A new approach to diagnose induction motor defects based on the combination of the TSA method and MCSA technique

Nabil NGOTE[(1)], Saïd GUEDIRA[(1)], Mohamed CHERKAOUI[(2)]
[(1)] Laboratoire CPS2I (Commande, Protection et Surveillance des Installations Industrielles)
Ecole Nationale de l'Industrie Minérale (ENIM)
BP 753, Agdal, Rabat
MAROC
[(2)] Equipe de Recherche en Machines Electriques
Ecole Mohammadia d'Ingénieurs (EMI)
BP 765, Agdal, Rabat
MAROC
ngotenabil@gmail.com , guedirasaïd@gmail.com, cherkaoui@emi.ac.ma

Abstract: - In this article, we are trying to exploit the cyclostationary characteristics of electrical signals in order to detect the rotor faults of an asynchronous machine. These defects are the most complex in terms of detection since they interact with the 50 Hz carrier with a weak band occupied in frequency. The test bench used includes an industrial three-phase wound rotor asynchronous motor of 400V, 6.2A, 50Hz, 3kW, 1385rpm characteristics (Fig. 15). The rotor fault has been carried out by adding an extra 40mΩ resistance on one of the rotor phases (i.e. 10% of the rotor resistance value per phase, R_r=0,4Ω). From the stator voltage and current acquisition, and by application of the Time Synchronous Averaging (TSA) method to the stator current, we condition the electrical signal in order to obtain a sensitive indicator allowing to easily distinguish the healthy cases from defective ones; this indicator will allow the motor monitoring. In a second step, we will apply the Motor Current Signature Analysis (MCSA) technique to the stator current, in order to identify the type of the detected fault. This will allow to go further and diagnose the motor defect.

Key-Words: Cyclostationarity; Time Synchronous Averaging (TSA); Monitoring; Rotor fault; Spectral analysis; Motor Current Signature Analysis (MCSA)

1. Introduction

The electrical drives using asynchronous machines are very common within industrial applications due to their low costs, high performance and robustness. However, there are various reasons, related to the stator or rotor, which can sometimes affect the well-functioning of these machines [1] [2] and [3]. The appearance of a fault in the drive modifies its operation and affects its performance. There are mainly two approaches for the monitoring of the electrical-drive system: the mechanic's, based on the vibration, speed and torque measures, and the electro-technician's, based on the current and voltage measures.

A simple comparison between the stator current RMS in the healthy and defective modes of the no-load machine does not allow us to detect the failure (the variation is about 1% only). The stator current RMS cannot thus be used as a sensitive rotor defect indicator. A preliminary conditioning of this indicator will precisely make it possible to exploit the stator current cyclostationarity. By application of the TSA method [8] and [9], we obtain by subtraction the residue related to the machine mechanics. After conditioning, the new energy indicator will allow the easy distinction of the healthy and defective cases (the variation of the indicator value being clearly higher) [15].

We'll also present an approach combining the TSA (Time Synchronous Averaging) and the MCSA (Motor Current Signal Analysis) methods in order to identify the induction motor faults detected by the energy indicator.

Indeed, the current signal presents a non-stationary behavior related to the machine operating process and the electrical phase fluctuations [4]. Very little work has been done to exploit the electrical-signal cyclostationary characteristics [4], and it seems interesting to adapt these signal treatment tools to the electrical signal case. We are particularly interested in the rotor failures. Those generally lead to an increase of a one-phase rotor resistance value [1] [2] [5] [6] and [7]. Therefore, we have created a rotor defect by adding a 10% value extra resistance on one phase of the rotor, and acquired the stator voltage and current signals.

A simple comparison between the stator current spectrum in the healthy and defective modes of the no-load machine does not allow us to detect the failure (the lines of the spectra are quasi confused). A preliminary conditioning of this spectrum will precisely make it possible to exploit the stator current cyclostationarity. By application of the TSA method [8] and [9], we obtain by subtraction the residue related to the machine mechanics. After conditioning, the new spectrum will allow the easy diagnosis of the defect.

2. Motor Current Signal Analysis (MCSA)

2.1.MCSA definition

The occurrence of a fault in the drive modifies its operation and affects its performance.

