J. Appl. Comput. Mech., 7(3) (2021) 1764-1773
DOI: 10.22055/JACM.2021.37798.3089

ISSN: 2383-4536
jacm.scu.ac.ir

Shahid Chamran University of Ahvaz

Journal of Applied and Computational Mechanics

Research Paper

Analysis and Recognition of Standards in Intelligent Hybrid Systems using Natural Computing

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Received June 21 2021; Revised July 01 2021; Accepted for publication July 01 2021.
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Abstract. This work shows the application of one of the techniques of bioengineering, the perceptron network in the detection of system failures, and also allows the use of the perceptron network technique in choosing the location of the best sensor to be used in the dynamic system. The application of the perceptron network was adopted because it is considered the best binary linear classifier. This work is considered multidisciplinary and difficult to develop. The final result demonstrates a severe application of pre-processing and processing, until the classification and grouping of signals in the two phases of the work. Through the results found, this work can be considered successful and can be applied in several areas of engineering for structural analysis.

Keywords: Vibration; hybrid system; perceptron network; natural computing; predictive system.

1. Introduction

The consumer market has undergone transformations and has demanded more of the concept and characteristics of product development, consequently its intrinsic quality. Industries have been significantly transformed to implement automation and artificial intelligence principles, meeting the flexible factory prerogative. The gains of the adoption and implementation of these technologies have been seen in relation to morale, costs, quality and delivery time [1].

The proper maintenance process helps minimize process and product problems, reduces the risk of failure, enables increased productivity, and reduces production costs. This equivalence determines the principle of maintaining a healthy company that is a maintenance management activity. Its strategic effectiveness stems from the increase in society and global competition [2]. The habit of maintaining the maintenance of a machine, allows the increase of the probability of its operating health, with this predictive maintenance techniques can be increased to identify damage and failures in the system [3]. Basically, the identification of damages and failures are treated in the concept of structural analysis that analyzes and studies the deformation and stress of a given body, under the action of a given force [4].

The applications of failure analysis in structural analysis can be shown by different researchers: in this work the failures of a dynamic rotor using artificial immune system are analyzed, the result of which demonstrates the prognosis of failures of the dynamic behavior of the system [5]. This other work shows the application of fault detection in tubes, using the concept of negative selection immune systems, whose result enables a methodology linked to the condition of structural health monitoring (SHM) [6]. This other researcher demonstrates the analysis and prognosis of failures in a diesel engine, located in the open field, using the theory of vibration and acoustics applied to bioengineering, whose result show successfully and efficiently the versatility of use of the different theories [7].

The objective of this work is to show the application of the perceptron network in the detection and analysis of failures of a dynamic system. For this, this work was divided into two distinct phases, the first phase being conceptualized to determine the quality of the sensor to be used to capture the vibration signal. The second phase specifically deals with detecting and determining the prognosis of vibration signals, considering system failures.

Published online: July 04 2021

2. Intelligent Hybrid Systems – Random Vibration.

The hybrid system is considered a model that describes the dynamics of objects containing electrical and mechanical components, whose behavior of this system can be represented by a mathematical model with specific differential equations [8]. It is possible to obtain different architectures of a hybrid system, whose efficiency and precision in obtaining pattern recognition can be optimized considering the introduction of different techniques of neural networks, fuzzy logic and genetic algorithm. With this, it is possible to solve specific problems by improving the accuracy and learning [9].

Using the principle of the hybrid system it is possible to define that an intelligent hybrid system is the interaction between the machine and man, whose function is to obtain metrics for decision making. That's why industries optimize processes, solve problems, and develop diagnostics quickly. Basically an intelligent hybrid system is defined by the type of problem addressed that varies from the needs of psychology, linguistics, business and engineering. Intelligent hybrid systems are divided as: fusion systems, transformation systems, combination systems and associative systems. In particular, combination systems involve different intelligent methodologies for solving real-world problems [10].

The hybrid neural system is based on artificial neural networks and allows interaction with symbolic components, performing symbolic reasoning, which allows processing the combination of different mechanical information, such as oscillation signals. The advantage is fast, variable and easy-to-interpret encoding [11]. Mechanical systems, used in various industrial branches, are difficult to analyze, and problems of detection, prognosis and fault diagnosis are increasingly important in the decision-making process. Monitoring a hybrid system requires the estimation of state variables intermittently and constantly, whose components, in the continuous and discrete state, can demonstrate the failures. The aspects of diagnosis and prognosis of failures in theoretical and experimental hybrid systems can be demonstrated by modeling hybrid bonding graphs that is based on the principle of structural health monitoring (SHM) [12].

