THE USE OF IMPROVED ROOT-MUSIC FREQUENCY ESTIMATION METHOD FOR THREE PHASE INDUCTION MOTOR INCIPIENT ROTOR'S FAULTS DETECTION

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ABSTRACT

Broken rotor bars in an induction motor create asymmetries and result in abnormal amplitude of the sidebands around the fundamental supply frequency and its harmonics. So, in order to detect an incipient fault, we must pay a special attention to the spectral analysis of stator current. Several frequency estimation techniques have been developed and used to help induction motor fault detection and diagnosis. In this paper, a new application of the Root-MUSIC method to improve the diagnosis is proposed. This method is a variant of the well known MUSIC (MUltiple SIgnal Classification) method. This is a powerful tool for extracting meaningful frequencies from the signal, which is in our case the stator current. Unfortunately, the Root-MUSIC method takes a long computation time to find more frequencies by increasing the order of the frequency signal dimension. To solve this problem, this method will not be applied to the totality of the signal spectrum but only to a bandwidth of specified frequency. A technique RMIF (Root-MUSIC Improved by Filtering) based on a digital pass-band filter within a specific frequency range is proposed with Root-MUSIC in order to improve the diagnosis performances for frequencies extraction. The proposed technique is tested on synthetical signals and the results are compared with those obtained by the classical Power Spectral Density (PSD) method, to show the various merits of the RMIF method compared to the classical PSD method.

***Keywords*:** *Broken bars, fault detection, induction motors, stator current, spectral estimation techniques, PSD, Root-MUSIC, Pass-band filter.*

1. INTRODUCTION

Induction motors especially squirrel cage have a very important role in industry. They are robust and simple in their construction. However, an interruption of a manufacturing process due to a failure in an induction motor can induce a serious financial set for the company. It is therefore necessary to detect a faulty condition and avoid its increase, before resulting in a catastrophic failure. For this reason, the early detection of the incipient motor fault is very important [1]. Among the various faults, rotor faults account for about 10% of total induction motor failures. Broken rotor bars can be a serious problem when induction motors (*IM*) have to perform hard duty cycles. Broken rotor bars do not initially cause an *IM* to fail, but they can cause serious mechanical damage to the stator windings if they are left undetected [2]. Moreover an *IM* with broken rotor bars cannot operate in dangerous environments due to sparking at the fault site.

The techniques more efficient in identifying rotor faults are mainly based on analysis of stator currents via Fast Fourier Transform (*FFT*) algorithm. *FFT* yields efficient and reasonable results, which makes it a powerful tool as a diagnostic technique. Among these techniques, we have Power Spectral Density (*PSD*). There are several approaches to calculate *PSD* estimates. Periodogram technique, which is known as the classical way to estimate *PSD*, is one of these methods [3]. However, a main disadvantage of these techniques is the problem of resolution. Indeed, when we have two harmonics close one to the other with very different amplitudes, the lobe of the low amplitudes' harmonics will be buried in that of the main harmonic.

In recent years, several advanced signal processing methods such as High Resolution Spectral Analysis have been applied to diagnose *IM* faults. Among these methods, *Root-MUSIC* algorithm has been used both to distinguish the fundamental frequency and the twice slip frequency side bands caused by broken rotor bars. In this application, fault sensitive frequencies have to be found in the stator current signature. They are often numerous in a given frequency range and they are affected by the signal-to-noise ratio. In this condition, the *Root-MUSIC* method takes a long computation time to find more frequencies by increasing the order of the frequency signal dimension. To solve this problem, the idea is to focus on some special frequency bins without taking care of the full length *FFT* in the entire frequency range. With this idea the following features are obtained [4]:

- Reduction of computation time.
- Saving of more space in memory.
- Accuracy in a specified frequency range.

In this paper, an algorithm is being proposed; based on the Root-MUSIC combined to a digital pass-band filtering applied within a specified frequency range; in order to improve diagnosis performances. The results obtained with this algorithm RMIF will be compared with the classical spectral estimation *PSD* technique.