The purpose of searching defect called signatures is to characterize the system operation and identify type and origin of each defect.

There are several techniques that can be used to detect induction motor defects.

The Motor Current Signal Analysis (MCSA) is one of the most popular used methods because of the following reasons. Firstly, it is noninvasive. The stator current can be detected from the terminals without breaking off the drive operating. Secondly, it can be measured online therefore makes online detection possible. Thirdly, most of the mechanical and electrical faults (such as broken rotor bars, short circuit, bearing damage and air gap eccentricity) can be detected by this method [19].

MCSA is based on the spectral decomposition of stator current through the Fast Fourier Transform FFT. In the MCSA method, the current frequency spectrum obtained and specific frequency components are analyzed. These frequencies are related to well-known machine defects. Therefore, after the stator current treatment, it is possible to conclude about the machine's condition [16], [17] & [18].

2.2.Frequencies induced by the broken bars fault

The frequencies of the signals induced by each fault are calculated as a function of some of the motor's characteristic data and operating conditions.

The characteristic frequencies of the broken bars defect are given by the following relations [1]:

$$f_{b1} = (1 - 2 \cdot s) \cdot f_s \tag{1}$$

$$f_{b2} = (1 + 2 \cdot s) \cdot f_s \tag{2}$$

Where f_s is the electrical supply frequency and s is the per unit slip.

As shown, given a motor's characteristic data, its current's samples and the value of the slip, it is possible to determine the frequencies of the signals induced by the fault.

3. Cyclostationarity

3.1.Strict-sense stationarity

Strictly speaking, it is said that a random process $\{x(t)\}$ is stationary [10] if its statistical properties are invariant by translation in time, particularly its probability density:

$$\begin{aligned} p(x_1, \dots\dots\dots, x_n; t_1, \dots\dots\dots, t_n) \\ = p(x_1, \dots\dots\dots, x_n; t_1 \\ + \tau, \dots\dots\dots, t_n + \tau) \end{aligned} \tag{3}$$

for all n, for all τ and for any vector time $\{t_i\}_{\ i=1,\dots,n}$; $\{x_i\}_{\ i=1,\dots,n}$ being a realization.

So every moment of this random process is invariant by temporal translation.

3.2.Wide-sense stationarity

Broadly speaking, a random process is stationary if:

• Its average is constant:

$$m_x(t) = m_x \tag{4}$$

• Its covariance function depends only on the temporal variation:

$$K_x(t_1, t_2) = K_x(\tau)\ where\ \tau = t_1 - t_2 \tag{5}$$

When the process is not stationary, its probability density can vary randomly. A very particular class of non-stationary signals is referred to as the cyclostationary signals. A signal is known to be cyclostationary [11] if we find periodicities in some of its statistics. Thus, each period (or cycle) of this signal could be regarded as the realization of the same random process.

3.3.Strict-sense cyclostationarity

A random process $\{x(t)\}$ is known as strict-sense cyclostationary, of T cycle, if its probability density is periodic of T period:

$$p(x_1, \dots\dots\dots, x_n; t_1, \dots\dots\dots, t_n) = p(x_1, \dots\dots\dots, x_n; t_1 + T, \dots\dots\dots, t_n + T) \quad (6)$$

3.4.First-order cyclostationarity

The basic, or first-order, cyclostationary signal is the one with a T-period moment of order 1 (or average):

$$m_x(t) = E\{x(t)\} = m_x(t+T) \quad (7)$$

$E\{x(t)\}$ is the overall statistical average (not to be confused with the temporal average). In practice, only one realization is often available, so we replace the overall average with a cycle average called **synchronous average** [4].

3.5.Second-order cyclostationarity

A second-order cyclostationary signal is a signal whose 2nd order moments are periodic. In particular, the function of autocorrelation $C_x(t,\tau)$ is a T-periodic function:

$$C_x(t,\tau) = E\{x(t)x^*(t-\tau)\} = C_x(t+T, \tau+T) \quad (8)$$

Where $x^*(t)$ is the transposed conjugate of $x(t)$.

3.6.Wide-sense cyclostationarity

Wide-sense cyclostationary signals are the signals which are both first and second order cyclostationary.

