Detection, Location and Quantification of Structural Faults in a Two-Story Building Using the Artificial Immunological System

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ABSTRACT

Large buildings and skyscrapers are vulnerable to environmental, temporal, and anthropological stresses, generating wear and tear that can lead to this social and economic impediment's collapse. The technological improvements of the fourth industrial revolution have resulted in changes in the connection between physical space and man, known as the cyber physic model, which necessitates monitoring systems to protect the structural branch and so correct this structural vulnerability. Thus, the structural health monitoring system is the exact measure of the evolution required by the cyber physic model in construction and the protection of the monumental buildings, ensuring not only their economic development but also the safety of society. Therefore, this research work presents the innovative proposal of the cyber-physical structural health monitoring system aimed at buildings and skyscrapers, based on and differentiated by intelligent computing techniques, using the negative selection algorithm to perform the analysis and monitoring of structural integrity, overcoming the existing traditional work. The cyber-physical structural health monitoring system will be applied to experimental data obtained from the shear building model that represents these imposing skyscrapers. An artificial immune system will be developed and used in the decision-making process based on the acquisition and processing of the obtained signals to perform the identification, localization, and quantification of possible structural damage. Observing the results, this work proved to be efficient, robust, and economically feasible, having high performance and overcoming the shortcomings of traditional techniques. It represents the perfect measure of cyber physics in the monitoring of large buildings and skyscrapers.

1. Introduction

The fourth industrial revolution transformed the relationship between physical space and man, by developing the cyber physics paradigm through technological innovation. Thus, industries have overcome the robotic framework and moved towards computational means consisting of collaborative systems, in which operations are monitored, coordinated, controlled, and integrated through communication and computational cores. This transformation has gone beyond the walls of Industry 4.0, establishing itself and requiring technological restructuring in all social sectors [1,2].

In the structural branch of civil engineering, it is no different. The evolution of society has always been linked to the power of modifying the space in which humans live, and the structural development responsible for economic and social consolidation. And so, economic and social power have become intertwined with the imposing constructions that go beyond the ground floor buildings to the monumental skyscrapers [3,4].

These structures present wear and tear from environmental, temporal, and human stresses that, when propagated, make these grand building structures vulnerable to collapse. This extreme failure promotes not only economic losses but also traumatic events due to the deaths of people, requiring the Cyber Physics model to protect the structural branch and thus correct this vulnerability [5].

Thus, monitoring and diagnostic systems tend to become part of the cyber-physical system as a result of the development of new technologies and the evolution of signal processing and interpretation techniques to efficient methods of structural integrity analysis, preventing catastrophes and/or accidents, ensuring people's lives and avoiding economic losses [4, 6].

It is within this concept that the Structural Health Monitoring System (SHM) is established. Concisely, the SHM is described as a method for implementing strategies for the identification of structural failures, being able to execute tasks such as acquisition and processing of data, validation, and analysis; enabling the identification and interpretation of adverse variances in a structure, aiming to facilitate decision making and ensure safety, in the non-destructive analysis [7-9].

Thus, SHM is the exact measure of the evolution required by the Cyber Physics model in Civil Construction that offers the protection of buildings, ensuring not only the economic development but also, the safety of society. For this reason, the literature, currently, is verified a range of works involving the SHM, covering techniques and various monitoring methods: x-ray techniques [10], neural networks [11], acoustic techniques [12], among other various traditional techniques.

However, as Moro [6] points out, while these traditional works present a good methodology and good results, they also present a high cost with specific devices that do not cover the entire structure and do not present the ability to identify, locate, and quantify potential structural damage, which is required by the Cyber-Physical Model and necessary for the social and economic well-being of large buildings.

Therefore, this research work presents the innovative proposal of the Cyber-Physical Structural Health Monitoring System aimed at buildings and skyscrapers, based on and differentiated by Intelligent Computing (IC) techniques, the Negative Selection Algorithm [13] to perform structural integrity analysis and monitoring.

The methodology will be applied to experimental data obtained from the share building model that represents these grand skyscrapers. From the acquisition and processing of the signals obtained, the Negative Selection Algorithm (Artificial Immune System) will be elaborated and applied in the decision-making process to perform the identification, localization, and quantification of possible structural damage. This work is divided into the following sections: Artificial Immunological System: presenting the theory and methodology of data processing performed by the Negative Selection Algorithm; Experimental Equipment: presenting the experimental workbench; Failure Location and Damage Quantification: presenting the methodology and theory for structural failure localization and quantification; Experimental Methodology: presenting the experimental development for structural data acquisition; Results and Discussions – presenting the data after the application of the Negative Selection

Algorithm and the decision-making process derived from these data, and finally the Conclusion about the developed work.

2. Artificial Immunological System

The Artificial Immune System (AIS) emerges in the scientific space from the inspiration of the Biological Immune System, absorbing the biological defense paradigms, capabilities, and characteristics [15].

