26th ABCM International Congress of Mechanical Engineering
November 22-26, 2021. Florianópolis, SC, Brazil

COB-2021-0742
ANALYSIS AND CLASSIFICATION OF THE CAVITATION LEVEL IN CENTRIFUGAL PUMPS USING THE POWER SPECTRUM AND ARTIFICIAL NEURAL NETWORKS OF VIBRATION SIGNALS

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Abstract. *The cavitation phenomena may produce wear and erosion in the rotor blades from centrifugal pump. Thus, it is interesting to detect the cavitation level in pumps in order to optimize its operation conditions. In this sense, the vibration signal processing measured in the centrifugal pump in operating may be used to identify the cavitation level. In this work, it was used the Power Spectrum in order to extract the frequency components generated by the cavitation. The vibration signals were measured in the centrifugal pump by operating in the rotation range of 2500 to 3100 rpm. Subsequently, an artificial neural network was designed and trained to detect the presence of the cavitation in the centrifugal pump. During the learning process from neural network, it was used several samples of the vibration signal have processed by the Power Spectrum and measured in the axial and radial directions with respect to the pump rotor. The results proved that the Power Spectrum and neural network may be successfully used in the classification procedure of the cavitation phenomena in centrifugal pumps.*

Keywords: *cavitation, centrifugal pumps, neural network, vibration signal.*

1. INTRODUCTION

Cavitation phenomena in centrifugal pumps usually decrease their hydraulic performance. Furthermore, the cavitation may damage several components from centrifugal pumps, such as, pitting and material erosion of the rotor blades (Cudina, 2003; Sakthivel, 2010). During the cavitation process, the fluid starts to flash and vaporization occurs. Hence, the rotor blades are bombarded by the bubbles due to the vaporization and material erosion may occur during this process. The bombardment of the bubbles on the pump components produces random vibrations with frequencies to be determined in the spectrum of measured signals. Thus, the application of signal processing techniques, such as the Power Spectrum and time-frequency analysis for the diagnosis of cavitation in pumps are important tools to be used in the identification and classification of the phenomena (Guimarães and Oliveira Filho, 2020).

In the condition monitoring of the centrifugal pumps, it is usually used vibration signals or acoustic signals for the analysis of the cavitation level (Cudina, 2003; Sakthivel et al., 2010, Zhang et al. 2014). In some cases, it is possible to visualize the bombardment process of bubbles on the rotor blades by using the image processing techniques. Cudina (2003) has applied the Fourier Transform to the acoustic signals measured in the centrifugal pumps with microphones to detect the frequency tone produced by the cavitation. Sakthivel et al. (2010) have developed a pump faults classification system using the measured vibration signals with accelerometers and the logic fuzzy for the automatic identification of the cavitation, bearing fault, seal and impeller faults. Zhang et al. (2014) have studied the vibration characteristics caused by the cavitation in centrifugal pumps using the signal processing techniques in the time domain, such as the amplitude analysis and the energy level in the measured signals. Ramadevi (2014) applied the Discrete Wavelet Transform for detect the transient vibration components produced by the cavitation phenomena. More recently, Guimarães and Oliveira Filho (2020) used the Continuous Wavelet Transform and statistical techniques to extract the vibration features generated by the cavitation phenomena in centrifugal pumps.

In this work, it is proposed a methodology for the analysis and classification of the cavitation level in centrifugal pumps by using the Spectral Analysis and Artificial Neural Networks. The vibration signals to be employed in the training process from neural networks were measured using 2 (two) accelerometers mounted in the case from pump in the radial and axial directions. The vibration signals in the time domain will be measured with the centrifugal pump operating in different rotations, 2500, 2600, 2700, 2800, 2900, 3000 and 3100 rpm, respectively. Subsequently, it was applied the Fourier Transform to vibration data in order to extract the energy density of the components due the cavitation phenomena. The vibration patterns in the frequency domain displayed in each operating rotation from centrifugal pump were used in the training process of a Perceptron Neural Network for the classification of the cavitation level. The results proved the methodology has proposed in this work may be successfully used in classification process of the cavitation level of centrifugal pumps.

2. CAVITATION IN CENTRIFUGAL PUMPS

2.1 Description of the phenomena

A centrifugal pump is a hydraulic machine that transforms work from drive motor into the mechanical energy of the flowing liquid. The main components of a centrifugal pump are the rotor shaft, the blades, the pump wall and the bearings. In hydraulic systems, cavitation naturally occurs due to the acceleration of the fluid caused by the transformation of the rotor blades work in fluid kinetic energy. According to the mechanic energy conservation principle, when the liquid is accelerated its pressure diminished. Since the absolute static pressure of fluid is lower the saturated vapour pressure in some points of the flow, at the prevailing temperature conditions, the fluid starts to flash and vaporization occurs (Cudina, 2003). Because of this, bubbles are caught up by the flowing liquid which causes the collapse of these on the rotor blades and on the centrifugal pump wall. Usually, the collapse time of the bubble implosion is very small (approximately 0,003 s) which increases the bubbles impact pressure on the centrifugal pump components.

