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Damage Detection in a Pipe Using an Artificial Immune System Optimized by the Clonal Selection Algorithm

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Abstract. This work presents an innovative Structural Health Monitoring (SHM) applied to acoustic tubes. This system emerges as an alternative to traditional inspection methodologies in mechanical structures providing high efficiency combined with speed and monetary savings. This system has the ability to assess the remaining life of the structure and assist in decision-making, being able to intervene in situations of critical stress, preserving lives and the long-term functioning of the structure. The objective is the theoretical basis and the detection of failures in pipes

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by acoustic means. The Clonal Selection Algorithm is based on the continuous learning capacity of the biological immune system, having the ability to learn by repetition and memory. This method requires less training data than is usually used in the literature, with approximately 71% less data. The results presented showed how it is possible and effective to detect failure with a 100% accuracy.

Keywords: Artificial immune systems, Negative selection algorithm, Clonal selection algorithm.

2000 Mathematics subject classification: 68T05, 68W40, 74H45.

1. Introduction

Aeronautical, civil or mechanical structures are subject to failure due to wear by time, human and environmental factors. Thus, the structures require a determined frequency of maintenance in order to prevent accidents.

The industry along the history has increased the investments in the development of researches related to the analysis and Structural Health Monitoring, avoiding disasters and environmental, humanitarian and economic prejudices.

It is called Structural Health Monitoring (SHM) the important and current line of research that consists in the detection of failures in their initial state in order to intervene in their propagation and avoid damage [25, 27].

Data acquisition and processing, signal validation and analysis, fault identification and characterization, interpretation of adverse changes in a structure and making decision are the main requirements that an SHM need to accomplish, as highlighted by [14, 13, 30, 11, 15].

The evaluation of the integrity of mechanical structures performed by non-destructive assays such as penetrating liquids, magnetic particles, ultrasonography, radiography, among other traditional techniques, despite having good instrumental apparatus and are diversely employed, do not fully satisfy the growing industrial needs [10, 31].

The ClonalG algorithm works in 8 steps, including the selection of a specific population of antibodies that are cloned and hypermutated for further evaluation of the affinity between these and the antigens. After, the re-selection process occurs and the best clones are selected to be evaluated and mutated in order to obtain the best possible combination between antigen and antibody [7].

In comparison with the works of [27, 22], the differential of this work is the optimization with the use of Clonal Selection Algorithm. In this case, approximately 71% less data are required in the training phase. In addition, the system is able to identify and categorize any type of failure, due to the ability of continuous learning. A fault never before presented to the system can be learned by it as a new fault pattern, for future identification and locations.

Mechanical structures such as pipes, for example the Bolivia-Brazil Gas Pipeline, also known as *"Gasbol"*, need constant maintenance and verification of their structural health.

Failure detection and monitoring of the structural integrity of pipelines by acoustic means is still little researched and used. The differential of this work is the use of machine learning to analyze sound wave signals to detect any type of failure that could affect the functioning of a pipe, using up to 70% less data than usually in the training phase. The algorithm was able to detect 100% of the failure situations, and correctly categorize all signals in normal situation as well.

2. Theoretical foundation

Artificial Immune Systems (AIS) and the Clonal Selection Algorithm are composed of intelligent methodologies, inspired by the biological immune system, for solving real world problems [5]. According to [6], immunological engineering can be defined as a process of meta-synthesis.

Faithfully pursuing partial or total reconstruction of the immune system is not the best way. Therefore, the immunological engineering should seek to develop pragmatic models inspired by the immune system that preserve some of the primary biological characteristics, and that are presented as possible in the computational implementation and effective in the development of engineering tools.

2.1. **Artificial immune system (AIS).**

The proposed SHM system is based on AIS, especially on the Negative Selection Algorithm. The Negative Selection Algorithm (NSA) was proposed by [9], to detect changes in states of computational systems. This technique is inspired by the process of negative selection of T lymphocytes, which occurs in the thymus, this process represents the discrimination that the organism performs with the cells of the body, between them proper cells and non-proper cells.

