# Mechanical Failures Detection by Vibration Analysis in Rotary Machines Using Wavelet and Artificial Neural Network in the Gera Maranhão Plant.

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## Abstract

*This article presents aspects of a tool to assist in predictive maintenance based on vibration analysis in rotating machines using wavelet transform and artificial neural networks. The work analyzed the experimental results of applying a methodology based on the combination of the discrete wavelet transform using a Gaussian window with an artificial neural network for condition monitoring of three-phase induction motors. This approach consisted of simulating faulty and flawless signals using software developed in LabVIEW, their processing, appropriate choice of signals, establishing statistical measures of the chosen signs, and forming the input vectors presented to the artificial neural network. The input vectors are constituted based on statistical measures involving measures of central tendency (mean and centroid), measures of dispersion (RMS value and standard deviation), and a measure of asymmetry (Kurtosis). The most promising configuration was the Multiple Perceptron Layer (MPL) network with four hidden layers containing 256 neurons. Such network showed satisfactory performance for both mechanical failures, with a correct range of around 97%. These results proved to be very effective for detecting mechanical failures, thus being an auxiliary instrument in predictive maintenance.*

**Keywords**: Vibration analysis. Wavelets. Artificial neural networks. Maintenance.

## 1. Introduction

Organizations are increasingly seeking excellence in their maintenance process. This search has led to the application of new management tools and improved techniques that optimize maintenance. Right after World War II, with the expansion of industrialization and the increase in demand for industrialized products, the concern with the downtime of machines began. Until the mid-1960s was common practice to continue using the equipment until it became severe, this approach has led to many catastrophic failures in performance problems or even crashes. After the '60s, a way to optimize the useful life of the equipment was sought, with preventive maintenance emerging, this method of maintenance, effectively minimizing severe failures. However, its most significant limitation is that fixed scheduled maintenance can sometimes result in frequent, costly inspections. According to Branco Filho, 2020, preventive care is carried out at predetermined intervals, depending on the useful life and operating cycle, to reduce the possibility of the equipment reaching a condition below the required acceptance level. This maintenance may be based on predetermined time intervals or pre-established operating conditions and may also need that, for its execution, the equipment entirely stop [1]. The predictive maintenance resolved the broken machine problem that emerged in the mid-1970s, bringing a new way of monitoring assets before this invasive process required equipment shutdown, such as corrective and preventive maintenance. With the predictive methodology, it was possible to detect failures in advance, avoiding unwanted stops, as it performs real-time monitoring based on online tracking results. According to ANHESINE, 1999, the main methods used for induction motors are the following: ultrasound, vibration, electrical signature (ESA), thermography, infrared, among others [2]. In combination with wavelets, which have, as one of the advantages in their favor, the ability to observe transient phenomena [3] and decompose the signal into various scales, making it possible not only to locate a phenomenon in time but to examine the signal in frequency, such a tool gives the user the possibility to collect a signal from nature and visualize it in all its subtleties. The wavelet transform has shown a wide applicability in the field of power systems, from the protection of three-phase generators [4-6] or the monitoring of other types of rotating machines through vibration analysis, to the protection of power system elements such as transmission lines [7] and distribution networks[7]. Artificial neural networks have been of great value in terms of the automation of the diagnostic system, making it intelligent [8-10], providing an excellent capacity for non-linear mapping and self-learning, efficiently complementing the recognition of failure patterns. This feature is particularly interesting for the purpose of this project, which is to present a methodology in which the application of the wavelet transforms the motor vibration signals and its statistical measures. Such measurements will give the intelligent system, in this case, an artificial neural network, with pattern recognition, can perform to make a multi-classification among the various forms of mechanical defects that the engine may be subject to.

