Trends in Computational and Applied Mathematics

Trends in Computational and Applied Mathematics, **26** (2025), e01414
Sociedade Brasileira de Matemática Aplicada e Computacional
Online version ISSN 2676-0029 www.scielo.br/tcam
ORIGINAL ARTICLE
doi: 10.5540/tcam.2025.026.e01414

Analysis and Numeric Formation

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Received on January 13, 2020 / Accepted on December 3, 2024

ABSTRACT. Structural health monitoring (SHM) is a system that assesses the state of structures, whether aeronautical, civil or mechanical, and provides a prediction of their remaining life. This has arisen with the need for more economic viability in the monitoring of structures and in fault identification. Thus, this system was defined as a prophylactic, reliable and effective measure against structural failures. This work has as objective the theoretical basis and a bibliographical revision necessary for the execution of the acoustic impedance tube experiment, following the ISO10534-1(1996), as well as numerical simulations. The experimental data are compared with the numerical simulation of the acoustic pressure inside the impedance tube and the artificial immune system is used to characterize the experiment.

Keywords: Structural Health Monitoring, SHM, Acoustic Impedance Tube, Artificial Immune System, Negative Selection Algorithm.

1 INTRODUCTION

Due to wear, due to human, temporal and environmental factors, the useful life of any structure, whether aeronautical, civil or mechanical, may be shortened and may fail early. Thus, structures require a certain maintenance frequency to avoid failures.

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The industry over the course of history has increased investments in the development of research aimed at analyzing and monitoring structural health, avoiding disasters and environmental, humanitarian and economic damage.

It is called Structural Health Monitoring (SHM) the important and current line of research that consists of detecting faults in their initial state so that they can intervene in their propagation and prevent damage [13].

Data acquisition and processing, signal validation and analysis, fault identification and characterization, interpretation of adverse changes in a structure and decision-making are the main requirements that an SHM must meet, as highlighted by [8].

The assessment of the integrity of mechanical structures by non-destructive tests such as penetrating liquids, magnetic particles, ultrasound, radiography, among other traditional techniques, does not fully meet the growing industrial needs [6].

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.

Fault detection and structural integrity monitoring of pipe using acoustic means is still poorly researched and employed. The differential of this work is the use of a sound wave propagating in the air to detect any type of damage that may compromise the operation of a tube.

Section 3 shows the theoretical basis for the development and programming of an SHM, section 4 the materials used and the assembly of the experimental bench, section 5 the project development. The survey results are displayed and discussed in section 6, and the section 7 is devoted to the conclusions.

2 RESEARCH OBJECTIVE

The objective of this research work is to develop a SHM for mechanical structures using negative selection algorithm (NAS) techniques [5] to perform the experiment characterization, the analysis and monitoring of the structural integrity of an acoustic impedance tube. Starting from the collection of acoustic pressure in positions inside the pipe based on ISO10534-1 (1996).

3 THEORETICAL FOUNDATION

The negative selection process that occurs in the T lymphocyte thymus discriminating proper and non-proper cells is the work basis of the negative selection algorithm proposed by [5] to detect changes in system state. The NAS is divided into two parts: Censor phase and Monitoring.

The Censor Phase phase consists of determining a set of protected eigenvectors and making random sets that will form the base line after assessing the affinity between these and the eigen signals in order to reject a particular chain that has higher affinity than the stated affinity. In monitoring, defined the baselines, the affinity between these and the set of detectors is evaluated. If the affinity is higher than a stipulated threshold, a non-self element is identified [2] .

Figures 1 and 2 illustrate the Censor Phase and Monitoring phase of the NSA.