2. STATOR CURRENT SIGNATURE ANALYSIS

A current spectrum contains potential fault information. Frequency components have been determined for each specified fault. These frequencies are derived from the physical construction of the machine. It is important to note that, as in vibration analysis case, the more the fault progresses, its characteristic spectral components continue to increase with time [5]. *Kliman*, *Elkasabgy* [6], [7] used motor current signature analysis techniques to detect broken rotor bar faults by investigating the sideband components around the supplied current fundamental frequency (i.e. line frequency), f_s. Broken rotor bars give rise to a sequence of side-bands given by [1], [3]:

$$f_b = (1 \pm 2.k.s).f_s \quad with \quad k = 1,2,3\ldots \tag{1}$$

Where f_b are the sideband frequencies associated with the broken rotor bar, s is the per unit motor slip [3], given by:

$$s = \frac{w_s - w_r}{w_s} \tag{2}$$

w_r is the relative mechanical speed of the motor. The motor synchronous speed, w_s, is related to the line frequency f_s, as:

$$w_s = \frac{120.f_s}{P} \tag{3}$$

Where P is the number of poles of the motor.

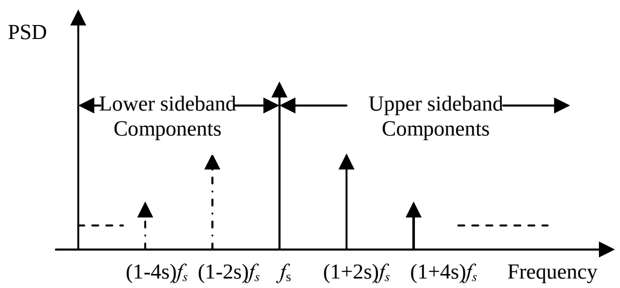

Fig. 1 Sideband frequencies around the fundamental line frequency

Figure 1 shows the frequency components specific to broken rotor bar fault, as given in equation (1) for *k=1* and *2*. These frequencies are located around the fundamental line frequency and are called lower sideband and upper sideband components.
In addition with the previous equation, broken rotor bars generate additional sidebands near the space harmonics frequencies [8], given by:

$$f_{rsb} = f_s \cdot \left[\frac{k}{P}(1-s) \pm s \right], \; with\ k/P = 1,\ 3,\ 5\ldots \tag{4}$$

The evolution of these sidebands magnitudes makes an efficient diagnosis of induction motor possible.

3. ROOT-MUSIC METHOD

3.1. Basic theory

Root-MUSIC method is generally used in signal processing problems. This method estimates the frequencies of the complex sinusoids that best approximate a noisy signal by using an eigen based decomposition method [9], [10], [11]. Let us consider a stator current $i_s(n)$ as a sum of L complex sinusoids and white noise:

$$i_s(n) = \sum_{i=1}^{L} I_i e^{j(2.\pi.\frac{f_i}{f_{sf}}.n+\phi_i)} + w(n) \tag{5}$$

With n=0,1,2…..N-1

Where I_i, f_i, *and* Φ_i are the amplitude, the frequency and the random phase of the i^th complex sinusoid (harmonic components) respectively, $w(n)$ is white noise, f_{sf} sampling frequency and N is the number of sample data.

The autocorrelation matrix of the noisy signal i_s is the sum of the autocorrelation matrices of the signal i_s and the noise w defined as follows:

$$R_i = E[i_s(n).i_s^H(n)] = R_s + R_w = S.A.S^H + \sigma_w^2.I \tag{6}$$

Where:

- S is the Vandermonde matrix:

$$S = [s_1 \ \ldots \mathrm{s_i} \ldots s_L]$$
$$s_i = [1 \ \ e^{j.2.\pi.\frac{f_i}{f_{sf}}} \ \ e^{j.4\pi.\frac{f_i}{f_{sf}}} \ \ \ldots \ \ e^{j.2\pi(N-1)\frac{f_i}{f_{sf}}}]^T \tag{7}$$

- A is the power matrix of the harmonics.

$$A = diag[I_1^2 \ \ I_2^2 \ \ \ldots \ \ I_L^2] \tag{8}$$

- H is the Hermitian transpose.

