform (SGWT) was introduced as a cost-effective alternative [22]-[25]. This alterative is faster and lesser demanding in terms of computational cost, since it performs an in-place calculation and does not require convolutions to compute the coefficients [22], [23].

The contribution of the present study is the combination of the SGWT and the information entropy in order to detect a 3 mm depth incipient outer cage's bar in a DC-IM. Other rotor faults are also diagnosed under different load levels. This approach solve this issue using only 7000 Samples and a sampling frequency of 1400 Hz.

In this regard, the paper is structured so that a brief review of conventional wavelet transforms and

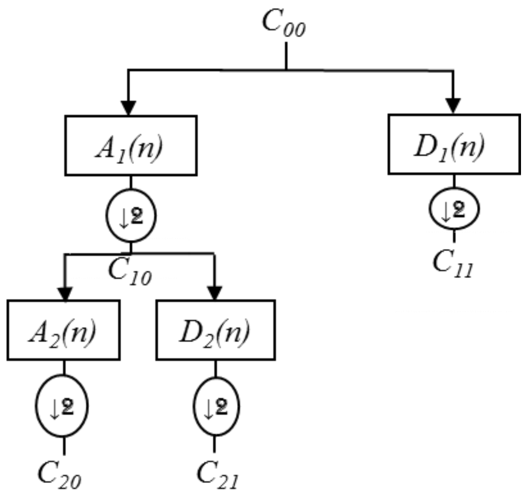

Fig. 1. DWT decomposition tree

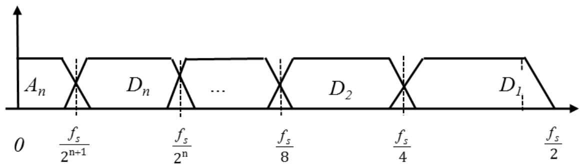

Fig. 2. Frequency domain representation of DWT

second-generation wavelet transforms is presented in Section 2. Section 3 focuses on the explanation of the effect of the rotor cage's bar fault on the stator current, whereas Section 4 addresses the fault detection algorithm proposed in this paper. An experimental study is conducted to demonstrate the effectiveness of the proposed approach as described in section 5. Finally, section 6 concludes the paper with several highlights and perspectives.

2. Wavelet transforms

2.1. Discrete wavelet transform

In the context of IM fault detection using MCSA, the stator current is not as commonly known a stationary signal. Previous studies show that frequency-based techniques are not the most appropriate for the analysis of this type of signals [26]. To overcome this disadvantage, the techniques based on the spectro-temporal transforms were introduced. Several approaches were elaborated in the literature, namely, the Short-Time Fourier Transform, the Empirical Mode Decomposition and the Hilbert-Huang transform. Similarly, the wavelet transform represents a powerful signal-processing tool for fault detection [4], [5], [6], [19] and [20]. This transform splits the signal into special functions called Wavelets [27]. By definition, a wavelet is an oscillating function of zero mean value. A wavelet is defined by:

$$\psi_{a,\tau}(t) = \frac{1}{a}\psi\left(\frac{t-\tau}{a}\right) \quad (1)$$

where a is the scale factor and τ is the translation factor. The continuous wavelet transform of a finite energy current signal C_{00} is defined by the following equation:

$$CWT_{C_{00}}(a,\tau) = \int_{-\infty}^{+\infty} C_{00}(t).\psi^{*}_{a,\tau}(t)\,dt \quad (2)$$

where Ψ^* denotes the complex conjugate of the wavelet Ψ. However, the continuous wavelet transform suffers from a very high computational time, for the simple reason that it calculates all wavelet coefficients at all levels.

Derived from the discretization of the continuous wavelet transform, Mallat developed the Discrete Wavelet Transform [27]. The application of multi-resolution analysis is the basis of the DWT. The latter consists in filtering the signal through a series of low-pass and high-pass filters. As a result, the outputs of the filtering process are Approximations (A) and Details (D) coefficients. A multi-level decomposition tree is then generated by repeating this process several times. Only the approximation coefficients are filtered similarly to each level. The decomposition structure of a two-level DWT is shown in Fig.1.

2.2. Second generation wavelet transform

The SGWT was initially developed by Sweldens [22]. The SGWT is an alternative implementation of DWT using lifting schemes. This technique allows designing wavelets without Fourier transform. The second-generation wavelets are therefore no longer constructed by translation and dilation of a fixed function. While the DWT applies a recursive filtering to the signal, the SGWT divides the signal such as a zipper. It conserves the time-frequency properties and the multi resolution characteristics of DWT. The lifting scheme, which constructs the SGWT consists of three phases: splitting, predicting and updating.

