Article

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Method to detect faults in the rotor squirrel cage with low load in permanent state using DWT

Método para detectar fallas en el rotor de jaula de ardilla con baja carga en estado permanente usando DWT

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Abstract

Although there are several methods that can be used, the Continuous Wavelet Transform and its discrete version have demonstrated their ability to work with these signals. This article presents a new method to help detect early faults in the rotor squirrel cage of induction motors no-load and operational state, specifically in bars and rings. Using three techniques on the whole as it is the motor current signature analysis (MCSA), discrete wavelet transform (DWT) and multi-resolution analysis (MRA) with a decomposition tree reduced and apply a suitable index that determines the condition of the rotor. A brief description of the case study on which the research carried out is based is offered, which is used here successfully to generate a new alternative to determine the condition of the rotor squirrel cage. The performance of the results is get from the experimentation carried out and determined through comparison between the DWT conventional analysis and the new method, also exposing a brief comparison using the fourier transform. This new method reduces the uncertainty when performing the rotor diagnosis and improves the accuracy to differentiate the condition where it is.

DWT, Fault detection, Induction motor

Resumen

Aunque existen varios métodos que se pueden utilizar para el análisis de motores de inducción, la Transformada Wavelet Continua y su versión discreta han demostrado su capacidad para trabajar con estas señales. Este artículo presenta un nuevo método para ayudar a detectar fallas tempranas en el rotor de jaula de ardilla de motores de inducción sin carga y en estado operativo, específicamente en barras y anillos. Utilizando tres técnicas en su conjunto como lo es el análisis de firma de corriente del motor (MCSA), la transformada wavelet discreta (DWT) y el análisis multiresolución (MRA) con un árbol de descomposición reducido y aplicando un índice adecuado que determina el estado del rotor. Se ofrece una breve descripción del caso de estudio en el que se basa la investigación realizada, el cual se utiliza aquí con éxito para generar una nueva alternativa para determinar el estado del rotor de jaula de ardilla. El rendimiento de los resultados se obtiene a partir de la experimentación realizada y se determina mediante la comparación entre el análisis DWT convencional y el nuevo método, exponiendo además una breve comparación utilizando la transformada de Fourier. Este nuevo método reduce la incertidumbre a la hora de realizar el diagnóstico del rotor y mejora la precisión para diferenciar el estado en el que se encuentra.

TDW, Detección de fallas, Motor de inducción

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Introduction

There are many techniques and monitoring methods used for the diagnosis or evaluation of the state of induction motors [1-3]. The most used technologies and techniques are vibration analysis, thermography, ultrasound, current and voltage analysis, better known as MCSA [4-6], latter is most used due to its characteristics, since it is a non-invasive technique, until certain point practical and relatively simple to acquire the study signal.

However, when the type of electrical signals used for current analysis in electric motors is explored, an open field of research appears to find new methods and tools that are better adapted to their analysis, so far there are several methods that use the Wavelet Transforms in their discrete version that have demonstrated the ability to work with signals that can be generated from the use of faulty A.C. induction motors as [7-10].

There are various works that address the detection of faults in induction motors and specifically in the rotor, but nevertheless many work consider detection and classification interchangeably, it seems that both must be necessarily linked when the study of the faults of motor is carried out, it must be taken into account that detection is the action of capturing, noticing or perceiving the presence of a particular signal related to the failure and the classification is based on this so that applying tools such as support vector machines (SVM) [11], fuzzy logic [12], arrangements of neural networks (NNA) [13], [14] among many others is carried out, consequently if the method or tool used for detection is not adequate, uncertainty will always exist to a lesser or greater extent.

In this work was developed a new method that is based on the apply of the Discrete Wavelet Transform and the analysis of permanent stator current, with motor no-load. It focuses on study of the coefficients resulting from decomposition through of high-level wavelet signals in permanent or stable current, as a way of detecting the presence of left sideband component from multiresolution analysis. Energy of these coefficients shows a clear difference when a breakage of the rotor ring or bar has occurred.

The comparison of analysis results of signal has been made using the tools Python and Matlab, first comparison with the results of the analysis of signal using a classic tool as Fourier Transform was made, second with the Discrete Wavelet Transform was made, in this last the results of the usual or conventional analysis is made compared the method developed with a pre-processing specific to optimize the analysis and detect faults early induction motors rotor.