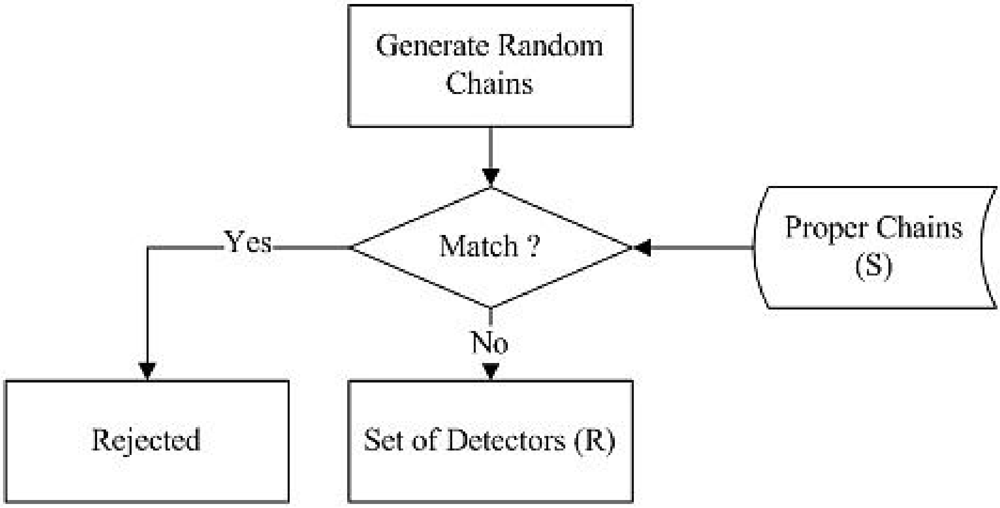

Figure 1: Flowchart of the censo phase of the NSA. From [3].

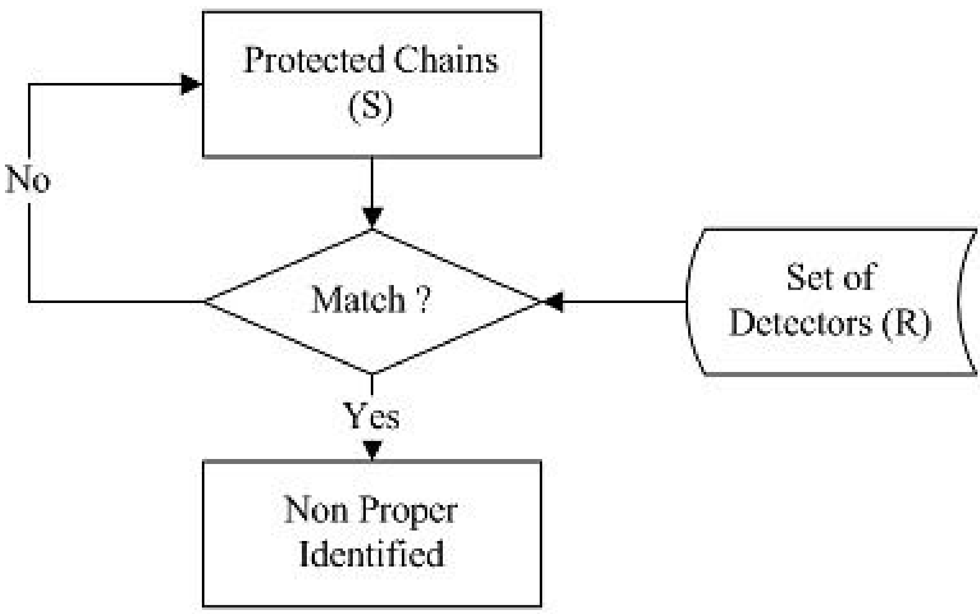

Figure 2: Flowchart of the monitoring phase of the NSA. From [3].

Initially, in the censo phase, own chains are defined, representing a normal situation. The detector set, with the ability to recognize non-proprietary patterns, is generated in sequence. Random strings are chosen, starting from reading the data. Detectors function as mature T-type cells that have the ability to recognize pathogens, that is, the ability to detect almost every non-self element. Affinity is verified by comparing randomly chosen chains to the set of eigen chains. If the affinity exceeds a pre-established threshold, the vector is rejected. Otherwise, the chain is placed in the detector set and it will be used in the classifications during data monitoring [10].

