A new approach experimental to diagnosis of the failures in mechanical structures using the artificial immune algorithm with negative selection

Uma nova abordagem experimental para o diagnóstico das falhas nas estruturas mecânicas utilizando o algoritmo de imunidade artificial com seleção negativa

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ABSTRACT
In this paper we present a new experimental approach to diagnose failures in mechanical structures using as decision tool an artificial immune algorithm with negative selection. This method is divided into two modules, and the acquisition and data processing module and analysis, detecting and characterizing flaws module. The module for data acquisition and processing of the experimental apparatus is constituted as sensors and actuators, so as to capture the signals in the structure and store it in the computer. From the signal acquisition executed if the negative selection algorithm to identify and characterize flaws in the structure. The main application of this methodology is to assist in the inspection process of mechanical structures in order to identify and characterize the flaws, as well

as perform the decisions in order to avoid accidents. To evaluate the proposed methodology, experiments were performed in the laboratory where a real signs database was captured in a structure of the beam type, made of aluminum. The results obtained in the tests show robustness and efficiency when compared to literature.

Keywords: Failures Diagnosis, Experimental Analysis, Mechanical Structures, Negative Selection Algorithm, Artificial Immune Systems.

RESUMO
Neste artigo apresentamos uma nova abordagem experimental para diagnosticar falhas em estruturas mecânicas utilizando como ferramenta de decisão um algoritmo imunitário artificial com selecção negativa. Este método está dividido em dois módulos, e o módulo de aquisição e processamento de dados e análise, detectando e caracterizando as falhas do módulo. O módulo de aquisição e processamento de dados do aparelho experimental é constituído como sensores e actuadores, de modo a captar os sinais na estrutura e armazená-los no computador. A partir da aquisição do sinal executado se o algoritmo de selecção negativo para identificar e caracterizar as falhas na estrutura. A principal aplicação desta metodologia consiste em ajudar no processo de inspecção de estruturas mecânicas, a fim de identificar e caracterizar as falhas, bem como executar as decisões de modo a evitar acidentes. Para avaliar a metodologia proposta, foram realizadas experiências no laboratório onde foi capturada uma base de dados de sinais reais numa estrutura do tipo viga, feita de alumínio. Os resultados obtidos nos testes mostram robustez e eficiência quando comparados com a literatura.

Palavras-chave: Diagnóstico de falhas, Análise experimental, Estruturas mecânicas, Algoritmo de selecção negativa, Sistemas Imunitários Artificiais.

1 INTRODUCTION

Many research and investments were used to develop methodologies and efficient monitoring systems of structural integrity in order to avoid disasters and / or accidents, ensuring people's lives and minimize economic losses.

Structural Health Monitoring (SHM) operates in the analysis and fault detection in early stages, in aiming at intervene their spread and consequently prevent disasters and / or accidents occur, leading to failure or damage to the structure. As mentioned in [1] a SHM must meet requirements such as:

- Acquisition and processing of data;
- Validation and signal analysis;
- Identification and characterization of flaws;
- Interpretation of adverse changes in a structure;
- Assist the decision-making.

Structural flaws are caused as a consequence of various factors such as component wear, cracks, loosening of screw connections and, or simply the combination of these.

The flaws in most cases, regardless of origin or intensity, cause a substantial change in the structure of spatial parameters by generating a reduced structural rigidity, reducing the mass and also the increased damping so that the dynamic behavior of the structure is changed, and thus causing the loss of control and possibly going to stop or damage to the structure [2].

In order to solve this problem, one can cite various SHM traditional methods that have been proposed for perform evaluations and integrity test structures. Traditional methods perform an analysis on the structure before it is put into use, so-called non-destructive evaluations (NDE), which aims to estimate the degree of safety and reliability of the structure. Among the main traditional methods has been the ultrasonic inspection techniques, X-ray, acoustic emission testing, among others.

Traditional methods of SHM may even have a instrument apparatus good and they are well formulated, with good results in the analysis of structural integrity, however, are unable to meet growing needs of industries, especially when such structures are in motion [3], as is the case of most part of the mechanical structures. Thus, an alternative solution to this problem is the use of intelligent sensors and / or computational intelligence techniques (artificial neural networks [4], fuzzy logic [5], artificial immune systems [6], [32], etc.), which enable skills as the extraction of knowledge and complex processes information, and can be easily modified in order to fill the continuous technological development of industries and automate decision making in SHMS.