The experiments with a squirrel cage induction motor on a test base built for diagnostic purposes have been carried out. A data acquisition system based on an embedded board and an analog-to-digital converter module with programmable gain and high resolution was developed. It is very important given that the high resolution will allow detection of failures with a reduced decomposition tree. An important advantage of this tested method is that it leads to a correct diagnosis in some times where Fourier Transform approach does not provide as accurate results, such as no-load or low-load machines, this method improves the ability to distinguish between rotor states and makes the difference in their condition obvious comparing against usual DWT analysis, where in different works, only the selection of mother wavelet used or sampling frequency of signal changes for application of the decomposition tree example of this can be seen in [15-18].

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Case study: method basis

The extensive study of induction motors has yielded multiple findings on its operation, in this work we focus on the operation and characteristics of rotor of squirrel cage induction motors, within the various studies of this area of motor, it has been shown that broken bars produce induced frequency components in the current spectrum in $[(1 \pm 2s) * f_1]$, where "s" is the slip and "f_1" is the supply frequency or fundamental frequency.

It has been known since the 1920s that an asymmetrical rotor winding, whether in a three-phase cage or slip-ring induction motor, will induce a voltage in the stator winding at a frequency of $f_1 * (1 - 2s)$ Hz and, therefore, conduct a current at that frequency in the stator.

The cyclical variation in current caused by a broken rotor bar produces a torque variation at twice the slip frequency and this produces a speed variation that is a function of driveshaft inertia. This normally reduces in the magnitude of the current component $f_1 * (1-2s)$ and a new current component appears in $f_1 * (1+2s)$ and its magnitude can be improved by modulating the third harmonic flow of time in the stator. The greater the inertia of the drivetrain, the greater the resistance to oscillation of torque and speed at $2sf_1$ and therefore the smaller the magnitude of the upper sideband at $+2sf_1$ compared to the lower sideband $-2sf_1$ around *f*, the supply or fundamental component. Therefore, the cage winding breaks produce two sidebands at $\pm 2sf_1$ around *f*, and given by the aforementioned equation, the magnitude of the supply frequency component can be 20 to 1000 times greater than the magnitude of the sidebands according to [19].

In summary, electromagnetic field anomalies in the air gap create sideband harmonic components in the stator current spectra. It is here in the stator winding which is traversed by a balanced system of currents (three-phase current) that gives rise, because of the Ferraris Theorem, to a rotating magnetic field whose speed is known as synchronism speed and is in Hz is calls n_1, this is calculated from the line or fundamental frequency f_1 of the stator currents and the number of even poles by the following quotient.

$$n_1 = \frac{60 f_1}{p} \tag{1}$$

In the rotor, which is the rotating part made up of an axis or central arrow with a series of laminations in a block or package with slots in which a series of conductors known as closed bars with a pair of rings at their ends are fused that short-circuit each busbar. In motors with a squirrel-cage rotor, the rotating field created in the stator generates electromotive forces (e.m.f.s.) in the rotor winding and when this is short-circuited, currents appear that generate a magnetic field, which when interacting with the rotating field of the stator move it at a speed close to but below the synchronism known as the mechanical speed of the motor (*n*), in such a way that the general expression for this type of machine is given by

$$f_2 = f_1 - \frac{n * p}{60} \tag{2}$$

The relative difference between the stator (synchronous) and rotor (mechanical) magnetic flux speeds is known as “slip” (*s*). Is called slip s to following relationship

$$s = \frac{n_1 - n}{n_1} = \frac{\Omega_1 - \Omega}{\Omega_1} \tag{3}$$

in Hz and radians respectly, substituting equation (1) in (3) it is expressed as follows

$$s = \frac{\frac{60 * f_1}{p} - n}{\frac{60 * f_1}{p}} \tag{4}$$

Now the conductors of rotor winding (bars) see the field originated by the stator winding rotate with a relative speed n_2 (value of the speed of the rotating field, synchronous speed, from the point of the bars), which can be expressed as:

$$n_2 = n_1 - n = s * n_1 \tag{5}$$

Consequently, since this magnetic field has *p* pairs of poles, in one minute a rotor driver has seen n_2*p magnetic cycles pass in front of him (each pair of poles makes up a cycle of the wave of magnetic field in air gap, which is repeated in the next pair of poles and so on in all the pairs of poles of the machine). Each magnetic cycle induces a period of the e.m.f. time wave when turning ahead of a rotor driver. This causes the rotor phases to induce an e.m.f.s whose frequency is $n_2 * p$ cycles per minute, that is a frequency f_2 that measured in Hz (cycles per second) can be calculated as:

$$f_2 = \frac{n_2 * p}{60} = s\left(\frac{\frac{60 * f_1}{p} * p}{60}\right) \tag{6}$$

