Feature extraction for the prognosis of electromechanical faults in electrical machines through the DWT

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***Abstract*—Recognition of characteristic patterns is proposed in this paper in order to diagnose the presence of electromechanical faults in induction electrical machines. Two common faults in this type of machines are considered; broken rotor bars and mixed eccentricities. The presence of these faults leads to the appearance of frequency components following a very characteristic evolution during the startup transient and other transients through which the machine operates. The identification and extraction of these characteristic patterns through the Discrete Wavelet Transform (DWT) has been proven to be a reliable methodology for diagnosing the presence of these faults, showing certain advantages in comparison with the classical FFT analysis of the steady-state current. In the paper, a compilation of healthy and faulty cases are presented; they confirm the validity of the approach for the correct diagnosis of a wide range of electromechanical faults.**

Keywords—electric machines, fault diagnosis, wavelet tramsform, broken bars, eccentricties

I. INTRODUCTION

Electrical induction machines are of extensive use in many industrial processes. An unexpected fault in these machines can lead to high expenses in terms of time and costs, since most of the times they are critical elements in those processes in which they are involved. Due to this fact, the diagnosis of the possible faults taking place in these devices has become a topic of special interest and concern in the industrial environment [1-2]. The development and optimization of techniques being able to detect the possible failures in an earlier stage have been the motivation of many works during these last few years.

Statistical studies [1] on the occurrence of electromechanical faults in asynchronous machines show a significant percentage of faulty events related to the rotor, such as rotor bar breakages and various modalities of eccentricities; they have been deeply analyzed in the literature due to their particular hazard caused by the progressive propagation or the possibility of rotor to stator rub [3-5].

Most of these faults lead to some effects in the different electromechanical quantities of the machine (currents, vibrations, fluxes, torque…) which may help to diagnose the presence of the corresponding failure. Indeed, some studies have investigated the effect that each particular fault provokes on the different electrical quantities, trying to obtain the most suitable for diagnosing the presence of each failure, according to its sensitivity, non-invasive nature and other criteria.

In the industrial environment, the most common approach for the diagnosis of most of the faults (for instance, rotor asymmetries or different types of eccentricities) is based on the analysis of the current demanded by the machine; this is a quantity easy to be measured in a non-invasive way, this is, without interference on the usual operation of the machine. The equipment required for capturing the current signal is very simple and also the software needed for its computation.

The classical diagnosis method based on current analysis, is focused on applying the Fourier transform to the current of the machine during its steady-state operation. Under ideal operation and healthy condition, this should be a pure sinusoidal signal, so the Fourier analysis would reveal the presence of a single frequency component at the supply frequency. However, even under healthy condition, this spectrum is usually polluted by other frequencies caused by the slotting, non-ideal winding distribution, perturbations in the operation of the machine, noises, transient oscillations or even rotor imperfections due to the manufacturing process [6-7].

In the case of a faulty machine, for instance a machine with rotor asymmetries or a machine with certain level of eccentricity, some particular frequency components appear in the Fourier spectrum of the steady-state current. Many authors have studied the frequencies amplified by the presence of these faults; these works have led to expressions that have become very common in the industrial environment for diagnosis purposes; for instance, in the case of rotor bar breakages, the main frequencies amplified by the presence of the fault are given by (1) (with s=slip and f=supply frequency) and they are known as sideband components [4]. These components are shown in Figure 1, corresponding to a loaded machine with two broken bars. Analogue expressions are obtained for the case of static, dynamic or mixed eccentricities.