The NSA is a technique that is based on the pattern recognition process exercised by the biological immune system. Based on this algorithm, the diagnostic system consists of two phases: The Censor Phase and Monitoring; as illustrated and shown by Fig. 1.

In the Censor Phase, a census is performed on the data, creating a set of detectors, to identify anomalies in the monitoring process. In the monitoring, the data are analyzed in real time, being compared with the set of detectors created in the before phase, aiming to present a diagnosis (decision making) discrimination as proper/non-proper [6, 22].

On the left of the Fig. 1, the Censoring Module is showed. In this step, after a signal is randomly selected, its matching with the proper detectors is checked.

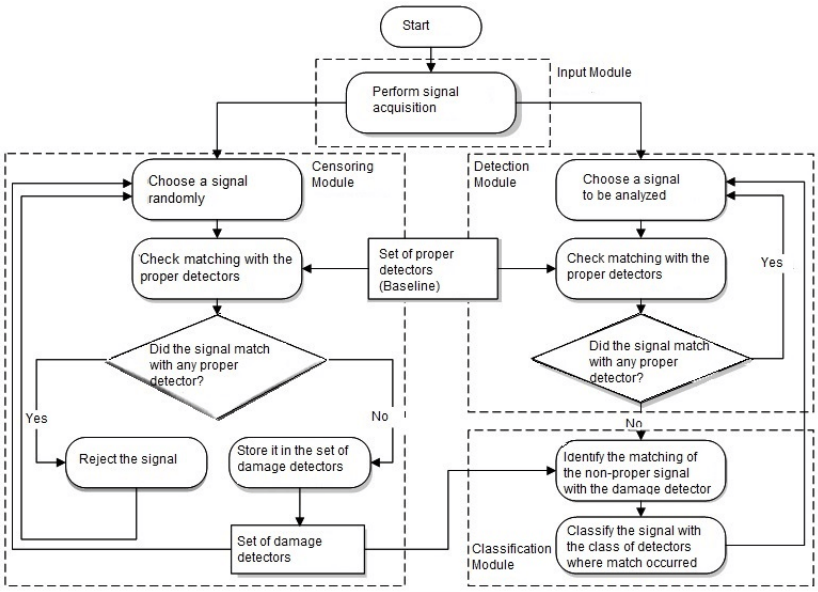

FIGURE 1. Flowchart of the censor phase and monitoring of the NSA. From [23].

If the signal is very similar to the detector array, it is discarded. Otherwise, it is saved in the set of damage detectors [24, 29].

To the right of the Fig. 1, a signal from the structure is checked with the proper detectors, if the signal is close enough to this matrix, the system jump for the next signal. Otherwise, an abnormal situation is detected and this signal will be classified [22].

If the affinity is higher than the calcuated affinity rate the signals being analysis are categorized as satisfactory with respect to the set proper detectors and so classified as being of the normal structure situation. If the affinity is less than the affinity rate the signal is classified as an abnormality and a structural fault is identified.

The match ratio (TAf) represents the degree of similarity necessary for match to occur between two chains under analysis. It is defined according to the following equation (1) [27, 29]:

$$TAf = \frac{An}{At} * 100 \tag{2.1}$$

Where:

TAf: match ratio;
An: number of normal vectors (proper chains) of the baseline;
At: total number of vectors in the problem (proper and nonproper chains).

The criterion known as marriage, that can be perfect or partial, is used to analyze the affinity between signais and to verify if there similarity/equality.

A perfect match occurs when all signal positions have the same values, ie both are perfectly equal. A partial match occurs when a predetermined amount of positions between signais has the same value. This amount is called the affinity rate.

In this work was use the partial marriage criterion proposed by [3] and a 12% deviation in the proper detectors.