Then, taking relationship (1) into account, it can be deduced from the above that there is a frequency in the rotor phases that is expressed according to the following relationship.

$$f_2 = s * f_1 \tag{7}$$

Fourier Transform

In signal analysis there are many tools that can be used, among which the Fourier Transform [20-24] or stands out and is also one of the most common, thanks to its relative simplicity of use application and its ability to deliver a representation of the frequency content that a certain signal has, however, due to the limitations of said tool, new tools have been developed that allow an analysis of the signals from another perspective as the STFT [25], [26] due to the need to analyze signals that do not behave in a stationary way and/or that present abrupt changes in very small intervals, another one of these tools is the Wavelet Transform as mentioned in [27-35]. To better understand these signal analysis tools and observe how WT eliminates the limitations of FT, they are presented next.

Beginning with the Fourier Transform, the purpose of the mathematical transformations that apply to the signals is to get more information from them than that which can be extracted from the signal in time, the Fourier Transform allows a signal to be decomposed into its components sinusoidal and cosine waveforms of different frequencies and amplitudes, it can be seen roughly as a mathematical tool or technique to transform the point of view of the signal from a time basis to a frequency basis, as illustrated in figure 1.

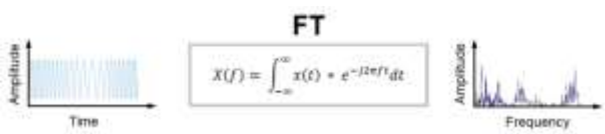

Figure 1 Fourier Transform

In most cases, the analysis by Fourier Transform is useful, however when passing a signal to the frequency domain, the information regarding time is lost, because when a signal is observed to which the Transformation of Fourier, it is impossible to determine exactly when a given frequency occurs or is present (in the time domain).

Discrete Wavelet Transform

Wavelet Transform applied to a series of numerical data makes it necessary to implement a Discrete Transform [36-42]. Considering the Wavelet Transform of a continuous signal $x(t)$, but with discrete translation and scaling parameters a and b. A natural way to sample the parameters a is by using logarithmic discretization of the scale a and binding it to the step size of b, that is moving in discrete steps to each location of b which is proportional to the scale a. This discretization of the Wavelet has the following form:

$$\psi_{m,n}(t) = \frac{1}{\sqrt{a_0^m}}\,\psi\left(\frac{t - nb_0a_0^m}{a_0^m}\right) \tag{8}$$

where m, $n \in \mathbb{Z}$ control scaling and translation respectively, a_0 is the fixed expansion step size greater than 1 and b is the location parameter that must be greater than zero. From equation (8), the translation step size $\delta b = b_0 a_0^m$ is directly proportional to the wavelet scale a_0^m. Therefore, the Wavelet Transform of the continuous signal x(t) using discrete Wavelets of the form (8) is given by:

$$\mathrm{T}_{m,n}x = \int_{\mathbb{R}} x(t) * \frac{1}{a_0^{m/2}}\psi\,(a_0^{-m}t - nb_0)dt \tag{9}$$

The most common values of a_0 and b_0 are 2 and 1 respectively, the logarithmic scaling in powers of two of the step sizes of translation and dilation is known as dyadic mesh array. Substituting $a_0 = 2$ and $b_0 = 1$ in equation (8), the wavelet of the dyadic mesh is written as:

$$\psi_{m,n}(t) = \frac{1}{\sqrt{a_0^m}}\psi\left(\frac{t - nb_0a_0}{a_n^m}\right) \tag{10}$$

First approach: Analysis based on the Fourier transform

First analysis was carried out with the Fourier Transform, analyzing the resulting spectrum of the study signal before and after the application of the one-sideband signal preprocessing and conditioning system (SCPS-1SB) figure 2, with a healthy motor. Which has as its main element a special filter of specific characteristics, or Band Pass-Filter of specific selection exclusive (FPB-ESE) antialiasing.

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Specifically designed to contribute to the detection of signals near to the line frequency in order to more easily detect faults rings or bars.