1) Splitting: is to decompose the original signal $C_{00}[n]$ into two separated sequences. The original dataset is usually split into odd and even subsets. The even subset is indexed $C_{00\,even}[n]$, while the odd one is $C_{00\,odd}[n]$.

$$C_{00\,even}[n] = X[2n] \quad (3)$$

$$C_{00\,odd}[n] = x[2n+1] \quad (4)$$

Assuming that data are similar, $C_{00\,odd}[n]$ can be predicted from $C_{00\,even}[n]$ through an independent predict operator P.

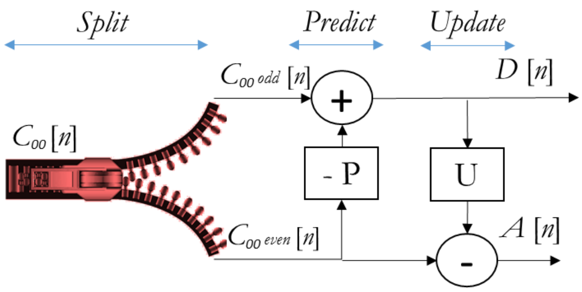

Fig. 3. Lifting steps: Split, Predict and Update

2) Predicting: Using P, $C_{00\,even}$ predicts $C_{00\,odd}$. Therefore, the difference is the detail signal D, which is expressed as:

$$D = C_{00\,odd} - P\,C_{00\,even} \quad (5)$$

3) Updating: To obtain the approximation coefficients A, the even subset $C_{00\,even}$ is combined with the details D after the application of an updating operator U on D.

$$A = C_{00\,even} + U\,D \quad (6)$$

The decomposition structure of the SGWT is depicted in Fig.3. The SGWT has several benefits compared to the classical wavelet transforms, since it is appropriate for nonlinear and adaptive design; it allows in-place calculations, integral wavelet transform and irregular samples [22], [23]. The implementation of the SGWT using Lifting schemes is therefore quicker than the classical wavelet transform. Another strength of the lifting schemes is that they do not refer to Fourier transforms to design the second-generation wavelets [22], [23].

3. Motor current spectral components for broken rotor cages

Among several condition monitoring techniques, the Motor Current Signature Analysis is used for the fault diagnosis in induction motors, [2]-[20]. This technique was originally conceived for inaccessible IMs in nuclear power plants, and recently, it has been increasingly investigated in industry applications. Several IM faults of electric or mechanic origins can modulate the motor current signal, that lead to further sideband harmonics appearence in the current spectrum. Based on the amplitudes and the frequencies of these signatures, the motor defects can be detected and classified with the assessment of their severities.

DC-IM are among the most important types of IMs. Two short-circuited squirrel cages compose the