$$f_s = f \cdot (1 \pm 2 \cdot s) \qquad (1)$$

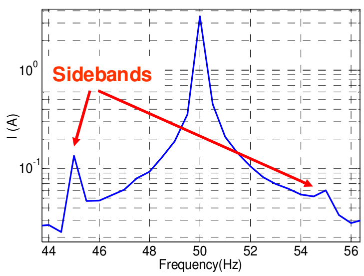
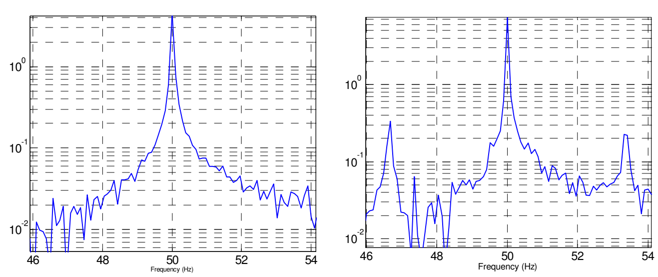


Figure 1. FFT of the steady state current for a loaded machine with two broken bars.

This classical approach based on the steady-state analysis of the current, has some drawbacks reported by several authors [6-7]; for instance, when the machine is unloaded or lightly loaded, the diagnosis of rotor asymmetries or even eccentricities can become specially difficult due to the low value of the slip [6-7], causing that the frequency components used for the diagnosis overlap the frequency of supply (Figure 2(a)). Moreover, other common phenomena such as load fluctuations or voltage oscillations can introduce frequencies very close to those amplified by the previous faults, leading to confusion or even to a wrong diagnosis (Figure 2(b)).



(a) (b)

Figure 2. FFT of the steady state current fo: (a) unloaded machine with two broken bars (b) healthy machine with fluctuating load torque .

Due to all these facts, some authors have proposed the study of the transient processes of the machine as an alternative way to obtain additional information which could complement that provided by the steady-state methods. In this context, the study of the current during the connection process of the machine (startup transient) has drawn most of the attention [7-12]. The implicit common basis of these methods is the detection of the evolution during that transient of certain characteristic components created by the corresponding fault.

In this context, a new methodology based on the application of the Discrete Wavelet Transform (DWT) to the startup current, and the subsequent study of the wavelet signals resulting from the transform was proposed recently [8-12]; these signals enable not only the mere detection, but also the extraction of the evolution during the transient of the components created by each fault, arising characteristic patterns that could be used for the reliable diagnosis of the fault. The further automatic recognition of these patterns, using modern image recognition algorithms would enable the on-line diagnosis of the corresponding fault as well as the quantification of the degree of severity.

The aim of this paper is to review the proposed diagnosis methodology, presenting a compilation of different cases. These experimental cases are referred to a 1.1 kW machine operating under various conditions and with different faults. In some of the presented cases, the classical diagnosis method, currently used in the industrial environment and based on the application of the FFT to the steady-state current, is not suitable or leads to a confusing diagnostic. The results show the validity of the method for the reliable diagnosis of the failure. This might lead to the possible future implementation of portable condition monitoring devices based on this methodology.

II. ELECTROMECHANICAL FAULTS DURING THE STARTUP

Two main faults are considered in the paper; broken rotor bars and dynamic eccentricities:

A. Broken Rotor Bars

The presence of broken rotor bars introduces, in the steady-state current spectrum, two sideband components around the supply frequency, with frequencies given by (1). During the startup transient, the slip s changes from 1 to a value very close to 0. As the slip varies, the frequency of the component with negative sign in (1) (left sideband component) also changes; it decreases firstly from a value equal to the supply frequency to 0 Hz and it increases again up to reaching a value very close to the supply frequency [7]. Its amplitude also evolves in a very characteristic way [8]. The extraction of that characteristic transient waveform has revealed as a reliable way for diagnosing the presence of the asymmetry in the machine.

B. Dynamic eccentricities

Some authors [3] have provided a general expression for the frequencies amplified by mixed eccentricities:

$$f_{ecc} = f_1 \left[(1 \pm m(\frac{1-s}{p}) \right] \qquad (2)$$

where p= number of pole pairs and m=1,2,3…

As it was proven in previous works [9], the slip variation during the startup leads to a particular evolution of the frequency components created by the eccentricity. For m=p/2, considering f=50Hz, two frequency components with very characteristic evolutions appear; one of them evolving during the transient from 50 Hz to 25 Hz and the second changing from 50 Hz to 75 Hz [9]. This variation, totally different from that of the broken bars, can be also used for the diagnosis of the eccentricity.