In this sense, we can highlight several works using intelligent materials and computational intelligence techniques in the development of SHMS, which have robustness, accuracy and good performance. Following we present the most relevant studies available in the literature.

In [7] showed the application of a genetic algorithm in conjunction with a Perceptron multi-layer neural network with backpropagation to perform the fault detection and location in a numerical model of a beam. [8] we used the method of electromechanical impedance to monitor aerospace structures with piezoelectric sensors coupled. In [9], a methodology was presented for structural analysis of buildings using a non-destructive method (NDT). To evaluate this methodology was carried out experiments with a building mounted in the laboratory. On paper [10], the authors proposed a fuzzy inference system to perform the detection of structural faults using signals of the curvatures mode shapes of the structure.

In [11] a SHMS based on wavelet transform to evaluate the integrity of bridge structures using the vibration signal has been proposed. For SHM validation the authors performed laboratory experiments. In [12] introduced a system of identification and location of damage to an airplane wing using a probabilistic neural network. [13] proposed a multimodal genetic algorithm to identify damage in a bridge steel truss type mounted in the laboratory. In [14], the authors proposed an experimental method to perform structural analysis of buildings. All tests were performed in the laboratory with the use of intelligent sensors of the type PZT.

In [15], the authors showed an SHM based on ARTMAP-*Fuzzy* neural network to diagnose faults on data generated from a model number of a building. [16] presented a hybrid method based on ARTMAP-*Fuzzy* neural network and discrete wavelet transform to diagnose faults in a numerical model of a simulated aluminum beam. In [17], the authors proposed a methodology based on neural network Fuzzy ARTMAP-and wavelet transform to identify and characterize faults in a building. To evaluate this method the authors used the numerical model proposed in [15]. In [18] presented a tool for analysis of failures in aircraft structures using wavelet transform complex. To assess the tool a numerical model was also used. In [19] the authors proposed a methodology for location bridges damage using a DRD interpolation method.

In this paper, we present a new experimental approach to diagnose failures in mechanical structures using an artificial immune algorithm with negative selection. This SHM is divided into two main modules, and the acquisition and data processing module and analysis, detecting and characterizing flaws module. From the acquisition and processing of the signals obtained from laboratory experiments, applies the immune algorithm negative selection to perform the analysis, detection and characterization of faults. To evaluate the proposed method were performed laboratory experiments, aiming to generate a real signs database, captured in a structure of the beam type, made of aluminum, which in this case symbolizes a mechanical structure.

We chose to use the immune algorithm negative selection because the techniques of artificial immune systems (SIA) are promising tools in the field of computational intelligence, and its conception is inspired in the biological immune system, to reproduce computationally its main characteristics, properties and abilities [6, 20]. The techniques based on SIA are appropriate tools for diagnostic problems because they have natural characteristics of change detection and identification of diseases in the body [21].

Thus, it is important to note that the methodology presented in this paper is an inedited approach, which can greatly contribute to the development of SHMS, this because it has a stable, reliable, and adaptive architecture, allowing the inclusion of the continuous training module. This is the advantage of this methodology in relation another methodology.

This paper is organized as follows. Section 2 presents the negative selection algorithm (ASN). The description of the experimental modeling is in section 3. Section 4 presents the proposed methodology. The results are presented in section 5 and section 6 presents the conclusion of this work.

2 NEGATIVE SELECTION ALGORITHM (NSA)

The negative selection algorithm proposed in [22], for detecting changes in computer systems based on negative selection of T lymphocytes that occurs in the body. This process carries out the discrimination proper cells and non-proper, and this is the principle of recognition of organism standards. The algorithm is implemented in two main phases, as described below [23, 24]:

1. Censor phase.

a) Set the set of proper chains (S) to be protected;

b) Generate random chains and evaluate the affinity (Match) between each of them and their proper chains. If the affinity is greater than a specified threshold, reject the chain. Otherwise, store it in a set of detectors (R).