SHM is a combination of health-related words that associates well-being with control and monitoring of the physical body. This term, adapted for engineering, analyzes the safety and risk of a structure in relation to dynamic and static load applications. Therefore, through this technique it is possible to define the health status of the structure considering the damage and failures in relation to its tolerances. Inspections for failure prognosis analysis depend on the nature of the project, resulting in random or constant observation of each component of the dynamic system. Therefore, factors such as availability, lightness, efficiency, costs and reliability are of interest in a structural analysis [13].

A dynamic structure can be monitored by several sensors integrated or not, considering inspection intervals or under continuous aspect, which is possible to detect damage at an early stage and/or track them continuously. The SHM allows the analysis of techniques such as vibration and acoustics applied in a structure, whose sensors can illustrate the difference of state between materials considering their damage and failures [14]. Fig. 1 shows the SHM model of a dynamic system.

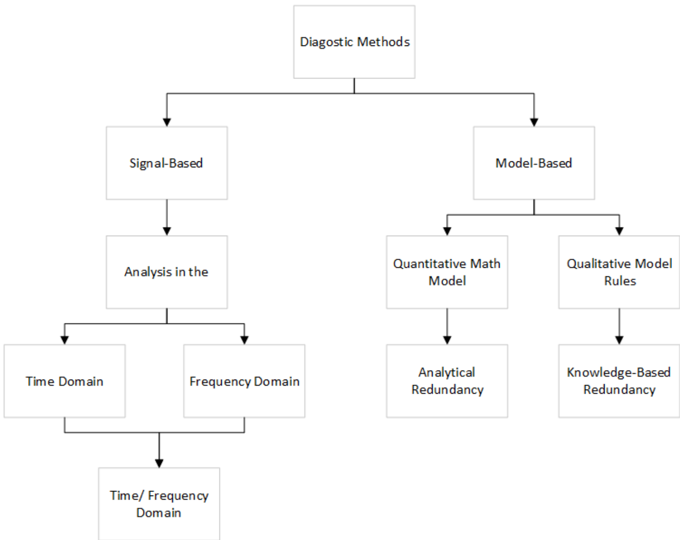

Fig. 1. SHM – Diagnosis. Adapted [14].

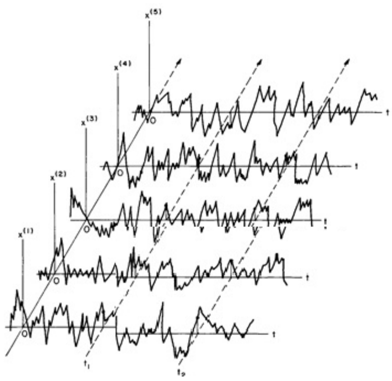

Fig. 2. Random Process [16].

The definition of vibration is a repetitive movement of a given mass that oscillates in relation to a reference point (equilibrium point), whose characteristic of the oscillation can be: periodic; transitional; or random [15].

The dynamic system when oscillating can be measured using specific sensors, the result of which can indicate a linear vibration if the comparison is close to an analytical result. Considering the repeatability of the experiment several times, and the comparison of the results is different from the analytical result, it is possible to say that the vibration is random [16]. Fig. 2 shows a random process.

Random signals can be analyzed using the concept of a degree of freedom (SDOF) and introducing statistical concepts [16; 17].

3. Data Mining and Artificial Neural Networks

The analysis of a certain amount of data is necessary to understand the physical behavior of certain systems, so it is necessary to introduce the concept of automatic data mining tools. With this, it is possible to use the concepts of classification and regression, to predict the behavior of a given model. Classification occurs when the concise model of the attribute distribution is dependent on the attributes of the predictor, resulting in models of values of known and unknown predictor attributes, of the dependent attribute [18].

The association rules use two distinct concepts, the first being the induction classification rule, which aims to acquire the ability to make predictions. The second is the discovery classification rule that determines the association by affinity between two sets, whose antecedent and consequent, may contain a single associated [19; 20].

Neural networks are applied to data mining because it is a binary neuron-based technology, a result of the human brain as a computational model. With this, Frank Rosenbaltt developed the perceptron network, using a concept of numerical manipulation represented by symbols [21; 19].

The perceptron network is an interactive procedure that adjusts the increment w and θ, until the decision limit is able to separate into two training classes. With this, a noise can be separated into classes [22; 19]. The perceptron network belongs to the single-layer feedforward architecture, whose flow of information flows from the input layer to the output layer, without any feedback produced by the neuron. Fig. 3 shows the perceptron network.

