An hybrid artificial inteligence aplied to diagnosis of failures in aeronautical and civil structures

Uma inteligência artificial híbrida aplicada ao diagnóstico de falhas em estruturas aeronáuticas e civis

Fernando Parra dos Anjos Lima
Doutor em Engenharia Elétrica pela Universidade Estadual Paulista
Instituição: Instituto Federal do Mato Grosso, Campus Avançado Tangará da Serra
Endereço: Rua 28, 980N – Vila Horizonte, Tangará da Serra – MT, Brasil
E-mail: fernando.lima@ifmt.edu.br

Simone Silva Frutuoso de Souza
Doutora em Engenharia Elétrica pela Universidade Estadual Paulista
Instituição: Universidade do Estado de Mato Grosso, Campus Tangará da Serra
Endereço: Rodovia MT 358, Km 07 (s/n) - Jardim Aeroporto, Tangará da Serra – MT
Brasil
E-mail: simonefrutuoso.mat@gmail.com

Fábio Roberto Chavarette
Doutor em Engenharia Mecânica pela Universidade Estadual de Campinas
Instituição: Universidade Estadual Paulista, Instituto de Química de Araraquara
Endereço: Prof. Francisco Degni, 55 - Quitandinha, Araraquara – SP, Brasil
E-mail: fabio.chavarette@unesp.br

ABSTRACT
This paper presents a new hybrid methodology to diagnose failures in aeronautical and civil structures using as a tool the Perceptron multi-layer artificial neural networks and ARTMAP-Fuzzy and the wavelet transform. The main application of this hybrid methodology. The main application of this methodology is the auxiliary structures inspection process in order to identify and characterize the flaws, as well as perform the decisions aiming at avoiding accidents or disasters. In order to evaluate this methodology, we carried out the modeling and simulation of signals from a numerical model of an aluminum beam and a building. The results demonstrate the robustness and accuracy methodology.

Keywords: hybrid methodology, structural health monitoring, intelligent systems.

RESUMO
Este documento apresenta uma nova metodologia híbrida para diagnosticar falhas em estruturas aeronáuticas e civis utilizando como ferramenta as redes neurais artificiais multi-camadas Perceptron e ARTMAP-Fuzzy e a transformação wavelet. A principal aplicação desta metodologia híbrida. A principal aplicação desta metodologia é o processo de inspecção de estruturas auxiliares, a fim de identificar e caracterizar as falhas, bem como executar as decisões destinadas a evitar acidentes ou desastres. Para avaliar

esta metodologia, realizámos a modelação e simulação de sinais de um modelo numérico de uma viga de alumínio e de um edifício. Os resultados demonstram a robustez e a metodologia da precisão.

Palavras-chave: metodologia híbrida, monitorização estrutural da saúde, sistemas inteligentes.

1 INTRODUCTION

In recent years the civil and aeronautical industries, started applying many investments in research and technological development in order to obtain efficient methods to analyze the integrity of structures and to prevent disasters and/or accidents from happening, ensuring people's lives and avoid economic damages.

Fault diagnosis systems, or as better known, "Structural Health Monitoring (SHM) system" perform tasks such as: acquisition and data processing, validation and analysis, detection, characterization and interpretation of adverse changes in a structure so to assist taking decisions and identify structural faults (Hall, 1999).

Structural failures occur as a consequence of factors such as component wear, cracks, loosening of screw connections, or simply the combination of these. The flaws in most cases, not dependent on the source or current, causes a variation of spatial parameters of the structure, generating a reduced structural rigidity, mass, and also the increased damping so that the dynamic behavior of the structure is changed (Zheng et al., 2004).

To solve this problem, several solutions have been proposed, such as traditional SHMS based on ultrasonic inspection, radiography (X-ray), acoustic emission testing, among others. However, these traditional techniques cannot meet increasing demands of industries, especially when the structures are in motion (Franco et al., 2009). Thus, a solution to develop the most modern and efficient SHMS is the utilization of smart materials and techniques, and efficient data acquisition systems.

In the literature, several studies that utilize smart materials and SHM systems are available, which have robustness, accuracy and good performance. Following presents the most relevant papers.

In (Krawczuk et al., 2000), the authors presented the application of a genetic algorithm in conjunction with a Perceptron Multi-Layer neural network with backpropagation to perform fault detection and location in a numerical model of a beam. Giurgiutiu (2005) used the method of electro-mechanical impedance to monitor aerospace

structures with assets piezoelectric sensors attached. Palaia (2007) presents a methodology for structural analysis of buildings using a non-destructive method (NDT). Chandrashekhar and Ganguli (2009) propose a fuzzy system to detect structural faults using curvature mode shapes.

In the work (Xiang-Jun et al., 2010) proposed a model using wavelet transform to evaluate integrity of bridge structures through the vibration signals. A system for the identification and location of damage to an airplane wing using a probabilistic neural network was proposed in (Shen et al., 2011). In (Wang et al., 2013) proposed a multimodal genetic algorithm for diagnosing damage in a steel truss bridge. Song et al. (2012) proposes an experimental method for performing structural analysis of buildings. In (Souza et al., 2013) proposes an ARTMAP-Fuzzy neural network applied in the diagnosis of faults in buildings. Already in (Lima et al., 2013; Souza et al., 2021a; Souza et al., 2021b) proposed an immune algorithm with negative selection to diagnose failures in aircraft structures.