## 2. Method

The wavelet transform, in recent years, was extensively researched and discussed. Due to their characteristics, they allow extracting and analyzing the local aspects of the signal. Thus, spectrum analysis can be performed at a certain point in non-stationary signals, differently from other traditional methods [11]. As they have location attributes that require only a small number of coefficients to represent a signal with a lot of information, wavelets are gaining more and more space in the field of signal analysis [12]. Engineer Jean Morlet introduced this tool from France, who proposed the concept of "mother wavelet." Modifying the parameters mother wavelet creates new analysis functions [13]. Wavelets analyze the signal based on a time-frequency profile, that is, how the signal's frequency varies with time [14] due to its strong ability to extract information in the time and frequency domain. The wavelet transform comprises the Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). Let x(t) be the sign, the CWT and DWT of x(t) are the following:

$$CWT(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} x(t)\psi * \frac{(t-b)}{a} dt \tag{1}$$

$$DWT_{m,n} = \int_{-\infty}^{\infty} x(t)\, \psi_{m,n}(t)\, dt \tag{2}$$

$$\psi(t) = \frac{1}{\sqrt{a}}\, \psi \frac{(t-a)}{a} \tag{3}$$

Where $\Psi^*(t)$ is the mother wavelet $\Psi(t)$ conjugate function, $a$ and $b$ are the dilation and translation parameters, respectively. The factor $\frac{1}{\sqrt{a}}$ in ensuring energy conservation.

**Wavelets for vibration analysis in rotating machines**

The industry uses rotating machines widely. Unwanted occurrences can result in costly downtime. Without effective defect diagnosis, it is impossible to predict the time to failure. Therefore, it is desirable and imperative to perform effective fault detection and identification. However, diagnosing rotating machinery failures is often a labor-intensive and time-consuming practice. Daily, achieving an effective and efficient fault diagnosis is challenging for technicians and plant maintainers. Each fault generates a unique signature in the measured vibration data corresponding to the machine's specific operating condition. Thus vibration analysis can be an essential tool for machine condition monitoring. Vibration measurement is applied to condition monitoring and fault diagnosis and requires different equipment and techniques. It depends on the investment and experience available. It is essential to have a means of vibration analysis, which can consist of the following: in addition to the studied structure itself, sensors, data collectors, and the analyzer. The experimental equipment used throughout this article performs condition monitoring of rotating machines, consisting of reading the vibration signal, extracting features, training the neural network, and diagnosing faults.

**Types of detectable failures**

There are several types of faults identifiable through the frequency spectrum, which we can mention: unbalance, misalignment, backlash, resonance, crooked bearing, damaged teeth in c gears, among others

[15]. Mass imbalance is one of the most common causes of vibration. Unbalance is a condition where the center of mass does not coincide with the center of rotation due to the uneven distribution of mass around the center of rotation. This type of failure creates a vibration frequency precisely equal to the rotation speed, with amplitude proportional to the amount of unbalance [16], as shown in Figure 1:

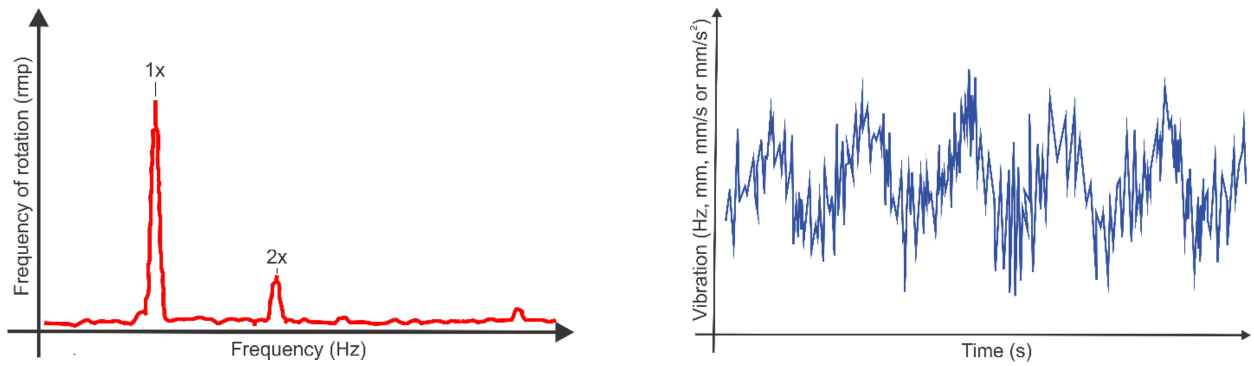


Figure 1- Spectrum and waveform of a motor with an unbalance defect.

