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FAULT DIAGNOSIS OF INDUCTION MOTORS ROTOR USING CURRENT SIGNATURE WITH DIFFERENT SIGNAL PROCESSING TECHNIQUES

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Abstract

The popularity of asynchronous machines, particularly squirrel cage machines, stems from their inexpensive production costs, resilience, and low maintenance requirements. Unfortunately, potential flaws in these devices might have a negative impact on the facility's profitability and service quality. As a result, diagnostic tools for detecting flaws in these types of devices must be developed. Asynchronous machine problems can be diagnosed using a variety of methods. Signal processing techniques based on extracting information from characteristic quantities of electrical machine operation can provide highly useful information about flaws.

The purpose of this research is to develop efficient algorithms based on numerous signal processing approaches for correctly detecting asynchronous cage machine rotor defects (rotor bar ruptures).

Keywords: asynchronous machine, rotor defect, diagnostic, signal processing, FFT, HT, WT.

1. INTRODUCTION

Operational safety is a crucial issue in many industrial sectors to ensure optimal competitiveness of the production tool in a highly competitive international environment where productivity increases are a daily worry for company leaders.

Electrical machine diagnosis has grown in popularity in the industrial world as the quest for a more secure production line has become increasingly important for particular applications. Any failure, even a tiny fault, might result in irreversible material or bodily damage, hence production lines must be fitted with a reliable protective mechanism. For decades, researchers have been attempting to improve diagnostic methods around the world in order to avoid these issues. This topic's main goal is to alert users to a potential risk that may develop at a specific point in the system [1].

Because of the simplicity of the sensor used(accelerometer or current sensor) and the fact that this current can be measured without halting the machine and without access to the stator's body, spectral analysis of stator current is a commonly used approach for monitoring and diagnosing defects [3].

The goal of this topic is to run a simulation to detect rotor defect signatures using spectral analysis of the stator current and signal processing techniques.

2. SIGNAL PROCESSING METHODS

We are obliged to use signal processing techniques since temporal patterns do not provide much information.

For a long time, numerous signal processing techniques have been employed to examine the spectral content of various signals generated by electrical devices, such as currents, powers, torque, speed, flow, vibrations, and so on. We will briefly discuss innovative techniques such as the Hilbert transform and Fourier transforms, fast Fourier transforms (FFT), and the wavelet transform (WT), ESPRIT, MUSIC in the sections that follow.

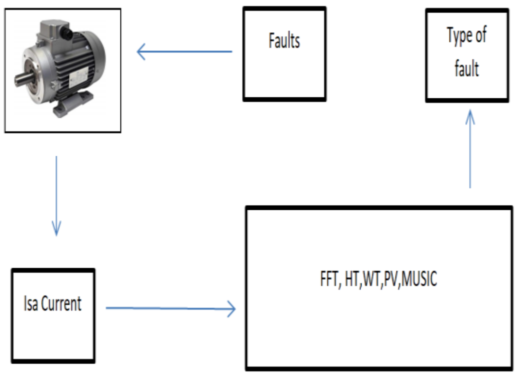

Fig. 1. Schematic representation to detect a rupture of the rotor bars using signal processing

3. SPECTRAL ANALYSIS

For many years, spectral analysis has been used to detect defects in electrical machines, primarily breakage in the rotor bars of asynchronous machines, bearing degradation, eccentricities, and winding short circuits. Insofar as many processes result in the appearance of frequencies directly connected to the speed of rotation or multiples of the supply frequency, these cases lend themselves nicely to this technique.

The asynchronous machine's spectral analysis monitoring comprises of doing a Fourier transform of the values affected by the defect and viewing the parasitic frequencies that make up the machine's signature. Electrical or mechanical magnitudes (courant,electromagnetic torque, speed,vibration,) are used. Because it only requires a simple current or vibration sensor, this technology enables for quick and low-cost monitoring [3].

3.1. Fast Fourier Transform (FFT)

In asynchronous machines, the Fast Fourier Transform (FFT) is a popular technique for fault detection. It performs well in high-power or constant-torque tasks, but struggles in operations with varying load torque, rotating speed, or supply voltages. As a result, non-stationary signals necessitate the development of new signal processing algorithms [4].