Lima et al. (2014a) was shown a SHM based on ARTMAP-Fuzzy neural network and wavelet transform to diagnose faults in buildings. In (Lima et al., 2014b; Campos et al., 2020; Oliveira et al., 2020) a hybrid method based on ARTMAP-Fuzzy neural network and wavelet transform to diagnose failures in aluminum beams was presented. Abreu et al. (2014) presented a failure analysis tool in aircraft structures using complex wavelet transform.

In this paper, presents a new approach to fault diagnosis in aeronautical and civil structures using a hybrid method based on artificial neural networks (ANN) Perceptron Multi-Layer and ARTMAP-Fuzzy and the wavelet transform. This methodology is divided into three main modules, with the acquisition and processing of data, fault detection and classification. From the acquisition of the signs applies to wavelet transform, decomposing the signs at 3 levels of resolution. After you obtain the processed signals via the wavelet transform, applies to Perceptron Multi-Layer ANN to perform the detection of abnormalities in the structure. When an abnormality is identified applies ARTMAP-Fuzzy ANN to perform the characterization of structural faults detected. In this work we applied the Perceptron Multi-Layer ANN and ARTMAP- Fuzzy because of the quality and efficiency of both ANNs, as shown in other studies, for pattern recognition and diagnosis. The use of the wavelet transform provides a more sensitive diagnostic system, where the presence of abnormalities in the signal is identified easily.

In order to evaluate the proposed methodology, we used two databases containing

the signals numerically simulated from two mathematical models, and a model of an aluminum beam and a model of a two-story building. Both structures were modeled by finite elements and simulated. The results demonstrate the efficiency, accuracy and robustness of the proposed method.

2 MULTI-LAYER PERCEPTRON AND BACKPROPAGATION ALGORITHM

The Perceptron Multi-Layer (PML) ANN corresponds to a parallel processor composed neurons (processing units). Neurons are arranged in one or more layers interconnected by a large number of connections. The connections are associated with weights representing knowledge. The learning of PML network is named training and occurs by adjusting the weights. The common learning is performed using a training algorithm. In this work we adopted the backpropagation algorithm, which is the best-known algorithm for training PML networks. The backpropagation algorithm is a supervised learning technique that utilizes pairs (input and desired output) for through the Error calculation, adjust the weights of the network and gain knowledge (Haykin, 1994).

In more detail, the process of learning the MLP network using backpropagation is run through the following steps (Werbos, 1974):

1. The start with random values and nonzero the weights;
2. Show a pattern of input and propagate it to the exit of the network;
3. Calculate the instantaneous error at the network output (E), wherein (2.1) represents the calculation of error of each neuron network at time n, and (2.2) is the calculation of the total error at time n;

$$e_j(n) = d_j(n) - y_j(n) \tag{2.1}$$

$$E(n) = \frac{1}{2}\sum_{j=1}^{m} e_j^2(n) \tag{2.2}$$

4. Calculate the local gradients (δ) of the neurons of the output layer, given by equation (2.4). The gradient of neuron j is the product resulting from the error of neurons (j) to the derivative of the activation function (Q') applied to the local field induced vj calculated in (2.3) where wij is the weight input is associated with each neuron j;

$$v_j(n) = \sum_{i=0}^{m} w_{ij}(n) - y_i(n) \tag{2.3}$$

$$\delta_j(n) = e_j(n)Q'(v_j(n)) \tag{2.4}$$

5. Adjust the output layer weights using the expressions (2.5):

$$\Delta w_{ji}(n) = \eta \delta_j(n) y_i(n)$$
$$w_{ji}(n+1) = w_{ji} + \Delta w_{ji}(n) \tag{2.5}$$

6. Calculate the local gradients of neurons in the hidden layer using (2.6), where p refers to the number of neurons connected to the right j:

$$\delta_j(n) = Q'(v_j(n))\sum_{k=1}^{p} \delta_k(n) w_{kj}(n) \tag{2.6}$$

7. Adjust the weights of the hidden layer using the expressions in (2.7);

$$\Delta w_{ji}(n) = \eta \delta_j(n) y_i(n)$$
$$w_{ji}(n+1) = w_{ji} + \Delta w_{ji}(n) \tag{2.7}$$

8. Repeat steps 2-7 for all training patterns (1 epoch);
9. Calculate every epoch the mean square error (MSE) for the training using the expression (2.8), where N is the number of patterns used for training;

$$MSE = \frac{1}{N} \sum_{j=1}^{N} E(j) \tag{2.8}$$

10. If the MSE is greater than the desired value (DV) or whether the time counter is less than the maximum number of times (MNTp) repeat step 8. Otherwise stop;

3 ARTMAP-FUZZY ARTIFICIAL NEURAL NETWORKS

The ARTMAP-*Fuzzy* artificial neural network corresponds to a supervised learning system comprised of a pair of modules Adaptive Resonance Theory (Carpenter, Grossberg, 1987), *ART_a-Fuzzy* and *ART_b-Fuzzy*, interconnected by inter-*ART* associative memory module. This neural network architecture incorporates *fuzzy* set theory, the AND *fuzzy* operator (^) enabling the learning of the neural system in response to binary input patterns and analog, belonging to the interval [0 1] (Carpenter et al., 1992).