The next phase is to monitor the data in order to identify changes in the behavior of the samples and classify these changes using the set of detectors created in the Censo Phase. Then, a non-self element is detected and classified when the affinity between strings is above a pre-set threshold. [12].

The criterion known as marriage, which may be perfect or partial, is used to assess the affinity between chains and to verify that they are the same/similar.

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

Structural Health Monitoring (SHM) arises from the industrial need to detect faults in their initial state and thus prevent their spread and prevent damage. An SHM must address the following points: Data acquisition and processing, signal validation and analysis, fault identification and characterization, interpretation of adverse changes in a structure, and decision-making aid [8].

The negative selection algorithm-based SHM has the differential of stability, being able the system learning over time, and of plasticity, the ability to continue learning with new patterns included while maintaining prior knowledge [4].

A SHM based on AIS, in particular the NSA [5], has its diagnosis composed of two phases: Censo Phase and Monitoring. In Censo Phase, a census of data is performed to create the detector set and after will be use to recognize faults during monitoring [13].

As shown in Fig. 3, the censoring phase is divided into two modules. In the input module, which makes up the experimental bench, the signals are acquired. In Censo Phase the set of own detectors is generated that will be used in the Monitoring of the data. The detectors themselves are composed of a group of signals in normal situation, ie: No structure failures. They serve as a benchmark for fault identification and are named baseline. A signal collected from the structure in a fault situation will not have satisfactory affinity with the baseline, so that the fault present in the structure can be identified. Already a signal with the structure in normal situation when compared with the detector set will have high affinity and no fault will be identified [11].

The flowchart of Fig. 4 illustrates the monitoring phase which is also divided into two steps. In the first stage the data acquisition is performed, while in the second stage the discrimination between the signals as self/non-self.

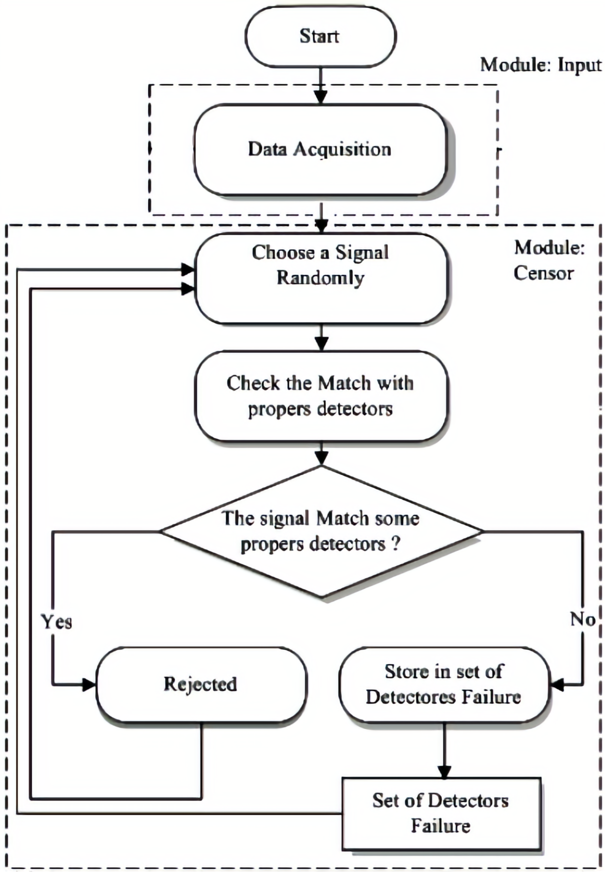

Figure 3: Flowchart Censo Phase SHM. Adapted from [11].

In the monitoring the data is analyzed in real time comparing them with the detectors created in the previous phase, trying to facilitate the decision making through the differential diagnosis.

After the acquisition of the signals, the detection module is executed, where the signals under analysis are compared with the proper detectors, trying to analyze the marriage between the signals.