Figure 2 SCPS one-sideband

In conventional analysis with FT, to detect frequency of broken bars and rings during steady-state operation, a fast Fourier Transform is performed on the study signal. The frequency amplitude of broken bars and rings is more noticeable when the load or the number of broken bars increases and as the motor load approaches the full load condition, the motor speed is below motor speed without load so the frequency of broken bars and rings is more separated from the line frequency, making it easier in this condition to locate and identify the frequency of broken bars and rings.

On the contrary, if motor load is near or in the unloaded condition, frequency of broken bars and rings is very close to the line frequency, making it very difficult and even indistinguishable, and therefore the condition broken bars cannot be detected, and under any other load condition, the amplitude of the broken bars and broken ring frequency is very small compared to that of the line frequency, requiring a high-speed analog-to-digital converter or high resolution, in this work, high resolution was chosen instead of high sampling as in most of the works that were reviewed and carried out up to now.

Figure 3 shows spectrum of the raw signal healthy versus the spectrum of signal applying the preprocessing to the SCPS-1SB signal healthy. In this comparison we can see that there are slight differences in magnitude between the two spectra because of the filtering so close to the line frequency that was carried out, although no difference that could be of importance is observed, the differences that are observed are due to the work that the signal processing. In figure 4 shows comparison of spectra of the healthy signal and with failure, both with signal processing, in which it is possible to notice a greater difference in signal level, but at very low levels.

This makes it difficult to differentiate between the states of healthy and failed motor using only the spectra, getting worse much with variable loads, since line frequency is still too high, eclipsing the signals of interest.

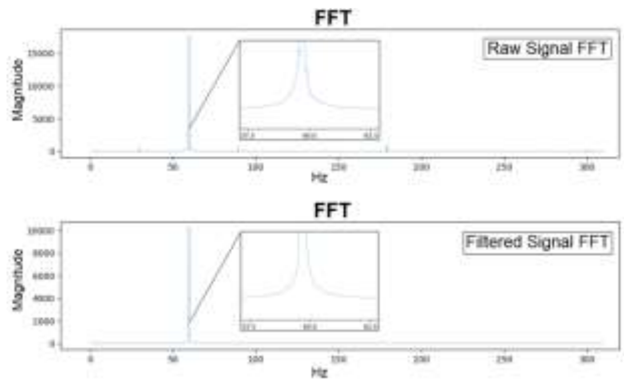

Figure 3 Spectrum of signal FT without and with SCPS-1SB

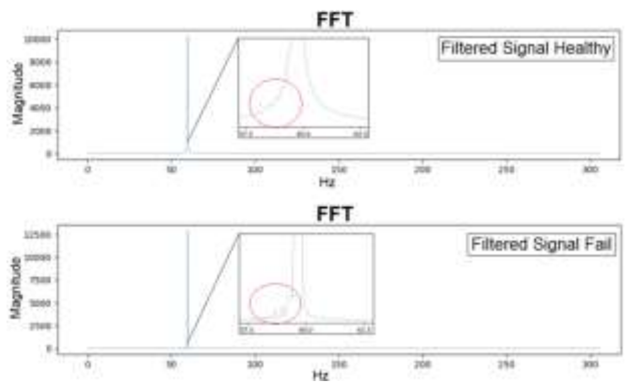

Figure 4 Spectrum of signal FT healthy vs fault.

Second approach: Analysis based on the Discrete Wavelet transform

Second analysis was performed with the Discrete Wavelet Transform 1-D. After performing the signal conditioning is done preprocessing where the SCPS-1SB is applied, the next step is the application of the signal to the decomposition tree or multi-resolution analysis based on the transform algorithm fast wavelet using matlab, for this some aspects must be considered, the first is the choice of a mother wavelet in which the correlation of this with the study signals must be considered, in the same way the necessary decomposition levels must be calculated, the number of these will result according to the sampling frequency used, this can be done by means of an expression which is used with some variations by as shown in [10], [14].

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There are multiple variations of the equation to determine the limit of decomposition levels according to the main purpose and the specific data for this work. In this particular case, the line frequency is 60 Hz according to our geographical region and the sampling frequency is 720 Hz, low compared to that used in other works but it does not prevent the effectiveness of method, which is result of operation of data acquisition module and board with embedded system used.