A internal mechanism called *match-tracking* is responsible for self-regulating process of the neural network, in which maximize generalization and minimize the error. When the neural network makes a prediction wrong, through an associative connection instructed, the monitoring parameter of *ART_a-Fuzzy* module is incremented in minimum amount necessary to correct the error in the *ART_b-Fuzzy* module.

The ARTMAP-*Fuzzy* architecture has three main parameters for the development, namely, parameter choice α ($\alpha > 0$), rate training β ($\beta \in$ [0 1]) and parameter monitoring (ρ_a, ρ_b e $\rho_{ab} \in$ [0 1]) (Carpenter et al., 1992). If ρ has a large value, the neural network becomes more selective reducing its generalizability. If ρ has a small value, it reduces the number of categories created, increasing the generalization capability of the ARTMAP-*Fuzzy* network.

The selection of the category is performed as (3.1), *J* is active index of *F_2* (Carpenter et al., 1992).

$$T_j = \frac{|I \wedge w_J|}{\alpha + |w_J|}$$

$$J = \arg \max T_j \tag{3.1}$$

Resonance occurs if the vigilance test (3.2) is satisfied for the active index *J* (Carpenter et al., 1992).

$$\frac{|I \wedge w_J|}{I} \geq \rho \tag{3.2}$$

If vigilance test (3.2) is not satisfied, the *reset* occurs and the choice function continues until a new category *J* satisfies (3.2). After the process of resonance and the

modules ART_a and ART_b should check the match tracking of categories in both modules, this step is taken by Inter-*ART* module.

The Inter-*ART* module verifies the Match Tracking of information between *ART* modules. This process is done by the *Match Tracking* described in (3.3), where y^b is the vector of activity module ART_b (Carpenter et al., 1992).

$$\frac{\left| y^b \wedge w_{JK}^{ab} \right|}{y^b} \geq \rho_{ab} \tag{3.3}$$

If the test *Match Tracking* (3.3) is not satisfied, a new category of ART_a module should be chosen and introduced in the training process until this criterion is satisfied. After making the resonance processes for modules ART_a and ART_b and the *Match Tracking* for the Inter-*ART* module is made adaptation of the synaptic weights w_J^a, w_K^b and w_{JK}^{ab} as (3.4), J and K are active index (Carpenter et al., 1992).

$$
\begin{aligned}
w_J^{a+1} &= \beta(I \wedge w_J^a) + (1-\beta)w_J^a \\
w_J^{b+1} &= \beta(I \wedge w_K^b) + (1-\beta)w_K^b \\
w_{JK}^{ab+1} &= \begin{cases} 1 \to J = j, K = k \\ 0 \to J \neq j, K \neq k \end{cases}
\end{aligned}
\tag{3.4}
$$

4 WAVELET TRANSFORM

The wavelet functions are mathematical transforms able to decompose functions, allowing rewriting these functions more detailed, i.e. with a global vision. Thus, it is possible to differentiate local characteristics of a signal in different sizes (resolutions) and, analyze all the signals by translations. As the most of wavelets has compact support, they are useful in analyzing non stationary signals. There are several wavelet families. This work considers the orthonormal family functions and the Daubechies discrete family (Daubechies, 1992) due to have faster computational algorithms (Mallat, 1999).

Define a signal $y[t] = (y_0, \ldots, y_{n-1}, y_n)$ representing a discrete vector then it can be represented by a wavelet series as follows (Mallat, 1999):

$$y[t] = \sum_{k=0}^{N_J} c_{J,k}\phi_{J,k}(t) + \sum_{j=J}^{1}\sum_{l=0}^{N_j} d_{j,k}\upsilon_{j,k}(t), \nabla t \in [0, N_0] \qquad (4.1)$$

where: J represents the resolution level, $N_j = (N/2) - 1$ represents the quantity of points in each new vector obtained by transformation, $\phi_{j,k}(t)$ and $\upsilon_{j,k}(t)$ are the wavelet and scale functions that execute the transformation; j is the scale (dilation) and k the position (translation).

The discrete wavelet transform (DWT) when applied directly to a signal to generate a set of coefficients is calculated by several entrances into a G filter (low pass) and H filter (high pass), or known as resolution levels. The filters G and H are vectors with constants already calculated that provide an orthogonal base related to the scale and wavelet functions respectively. This process IF known as Mallat Pyramidal algorithm (Mallat, 1999) and is shown in figure 1 (a).

Figure 1. Pyramidal algorithm for DWT.

