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Application of Signal Processing Tools for Fault Diagnosis in Induction Motors-A Review-Part II

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ABSTRACT: The use of efficient signal processing tools (SPTs) to extract proper indices for the fault detection in induction motors (IMs) is the essential part of any fault recognition procedure. The 2nd part of this two-part paper is, in turn, divided into two parts. Part two covers the signal processing techniques which can be applied to non-stationary conditions. In this paper, all utilized SPTs for non-stationary conditions have been employed in details for fault detection in IMs. Then, their competency and their drawbacks to extract indices in the transient state modes are investigated from different aspects. The considerable experimental results are given to certify the present discussion. Different kinds of faults including eccentricity, broken bar, and bearing faults as major internal faults in IMs are investigated.

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1- Introduction

Recently different signal processing tools have been employed for a fault diagnosis of induction motors (IMs). Fourier transform is a powerful and efficient tool for detection of the most faults in IMs under stationary conditions. In order to have a good frequency spectrum and avoid spectral leakage phenomenon, Fourier transform needs the signals to be captured for a time longer than 10s. However, this can increase the risk of confrontation with external disturbances in some applications. These disturbances can distort frequency spectrum [1]. Moreover, in some applications there is not enough stationary condition at the operating times; therefore, Fourier transform is not applicable to them [2]. In order to solve this problem, Fourier transform has been extended for transient cases by considering a sliding window in which signal can be assumed to be stationary and Fourier transform can be applied on it. However, windowing requires a compromise between the time and frequency resolution. In fact, the length of the window is a parameter that should be chosen according to the required time or frequency resolution and the both are not achievable at the same time. Therefore, its resolution is limited.
In the present paper, contrary to the part I, other signal processing techniques, which are capable of handling non-stationary conditions, are studied. Different internal faults of IMs are considered as a case study for these tools.

2- Wavelet Transform

The wavelet transform is a method that converts the time domain signal to a series of wavelet coefficients in a time-scale domain. Mother wavelets are small waves with oscillating property and concentrated energy in a short interval of time which are used for implementation of this transform [3], [4]. In other words, Fourier analysis of a signal is expressed as the sum of several sinusoidal functions, but in the wavelet transform a signal is expressed as the sum of several functions that these functions are the displaced and scaled version of the main function [5]. Therefore, unlike STFT, the wavelet transform is a multi-resolution transform due to the capability to stretch or squeeze the main function. Wavelet transform is able to show some characteristics of the signal that cannot be shown by other transforms because they eliminate these characteristics during the transform. These include high slopes of the function, turning points of the function, non-continuity of high-order derivatives of the function, the sharp point of a maximum of the function and its self-similarity [3].
Considering the above-mentioned points, wavelet transform gives a detailed and fully localized view of the function. Due to the inverse relationship between scale and frequency, tracking frequency harmonics in time-scale plane is more difficult. Therefore, it is more desirous to introduce wavelet transforms as a function of time and frequency [6]. Having frequency components caused by the internal fault of the motor (which are not known as *a priori*), this transform can concentrate on particular regions and this can enhance the precision, while Fourier series provides a general view over a period of the signal [7].
Classical wavelet transform can be categorized as continuous wavelet transform (CWT), discrete wavelet transform (DWT) and wavelet packet transform (WPT). Recently the second generation of wavelet transform (SGWT) has been considered as an alternative implementation of the classical DWT.

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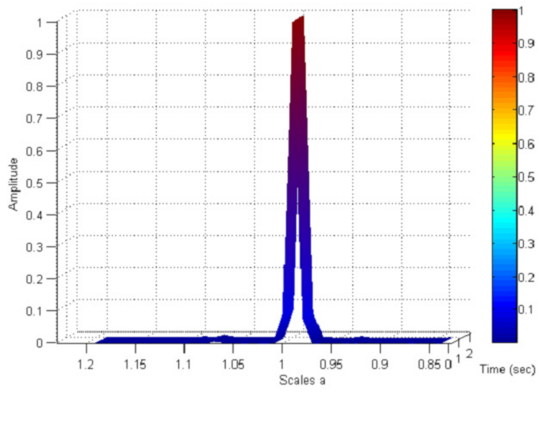
2- 1- Rotor Bars and End Ring Breakage

