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WAVELET TIME-FREQUENCY ANALYSIS WITH DAUBECHIES FILTERS AND PRINCIPAL COMPONENT ANALYSIS FOR FAULT IDENTIFICATION INDUCTION MACHINE IN STATIONARY OPERATIONS

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Abstract. *This work is a contribution to the study of Signal Processing Techniques based on the Wavelet Transform for extracting Energy and Entropy parameters from vibration signals for detecting faults in stationary induction motors. Together with the Wavelet Transform, the Principal Components Analysis (PCA) is used for reducing the dimension of the dataset. The use of an experimental bench brings high-precision results.*

Keywords: *Induction Machine, Wavelet, Vibration, Principal Component Analysis*

1. INTRODUCTION

Electric induction motors are highly important components of industrial equipment and plants. The several faults that occur with induction machines may have serious consequences for the industrial process, the main problems being in increasing production costs, worsening of the process and safety conditions, and above all lower quality of the end product (BOUZIDA, 2011). Many of these faults are progressive. The vibration analysis has been one of the most used techniques for fault detection and diagnoses due to features such as easiness of use, relatively low cost, non-intrusive technique, among others. Through the analysis of the vibration signal spectrum it is possible to detect both mechanical and electrical defects (Hu, 2008). Although many different techniques available are better for detecting type-specific faults (Benbouzid, 2000), the ability to detect a higher number of different faults with a single technique results in cost reduction and process optimization.

2. BACKGROUND

2.1 Wavelet Packet Transform (WPT) Energy Entropy

Wavelet packet transform (WPT) is the generalization of the classic wavelet transform. In WPT, the coefficients of detail are decomposed at the first decomposition level, generating what is known in the literature as wavelet packet tree (Yan, 2014). In this way, results are obtained with better time and frequency domain resolution (Mallat, 2008; DAUBECHIES, 1992). The wavelet packet transform of a signal x(t) is defined in equation (1).

$$x_p^{n,j} = 2^{-j/2}\int_R x(t)\overline{\mu_n(2^{-j}t-p)}dt \tag{1}$$

$\mu_n(t)$ is the function wavelet packet; j represents the number of decomposition levels, also known as scale parameters; the symbol p represents the position parameter; n is the number of packets (Frequency Sub-band) due to decomposition process (KANKAR, 2011). To the signal x(t), decomposed by WPT, it is used the expressed by :

$$\begin{aligned} W_{2n}(t) &= \sqrt{2}\sum_l h_l W_n(2t-1) \\ W_{2n+1}(t) &= \sqrt{2}\sum_l g_l W_n(2t-1) \end{aligned} \tag{2}$$

The operators g and h are known as Quadrature Mirror Filters (QMF) and must satisfy the following orthogonality conditions (Mallat, 2008):

$$HG^* = GH^* \tag{3}$$

$$HH^{*} = GG^{*} = I \tag{4}$$

The calculation energy method of each packet from decomposition WPT is a more robust signal representation than using directly the decomposition coefficients (Hu 2008; Peng 2004). The energy associated with the wavelet packet decomposition is given by.

$$E_i = \int_{-\infty}^{+\infty} x_j^i(t)dt \tag{5}$$

The total signal energy is expressed by:

$$E_{tot} = \sum_{i=1}^{2^j} E_i \tag{6}$$

The energy of each sub-band is defined as E_i . The normalized energy value, which corresponds to the energy of each wavelet packed is given by:

$$P_l = \frac{E_i}{E_{tot}} \tag{7}$$

where P_l is the probability distribution of each sub-band.

R The concept of entropy has been widely used as a measure of the system disorder (Gray, 2011). In this paper, the entropy is obtained by the WPT. The energy probability distribution for each sub-band was given by Equation 7.