Note that, $X_1, \dots, X_n$ correspond to the input variables of a process; $w_1, \dots, w_n$ correspond to the weights (weightings); the θ is the activation threshold; the u is the activation potential; the $g(\cdot)$ is the activation function; the y matches the output [23]. The perceptron network equation is

$$\begin{cases} u = \sum_{i=1}^{n} w_i X_i - \theta; \\ \quad y = g(u), \end{cases} \tag{1}$$

and the signal activation function is [23],

$$y = \begin{cases} 1, & \text{se} \sum w_i X_i - \theta \geq 0 \Leftrightarrow w_1 X_1 + w_2 X_2 - \theta \geq 0; \\ -1, & \text{se} \sum w_i X_i - \theta < 0 \Leftrightarrow w_1 X_1 + w_2 X_2 - \theta < 0. \end{cases} \tag{2}$$

The perceptron network training process, based on Hebb's learning rule (1949) determines that the output produced by the perceptron network is not coincident with the desired output, the sinatic weights and activation thresholds of the network should be incremented in proportion to the values of its input signals. This process is done repeatedly and sequentially in all training samples, until the output of the perceptron network is similar to the desired output [21; 23]. The rules of adjustments and weights can be defined as,

$$\begin{cases} w_i^{\text{atual}} = w_i^{\text{anterior}} + \eta(d^K - y)X_i^K; \\ \theta_i^{\text{atual}} = \theta_i^{\text{anterior}} + \eta(d^K - y)(-1), \end{cases} \tag{3}$$

with that, we will have,

$$w^{\text{atual}} = w^{\text{anterior}} + \eta(d^K - y)X^K, \tag{4}$$

where η is the learning parameter (step); K is the training sample; and d is the desired value for the K-th training sample [21; 23]. The training pseudocode can be shown in Fig. 4. The pseudo operation code can be shown in Fig. 5.

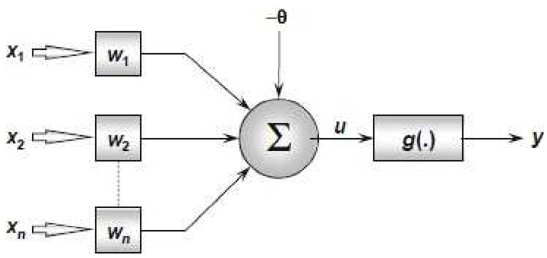

Fig. 3. Perceptron network of a single output neuron [23].

Begin {PERCEPTRON Algorithm – Training Phase}
<1> Obtain the set of training samples $\{\boldsymbol{x}^{(k)}\}$;
<2> Associate each desired output $\{d^{(k)}\}$ to each sample;
<3> Initialize vector $\boldsymbol{w}$ with small random values;
<4> Specify the learning rate $\{\eta\}$;
<5> Initialize the epoch counter {*epoch* ← 0};
<6> Repeat the following instructions:
<6.1> *error* ← "none";
<6.2> For all training samples $\{\boldsymbol{x}^{(k)}, d^{(k)}\}$, do:
<6.2.1> $u \leftarrow \boldsymbol{w}^T \cdot \boldsymbol{x}^{(k)}$;
<6.2.2> $y \leftarrow \text{signal}(u)$;
<6.2.3> If $y \neq d^{(k)}$
<6.2.3.1> then $\begin{cases} \boldsymbol{w} \leftarrow \boldsymbol{w} + \eta \cdot (d^{(k)} - y) \cdot \boldsymbol{x}^{(k)} \\ error \leftarrow \text{"existent"} \end{cases}$
<6.3> *epoch* ← *epoch* + 1;
Until: *error* ← "none"
End {PERCEPTRON Algorithm – Training Phase}

Fig. 4. Training Pseudo code [23].

Begin {PERCEPTRON Algorithm – Operation Phase}
<1> Obtain one sample to be classified $\{\boldsymbol{x}\}$;
<2> Use the vector $\boldsymbol{w}$ adjusted during training;
<3> Execute the following instructions:
<3.1> $u \leftarrow \boldsymbol{w}^T \cdot \boldsymbol{x}$;
<3.2> $y \leftarrow \text{signal}(u)$;
<3.3> If $y = -1$
<3.3.1> then: sample $\boldsymbol{x} \in$ *{Class A}*
<3.4> If $y = 1$
<3.4.1> then: sample $\boldsymbol{x} \in$ *{Class B}*
End {PERCEPTRON Algorithm – Operation Phase}

Fig. 5. Pseudo Operation Code [23].

Fig. 6. Physical Experiment

Fig. 7. Positioning of Vibration Sensors

4. Experimental Methodology

This work demonstrates two distinct phases, the first being the phase of location of the best sensor for signal collection. The second phase is the digital analysis of the signal applied to the perceptron network, which defines the classification and prognosis of system failures.