Axial air ducts in large induction machines are widely used for cooling purposes. However, these air ducts cause asymmetry in rotor flux patterns. In some cases, these asymmetries produce frequency components that overlap with rotor fault components in classical Machine current signature analysis (MCSA) which reduce the reliability of these methods. Under high slip operations, penetrated flux into rotor is limited; therefore, by investigating the startup currents, the influence of air ducts can be eliminated. These cases are studied in [8]. Various wavelet transforms have been ever used for fault diagnosis. Most of these methods are based on the sidebands harmonics of the frequency spectrum of the current signal. Broken rotor bars cause air gap flux density and current harmonics and this will change the wavelet spectrum of the mentioned signals. In [9], following wavelet transform on the transient current signal, energy of a bandwidth is used to diagnose the fault in which the load impact is also taken into account. Since DWT has a better clarity over the low frequencies, the use of the current spatial vector which is in harmony with lower frequencies will yield more precise results [10], [11]. To delete the fundamental harmonic for FFT, slip approximation is required in low load, and the method introduced in [9] obviates this requirement. Orthogonal wavelet in addition to its filtering structure provides useful data. In [12], a method based on CWT has been used to diagnose the fault in different drives. Fig. 1 shows a 3D CWT modulus for healthy and broken bar fault. However, there is no physical interpretation of the fault diagnosis using the figures.



(b)

Fig.1. 3D CWT module, (a) healthy, (b) broken bar fault motor [12].

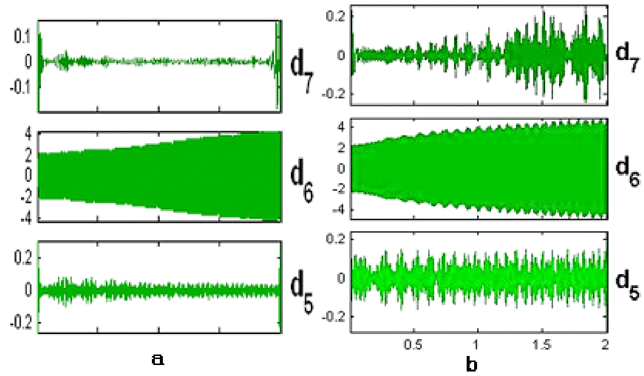


Fig. 2. Pattern of current signal wavelet transform, (a) healthy, (b) rotor broken bar motor [13].

In [13], PSD values details signal in any level of the transform is fault diagnosis criterion. Fig. 2 shows the pattern of the current signal wavelet transform of healthy and rotor broken bars motor. In [14], the reason for the application of DWT in the papers has been noted. There is not a suitable physical description for the results, complicated trend and algorithm of other wavelet methods and ambiguous results. A dimensionless parameter for the fault diagnosis has been introduced in [15]. In [14], a fault has been diagnosed using the envelope of the starting current signal, and a procedure has been introduced to extract the envelope signal considering the impact of the broken bars on the settling time and amplitude of the envelope of the starting current.

Fig. 3 shows the transient wave and its components. If the current signal is transferred to the synchronous frame, unbalanced flux density influences d and q components, but the load fluctuations only affect q component [16]. Fault diagnosis from the effective value of the signal over the low frequency is possible and the increase of broken bars reduces the effective value of the signal [17]. The starting time of a machine as an important factor in fault diagnosis with the help of FFT and wavelet methods has been given in [18]. To solve this problem, the starting time must be longer, or the voltage must be reduced. Also, determination of wavelet

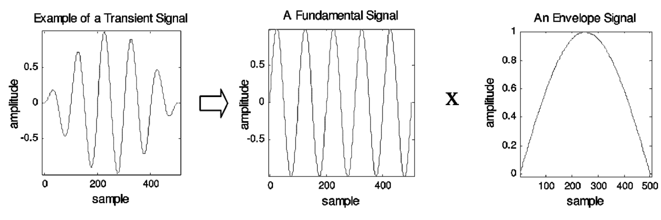


Fig. 3. A transient wave and its components [14]

main function is important in fault diagnosis.

Harmonics due to torque ripples and unbalanced voltage generate harmonics which are similar to that of the broken bar and this reduces the accuracy of the fault diagnosis process. However, this can be solved by the application of DWT transform [18]. In [19], a fundamental harmonic deletion algorithm and application of DWT are suggested for fault diagnosis. This method does not depend on the load. However, some figures in [19] do not support this claim. Fig. 4 indicates that this method depends on the load. A new signal, say $Z_s(t)$, can be defined that has the phase angle and amplitude identical with the initial signal conditions [20]. In addition to DWT and CWT, there is another wavelet called Wavelet Packet Decomposition (WPD), which yields more precise results but it is time-consuming [21]–[23]. Sidebands move to higher-order nodes WPD transform due to the load fluctuations [21]. Note that in this transform a proper node for the fault diagnosis is used. For high loads, the low-order nodes and for the low loads high-order nodes are investigated [21].

