CLASSIFICATION OF SIMULATED MOTOR SIGNALS WITH BEARING FAULTS USING NEURAL NETWORKS, WAVELETS, AND PREDICTABILITY MEASURES

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Abstract— Three-phase induction motors fault analysis has shown a large growth in the last years, specially bearing faults, which represent a large part of the total faults in this type of motor. In this work we use a signal simulator, that permits the adjustment of the main parameters of the generated signals, such as sampling frequency, number of points, and noise level. Also, it is possible to generate signals with localized and generalized failures from the characteristic frequencies of each type of failure and the parameters of the bearings geometry. This work presents a proposal of application of artificial neural networks for the detection of bearing failures using a set of predictability measures based on relative entropy and Bhattacharyya distance of the simulated signals. These measures are obtained from wavelet-packet decomposition components. With this method we obtained classification performances close to 100% with the radial basis function network topology. This research aims at the acquisition of knowledge for next works using real motor signals.

Keywords— Pattern recognition, bearing faults, wavelets, neural networks.

Resumo— Nos últimos anos, a análise de falhas em motores de indução trifásicos têm apresentado grande crescimento, especialmente falhas em rolamentos, que representam grande parte do total de falhas existentes nesse tipo de motor. Neste trabalho utiliza-se um simulador de sinais, no qual é possível ajustar os principais parâmetros dos sinais gerados, como frequência de amostragem número de pontos e nível de ruído. No simulador, e possível gerar sinais com falhas localizadas e distribuídas a partir das frequências características de cada tipo de falha e dos parâmetros referentes à geometria dos rolamentos estudados. Este trabalho apresenta uma proposta de aplicação de redes neurais artificiais em um conjunto de medidas de previsibilidade baseados em entropia relativa e distância de Bhattacharyya de sinais simulados, a partir de componentes da transformada *wavelet-packet*, detecção de falhas em rolamentos. Os resultados obtidos apresentam taxa de acerto de 100% com a rede RBF na classificação dos sinais analisados. Tal pesquisa inicial visa obtenção de experiência para futura implementação com sinais reais.

Palavras-chave— Reconhecimento de padrões, falhas de rolamentos, *wavelets*, redes neurais.

1 Introduction

Three-phase induction motors are heavily present in most industries and can be found in various applications such as fans, compressors, tracks and pumps. Although they are robust machines, factors such as adverse environmental conditions, improper operation and design errors can cause the emergence of various faults in its components, predominantly failures related to the machine stator, the rotor, and the bearings.

Recent researches show that failures related to bearings represent 40% to 60% of total failures (Zhang et al., 2011; Zhou et al., 2007). These failures are divided into two types: (1) localized failures, in which the defects occur in specific elements of the bearings (races, balls, or cage), and (2) generalized failures, in which the bearings are damaged as a whole.

Monitoring the conditions of a three-phase induction motor allows the prediction of failures, enabling the application of corrective actions and reducing losses due to unplanned stops. Bearing analysis is commonly performed on vibration signals, acoustic emissions, or stator current signals (Zhou et al., 2007).

The analysis of vibration signals demands high cost equipments and contact with the engine is necessary in order to perform the acquisitions, therefore it is an invasive technique (Zhou et al., 2007). On the other hand, analysis of stator current signals requires relatively low cost instrumentation and allows remote monitoring. Trajin et al. (2010) presents a comparative study between techniques involving vibration signals and current signals to detect localized bearing faults.

Various signal processing techniques can be applied to detect bearing failure using stator current signals, as shown in Blodt et al. (2004), whom performed spectral analyzes using FFT. Also, in Silva and Cardoso (2005), the authors used Park's vector approach and FFT of signals with localized failures in the bearing races.

Spectral analysis of FFT is more suitable for steady state signal analysis. For transient applications, the use of techniques in the time-frequency domain is preferred, as the Short Time Fourier Transform (STFT) and the wavelet transform (Zhou et al., 2007).