The choice of mother wavelet is of the utmost importance, in this study wavelet Daubechies-44 (db44) was used, and although due to its level it requires a large computational load, its good work has been demonstrated in the detection of failures in broken bars and rings in induction motors compared to other [10], [14], [35]. It is the one that are selected as the mother wavelet, since they is provide a more precise detail signal with lower harmonics since as the wavelet is of a higher level, it is located less in time and oscillates less due to the dilation nature of wavelet transform, this means that at a higher level it behaves like a filter more ideal.

The equation chosen to calculate the levels of decomposition or branches is:

$$n + 1 = int\left(\frac{log\left(\frac{f_s}{f_L}\right)}{\log(2)}\right) + 1 \qquad (11)$$

The result that calculation gave us using suitable sampling frequency and line frequency gave us a decomposition tree made up of 4 levels, one thing to remember is that the decomposition tree has a decimated dyadic structure, this means In other words, for each level that increases the samples are reduced in powers of two, this type of structure optimizes the characteristics of the system since it avoids having redundancy in the output data (coefficients C_A, C_D).

This can be seen in the multi-level or multi-resolution decomposition tree figure 5, in which the four levels are shown with the respective outputs of the detail coefficients and the output for level four of the approximation coefficients.

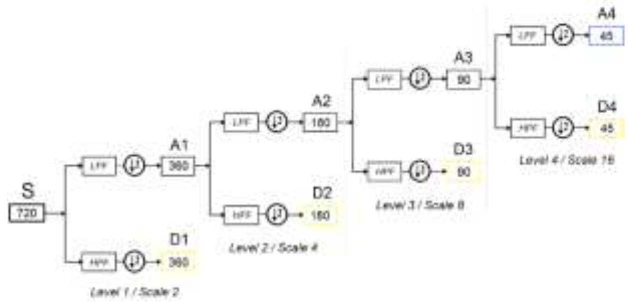

Figure 5 Multiresolution decomposition tree.

This method is based on three tools which are:

Techniques applied in the method		
MCSA - Motor Current Signature Analysis	AWT – Analysis wavelet transform	AMR - Analysis Multiresolution
Pre-processing		
Post processing		

Diagram 1 Techniques and processing

Experimental results.

For validation of method, several tests were carried out with a 4-pole 2Hp squirrel cage induction motor. The motor was initially tested in a healthy state, later proceeded ring and rotor bar breaks were performed in a laboratory; the separation was made in the ring's width and the bar with an approximate thickness of 1mm. After finishing the tests in a healthy state, the motor was disassembled to gain access to the rotor and be able to carry out in the failure's simulation, material was artificially removed to generate the break in the ring and the bars (Fig. 7) The data on study's motor nameplate are: brand: WEG, model: 00218ET3EM145TCW, Star connection, nominal voltage: 230 V, nominal primary current: 5.52 A, nominal power: 2Hp, 4 individual poles, nominal speed: 1755 rpm, service factor: 1.25, Insulation class: F and number of rotor bars: XX. The figure 6 shows the diagram of acquisition and processing of signal.

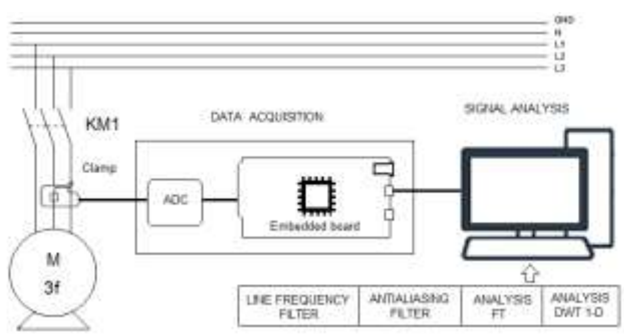

Figure 6 Data acquisition and processing

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Figure 7 Tool and ring and bar failure simulation, broken rotor

To select the line where the current data would was get, an initial comparison was made in the three phases, taking into account as selection criterion which was the most stable and with the least variations between tests, was selected the phase or line number 2, for having the greatest stability and least variation between tests. In this, the primary current was measured during permanent state for the different cases tested, for this condition the samples were taken after 10 seconds of starting the motor. To capture data, an analog-to-digital converter was used with a sampling frequency of 860 samples/s theorist with programmable gain and 16-bit resolution. To carry out the acquisition of the current signal, Python was used and the analysis was carried out with the DWT, it was done with MATLAB. A 4-level decomposition was performed using the mother wavelet Daubechies-44 for analysis. Table I shows frequency bands corresponding to high-order wavelet signals resulting from the analysis, according to sampling rate used for tests.