Consider the signal X (t) is a continuous time. If X is at finite energy, its Fourier transform at frequency f is as follows:

$$X(f) = \int_{-\infty}^{+\infty} x(t)e^{-2\pi f}dt \qquad (1)$$

Its inverse is given by:

$$x(t) = \int_{-\infty}^{+\infty} X(f)e^{-2\pi f}df \qquad (2)$$

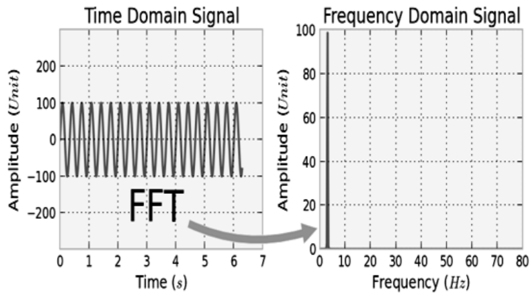

Fig. 2. Time to frequency domain representation

3.2. Wavelet transform

The wavelet transform is a recent signal processing tool. Its principle is based on the decomposition of a signal in a database of particular functions. From this point of view, it is quite comparable to Fourier analysis. However, wavelets are oscillating functions in the broad sense, quickly damped, unlike the sinusoidal functions of Fourier analysis. In addition, wavelets have the property of being able to be well localized in time or frequency, which mainly differentiates them from classical time-frequency analysis.

The family C (s, u) wavelet coefficients that depend on the two parameters s and u, where s is the scale and u is the position factor to be studied, make up the wavelet transform of a signal f. The parameters (s, u) can be employed continuously (CWT) or discretely (DFT) depending on the needs of the signal analysis (DWT). The continuous wavelet transform, which requires that the values of the parameters (s, u) remain constant, is used to analyse the shape of the signal (approximation), whereas the discrete wavelet transform, which relies heavily on the complementarity of the two filters (high pass and low pass), is used to extract information characterizing the signal's fast transitions [16, 22].

3.3. Park vector analysis

The phenomenon of three-phase asynchronous motors can be described using a two-dimensional model. The calculation of so-called Park currents is one of the most well-known and appropriate methods. The Park currents id (t) and iq (t) may be determined using the following two relationships based on the phase currents isa (t), isb (t), and isc (t):

$$i_d(t) = \sqrt{\frac{3}{2}} i_{sa}(t) - \frac{1}{\sqrt{6}} i_{sb}(t) - \frac{1}{\sqrt{6}} i_{sc}(t) \qquad (3)$$

$$i_q(t) = \frac{1}{\sqrt{2}} i_{sb}(t) - \frac{1}{\sqrt{2}} i_{sc}(t) \qquad (4)$$

It is an effective method for the diagnosis of Asynchronous Machine faults.

3.4. Hilbert transform

The Hilbert transform is a diagnostic method based on the calculation of the analytical signal phase obtained by a Hilbert transform of the spectral amplitude of the current absorbed by the induction machine. In other words, instead of working directly on stator current (time signal), we propose to work with the modulus of its Fourier transform, the Hilbert transform of a signal returns a representation of this signal in the same domain. Thus, if we apply the Hilbert transform of the modulus of the Fourier transform of the stator current, then the resulting signal will be expressed in the frequency domain[12].

In other words, rather than working directly on the stator current (time signal), we suggest working with the modulus of its Fourier transform. As previously mentioned, the Hilbert transform of a signal returns a representation of that signal in the same domain [4].

4. HIGH RESOLUTION METHODS

4.1. Multiple Signal Classification (MUSIC)

The noise at the least eigenvalue of the noise variance is associated with the multiple signal classification method (MUSIC), which allows for low signal-to-noise frequency component estimation and frequency estimation is based on the orthogonality of the signal vectors to the noise eigenvectors [13].

4.2. Estimation of Signal Parameters by Rotational Invariance Techniques (ESPRIT)

There is a description of a method for estimating signal parameters in general. Instead of using a typical least squares criterion, the algorithm uses a total least squares criterion. ESPRIT can be applied to a wide range of applications, including the precise detection and estimation of sinusoids in noise, despite being described in the context of calculating direction of arrival. It exploits an underlying rotational invariance among signal subspaces induced by an array of sensors with a translational invariance structure. The technique, when applicable, manifests significant performance and computational advantages over previous algorithms such as MUSIC [14].

5. ASYNCHRONOUS MACHINE ROTOR FAULT MODEL

The ability to simulate errors is the primary motivation for developing a model in the context of diagnostics. [20] Baghli et al. offer a multi-mesh modeling of the rotor of an asynchronous squirrel cage machine that takes into account the electrical properties of the bars and ring. The disadvantage of these models, aside from their complexity, is that they necessitate a thorough understanding of the machine's electrical properties. Because of the large number of factors that govern these models when using a parametric approach, they are ineffective.