2.2. **Clonal Selection Algorithm.**

The Clonal Selection Algorithm (ClonalG), originally proposed by [7], is based on the functioning of the adaptive immune response, with the affinity maturation process and the clonal selection principle proportional to the affinity, are the pillars of ClonalG work.

As [6] says, in ClonalG the maintenance of memory cells works independently of the repertoire. With the most stimulated cells occurs selection and reproduction (cloning). For the least stimulated cells, only death. Then, with clones with greater antigenic affinities, affinity maturation and hypermutation proportional to cell affinity occur. After this process, this clones are re-selected and re-added to the initial group, if that way it respect the maintenance of the group's diversity.

The CLONALG for recognition problems and machine learning has the following steps, as shown in Fig. 2 [6, 4, 26, 24]:

1. **Initiation:** A population of antibodies is randomly generated (Ab) composed of $Ab = Ab_{\{m\}} + Ab_{\{r\}}$ with N lymphocytes for each of the antigens (Ag_j), where N is the sum of M plus R;
2. **Affinity rating:** An affinity vector is determined between each (Ag_j) and the lymphocytes in the population (Ab).
3. **Selection:** Are removed from the population Ab the n antibodies with greater affinities, in order to compose a subpopulation $Ab^j_{\{n\}}$;
4. **Cloning:** The selected antibodies will proliferate (cloning) in proportion to them affinities with the antigen, generating a new set C of clones. The greater the affinity f, the greater the number of clones of each of the selected lymphocytes;
5. **Hypermutation:** Then, the C population of clones is subjected to the affinity maturation process generating a new population C^*, where each antibody will undergo a mutation with a rate inversely proportional to its affinity: the greater the affinity, lower will be the mutation rate;
6. **Affinity rating:** A new vector f^* is generated to comparing the set C^* and the antigens (Ag_j);

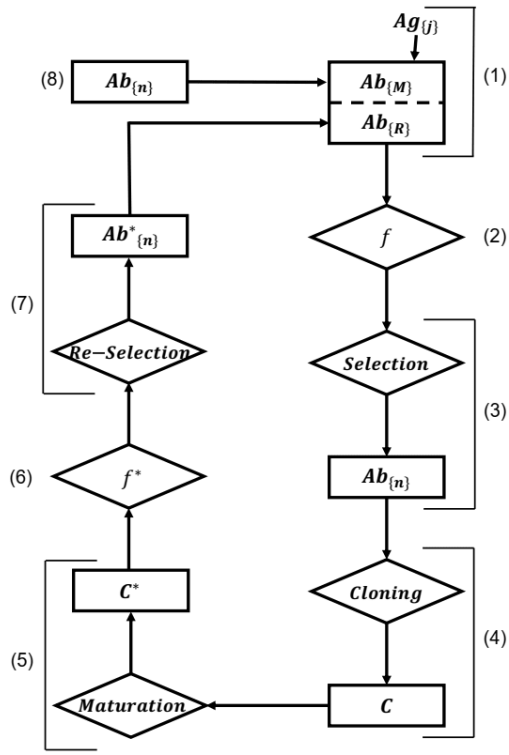

FIGURE 2. Flowchart of the Clonal Selection Algorithm for the pattern recognition problem.

7. **Re-selection:** From this mature population C^*, re-select the n best antibodies, the subset $\left(Ab_{\{n\}}\right)$, in order to be candidates for entering the memory set $\left(Ab_{\{m\}}\right)$. One lymphocyte will be able to enter in the memory set when it has higher affinity rates than another memory lymphocyte inside the set, replacing it;
8. **Metadinamics:** Replace D antibodies from R with D new individuals, inducing diversity in the repertoire. Antibodies with lesser affinities are chosen to be replaced.

The process is then repeated from 2 to 8 until the stopping criterion is satisfied.

After the stop criterion is satisfied, the set of memory lymphocytes $\left(Ab_{\{m\}}\right)$ have m sensors with high affinity rates with the presented antigen population $\left(Ag_{\{i\}}\right)$. This select group will be used by the NSA in the detection and classification of antigens.