III. DISCRETE WAVELET TRANSFORM

The main idea that underlies the application of the DWT is the dyadic band pass filtering process carried out by this transform. Provided a certain sampled signal s= (i_1, i_2, …i_N) , the DWT decomposes it onto several wavelet signals (an approximation signal a_n and n detail signals d_j) [7, 13]. A certain frequency band is associated with each wavelet signal; the wavelet signal reflects the time evolution of the frequency components of the original signal s which are contained within its associated frequency band [7, 14].

More concretely, if f_s (samples/s) is the sampling rate used for capturing s, then the detail d_j contains the information concerning the signal components with frequencies included in the interval:

$$f(d_j)\in[2^{-(j+1)}\cdot f_s\,,\ 2^{-j}\cdot f_s]\ Hz. \tag{3}$$

The approximation signal a_n includes the low frequency components of the signal, belonging to the interval:

$$f(a_n)\in[\ 0,\ 2^{-(n+1)}\cdot f_s]\ Hz \tag{4}$$

Therefore, the DWT carries out the filtering process shown in Figure 1. Note that the filtering is not ideal, a fact leading to a certain overlap between adjacent frequency bands [7, 12, 15]. This causes some distortion if a certain frequency component of the signal is close to the limit of a band.

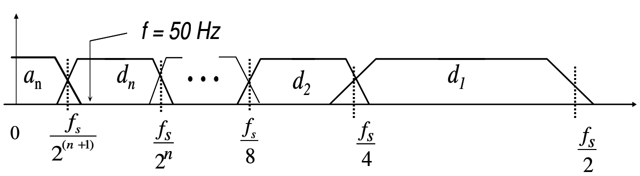
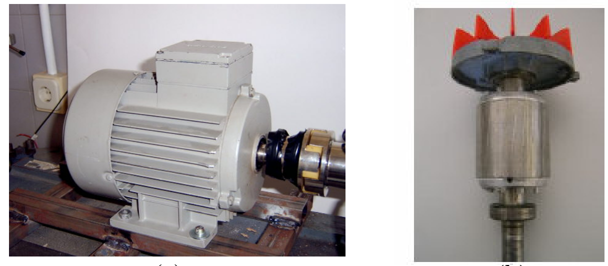


Figure 3. Filtering process performed by the DWT.

Due to the automatic filtering performed by the wavelet transform, the tool provides a very attractive flexibility for the simultaneous analysis of the transient evolution of rather different frequency components present in the same signal. At the same time, in comparison with other tools, the computational requirements are low. In addition, the DWT is available in standard commercial software packages, so no special or complex algorithm is required for its application.

IV. EXPERIMENTAL RESULTS

In this section the presented methodology is applied to the diagnosis of several machines under different fault and operation conditions. The tests were performed in the laboratory, using commercial cage motors with 4 poles, 28 rotor bars, rated 1.1 kW, 400V, 50 Hz, coupled to two different DC machines acting as loads (load 1 (direct coupling) and load 2 (coupling through straps)). Figure 4(a) shows the motor under test.



(a) (b)

Figure 4. (a) 1.1 kW motor under test (b) Rotor with one broken bar.

A phase current was used as diagnostic signal; this current was captured using a 15/5, class 0.5 current transformer and a 1A, 60 mV shunt; the resulting voltage signal was captured by means a digital oscilloscope with a sampling frequency f_s = 5000 samples/s, and finally transferred to a PC for the analyses. The standard MATLAB Wavelet Toolbox was used for performing the DWT of the signals; Daubechies-44 was selected as mother wavelet. Figures in the next sections show the wavelet signals resulting from the transform, as well as their associated frequency bands.