Misalignment occurs when the axis centerlines of two directly coincident components meet at angles and offset from each other. Misalignment of couplings and bearings typically results in high radial and axial vibrations. There are two types of misalignments, parallel and angular. The first occurs for Silva [17] when "The centerline of the two axes intersects at an angle between them." The second, for the same author Silva [17], occurs when "... the center lines of the axes are parallel to each other and present an offset." Figure 2 illustrates the presented misalignments. Angular misalignment typically produces higher axial amplitudes with a 180-degree phase difference axially between the couplings. Displacement misalignment generally has high radial amplitudes with a phase difference of 180 degrees radially between couplings. A misalignment problem will typically create dominant frequencies at 1xRPM and 2xRPM, depending on the degree of angular misalignment relative to displacement misalignment and the type and design of the couplings. Phase readings are essential to distinguish from an imbalance problem in situations where 1xRPM dominates due to a misalignment problem. Waveforms generally show periodic repeatable patterns with one or two clear cycles per axis revolution [18].

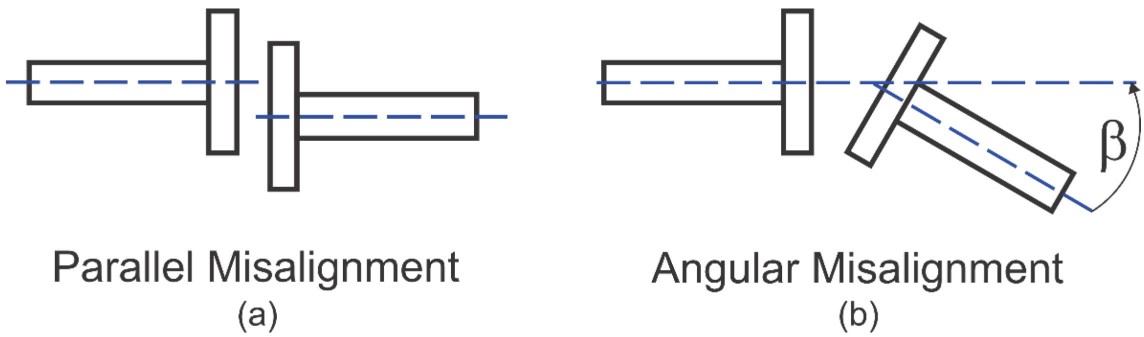


Figure 2 – Parallel (a) and angular (b) misalignment

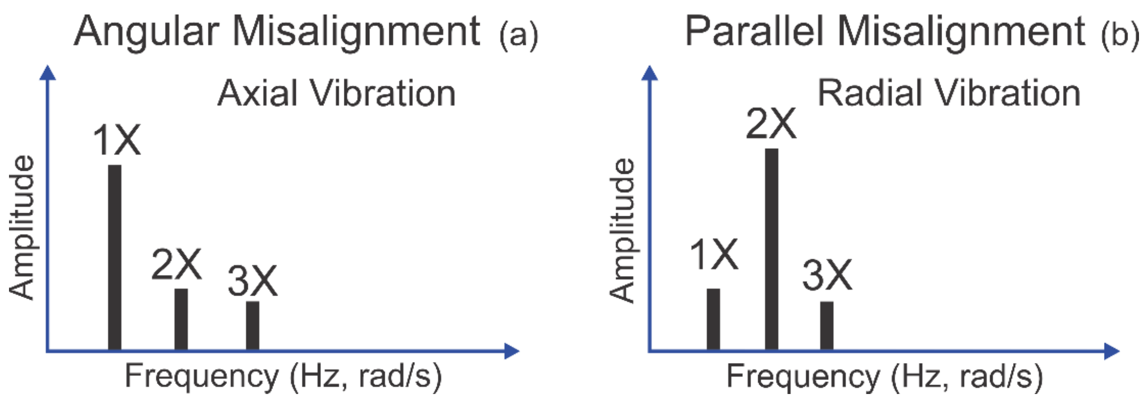


Figure 3 – Spectrum of an axial vibration from an angular misalignment and the spectrum of a radial vibration from a parallel misalignment.