Figure 1. Damage of the centrifugal pump rotor caused by the cavitation.

In practice, the cavitation could be interpreted as the bombardment of the bubbles on the rotor blades and centrifugal pump case. Figure 1 illustrates an example of the damages caused by the cavitation phenomena in rotor blades of a centrifugal pump. Since the bombardment frequency of the bubbles and its intensity (amplitude) is not defined, it is difficult to predict analytically the features of the vibration signals produced by the cavitation in centrifugal pumps.

2.2 Characteristics of the vibration signals measured in centrifugal pumps

In a general way, each pump component generates a vibration signal component with a determined frequency. For example, the vibration frequency of the rotor shaft is the rotation frequency of the centrifugal pump working. The vibration signals components produced by the rotor blades have a frequency which is obtained by multiplying the number of blades by the rotational frequency of the rotor shaft. On the other hand, the vibration caused by the rolling bearings from rotor is similar to the vibration of a single-degree-of-freedom mechanical system which excites the high frequencies range of the spectra. All these vibration components abovementioned are deterministic and could be easily detected by analyzing the frequency spectrum of the measured signals in the centrifugal pumps (Sakthivel et al, 2010).

Identification of the vibration frequencies caused by the cavitation in centrifugal pumps is more difficult by using the signal frequency spectrum. For the cavitation, the frequency of the bombardment of the bubbles on the rotor blades is not defined and usually excites a frequency band in the Spectrum (Cudina, 2003). Thus, it is easier to detect the frequency range of vibration produced by the cavitation due to the random nature of these signals. For the velocity signals, the frequency range of the cavitation vibration is placed on low frequency range of the spectrum. In the case of the acceleration signals, the cavitation excites the high frequencies range of the measured vibration signals. In this work, it will be used the Spectral Analysis to extract the frequency bands generated by the cavitation, as well as, the frequency components produced by the pump rotor and blades.

3. TOOLS FOR THE VIBRATION SIGNALS ANALYSIS AND CLASSIFICATION OF THE CAVITATION LEVEL IN THE CENTRIFUGAL PUMP

3.1 Power Spectrum

The Fourier Transform (TF) could be defined using the correlation concept of the signal. In the traditional spectral analysis, the vibration signal in the time domain is compared with harmonic functions. In this way, by using the Fourier Transform (TF), the vibration signal could be decomposed in the individual frequency components. Although the FT is a powerful tool in the signal processing context, its main disadvantage is that the transient vibration signals caused by the cavitation in pumps could not be easily extracted by the conventional spectral analysis. Since that the window in the time domain used in the FT has infinity duration, it is not possible to extract neither when the transient component has occurred and nor its duration in the time-frequency plane (Cohen, 1995). However, as the objective is to extract the global frequency energy density from cavitation signal, the TF will be used in this work in the vibration analysis of centrifugal pump.

The TF of the vibration signal measured in the centrifugal pump is defined by (Randall, 2011):

$$X(f) = \int_{0}^{\infty} x(t) e^{-j2\pi ft} dt \tag{1}$$

where $x(t)$ is the vibration signal in the time domain measured in the centrifugal pump, f is the frequency in Hz, j is the pure imaginary and $X(f)$ is the signal in the frequency domain. In the practice, for the Spectral Analysis of the pump cavitation and classification task, it will be used the magnitude from signal squared, $X(f)^2$, in order to extract the frequency energy density. Therefore, by using the $X(f)^2$, the signal analyst may verify what signal components have more energy in the frequency domain (Randall, 2011).

3.2 Artificial Neural Networks for Classification of the Cavitation Level

An Artificial Neural Network may be defined as a computational model inspired in the nervous system from humans (Haykin, 1994). In the signal processing context, the Multi-layer Perceptron Neural Networks have been largely used in mechanical vibration problems, as for classification tasks, as for regression and modeling problems by using input and output data measured in the system (Worden et al., 2011). In a general way, for a Perceptron Neural Network (PNN), usually the input data are transmitted for the next neurons layer by means of the synapses and so on, until the last neurons layer which are transformed in the output data. Each neuron of the neural network is modeled by an activation function, or transfer function, and the most common models available in the literature are the sigmoidal function, the hyperbolic tangent function and the linear one (Haykin, 1994; Worden et al., 2011). On the other hand, in classification problems, the last neurons layer is modeled by the hyperbolic tangent or sigmoidal activation functions (output data is 0 or 1). In the other hand, in regression problems, the last neurons layer uses linear activation functions (continuous output data).