If the affinity is higher than the defined affinity rate the signals under analysis are categorized as satisfactory with respect to the set of 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.

In this work was use the partial marriage criterion proposed by [1] and a 30% deviation in the detectors.

Being the objective of this work the characterization of the experiment the base-line is composed only by a mathematically generated normal signal. The signals collected from the structure with-

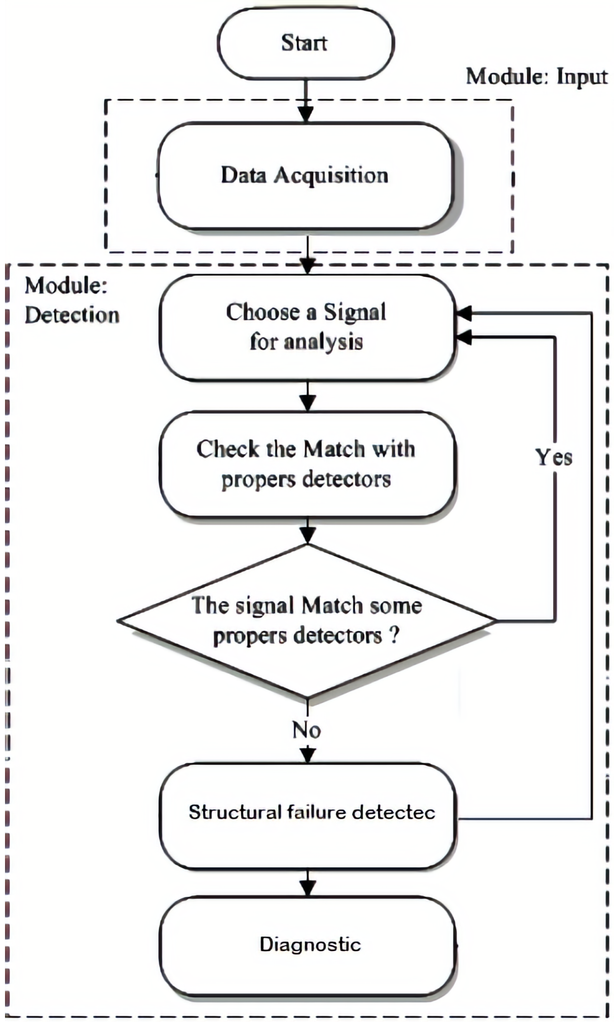

Figure 4: Flowchart Monitoring Phase SHM. Adapted from [11].

out failures are compared with this normal signal, ideally the system will not detect failures for the experiment to be characterized.

4 ADOPTED METHODOLOGY

This work is based on ISO10534-1 (1996). That is, a straight, rigid tube with non-porous walls without holes or cracks was used. The cross section of the pipe used is circular. The norm technique is the incidence of a sine wave by a sound source at one end of the tube. Being the wave propagated in the air and having a determined frequency. At the opposite end is firmly fitted the lid with a hole in its center. Through the hole passes the probe, with the microphone, which moves axially and internally in the tube, collecting the pressures. Figure 5 illustrates assembly of the experiment.