3. Material and methods

This work is based on norm ISO10534-1 (1996) (This standard was last reviewed and confirmed in 2016. Therefore this version remains current). That is, a straight, rigid pipe without porous walls and without cracks was used. The cross section of the pipe used is circular. The technique of norm is the incidence of a sine wave by a sound source at one end of the pipe. Being the wave propagated in the air and having a determined frequency. At the opposite end is firmly fitted the pipe cap with a hole in it is center. Inside the hole passes the probe, with the microphone, which moves axially and internally in the pipe, collecting the pressures point to point every centimeter. Figure 3 shows assembly of the experiment.

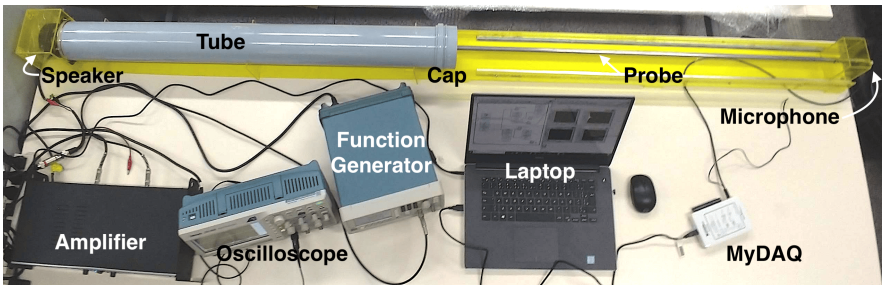

Figure 3. Upper view of experimental table.

As shown in Fig. 3, the Function Generator (*Tektronix* - AFG1022) is connected in the Amplifier (*LL AUDIO - PRO*-1600), which is connected to the speaker and oscilloscope (*Tektronix* - TBS1052B). The probe microphone, which plugs into the *National Instruments* (NI) *myDAQ* acquisition board, collects the signal that is stored in the laptop using *National Instruments LabView Student Edition 2013*.

The signal collection is performed by translating the probe horizontally in the tube. The data is processed by Labview, where a simple common routine was set up to store the data captured by the microphone in the computer. As explained in the ISO10534-1 (1996), one (vector) collection consists of the joining of all 100 points (the total compliment of the tube is 100 cm, each centimeter is equivalent to one point).

The signal that has its frequency determined in the Function Generator is received and amplified by the amplifier, which can be viewed on the Oscilloscope. Then, the speaker emits the sine wave inside the tube and, after the system establishes a steady state, the collection is carried out point by point every centimeter by the probe.

The upper frequency limit is 2008 Hz, determined algebraically in [21, 17], for the pipe diameter used (100 mm); Frequencies above this value can not be

studied under these conditions. The amplitude of the signal emitted by the sound source must be in accordance with norm ISO10534-1 (1996), it determines that the wave emitted by the source is preferably 10 dB greater than the largest background noise for the frequency at which it operates.

4. Results and discussion

The experimental collection from the system with and without failure, was carried out in a 1 meter long PVC tube. Following the procedures expanded in last section, 10 signals from the tube in normal structural situation and 3 more signals in failure situation were collected. In this case, the failure of the pipe was simulated by a lateral hole in the surface.

In order to avoid overfitting, data were separated into two groups, training and validation, and cross-validation was used. In this validation technique the data set T of size N (T=N) is subdivided into K random disjoint subsets of equal size [16]. That is, $T_1, T_2, \cdots, T_K \subset T$ with $T_i \cap T_j = \emptyset$ for all $i, j = 1, 2, \cdots, K$, with $i \neq j$, being $T_i = N/K$ for all i. In the p-th iteration, the subset Tp is selected for validation and the others Tm, where $m = 1, 2, \cdots, K$, with $p \neq m$, are used for induction (training) and this procedure is executed sequentially.

Figure 4 shows an example of a signal collected from the tube in a normal structural situation.