The use of wavelet transform in fault detection in three-phase induction motors has grown in recent years. Examples are Gong and Qiao (2011), in which energy measures from wavelet transform are used to detect generalized bearing failures, and

Eren and Devaney (2004), in which similar analyses were performed on signals with failures on the outer race.

Another approach is the use of information theory measures, as in Seryasat et al. (2010), in which measures of entropy and wavelet coefficients energy of vibration signals of bearings with faults in the balls.

A common choice to classify caracteristic measures of stator current signals is the artificial neural networks (ANN), as in Eren et al. (2004). In this paper, networks with the topologies multilayer perceptron (MLP) and radial basis functions (RBF) were used to analyze energy measures from different frequency bands of wavelet components. Vibration signals can also be classified using ANNs, such as in Prieto et al. (2013), where MLP and RBF networks were also used. Another topology for failure detection is the self-organizing maps, that also have the ability to monitor the evolution of the failures (Hu et al., 2011).

This paper presents a methodology for detection of localized failures in bearings using predictability measures of wavelet components and classification with ANNs in groups with and without failures. The analyzed signals were obtained using a signal simulator with bearing failures. This research presents the evaluation of the efficiency of the proposed method for future analysis of real signals.

In the next section, Theory, we present the main theoretical concepts of this research, followed by Methodology, in which we present the simulator and the analysis technique. In Results and Discussions, we present the performance of the ANNs, and, lastly, in Conclusions, we present the final considerations.

2 Theory

A bearing with a localized failure in some of its elements causes vibrations in the machine axis, and variations in the flow of the airgap, which reflects in the stator current, producing harmonics related to the vibration frequencies of each type of failure (Blodt et al., 2004; Devaney and Eren, 2004).

Mechanical pulsing vibration caused by faults can have its frequencies calculated through bearing geometry parameters and the machine axis velocity of rotation (Devaney and Eren, 2004). Vibration frequencies related to the inner race (f_{pi}) and outer race (f_{pe}) faults are given by the Equations (1) and (2) respectively (Devaney and Eren, 2004).

$$f_{pi} = \frac{n}{2}.f_r.\left(1 + \frac{BD}{PD}.\cos\phi\right) \tag{1}$$

$$f_{pe} = \frac{n}{2}.f_r.\left(1 - \frac{BD}{PD}.\cos\phi\right) \tag{2}$$

The machine rotation velocity is f_r, n is the number of balls, BD is the balls diameter, PD is the race diameter and ϕ is the contact angle of the balls. The characteristic fault frequencies (f_b), reflected in the signals current spectrum are calculated by the Equation (3) (Devaney and Eren, 2004).

$$f_b = |f_e \pm m.f_v| \tag{3}$$

The source frequency is f_e, m is an integer and f_v is one of the characteristic vibration frequencіees defined by (1) or (2).

2.1 *Wavelet-Packet Decomposition*

The wavelet transform generates a signal representation from shifted and scaled versions of the wavelet function (ψ) and scale function (ϕ) (Mallat, 1989). It differs from the Fourier transform that only decomposes signals into sums of sinusoids.

Specifically, the discrete wavelet transform (DWT) can be understood as a process of discrete filtering using a bank of perfect reconstruction filters (Mallat, 1989). In the wavelet transform decomposition, the signal is divided into approximation and detail coefficients, referring to the low and high frequencies signal components respectively. One practical way to compute the DWT of a signal $x[n]$ is described in Guido et al. (2006) using Equations (4) and (5), where g_0 and h_0 are the low-pass and high-pass decomposition filters and N is the signal size.

$$A[n] = x[n] * g_0[n] = \sum_{k=0}^{N-1} g_0[k].x[2n-k] \tag{4}$$

$$D[n] = x[n] * h_0[n] = \sum_{k=0}^{N-1} h_0[k].x[2n-k] \tag{5}$$

The multiresolution analysis is obtained by successively decomposing the aproximation coeficients using the same filter bank. On the other hand, in the wavelet-packet decomposition (WPD), both components (aproximation and detail) are decomposed, creating a full decomposition tree, as shown in Figure 1.