Using the definition proposed by Shannon, the entropy is expressed by (Peng, 2004):

$$S = -\sum P_l \ln(P_l) \tag{8}$$

2.2 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is a statistical technique applied in several fields and it is widely used to find patterns in high dimension data, reducing the redundancy of informations presented in a data block through the projection of the original data group onto a subspace which has reduced dimensions and defined some orthogonal variables that contain the most part of the original data variance (JOLLIFFE, 2006).

$$X = TP^T = \sum_{i=1}^{m} t_i p_i^T \tag{9}$$

Principal Component Analysis (PCA) is a statistical technique applied in several fields and it is widely used to find patterns in high dimension data, reducing the redundancy of informations presented in a data block through the projection of the original data group onto a subspace which has reduced dimensions and defined some orthogonal variables that contain the most part of the original data variance (JOLLIFFE, 2006; Martis, 2009)

Considering $X = (x_1, x_2, ..., x_m)$ a set of data which has the dimension . X can be decoupled in the following way showed by Equation 9:

This was the matrix X can be rebuilt as the summation that involves an estimation value and the residual effect R, so:

$$\hat{X} = \sum_{i=1}^{k} t_i p_i^T \tag{10}$$

$$X = \hat{X} + R \tag{11}$$

where k represents the number of principal components. The score vectors form a reduced dimension subspace to be used for subsequent analysis (Zao, 2011)

3. PROPOSED METHODOLOGY

3.1 Test bench

The experiments were carried out at the Laboratory of Vibrations and Control of the Faculty of Mechanical Engineering, State University in Campinas. The test bench used in this occasion comprised a three-phase induction motor {1}, a direct current machine {4}, a variable resistors bench, a three-phase varivolt, a measuring system, and a microcomputer. The direct current machine serves as generator and supplies a variable resistors bench acting as load for the induction motor. By altering the excitation current of the DC generator or altering the resistors bench it is possible to vary the load of the motor. Figure 1 offers an overview of the test bench.

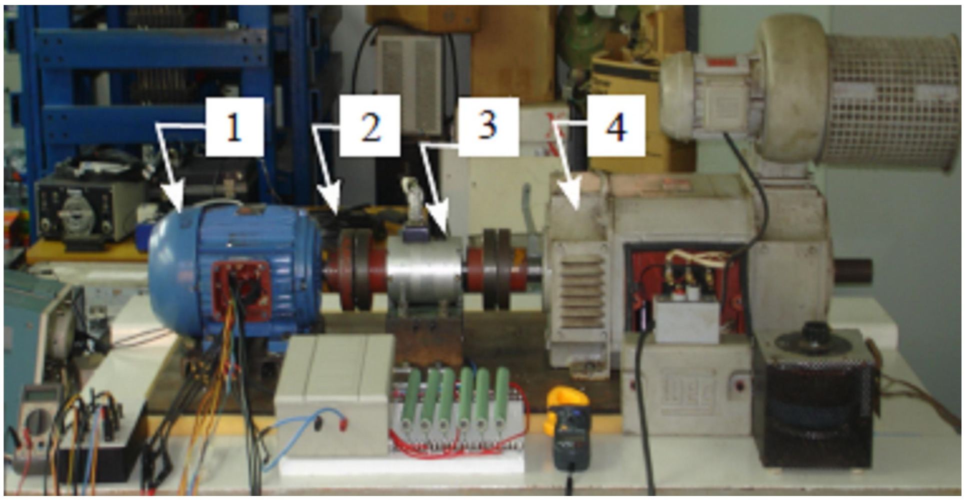

Figure 1. Test bench

The faults were introduced to the squirrel case rotor WEG (FH 88747) electric motor, 5 CV, 1730 rpm, 220 V, 60 Hz, 4 poles, category N, 44 bars, 36 slots, bearing SKF 6205–2Z, ID–1, housing 100L, isolation class B, FS 1.15, Ip/In 7.5, IP 55, 13.8 A. The generator is connected to the electric motor through flexible couplings {2} a torque wrench {3} model MCRT 9-02T (1-3), 0-7500 rpm, bidirectional and maximum torque of 1000 lb-in from S. Himmelstein & Co. The short-circuit current was limited to 10A by inserting a resistor between the terminals of the short-circuited turns to make sure the motor would work continuously without compromising its isolation and characterizing the beginning of a real, low isolation (short circuit) situation among turns. The unbalance excitation of the phase was obtained by inserting a variable series resistor to one of the phases supplying the electric motor. For mechanical faults, the unbalance was introduced by putting masses at the extreme of the axis, to the uncoupled part of the electric motor. The mechanical clearance was introduced by loosening the electric motor fastening screws.