2. Monitoring

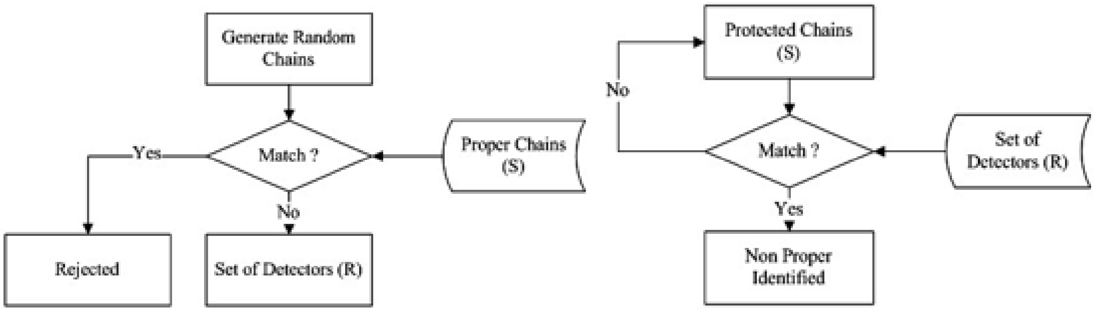
a) Given the set of chains to be protected (protected chains), evaluate the affinity between each of them and the array of detectors. If the affinity is higher than a predetermined threshold, then a non-proper element is identified.

The phase censor of ASN basically consists on generating a set of detectors from the data, and the same randomly picked and it is verified that have the ability to recognize a pattern non-proper. The detectors are analogous to the matured T cells capable of recognizing pathogens [6].

The monitoring phase consists monitoring in a system to identify a change in its behavior and thus classify this change using the set of detectors created in censor phase. The censor phase occurs offline mode the monitoring phase occurs in real time [6, 20].

In the Figures 1 (a) and 1 (b) illustrate to the flowcharts of censor phase and monitoring of ASN.

Figure 1. Flowcharts of censor phase and monitoring of ASN.



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2.1 MATCHING CRITERION AND AFFINITY

To assess the affinity between the chains and attest to combination / likeness, we use a criterion known as matching criterion, or also known as combination. Marriage can be perfect or partial [25].

The perfect matching is when the two chains, which are being analyzed, are exactly equal, i.e. have the same values in all positions. In partial matching, only a number of positions between the standards should be the same for you to confirm the marriage, being defined amount previously [24].

This amount previously defined is denominated affinity rate. (*TAf*). The *TAf* represents the degree of likeness required to occur marriage / combination of the two chains under analysis [20]. In [25] the *TAf* is defined by the following equation

$$TAf = \left(\frac{An}{At}\right) * 100 \qquad 1)$$

begin:

TAf : affinity rate;

An : number of normal chains in the problem (proper chains);

At : total number of chains in the problem (proper and not-proper chains).

Equation (1) it is possible to calculate precisely the value of the affinity rate for the proposed problem, where the equation (1) proposes a statistical relationship among all samples of the problem.

To quantify / measure total affinity between the standards under analysis uses the expression (2) [25]:

$$Af_T = \frac{\sum_{i=1}^{L} Pc_i}{L} * 100 \qquad 2)$$

where:

Af_T : % affinity with patterns analyzed;

L : the total number of positions;

Pc : married position;

$\sum_{i=1}^{L} Pc_i$: sum (quantity) of married positions.

From these quantities can make decision making in the iterative process of ASN. Thus, if Af_T is greater than or equal to TAf occurs the combination / marriage patterns, that is, the standards are considered equal / similar. Otherwise does not occur marriage patterns.

3 EXPERIMENTAL MODEL

In this section we present a description of the testing bench used, the system of generation and data acquisition, the test methodology and data processing.

3.1 COMPOSITION OF EXPERIMENTAL MODEL

The experimental model was it build to carry out the testing in the laboratory consists of an aluminum beam in the free-free condition supported by a foam backing, as illustrated in Figure 2. The beam is instrumented with sensors / piezoelectric actuators of the PZT-81 type (ring ceramic chip). The sensors / actuators are responsible for generating the excitation signal and capture the response signal in the structure during the tests.

Figure 2. Experimental model.