- $\boldsymbol{\sigma_w^2}$ and I are respectively the variance of the white noise and the identity matrix of size (N x N).

The eigen decomposition of the autocorrelation matrix R_i is given by:

$$R_i = \sum_{k=1}^{N} \lambda_k.u_k.u_k^H = \underbrace{U_s.D_s.U_s^H}_{R_s} + \underbrace{U_w.D_w.U_w^H}_{R_w} \tag{9}$$

Where:

$$U_s = [u_1 \ \ldots \ u_L] \ ; \ D_s = diag[\lambda_1 \ \ldots \ \lambda_L]$$
$$U_w = [u_{L+1} \ \ldots \ u_N] \ ; \ D_w = \sigma_w^2.I_{N-L} \tag{10}$$

U_s and U_w matrices are composed by the eigen vectors u_k related to eigen values arranged in descending order. This equation shows that, we may divide these eigenvectors into two groups or subspaces: the L signal eigen vectors corresponding to the L largest eigen values (signal subspace), and N-L noise eigen vectors that, ideally, have eigen values equal to σ_w^2 (noise subspace). Diagonal matrices D_S and D_w contain eigen values λ_k corresponding to eigen vectors u_k .

As the eigen values of noise are equal to the variance of noise, matrix D_w can be written as shown in equation (10). By comparing equations (6), (9) and (10) we can write:

$$\begin{aligned} R_i.U_w &= U_w.D_w = \sigma_w^2.D_w \\ &= S.A.S^H.U_w + \sigma_w^2.U_w \end{aligned} \quad (11)$$

This implies that:

$$S^H.U_w = 0 \quad (12)$$

The *Root-MUSIC* method uses the principle of this orthogonality between the signal subspace and the noise subspace. The required frequency estimates $z_i = e^{j.2.\pi.\frac{f_i}{f_{sf}}}$ are the roots of this equation [11]:

$$s_i^H U_w.U_w^H.s_i = 0 \quad with\ \ i=1,...L \quad (13)$$

The roots of (13) will come in pairs (i.e. if z_i is a root, so is ($1/z_i$*)). Those roots with magnitude greater than unity will be filtered out. The L roots closest to the unit circle correspond to possible harmonics according to:

$$f_i = \frac{f_{sf}}{2.\pi}.\arg(z_i) \quad with\ i=1,..., L \quad (14)$$

3.2. Harmonics powers estimation

Knowing that:

$$R_s = S.A.S^H = \sum_{k=1}^{L}(\lambda_k + \sigma_w^2)u_k.u_k^H \quad (15)$$

We notice that it is easier to inverse R_s than to inverse S. Therefore the harmonics powers can be estimated by the following method [11], [12]:

$$Q = A^{-1} = \frac{1}{S^H\ R_s^{-1}\ S} \quad (16)$$

Where:
$$\begin{cases} R_s^{-1} = \sum\limits_{k=1}^{L} \dfrac{1}{\lambda_k + \sigma_w^2} u_k.u_k^H \\ \sigma_w^2 = \dfrac{1}{N-L} \sum\limits_{k=L+1}^{N} \lambda_k \end{cases} \quad (17)$$

Identification problem is resolved by knowing the frequencies and the powers of the various harmonics.

Furthermore, the rank of the signal subspace determines the number of harmonics that is the eigenvectors spanning this subspace which allows us to estimate the frequency set. Due to the finite data length, we can not precisely compute the correlation matrix R_i. However, it is possible to estimate it [11]:

$$\hat{R}_i = \frac{1}{N-M+1} D.D^H \quad (18)$$

Where D is a Hankel data matrix given by:

$$D = \begin{bmatrix} i_s(0) & . & . & . & i_s(N-M) \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ i_s(M-1) & . & . & . & i_s(N-1) \end{bmatrix}$$

M is the data matrix order.