3.2 Signal Vibrations measurements

A National Instruments NI-6251 plate was used to obtain the data. The vibration signals were passed through an anti-aliasing filter with a 2 kHz cutting frequency. Prior to the tests, the bench was balanced and aligned so as to eliminate any undesirable source of vibration. This way it was possible to determine the normal working conditions of the motor-generator assembly (the bench signature), which was stipulated as being max. 0.5 mm/s vibration amplitude in the stationary condition as per standard VDI 2056, (VDI, 1964). The signals were obtained in the radial plane (vertical and horizontal positions) of the electric motor, both on the coupling side and the fan side (opposite to the coupling side). The signals were collected at a sample frequency of 5 kHz and 20,480 points so as to analyze the entire frequency range at which the relevant defects are identified.

There were randomly collected 480 vibration signals that were distributed among the faults under study: 240 signals collected for each one of the mechanical faults and for the faultless condition, and 360 signals collected for each regime and each one of the electrical faults and for the faultless condition. Figure 2 shows a typical vibration signal obtained with a sample frequency of 5 kHz and 20,480 points. There was no load variation during the tests. For the Normal (faultless) condition 960 signals were obtained in permanent regime resulting from 360 measurements carried out with 3 accelerometers placed on the induction motor. For the fault signals, 360 signals were obtained in permanent regime for each fault condition (phase imbalance, short circuit, unbalance and mechanical clearance) resulting from 120 measurements (for each fault condition) taken randomly with 3 accelerometers placed on the induction motor. The accelerometers were placed on three different positions as shown in Figure 3: Accelerometer 1 (Sensor 1), Accelerometer 2 (Sensor 2) and Accelerometer 3 (Sensor 3).

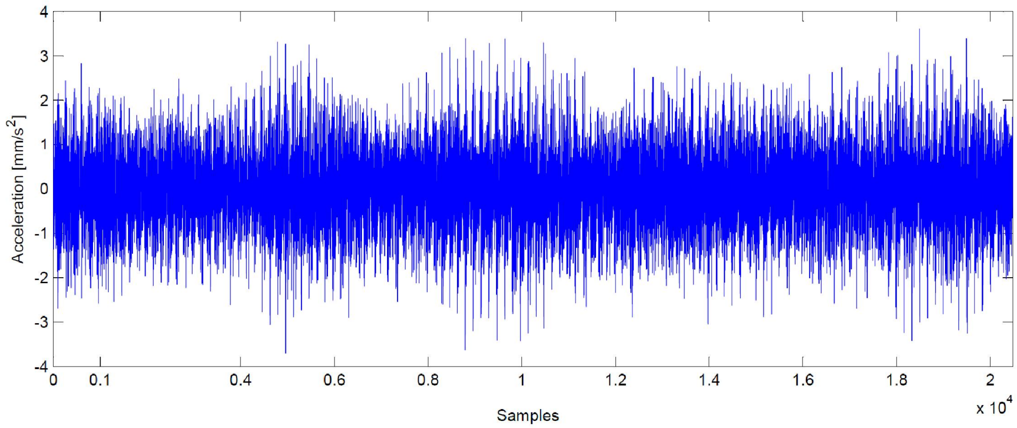

Figure 2. Typical vibration signals of the stationary condition motor.

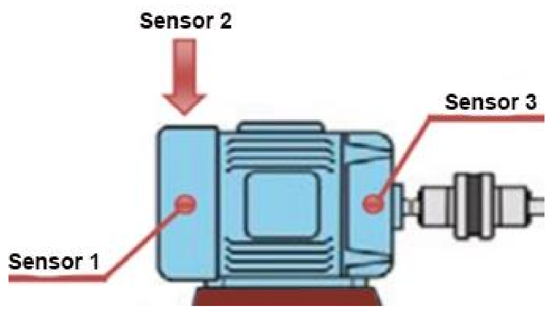

Figure 3. Position of the accelerometers on the induction motor.

3.3 Model for Classification

The classification method consists of applying the WPT to all signals up to the fourth level of decomposition, which results in 16 frequency subbands (Packet). The decomposition to the fourth level proved sufficient for detecting alterations in the frequency spectrum (Yan, 2014; Gen, 2006)

The energy, relative energy (Figure 4), and entropy of each frequency subband of the fourth level of decomposition are calculated. Another point to justify the WPT decomposition only up to the fourth level is that the energy of the signals under analysis is most concentrated up to the eighth frequency subband.