The impact of load fluctuations on wavelet coefficients of the stator current spectrum of a motor under the broken bars fault has been studied in [14], [16], [19]. Table 1 summarizes the variations of D4 coefficient and values of a function defined in the reference. As can be seen, a higher load decreases the mean value of the stator current signal, and this largely increases the criterion function and helps with fault diagnosis [16].

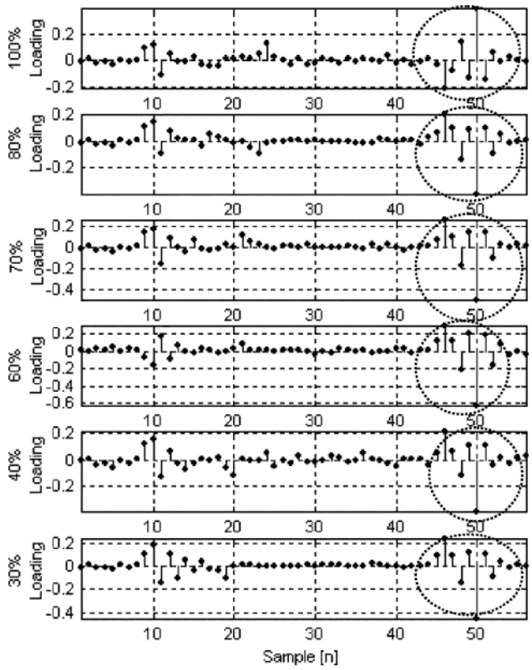


Fig. 4. Wavelet decomposition levels d9 of a damaged machine loaded 30% to 100% [19].

Fig. 5 indicates the time variations of D4 coefficient at three different loads [16]. Load increment causes larger variations of D4 coefficient waveform that increases the coefficient of 3rd column of the table by increasing the load. In [24], [25], the impact of the drive in the broken bar diagnosis using wavelet transform has been proposed. Although fault diagnosis procedure and load impact have been considered in the above-mentioned reference, the location of the broken bars has not been taken into account.

In [26], an intelligent fault detection scheme based on analysis of startup currents is proposed. First, startup current is analysed by the Meyer mother wavelet and broken bar related fault components is isolated by its approximation signal. Then, some preprocessing measures (symbolic analysis) are being taken to extract required features for classification of the fault and decision making. In classification stage, a good discrimination of the data for each class is one of the advantages of the method that leads to reliable decisions.

A new method for fault diagnosis of induction motor broken bars has been presented in [6]. In this method, a set of mother wavelets, called frequency B-spline, are used for tracking related fault harmonics in t-f plane of the startup currents. The advantage of using these mother wavelets compared to other mother wavelets such as Gabor wavelets is its superiority of filtering fundamental components which mask fault harmonics.

Table. 1. Variations of D4 coefficient of wavelet transform of current signal of the motor under broken bar fault vs. load [16]

% of rated load	Mean Current (A)	Mean distortion in D4	Index2
0	9.54	0.0923	0.97%
33	8.92	0.3220	3.61%
66	8.81	0.4044	4.59%
100	8.74	0.5469	6.25%
133	8.57	0.5674	6.62%