However, in our scenario, it is vital to try to construct a rotor defect model that describes the imbalance with the fewest possible parameters. These parameters must be a representation of the machine's issue, allowing it to be quantified and located.

Figure 3 illustrates the conventional modelling of the rotor by elementary dipoles with a broken bar [16, 18, 19, 21].

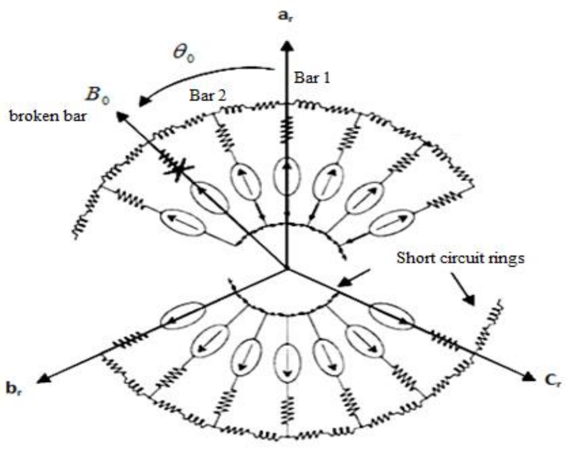

Fig. 3. Model by elementary dipoles of the faulty rotor

5.1. Modelling of the induction motor in the presence of broken rotor bars

Baghli, [9] Saddam et al [22], Khodja[27] and Ameid et al[27]presented a special model, namely, a "reduced model" of three-phase which allows the simulation of the induction machine in healthy or faulty state.

(BRB) Broken Rotor Barsfault the rotor cage is made up of Nr bars, which are a series of interconnected meshes produced by two adjacent bars and two end rings segment segments that connect them. Figure 1 depicts the rotor cage, with Ir denoting the rotor-loop current, Ib denoting the rotor-bar current for i=1, 2, 3,... and Nr and Ie denoting the end ring currents.

In Park's axis (dq), the rotor defective model is defined as:

$$\begin{cases} \dot{X}(t) = A(t)X(t) + Bu(t) \\ Y(t) = CX(t) + Du(t) \end{cases} (5)$$

Where

$$X = \left[i_{ds} i_{qr} \varphi_{ds} \varphi_{dr}\right]^{t}, u = \left[U_{ds} U_{dr}\right]^{t} \text{ et } Y = \left[i_{ds} i_{qr}\right]^{t}$$

$$A(\omega) = \begin{bmatrix} -([R_s] + [R_{eq}])L_f^{-1} - \omega P\left(\frac{\pi}{2}\right) & (([R_{eq}]L_m^{-1}) - \omega P(\frac{\pi}{2}))L_f^{-1} \\ [R_{eq}] & -[R_{eq}]L_m^{-1} \end{bmatrix}$$

$$[R_{eq}] = [R_r]\left(1 - \frac{\alpha}{1+\alpha} Q(\theta_0)\right)$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

$$B = \begin{bmatrix} \frac{1}{L_f} & 0 \\ 0 & \frac{1}{L_f} \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$$P(\theta) = \begin{bmatrix} cos(\theta) & cos(\theta + \pi/2) \\ sin(\theta) & sin(\theta + \pi/2) \end{bmatrix}$$

6. SIMULATION RESULTS OF BROKEN ROTOR BAR FAULT

The simulation was run with the parameters of a three-phase SCIM type LS9O, LER0Y S0MER, with the number of pole pairs p = 2, the supply frequency fs = 50 Hz, the nominal speed n = 1425 [rpm], the rated power of 1.1kW, and the supply voltage of 220/380V. Table I lists all of the machine's electrical and mechanical specifications. The simulation results were produced using MATLAB/Simulink and the fourth-order Runge-Kutta method, with a time step of 1e-4s:

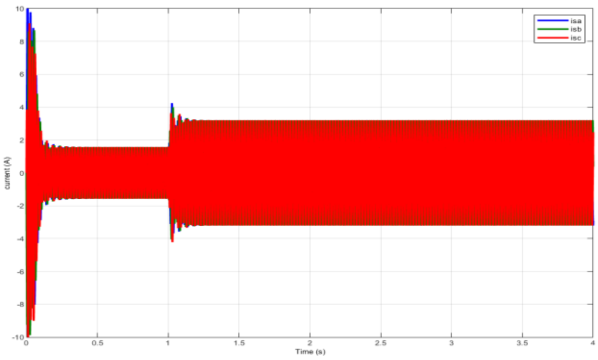

Fig. 4. Courant ISa of machine in a healthy state

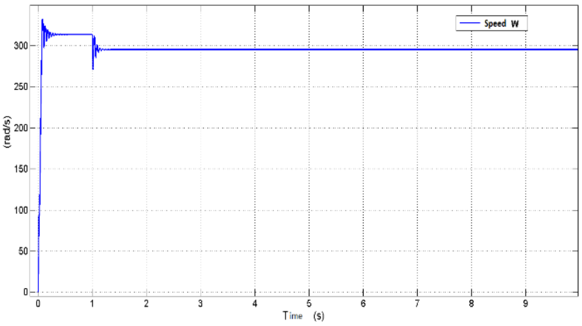

Fig. 5. Rotational speed W simulation of machine in a healthy state

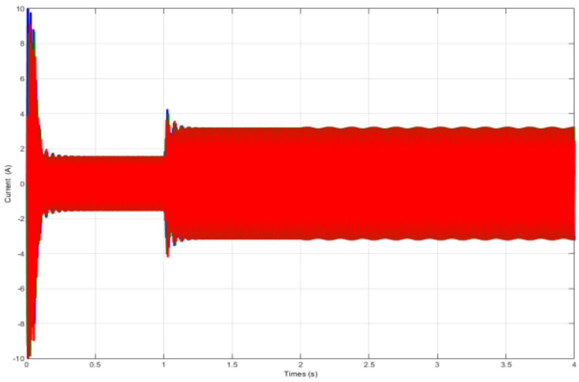

Fig. 6. Courant ISa of machine Case of one broken bars

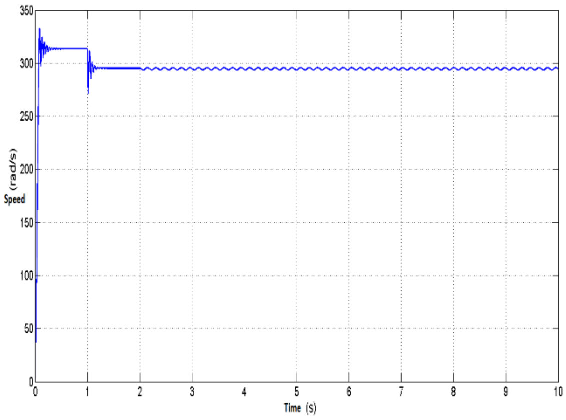

Fig. 7. Rotational speed W of machine Case of one broken bars

In healthy operation, we started the machine empty until the instant t = 1s and a resistive torque of 5 Nm. The simulation results show that at the instant t = 1 the electromagnetic torque and the stator current increase, however the speed decreases and this due to the effect of the load.

7.1. Rotor bar fault detection results based on the stator current analysis FFT

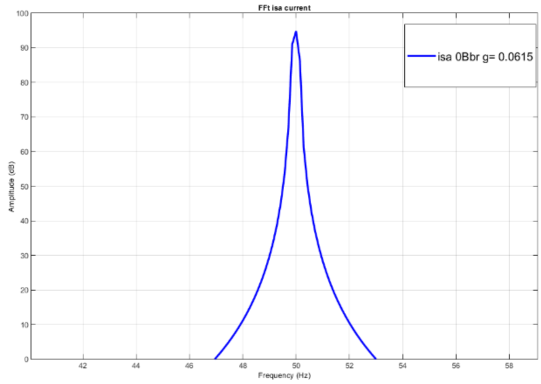

Fig. 8. Current spectrum of phase a, Healthy machine case

In healthy state of the machine, the spectral stator current does not record any lateral line around the fundamental at 50 Hz.