## 3. Problem Formulation

**Engine maintenance management**

Generally, the induction machine is susceptible to numerous failures. The primary sources of induction motor failures are internal, external, and environmental factors. Internal faults can be concerning their origins, i.e., mechanical and electrical, or related to their location, i.e., rotor or stator. Figure 4 shows the schematic overview of the block diagram representation of the fault diagnosis scheme. The subsections below describe the condition monitoring procedure step.

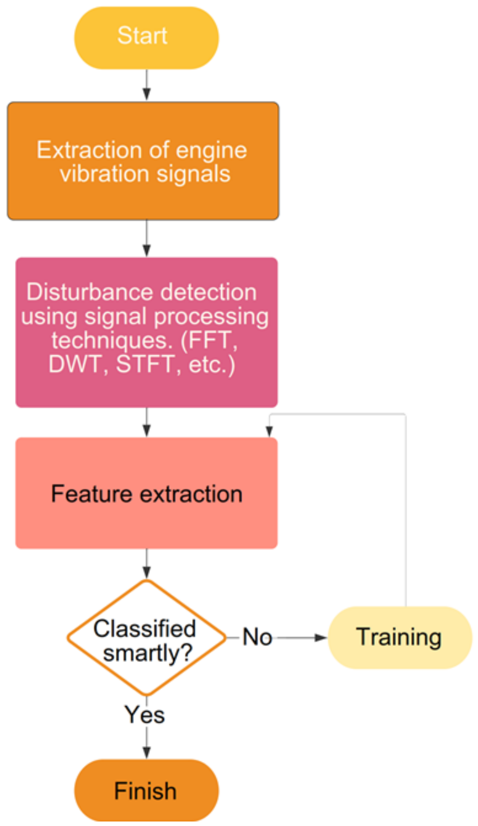


Figure 4- Fault Diagnosis Overview Diagram.

According to studies by the Institute of Electrical and Electronics Engineers (IEEE) and the Electric Power Research Institute (EPRI), about 42% of induction motor failures are caused by bearing failure, as depicted in Figure 5. induction comprises an outer ring, an inner ring and a set of bearings, balls placed in the races rotating inside the rings. The continuous stress on these bearings can cause fatigue failures. Whenever there is a failure, it will result in certain vibration, which influences the eccentricity between the rotor and the stator and increase noise levels. Improper insulation, corrosion, contamination, inadequate lubrication are the factors that are also responsible for bearing failures. Failures that occur in bearing are cyclic and non-cyclic. Based on the fault position, Cyclic faults can be internal lane defects, external lane defects, cage failure, and ball defects. Acyclic failure produces an impact in the middle of the raceway, and the bearing results in determinable vibration [12]. Figure 5 below illustrates the frequency of failure occurrences in induction motors:

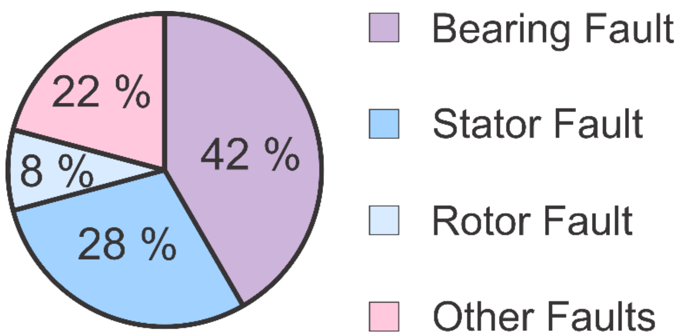


Figure 5- Induction Motors Fault Occurrences [12].