2.2 *Predictability Measures*

One method of assessing the signal predictability is by the difference between two probability density functions (PDF), where one is formed with current data and other is formed with predictions (Scalassara et al., 2009).

In this research, we used the WPD to obtain the predictions of the signals, evaluating their predictability using relative entropy and the Bhattacharyya distance (Cover and Thomas, 2006;

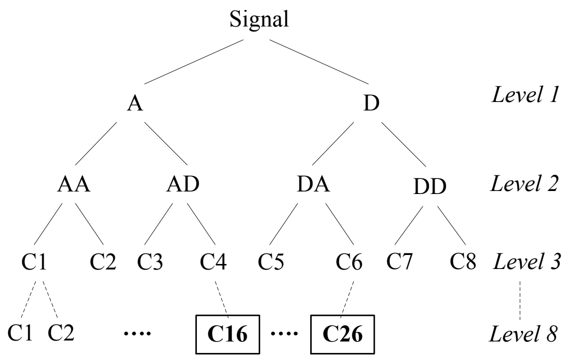

Figure 1: Wavelet-packet decomposition.

Kailath, 1967), Equations (6) and (7) respectively. These measures are estimated using the PDF p_x of the original signal $x[n]$ and the PDF p_e of the prediction error $e[n]$, C is the number of cells of the histogram. The PDFs were estimated using constant quantization step Scalassara et al. (2011).

$$D_{p_x||p_e} = \sum_{i=1}^{C} p_x(i).\log_2 \frac{p_x(i)}{p_e(i)} \tag{6}$$

$$d_B(p_x : p_e) = \sqrt{1 - \sum_{i=1}^{C} \sqrt{p_x(i).p_e(i)}} \tag{7}$$

2.3 Artificial Neural Networks

ANNs are adaptive systems based on the operations performed by the biologic neurons, which are able to learn about the system under in study using experimental data. They are commonly used for function approximation, pattern classification and clustering, and system identification and otimization (Haykin, 1999).

For bearing fault analysis, the most widely used network topologies are the MLP and RBF, Figure 2 (Prieto et al., 2013; Eren et al., 2004; Hu et al., 2011). Therefore, in this research, we used these two topologies to classify signals in two groups: with and without the presence of bearing failures.

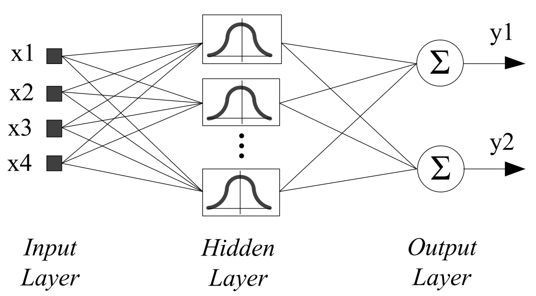

Figure 2: RBF neural network.

3 Methodology

In this section, we present the proposed methodology, that is composed by the determination of the regions of interest, extraction of the characteristics, and classification using ANNs.

3.1 Signal Simulator

In order to perform the initial tests with motor signals, as well as to correct possible errors in the algorithms, we developed a signal simulator of stator current similar to the one presented in McInerny and Dai (2003). It is possible to simulate signals with localized and generalized failures, and also control the main parameters of the signals. A screenshot of the graphical user interface (GUI) of the simulator is shown in Figure 3.

This simulator outputs three-phase currents and it is based on real signals from a motor with 1 HP and 4 poles, operating with various torque ranges. The simulated faults are in bearings 6204 and 6203. More details about these signals can be found in Santos et al. (2012).

Initialy, for the simulator usage, one must select the type of fault and its amplitude range (a percentage of the signal normalized amplitude). After that, the bearing geometry parameters must be set.

Then, the main parameters of the signals must be defined, such as sampling frequency, torque applied to the machine axis, noise level to be added to the signals, number of points, number of harmonics of the fault frequencies, and number of signals. The amplitude range is randomly applied to the signal and it decreases at a rate of 80% for each failure harmonic, as discussed in Silva and Cardoso (2005) and Devaney and Eren (2004).