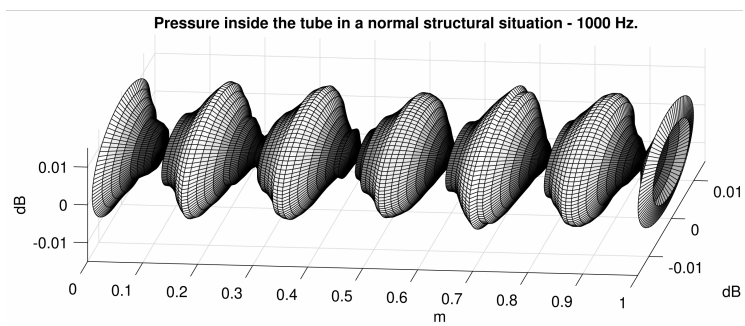

Figure 4. Pressure inside of tube in a normal structural situation - 1000 Hz.

Figure 4 shows the most classic format of a stationary wave, with well-defined maximum and minimum pressure points.

The structure damage was simulated by a hole in the side of the tube 0.45 m from the end with the speaker. Figure 5 shows one of the experimental signals performed in the pipe with a structural failure situation.

Comparing Figure 4 with Figure 5, it can be noted that the fault causes constructive interference at the minimum pressure points of the standing wave. In addition, in the situation without failure there are 6 well-defined minimum pressure points, while in the situation with failure there are 5 points. It is

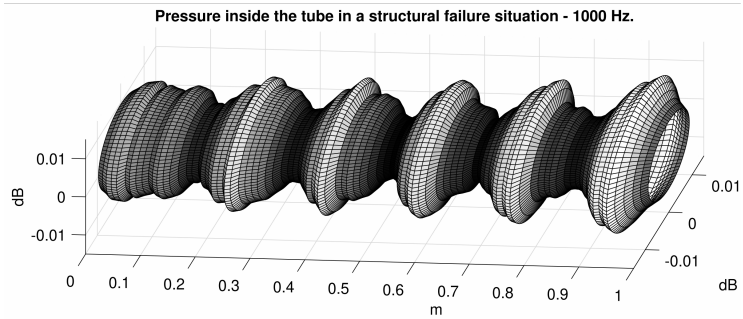

FIGURE 5. Pressure inside of tube in a structural damage situation - 1000 Hz.

possible to visualize a horizontal displacement of the wave to the right, having as reference the wave valleys, being identified by the AIS in the detection of the failures performed. For the case studied at the frequency of 1000 Hz, the maximum pressure points did not show considerable variations in amplitude in the failure condition.

Figure 6 shows the ClonalG convergence graph for the NSA Censor phase, for the frequency of 1000 Hz.

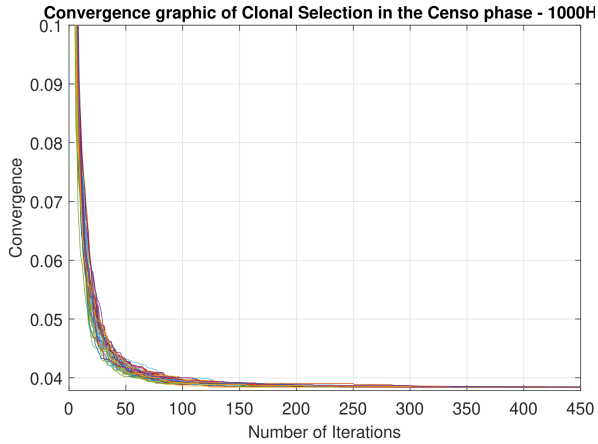

FIGURE 6. Convergence of ClonalG in the Census Phase.

As shown the graph of Figure 6, above 350 iterations there is practically no change in the final result, with 300 iterations is represented a solid result, very close to the end. The processing time for 450 iterations was 2.595 seconds, where all system signals were analyzed, showing it processing speed also on normal desktop computers.