The experiment was developed considering a 3CV – 60Hz, 320V WEG electric motor, a generic flexible coupling, an IMBIL type reducer, and a WEG CFW10 frequency inverter internally positioned in the control box. The experiment was developed to simulate a field condition, considering the assembly between an electric motor and a hydraulic motor pump. The main concept of analysis is in flexible coupling, which allows the union of two axes, transferring the rotating energy between the systems. The flexible coupling allows for a certain adjustment that eliminates mounting problems such as misalignment and clearances.

The methodological principle of the experiment allows measuring the vibration of the reduction box by varying the limits of the parameters of the flexible coupling, between the electric motor and the reducer. The variation of the speed of the electric motor, made by the frequency inverter, is 2Hz to 10Hz every 2Hz. Fig. 6 shows the experiment containing the electric motor (left side), the generic flexible coupling (to the center in orange color), and the reducer (on the left side).

Considering that one of the conditions of this work is to understand the vibration behavior at each strategic point of the reducer structure using the vibration signal, 3 most likely points were identified in which the structure could be affected by vibration. Fig. 7 shows the location of the points chosen for fixing the MPU6050 sensor and collecting the vibration signal.

Note that, position 1 of the MPU6050 sensor determines an almost direct analysis of the vibration behavior transmitted from the flexible coupling. Position 2 illustrates the behavior of the junction between the reducer and the flange. Position 3 illustrates the vibration behavior of the reducer fixation to the structure. The different positions allow the dynamic system to be analyzed by observing different characteristics of the variation of the rotary energy, transmitted by the motor in the flexible coupling.

The samples collected from each point were developed as follows: 5 signals with 4000 samples each were collected, thus being 5 1x4000 signals of each frequency from 2Hz to 10 Hz every 2Hz. In total, 25 1x4000 size signals were collected from each sensor configuration. For the sample size to be valid, the finite sampling calculation was applied to 4000 samples with 2% error and 95% confidence level. The result of the calculation determines that 1111 should be sufficient for this result to be valid. As a deal, 4000 samples are more than enough to ensure the quality of the sampling.

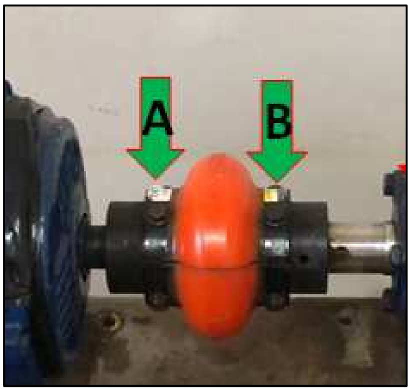

Fig. 8. Location of the Removal of Screws A and B

The configuration of the data collection process was distributed as follows:

1. System coupled according to the normal specifications of the coupling adjustment limits, between the electric motor and the reducer (normal configuration);
2. System coupled outside the normal specifications of the coupling adjustment limits, between the electric motor and the reducer (abnormal configuration – pulling out a screw from each side holding the flexible coupling). Fig. 8 shows the location of screws A and B to be removed.

Three different databases were formed. Each database is composed of 25 signals from each sensor, totaling 75 signals from the first database of configuration 1, considered a good signal. From configuration 2, 75 signals, considered bad. The database contains 75 good signals and 75 bad signals.

4.1 Phase I

The structural system receives rotational energy from the electric motor by means of flexible coupling, and this energy is propagated throughout the structure. The vibration of the system is found throughout the structure, however, in an open field case it is difficult to identify the best position seen the weathering of the site. The condition of phase I, choosing the best sensor, is a fundamental step to understand the best point of signal collection procedure. This phase can also be considered a way to understand the behavior of the vibration signal at different collection points.

Considering the details of the location configuration of the MPU6050 sensors by the structure, 75 signals were collected in total. That's five signals from each frequency per sensor. At first, the FRF of each frequency-sensor was analyzed, the result of which demonstrates the variation of the information for the best choice of the sensor. Table 1 shows the FRF result for each frequency, and Fig. 9 shows the graphical shape of each FRF for each frequency-sensor.

Based on the degree of difficulty of choosing the sensor, the perceptron network was introduced for the best choice. The result of the application of the perceptron network demonstrated sensor 2 as the best choice.

4.2 Phase II

Phase II is defined as the analysis of continuous signals by the perceptron network using sensor reference 2, whose result determines the prognosis and probability of system failures. Database processing is done by the perceptron network algorithm, as it is considered the best binary linear classification algorithm.

In this process, the database is composed of the signal of the condition in which the system is flawless, and the condition in which the system contains faults, which is the removal of two screws, one on each side (A and B) of the flexible coupling. This process simulates the condition that the system operates with information on horizontal shaft misalignment, excessive coupling clearance, among others connected to the coupling system between the shafts.