4. Signal synchronization

The asynchronous motor operating process and the electric supply fluctuations cause the non-stationary behavior of the stator current signal. Previous research [11] [12] and [13] has applied time/frequency representation techniques with an aim of identifying the signatures of the faults not in the frequential field, but in the time/frequency plan. However, there has been very little work [4] exploiting the electrical-signal cyclostationary characteristics to identify the faults which occur in an asynchronous-motor drive. The idea is to extend the application of these signal-processing tools to the case of electrical signals.

In this work, we largely exploit the first-order cyclostationarity of stator current and voltage. However, we notice a problem of cycle drift from one electric cycle to another, due to the electrical supply fluctuations. Fig. 1 represents the superposition of 1000 electric cycles acquired in a temporal way, and it clearly illustrates the shift between the 1st and the 1000th voltage signal cycle. The sampling rate taken is 25.6 kHz, so we have 512 samples per average cycle of 50Hz (25 600/50 = 512).

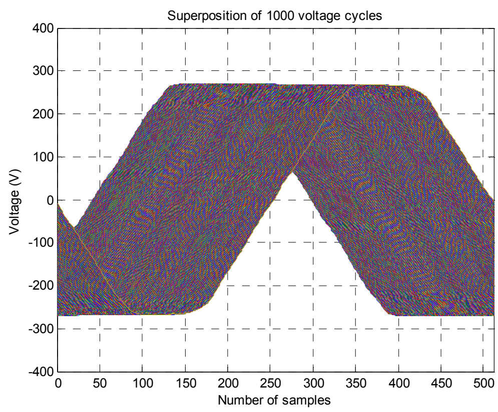

Fig. 1 – Superposition of 1000 voltage cycles

The cyclic statistic rules cannot be directly applied to these signals to extract desired information, except if we propose a way to compensate these fluctuations.

A preliminary stage is needed: we have to re-sample the current and voltage signals according to a reference which "follows" these fluctuations: it's "the synchronization of the current and voltage signal". Therefore, we develop a re-sampling algorithm which allows synchronizing the acquired signals (stator current and voltage). Synchronization is operated by compensation of the delay between the various electric cycles.

The purpose is to synchronize all electric cycles according to the same reference, so all cycles must be superimposed after the synchronization process.

To do this, voltage signal is first cut out in slices, each one corresponding to one period (20 ms), and each period containing an integer number of samples N. In our case, the sample rate is 25.6 kHz, so N = 512 samples per period (512 = 25.6kHz x 20ms). Then, by using the detection of zero crossing method, we estimate the shift between the first period, taken as a reference, and the others. We then shift each period to make it coincide with the first one (reference). If the two periods are already synchronous, the shift is then null. The obtained signal is represented in Fig. 2.

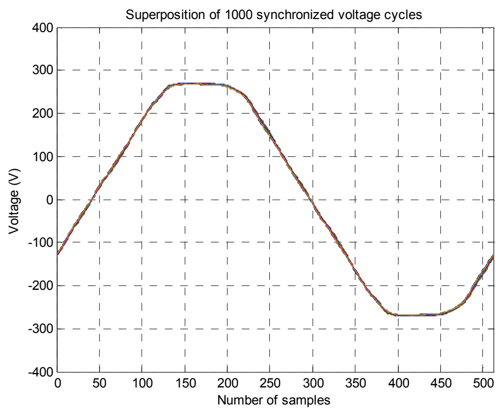

Fig. 2 – Superposition of 1000 synchronized voltage cycles

The current signal will be similarly synchronized; but by using the same voltage-shift values. Therefore, the fluctuations related to the supply frequency, which are present in the voltage signal, will be compensated. So, only the fluctuations due to mechanical will remain in the synchronized current.

Fig. 3 & Fig. 4 illustrate the superposition of 1000 stator current cycles, respectively in healthy and defective cases before synchronization.