The objective of this work is the classification of the cavitation level of a centrifugal pump using a Multi-layer Perceptron Neural Network based on the Power Spectrum of the vibration signals. For this objective, the input will be a vector with the Power Spectrum of vibration signal measured and the outputs are vectors displaying the cavitation level from centrifugal pump in each rotation.

In the training process of a PNN, the weights of each neuron are fixed by the minimization of the error between the desired output and the computed output by the neural network. After the optimization, it is expected that the output from PNN is as close as possible of data used for the training or learning of the neural network. For the training of the PNN, it will be applied the backpropagation algorithm available in the software Matlab® (Haykin, 1995). In the training process, the weights and bias are adjusted until the convergence. After the training, the weights and bias optimized and applied to the trained PNN generates the best output and with the minor error between the desired output and computed by the PNN.

The equation for training of the PNN in the Feedforward algorithm is the following (Haykin, 1994):

$$[w]^{e+1} = [w]^{e} + \eta\left([y]_r^e - [y]_d^e\right)[x]^e \tag{2}$$

where w represents the vector with the weigths and the bias from PNN of each layer, "e" is the iteration index used in the updating of the vector w, x is the vector input, y_r the output computed by the PNN and y_d the desired output by the PNN. The parameter η is the learning rate and indicates the convergence rate of the iterative training procedure of the PNN. For the training, it was used the Levenberg-Marquard algorithm available in the software Matlab® for improve the convergence rate of the optimization procedure.

4. MEASURING AND PROCESSING OF THE VIBRATION SIGNALS

Before the acquisition of the vibration data and training of the artificial neural network, it was measured some parameters that could also have influence about the cavitation level of the centrifugal pump. Therefore, by using the measurement system available by the centrifugal pump test bench, it was measured the following parameters: rotation, torque, power and the opening of the valves. The objective of this analysis is to order the possible parameters of the pump operation have more influence on the cavitation phenomena. In this research, it was used the H47 model centrifugal pump test bench from Nova ND Tecnologia® manufacturer. For this study, it was used the Pycaret library in Phyton language for the classification of importance of these parameters on the cavitation level by using machine learning.

In the classification of the parameters according to centrifugal pump cavitation level, the Pycaret library use some models commonly used in machine learning, as for example, the area under the curve, accuracy and precision (Nicholson, 2021). After the processing and analysis of the features, rotation, torque, power and opening of the valve in the Pycaret library, the most important parameter to be used in the cavitation level classification of the centrifugal pump is the rotation, as described in the Table 1. Following the classification scale displayed in the Table 1, the torque and the power of the pump motor have also significant importance on the cavitation level. The opening of the valve has little influence on the cavitation classification. Thus, according the highlighted results by the machine learning process, it will be used the vibration signals measured in several rotation frequencies for the classification of the cavitation level in the centrifugal pump.

Table 1. Importance of the features to be used in the classification of the centrifugal pump cavitation.

Feature	Rotation	Torque	Power	Opening of the valve
Variable Importance	0.41	0.20	0.18	<0.10

For the measuring of vibration data, it was used 2 (two) accelerometers have mounted on the centrifugal pump case, as illustrated in the Fig. 2. These 2 accelerometers measured the acceleration vibration signals simultaneously in the radial and axial directions. The vibration signals were measured for different rotations of centrifugal pump, 2500, 2600, 2700, 2800, 2900, 3000 and 3100 rpm, respectively. The control valve of the flow in the pump was totally opened during the measuring of vibration signals. It was experimentally observed that, the larger the pump rotation, the larger is the cavitation level. The centrifugal pump user manual also describes the cavitation level increases when the pump rotation is larger.