A. *Unloaded healthy machine*

Figure 5 shows the DWT of the startup current for the healthy motor coupled to load 1. The wavelet signals resulting from the analysis (approximation and detail signals) do not show any significant oscillations once the electromagnetic transient, occuring at the beginning of the startup in every machine, is finished. This shows the absence of any fault component, confirming the healthy condition of the machine.

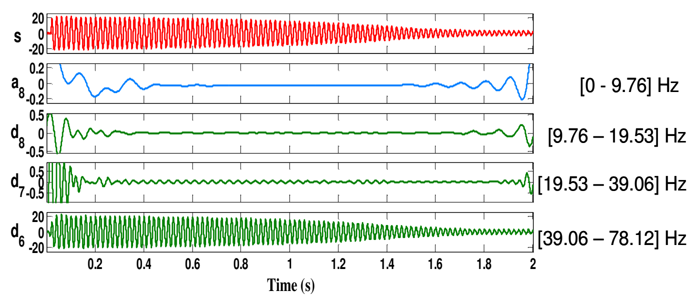


Figure 5. 8-level DWT of the startup current for the unloaded healthy machine.

B. *Unloaded machine with one broken bar*

A bar breakage was artificially forced in the laboratory, by drilling a hole in the selected rotor bar. Figure 4 (b) shows the rotor after the breakage. Figure 6 shows the application of the DWT for the case of a machine with 1 broken bar and coupled to load 1. Clear oscillations appear in the wavelet signals resulting from the analysis. Moreover, they are arranged in such a way that they reflect the evolution of the left sideband component created by the breakage (first decreasing from the supply frequency towards 0 Hz and later increasing towards the supply frequency again).

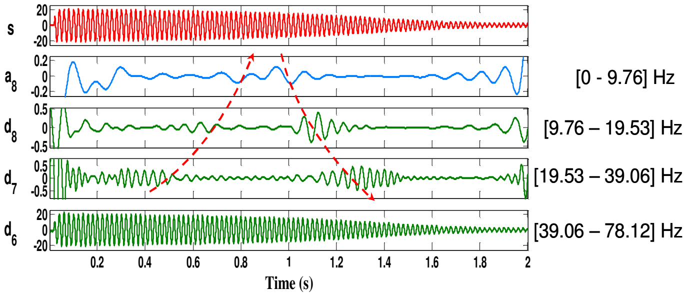


Figure 6. 8-level DWT of the startup current for the unloaded machine with one broken bar.

If the classical diagnosis methodology, based on the FFT of the steady-state current, is applied in this case the diagnosis conclusion could not be reached. This is due to the fact that the machine is unloaded and, therefore, the slip *s* is very low, so the sideband components given by (1) overlap the supply frequency. This is shown in Figure 7, where the sidebands are not detectable due to this fact.

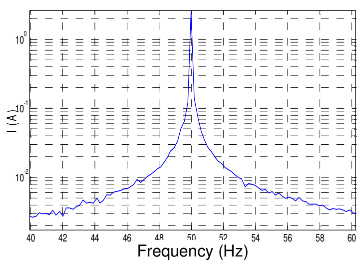


Figure 7. FFT of the steady state current for the unloaded machine with one broken bar.

C. *Unloaded machine with two broken bars*

Figure 8 shows the application of the diagnosis methodology to an unloaded machine with two broken bars and coupled to load 1. The conclusion is similar to that of the previous case; the characteristic pattern caused by the evolution of the left sideband is clear in the wavelet signals resulting from the DWT. Moreover, the oscillations within the signals a8, d8 and d7 have higher amplitudes, due to the higher degree of severity of the fault, in comparison with the previous case. This indicates the possibility of introducing parameters for quantifying the degree of severity of the fault based on the energy of the wavelet signals.