As can be seen, the most frequent failures in the induction motor are bearing failures.

Table 1 below shows some of the main failures that occur in induction motors:

**Main failures in induction motors**

| **Rotor failures** | **Causes** | **Stator failures** | **Causes** |
|---|---|---|---|
| **Bearing failures** | Insulation defect, Load imbalance, Loss of lubrication, and oil contamination. | Vibration | Overload, magnetic unbalance, electrical installation defects, and unbalanced voltage source. |
| **Bearing misalignment** | Overload and insulation failure. | Short circuit to the ground | Short between one or more phases and the motor frame. |
| **Rotor misalignment** | Bearing failure and insulation defect. | Insulation failure | Excessive turn-ons, damage during |

| | | | |
|---|---|---|---|
| | | | installation or maintenance of the motor, and humidity and temperature variations. |
| **Lack of bearing lubrication** | Oil contamination and seal failure | Short-circuit between phases | High temperature, voltage imbalance, and installation and maintenance failure. |

At thermoelectric plant Gera Maranhão, maintenance management is carried out through preventive, corrective, and predictive maintenance. Many efforts by teams of maintainers have been directed to the establishment of condition-based maintenance strategies - (Condition-Based Maintenance - CBM) in parallel with conventional preventive maintenance programs to avoid the occurrence of unexpected failures, reduce downtime, increase the time interval between scheduled stops for
standard maintenance, reduce operating costs due to corrective maintenance and avoid running electrical machines in an unsafe condition. A survey of the history of occurrences shows that the plant's induction motors' most common failures are low insulation, unbalance, and misalignment. So, the tool has the proposal to assist in detecting unbalance and misalignment in engines.

## 4. Tool for Signal Processing

Figure 6 shows the developed tool. Its characteristics are generating vibration signals from rotary induction machines; Neural network training with four hidden layers and 256 neurons; Signal characteristics extraction using Discrete Wavelet Transform with Gaussian window, and Sim4 mother wavelet.


Figure 6 - Developed tool

## 5. Results

Figure 7 shows the processing of a vibration signal that contains a force imbalance fault. Note that the result of signal processing (Processed Signal) is evidenced in the EEPA signal waveforms, which is the envelope of the Aggregated power spectrum, and the EEA signal, which is the envelope of the aggregated spectrum, of these signals, the math tools are applied.