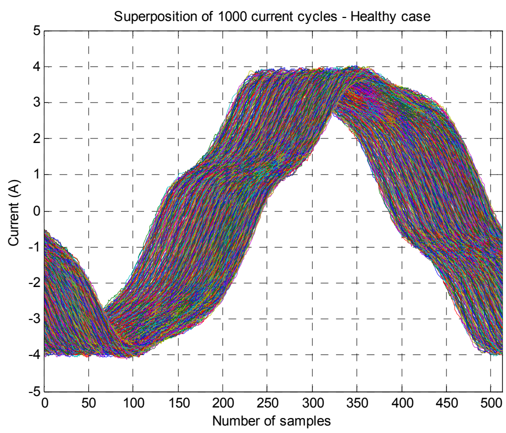

Fig. 3 – Superposition of 1000 current cycles – Healthy case (Before synchronization)

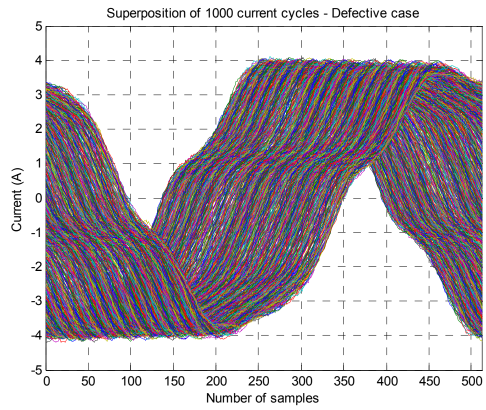

Fig. 4 – Superposition of 1000 current cycles – Defective case (Before synchronization)

Fig. 5 & Fig. 6 show the superposition of 1000 synchronized stator current cycles respectively in healthy and defective cases.

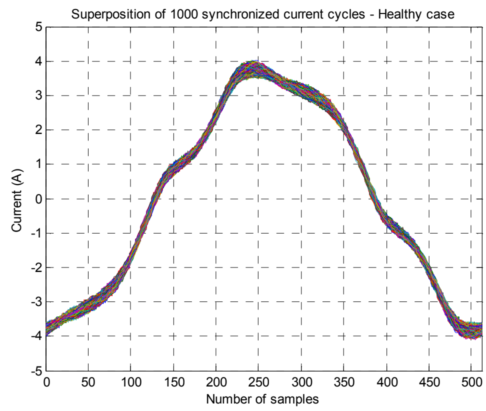

Fig. 5 – Superposition of 1000 current cycles – Healthy case (After synchronization)

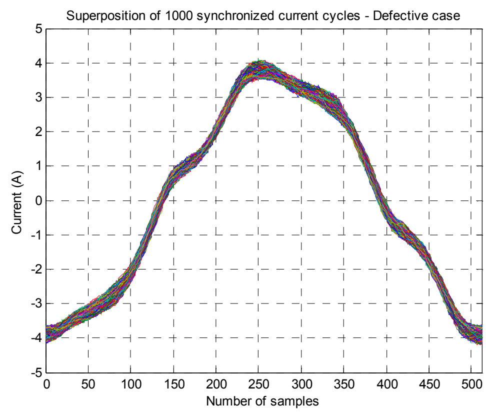

Fig. 6 – Superposition of 1000 current cycles – Defective case (After synchronization)

Once all cycles are synchronized, the signal is rebuilt by setting these cycles end to end.

Fig. 7 illustrates synchronized current in healthy (a) and faulty (b) cases.

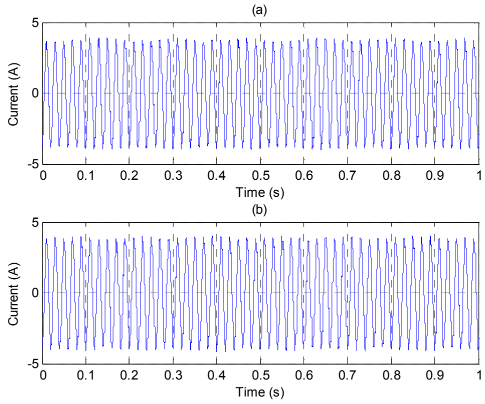

Fig. 7 – Synchronized stator current
(a) Healthy case (b) Defective case

All cycles are now synchronous and the "synchronous averaging" can be carried out.

5. Time Synchronous Averaging (TSA)

A rotor fault can be detected by highlighting a stator-current amplitude or phase modulation. However, the modulated-signal weak frequency band makes it too difficult to detect modulation. An alternative to overcome this difficulty is proposed by [8]: the Time Synchronous Averaging (TSA) method. It's a way to reshape the signal before its processing. The TSA method allows the separation between the excitation sources and, consequently, fault identification.