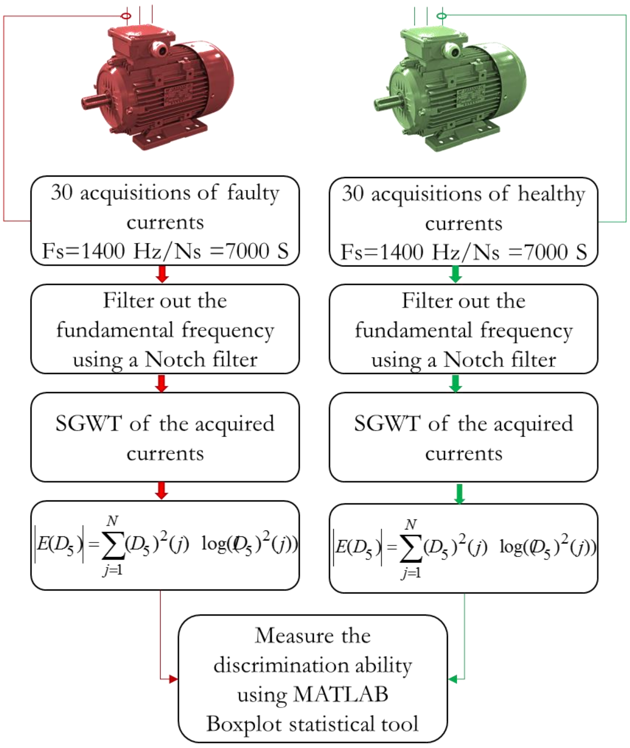

Fig. 4. Fault detection algorithm

rotor of DC-IM. In order to offer a sufficient starting torque, the construction of the outer cage is higher resistant than the inner cage construction. However, the outer cage is usually exposed to damage. The rotor bar fault initiates as slight cracks in the outer cage's bar, that gradually grow into a critical defect as a broken rotor bar [19], [20].
Once a bar is broken, it provokes the rise of current in the adjacent rotor bars, leading similarly to their breakage and can induce an inadequate starting torque. The fast and early detection of the incipient outer cage's bar (IOCB) fault of a DC-IM is therefore a key issue to prevent such process from occurring. However, it is considerably more complicated than the BRB detection in a single cage IM. Compared to the BRB fault in a single cage IM, the sensitivity of the MCSA to the IOCB fault is extremely reduced [20]. The conventional FFT-based techniques are not sufficient for the detection of IOCB defects [19], [20]. Advanced signal processing tools are needed. The rotor bar faults are commonly assessed by monitoring their related harmonics in the current spectrum given by [5]:

$$f_{BRB} = f_f\left(1 \pm 2\cdot k\cdot s\right) \qquad k = 1, 2, 3.... \quad (7)$$

where f_f *is* the fundamental supply frequency and s represents the slip value. According to (7), the current signatures obtained with k=1 are adjacent to the

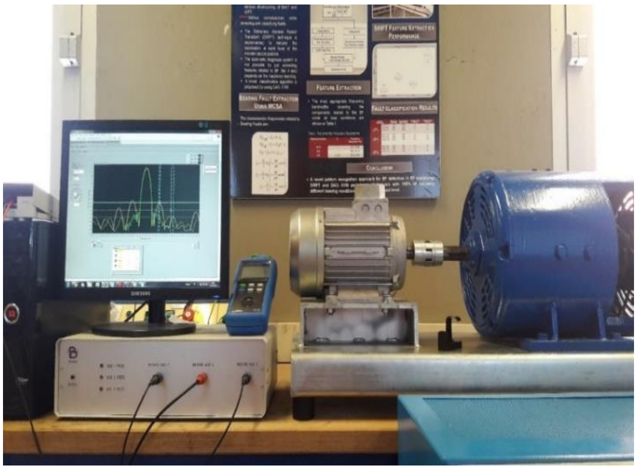

Fig. 5. Experimental setup for fault detection

Fig. 6. Incipient outer cage bar fault

fundamental frequency. These harmonics are widely used to assess the rotor bars condition. However, the fundamental frequency overwhelms the diagnosis of the BRB faults by the motor current. Filtering the fundamental frequency component is therefore indispensable. The proposed solution consists of using a notch filter, which is a band-stop filter with a narrow stop-band.

4. Fault detection algorithm

Feature extraction is the key step in fault detection. The statistical representations of signals are descriptive features of faults. Combining the statistical features with the wavelet transform is highly efficient. Features such as crest factor, Skewness, standard deviation, energy and root mean square are very suitable [28]. Information entropy is an additional efficient statistical feature. The Shannon entropy measures the uncertainty of the signals, the reason why it is a highly sensitive feature to IM faults. Wavelet entropy proved its efficiency in analyzing faulty signals [29].

The wavelet entropy is defined by the following expression:

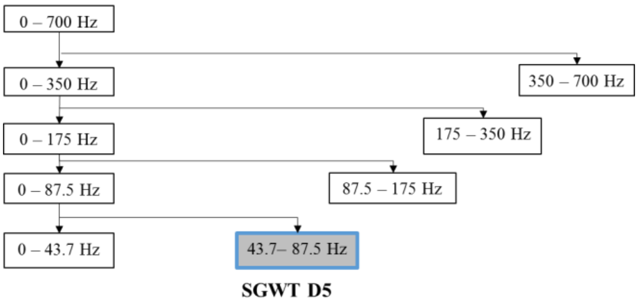

Fig. 7. SGWT decomposition tree for a sampling rate of 1392 Hz

$$\left|E(A/D)_i\right| = \sum_{j=1}^{N}((A/D)_i)^2(j)\log((A/D_i)^2(j)) \quad (8)$$

The entire fault detection algorithm is illustrated in Fig.4.