(a)

(b)
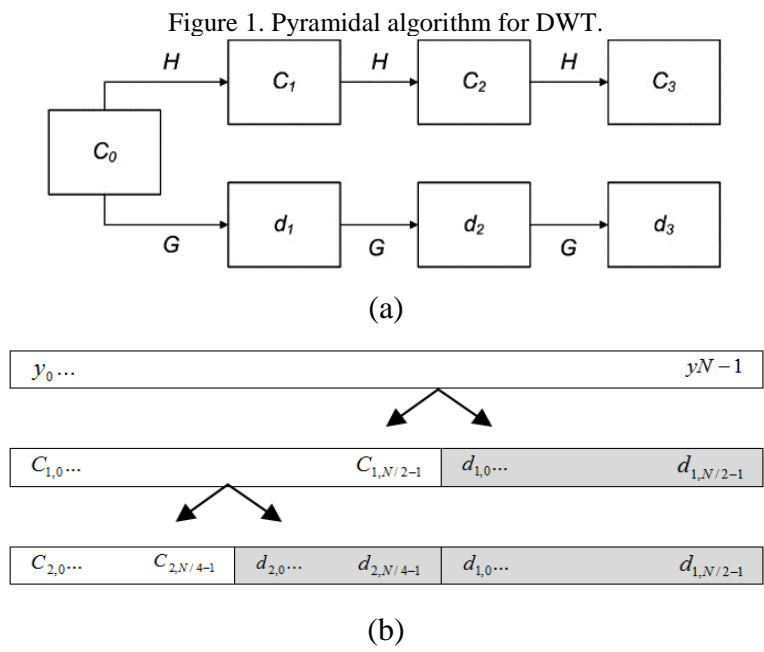
At figure 1 (a), C_0 corresponds to the original discrete signal ($C_0 = y[t]$), H and G represent the low pass and high pass filters respectively. The parameters d_1, d_2 and d_3 are the wavelet coefficients or detail in each resolution level and C_3 are the scale coefficients or approximation at the last level of the transform. These coefficients are obtained by convolution of the constants at filters (4.2) and (4.3), (Mallat, 1999):

$$C_{j+1,k} = \sum_{l=0}^{D-1} h_l C_{j,2k+l} \tag{4.2}$$

$$d_{j+1,k} = \sum_{l=0}^{D-1} g_l C_{j,2k+l} \tag{4.3}$$

where: $k = [0, ..., (N/2^j) - 1]$ and D the quantity of constants of the filter. Thus, the coefficients $C_{j,k}$ represent the average local media and the wavelet coefficients $d_{j,k}$ represent the complementary information or the details that run away from the average media. Therefore, the transform coefficients ordered by scale (*j*) and position (*k*) are represented as follows (Mallat, 1999):

$$\psi = \left((C_{J,k})_{k=0}^{N_J}, \left((d_{j,k})_{k=0}^{N_J} \right)_{j=J}^{1} \right) \tag{4.4}$$

such that ψ is the finite representation in terms of the coefficients of the signal decomposition in equation (4.4). Figure 1 (b) shows the decomposition process of a signal in two resolution levels. Observe that in each transformation level the size of the vectors is reduced by half ($N/2^J$).

5 MODELING AND SIMULATIONS

5.1 ALUMINUM BEAM

The aluminum beam model proposed to evaluate the methodology, obtained by finite element method, was an aluminum beam in the cantilever-free condition discretized with 10 finite elements with 2 degrees of liberty each. The material properties used are the modulus of elasticity (E = 700 GPa) and the density (γ = 2710 kg/m^3). The dimensions are 500*mm* long, 25*mm* wide and 5*mm* thick. Figure 2 (a) illustrates the patterned beam (Lima et al., 2014c).

From the beam model were performed several simulations with different percentages of wear and locations of faults. The database consists generated signal captured by an accelerometer attached to the beam. In all simulations the beam was excited in the 3rd degree of freedom (finite element 2) and the signal was captured on the 19th degree of freedom (finite element 10). Thus, were simulated 1400 signals in the structure, 500 without wear (base-line condition) and 900 signs with wear (structural

failure), being 150 signs for each type of failure. The signals at failure were simulated in wear levels 5, 10, 15, 20, 25 and 30%. For each level of wear failure was placed in two locations (finite elements 3 and 5). Figure 2 (b) presents two signals that had been captured in the simulations, the 15% failure and another under ordinary conditions. Following applies wavelet transform to obtain the signals shown in figure 2 (c). The data set is formed by signals processed by the wavelet transform, in the wavelet domain.

Figure 2. (a) Beam modeled, (b) Simulated signal, (c) Wavelet domain.

(a)