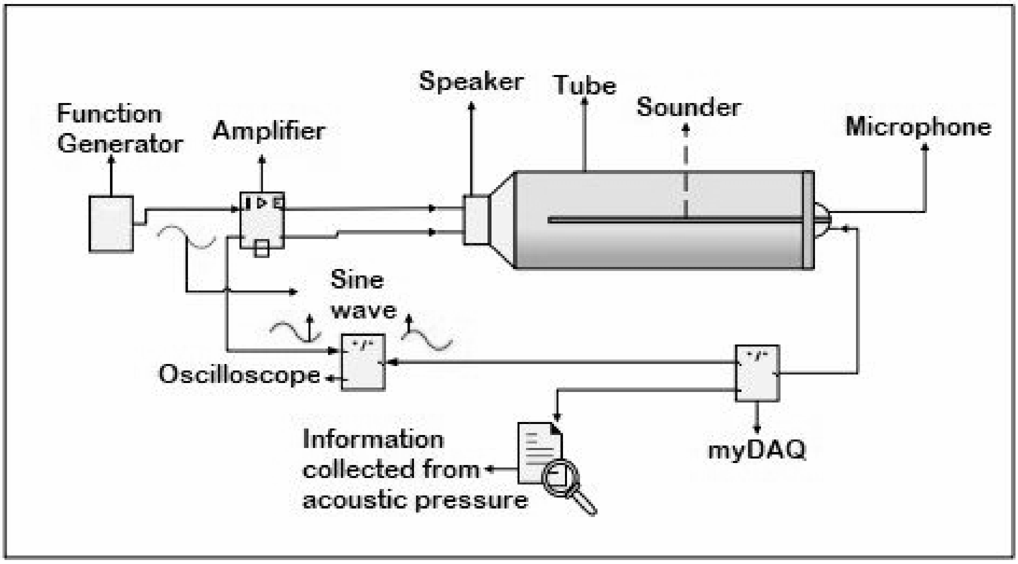

Figure 5: Schematic drawing of the experiment setup. Adapted from [14].

As shown in Fig. 5, the Function Generator is turned on in the Amplifier, which in turn is connected to the speaker and oscilloscope. The probe microphone, which plugs into the *National Instruments* (NI) *myDAQ* acquisition board, collects the signal that is stored in the Notebook using *National Instruments LabView Student Edition 2013*.

The cutoff frequency is 2008 Hz, determined algebraically in [7] , for the pipe diameter used (100 mm); Frequencies above this value cannot be studied under these conditions.

The amplitude of the signal emitted by the sound source shall be in accordance with 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.

In Fig. 6 it is possible to visualize the experimental bench assembled with the equipment used in the signal capitation.

5 DEVELOPMENT

Reflected and transmitted waves are generated when a flat acoustic wave, propagating in a medium I, meets the boundary surface of its medium, and the beginning of medium II. So the reflected wave is formed in the medium I, while the transmitted wave in the medium II, as shown in Figure 7, says [9].

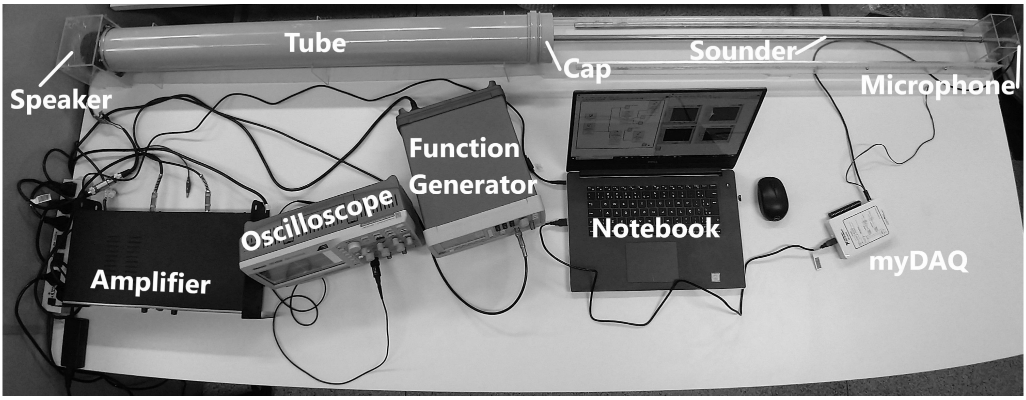

Figure 6: Upper view of experimental bench.