Table I shows bandwidth with which each level remains for details or high-frequency signals, as well as for approximations or low frequency signals. In this table, It can be seen that our area of interest focuses mainly on the level four of details, since in this they will meet the signs of interest.

Level	Approximations	Details
1	A1 : [0 , 360]	D1 : [360 , 720]
2	A2 : [0 , 180]	D2 : [180 , 360]
3	A3 : [0 , 90]	D3 : [90 , 195]
4	A4 : [0 , 45]	**D4 : [45 , 90]**

Table 1 Frequency bands in hz for twd with f_s=720 Hz

Analysis and comparison of the signals

Figures 8 and 9 show analysis multi-resolution of the signal no-load state of motor, where in the first (figure 8) the levels of the raw signal or without process are shown, according to the amount of data and algorithm that Matlab uses, the decomposition levels should be 13, having several levels that are not relevant for the study of the signals that indicate rotor failures, or of interest (d6-d13), this can be seen clarity in figure 9 since after applying the SCPS-1SB, where only the signals that would indicate the failure in the rotor of the squirrel cage induction motor appear, these levels lack of any variation in the signal. Thus we can see that an analysis can be carried out with fewer levels, more stable and without variations after the application of SCPS-1SB without losing the characteristics or signals of our interest for the detection of failures, and be able to differentiate with total clarity the moments of inflection.

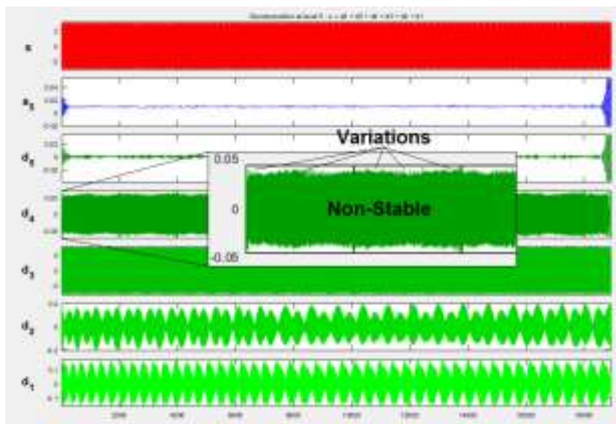

Figure 8 Raw signal no-load motor, figure shows the decomposition of 5 levels showing variations in the last three levels

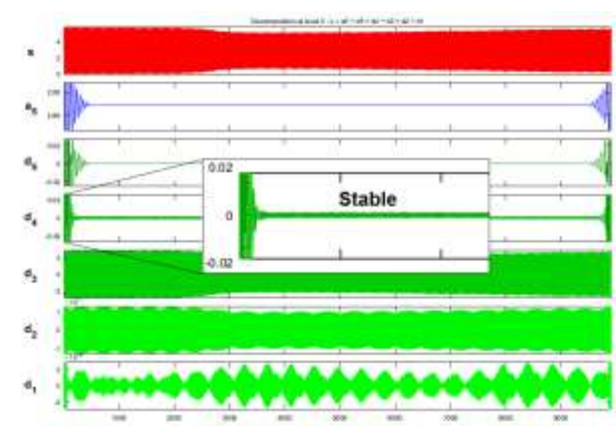

Figure 9 Signal SCPS-1SB no-load, figure shows the decomposition of 5 levels without variations in the last three levels

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This small difference and elimination in the oscillation of the resulting signals is a great advance of the utmost importance since for analysis of the signals of faults a small difference can cause an increase in their energy, and if don't have stability, this could be inconvenient since the variations cause uncertainty and mistakes when differentiating the state where motor is located, provoking diagnoses doubtful or wrong.

The index used to determine the state of rotor is governed under the condition of having a stable signal, when applying the SCPS-1SB the graphs of the different levels of coefficients show that a smaller number of levels is required for analysis of signal, from here the analysis is carried out with fewer levels giving way so to comparison between the resulting of signals in a healthy and with failure state.