We can decompose the stator current $I_s(t)$ as follows:

$$\boldsymbol{I_s(t) = I_{s_h}(t) + I_{s_{mec}}(t) + n(t)} \quad (9)$$

Where $I_{s_h}(t)$, $I_{s_{mec}}(t)$ and $n(t)$ are respectively the stator-current harmonic component, the mechanical-structure-related stator current and the noise.

In fact, the asynchronous motor monitoring consists of supervising the signal harmonic part. So we have to separate between harmonic frequency (50Hz) which is related to electrical phenomena and mechanical-structure-related frequency.

For this purpose, we will apply the TSA method to the stator current. In fact, the stator current is the sum of a determinist signal $I_{s_h}(t)$ and a random signal $I_{s_{rand}}(t)$ (sum of $I_{s_{mec}}(t)$ and $n(t)$); whose average value is zero:

$$I_s(t) = I_{s_h}(t) + I_{s_{rand}}(t) \quad (10)$$

$I_{s_{rand}}(t)$ is the stator-current random component.

The synchronous averaging of N stator-current samples is done by:

$$I_{s_{avg}}^N(n \cdot T_{samp}) = \frac{1}{N}\sum_{k=1}^{k=N} I_s^k(n \cdot T_{samp}) \quad (11)$$

Where:

- $T_{samp} = \frac{1}{f_{samp}}$, where f_{samp} is the sampling rate (25.6kHz)
- I_s^k is the k[th] synchronized stator current cycle
- n is the sample row (n=1 to 512; 512=25.6k/50; 512 is the number of samples per 50Hz cycle)

For the large value of N, we have:

$$\boldsymbol{\lim_{N\to\infty} I_{s_{avg}}^N(t) = I_{s_h}(t)} \quad (12)$$

We note that only the harmonic part $I_{s_h}(t)$ corresponding to 50Hz frequency remains in the averaged signal; since the random-component average value is zero.

Thus, the synchronous averaging allows an effective separation between electrical-related and mechanical-related components.

The subtraction between the stator current $I_s(t)$ and the synchronous averaged current $I_{s_{avg}}^N(t) \approx I_{s_h}(t)$ (for the large value of N) gives the residual current $I_{s_{res}}(t) = I_{s_{rand}}(t)$ where only mechanical-related frequencies remain.

It's a very interesting property that will allow us to condition a mechanical-structure-related indicator monitoring eventual faults (such as rotor defects.)

We note that the TSA current has the same shape as the current signal. Fig. 8(a) and (b) respectively show the healthy and defective currents. We note that the Fig. 7 modulation has disappeared.

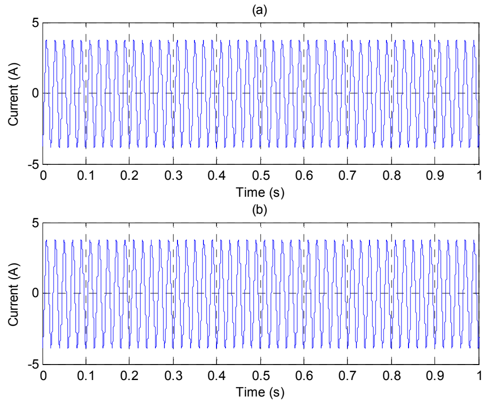

Fig. 8 – TSA stator current
(a) Healthy case (b) Defective case

We obtain the residual signal by subtraction of the TSA signal from the synchronized signal. This action reduces the electrical contribution, and, consequently, makes the extraction of mechanical-related information easier.

6. Conditioning of an indicator

We are now interested in signal conditioning for the development of an asynchronous motor monitoring indicator. We carry out two tests:

• Test n°1: No-loaded motor. This particular case allows the detection of an inherent motor fault, without load influence;

• Test n°2: Motor with a 65% nominal load.

The rotor fault has been carried out by adding an extra 40mΩ resistance (Fig. 18) on one of the rotor phases.

The current and voltage signals are acquired using a data acquisition system (Fig. 16) and the velocity is measured with an optical tachometer (analog measurement).