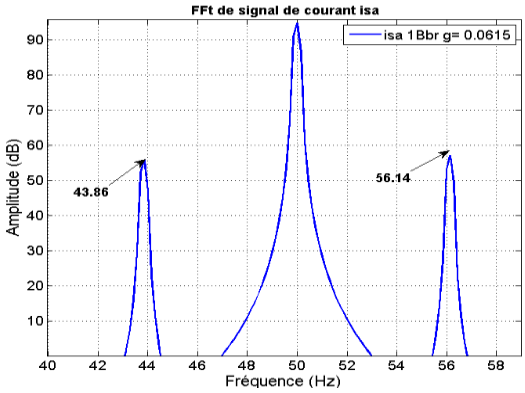

Fig. 9. Current spectrum of phase a, Case of a broken bar

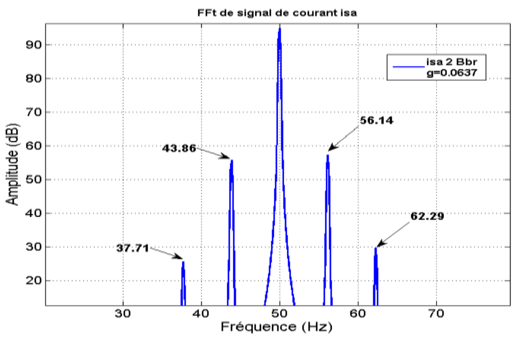

Fig. 10. Current spectrum of phase a, Case of two broken bars

However, in abnormal machine operation, a bar (figure 9) and two bars (figure 10) are broken (figure 9). The presence of lateral lines near the fundamental, which correlate to fault lines, is quite obvious. The harmonics that characterize the rotor bar breaking fault are clearly identified in figures 9 and 10. It's also worth noting that the appearance of symmetry lines around the fundamental frequency varies depending on the broken bars.

When a rotor bar breaks, an inverse rotating field of frequency fs is created in the machine's air gap. In the stator current spectrum, the interaction of this rotating field with the rotor speed produces a frequency (1-2g) s f component. The existence of this harmonic in the stator current causes an oscillation at the frequency of 2g fs at the level of the electromagnetic torque. This torque oscillation almost likely causes a rotor speed oscillation at the same frequency, resulting in a new frequency component (1 + 2g) s f in the stator current spectrum. We may also get a series of harmonics of frequencies given by.

$$f_d = f_s(1 \pm 2kg) \tag{6}$$

With: k = 1,2,3, ... number of broken bars, s f = 50Hz network frequency and g: slip.

The frequencies of the induced harmonics in the stator currents calculated following a one-bar and two-bar rotoric breaking fault are presented in the table below (Table 1). These frequencies are determined using an equation and immediately deduced using the FFT form [16].

Table 1. Amplitudes of faults in the frequency domain

Slip (g)	$f_{defect}(Hz)$	$50(1+2g)$	$50(1-2g)$
g=0.0615	$f_{calculated}(Hz)$ 1Bbr	56.15	43.85
	$f_{observed}(Hz)$ 1Bbr	56.17	43.86
g=0.0637	$f_{calculated}(Hz)$ 2Bbr	56.37	43.63
	$f_{observed}(Hz)$ 2Bbr	56.14	43.86

According to table 1, we notice that the frequencies of the lateral lines deduced from the curves of the spectral analysis correspond to the theoretical (calculated) values of these frequencies. So we may note that the fault lines of two bars are of greater value than the fault of a single bar.

7.2. Wavelet transform

The multi-level decomposition of the stator current is carried out using the function of wavelet Daubechies 44 (dp44), the necessary level of decomposition is calculated by the relation next: [23, 24].

$$N_{is} = \text{int}\left(\frac{log\left(\frac{f_e}{f_s}\right)}{log\ 2}\right) + 1 \tag{7}$$

with:

f_s : Network frequency. f_e : Sampling frequency

Knowing f_s = 50Hz, we can calculate the number of decompositions from the previous relation

$$N_{is} = \text{int}\left(\frac{log\left(\frac{10^4}{50}\right)}{log\ 2}\right) + 1 = 9 \text{ level}$$