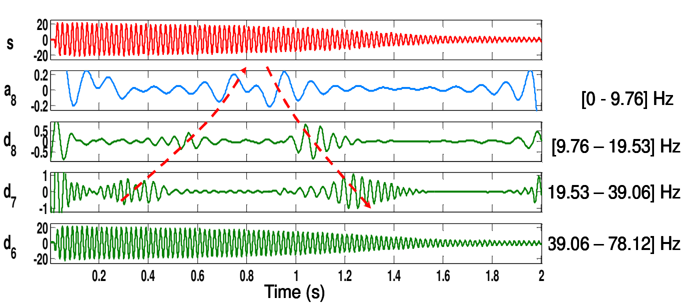


Figure 8. 8-level DWT of the startup current for the unloaded machine with two broken bars.

D. *Unloaded machine started through soft-starter.*

This test was carried out using the unloaded machine with one broken bar, coupled to load 2 and started by means of a soft starter. The soft starter controls the voltage supplied to the motor during the startup, increasing it progressively during the transient. This starting method is also common in the industrial environment. Figure 9 shows schematically the test-bed for the experiment.

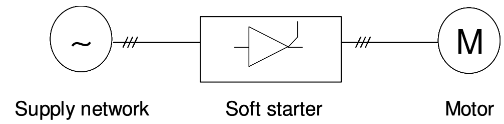


Figure 9. Simplified scheme for the test.

Figure 10 shows the DWT analysis of the startup current for this case. The characteristic pattern caused by the evolution of the left sideband appears clearly, confirming also the validity of the approach in this situation.

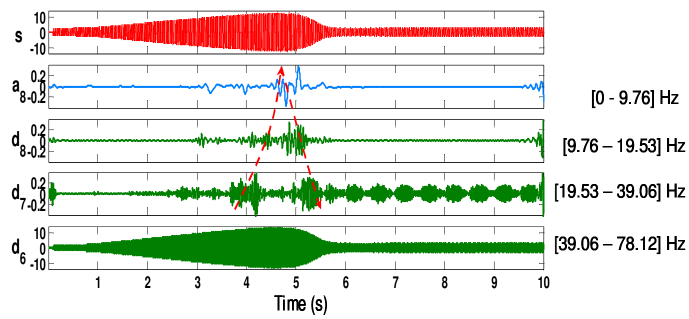


Figure 10. 8-level DWT of the startup current for the unloaded machine with one broken bar started through soft-starter.

E. *Machine with mixed eccentricity*

Figure 11 shows the application of the methodology for a machine with mixed eccentricity, considering now 6 decomposition levels. The evolution of the aforementioned fault components is clearly noticed; there is one component whose frequency evolves from 50 Hz to 25 Hz during the transient and a second one evolving from 50 Hz to 75 Hz. Therefore, a characteristic pattern really different from that associated with the bar breakage arises.

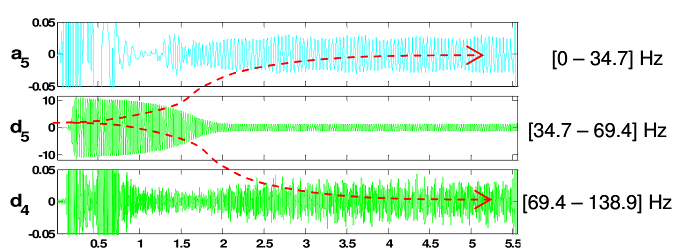


Figure 11. 6-level DWT of the startup current for the machine with mixed eccentricity.

V. INTRODUCTION OF QUANTIFICATION PARAMETERS

Once the condition of the machine has been preliminarily diagnosed, using the qualitative identification of characteristic patterns, it is necessary to compute the quantification parameter defined for the corresponding fault, in order to quantify the degree of failure in the machine.