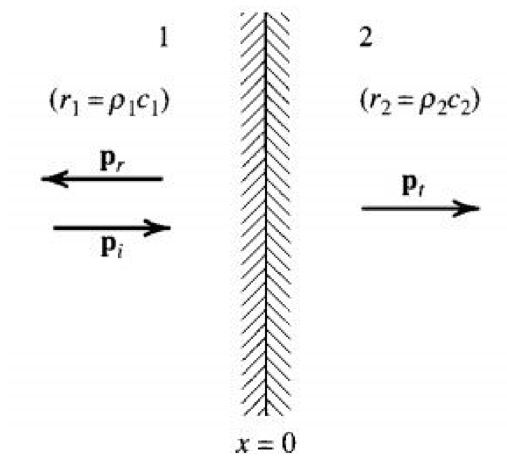

Figure 7: Reflection and transmission of a plane wave incident on the planar boundary between fluids with different characteristic impedances. From [14].

In Fig. 7 the MN membrane divides the media I and II. The incident flat wave propagates in medium I, in the positive direction of x, and reaches perpendicularly to the membrane, with x increasing in the direction of medium II - from the reference (x = 0) adopted in Fig. 7.

With the incident wave, the reflected wave forms in the medium I while the transmitted wave in the medium II [7].

Inside the tube, with the propagation of the incident wave with an adequate amplitude, there is the reflected wave formation, considering the theory of transmission and reflection in two media [9]. The principle of wave overlap in the tube is then observed. The sum of the incident wave with the reflected wave. The wave obtained from this superposition is called the stationary wave.

The probe (sounder) moves horizontally inside the tube collecting the sound pressure of each position (1 to 100 cm), the set of pressures of each position make up a collection. The collections were stored in a matrix with the experimental data.

For the second stage of the project was made an algorithm using the Octave to plot the pressure inside the pipe using numerical simulation. The normal signal of Figure 8 was then generated.

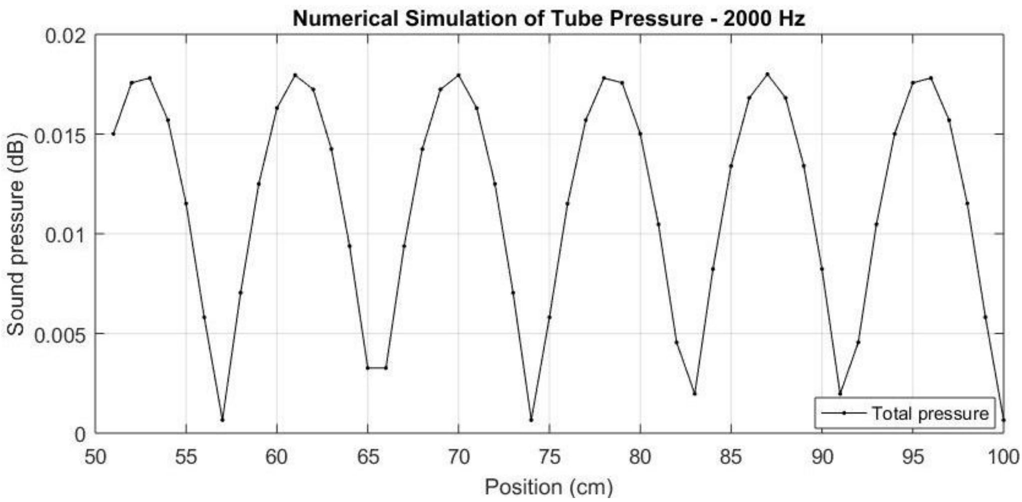

Figure 8: Computational mathematical simulation for 2000 Hz frequency.

6 RESULTS

An AIS was then assembled to categorize the affinity of each experimental collection with the computationally simulated normal signal using Octave. Figure 9 graphically shows AIS performance with a standard deviation of 30% of the normal signal for the 2000 Hz frequency.

Figure 9 shows the computationally simulated normal signal, identified in the legend. The upper and lower limits of deviation for each of the collection points are shown. The other curves represent the experimental signal collected from tube.

Table 1 shows the results obtained by the experimental characterization performed by AIS, where the variance and standard deviation of each signal in relation to the normal signal are also found.