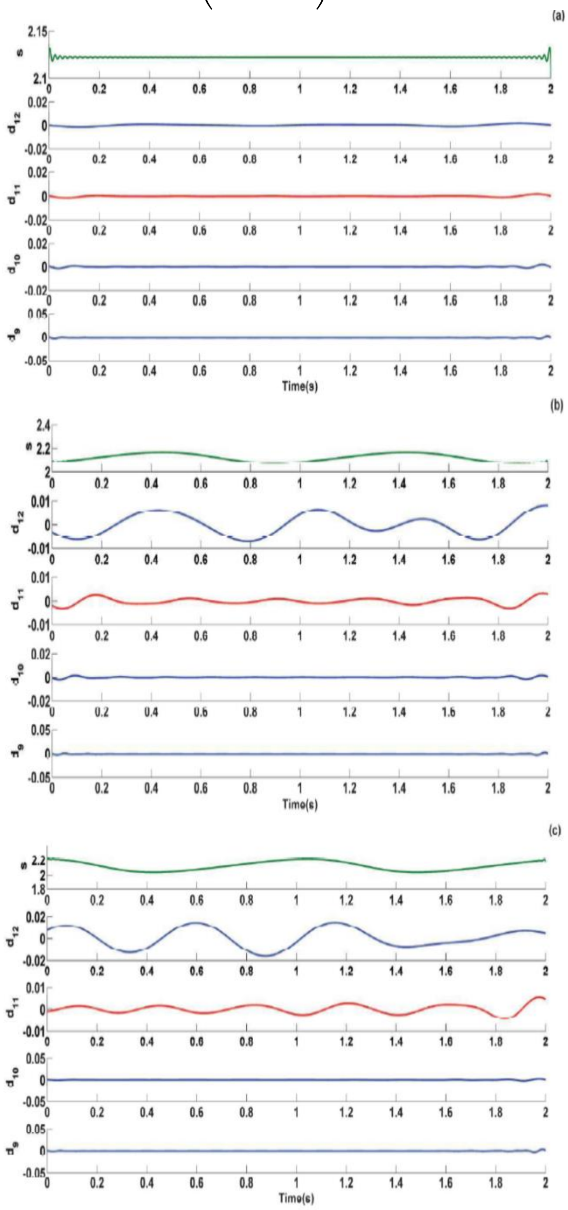

Fig. 11. Details and approximation at low load (s=1%) for (a) healthy, (b) one broken bar, (c) two broken bars

The evolution in the observed frequency bands of the relative signal to the rotor defect can be analyzed using coefficients d12, d11, and d10 to d9. Figures 11a, b, c, displayed, the DWT of Stator Current envelope, the evolution in the observed frequency bands of the relative signal to the rotor defect can be analyzed using coefficients d12, d11, and d10 to d9. When looking at the influence of the rotor defect in the bands of interest, it's clear that the energy varies depending on the type of defect. The study of the wavelet decomposed signals in Fig. 11 shows a distinctive fluctuation at the d12 level, which fits the typical pattern indicated earlier, caused by the machine defect (broken rotor bars). We could find important differences for the motor broken rotor bars since they contain the frequency components 2ksf, where give d12 all the information in the frequency band (1.22-2.44Hz). From this, it can be affirmed that the method provides information about the presence of broken rotor bars at low load and non-stationary state [23].

We see disturbances which manifest themselves in the form of oscillation at the coefficients (D9, D10, D11, D12 and S), increased in the fault state compared to the healthy case of the machine.

This increase in the signals (D9, D10, D11, D12 and S) is due to the effect that the corresponding frequency bands are affected by the different types of faults.

7.3. Park vector analysis and their module

Detection of bar defects can be easily obtained by observing the thickness of the Lissajou curve. This is possible even in the event of a single rotor bar breakage of a motor driven under load.

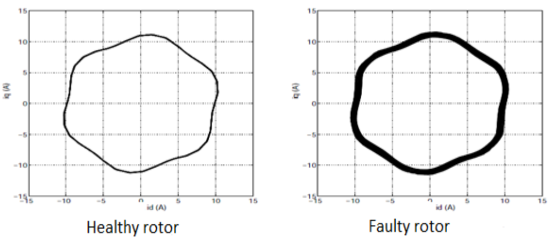

Fig. 12. Park's vector approach of the stator currents

The interest of the Park vector lies in the possibility of detecting the bar defect by the deformation of the Lissajou curve with respect to a reference, which is that obtained in the case of a healthy engine.

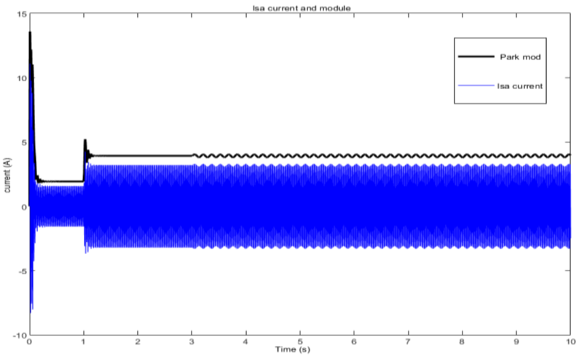

Fig. 13. The modulus of Park's vector approach and stator currents

7.4. Spectral analysis of the stator current envelope by FFT

Figure 15, 16, 17 represents the spectra of the FFT of the modulus of Park currents around the characteristic fault frequency for different cases of engine operation. We notice the presence of harmonics characterizing the breaking fault at the frequency 2kgf.