After the signal generation, a preview of this signal is displayed along with its frequency spectrum. Then, it is possible to assign an identification and save the group of signals.

In this research, we created groups of normal signals and with inner and outer race failures, in an amount of four groups with five values of torque each, accounting for 180 signals. The amplitude of the failure components range from 2% to 5% of the normalized signals amplitude, aiming to characterize early stages of the faults.

3.2 Feature Vector

The regions of interest of the frequency spectrum of the analyzed signals were represented by the WPD components. We considered a number of fault harmonics $m = 4$, generating a great number of characteristic fault frequencies. In order to select these components we used a histogram of fault frequencies, as shown in Figure 4.

For the eight levels of the WPD, we selected from the histogram the first two components in

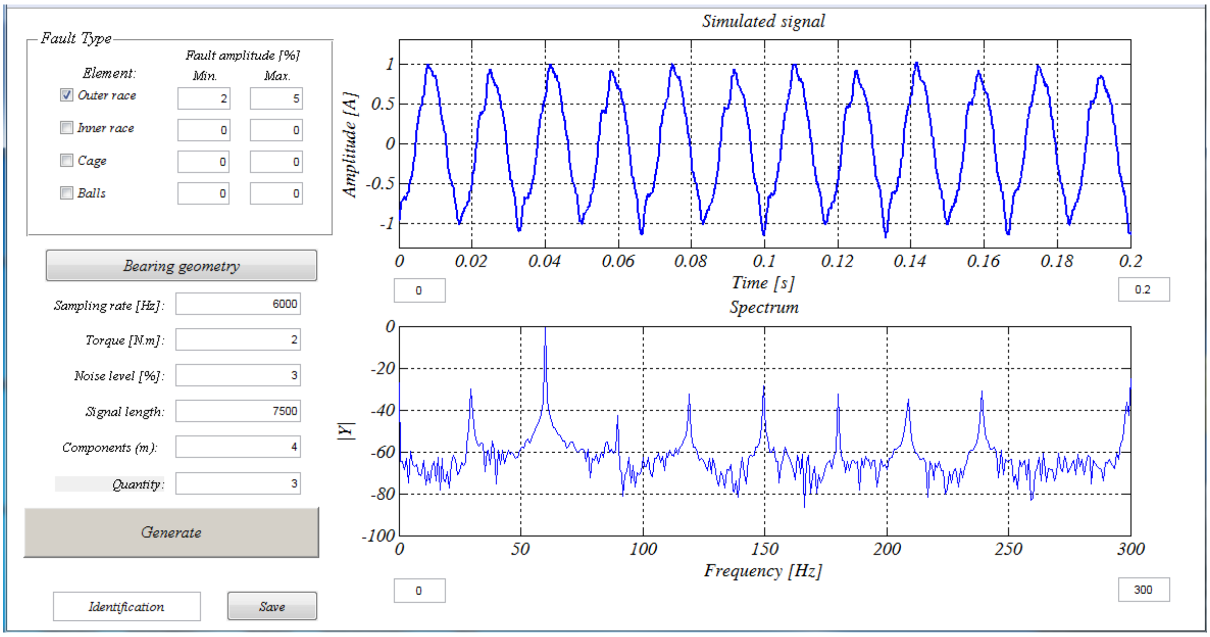

Figure 3: GUI of the bearing fault simulator.

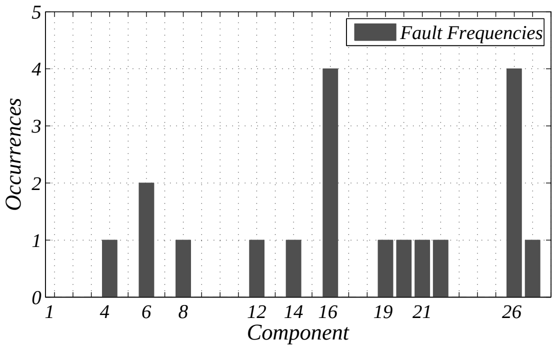

Figure 4: Histogram of bearing faults frequencies.

which there were more events of frequency faults, the components $C16$ and $C26$. These components were chosen due to their higher probability of changes in case of failures.