3.3. Choice of *L* and *M* parameters

Obviously, this estimator requires the a priori knowledge of the number of frequencies L (model order) and the autocorrelation data matrix order M. For M, there is no rule to determine it. But some authors use empirically the parameter M, between $N/2$ and $N/3$ [13]. If the model order that is used is too small, then we will have less harmonics (an under estimation). If, on the other hand, the model order is too large, then the spectrum may contain spurious harmonics (an over estimation). Therefore, it would be useful to have a criterion that indicates the appropriate model order to use for a given set of data [14]. Among these criteria, we can quote the Akaike Information Criterion (*AIC*) [15] and the Minimum Description Length (*MDL*) proposed by Rissanen [16]. In this work, we have used the *AIC* criterion.

4. IMPROVEMENT OF THE ROOT-MUSIC TECHNIQUE

Actually, it is difficult to find out small magnitude frequencies around the main ones by the *Root-MUSIC* method because it takes a long computation time when the order of the autocorrelation matrix and the number of sample data increases. This computation time depends on N^3 compared with $N\log_2 N$ for the conventional *FFT* [10]. The suggested idea consists to process the data on a given frequency bandwidth and not on all the spectrum of the stator current, this will enables us to reduce the computation time and to optimize the frequency component estimation. For example, in a three-phase induction machine with broken rotor bars, the side-band frequencies around the fundamental are important for fault detection [1], [4]. The proposed algorithm *RMIF* is based on a band-pass filter [f_l, f_h] where f_l, f_h are the low cut-off and high cut-off frequency of the band-pass filter respectively. Initially, the sequence $i_s(n)$ is obtained after sampling the signal $i_s(t)$ at the frequency f_{sf}. So, it would be possible to make a filtering in the bandwidth $[0, f_{sf}/2]$. However, the band-pass filter must have a flat response in the given bandwidth. After filtering, the frequency range becomes [f_l, f_h]. Therefore with this approach, the new sequence $i_{sf}(n)$ has ($2.N.f_p / f_{sf}$) samples, where $f_p = f_h - f_l$, reducing consequently the frequency signal dimension order for a reduced computation time in the frequency estimation for the given bandwidth.

In addition, the rotor faults signature exists practically on each phase current spectrum. To make a diagnosis on each phase current will be penalizing in computation time. For this reason, we proposed the spectral analysis of the combination of the three phase currents, represented by the direct component i_{sd} [1], [17].

$$I_{sd} = \frac{I_a + \alpha . I_b + \alpha^2 . I_c}{3} \tag{19}$$

Where: $\alpha = e^{j\frac{2.\pi}{3}}$, I_a, I_b , I_c are the spectra of the three phases currents, and I_{sd} is a spectrum of direct component $i_{sd.}$

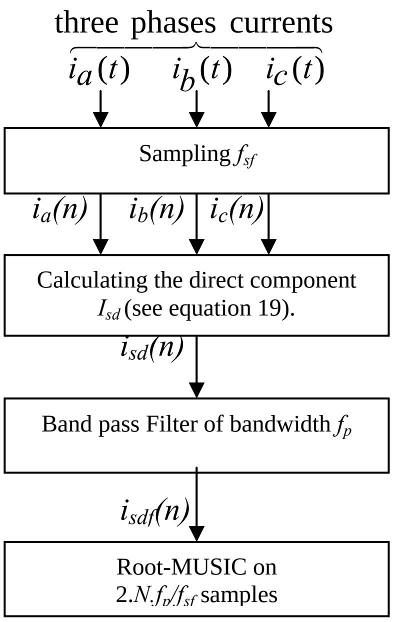

Fig. 2 Flowchart of the *RMIF* algorithm.

5. SIMULATIONS AND ANALYSIS

In these simulations, we have implemented both the *RMIF* and *PSD* (estimated by using periodiogram algorithm methods) and then a comparison of the faults detection and a performance identification of each method is being established. Usually, a machine fault modifies the stator current spectrum of the healthy motor by changing powers of some components already present in the spectra. Rotor faults affect spectral components whose frequencies depend on the per unit slip s, related itself to the load.