The harmonic modulus FFT characteristic of the bus bar fault appears at the frequency 2kgf. We find that the amplitude of the characteristic harmonic of the fault increases with increasing degree of fault. We can also see that the FFT of the Park envelope gives a better result than the classic FFT.

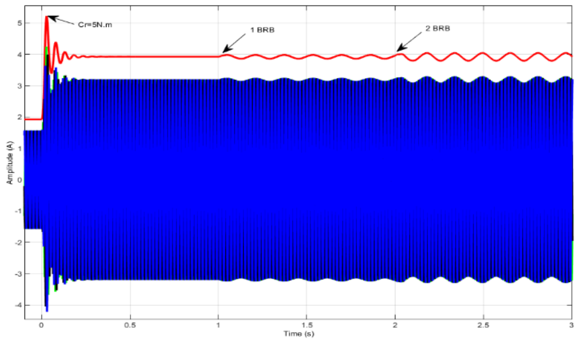

Fig. 14. Zoom of the modulus of the Park vector approach and the stator currents

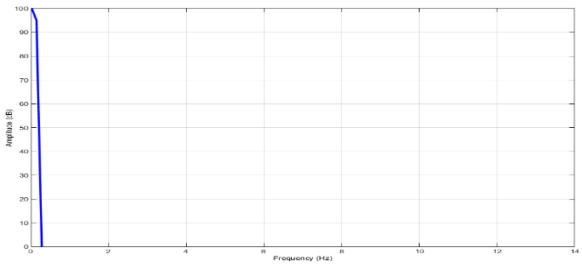

Fig. 15. Park envelope FFT for 0 broken bars

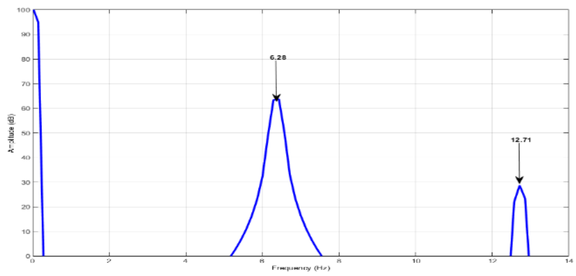

Fig. 16. Park envelope FFT for 1 broken bar

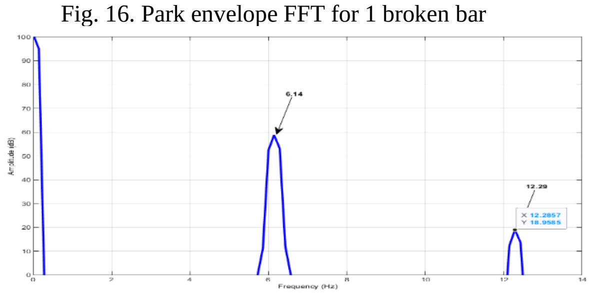

Fig. 17. Park envelope FFT for 2 broken bars

7.5. Hilbert transform

Using the signal analysis accessible from the machine, the spectral analysis of the stator current envelope makes it possible to determine the healthy or faulty state of the operation of the machine.

Its principle is based on the use of the Hilbert transform which is a technique best known in the field of signal processing [22, 23, 25].

The calculation of the modulus of y(t) gives the envelope of the signal y (t) and the calculation of its phase gives us its phase modulation as well as its frequency modulation as a function of time. We present in figure 18 the stator current and its envelope for a fracture fault of one and two rotor bars.

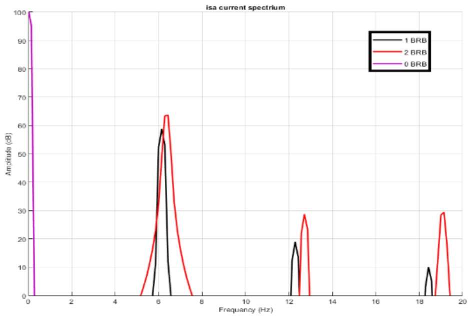

Fig. 18. FFT of the Hilbert envelope

7.4. Multiple Signal Classification (MUSIC)

In this section, we are interested in using the MUSIC method to diagnose rotor defect. The results obtained by this technique are illustrated in Fig. 19.