Table 1 shows the data for the AIS operation. In the results presented, 20% of the normal signals, chosen at random, were selected to compose the base-line.

Collection	Affinity	Variance	Standard deviation
1	85.00%	0.0000002	0.000486394
2	88.00%	0.0000003	0.000521181
3	87.00%	0.0000003	0.000509307
4	86.00%	0.0000003	0.000549559
5	87.00%	0.0000003	0.000502064
6	81.00%	0.0000003	0.000501108
7	91.00%	0.0000004	0.000597634
8	87.00%	0.0000003	0.000514346
9	90.00%	0.0000002	0.000499061
10	91.00%	0.0000003	0.000518422
11	13.00%	0.0000001	0.000286915
12	12.00%	0.0000000	0.000216709
13	13.00%	0.0000001	0.000234376

Table 1. Fault detection by Clonal Selection Algorithm with 20% of normal signals composing the base-line - 1000 Hz.

In Table 1, signals 1 to 10 are signals collected from tube in a normal structural situation. While signals 11 to 13 refer to structural failure situation.

The AIS was able to identify the 10 curves of the system in a normal situation (1 to 10) and differentiate the 3 in a failure situation (11 to 13), using affinity. According to [22], it is recommended to use up to 70% of the system's normal signals in the Censor phace. In the case of the algorithm developed in this work, as previously said, only 20% of the data was necessary for the algorithm get 100% accuracy.

Analyzing the table 1 it is possible to observe that the data from 1 to 10 shows satisfactory affinity, bigger then calculated affinity rate (76.92%, calculated by equation 1), which were identified by the AIS as being from the structure in a normal situation. Conversely, signals from 11 to 13, where it is possible to calculate an error of 83% between the affinity of each and the calculated affinity rate, which justified the categorization of structural failure situation pointed out by the AIS.

Table 2 shows the results of identification of the type of damege identified by ClonalG in the ASN Monitoring phase. The lines show the signals captured from the physical system, while in each column the antibodies designated by ClonalG to identify the fault.

Sign\Antibody	11	12	13
11	100.00%	91.00%	86.00%
12	88.00%	100.00%	91.00%
13	87.00%	89.00%	99.00%

Table 2. Identification of the type of failure performed by ClonalG Acoustic during the Monitoring phase - 1000 Hz.

As Table 2 shows, the signals 11, 12 and 13, identified as failure by the NSA because it has an affinity lower than the calculated affinity rate, have a high affinity with the antibodies designated by ClonalG, as observed if the main diagonal of the Table, 100.00 %, 100.00 % and 99.00 %, respectively.

The application of ClonalG in the Monitoring phase of the NSA enabled to identify the type of failure, due to the ability of continuous learning. As the 3 failure signals are of the same type, the failure signals have high affinities with all antibodies indicated by ClonalG. If there was another type of fault in the system, ClonalG would have the ability to learn it to identify possible other faults similar to it, as shown in Table 2.

The 3 signals were also correctly categorized as the same type of failure by the ClonalG, because it has a high affinity between it. That is, the antibodies designated by ClonalG in the identification of faults close to antigen 11 have 100.00% of affinity with signal 11, 88.00% with the signal 12 and 87.00 % with the signal 13. Analogously for antibodies of antigens 12 and 13.

5. Conclusion

The results obtained by the NSA were: 0% false positives, 0% mistakes 100% hit rate. Exhibiting the robustness and effectiveness of system in identifying and categorizing the proper and non-proper signals.

For the reasons cited, AIS has proved to be an interesting alternative for detecting tube failures, and can also be applied to acceleration signals of tubes to perform the fault location.

In addition, the use of the Clonal Selection Algorithm optimizing the SHM caused a 33.33% reduction in the need for system training data, improving the efficiency of the system. Before the use of ClonalG it was necessary to use 30% of normal signals - from the same physical system - in the base-line to guarantee the security of the system, this number dropped to 20% with use. In this failure detection method, with the optimization used, 71.42% less training data is needed than what is usually used in other works and recommended in the literature. This directly saves time and money, as well as greater security.