The Biological Immune System is the barrier and fighter that prevents microorganisms from colonizing the intracellular environment. Without this defense mechanism, animals would be at the mercy of countless infectious agents present in the environment that would invade the human body and cause the collapse of the systems that compose it [14].

For this reason, the AIS is highlighted by Lima [16] as being an example of Immunological Engineering. That is, based on the characteristics of meta-synthesis, which defines tools for solving or optimizing problems based on the characteristics of the problem itself, for subsequent resolution, characterizing it as immunological engineering.

To do this, AIS transforms the association of organ biological tissues and cells into algorithms that represent methodologies for data manipulation, classification, representation, and reasoning that follow the biological paradigm of defense [17].

Within this concept, the Negative Selection Algorithm (NSA), proposed by Forrest [13], stands out. This algorithm has as its biological defense paraphrase, the differentiation of good lymphocytes, said to be proper for the body, from bad lymphocytes, said to be not proper to the body. Therefore, NSA presents the feature of Pattern Recognition, Data Analysis, and Associative Memories as being fundamental in the Recognition of anomalies and failures, and therefore, the differential of this work that promoted the evolution of the SHM.

These properties stem from the algorithm's operation through the matching method. The matching or combination criterion, according to Moro [6], is used to evaluate affinity between the chains (antigen and antibody) and prove whether they are similar or equal. This matching can be perfect or partial.

If the match is perfect, it means that the two analyzed chains have the same values, and therefore, both must be perfectly equal. However, if only some positions between the patterns have the same value, this matching is defined as partial matching.

The antigen (Ag) is the signal to be analyzed in the negative selection algorithm and can be represented by Eq. 1. The detectors represent the antibodies (Ab) and are expressed according to the Eq. 2 [17].

$$Ag = Ag1, Ag2, Ag3, ... , Agl \tag{1}$$

$$Ab = Ab1, Ab2, Ab3, ... , Abl \tag{2}$$

In this case, the number of equal positions follows a preset threshold called the affinity ratio.

According to Lima [16], perfect matching between data chains is almost impossible to achieve experimentally, due to the numerous variables that permeate and alter the empirical data. Therefore, the use of partial matching and affinity ratios proves to be much more advantageous. The affinity rate, therefore, is used as the degree of similarity required for partial matching to occur, evaluated for real numbers, is defined as:

$$TAf = \left(\frac{An}{At}\right) \cdot 100 \tag{3}$$

where *TAf* is affinity rate; *An* is a number of normal chains in the problem (own chains); *At* is the total number of chains in the problem (own and not own chains).

In addition to the Affinity Rate, the Total Affinity, defined as:

$$Af_e = \frac{\sum_{i=1}^{L} Vc}{L} \cdot 100 \tag{4}$$

where *Aft* is the percentage of affinity between the analyzed standards; *L* is the total amount of variables and *Vc* is the married variables;

Thus, if *Aft* is greater than or equal to *TAf* then partial matching occurs and the chains are considered similar. On the other hand, if *Aft* is less than *TAf* , the detector does not recognize the chain, and thus no matching occurs between the patterns.

Based on the partial matching criterion of data analysis, the implementation of the Negative Selection Algorithm consists of two phases: a Positive Selection phase called Censoring and a Negative Selection phase called Monitoring [17].

In the NSA Censoring phase, represented by Fig. (**1**), the proper detectors are defined, which represent the normal condition of the system, and the set of detectors (R) is produced, which can recognize non-own patterns, that is, fault or damage situation. Therefore, by reading the data, the affinity of random chains is verified, comparing these chains to the set of own chains.

If the affinity is above a pre-set threshold, the chain is rejected. However, if the affinity is below the threshold, the chain is added to the set of detectors, this being the learning phase of the algorithm used in monitoring.
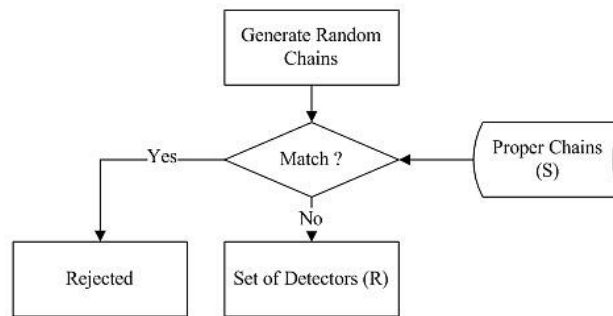

Figure 1: Flowchart of the Census Phase. **Source**: [16]**.**

In the Monitoring Phase, represented by Fig. (**2**), the data is monitored to identify anomalies in the samples. Thus, with the set of detectors coming from the Censoring phase, classifying this anomaly.