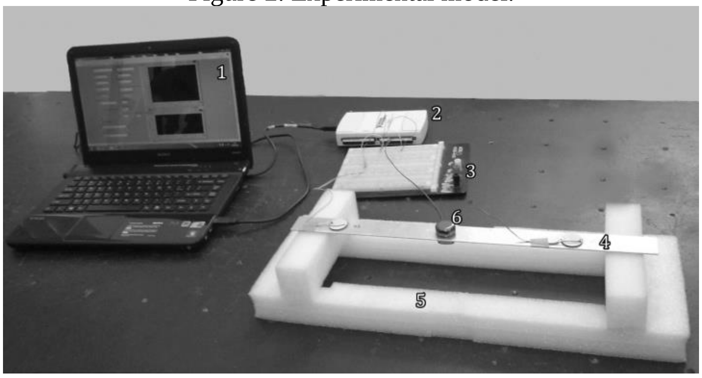

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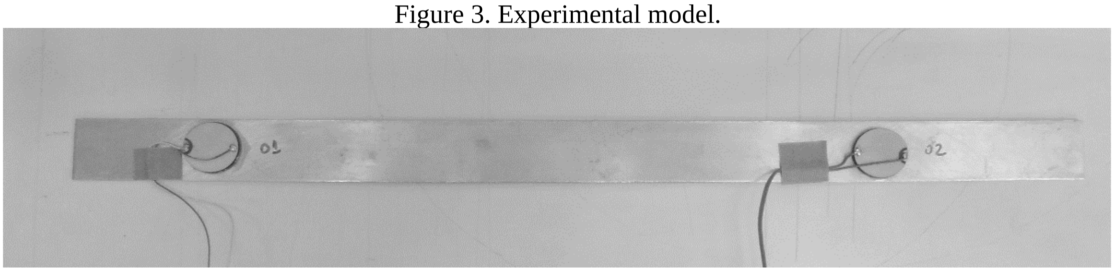
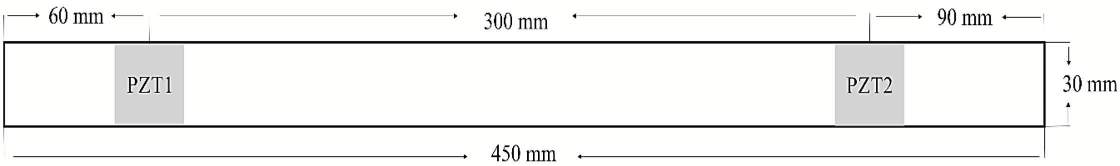
Figure 2 shows the experimental model which consists of: (1) computer, (2) data acquisition system, (3) binding and measuring circuit (4) Aluminum beam (5) and foam backing (6) ceramic magnet (fault condition).

Figure 3 illustrates the aluminum beam used in the tests, the dimensions and positions of the PZTs. The beam has 450 mm in length, 30 mm width and 2 mm thickness. The PZTs are fixed at 300 mm between them, the PZT1 is fixed at 60 mm from the beam beginning and the PZT2 is fixed at 90 mm from the end of the beam.

Figure 3. Experimental model.



(a) Aluminum beam.



(b) Beam dimensioned
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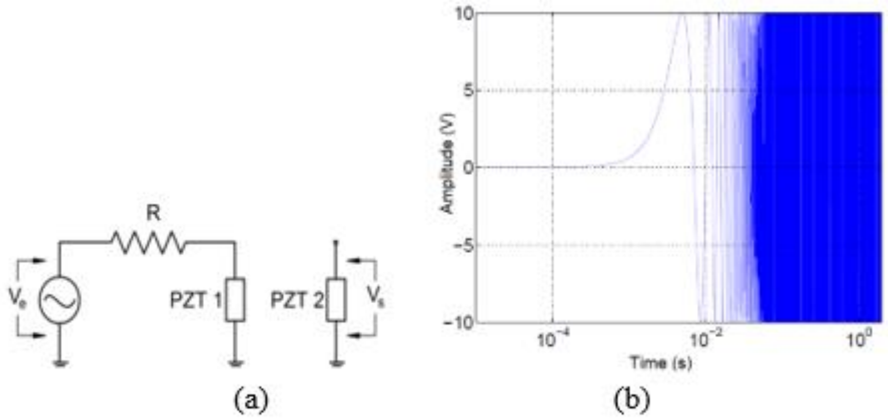
3.2 SYSTEM GENERATION AND DATA ACQUISITION

The generation and signal acquisition is performed using the USB-6211 data acquisition board from National Instruments®. The control board has been programmed in software LabVIEW®

A geração e aquisição dos sinais foi realizada com a utilização da placa de aquisição de dados USB-6211 da National Instruments®. O controle da placa foi programado no software LabVIEW® [26] for the signal generation channel was synchronized with the acquisition channel, and thus the captured signals presented coherence. In Figure 4 (a) illustrates the connection circuit used for testing and measuring.

Figure 4. (a) connection circuit, (b) excitation signal.