Fault detection was also performed for the frequencies of 500 and 2000 Hz, in addition to the 1000 Hz presented. Fault detection and location was also

performed for the same 3 frequencies, using vibrational medium. As well the comparison between the two methods. All SHM applications were satisfactory.

The proposed methodology for the detection of failures is unprecedented for the SHM area in the use of the acoustic medium, which is a differential of this work.

Acknowledgments

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References

1. G. L. Ada, S. G. Nossal, The Clonal-Selection Theory, *Scientific American*, **257**(2), (1987), 62-69.
2. D. Balageas, C. P. Fritzen, A. Güemes, *Structural Health Monitoring*, John Wiley & Sons, 2010.
3. D. W. Bradley, A. M. Tyrrell, Immunotronics-Novel Finite-State-Machine Architectures with Built-in Self-Test Using Self-Nonself Differentiation, *IEEE Transactions on Evolutionary Computation*, **6**(3), (2002), 227-238.
4. L. N. Castro, L. N. de Castro, J. Timmis, *Artificial Immune Systems: A New Computational Intelligence Approach*, Springer Science & Business Media, 2002.
5. D. Dasgupta, F. Nino, *Immunological Computation: Theory and Applications*, CRC press, 2008.
6. L. N. de Castro, Engenharia Imunológica: Desenvolvimento e Aplicação de Ferramentas Computacionais Inspiradas em Sistemas Imunológicos Artificiais, Universidade Estadual de Campinas, Campinas-SP, 2001.
7. L. N. de Castro, F. J. Von Zuben, The Clonal Selection Algorithm With Engineering Applications, *Proceedings of GECCO*, (2000), 36-39.
8. S. W. Doebling, C. R. Farrar, M. B. Prime, A Summary Review of Vibration-Based Damage Identification Methods, *Shock and vibration digest*, Washington, DC: The Center, **30**(2), (1998), 91-105.
9. S. Forrest, A. S. Perelson, L. Allen, R. Cherukuri, Self-Nonself Discrimination in a Computer, Proceedings of 1994 IEEE computer society symposium on research in security and privacy, 1999, 202-212.
10. V. R. Franco, D. D. Bueno, M. J. Brennan, A. A. Cavalini Jr, C. G. Gonsalez, V. Lopes Jr, Experimental Damage Location in Smart Structures Using Lamb Waves Approaches, Brazilian Conference on Dynamics, Control and Their Applications–DINCON, (2009), 1-4.
11. A. Gaffar, A. B. Joshi, S. Singh, V. N. Mishra, H. G. Rosales, L. Zhou, A. Dhaka, L. N. Mishra, A Technique for Securing Multiple Digital Images Based on 2D Linear Congruential Generator, Silver Ratio, and Galois Field, *IEEE Access*, **9**, (2021), 96125-96150. DOI: 10.1109/ACCESS.2021.3094129.
12. S. N. Y. Gerges, *Ruído: Fundamentos e Controle*, Florianopolis: *NR Editora*, 2000, 696.
13. S. Gopalakrishnan, M. Ruzzene, S. Hanagud, *Computational Techniques for Structural Health Monitoring*, Springer Science & Business Media, 2011.