In this way, comparing the protected chains (S) with the set of detectors (R), the affinity between the chains is assessed. If the affinity exceeds a pre-set threshold, a non-own element is identified and classified.
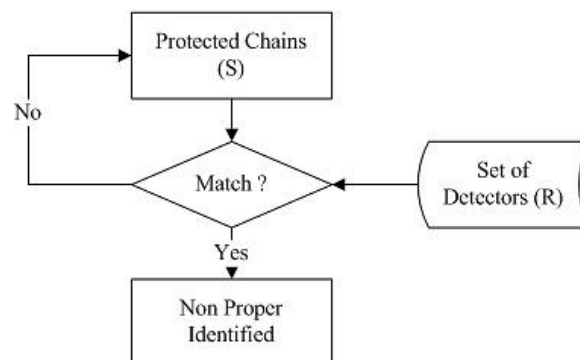

**Figure 2:** Flowchart of the Monitoring Phase. **Source**: [16]**.**

3. Experimental Equipment

As seen, the large buildings and spider skies are vulnerable to cyclical stresses, generating wear and tear that can lead to the collapse of this social and economic imposing requiring the monitoring established in the Cyber-Physical model to remedy this problem.

Regardless of the mode, these wears modify the spatial parameters and consequently impact on the structural dynamic characteristics: frequency response functions, resonance frequencies, damping ratio, and structure's modes [18].

Therefore, to implement the SHM in the face of non-destructive testing, the experimental apparatus was configured as a two-story building model. Despite presenting a reduced scale of floors and dimensions, the structural dynamics will present similarities (displacement, velocity, and acceleration) and, therefore, will assimilate, to a lesser extent, the response of large building structures.

Thus, the experimental setup was defined by a shear building model of a two-story building, represented by Fig. (**3**).
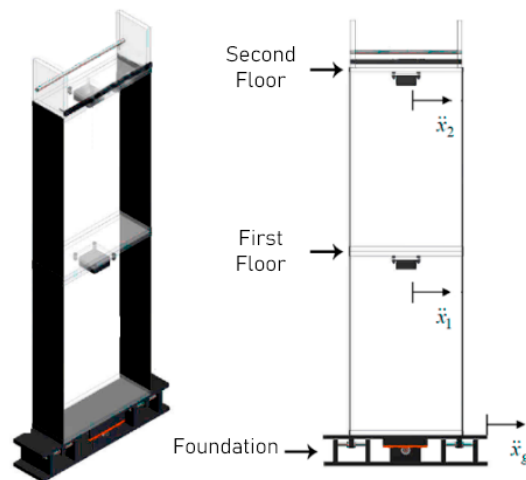
Figure 3: Two-story building model. **Source**: [6]**.**

This structural model is composed of a structure manufactured by Quanser Consulting Inc, built by a steel frame, representing a flexible building. Since it is a shear building model, it presents some simplifications defined by:

- Only the horizontal displacement;
- The masses are concentrated on the structural nodes;
- The mass of the columns is neglected;
- Infinite stiffness of the slabs;
- The actions are applied only in the planes of the frames;
- The stress-strain curve is considered elastoplastic ideal.

Thus, the deferred effect influencing the structure comes from the structural dynamics - displacement, velocity, and acceleration - parameters that act in any real structure and those present sensitive variations with physical structural modifications, such as wear and tear.

The structural model presents, coupled at its base, a shake table, represented in Fig. (**4**). This shake table produces an external force on the base of the structure, defining an acceleration ($\ddot{x}_g$) resulting in the accelerations of the first ($\ddot{x}_1$) and second floor ($\ddot{x}_2$) floors.
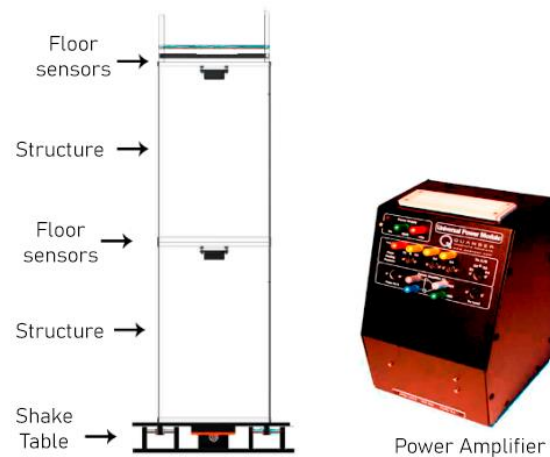
Figure 4: Experimental Apparatus. **Source**: [6]**.**

In addition to the elements that make up the two-story building model, a power amplifier was used, responsible for powering the shaking table. The UPM 1503 amplifier, is also manufactured by Quanser Consulting Inc.