The Energy/Entropy vector is obtained for each signal by using the values obtained in the calculation of relative energy and entropy. A 32-characteristic vector is obtained with 16 relative energy parameters and 16 entropy parameters.

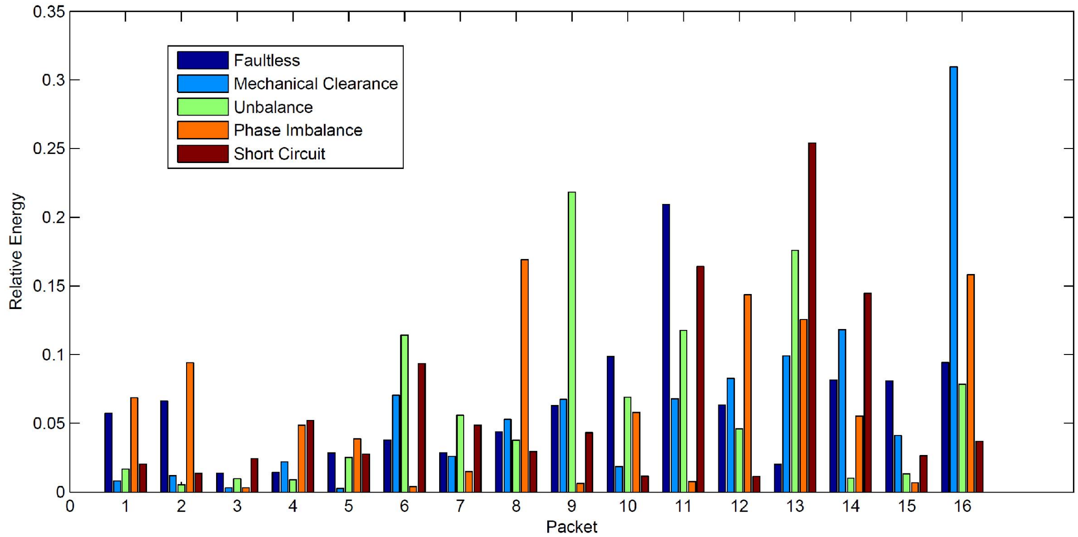

Figure 4. Relative Energy distribution for each class.

The dimension of the characteristic vector of each signal is reduced by separately using the Principal Components Analysis (PCA) methods. Finally, the classification is carried out by using the parameters of the reduced vector and the "k-Nearest Neighbor" (kNN) algorithm. Figure 5 shows the diagram of the proposed methodology for classification.

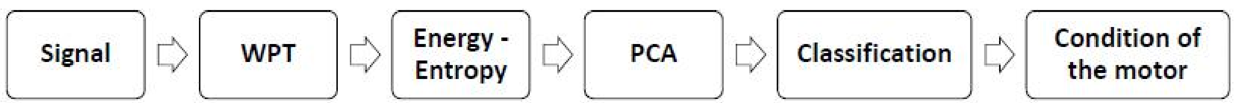

Figure 5. Diagram of the proposed processing for classification.

4. RESULTS

Initially, the classes are divided into electrical faults and mechanical faults, and the classification is separately done and tested using parameters extracted from several different filters for comparison. 30% of the classes are used for training, and 70% for classification. The filters used are of the Daubechies type (Haar, Daub-2, Daub-4, Daub-5, Daub-10, Daub-20, and Daub-40).

4.1 CLASSIFICATION BASED ON ENERGY AND ENTROPY PARAMETERS ALONE

The objective was to demonstrate that the Energy and Entropy parameters alone related to the Wavelet Transform Packet, that is, without the reduction of the characteristics vector, are not sufficient for an efficient classification. For this purpose three classes were used for the classification of the following conditions of the motor: Faultless, Short circuit, and Phase imbalance. This analysis was only performed in the stationary condition. For this analysis will be used Daubechies type filters for extracting the energy and entropy parameters. The results stated in Table 1 show that the hit rate was very low (around 60%). Such hit rate in the classification is due to the classes having very subtle variation in the amplitudes of energy and entropy values along the frequency subbands, which does not allow the classifier that was used to conduct a correct differentiation between classes. The same occurs with the mechanical faults and shows that the energy and entropy parameters alone are not sufficient for a satisfactory detection and classification of faults.