In the case of rotor asymmetries, a quantification parameter γ_{asym} was defined in previous works [16]. It was based on the energy of the wavelet signal with the next level higher than the signal containing the fundamental. This parameter is given by (5).

$$\gamma_{asym}(dB) = 10 \cdot \log\left[\frac{\sum_{j=Nb}^{Ns} i_j^2}{\sum_{j=Nb}^{Ns}\left[d_{nf+1}(j)\right]^2}\right] \quad (5)$$

where i_j is the value of the jth sample of the startup current signal i(t); $d_{nf+1}(j)$ is the j element of the detail with level $nf+1$ (nf=level of the signal containing the fundamental); N_s is the number of samples of the signal, until reaching the steady-state and N_b is the number of samples between the origin of the signals and the extinction of the oscillations due to border effect.

According to the experience achieved by tests carried out in motors with this range of powers (few kW), a value for γ_{asym} higher than 40 dB is indicative of a healthy condition in the machine. Values between 30 dB and 40 dB mean that a partial breakage or one broken bar is present in the machine. Values around 30 dB or lower are usually obtained when at least two bars are broken.

Table I shows the results obtained when computing this indicator for different cases tested, as well as the deviations with respect the healthy condition for each machine. The values obtained confirm the ranges commented above.

In the case of mixed eccentricities, a quantification parameter γ_{mecc} could be also defined, based on the energy of the approximation signal with the next level higher than that containing the fundamental component. This parameter would be according to (6).

$$\gamma_{mecc}(dB) = 10 \cdot \log\left[\frac{\sum_{j=Nb}^{Ns} i_j^2}{\sum_{j=Nb}^{Ns}\left[a_n(j)\right]^2}\right] \quad (6)$$

where i_j is the value of the j sample of the current signal; $a_n(j)$ is the j element of the order n approximation signal; N_s is the number of samples of the signal, after finishing the first 10 cycles in the steady-state regime and N_b is the number of samples between the origin of the signals and the extinction of the oscillations due to border effect.

Machine	**Condition**	γ_{asym}	$\Delta\gamma_{asym}$
1.1 kW motor coupled to load 1	Healthy	47.1	-
1.1 kW motor coupled to load 1	1 broken bar, unloaded	37	-10.1
1.1 kW motor coupled to load 1	1 broken bar, 80% load	36.2	-10.9
1.1 kW motor coupled to load 1	1 broken bar, full-load	35.2	-11.9
1.1 kW motor coupled to load 1	2 broken bars, unloaded	30.6	-16.5
1.1 kW motor coupled to load 1	2 broken bars, 60% load	30.0	-17.1
1.1 kW motor coupled to load 1	2 broken bars, full load	30.1	-17
1.1 kW motor coupled to load 2	Healthy	44.4	-
1.1 kW motor coupled to load 2	1 broken bar, unloaded	35.6	-8.8
1.1 kW motor coupled to load 2	1 broken bar, 80% load	35.4	-9
1.1 kW motor coupled to load 2	1 broken bar, full-load	35.1	-9.3
1.1 kW motor coupled to load 2	2 broken bars, unloaded	30.7	-13.7
1.1 kW motor coupled to load 2	2 broken bars, full load	31.8	-12.6

VI. ADDITIONAL CONSIDERATIONS FOR THE APPLICATION OF THE METHOD

The different experiments performed showed the suitability of the method for the diagnosis of electromechanical faults introducing slip-dependant components. Nevertheless, additional considerations need to be done regarding the different parameters of the DWT decomposition, such as the type of mother wavelet, the order of the mother wavelet or the number of decomposition levels.

With regards to the type of mother wavelet, the Daubechies family was well suited for the application of this method, due to its inherent properties, although other families (symlet, biorthogonal, Gaussian, and specially dmeyer) also enable a clear detection of the patterns, despite their different mathematical characteristics. As an example, Figures 12 (a) and (b) show the application of the method for the case of unloaded machine with one broken bar and coupled to load 2, using symlet-30 and dmeyer, respectively. The similarities between both figures are obvious, appearing the characteristic pattern caused by the sideband.