14. S. R. Hall, The Effective Management and Use of Structural Health Data, Proceedings of the 2nd International Workshop on Structural Health Monitoring, 1999, 265-275.
15. S. P. Jakhar, A. Nandal, A. Dhaka, B. Jiang, L. Zhou, V.N. Mishra, Fractal Feature Based Image Resolution Enhancement Using Wavelet-Fractal Transformation in Gradient Domain, *Journal of Circuits, Systems and Computers*, **32**(2), (2023), DOI: https://doi.org/10.1142/S0218126623500354.
16. G. James, D. Witten, T. Hastie, R. Tibshirani, *An Introduction to Statistical Learning*, Springer, 112, 2013.
17. L. E. Kinsler, A. R. Frey, A. B. Coppens, J. V. Sanders, *Fundamentals of Acoustics, Fundamentals of Acoustics, 4th Edition*, Wiley-VCH, 1999, 560.
18. F. P. A. Lima, Análise de Distúrbios de Tensão em Sistemas de Distribuição de Energia Elétrica Baseada em Sistemas Imunológicos Artificiais, Universidade Estadual Paulista (UNESP), 2013.
19. F. P. A. Lima, Monitoramento e Identificação de Falhas em Estruturas Aeronáuticas e Mecânicas Utilizando Técnicas de Computação Inteligente, Universidade Estadual Paulista (UNESP), 2014.
20. F. P. A. Lima, Diagnóstico de Distúrbios de Tensão em Sistemas de Distribuição Baseado num Sistema Imunológico Artificial com Aprendizado Continuado, Universidade Estadual Paulista (UNESP), 2016.
21. R. Lanoye, G. Vermeir, W. Lauriks, R. Kruse, V. Mellert, Measuring The Free Field Acoustic Impedance and Absorption Coefficient of Sound Absorbing Materials With a Combined Particle Velocity-Pressure Sensor, *The Journal of the Acoustical Society of America*, **119**(5), (2006), 2826-2831.
22. F. P. A. Lima, F. R. Chavarette, S. S. F. Souza, M. L. M Lopes, Monitoring and fault identification in Aeronautical Structures Using an Wavelet-Artificial Immune System Algorithm, *Probabilistic Prognostics and Health Management of Energy Systems, Springer*, (2007), 203-219.
23. F. P. A. Lima, F. R. Chavarette, S. S. F. Souza, A. S. Souza, M. L. M. Lopes, Artificial Immune Systems Applied to the Analysis of Structural Integrity of a Building, *Applied Mechanics and Materials*, **472**, (2014), 544-549.
24. F. P. A. Lima, M. L. M. Lopes, A. D. P. Lotufo, C. R. Minussi, An Artificial Immune System With Continuous-Learning for Voltage Disturbance Diagnosis in Electrical Distribution Systems, *Expert systems with applications*, **56**, (2016), 131-142.
25. I. F. Merizio, F. R. Chavarette, R. Outa, Characterization of an Acoustic Impedance Tube Using Natural Computer, *Colloquium Exactarum*, **11**(4), (2019), 62-72.
26. D. C. Oliveira, F. R. Chavarette, F. P. A. Lima, Structural Health Monitoring using Artificial Immune System, *Brazilian Journal of Development*, **6**(4), (2020), 16948-16963.
27. D. C. Oliveira, F. R. Chavarette, M. L. M. Lopes, Damage Diagnosis in an Isotropic Structure Using an Artificial Immune System Algorithm, *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, **41**(11), (2019), 485-492.
28. R. Outa, F. R. Chavarette, Caracterização do Experimento do Tubo de Impedância de um Microfone, Boletim Tecnico da FATEC-SP — BT/39 — Junho, 2015.
29. R. Outa, F. R. Chavarette, V. N. Mishra, A. C. Gonçalves, L. G. P. Roefero, T. C. Moro, Prognosis and Fail Detection in a Dynamic Rotor Using Artificial Immunological System, *Engineering Computations* **37**(9), (2020), 3127-3145.
30. M. K. Sharma, Sadhna, A. K. Bhargava, S. Kumar, L. Rathour, L. N. Mishra, S. Pandey, A Fermatean Fuzzy Ranking Function in Optimization of Intuitionistic Fuzzy Transportation Problems, *Advanced Mathematical Models & Applications*, **7**(2), (2022), 191-204.
31. S. L. Wiggers, P. Pedersen, *Structural Stability and Vibration: An Integrated Introduction by Analytical and Numerical Methods*, Springer, 2018.