Table 1. Overall Hit Rates in the classification of eletrical faults – permanent condition.

Electrical faults (Without PCA)	
Filter	Overall Hit Rate
Haar	61.00 %
Daub-2	62.45%
Daub-5	63.45%
Daub-10	63.45%
Daub-20	63.80%
Daub-40	63.80%

4.2 CLASSIFICATION BASED ON ENERGY AND ENTROPY PARAMETERS ALONE

For classifying faults three types of analysis are conducted as follows. In every analysis, for extracting the energy and entropy parameters the aforementioned Daubechies filters are used. The energy/entropy vector will have its dimensions reduced through the Principal Components Analysis (PCA) method and delivered to a kNN type classifier.

Electrical faults: three classes will be used for classification based on the following motor conditions: Faultless, Short circuit and Phase imbalance. Mechanical faults: three classes will be used for classification based on the following motor conditions: Faultless, Unbalance, and Mechanical clearance. Electrical and mechanical faults: five classes will be used for classification, now simultaneously classified for the following motor conditions: Faultless, Short circuit, Phase imbalance, Unbalance, and Mechanical clearance.

Table 2 shows the hit rates for the classification of electrical faults with the motor permanently running. It is possible to observe a high hit rate for all of the filters proposed, as well as that there is a small increase as the filter support increases. This results from the fact that the perfect reconstruction of the signal, obtained by applying the Wavelet Transform Inverse, whether Discrete or Packet, requires the Wavelet high support and form compatible with the signal shape. Low support filters (low coefficients in the Discrete form) alter the signal shape (Guido, 2011).

Table 2. Overall Hit Rates in the classification of Eletrical faults – permanent condition.

Electrical faults (With PCA)	
Filter	Overall Hit Rate
Haar	89.35%
Daub-2	95.81%
Daub-5	98.72%
Daub-10	98.81%
Daub-20	98.80%
Daub-40	99.20%

Comparing the results obtained with and without dimension reduction by using the PCA method, from the high hit rate one can tell that the PCA method not only reduces the dimension of the vector of characteristics but also efficiently separates the classes.

The classification of the mechanical faults in permanent condition shows high hit rates and, again, from Table 3 it is possible to deduce that the higher the support of the Daubechies filter, the higher the hit rate.

The objective of the next test is to classify mechanical and electrical faults by using the proposed method. Table 4 shows the results of such classification. A reduction in the hit rate was observed due to the increase in the number of classes to be classified, although the overall results are high, which proves the method’s efficiency. Again, it is possible to relate an increase in the filter support to the increase in the overall hit rate.

Table 3. Overall Hit Rates in the classification of mechanical faults – permanent condition.

Mechanical faults (With PCA)	
Filter	Overall Hit Rate
Haar	91.00%
Daub-2	97.54%
Daub-5	98.85%
Daub-10	99.85%
Daub-20	99.89%
Daub-40	99.94%

Table 4. Overall Hit Rates in the classification of electrical and mechanical faults – permanent condition.

Eletrical and Mechanical faults (With PCA)	
Filter	Overall Hit Rate
Haar	90.80%
Daub-2	98.65%
Daub-5	98.80%
Daub-10	99.85%
Daub-20	99.85%
Daub-40	99.85%

5. CONCLUSIONS AND DISCUSSIONS

This objective of this work was the development of a model for automatically classifying anomalies in three-phase electric induction motors with the use of techniques based on the Wavelet Transform. The classification of anomalies was achieved by extracting and analyzing the characteristics of waveforms with the energy and entropy parameters associated to the Wavelet Transform Packet. The proposed method reduces the dimension of the data to be analyzed and the recognition of the signal main characteristics without losing its original characteristics. It is worth noting the efficiency in the classification of signal anomalies and the high hit rate in the permanent condition. The Daubechies filters provide for high hit rates as they are of the FIR (Finite Impulse Response) type with non-linear phase and a frequency response near-to-ideal as the support increases. For this reason it is possible to see that the best hit rates occur when higher support filters are used (Daub-20 and Daub-40).

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7. RESPONSIBILITY NOTICE

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