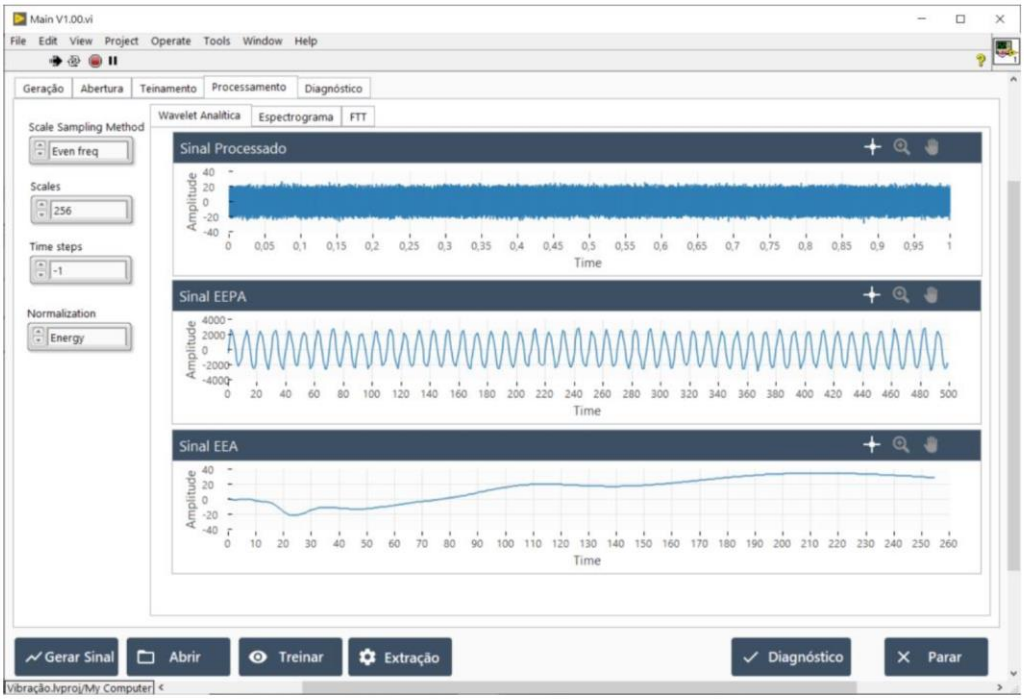

Figure 7 - Processed Signal, EEPA Signal, and EEA Signal

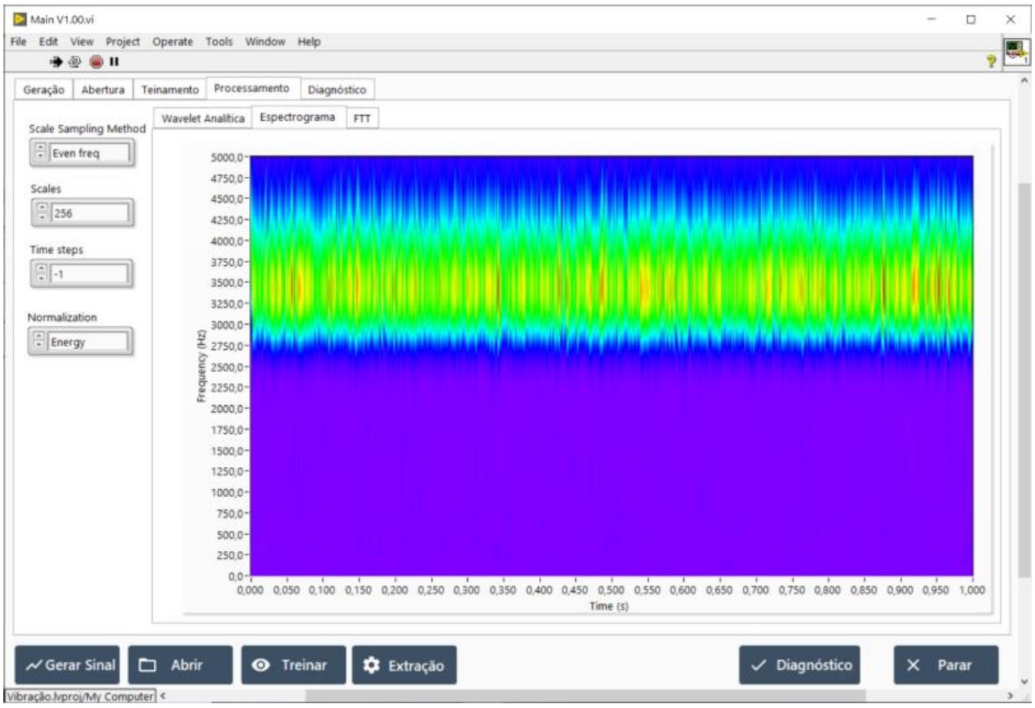

Figure 8 shows the scalogram of the processed vibration signal.

Figure 9 shows the result of the feature extraction. Where can note the existence of a frequency of 3550 Hz, this signal brings the frequency that characterizes the force unbalance failure.

Figure 9 – Signal force unbalance failure shown in Figure 6.

## 6. Conclusion

Thus, it is possible to conclude that the implementation of the fault detection tool provided numerous benefits, including the reduction of unscheduled jobs, which are generally more costly, drop off unwanted occurrences, the optimization of the use of person-hours, more excellent reliability and practicality in monitoring the condition of the asset. As the implementation has not yet been applied in practice, it is necessary to wait a more extended period to verify other possible changes that may arise in the process. After training the neural network of a set of one hundred files, 50% were missing, and the other 50% were not, and with the test of 20 files with and without failures, the neural network responded with 97% correct answers.