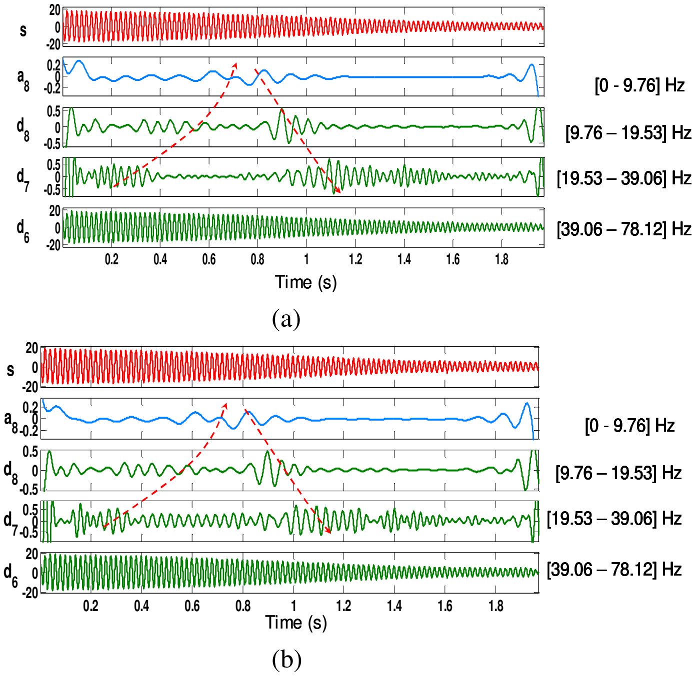


Figure 12. 8-level DWT of the startup current for the unloaded machine with one broken bar using: (a) symlet-30, (b) dmeyer.

When using the Daubechies family, an important fact observed was the overlapping between the frequency bands associated with successive wavelet signals resulting from the DWT of the current. This is due to the fact that the wavelet signals act as non-ideal filters, extracting the components of the signal included within a certain frequency band that can overlap partially with the adjacent band [7, 15]. In this sense, it was observed that, when using a high-order Daubechies wavelet for signal decomposition, the overlapping was smaller than when using a low-order one. In other words, high-order wavelets behave as more ideal filters, a fact that helps to avoid partially the overlapping between frequency bands.

Finally, the number of decomposition levels (n_d) is related to the sampling frequency of the signal being analysed (f_s). This parameter has to be chosen in such a way that the DWT supplies at least three high-level signals (two details and an approximation) with frequency bands below the supply frequency f; this condition implies:

$$n_d \geq n_f + 2 \quad , \tag{7}$$

being n_f the level of the detail which contains the supply frequency, that can be calculated using (8).

$$2^{-(n_d+1)} \cdot f_s < f \tag{8}$$

This condition means that the lower limit of the frequency band of the n_f level detail is lower than the supply frequency.

Thus:

$$n_d > \frac{\log(f_s / f)}{\log(2)} + 1 \qquad \text{(integer)} \tag{9}$$

VII. CONCLUSIONS

A diagnosis methodology is presented in this paper to diagnose the presence of electromechanical faults in electrical machines. It is based on the application of the DWT to the stator startup current and the further recognition of characteristic patterns created by each fault.

Several faulty cases are presented in the paper, all them confirming the validity of the approach, even in some cases in which the classical methodology, currently used in the industrial environment, might not lead to correct results.

The method admits the quantification of the degree of failure using parameters based on the energy of the wavelet signals resulting from the analysis.

Further step would be the application of image recognition algorithms for the automatic identification of these characteristic patterns, which could be the basis of the implementation of portable diagnosis devices.

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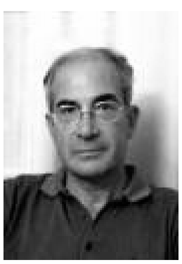

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