The simple comparison of the stator current RMS in the healthy and defective modes does not allow us to detect the failure. We define a first indicator K_1, such as the stator current RMS, according to the relation:

$$K_1 = \frac{I_{S_{RMS}}(healthy) - I_{S_{RMS}}(defective)}{I_{S_{RMS}}(healthy)} \quad (13)$$

Table 1 recapitulates the values of stator current RMS for the 2 tests:

	Stator current RMS		K_1 indicator
	Healthy case	Faulty case	
Test n°1	2.61 A	2.63 A	1.05 %
Test n°2	3.72 A	3.76 A	1.25 %

Table 1: Stator current RMS values – Healthy & Defective cases

There is too little variation of the K_1 indicator between the healthy and defective cases. It cannot be used like a sensitive indicator of rotor defect. The idea now is to compare the residual current RMS obtained after the TSA of the stator current. The residual current RMS is calculated according to the relation:

$$I_{res_{RMS}} = \sqrt{\frac{1}{N_{samp}} \sum_{n=1}^{n=N_{samp}} I_{res}^2\left(n \cdot T_{samp}\right)} \quad (14)$$

Where N_{samp} corresponds to the number of current samples ($N_{samp} = 512000$ = 512 samples per cycle x 1000 cycles).

Fig. 9 and Fig. 10 show the healthy and defective residual stator currents respectively for the 2 tests (no-loaded motor and motor with a 65% nominal load).

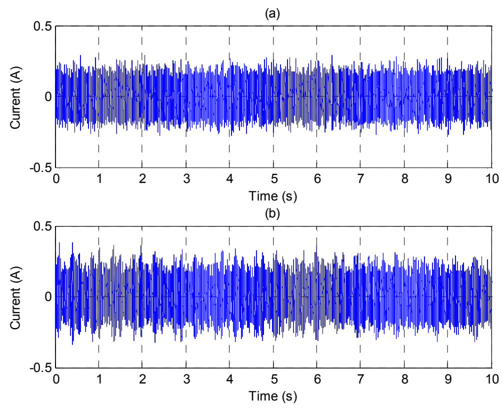

Fig. 9 – Residual stator current
(Test n°1: no-loaded motor)
(a) Healthy case (b) Defective case

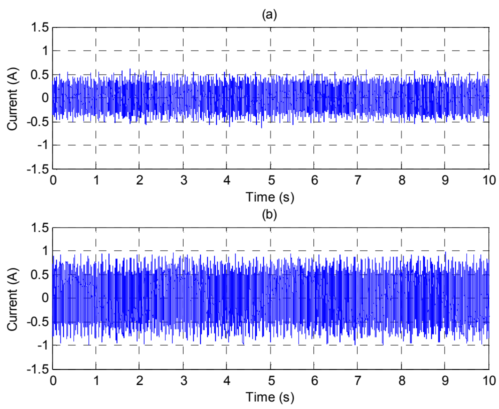

Fig. 10 – Residual stator current
(Test n°2: motor with a 65% nominal load)
(a) Healthy case (b) Defective case

We condition the electrical signal in order to obtain a second indicator K_2, obtained from the residual stator current RMS, according to the relation:

$$K_2 = \frac{I_{res_{RMS}}(healthy) - I_{res_{RMS}}(defective)}{I_{res_{RMS}}(healthy)} \quad (15)$$

Table 2 recapitulates the values for the 2 tests:

	Residual stator current RMS		K_2 indicator
	Healthy case	Faulty case	
Test n°1	0.0748 A	0.0914 A	22.07 %
Test n°2	0.1584 A	0.3858 A	143.6 %

Table 2: Residual stator current RMS values – Healthy & Defective cases

The conditioned indicator K_2, on the other hand, allows an easy distinction of the healthy and defective cases (the variation is from 22% for the no-loaded motor to nearly 144% in the case of the loaded motor).

7. Stator Current FFT analysis

The per unit slip (s) is calculated according to the relation:

$$s = \frac{n_s - n}{n_s} \quad (16)$$

Where n_s is the synchronous rotational speed and n is the rotational speed. In our case, the supply frequency value f_s is 50Hz and the number of pole pairs p is equal to 2, so $n_s = \frac{60 \cdot f_s}{p}$=1500rpm.