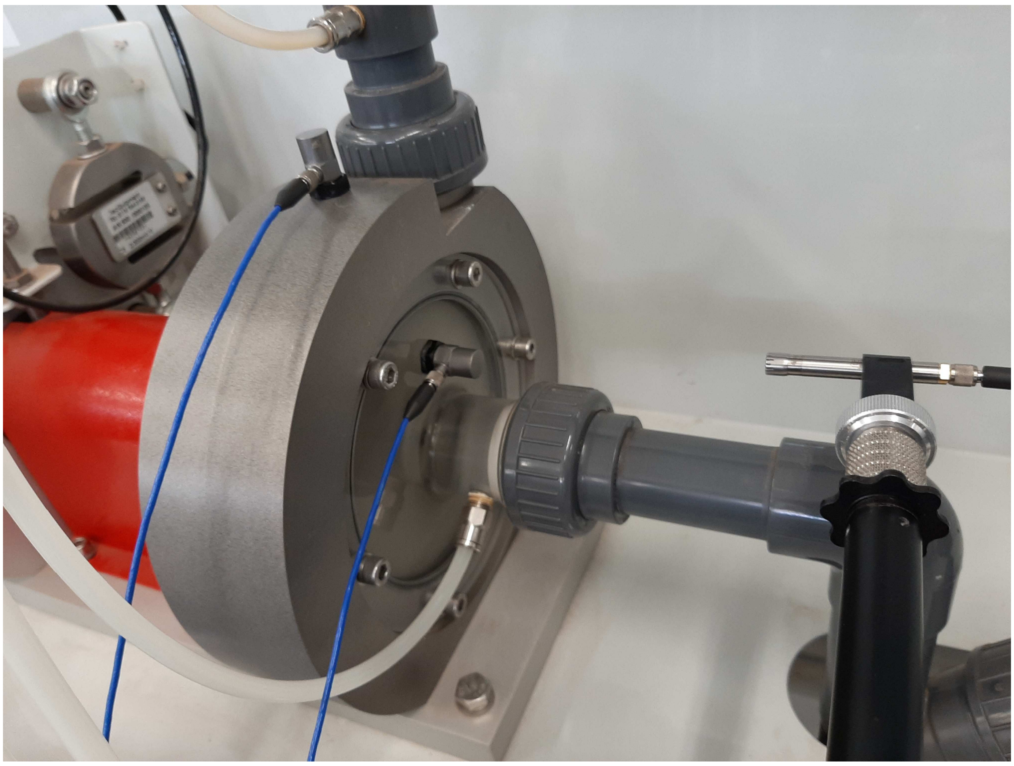


Figure 2. Image of the centrifugal pump case used in the analysis of the cavitation.

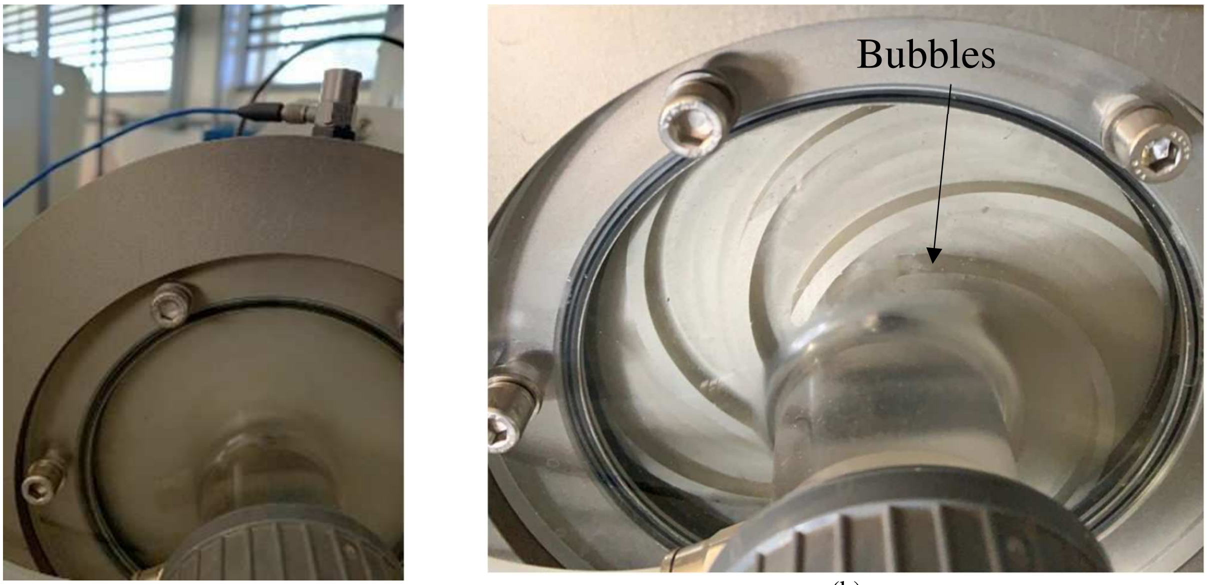
The vibration signals were measured by using two 352C33 model accelerometers from PCB Piezotronics® manufacturer. Table 2 describes the parameters values used for measuring the vibration data in the time domain. It was not necessary to use a signal conditioning unit since this accelerometer has an integrated signal pre-amplifier for increasing the output signal gain. The signals measured in the centrifugal pump were directly connected to a data acquisition board from National Instruments manufacturer. Subsequently, the software MATLAB® 2018 with a toolbox integrated to the software Labview® was used to save the data file in a txt format.

Table 2. Parameters values used in the acquisition of vibration signals measured in the centrifugal pump.