5. Results and discussions

As illustrated in Fig.5, the experiments are done through a test bed composed by a 3-kW DC-IM fed by an f_f of 50 Hz and loaded by a DC motor, which allows the motor load variation from no load to full load. The acquisition of the stator currents is allowed by Hall-effect transducers and a data acquisition card NI-PCI 6221. Three rotor faults are tested: the incipient outer cage's bar fault, the one broken bar (1BRB) and the two broken bars (2BRB) at 25%, 50%, 75%, and 100% load levels. The slip s consequently varies from 1.33% to 5.06 % and the BRB characteristic frequency varies from 47.4 to 49.3 Hz. The outer cage's bar is drilled at 3mm of depth to create the IOCB, which is illustrated by Fig.6. The piercing of the outer and inner cages' bars at a time allows the generation of the 1BRB fault. This same process is repeated in two different placements of the rotor in order to generate the 2BRB fault. The sampling frequency is selected at 1400 Hz. In order to get a frequency resolution of 0.2 Hz, every acquisition takes 5 seconds. The application of a 4^{th} order Notch filter with a center frequency of 50 Hz and a quality factor of 6 completely filters out the fundamental frequency component from the stator current spectrum, which allows to enhance the performance of the detection. Various mother wavelets such as Symmlet, Coiflet, Daubechies and Meyer perform comparable outcomes in fault detection [30]. Here in this paper, Meyer mother wavelets are selected. Five levels of SGWT decomposition allow the D5 generation, as shown in Fig. 7. The generated coefficient D5 covers the shifting of the characteristic frequency from 0% to 100% of load. The related frequency bandwidth is

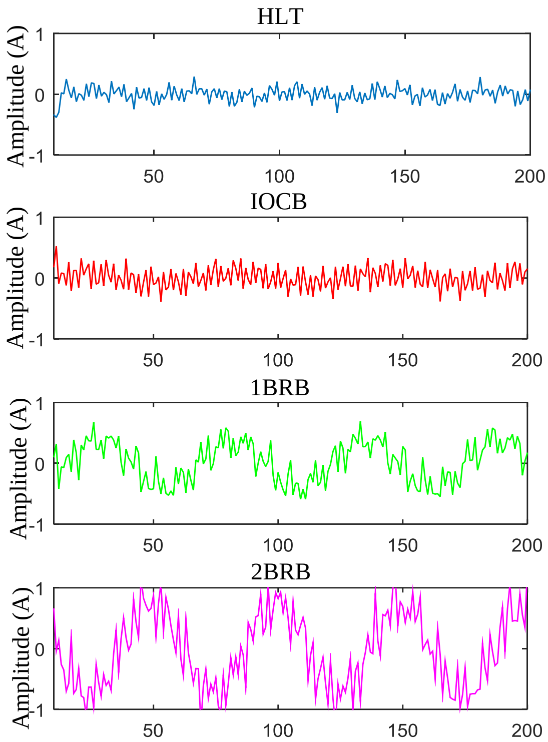

Fig. 8. D5 waveform for HLT, IOCB,1BRB, 2BRB conditions

[43.7 – 87.5 Hz]. Fig.8 shows the D5 waveform after filtering the 50 Hz frequency for healthy (HLT), IOCB, 1BRB and 2BRB motor conditions under 100% of load. It can be seen that under faulty rotor conditions, the magnitude of D5 increases correspondingly with the increase of the severity of the fault. The sensitivity of D5 to the motor and load conditions makes it a solid descriptor for BRB diagnosis. 30 current acquisitions are collected for every level of load and rotor condition with a total number of acquisitions of 480. The performances of the wavelet techniques are revealed with the analysis of variance tool (ANOVA) as shown in Fig.9. On each box, the upper and lower adjacents are respectively the maximum and the minimum entropies of the coefficient among the 30 acquisitions. The marks in the center of the boxes are the medians, while the upper and lower edges are the 25th and 75th percentiles. It can be clearly observed that the entropy median increases as long as the severity of the fault increases. It can be concluded that the SGWT coefficient is highly sensitive to rotor faults, even capable to detect the IOCB fault.

The distance e between the medians of each box indicates the ability of the differentiation between the rotor conditions. Here in these experiments, a remarkable dissimilarity between the boxes related to