(b)   (C)
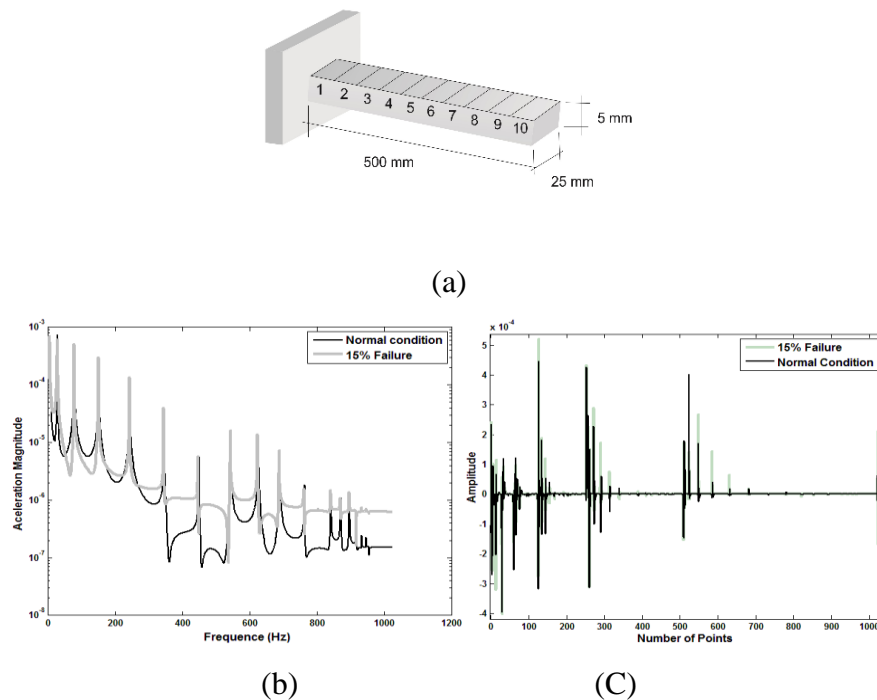
5.2 BUILDING

The Building model was developed using differential equations of a two storey building with two degrees of freedom each. The building is adimensional model and consists of two masses (M_1 and M_2), and the stiffness coefficients (k_1 and k_2) and elasticity (c_1 and c_2), see (Chavarette, Toniati, 2012; Lima et al., 2014a). The model is illustrated in figure 3 (a).

Figure 3. (a) Structure model, (b) Frequency response, (c) Wavelet domain.

(a)

(b)   (c)
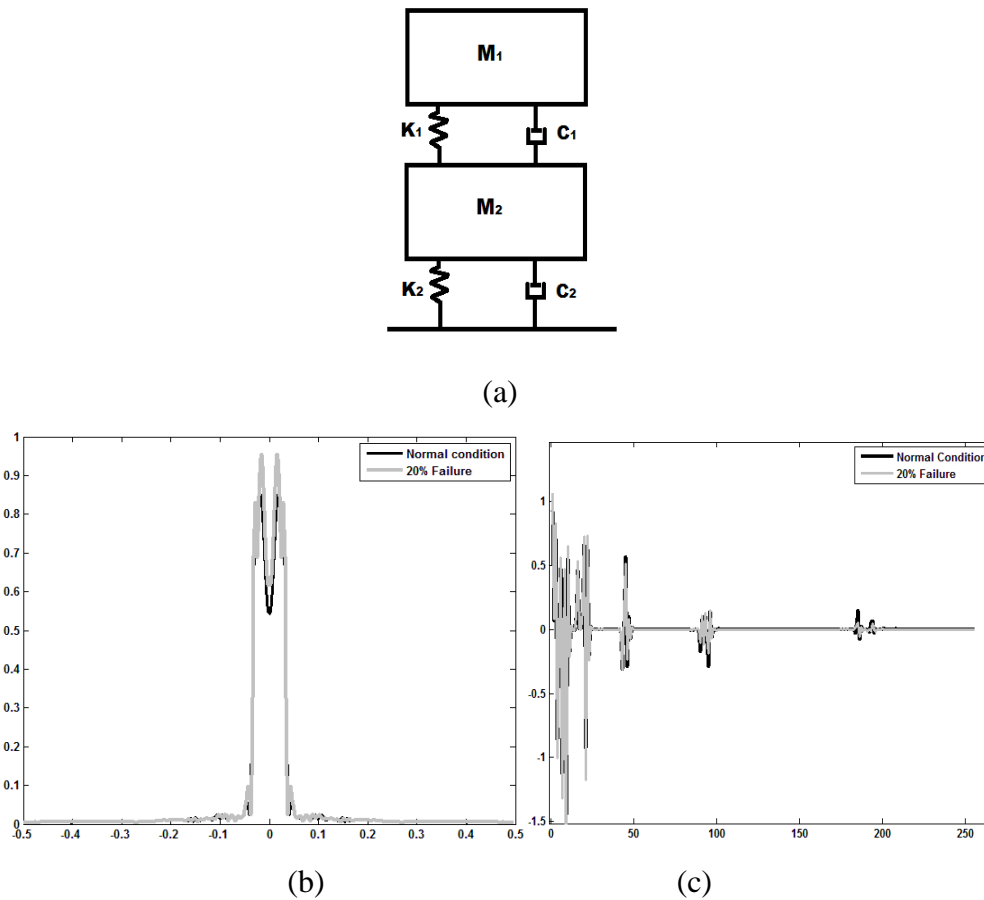
We simulated 1400 signs in the structure, being 500 signs in normal condition, i.e., without flaw (condition base-line) and 900 signals with structural flaws, being 150 signs for each type of failure. The signals faults were simulated with additions of 5, 10, 15, 20, 25 and 30% in mass M1 of the structure. The structure was excited by the signal (*S*) as (Chavarette, Toniati, 2012):

$$S = 1 * e^{-5\cos(t)} \tag{5.1}$$

After exciting the structure obtains the frequency response of the structure using the Fourier Fast Transform (FFT) (Chavarette, Toniati, 2012). The frequency response is obtained from the signals of the velocity and the displacement of the structure excited. Figure 3 (b) illustrate two signals are captured in the simulations, which has a signal with a 20% failure (red) and a signal in normal condition (blue). Following applies wavelet

transform to obtain the signals shown in figure 3 (c). The data set is formed by signals processed by the wavelet transform, in the wavelet domain.