The database is thus processed by the perceptron network algorithm, whose Euclidean distance determines the distance required for the determination of failure prognosis values. Fig. 10 shows the probability classification score and system failure predict based on the insertion of the 75 signals with system failures.

The symbols of the Fig. are: the circle represents sensor 1; the square represents sensor 2; inverted triangle represents sensor 3. The line remains green is the reference of the mean line of the mean of all sampled values; the black continuous line is the upper and lower reference of the standard deviation; the line remains blue is the top and bottom reference of 3 times the standard deviation. The black lines determine a confidence interval that 68.27% of the samples, conducted by the perceptron network, are within a control reference of greater specificity than, when compared, between the values found at the limits of the blue line (99.73%).

Table 1. Frequency-Sensor FRF

Equipment	FRF - Frequency (Hz)				
	2	4	6	8	10
sensor 1	1024	665	517	1826	1393
sensor 2	512	366	1404	1075	625
sensor 3	554	263	332	1297	209

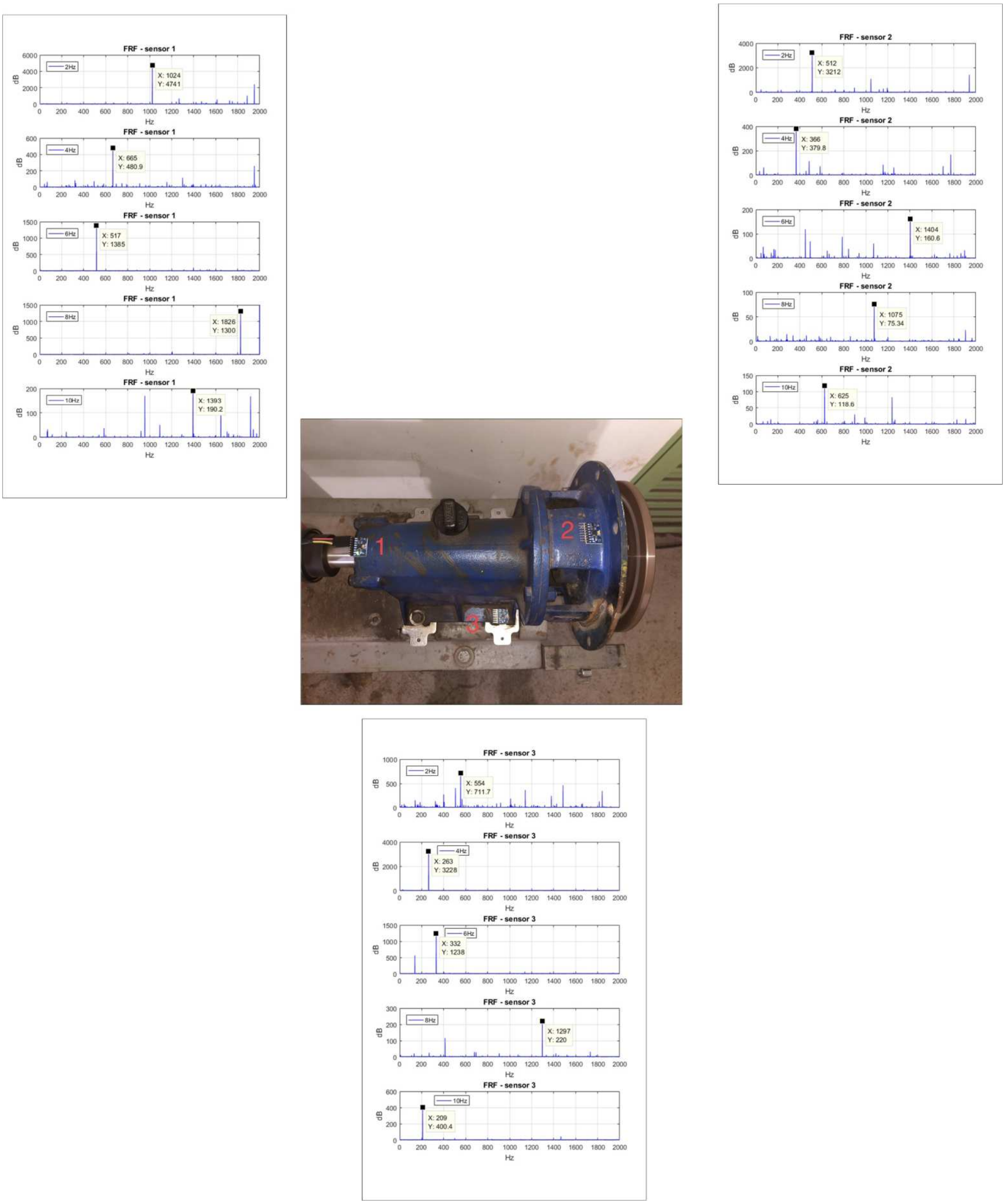

Fig. 9. Frequency-Sensor System FRF

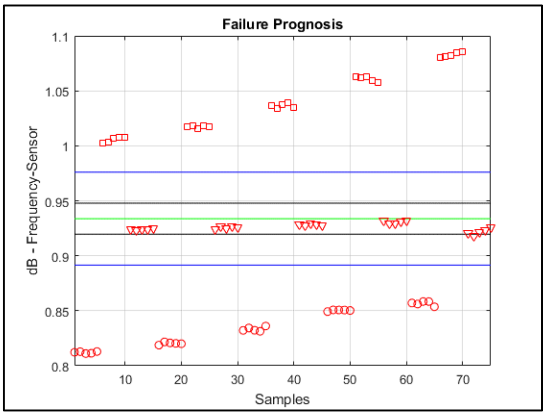

Fig. 10. Failure Prognosis

Fig. 11. Graphic Result for 2Hz

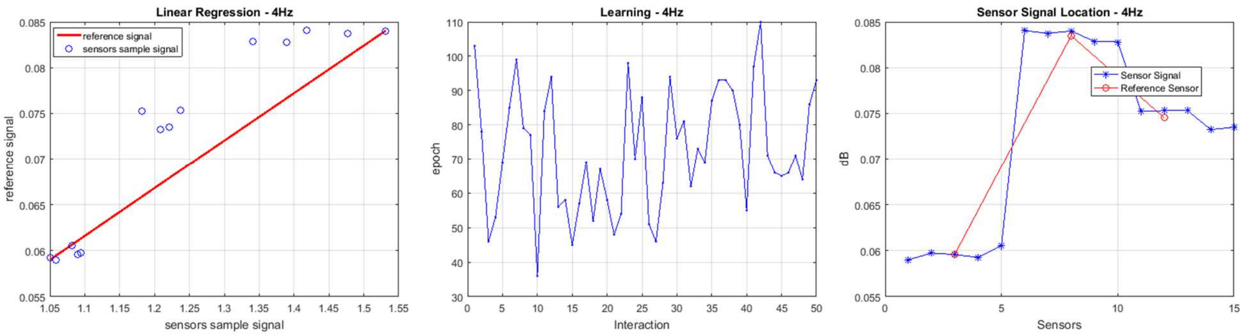

Fig. 12. Graphic Result for 4Hz

5. Discussion

5.1 Phase I - Discussion

Note that, it is difficult to choose the best sensor, based on an analysis parameter by FRF. Therefore, the concept of FRF should not be analyzed as a criterion of relevance in choosing the best sensor. For this, the concept of the perceptron network was introduced in the classification and grouping of signals, applied to the Euclidean distance theorem. Fig. 11 to 15 show the graphical results of frequencies from 2Hz to 10Hz, every 2Hz, which, for each figure; the one on the left side shows the result of the application of the linear regression of the 15 signals; the central figure, the representation of the evolution of the perceptron network; the on the right side, shows the comparison of the signal rating of each frequency-sensor group.

Note that each graphical result applied to each frequency contains a different response.

The interpretation for the results of linear regression graphs shows that, with the evolution of the frequency increase, the signals of each sensor tend to cluster, forming isolated and clearly defined groups. This strengthens the condition of future pattern recognition for each frequency-sensor.

The temporal evolution graph (epoc) illustrates that the result of the application of the neural network algorithm was developed for each frequency-sensor.

The sensor location graph shows that each signal was analyzed by the neural networks algorithm, sorting, classifying and grouping the different signals of each frequency.