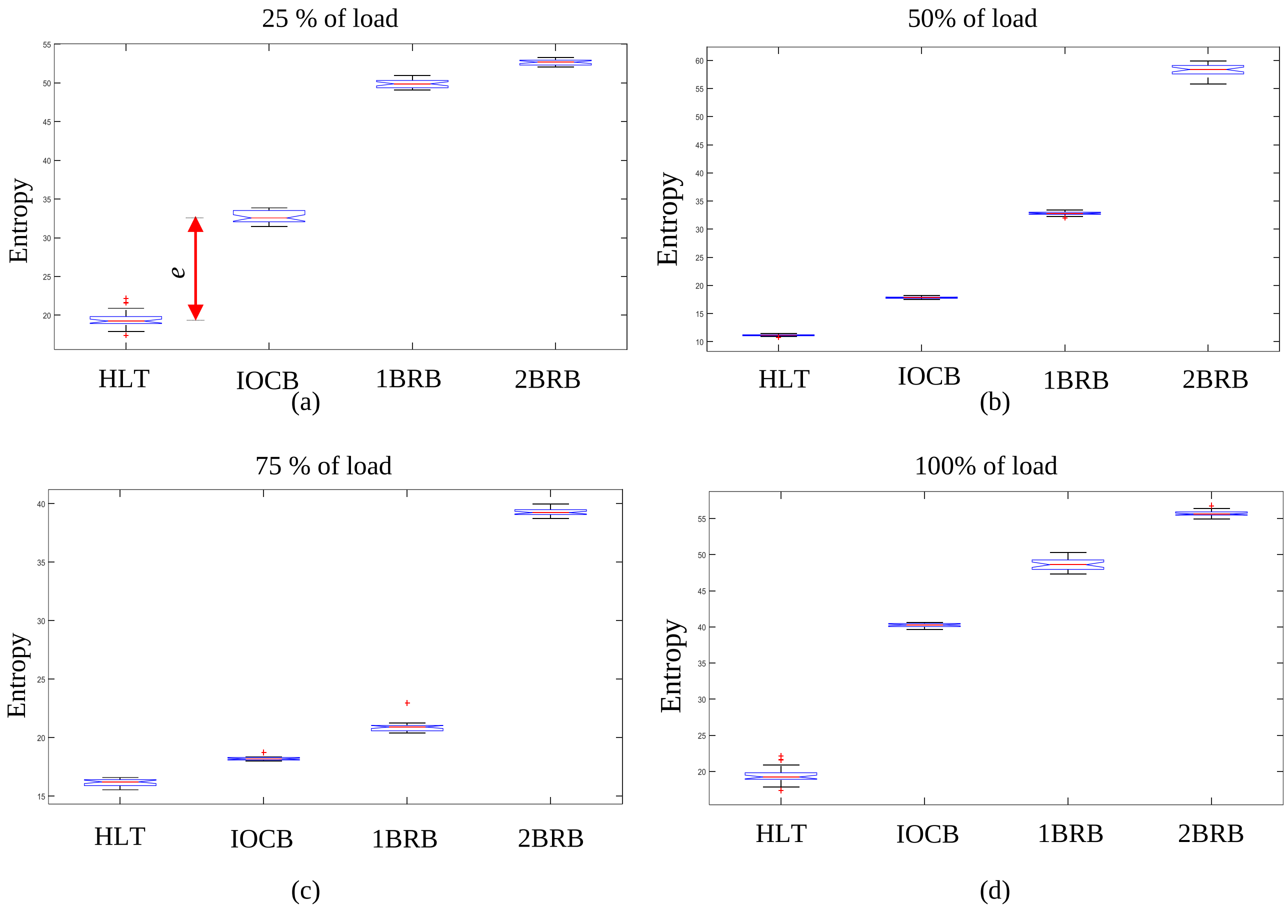

Figure 9. Distribution of D5 wavelet entropy

each rotor condition is shown, which confirms the efficiency of the SGWT coefficient in detecting and classifying the rotor faults. Using a processor Intel (R) Core™ i5 with 4 logical processors, 2 core and a CPU M430 @2.27 GHz, we compare the SGWT computing time with the DWT one. The SGWT offers a gain of 7.68 seconds in the computation of D5 for the aforementioned conditions. Actually, the reparation of the BRB faults is much simpler and more affordable as long as the detection is earlier, thus confirming the requirement of a fast algorithm, especially in case of online fault detection.

6. Conclusion

The present work proposes a new fault detection approach for incipient induction motor faults. The double cage induction motor, which is a specific commonly used type of IM, is monitored. The critical fault occurring to the DC-IM is the breakage of the outer cage's bar. As this fault could lead to an insufficient startup torque, its early detection becomes crucial. However, MCSA is lesser sensitive to this fault than the BRB in single cage IM. Therefore, the fault detection of the outer cage's bar fault requires powerful signal processing tools. The present approach consists of a combination of information entropy with second-generation wavelet transform. Several rotor conditions are tested and compared. The resulting performances show the ability of the proposed approach to design a fault descriptor, which performs a fast detection and a high sensitivity to faults, even at incipient stage. The average computing time of the SGWT is equal to 0.289s. In addition to the detection of faults, the SGWT-entropy based detection provides a possibility of discrimination between the fault severity levels. The analysis of variance ANOVA shows a notable distinction between the analyzed conditions. These contributions are reached under low data acquisition parameters and using only one fault descriptor. A promising extension of this approach is the hybridization of the SGWT-entropy with an artificial intelligence-based classifier to determine precisely the accuracy of the approach and to perform an automatic fault recognition. The performances of the SGWT-entropy are encouraging to be applied for other electrical drives fault diagnosis.

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