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where V_e the input signal, a ramp frequency, known as *chirp*, from zero to 50 kHz and 1 second duration (shown in figure 4 (b)), V_s is the output signal, R is the external resistance.

The parameters used in the data acquisition system are shown in table 1

Table 1. Parameters of the measuring system.

Parameter	Value
Acquisition rate (kHz)	100.00
Number of samples to measure	250000.00
Excitation signal amplitude (Volts)	10.00
External resistance (kΩ)	2.20

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3.2 TESTING METHODOLOGY

To evaluate the proposed ASN laboratory tests were performed by generating a database of signals captured from the structure (aluminum beam) using the testing bench presented in previous sections. The structure signals were captured in normal condition (base-line) and signal structure of the fault condition. To experimentally represent a structural failure was used a ceramic magnet 5g, which when added to the structure causes a mass increase, modifying their dynamic parameters. Thus, two experimental conditions were set, and the normal condition (original structure) and structural failure condition (fixing the ceramic magnet).

For each experimental simulation performed in the laboratory was used to test methods described in the following steps:

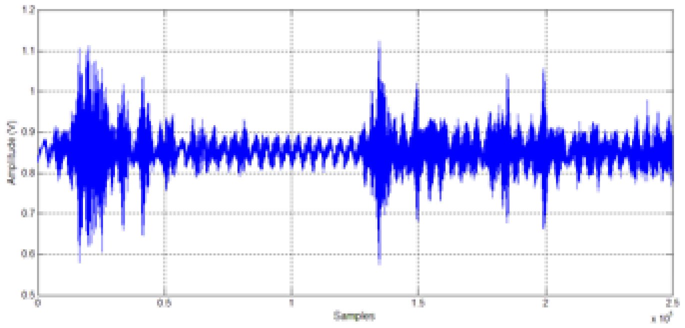
1. Generate the input signal (*chirp*) to excite the structure in LabVIEW system;
2. Excite the structure in PZT1;
3. Capture the response signal structure in PZT2;
4. Store the signs of excitement and response on the computer.

3.3 SIGNAL PROCESSING

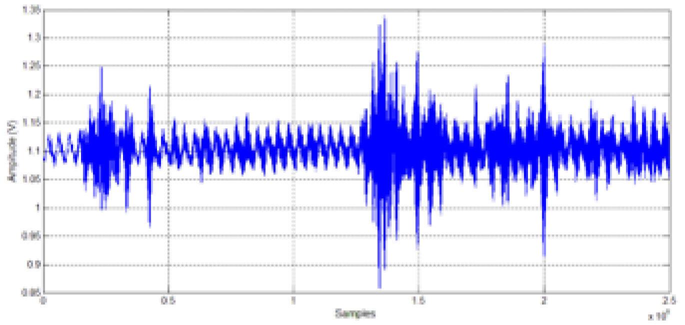
After capture and store the signs starting in experiments, we performed a processing using the transformed FRF (Frequency Response Function) [27, 28], showing the curve of vibration of the structure in frequency, from the initial excitation signal and the response signal captured in PZT2 structure.

Figures 5 (a) and 5 (b) illustrate the captured response in PZT2 for the two tests, one in normal condition (Figure 5 (a)) and another at structural failure condition (Figure 5 (b)).

Figure 5. (a) normal condition, (b) fault condition.



(a)



(b)

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From the response signals, applies the transform FRF generating a signal processed with 1024 points. Figures 6 (a) and 6 (b) illustrates the FRF of the response signals shown in Figure 5. Figure 6 (c) shows a graphical comparison of the FRFs, so that it is possible to see that the system response is in a condition normal and in failure.

3.4 COMPOSITION DATABASE

The database generated from the experiments performed in the laboratory in this section consists of 450 signs, with 300 signs in normal condition (base-line) and 150 signs on condition of structural failure. Table 2 shows the signs database composition obtained from the experiments.

Figure 6. (a) normal condition, (b) fault condition, (c) comparison.