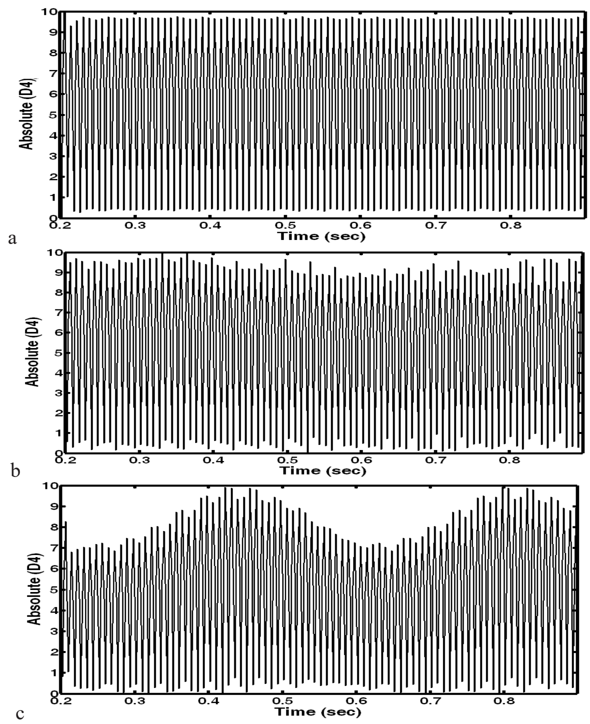


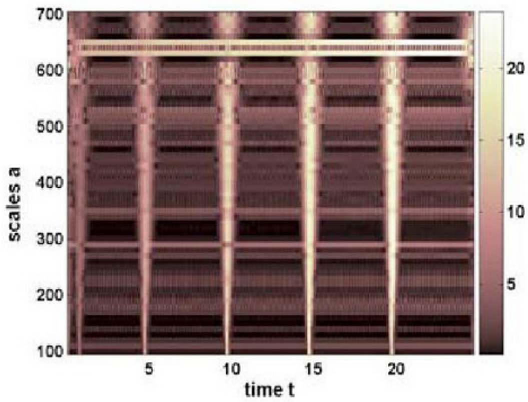
Fig. 5. Time variations of D4 coefficient of wavelet transform of the motor current signal under broken bar fault: a. no-load, b.33% rated load and c. 66% rated load [16].

In [27], transient analysis of startup currents is extended to different startup methods, including line start and soft-start. During startup, the time-frequency evolution of LSH due to broken bars leads to Λ-shaped patterns in the DWT signals which can be used for the fault diagnosis.

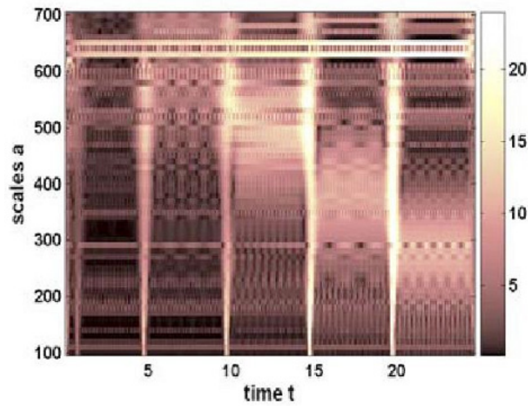
One of the major issues with regard to transient methods is the quantification of the time-frequency plane. In these methods, it is more complicated to specify a threshold for fault decision. This issue is addressed in [28] using fractional Fourier transform (FrFT) which is a generalization for the FT. DWT is used as a preprocessing tool for the extraction of LSHs from startup transient currents, then FrFT is applied on them and characteristic chirp components of the LSH in a faulty motor is detected. The slope of the resulting frequency-slip curve is used as a fault index and similar to the traditional method, this index can be easily calculated.

2- 2- Eccentricity Fault

For eccentricity fault diagnosis, FT-based methods are exploited. The reason is that monitoring low and high frequency harmonics is necessary for fault detection. In this case, wavelet application is time-consuming and complicated; however, in [29] the wavelet analysis on current spatial vector has been used for eccentricity fault diagnosis. Fig. 6 shows oscillogram spectrum of the stator current in a healthy motor and a motor with the broken bar and under eccentricity fault. DWT is applied upon transient currents of machines in [30] for fault detection of mixed eccentricity. Then, some quantification parameters based on the energy of the wavelet signal are used in order to quantify fault severity.



(a)



(b)

Fig. 6. Oscillogram spectrum of stator current: (a) healthy motor (b) motor with broken bars and 10% eccentricity [29].

2- 3- Bearing Fault

In [31]–[33], different kinds of wavelet transforms are used for bearing fault detection in induction motors. The bearing fault for PWM-driven motor has been studied in [34]. The wavelet in addition to intelligent methods has been used for fault diagnosis [35]. In [36], fault detection by WP in a motor with adjustable speed drive (ASD) drive has been proposed. Deletion of fundamental signal, diagnosed by FFT filter, causes an error. Bearing fault decreases the effective value of some nodes obtained by WP transform and this index is used for fault diagnosis. However, the choice of these nodes is itself a deterministic problem. Fig. 7 shows the coefficients variations of one of WP nodes due to the fault [36]. Comparison of WP coefficients values with base values can be used for fault diagnosis [37]. In this paper, deletion of power system harmonics is investigated but it is not shown how they are identified. In addition, the impact of load variations has been mentioned in conclusion but it is not investigated in the paper.