Using the selected components, we defined the feature vector given by Equation (8), composed of the relative entropy and Bhattacharyya distance between the original signals and the prediction errors using the recontructed WPD signals using the $C16$ and $C26$ components respectively. The predictability measures were obtained using the Daubechies wavelet family with filter order of 80 and the histograms were estimated with amplitude quantization step of 0.004.

$$[D_{(C16)} \;\; d_B\,(C16) \;\; D_{(C26)} \;\; d_B(C26)] \qquad (8)$$

The feature vector of Equation (8) was used as the set of inputs to ANNs. The details of the ANNs topologies are presented in Table 1. Considering the 180 original signals, 129 were used to train the neural networks and 51 to validate them.

Table 1: Characteristics of the ANNs.

Type	Network 1	Network 2	Network 3
Architecture	MLP	RBF	RBF
Training	S	US+S	US+S
Number of Hidden Layers	1	1	1
Neurons Hidden Layer	15	8	10
Neurons Output Layer	2	2	2
Training Algorithm	BP	k-means BP	k-means BP
Activation Function Hidden Layer	Logistic	Gaussian	Gaussian
Activation Function Output Layer	Logistic	Logistic	Linear

(S) Supervised
(US) Unsupervised
(BP) Backpropagation

4 Results and Discussions

The predictability measures of the groups of analyzed signals were similar, however, it was possible to separate them using the proposed ANNs. Table 2 presents the classification performance of the topologies studied.

Table 2: Classification Results.

	Number of Epochs	Accuracy	Classification Performance
Network 1	5141	10^{-7}	76.47%
Network 2	204	10^{-7}	98.04%
Network 3	436	10^{-10}	100%

The relative entropy and Bhattacharyya distance measures were higher for the signals without failures, representing the largest predictability of these signals. A higher prediction error is related to more similar PDFs of the signal and its prediction error, therefore, lower values of the estimated measures. Due to the presence of components related to the failures frequencies, the signals with faults were more unpredictable.

From Table 2, we notice a better performance of the RBF network when comparing to the MLP network, considering both the number of epochs and the classification performance.

5 Conclusions

In this research, we proposed the use of a methodology to detect localized bearing failures of three-phase induction motors from simulated current signals. The detection was based on the variation of the predictability measures between the original signals and the predictions performed from wavelet-packet transform components.

The signals analyzed in this paper, of bearings without failures, and with inner and outer race failures were created by a signal simulator. This simulator aimed at the realization of several tests with the possibility of diversifying the main parameters of the signals. The use of the simulator resulted in the achievement of knowledge necessary to apply the proposed analysis method to real signals.

Based on the obtained results, we noticed that the characteristic fault frequencies caused changes in the predictability measures in the interest regions in some WPD components. Thus, justifying the use of the proposed analysis method in real signals with faults emulated manually in the motor bearings.

Due to various parameters involved in the characteristic extraction, as the wavelets family, quantization step of the histograms, decomposition level and the criteria for choosing the components, this stage of this research must be refined to obtain best results of signals classification in groups with or without the presence of failures.

For future works, we are going to apply the method in real signals with localized failures emulated in the races, as well as the extension of this research to failures in the balls, in the cage, and generalized failures.

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References

Blodt, M., Granjon, P., Raison, B. and Rostaing, G. (2004). Models for bearing damage detection in induction motors using stator current monitoring, *IEEE International Symposium on Industrial Electronics*, Vol. 1, pp. 383–388.

Cover, T. and Thomas, J. (2006). *Elements of information theory*, John Wiley and Sons, Inc., New York.

Devaney, M. and Eren, L. (2004). Detecting motor bearing faults, *IEEE Instrumentation Measurement Magazine* **7**(4): 30–50.

Eren, L. and Devaney, M. (2004). Bearing damage detection via wavelet packet decomposition of the stator current, *IEEE Transactions on Instrumentation and Measurement* **53**(2): 431–436.