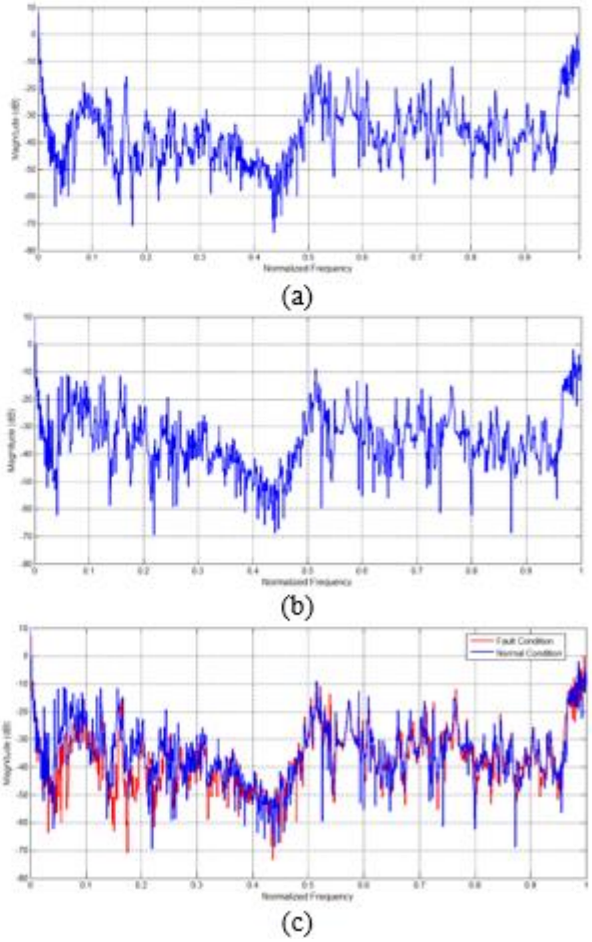

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Table 2. Composition signals database.

Features	Database
Normal Signals	300
Signals failure	150
Total signals	450
Number of points of each signal	1024

4 METHODOLOGY

This section presents the description of the proposed methodology for the detection and classification of structural failure as a tool using the ASN. This section presents the description of the proposed methodology for the detection and classification of structural failure as a tool using the ASN. This diagnostic system consists of two phases, the censor phase and monitoring data. In censor phase is realized in a census data, creating a set of detectors to identify anomalies in the monitoring process.

In the monitoring phase, data are analyzed in real time and compared with the set of detectors created in censor phase, aiming to present a diagnosis (decision-making) by proper / non-proper discrimination.

The following detail the calculating the affinity ratio and the censor phase and monitoring of ASN proposed in this work.

4.1 CALCULATION OF AFFINITY RATE OF ASN

Proposed ASN was used the concept of partial matching and affinity as [25]. To calculate the affinity rate using the equation (1).

Considering the test set, we obtain the following values: At = 450 and An = 300. The result of affinity rate calculation is presented in equation (3):

$$TAf = \left(\frac{300}{450}\right) * 100 = 66{,}6\% \tag{3}$$

The affinity rate is 66.6%, and this means that to attest a marriage between two patterns is necessary that a minimum 66.6% of the detector points are married.

Note that the affinity can be calculated based on a statistical calculation, as in this topic, or you can simply choose an arbitrary value. There is no rule to define the necessary affinity to confirm a marriage, for each type of problem exists a different context. But in this study we chose to use the affinity rate calculated by equation (1) because as mentioned in [24] is an efficient and safe way to get the parameter value.

4.2 CENSON PHASE OF ASN

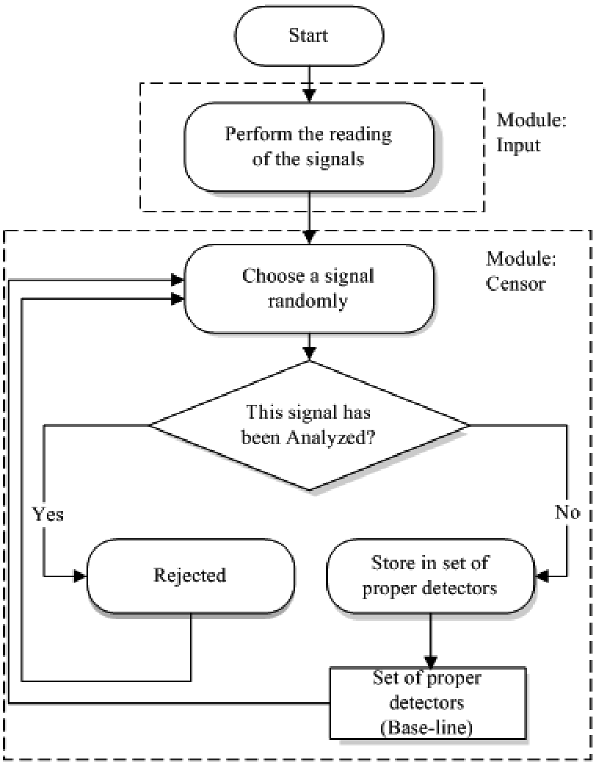
In the present discussion censor phase of ASN which is composed of two modules, and the input module and the censor module, as illustrated in Figure 7.