In this study, we focus on the spectrum powers of the stator current (one phase) at two main frequencies, *(1-2s)*f_s and *(1+2s)* f_s that are specific to broken rotor bar fault. Thus to estimate the three frequencies f_s, *(1-2s)* f_s *and (1+2s)* f_s, a pass-band filter centred on f_s is used. The filter used for *RMIF* is performed by a recursive *IIR* digital filter using a least square fit to specified frequency bandwidth [*40 Hz, 60Hz*]. The signal simulated was sampled at intervals of 1 ms and 4096 samples were used in these simulations.

5.1. First simulation

Knowing that the frequency resolution is equal to: $\Delta f = \frac{f_{sf}}{N}$, then to have a better resolution, it is necessary to increase the data length. But, with *Root-MUSIC* method this results in an increase in the computation time. This first simulation shows the inconvenience of this method. The simulated signal without noise for this test is defined as follows:

$$i_s(n) = 10\sin(2pi.\frac{50}{f_{sf}}.n) + 0.3\sin(2.pi.\frac{45}{f_{sf}}.n) + 0.2\sin(2.pi.\frac{55}{f_{sf}}.n) \tag{20}$$

Table I gives the results in the case of three harmonics estimation. We notice the important time used for the frequencies estimation and especially the size memory used when the data length increases. Besides, if the harmonics number to be estimated increases, the computation time and size memory used increases too.

Table I Computation time and memory size used with *Root-MUSIC* method

Data length	*Memory size used (Mbytes)*	*Computation time (s)*
4096	136.679	276.51
2048	34.26	33.64
1024	8.61	5.22

Table II shows an important reduction of the computing time and memory size with *RMIF* compared to the classical *Root-MUSIC* method. We can thus estimate the same frequencies in a given frequency bandwidth with a very reduced computing time. It is the first required advantage.

We also notice that there is a small difference in the power estimation. This is due to the attenuations brought by the band pass filter used.

Table II Speed computation comparison

Method	*Data length*	*Identification harmonics (Frequencies / Powers)*	*Memory size used (Mbytes)*	*Computation time (s)*
Root-MUSIC	4096	50.00 Hz / 16.41 dB 44.99 Hz / -14.02 dB 55.00 Hz / -17.57 dB	136.679	276.51
RMIF	164	50.00 Hz / 16.43 dB 45.00 Hz / -13.88 dB 54.99 Hz / -17.19 dB	0.576	0.42

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5.2. Second simulation

In this simulation, we will show the robustness of *RMIF* to the noise. For that we introduce the Signal Noise Ratio (*SNR*). This ratio *SNR* is given by: $SNR(dB) = 10.\log_{10}(P_{is}/P_w)$. Moreover, we choose *s=5%.* The simulated signal has been generated by:

$$i_s(n) = 10\sin(2pi.\frac{50}{f_{sf}}.n) + 0.3\sin(2.pi.\frac{45}{f_{sf}}.n) + 0.2\sin(2.pi.\frac{55}{f_{sf}}.n) + w(n) \quad (21)$$

Where *w(n)* is a Gaussian white noise. As it can be see, the signal $i_s(n)$ is composed of three frequencies components. One of them should have the largest amplitude which is in this case the fundamental. As our algorithm calculates harmonic powers rather than amplitudes, theoretically for these components, we will obtain the following powers respectively: *16.98, -13.46 and -16.98 dB*.

In the Table III, we see the *RMIF* frequencies and powers estimation for different levels of *SNR*. These estimations are better until *10 dB*. It is important to highlight that the level of *10 dB* can be considered high for many applications.