Sampling Frequency	**Number of Points**	**Acquisition Time**	**Sensitivity of Accelerometer**
51200 Hz	512000	10 s	1.05mV/m/s^2

After the vibration data acquisition, the signals in the time domain were processed to the frequency domain by using the FFT (Fast Fourier Transform) algorithm available in the MATLAB® R2018 software. This spectral analysis was necessary in order to identify the frequency components generated by the pump rotor and blades and the frequency bands produced by the random vibration due the cavitation. Subsequently, a multi-layer perceptron neural network was designed and trained for the cavitation level classification task.

In order to train the neural network, vibration data measured have to be labeled on cavitation or no-cavitation. For this purpose, it was used a stroboscopic lamp synchronized at pump rotation, enabling bubbles visualization of cavitation effect. Fig. 3 show a cavitation condition with stroboscopic lamp off (Fig. 3a) and stroboscopic lamp on (Fig. 3b), this ensures correct labeling vibration data.



(a) (b)

Figure 3. Cavitation condition with (a) stroboscopic lamp off and (b) stroboscopic lamp on.

5. ANALYSIS OF THE RESULTS

The Fig. 4 shows the vibration signals in the time domain measured in the centrifugal pump in the rotation of 2500 rpm and 3100 rpm. The signal has shown in the Fig. 4(a) represents the pump vibration by working in the rotation of 2500 rpm and the Fig. 4(b) illustrates the pump vibration by operating in 3100 rpm. It can be seen that the signal amplitude for the pump working in the rotation of 2500 rpm is small when compared to the pump vibration for the rotation of 3100 rpm. For the pump operating in the rotation of 2500 rpm, the rms level is about 7.85 m/s^2. Otherwise, the rms level of the vibration signal measured in the pump working in the rotation of 3100 rpm is approximately 30.43 m/s^2. Both signals illustrated in the Fig. 4 were measured with the accelerometer has positioned in the radial direction.

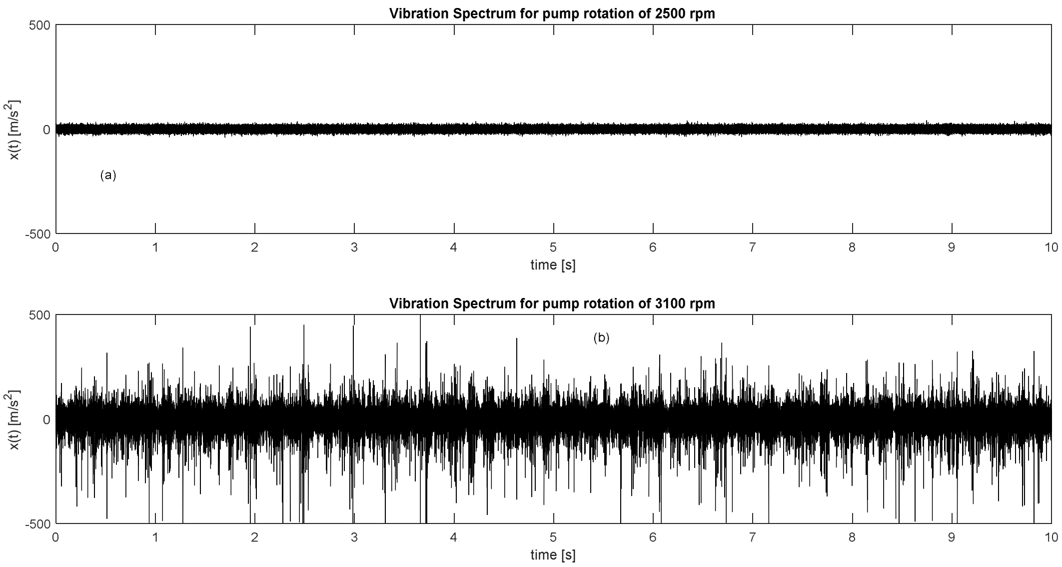


Figure 4. Vibration signals in the time domain measured in the centrifugal pump in the rotation of 2500 rpm (a) and 3100 rpm (b).