6 PROPOSED METHOD

The hybrid system for diagnosis of structural faults proposed in this paper consists of an offline phase (learning) and an online phase (monitoring), as shown in figure 4. In the offline phase is the training process of ANNs and get the knowledge to be used in the monitoring phase for detection and fault classification process. Also, there is the phase of acquiring and processing data. After performing signal acquisition using the wavelet transform to decompose the signals into 3 levels of resolution in the wavelet domain.

Figure 4. Flowchart of Proposed Methodology.
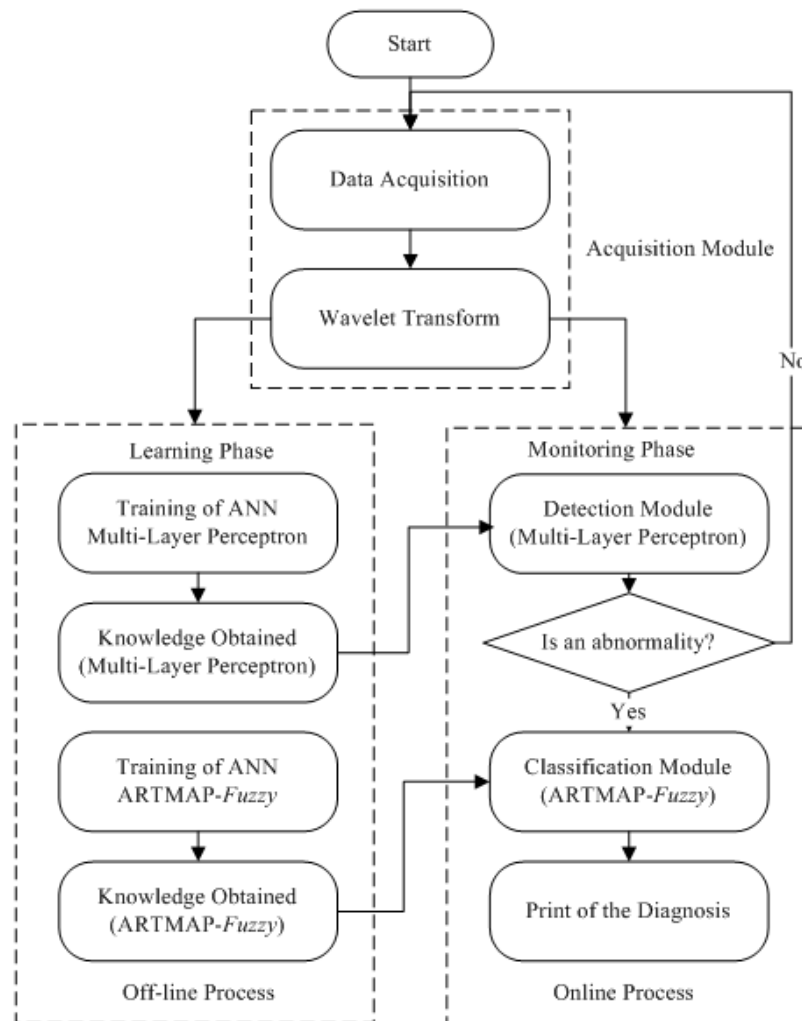
In the online phase is monitoring, which is divided into three main sections, and the acquisition and data processing (wavelet transform), the detection module (Multi-Layer Perceptron) and the classification module (ARTMAP-*Fuzzy*).

The data acquisition module consists of the experimental apparatus for capturing the signals at the aircraft structure, such as sensors, actuators, accelerometers, etc. After you obtain the frequency response signals, applies the wavelet transform, performing a decomposition in wavelet domain. These signals are used in the learning process and system monitoring.

The detection module is performed by the Multi-Layer Perceptron ANN using the knowledge gained in the training process to differentiate the signals in normal and abnormal. When a normal signal is detected, is automatically classified as a base-line condition of the structure (structure without fail). When an abnormal signal is detected the classification module is triggered in order to characterize the type of failure identified.

The classification module is performed by ARTMAP-*Fuzzy* ANN and aims to characterize the type of fault detected. In this process the ARTMAP-*Fuzzy* ANN use the knowledge gained in the training phase and classifies the abnormality identified in a simulated fault levels for the available databases.

We emphasize that for the process of training the neural network is used a different set of data from the data presented in the monitoring process

7 RESULTS

In this section we present the results obtained by applying the method proposed in both simulated databases.

7.1 PARAMETERS

For both problems was modeled one Multi-Layer Perceptron ANN with 1024 neurons in the input layer, 1200 in the intermediate layer and 2 in the output layer. The parameters used for the Multi-Layer Perceptron ANN were $\mathrm{MNTp} = 10^{4}$, $DV = 10^{-6}$ and the parameters used for the ARTMAP-*Fuzzy* ANN were $\alpha = 0,2$, $\beta = 0.9$, $\rho_{a} = 0,8$, $\rho_{b} = 1$ and $\rho_{ab} = 1$.