Table III Frequencies and powers estimated by *RMIF*

SNR (dB)	50	20	10	5
Estimated frequencies (Hz)	50.00	50.00	50.00	49.99
	45.00	45.00	45.03	44.69
	55.00	55.00	54.87	59.71
Estimated powers (dB)	16.43	16.44	16.34	16.55
	-14.08	-14.27	-12.43	-11.68
	-17.49	-17.75	-17.79	-15.54

Figure 3 shows that the *RMIF* method gives good results with a very good resolution. We obtain practically the same results for both methods suggested with a small noise (*SNR*=50dB). On the other hand, when the noise increases (*SNR*=10 dB), detection becomes practically impossible with the *PSD* for the low powers' harmonics. While the *RMIF* always gives highly reliable results (see Figure 4). It is the second required advantage.

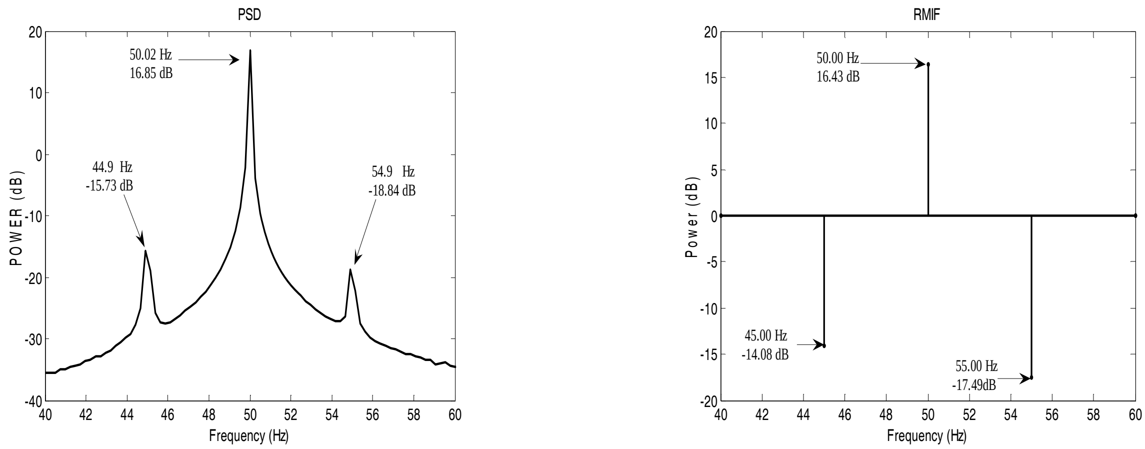

Fig. 3 Results for a signal moderately disturbed (SNR=50 dB)

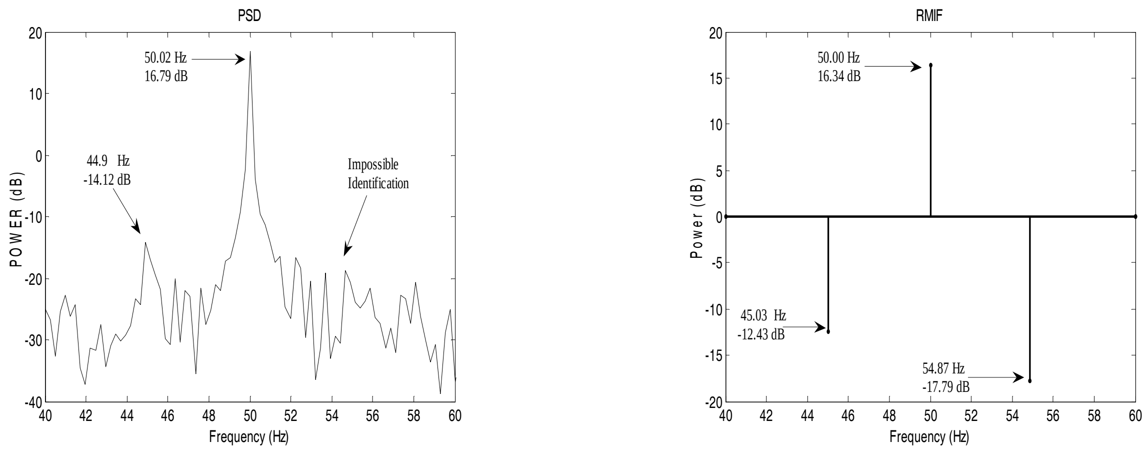

Fig. 4 Results for a signal highly disturbed (SNR =10 dB)