Fig. 13. Graphic Result for 6Hz

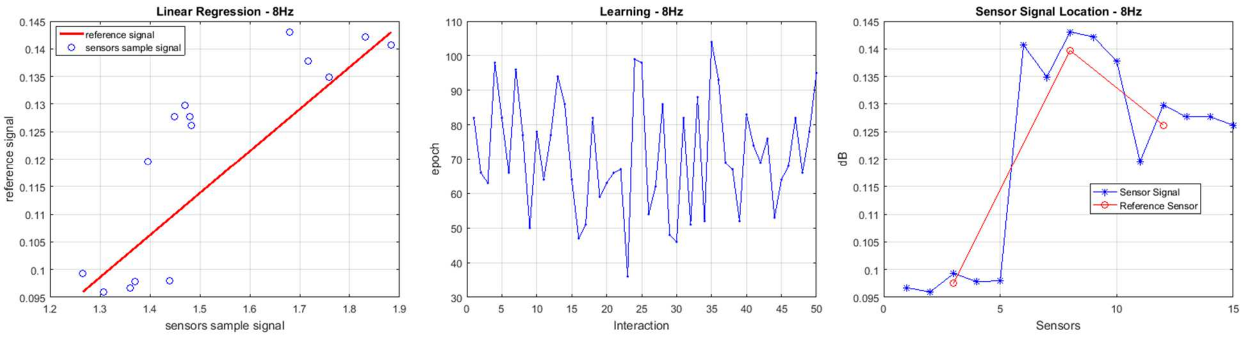

Fig. 14. Graphic Result for 8Hz

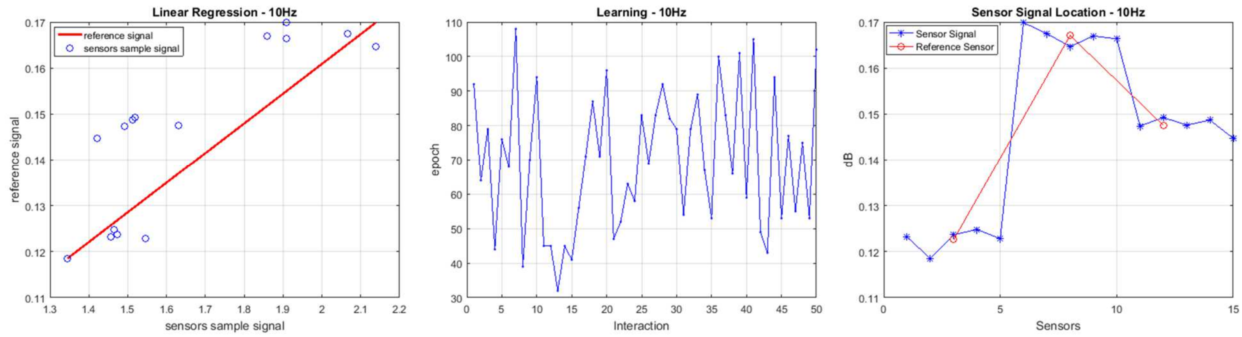

Fig. 15. Graphic Result for 10Hz

The choice of the best sensor for the vibration analysis of the system is based on the condition of greater amplitude, because it is possible to better analyze the interferences of the system, considering the displacement of the wave. In this case, the most appropriate choice is sensor 2, which contains the largest amplitude of the system. One of the conditions for this amplitude to be greater than the others can be observed in the concept of propagation waves in structures, considering that there are areas of different dimensions coupled in a single system.

5.2 Phase II - Discussion

In Fig. 10, note that the sensor 1 (circle) at the frequency of 2Hz is far from the blue line and with the increase in the frequency of the electric motor, demonstrates an approximation of the control lines. In sensor 2 (square) the reverse occurs, demonstrating a distance from the control line. Sensor 3 (inverted triangle) remains stable from application at 2Hz frequency.

The frequency evolution criterion demonstrates that sensor 2 data represent the best sensor to be studied, as it tends to capture the flaws of the structure behavior, given the distance from the control lines.

Using the failure severity criterion, and knowing that the system contains failures, the results can be analyzed by the following criteria:

a) The results that are between the black line and distant from the green line, can be conditioned the existence of failures, that is, 68.27% of the collected data contains failures;

b) If the results are between the blue line and the black lines are between the blue line and the black lines contain a greater amount of failures, that is, 99.73% of the collected data contains faults and are severe.

c) If the results are externally positioned the blue lines, the fault is already considered extremely serious and it is necessary to stop the equipment and condition it to corrective maintenance.

The proposed flowchart of the experimental methodology of signal analysis can be seen in Fig. 16.