Eren, L., Karahoca, A. and Devaney, M. (2004). Neural network based motor bearing fault detection, *Proceedings of the 21st IEEE Instrumentation and Measurement Technology Conference, 2004*, Vol. 3, pp. 1657–1660.

Gong, X. and Qiao, W. (2011). Bearing fault detection for direct-drive wind turbines via stator current spectrum analysis, *IEEE Energy Conversion Congress and Exposition (ECCE), 2011*, pp. 313–318.

Guido, R. C., Slaets, J. F. W., Koberle, R., Almeida, L. O. B. and Pereira, J. C. (2006). A new technique to construct a wavelet transform matching a specified signal with applications to digital, real time, spike, and overlap pattern recognition, *Digital Signal Processing* **16**(1): 24–44.

Haykin, S. (1999). *Neural Networks: Comprehensive Foundation*, Prentice Hall.

Hu, J., Zhang, L. and Liang, W. (2011). Degradation assessment of bearing fault using som network, *Seventh International Conference on Natural Computation (ICNC), 2011*, Vol. 1, pp. 561–565.

Kailath, T. (1967). The divergence and bhattacharyya distance measures in signal selection, *IEEE Transactions on Communication Technology* **15**(1): 52–60.

Mallat, S. (1989). A theory for multiresolution signal decomposition: the wavelet representation, *IEEE Transactions on Pattern Analysis and Machine Intelligence* **11**(7): 674–693.

McInerny, S. and Dai, Y. (2003). Basic vibration signal processing for bearing fault detection, *IEEE Transactions on Education* **46**(1): 149–156.

Prieto, M., Cirrincione, G., Espinosa, A., Ortega, J. and Henao, H. (2013). Bearing fault detection by a novel condition-monitoring scheme based on statistical-time features and neural networks, *IEEE Transactions on Industrial Electronics* **60**(8): 3398–3407.

Santos, T., Goedtel, A., Silva, S. and Suetake, M. (2012). An ann strategy applied to induction motor speed estimator in closed-loop scalar control, *XXth International Conference on Electrical Machines (ICEM), 2012*, pp. 844–850.

Scalassara, P., Guido, R. C., Maciel, C. and Simpson, D. (2011). Fuzzy c-means clustering of voice signals based on predictability measurements of wavelet components, *Anais do X Simpósio Brasileiro de Automação Inteligente*, Universidade Federal de São João del-Rei, São João del-Rei, MG, Brasil, pp. 75–80.

Scalassara, P. R., Maciel, C. D. and Pereira, J. C. (2009). Predictability analysis of voice signals, *IEEE Engineering in Medicine and Biology Magazine* **28**: 30–34.

Seryasat, O., Aliyari Shoorehdeli, M., Honarvar, F. and Rahmani, A. (2010). Multi-fault diagnosis of ball bearing using fft, wavelet energy entropy mean and root mean square (rms), *2010 IEEE International Conference on Systems Man and Cybernetics (SMC)*, pp. 4295–4299.

Silva, J. and Cardoso, A. (2005). Bearing failures diagnosis in three-phase induction motors by extended park's vector approach, *31st Annual Conference of IEEE Industrial Electronics Society, 2005. IECON 2005.*, pp. 2591–2596.

Trajin, B., Regnier, J. and Faucher, J. (2010). Comparison between vibration and stator current analysis for the detection of bearing faults in asynchronous drives, *IET Electric Power Applications* **4**(2): 90–100.

Zhang, P., Du, Y., Habetler, T. and Lu, B. (2011). A survey of condition monitoring and protection methods for medium-voltage induction motors, *IEEE Transactions on Industry Applications* **47**(1): 34–46.

Zhou, W., Habetler, T. and Harley, R. (2007). Stator current-based bearing fault detection techniques: A general review, *IEEE International Symposium on Diagnostics for Electric Machines, Power Electronics and Drives, 2007. SDEMPED 2007.*, pp. 7–10.