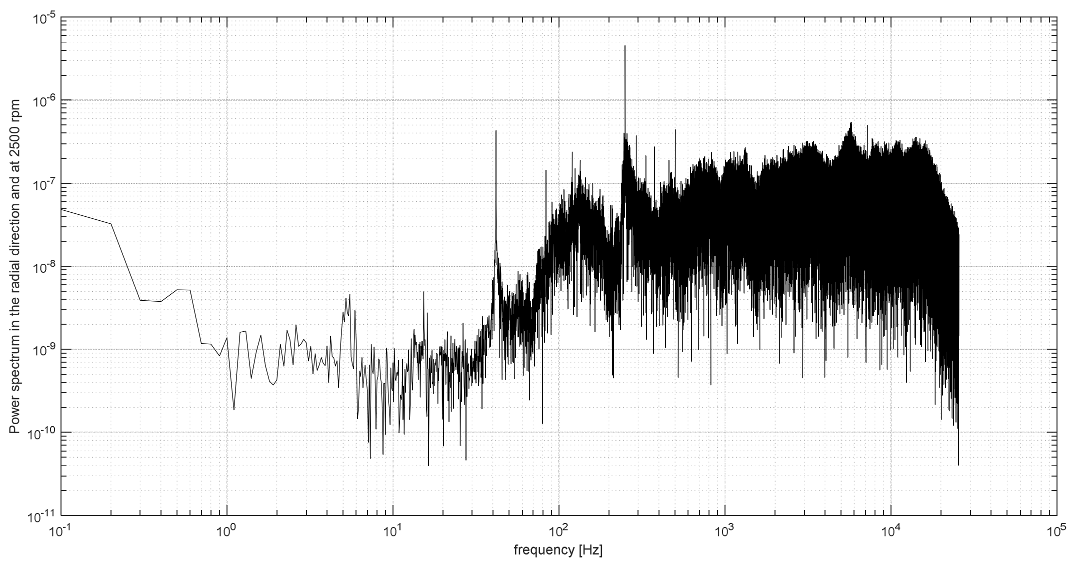


Figure 5. Vibration signal in the frequency domain measured in the centrifugal pump in the rotation of 2500 rpm.

The Power Spectrum of the vibration signals measured in the centrifugal pump in the rotations of 2500, 2800 and 3100 rpm are shown in the Figs. 5, 6 and 7. In the Spectrum processing, it was chosen samples of 16384 points of vibration signals measured in these rotations. For the lower rotation of pump, 2500 rpm, it possible to visualize the frequency components caused by the rotor vibration and the rotor blades vibration. In this case, the frequency band produced by the random vibration of the cavitation is small when compared to others rotations. It can be seen the signal component in the frequency of 250 Hz which was probably generated by the rotation frequency (41.67 Hz) of pump multiplied by the number of blades from rotor (6 blades).

When the rotation of the pump increases, the amplitude of the frequency band due to the cavitation also increase, as can be seen in figures 6 and 7. It means that the frequency energy density caused by the random vibration of the cavitation increases when the rotation is larger. For the vibration signal measured in the rotation of 3100 rpm, it can be observed that the amplitude or frequency energy density of the high frequency band is higher because of the cavitation random vibration components.

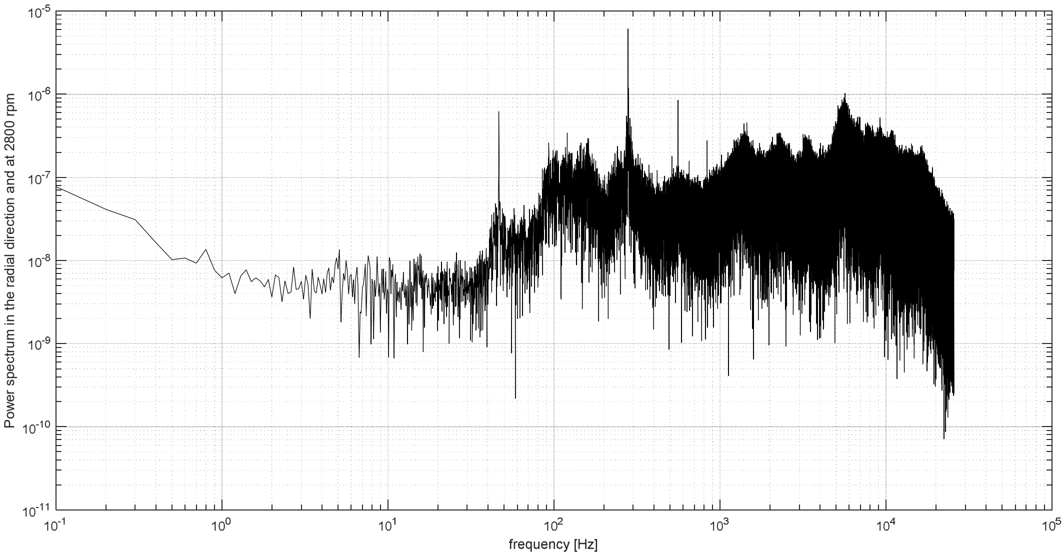


Figure 6. Vibration signal in the frequency domain measured in the centrifugal pump in the rotation of 2800 rpm.