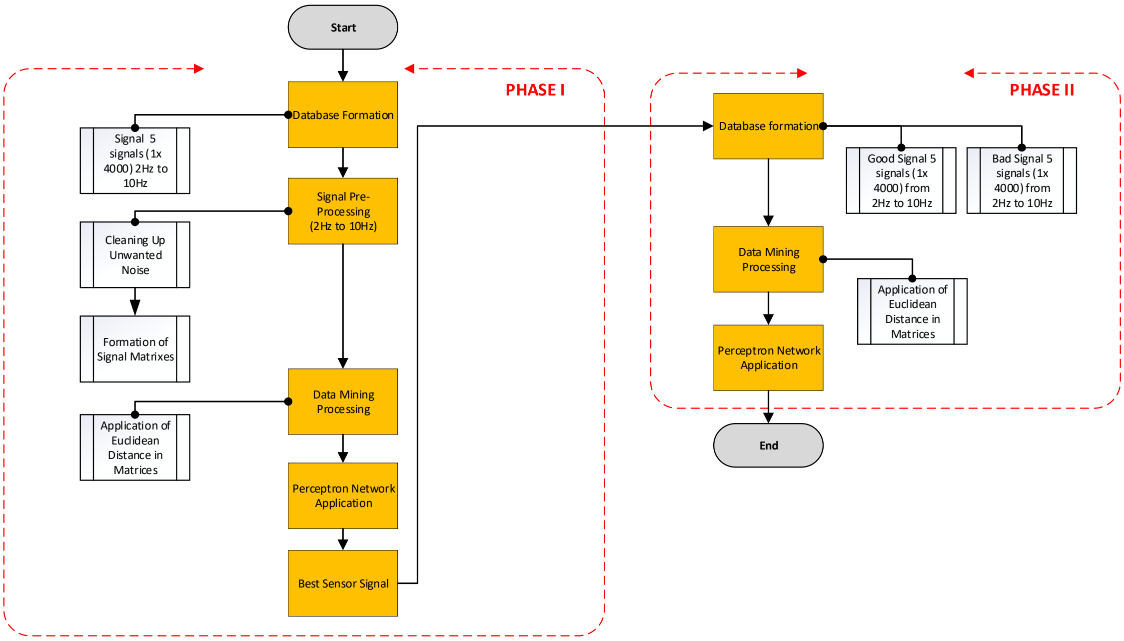

Fig. 16. Signal Analysis Flowchart

5. Conclusion

This work present multidisciplinary concept, whose results shown the efficiency of the application, and the methodological process become effective in the application for maintenance systems.

In phase I, the choice of the best sensor was application using the perceptron network technique that groups and classifies the signals of the different sensors. In this information processing, the Euclidean distance technique was introduced in the perceptron network so that the criteria of best choice were determined. In this concept, it is possible to understand that the methodology practiced defines characteristics to be adopted in the projects and used in the field, in the collection of signals. This demonstrates that the technique developed has flexibility and promotes cost reduction in decision making.

In phase II it was demonstrated that, with the insertion of the faulty database, the prognosis of failures can be identified by applying the perceptron network technique, which grouped and classified the signals, promoting the determination of the prognosis of failures on the limits of the samples.

In a comparative analysis, phase I and II demonstrate that sensor 2 is the best reference for signal collection and effective study of failure prognosis. This can be considered as a pattern recognition methodology for cyber systems. This application can be done in the maintenance activities of various areas of engineering.

The perceptron network is a simple but very effective technique, which allows different operations at the entrance considering the weights for a given desired output. With this, the application of the perceptron network has an advantage in binary linear classification jobs modeling the hierarchy of resources. On the other hand, the multilayer perceptron network technique, composed of more than one perceptron, enables the work of a nonlinear classification, because they are composed of a layer at the entrance and an output layer, and between these two, there is a hidden layer that approximates the function continues. Technically, for this work, the Euclidean distance mathematical technique was chosen in the application of the sensitivity of the choice of the best sensor and in the prognosis of the failure. However, it is possible to introduce in the pre-processing phase another technique that best suits the rationale.

This study directed to the perceptron network showed an effective result of excellent quality. Other bioengineering techniques can be inserted in this context; however, the results may not be as effective as that presented in this work. At this time, discussing the techniques of artificial immune systems, genetic algorithms, differential evolution, among others, becomes very fictitious, because it would be necessary to apply them to know the efficacy in the results. What can be affirmed is that each technique has its individual potential and that added to other mathematical techniques; the application itself becomes knowledge to be added and enhanced the area of engineering.

This multidisciplinary work met the initial proposal to study the behavior of signals and showing results that can become standards for future recognitions. Therefore, this work can be considered successful.

Author Contributions

The authors declared to have contributed in equal parts to the work.

Acknowledgments

The authors thank the Laboratory of Complex Systems (SISPLEXOS) of the Institute of Chemistry - UNESP, for ceded the physical space, the computer park and the Paula Souza Center – CPS for their support and encouragement of research in FATEC's.

Conflict of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and publication of this article.

Funding

The authors thanks the financial support of the São Paulo State Research Support Foundation (FAPESP), through the process 2019/10515-4 and to the National Council for Scientific and Technological Development (CNPq), through process 312972/2019-9.

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How to cite this article: Borges Loureço R.F., Outa R., Chavarette F.R., Gonçalves A.C. Analysis and Recognition of Standards in Intelligent Hybrid Systems using Natural Computing, *J. Appl. Comput. Mech.*, 7(3), 2021, 1764–1773. https://doi.org/10.22055/JACM.2021.37798.3089