The input module or data acquisition consists of the experimental apparatus to capture the signals in the structure, as described in section 3.

The censor module is performed off-line and serves to generate of set of proper detectors to be used in the monitoring of data. The set of proper detectors consists of signals that have the normal characteristic structure, i.e. without fail (base line). In this context, it generates the set of proper detectors choosing randomly normal signs do not repeated in database.

Note that the number of detectors used is determined by the diagnostic system operator. However, we recommend using 10-30% of the available data, as shown in [22]. The marriage criterion used is the partial matching proposed by [25].

Figure 7. Flowchart of censor phase of ASN.



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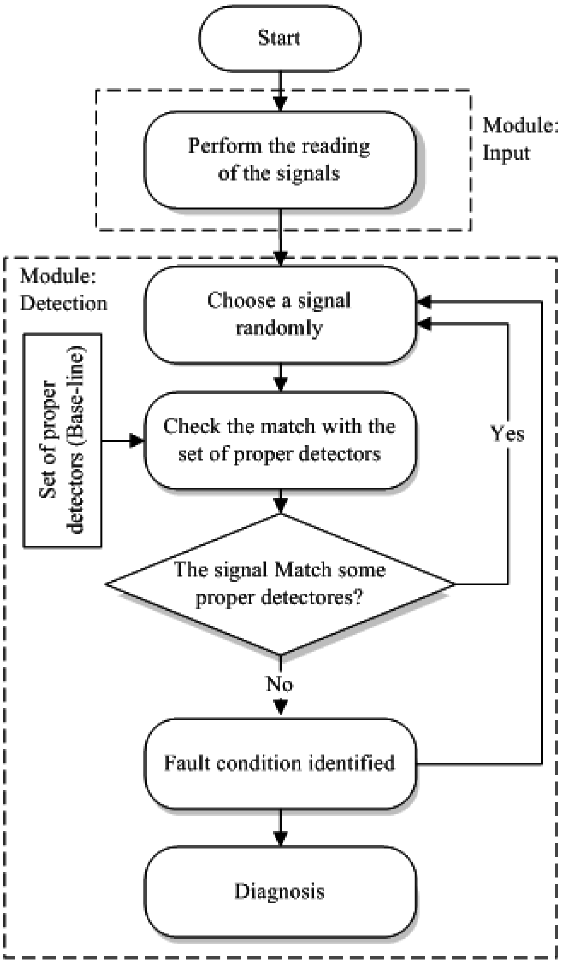
4.3 MONITORING PHASE OF THE ASN

The monitoring phase to the ASN is divided into two phases, the input module or data acquisition and detection module, responsible for performing proper / non-proper discrimination, analyzing, identifying and characterizing the structural failure. The functioning flowchart of this step is illustrated in Figure 8.

After performing the signal acquisition is run the fault detection module, which compares the signals under analysis with proper detectors (signals *base line*) aiming to identify the marriage between the signs. If the marriage and the affinity is higher than the affinity rate, the signals in question are considered equal/combined in this way, it is classified as the normal condition of the structure, and it has the characteristics of proper set of detectors.

Otherwise, the signal is classified as an abnormality, that is, as a structural flaw. This module returns a diagnosis of analyzed signals in proper (structure normal condition) and non-proper (the structure having the characteristic of fault).

Figure 8. Flowchart of the monitoring phase of the ASN.



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In the monitoring phase of the ASN, we used the partial matching criteria proposed by [25].

5 RESULTS

In this section we present the obtained tests and results, by applying the methodology proposed in the signs of the database obtained from experiments. All tests were performed using a PC Intel Core 2 Duo, 1.9 GHz, 2 GB of RAM, and Windows 7

Ultimate operating system, 32-bit. The proposed method was developed in MATLAB® [29].

5.1 SET OF TESTS

The set of tests to evaluate the method proposed in this paper consists of the database signals generated from the experiments performed in the laboratory described in section 4 of this paper. The test set consists of signals 450, as shown in Table 3.

Table 3. Set of tests.