The following results have been obtained by application of wavelet transform in fault diagnosis:

There is still the problem of low loads and deletion algorithms for fundamental harmonic. Also, in this transform, the choice of a suitable main wavelet function plays a major role in the accuracy of the method. This method requires an individual software set for calculations. Wavelet-based methods may be suitable for laboratory and a single machine but in industries, analysis of the results is difficult and time-consuming.

3- Hilbert Processor

Hilbert transform (HT) is an efficient demodulation method for extraction of desired harmonic information and estimation of instantaneous frequency from the signal. The real part of analytic signals is the original signals and the imaginary part is the HT of the original signal. This transform shifts frequency components by 90° without affecting their amplitude. This can be seen in relationship between Fourier transform of signal $x(t)$ and its Hilbert transform $\hat{x}(t)$:

$$F\left\{\hat{x}(t)\right\} = -j sgn(f) F\left\{x(t)\right\} \tag{1}$$

where *sgn* denotes the sign function and *j* is the solution of the equation $a^2 = -1$. It means that negative frequencies

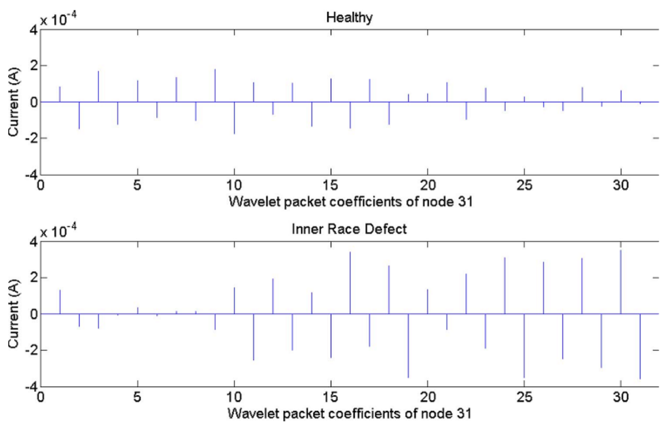


Fig. 7. Variation of coefficients of one WP node (node 31) due to inner race defect [36].

are shifted by $+\pi/2$ and positive frequencies are shifted by $-\pi/2$. By using HT, it is possible to form an analytic signal which is a complex-valued function. Analytic representation of the signal is a generalized form of the phasor concept that can be used for separation of the amplitude modulation and phase modulation effects [38]while the latter is based on torque perturbation. This paper is focused on the airgap variation model. The ball bearing fault is modeled by contact mechanics. External vibrations often occur in many industrial applications where externally induced vibrations of suitable amplitude cause cyclic radial loading on the machine shaft. The model is validated by experiments, owing to a dedicated test setup, where an external vibration source (shaker. HT is applicable only to mono-components signals; sinusoids and chirp like signals are in this class. In time-frequency plane, a mono-component signal is characterized by a single ridge. However, in real applications, signals are not so and even in some cases, they are non-linear or non-stationary. Therefore, it is necessary to decompose these signals to their initial mono-component signals before applying HT. This can be done by two common methods, namely, filtering and empirical mode decomposition (EMD) algorithm. The filtering is not adaptive; therefore, prior information of the fault frequency components is required. However, due to adaptivity of the EMD, frequency basis is defined as a-posteriori. EMD decompose a signal into its intrinsic modes of oscillation by a sifting process by which each mode is represented by an intrinsic mode function (IMF). IMFs are not simple harmonic components, but they can have variable amplitude and frequency. Application of EMD has one more advantage in applying to physical signals; unlike other decomposition methods, it can reveal the true physical meaning of the phenomenon in its IMFs. For instance, motor operating points in an induction motor, including inverter-fed and line-start modes can be distinguished by using appropriate IMFs [39].

As mentioned before, HT cannot be applied to non-stationary signals. Therefore, Hilbert-Huang transform (HHT) is introduced to address these challenges by applying HT on IMFs provided by EMD. In contrast to other mentioned transforms, non-linear signals can be also analyzed by HHT. The cost of using HHT as an adaptive approach is that there is no firm theoretical foundation for it and it is entirely empirical.

3- 1- Rotor Broken Bars and Short-circuit Rings

No-load and light load cases in rotor broken bars and end-rings have been considered in [40]. In this case there is no harmonic arising from the load, but harmonics are very close to the fundamental frequency. Here, a Hilbert vector is defined for signal and using this vector instead of the proposed signal has the following advantages,

1. the requirement of phase current,
2. generation of harmonic components due to fault and deletion of non-applicable harmonics,
3. elimination of frequency scattering, and
4. absence of fundamental frequency that allows to use a linear scale on the vertical axes instead of logarithm scale that clarifies the graphs.