Table 3 summarizes the values of speed and shift for the first test (no-loaded motor):

	Healthy case	Defective case
Speed (rpm)	1469	1467
Per unit slip	2.06%	2.2%

Table 3: Measurements summary – No-loaded motor

Table 4 recapitulates the values of speed and shift for the second test (motor with 65% nominal load):

	Healthy case	Defective case
Speed (rpm)	1417	1407
Per unit slip	5.53%	6.2%

Table 4: Measurements summary – Motor with a 65% nominal load

As a first step, we apply spectral analysis to stator current.

We note that the predominance of the 50Hz component in the stator current spectrum does not allow us to detect easily the failure. Especially, in the no-loaded case, we note that the healthy-case and the faulty-case spectra are quasi combined, as shown in Fig. 11.

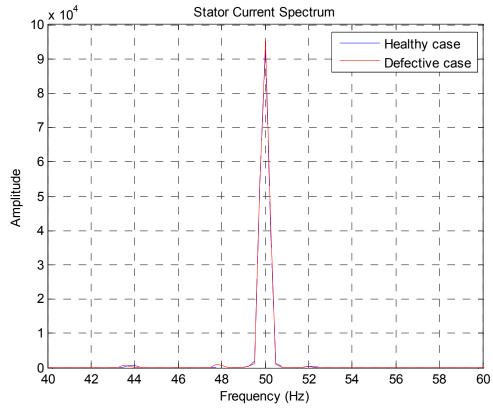

Fig. 11 – Stator current spectrum
No-loaded motor

In Fig. 12, the spectrum allows the rotor defect visualization. We note the presence of two sidebands at frequencies $f_1 = 43.75$Hz and $f_2 = 56.25$Hz; but their amplitude are very low compared to the 50 Hz line's amplitude (respectively 10 and 50 times lower).

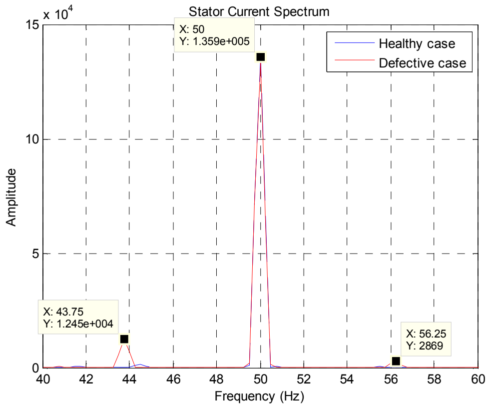

Fig. 12 – Stator current spectrum Motor with 65% nominal load

8. Residual Current FFT analysis

As seen above, the stator current spectrum does not clearly diagnose the fault, especially in the no-loaded case.

The idea is to make the residual-stator-current spectral analysis.

In the no-loaded case, the faulty residual current spectrum presents clearly two sidebands at frequencies $f_1 = 47.75\text{Hz}$ and $f_2 = 52.25\text{Hz}$ Fig. 13, while in the healthy residual current spectrum, there was no particular sideband.

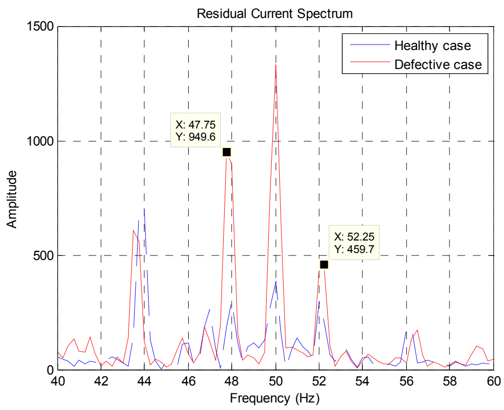

Fig. 13 – Residual current spectrum No-loaded motor

We note that the measured slip value is 2.2% (Table 3) and the electrical supply frequency value is 50Hz; so the theoretical values of f_{b1} and f_{b2} determined from the relations (1) & (2) are respectively 47.8Hz and 52.2Hz. These values correspond to the values f_1 & f_2 deduced from the spectrum Fig. 13.