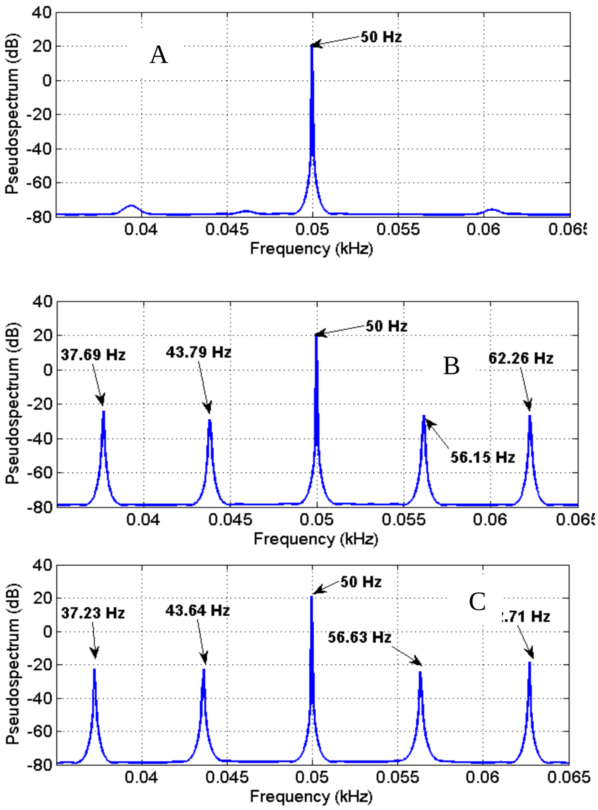

Fig. 19. Music of the current isa for 0, 1 and 2 broken bars

In healthy operation of the machine, no line is observed over the frequency range (35-65 Hz) figure 19a.

The figures 19b,c show the spectrum of the stator current for a fault of one bar and two broken bars

8. CONCLUSION

This work has been devoted to the diagnosis of rotor bar breakage faults using five signal processing techniques.

The classic FFT method has led us to good results but after an unreasonable simulation time.

Park's vector approach provides a good result without having the FFT of its envelope. In addition, the Park envelope FFT and the Hilbert transform have excellent results compared to the classical FFT.

Although the MUSIC method has certain advantages, however, the latter has two major drawbacks based on the definition of its parameters and the computation time consumed.

The drawback of classical FFT, Hilbert transform, Park vector and MUSIC methods is that these methods must be applied in a steady state, because these methods require the signals with frequency components which do not vary over time.

In contrast, the discrete wavelet technique shows its remarkable efficiency in diagnosing rotor faults with reduced simulation time. The others can be used in non-stationary mode. [26]

The possible development of this study, for the implementation in real time of the elaborate surveillance system, opens up some perspectives which seem interesting to us. Extend the application of these methods to detect and identify the various faults that may appear in asynchronous machines (stator fault, eccentricity, and bearing). By considering other more recent diagnostic approaches (shape knowledge, neural networks, neuro-fuzzy networks, etc.), also we can make current sensors fault detection and tolerant control strategy for other three-phase induction motor.

Machine settings

Rs=3.83[Ω] Strength of a stator phase
Rr=9.81 [Ω] Strength of a stator phase
P=2 Number of pole pairs
J=0.002 [Kg.m2] Moment of inertia
Nr=28 Number of rotor bars
Ns=464 Number of turns
Ls=0.436 [H] Leakage inductance of a statorphase
Lr=0.762 [H] Leakage inductance of a statorphase
Un: 220/400 [V] Nominal voltage
In: 4,3/2,6 [A]. Rated current
Nr=1425 [rpm]. Rated speed
Pn=1.1 [kW]. Nominal power
Cn= 7 [N.m] Rated torque

Author contributions: *research concept and design, D.R.; Collection and/or assembly of data, G.A.; Data analysis and interpretation, G.A.; Writing the article, G.A.; Critical revision of the article, G.A; Final approval of the article, B.S.A.*

Declaration of competing interest: *The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.*

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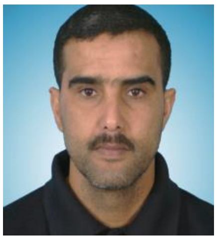

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