No need to sample with twice of Nyquist frequency; considering the proposed low frequencies, the sampling speed is reduced up to one-tenth of the normal case values, and this is useful in practice. In [41], a fault diagnosis method based on fundamental harmonic deletion and determination of Hilbert Modulus has been introduced. Fig. 8 shows Hilbert modulus for a healthy motor and a motor with broken bars. By increasing the fault severity, this modulus becomes larger due to the harmonics. In the following part, a dimensionless numerical criterion with a low dependency on the load is introduced.

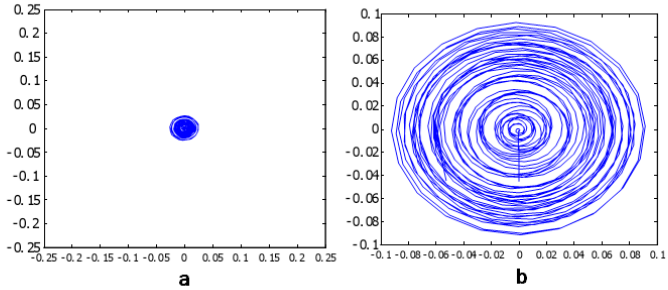


Fig. 8. Hilbert modulus: (a) healthy motor, (b) motor with two broken bars [41].

A comparison study on the application of DWT and HHT for fault detection of the broken bar under non-stationary conditions is done in [42]. Previous works show satisfactory results for DWT and these results can be a good criterion for evaluation of HHT performance. According to this study, patterns obtained by HHT are not as clear as DWT but it shows a higher resolution. In addition, a boundary effect which provokes oscillation at the beginning of signals and distorts fault patterns exists in both transforms. Also, selection of the most suitable number of IMFs for detection of the sideband is not known as a priori. However, HHT avoids dyadic frequency decomposition of DWT due to its operation based on the instantaneous frequency and allows a more accurate study of high-frequency components. Furthermore, IMFs can represent the theoretical waveform of LSH in a more accurate way. Post-processing operations on HHT output for quantification of the fault severity are more convenient using image recognition techniques.

In [43], broken bars are diagnosed by applying HT on steady-state current for extraction of the envelope of the signal. In order to avoid probable distortions, a Tukey window is pre-multiplied by the extracted envelope. Multi-resolution analysis of this envelope shows better results in comparison with direct analysis of the stator current.

A new method based on EMD analysis of the current for fault detection of the broken rotor bar under different conditions, including line-start, inverter-fed, various load torque and speed, and different fault location has been proposed in [39]. For this purpose, IMF3 in inverter-fed mode and IMF2 for line-start mode are selected as proper IMFs for the fault diagnosis. It is shown that contrary to previous works, in no/light loads, the fundamental component does not have a masking effect on fault components. Furthermore, analytical studies are carried out in order to investigate the effect of the speed variations in inverter-fed mode.

3- 2- Eccentricity Fault

HT-based methods are new methods. A few papers use such methods and they have been used for eccentricity fault processor. In [40], [44], HT has been used to diagnose the fault. Mixed eccentricity are diagnosed by applying HHT on start-up current in [45]. Fair discrimination with respect to other faults can be deduced from the obtained results.

4- Spectral estimation techniques

The main goal of spectrum estimation is determination of the power spectral density (PSD) from a sequence of time samples of the signal. Non-parametric and parametric approaches are two main categories for spectral estimation. Approaches that do not need any specific parametric model for PSD estimation are called non-parametric. They use estimated autocorrelation sequences of the signal. On the other hand, parametric methods are modeling the signal by a small number of parameters. Then, the estimated PSD of the signal will be expressed in terms of the model parameters. Spectral estimation methods offer a higher frequency resolution in their PSD than FFT-based methods (avoiding spectral leakage) and are more robust with regard to the noise which is a great advantage in dealing with early-stage faults [46]. Yule-Walker and Burg among parametric methods and multiple signal classification (MUSIC) and estimation of the signal parameters (ESPRIT) among nonparametric methods are the most used approaches for the fault detection of the IMs.