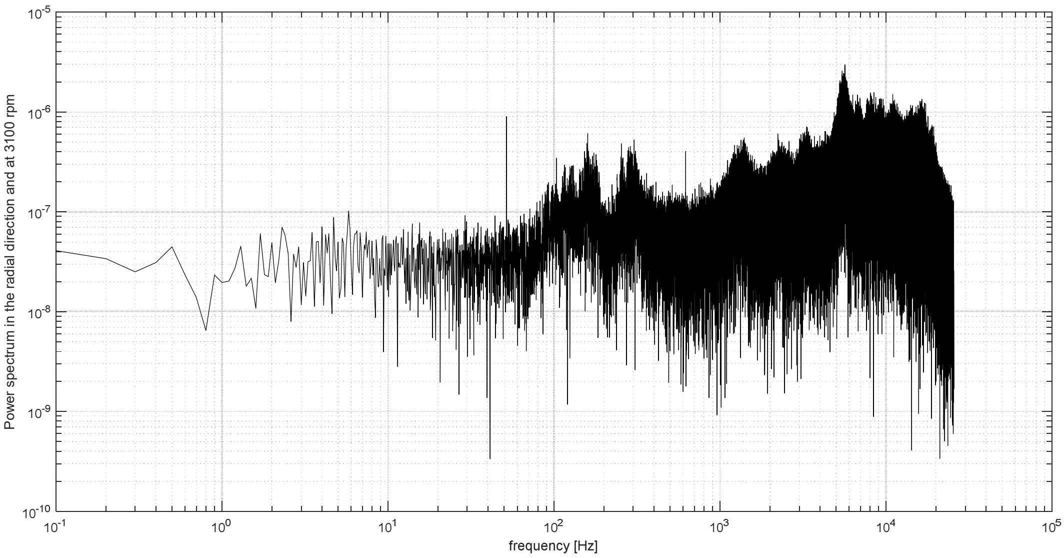


Figure 7. Vibration signal in the frequency domain measured in the centrifugal pump in the rotation of 3100 rpm.

After the signal processing to the frequency domain, these signals were used as the input samples for the Multi-layer Perceptron Neural Network training. The outputs of the neural network are the vectors representing the cavitation in each rotation. The neural network topology used for the classification of the cavitation level has 1 (one) input, that is, the vector with the amplitude of the signal vibration in the frequency domain, 20 neurons in the intermediate layer and 3 (three) outputs indicating the cavitation level, the vectors [1 0 0], [0 1 0] and [0 0 1], respectively. These vectors indicating the cavitation level may be classified as low, medium and high. The Figure 8 illustrates the neurons and the neural network topology used for this classification task. It was used the "patternnet" function available in the MATLAB® 2018 software dedicated to the classification task. The activation function used for the intermediate layer was the Sigmoidal and the activation function employed to the output layer was the min-max activation function.

The multi-layer perceptron neural network was trained once defined its topology for classification of cavitation level. During the training process, the weights and bias of each neuron were adjusted by an optimization procedure by using the Levenberg-Marquard algorithm available in the software MATLAB® 2018. The global error of the optimization procedure was $7.42\text{x}10^{-11}$ and the training process has converged with 28 iterations. The Figure 9 describes the parameters values used in the training process of the neural network. Because of the global error obtained during the training was very small, it means that difference between the desired output and the calculated output by the neural network was also small, that is, the output and input data were successfully adjusted during the optimization of the bias and weights from neurons.

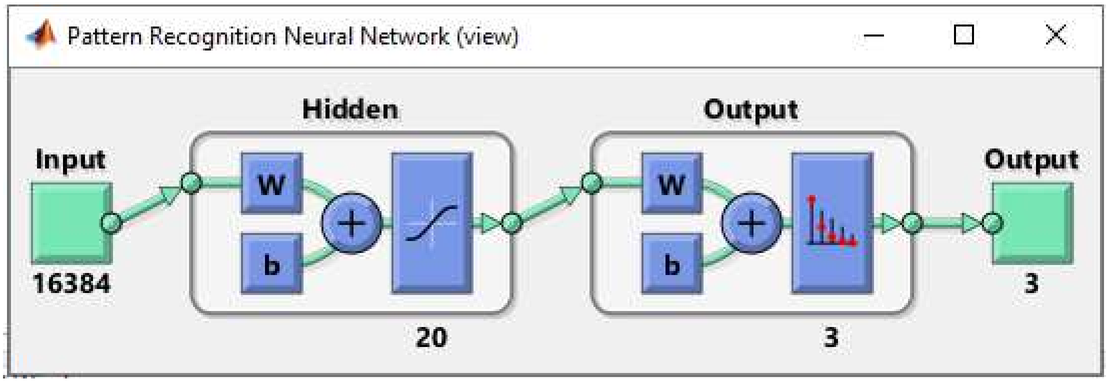


Figure 8. Topology of Multi-layer Perceptron Neural Network used for the classification of the pump cavitation level.