Considering that the calculated affinity rate was 59%, according to [1], the Artificial Immune System hit percentage was 100% and the experiment was correctly characterized. The Negative Selection Algorithm proved to be robust and effective in identifying signal matching.

7 CONCLUSIONS

Satisfactorily the characterization of the experiment was successfully performed by the programmed AIS, within the adopted parameters. Characterization was also performed for other

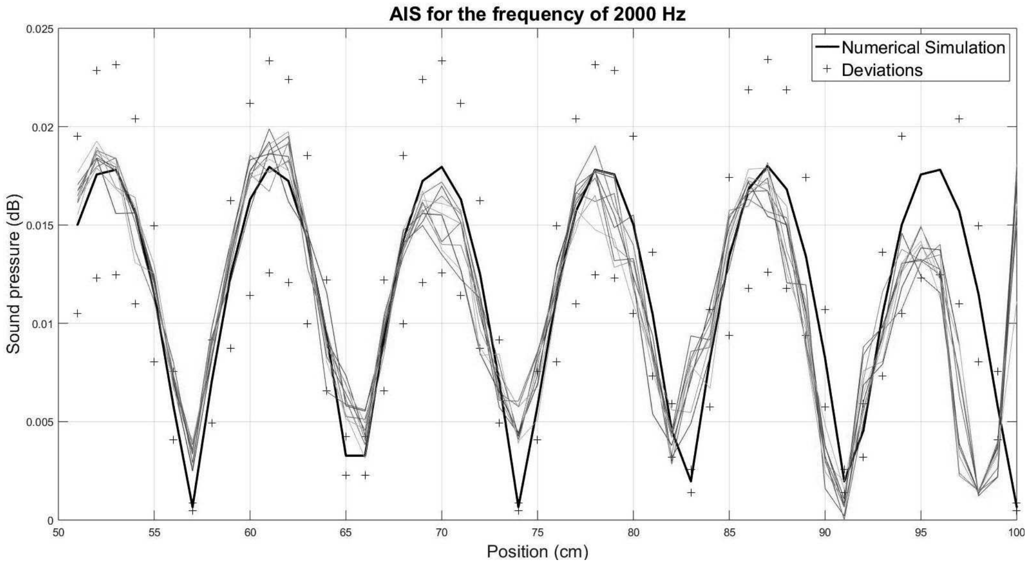

Figure 9: Visual identification of AIS operation for 2000 Hz frequency.

Table 1: Results obtained from AIS for the characterization of the impedance tube for a frequency of 2000 Hz.

Collection	Affinity	Variance	Standard deviation
1	70.00%	0.0000180	0.0042438
2	76.00%	0.0000189	0.0043517
3	78.00%	0.0000176	0.0041969
4	68.00%	0.0000186	0.0043085
5	76.00%	0.0000186	0.0043109
6	72.00%	0.0000183	0.0042773
7	70.00%	0.0000179	0.0042257
8	70.00%	0.0000171	0.0041344
9	76.00%	0.0000197	0.0044407
10	72.00%	0.0000182	0.0042677

octave band frequencies. In addition to the 2000 Hz frequency presented in this work, it was performed for the frequencies of 500 Hz and 1000 Hz.

The proposed methodology for fault detection, or in the case of characterization of the experiment, is unprecedented for the area of SHM in the use of acoustic means, which is a differential point of this work.

Continuing with this work, the next steps are the acquisition of failing pipe signals and then mounting a SHM for structural fault detection. Fault detection will still be done vibrationally to compare the methods.

Acknowledgments

The authors thank Fapesp (Proc. No. 2018/16447-8 and Proc. No. 2019/10515-4), CNPq Proc. No. 312972/2019-9, the SISPLEXOS Laboratory and UNESP for their support.

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How to cite
I. F. Merizio, F. R. Chavarette, R. Outa, L. G. P. Roefero & T. C. Moro. Analysis and Numeric Formation. *Trends in Computational and Applied Mathematics*, **26**(2025), e01414. doi: 10.5540/tcam.2025.026.e01414.