5.3. Third simulation

In practice, we can have a lower slip value, for example *s=1%.* In this case, the frequencies are very close and the simulated signal is composed by three components (*50 Hz, 49 Hz and 51 Hz*). As you see, the slip value is very low. However to represent an incipient rotor faults, we have choosen the power of one component very higher than the others.

$$i_s(n) = 20\sin(2\pi\frac{50}{f_{sf}}n) + 0.2\sin(2\pi\frac{49}{f_{sf}}n) + 0.2\sin(2\pi\frac{51}{f_{sf}}n) + w(n) \quad (22)$$

In this case (Figure 5), we see that the identification of the low powers harmonics using *PSD* is impossible (even with a small noise), this is because their spectra are embedded in that of the fundamental spectrum. But with *RMIF* we obtain very good results with a very good resolution. It is the third required advantage.

These simulations have proven to us that the suggested method (*RMIF*) improves considerably the harmonics identification with a very reduced computing time.

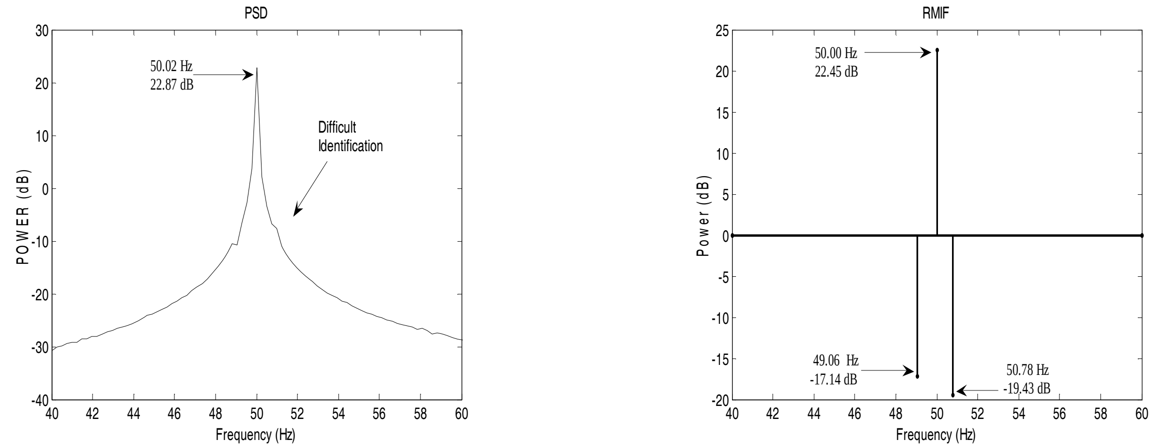

Fig. 5 Results for a signal slightly disturbed (SNR=80 dB)

6. CONCLUSION

It has been shown that the stator current high resolution spectral analysis (*Root-MUSIC*), proposed as a tool for induction motors faults detection, has several advantages over the traditionally used *PSD* analysis. The *Root-MUSIC* method is a powerful tool for detecting frequencies from the short data record signal buried in a noise. But its main disadvantage is a long computation time when a large frequency signal dimension order or a large number of samples are requested. For this reason this method can be to use only in off-line diagnosis. The proposed *RMIF* algorithm is a technique which makes the *Root-MUSIC* faster and more accurate in extracting frequencies in a specified bandwidth. The *RMIF* gives comparable results to *Root-MUSIC* but with less memory and smaller computation time. The statistical results based on simulation data clearly indicate that *RMIF* technique has better discrimination capability and is more robust compared to *PSD* method. The results also prove that *RMIF* technique is very effective in the case of incipient rotor fault. Extensive experimental studies are necessary to assess fully the usefulness and merits of the proposed technique for the preventive diagnostic in drive systems with induction motors.

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