Normal signs	300
Signs in failure	150
Total signs	450

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5.2 PARAMETERS USED

In the tests proposed in this article, an assessment of the proposed methodology was applied by checking the efficiency, accuracy and the computational time for different configurations of the set of ASN detectors. In this sense have been generated three sets of detectors (CD1, CD2 and CD3) using 10%, 20% and 30% of the normal signal (base-line), totaling 30, 60 and 90 of detectors respectively. The parameters used for the tests are shown in Table 4.

Table 4. Parameters.

Parameters	Value
TAf	66,66%
ε	3%
CD_1	30 detectors
CD_2	60 detectors
CD_3	90 detectors

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5.3 RESULTS

In order to evaluate the proposed methodology tests were performed considering different ASN settings. The results obtained in the tests are shown in Table 5.

Table 5. Results obtained in ASN.

	Samples Tests	Ratings proper	Ratings Non-proper	Correct ratings	Accuracy (%)	Processing time
CD_1	450	299	138	437	97,11	96,56
CD_2	450	300	141	441	98,00	98,47
CD_3	450	300	146	446	99,11	97,93

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The results presented in Table 5 represent the average values obtained by a cross-reference test was performed 20 times while performing the ASN for each set of detectors in order to guarantee the veracity of the results.

We notice that the ASN has a good performance (accuracy rate equal to 99.11% for the best configuration), and the quantity of detectors used in censor phase directly influences the fault diagnosis process. Thus, we suggest using 30% of database information to generate the set of detectors, aiming at providing robustness to the system. That is, the more knowledge available in the learning phase, the more efficient the process of diagnosis of ASN.

Finally, we highlight that the ASN is run with a time of less than 100 milliseconds, which provides the application of this system in real time, as decisions must be taken in time to prevent tragedies and disasters.

5.4 COMPARATIVE STUDY

In this section we present a comparative study with the results of other authors. For this comparison, we took into account the total accuracy of the methodologies for the detection and classification of structural failure.

Table 6 shows the comparison between the total hit obtained by the proposed method and the main methods available in the literature.

Table 6. Comparative Study.

Reference	Data Type	Technique used	Total Hit (%)
[13]	Experimental	Multi-objective Genetic Algorithm	93.70
[30]	Experimental	Multilayer Perceptron (Levenberg-Marquardt)	98.52
[10]	Simulated	Fuzzy Logic	98.74
[15]	Simulated	ARTMAP-Fuzzy	100.00
[16, 17]	Simulated	ARTMAP-Fuzzy-Wavelet	100.00
[31]	Simulated	Artificial Imunne System with Continuous Learning	100.00
Este Trabalho	Experimental	Negative Selection Algorithm	99.11

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In Table 6, we note that the proposed method in this research had a very good success rate (over 99%), when compared to other methods.

We emphasize that by evaluating the methodology with real data obtained experimentally the correct percentage is excellent when compared with methodologies evaluated with simulated data.

5.5 POSITIVE AND NEGATIVE ASPECTS OF THE PROPOSED ASN

After performing all tests and get the results to the ASN proposed in this paper, we present an analysis highlighting the main positive and negative aspects of the proposed methodology.

Positive Aspects:

- Regarding the accuracy in diagnosing the ASN has excellent performance, considering that the used signals obtained from measurements in a real system to perform its assessment;
- The proposed ASN runs with low processing time, which accredits this method to be applied in real situations, for decision making should be taken instantly, avoiding disasters;
- The ASN presented robustness because using 30% of the available information it is able to diagnose almost 100% of actual signals;
- Different from neural networks, the ANS is not necessary to perform the learning phase every time monitoring runs.

Negative Aspects:

- The ASN has parameters that must be carefully calibrated.

6 CONCLUSÕES

In this paper we propose a new approach based on the ASN to perform the fault detection and characterization in mechanical structures. In this context the ASN showed excellent results, obtaining a 99.11% success rate for the best system configuration. The censor phase of the ASN requires more computational time, however is performed off-line causing no damage to the system. The monitoring phase, from the acquisition of the signals, is carried out rapidly with time lower than 100 milliseconds, what allows this tool to be used in real time. Finally, we conclude that the proposed methodology is very efficient, reliable, robust and accurate for the detection and characterization of failures in mechanical structures.

We emphasize that this work contributes to the search area in SMH, introducing a new experimental approach to perform the monitoring of mechanical structures using intelligent techniques.

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