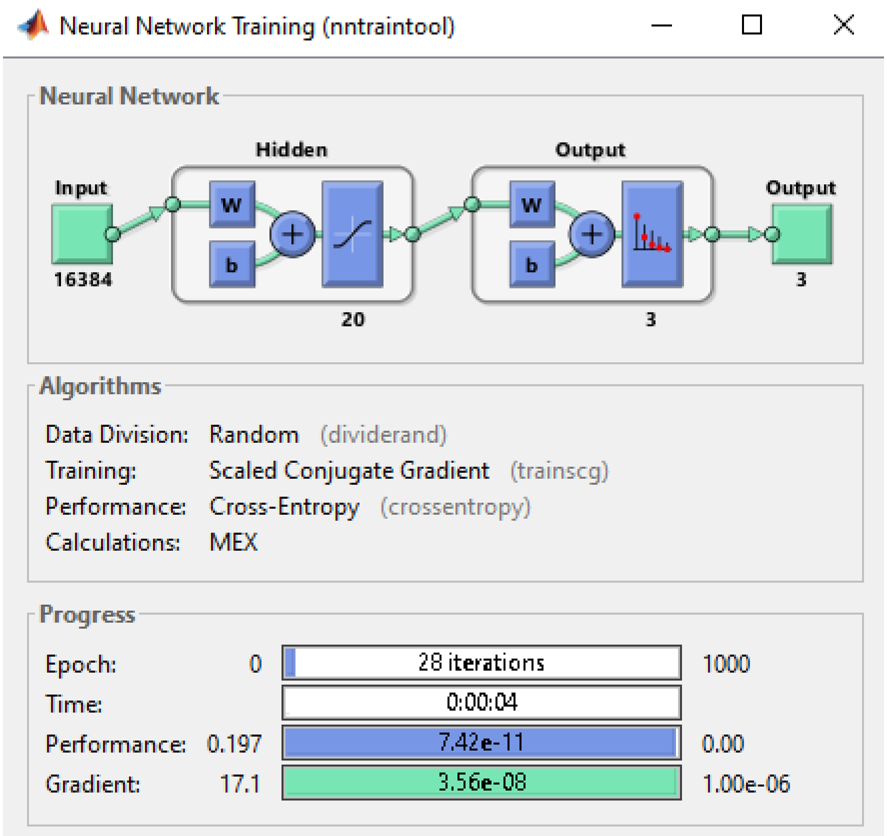


Figure 9. Parameters values obtained during the training process of neural network.

In order to check the performance of the neural network, some tests were done after the training. By using the samples of the vibration signals measured in the pump by operating in the rotations of 2500, 2800 and 3100 rpm as inputs, the response of the trained neural network was [1 0 0], [0 1 0] and [0 0 1]. For the vibration signals measured in the rotations of 2600, 2700, 2900 and 3000 rpm, the outputs from neural network were [0 1 0], [0 1 0], [0 1 0] and [0.0007 0.0000 0.9993], that is, these vibration signals may be interpreted according to neural network as medium cavitation in the rotations of 2600, 2700, 2900 and high cavitation for the rotation of 3000 rpm. Although the obtained results be interesting from the classification point of view, it is necessary more tests to check the accuracy and to validate the application of the proposed neural network in the cavitation classification problem of the centrifugal pump.

6. CONCLUSIONS

In this work, it was proposed a methodology for analysis of the cavitation level in centrifugal pumps by using the spectral analysis and multi-layer perceptron neural network. Initially, the vibration signals were measured on the pump case working in 7 seven rotations (2500, 2600, 2700, 2800, 2900, 3000 and 3100 rpm) by using the accelerometers in the radial and axial direction. In the following, the vibration signals in the time domain were processed for the frequency domains by using the Fast Fourier Transform. Subsequently, the spectra of the pump vibration signals measured in the rotations of 2500, 2800 and 3100 rpm were used as input data for the training of a multi-layer perceptron neural network for classification of the cavitation level.

After the creation and training of the neural network, others samples of the vibration spectra measured in the pump by operating in the rotations of 2500, 2800 and 3100 were used for check the accuracy of the classification procedure. Since the neural network training has converged, the outputs provided by classification model were the same used in the training process. For the vibration signals measured in the rotations of 2600, 2700 and 2900 rpm the neural network classified the cavitation level like medium. In the rotation of 3000 rpm, the response of the neural network was high cavitation. In the future, it will be used others parameters, such as the pressure and torque measured in the centrifugal pump in order to improve the accuracy of the cavitation level classification process.

7. ACKNOWLEDGEMENTS

The authors would like to acknowledge the UFTM (Federal University of Triângulo Mineiro) for provide the measuring system of the vibration signals and the centrifugal pump used in this research.

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