Also in the case of motor loaded with a 65% nominal load, we see that the rotor fault is considerably easier to detect in the residual current spectrum (Fig. 14). Indeed, the two sidebands at frequencies $f_1 = 43.75\text{Hz}$ and $f_2 = 56.25\text{Hz}$ are more visible now. We note that the measured slip value is 6.2% (Table 4) and the electrical supply frequency value is 50Hz; so the theoretical values of f_{b1} and f_{b2} determined from the relations (1) & (2) are respectively 43.8Hz and 56.2Hz. These values correspond exactly to the values f_1 & f_2 deduced from the spectrum (Fig. 14).

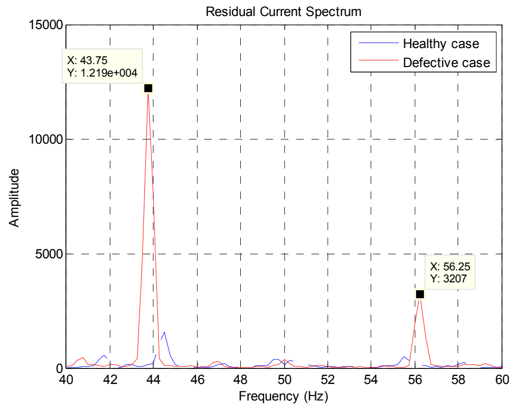

Fig. 14 – Residual current spectrum Motor with 65% nominal load

Finally, an important remark is there is quasi no sidebands in the healthy-case residual current spectrum (dotted blue curve) while they are very clear in the defective-case residual current spectrum (solid-line red curve).

9. Conclusion

In this article, the proposed method of asynchronous-motor-failure monitoring has two major advantages:

- First, it is a method which is based on the analysis of the “current” and “voltage” signals. We can therefore apply it even to the inaccessible engines (such as the engines immersed in the motor-driven pump groups), unlike the methods based on the analysis of the accelerometer signal, where we must have a direct access to the engine to be able to place the sensors there.

- Besides, the approach is relatively simple: the monitoring of the residual current RMS makes it possible to clearly detect the defective case. In fact, with a no-load engine, where the fault is hardest to detect, the K_2 indicator already shows a difference between healthy and faulty cases that exceeds 20%, to go beyond 150% for the loaded-engine case.

Finally, the combination of the TSA method and MCSA technique allows, through the residual-current spectrum analysis, an easy diagnosis of induction motor fault, even in the no-load case, where the defect is hardest to detect.

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Appendix: Test bench photos

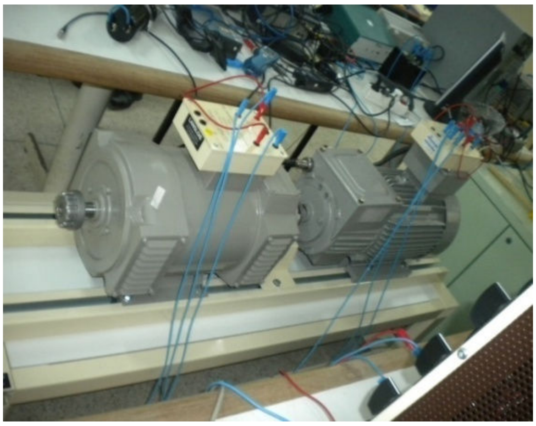

Fig. 15 - Wound rotor asynchronous motor associated to DC generator

Fig. 17 – Electrical load of the DC generator

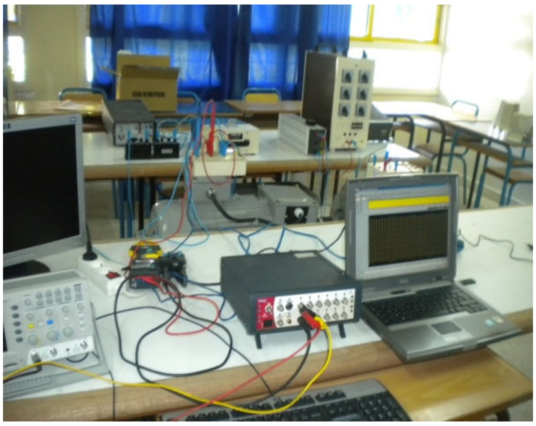

Fig. 16 – Data Acquisition System

Fig. 18 – Additional resistance (40mΩ)