Method for detecting faults

The tests show that Discrete Wavelet Transform performs a more adequate analysis for this type of signals caused by failures in rotor of induction motors carried out, getting results with greater precision due to the conditioning and preprocessing of signal, increasing the accuracy when diagnosing the condition of motor however the results of analysis with conventional method are not as noticeable or evident by the variations present in the resulting signal, variations that are reflected in the energy's magnitude of *f* the coefficients, in proposed method to detect faults in bars and rings of the squirrel-cage rotor certain features stand out to be able to detect with failures more clearly and easily to remove the uncertainty due to low visible difference but enough between motor states.

Figure 10 of signals of output SCPS-1SB no-load with fault motor and signal of output SCPS-1SB no-load without fault motor clearly show that there is a notable difference in the levels of the resulting coefficients at the level of interest (cD4), the level at which where are the signs related to failures in the rotor of induction motors, due to the special treatment that was done to the signal to it analysis, since the sideband method is used to detect faults.

To improve the results get and avoid the deviation in the value of the result of the coefficients, a statistical study of the resulting signals was made and a statistical analysis was carried out, where did it began debugging the signal considering only the values where the convolution of the signals completely overlap and the values outside the limit of the signal are not considered. Following this concept, it goes one step further and the study and analysis was carried out, reducing to the resulting signal 14 points less in both ends of the signal to reduce variation and improve accuracy of results.

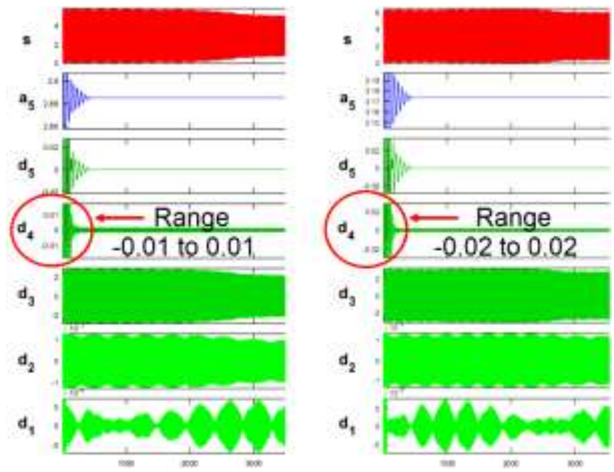

Figure 10 Levels at the output of the SCPS-1SB, figure on the left side shows the analysis of the motor signals without fault in no-load, the figure on the right side shows the analysis of the motor signal in no-load with fault

The calculation and comparison of energy of the coefficients was made where energy 1 is calculation of complete signal, energy 2 is calculation of the signal with the elimination of the length of kernel of convolution and energy 3 results from the signal removing the length of Kernel and 14 extra points. These points were taken according to the results of the graphs because of, the tests and analysis carried out, the basis that was taken was realization of an average of the results of energy of each test carried out, calculated with MATLAB the results.

Figure 11 shows comparison of the signals resulting from the level of interest (cD4) for detection of failures in the rotor of induction motors, it shows the graphs of complete signal, the signal with the elimination of kernel length of the convolution and the signal removing kernel length and 14 more points.

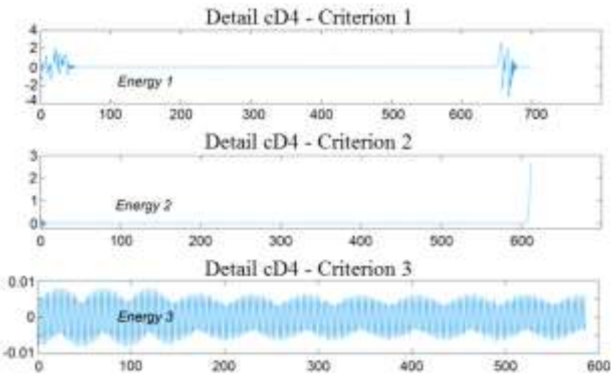

Figure 11 Coefficient signals level 4 (cD4)

Table II shows results of deviation get of the tests results indicating precision which we have an average deviation of 37% for original signal results, an average deviation of 56% for signal with elimination of kernel length and an average deviation of 13% of signal eliminating Kernel length and 14 points, these results clearly show an improvement in stability and precision of method regarding the usual analysis, as well as being more exact in differentiation of motor no-load states.