## 7. Reference

[1] Filho, G. B. A organização, o Planejamento e o Controle da Manutenção.1.ed.Ciência Moderna, 2008.

[2] ANHESINE, M., W.,. Uma abordagem sistêmica para diagnósticos em manutenção industrial. Tese de doutorado, apresentado à Escola de Engenharia de São Carlos-USP, São Carlos. 1999.

[3] ABDESH, M.; KHAN, S.; RAHMAN, M. A. A new wavelet-based diagnosis and protection of faults in induction motor drives. In: IEEE. Power Electronics Specialists Conference, PESC 2008. IEEE. 2008. p. 1536–1541.

[4] SILVA, K. et al. Haar wavelet-based method for fast fault classification in transmission lines. In: IEEE. Transmission & Distribution Conference and Exposition: Latin America. TDC'06. IEEE/PES. [S.l.], 2006. p. 1–5.

[5] JAWADEKAR, A. et al. Artificial neural network-based induction motor fault classifier using continuous wavelet transform. Syst. Sci. Control Eng. An Open Access J., v. 2, p. 684–690, 2014

[6] OLIVEIRA, H. de. Análise de Fourier e Wavelets. [S.l.]: Editora Universitária da UFPE, 2007.

[7] PINTO, S. C. D. Análise de Formas 3D usando Wavelets 1D, 2D e 3D. Tese (Doutorado) —Universidade de Sao Paulo, 2005.

[8] FANUCCHI, R. Z. A Detecção e a Localização de Faltas de Alta Impedância em Sistemas de Distribuição utilizando Transformadas Wavelets e Redes Neurais Artificiais. 176 p. Tese (Doutorado) — Universidade de São Carlos,
2014.

[9] DINIZ, P. S.; SILVA, E. A. da; NETTO, S. L. Processamento Digital de Sinais-

: Projeto e Análise de Sistemas. [S.l.]: Bookman Editora, 2014.

[10] BANDEIRA, G.; ABREU, G.; GIANELLI, R. Vibração e ruído em manutenção preditiva. UNESP, 2010.

[11] SILVA, Derick Henrique de Jesus. Processamento de Sinais para Monitoramento de Vibrações em Unidades Geradoras Hidrelétricas. UFMG, 2013.

[12] Ho, D., Randall, R.B., 2000, Optimisation of bearing diagnostic techniques using simulated and actual bearing fault signals, Mechanical Systems and Signal Processing, 14/5: 763–788.

[13] SANTOS, F. M. d. C. Identificação de falhas em motores de indução trifásicos usando sistemas inteligentes. Tese (Doutorado) — Universidade de São Paulo, 2013.

[14] MARTINS, J. F.; PIRES, V. F.; PIRES, A. Unsupervised neural-network- based algorithm for na on-line diagnosis of three-phase induction motor stator fault. IEEE Transactions on Industrial Electronics, v. 54, n. 1, p. 259–264, 2007. ISSN 02780046.

[15] YANG, B.-S. et al. Fault diagnosis of induction motor based on decision trees and adaptive neuro-fuzzy inference. Expert Systems with Applications, Elsevier, v. 36, n. 2, p. 1840–1849,2009.

[16] HOLANDA, S. M. Aplicação da manutenção preditiva por análise de vibrações em equipamentos de trens urbanos com plano de manutenção proposto. 2016. 7 f. Dissertação (Mestrado em Engenharia Mecânica) – Universidade Federal de Pernambuco, Recife, 2016.

[17] SILVA, Derick Henrique de Jesus. Processamento de Sinais para Monitoramento de Vibrações em Unidades Geradoras Hidrelétricas. UFMG, 2013.Disponível em: <https://www.ppgee.ufmg.br/defesas/1001M.PDF>. Acesso em: 02 julho 2021.

[18] Hansford Sensors, Imbalance, misalignment, looseness: know the difference, UK. 2021. https://www.hansfordsensors.com/blog/2017/02/07/imbalance-misalignment-looseness-know-difference/