For training the ANNs were used 70% of the data available for both problems, with 900 signs, of which 600 (300 signs the structure in normal condition and 50 signals for each level fault) for Multi-Layer Perceptron ANN and 300

(50 signals for each level fault) to the ARTMAP-Fuzzy ANN. The testing phase (monitoring) were used 30% of the remaining data (500 signals), of which 200 structure in normal condition and 300 failures in the structure (50 signals for each level fault). The simulated databases have six different types of faults levels.

7.2 RESULTS FOR ALUMINUM BEAM

Table 1 shows the results obtained by the proposed hybrid system, when applied to the data set of the aluminum beam.

Table 1. Results obtained by the proposed methodology.

Signals	Training Multi-Layer Perceptron		Training ARTMAP-*Fuzzy*		Diagnostic	
	Samples Used	Ratings Correct	Samples Used	Ratings Correct	Samples Used	Ratings Correct
Normal condition	300	300	-	-	200	200
5%	50	50	50	50	50	50
10%	50	50	50	50	50	50
15%	50	50	50	50	50	50
20%	50	50	50	50	50	50
25%	50	50	50	50	50	50
30%	50	50	50	50	50	50
Accuracy (%)	100.00		100.00		100.00	
Time (s)	3125.12		0.623		0.235	

The proposed hybrid system showed an excellent performance, with a 100% success rate in detecting and classifying faults to the problem of aluminum beam.

7.3 RESULTS FOR BUILDING

Table 2 shows the results obtained by the proposed hybrid system, when applied to the data set of the building model.

Table 2. Results obtained by the proposed methodology.

Signals	Training Multi-Layer Perceptron		Training ARTMAP-*Fuzzy*		Diagnostic	
	Samples Used	Ratings Correct	Samples Used	Ratings Correct	Samples Used	Ratings Correct
Normal condition	300	300	-	-	200	200
5%	50	50	50	50	50	50
10%	50	50	50	50	50	50
15%	50	50	50	50	50	50
20%	50	50	50	50	50	50
25%	50	50	50	50	50	50
30%	50	50	50	50	50	50
Accuracy (%)	100.00		100.00		100.00	
Time (s)	2985.68		0.586		0.198	

The proposed hybrid system showed an excellent performance, with a 100% success rate in detecting and classifying faults to the problem of building model.

8 CONCLUSION

In this paper we propose a new hybrid approach based on Multi-Layer Perceptron ANNs and ARTMAP-Fuzzy and the wavelet transform to diagnose failures in aeronautical and civil structures. In this context the hybrid system showed excellent results by getting a 100% success rate for the best system configuration for both analyzed problems. The learning phase of ANNs (training) requires more computational time; however, is executed off-line causing no damage to the system. Already the phase of monitoring is carried out rapidly with time less than 250 milliseconds. We emphasize that the processing performed with the wavelet transform provides increased efficiency to the system, because the decomposing signals into 3 levels of resolution, the abnormalities are easily identified. Finally, we conclude that the hybrid methodology proposed is very efficient, reliable and robust for fault diagnosis in aeronautical and civil structures.

REFERENCES

ABREU, C. C. E., CHAVARETTE, F. R., ALVARADO, F. V., DUARTE, M. A. Q., LIMA, F. P. A., 2014, Dual-Tree Complex Wavelet Transform Applied to Fault Monitoring and Identification in Aeronautical Structures, *International Journal of Pure and Applied Mathematics*, **97**, 89-97.

CAMPOS, M. B. P.; MACIEL, G. S.; SOUZA, S. S. F.; CHAVARETTE, F. R.; LIMA, F. P. A. Inteligência artificial com aprendizado continuado aplicada ao reconhecimento de padrões. Brazilian Journal of Development. v. 6, n. 5, p. 22778-22797, 2020.

CARPENTER, G. A., GROSSBERG, S., MARKUZON, N., REYNOLD, J. H., ROSEN, D. B., 1992, Fuzzy ARTMAP: A neural network for incremental supervised learning of analog multidimensional maps, *IEEE Transactions on Neural Network*, **3**, 5, 689-713.

CARPENTER, G. A., GROSSBERG, S., 1987, A massively parallel architecture for a self-organizing neural pattern recognition machine, *Computer Vision, Graphics, and Image Processing*, 54-115.

CHANDRASHEKHAR, M., GANGULI, R., 2009, Structural damage detection using modal curvature and fuzzy logic, *Structural Health Monitoring*, **8**, 267-282.

CHAVARETTE, F. R., TONIATI, A. L., 2012, Dinâmica e Controle de um Sistema Estrutural sob Excitação Sísmica, *Proceedings of the Congresso Nacional de Engenharia Mecânica*, 1–11.

DAUBECHIES, I., 1992, *Ten Lectures on Wavelets, Society for Industrial and Applied Mathematics*, Philadelphia.

FRANCO, V. R., BUENO, D. D., BRENNAN, M. J., CAVALINI JR., A. A., GONSALEZ, C. G., LOPES JR., V., 2009, Experimental damage location in smart structures using Lamb waves approaches. *Proceedings of the Brazilian Conference on Dynamics, Control and Their Applications*. 1-4.