# Test	% Energy 1	Abs	% Energy 2	Abs	% Energy 3	Abs
1	96.460	**3.539**	120.765	**20.765**	75.497	**24.502**
10	73.245	**26.754**	5.183	**94.816**	126.298	**26.298**
20	115.819	**15.819**	113.698	**13.698**	103.014	**3.014**
30	72.492	**27.507**	93.596	**6.403**	64.207	**35.792**
40	40.054	**59.945**	39.009	**60.990**	109.364	**9.364**
50	107.083	**7.083**	125.068	**25.068**	93.842	**6.157**
60	181.603	**81.603**	202.880	**102.880**	117.831	**17.831**
70	69.910	**30.089**	6.686	**93.313**	98.075	**1.924**
80	112.711	**12.711**	139.432	**39.432**	102.309	**2.309**
90	186.287	**86.287**	206.161	**106.161**	116.420	**16.420**
100	44.3304	**55.669**	47.518	**52.481**	93.136	**6.863**

Table 2 Absolute deviation of the signal in %.

Gratitude

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Conclusions

There are multiple methods and tools for the analysis of rotor failures, Fourier Transform is a powerful tool for the analysis of the line current signature in squirrel cage induction motors, however it is not the most appropriate since it does not behave in the best way in the analysis of resulting signals of processes where there is a variable load with sudden changes in a short time, as well as in signals where the motor has the minimum requirement having a low load, in this paper this last point is addressed.

In this paper, a novel and specific method for the detection of broken rotor rings and bars in induction motors no-load and in steady state is presented, an extreme condition where the detection of faults is the most difficult and very few works have studied. The method is based on specific treatment performing an adequate conditioning of the signal, designing and calculating a special filter, which performs three functions: first, it is responsible for filtering the line or fundamental frequency to avoid eclipsing signal that indicate a fault, as well eliminate signals that are not necessarily a sign of failure because of harmonics and for another, it performs an anti-aliasing, besides to restricting the window to a specific band where possible rotor failures are found only, ensuring its operation, filter job of this filter is based on the frequencies that have been extensively studied and that are known with theoretical certainty to be indicative of damage to the rotor, this special filter with the elements in charge of signal acquisition and preprocessing is called the signal conditioning and preprocessing system one-sideband (SCPS-1SB). The application of the preprocessing was effective since in the spectrum resulting from the analysis, only the band of interest for the detection of early failures is preserved.

Next, the calculation of bands or levels that make up the decomposition tree for multi-resolution analysis is performed based on the discrete wavelet transform, considering the sampling frequency that is given by the analog-to-digital converter module with 16-bit resolution, sampling frequency of 860 mps theoretical and programmable gain, there are 4 levels or branches left making resources efficient and demonstrating that a sampling high is not essential nor conditional, as has been done in most of similar works focused on this topic.

Within which there is a greater interest in level four of detail coefficients with this, it is shown that a decomposition with a tree of many levels is not required to get favorable results.

To further improve the precision of the results and have a good performance with the detection index a post-processing is applied to all this, it is used an adequate index where we work with the signal and the coefficients of the results, optimizing the signal (Level cD4), limiting the extremes of this and reducing the signal the length of the kernel plus 14 points getting a smaller deviation of the tests is get regarding the analysis of the original signals and without the application SCPS-1SB, in charge of a specific work and improvement of the results in the detection of failures in the rotor of induction motors. This criterion is also very useful for adjusting and optimizing the comparison of the state of the motor through the graph resulting from cD4.

The proposed method reduces the uncertainty increasing accuracy to differentiate with clearly the state in which the motor is differed considerably increases the possibility of detecting in the conditions of failure with the motor no-load and permanent state, of rings and broken bars compared with conventional DWT analysis, and can more accuracy diagnose the different conditions, being to able can detect incipient failures with a light or low load, besides to eliminating the inconvenience of the analysis with load variation, either using Fourier Transform or conventional wavelet transform analysis. Here we focus on the range and we refine the characteristics of the signal that provides us with the identification and maximizing the difference that determines the state of the motor. With this work, certain points are corroborated, the fact that although it is possible to use the Fourier transform to detect faults, it is very difficult due to its proximity to the line frequency and special conditions are needed; on the other hand, it is shown that with the use and combination of several suitable tools for failure analysis can clearly detect these failures even with low load without need to implement tools that demand so many resources, obtaining the same and better results, finally it is shown that although high sampling gives good results for failure detection, it is not essential for the detection of the failures having a high resolution in sampling.

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