After computation of autocorrelation matrix of the signal, MUSIC converts the problem to a generalized eigen-value problem by using signal and noise subspace. One of the challenges in application of the MUSIC for spectral estimation is that there are some noise related peaks (called spurious peaks) which make it difficult to distinguish them from true signal peaks. In addition, MUSIC offers a good frequency resolution in exchange for a very high computational burden and the obtained PSD is not identical to the real PSD; therefore, its PSD called pseudo PSD and the real amplitude should be estimated. ESPRIT also solves the generalized eigen-value problem in a more computationally efficient way than MUSIC. This is due to direct estimation of the harmonic components whereas MUSIC requires a peak detection process. On the whole, the both methods impose a very high computational burden. In order to address this issue, a zoom version of these algorithms is also proposed by focusing on specific frequency regions [46]. In addition to a shorter computation time, needing less memory storage and more accuracy on those regions are other benefits of using zoom version of the algorithms. ESPRIT can achieve a high-frequency resolution even with a short-time measurement data [47].

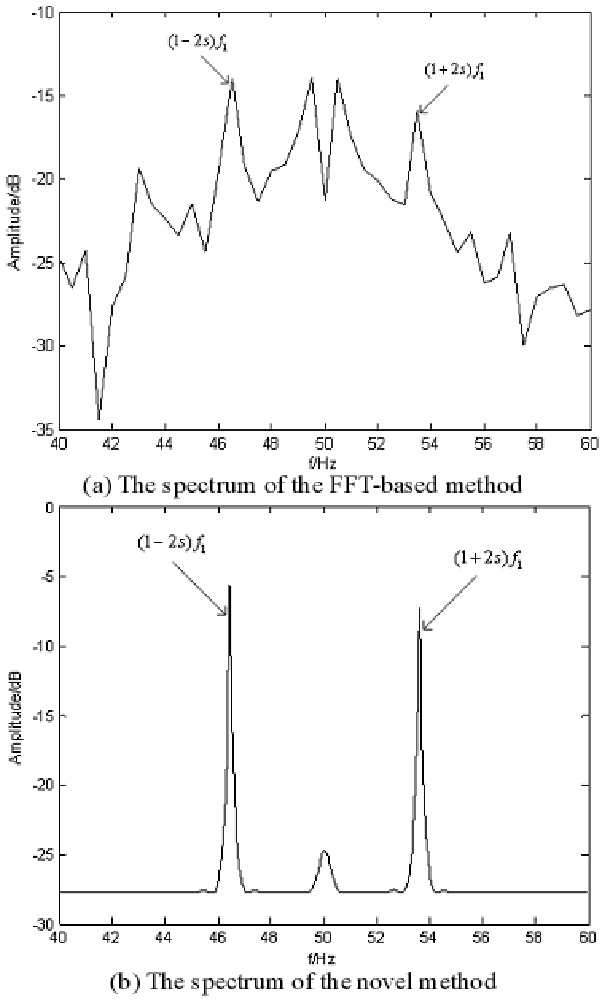


Fig. 9. Comparison of FFT and Music-based methods for a motor with 1 broken bar: (a). FFT, (b). Music [48].

4- 1- Rotor Bars and Ring Short-circuit

Combination of FFT and MUSIC methods and a method of fundamental harmonic deletion have been used for fault diagnosis in [48] because lonely application of MUSIC leads to an error. This method provides clearer results compared to FFT method. In Fig. 9, the results of the two methods have been compared. In [49], the frequency spectrum of output voltage after disconnecting the input supply obtained by FFT and MUSIC methods has been compared. It has been shown that a series of particular harmonics in the frequency spectrum is excited due to broken bars and these are shown. Reliability and low impact of noise are the advantages of this method compared with FFT method [49]. MUSIC-based methods similar to HT are the new methods which have precise results and its computation is quicker than the Wavelet method's. However, it needs improved algorithms for the deletion of the fundamental harmonic which complicates these methods. Since these methods are new, many fault diagnosis indexes have not been modeled by these methods yet.

A comparative study of the ZMUSIC and ZFFT based on sensitivity and computation time for the fault diagnosis of the broken rotor bar can be found in [50]. ZMUSIC needs less memory and smaller acquisition time, but more computation time. In [51],

MUSIC is used for the detection of multiple combined faults in induction machines, including broken rotor bar, bearing outer race damage and unbalanced pulley.

In combined occurrence of the faults, vibration is used as a supplementary signal for diagnosis, especially when the unbalanced pulley makes it difficult to detect a bearing defect. Band-pass filters are used to extract frequency bands related to each fault.