GIURGIUTIU, V., 2005, Tuned lamb wave excitation and detection with piezoelectric wafer active sensors for structural health monitoring, *Journal of Intelligent Material Systems and Structures*, **16**, 4, 291–305.

HALL, S. R., 1999, The effective management and use of structural health data, *Proceedings of the International Workshop on Structural Health Monitoring*, 265-275.

HAYKIN, S. H., 1994, *Neural Networks: A comprehensive foundation, MacMilliam College Publishing*, New York.

KRAWCZUK, M., OSTACHOWICZ, W., KAWIECKI, G., 2000, Detection of delamination in cantilevered beams using soft computing methods, *Proceedings of the Conference on System Identification and Structural Health Monitoring*, Madrid, 243–252.

LIMA, F. P. A., CHAVARETTE, F. R., SOUZA, A. S., SOUZA, S. S. F., LOPES, M. L. M., 2013 Artificial Immune Systems with Negative Selection Applied to Health Monitoring of Aeronautical Structures, *Advanced Materials Research*, **871**, 283-289.

LIMA, F. P. A., CHAVARETTE, F. R., SOUZA, S. S. F., LOPES, M. L. M., TURRA, A. E., Lopes Jr., V., 2014a, Analysis of Structural Integrity of a Building Using an Artificial Neural Network ARTMAP-Fuzzy-Wavelet, *Advanced Materials Research*, **1025-1026**, 1113-1118.

LIMA, F. P. A., CHAVARETTE, F. R., SOUZA, S. S. F., LOPES, M. L. M., TURRA, A. E., Lopes Jr., V., 2014b, Monitoring and Fault Identification in Aeronautical Structures Using an ARTMAP-Fuzzy-Wavelet Artificial Neural Network, *Advanced Materials Research*, *1025-1026*, 1107-1112.

LIMA, F. P. A., CHAVARETTE, F. R., SOUZA, S. S. F., SOUZA, A. S., LOPES, M. L. M., 2014c, Artificial Immune Systems Applied to the Analysis of Structural Integrity of a Building, *Applied Mechanics and Materials*, **472**, 544-549.

MALLAT, S., 1999, *A Wavelet tour of signal processing*, *Academic Press*, 2 Ed. New York, 637p.
OLIVEIRA, D. C.; CHAVARETTE, F. R.; LIMA, F. P. A. Structural Health Monitoring using Artificial Immune System. Brazilian Journal of Development. v. 6, n.4, p.16948-16963, 2020.

PALAIA, L., 2007, Strutural Failure Analysis of timber floors and roofs in ancient buildings at Valencia (Spain). *Proceedings of the International Conference on Mechanical Behaviour and Failures of the Timber Structures*, Florence, 1–11.

SHEN, T., WAN, F., SONG, B., WU, Y., 2011, Damage Location and Identification of the Wing Structure With probabilistic neural Networks. *Proceedings of the Prognostics and System Health Management Conference*, 1–6.

SONG, B. I., SEZE, H., GIRIUNAS, K. A., 2012, Collapse Performance Evaluation of Steel Building After Loss of Columns, Proceedings of the Structures Congress – ASCE (American Society of Civil Engineers), 213–224.

SOUZA, A. S., CHAVARETTE, F. R., LIMA, F. P. A., LOPES, M. L. M., SOUZA, S. S. F., 2013, Analysis of Structural Integrity Using an ARTMAP-Fuzzy Artificial Neural Network, *Advanced Materials Research*, **838-841**, 3287-3290.

SOUZA, S. S. F.; CAMPOS, M. B. P.; CHAVARETTE, F. R.; LIMA, F. P. A. A New Approach Experimental to Diagnosis of The Failures in Mechanical Structures Using the Artificial Immune Algorithm With Negative Selection. Brazilian Journal of Development. v. 7, n. 7, p. 66372-66392, 2021a.

SOUZA, S. S. F.; CAMPOS, M. B. P.; CHAVARETTE, F. R.; LIMA, F. P. A. Structural Failures Diagnosis using a Hybrid Artificial Intelligence Method. Brazilian Journal of Development. Brazilian Journal of Development. v. 7, n. 7, p. 66873-66893, 2021b.

WANG, F. L., CHAN, T. H. T., THAMBIRATNAM, D. P., TAN, A. C. C., 2013, Damage Diagnosis for Complex Steel Truss Bridges Using Multi-Layer Genetic Algorithm, *Journal of Civil structural Health Monitoring*, Springer-Verlag, 117–217.

WERBOS, P. J., 1974, Beyond regression: New tools for prediction and analysis in the behavioral sciences, PhD. Thesis, Harvard University.

XIANG-JUN, C., ZHAN-FENG, G., QIANG, G., 2010, Application of wavelet analysis in vibration signal processing of bridge structure. *Proceedings of the International Conference on Measuring Technology and Mechatronics Automation*, 671–674.

ZHENG, S., WANG, X., LIU, L., 2004, Damage detection in composite materials based upon the computational mechanics and neural networks, *Proceedings of the European Workshop on Structural Health Monitoring*, Munich, 609–615.