In order to apply MUSIC to induced voltages of the stator during switch-off, a windowed version of the MUSIC, called short-time MUSIC (STMUSIC) has been proposed in [52] to deal with this non-stationary signal. It will give frequency components in a time-frequency pseudo-representation.

In [53], a non-parametric autoregressive(AR)-based spectral estimation method is proposed for detection of the broken rotor bar faults. It is shown that application of the Yule AR method on captured currents cannot reveal fault-related sidebands. However, elimination of the main line frequency by a second order digital notch filter allows identification of the characteristic sidebands. The main advantage of this method is that extracted features will not be affected by low sampling rates, unlike traditional methods.

A three-level fault detection scheme for the broken rotor bar has been proposed in [46]. In the first level, Zoom ESPRIT is used for the accurate estimation of the fault components in a specific bandwidth. Then, by using least square (LS) estimator, the amplitude of the fault components is derived. Finally, an optimization is done on the fault threshold in order to minimize false alarms.

In [47], ESPRIT is used for rotor broken bar fault detection. Initial results show that ESPRIT can identify frequency components with a high-frequency resolution, even for the short signals. However, it will face difficulties in determination of the amplitude and initial phase of the components. It is proposed to use a simulated annealing algorithm for an accurate calculation of these amplitudes and phases. Capability of estimating fault components with a short-length signal makes it suitable for the fault detection of the broken bar in induction motors operating with small slip and fluctuation load.

5- Quadratic time-frequency distributions

Quadratic (or bilinear) time-frequency distribution is a nonlinear SPT for tracking frequency components of a non-stationary signal in the time-frequency plane. Wigner-Ville distribution (WVD) was introduced as the oldest member of these distributions which is generalized by distributions in Cohen's class. Contrary to linear methods, which decomposes the desired signal into its initial components, in these methods, the energy of a signal will be distributed on time-frequency plane by using appropriate distributions. Unlike STFT, WVD does not use any window function and due to its bilinear nature, tracking several components will end up with creation of undesirable interferences, called cross-term, which Besmirch time-frequency distribution. In fact, time-frequency distribution consists of distribution formed by every component (auto-term) and its interaction with other components (cross-term). Although cross-terms contributes to total distribution, it causes repetition in information and leads to a vague distribution. Therefore, in order to suppress these cross-terms, other members of the Cohen's class use a kernel function in exchange for a lower resolution. In fact, Cohen's class can be defined as a smoothed version of WVD. Choi-Williams, Zhao-Atlas-Marks, Born-Jordan are the other most applicable members of the Cohen's class which are defined based on their kernel and should be chosen according to the application. Backing to WVD, its other extensions such as pseudo-Wigner-Ville distribution (PWVD) and smoothed pseudo-Wigner-Ville distribution (SPWVD) are also introduced to tackle the previous problem [54]. The computational cost of these transforms is another issue in using these methods for different applications.

5- 1- Eccentricity

Fault diagnosis of the eccentricity under the presence of load torque oscillations is a difficult task due to their identical harmonic components and investigation of the lower fault-related components is not conclusive. Therefore, in [55], it is proposed to monitor higher-order components in transient startup currents as a supplementary for discrimination of these two phenomena. However, in order to monitor this component, it is necessary to use a high resolution time-frequency technique. Thus, in this method, WVD is preferred to the other members of the Cohen's class. Filtering and HT is proposed as a pretreatment process in order to minimize the cross-terms effect. Results show the superiority of this method in comparison with DWT when tracking higher-order harmonics.

6- Conclusions

Different methods and processors used for diagnosis of three internal faults of IMs were briefly investigated. To this end, four types of processors and their advantages and drawbacks were studied. It is clear that a single method and a common processor cannot be specified for all faults. Fourier processor as a most applied one for different faults has weak and strong points. Its most important weakness is in the processing of transient signals. To overcome this problem, an application of wavelet processor was suggested which provides more detailed view time and frequency view of the signal. Following wavelet pocket the simultaneous high precision of time and frequency is commonly used. These processors often are used for the broken bars fault but there are no appropriate studies on the number of broken bars and their location. Other drawbacks of this method includes time consuming and has a technique complexity. In recent years, Hilbert-based methods with high-frequency precision methods such as MUSIC have been proposed. Quadrature distributions provide a good t-f resolution, but they impose a high computational burden. The common point that must be taken into account in an appropriate fault diagnosis method in industry beside on-line case is that the method must be quick and at the same time must have a good accuracy.

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