For the sensing and collection of structural data, MPU6050 accelerometers coupled to the structure were used, establishing in the SHM precepts active monitoring, located as highlighted in Fig. (**5**).
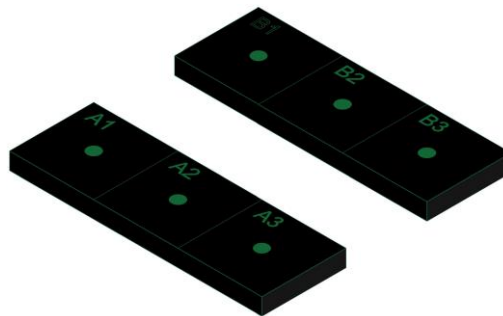
Figure 5: Schematic of the location of the accelerometers on the floors of the structure. **Source**: Elaborated by the author.

In this figure, the green points represent the coupling position of the sensors on the floors of the structure. It is worth noting that the sensors with the prefix A refer to the second floor and the sensors with the prefix B refer to the second floor.

The building model together with the amplifier was fixed on an inertial table. This has the objective of ensuring the stability of the experiment by reducing experimental noise.

4. Failure Location and Damage Quantification

The use of the Artificial Immune System and Statistic Inference allows structural fault localization and damage quantification, which are the work's innovative aspects.

The process of implementing the fault localization in the analyzed structure is based on the pattern detection of each sensor, i.e., there are six points in the structure for localization. The positioning of the sensors provides a sensing mesh that, depending on the location of the damage or structural failure, will have a greater influence on one of the sensors.

This permits global location by floor (on the first or second level) and local localization due to the Zone of Influence of Failures generated by the sensor mesh, which is depicted in Fig. (**6**).

It is worth noting that the zones of influence were first determined based on the sizing of the sensors, and then, for the structure monitoring analysis, they were named based on the main sensor that defines that mesh.
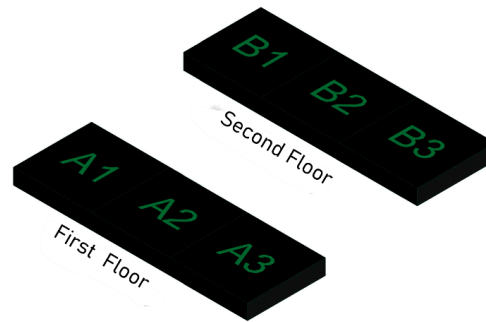
Figure 6: Failure Influence Zones for Prognosis. **Source**: Elaborated by the author.

Based on the influence zones, the localization has for implementation, the Negative Selection Algorithm itself presents the same matching criteria and the same operating phases. However, the censoring is established for each sensor separately and based on the monitoring, the non-own data of the structure is identified with the sensor and its location.

Thus, the localization can be summarized as a set of NSA sub-detectors, which receive as learning the data from each sensor and, based on that, locate the global and local positioning of the detected fault, as shown in Fig. (**7**).
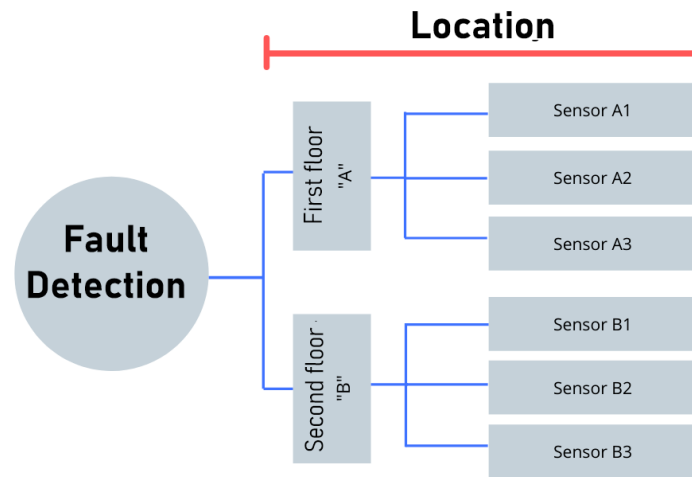
Figura 7: Location Flowchart. **Source**: Elaborated by the author.

The quantification of damage, on the other hand, is based not only on NSA but also on statistical inference. To be successful in quantifying the failure, it was first necessary to implement subprograms of NSA with knowledge of the existing failures. To do this, the fault database was separated into three banks, each corresponding to the signals of the three fault types. With this, it was possible in the Censoring phase to implement the knowledge of each fault type.

It is in the Monitoring phase that the differential for the algorithm occurs. It was constructed using summary measures based on the total possibility of failure, establishing the total failure median and total failure deviation using Statistical Inference.

At each monitored signal, should a failure be detected, the failure detectors go into action and determine the type of failure, as well as the median and standard deviation of the analyzed signal. Based on the Overall Median and the Median of the Fault Signal, the Severity Rate was defined by:

- Very Low Severity Level: Median rate less than 25%;
- Low Severity Level: median rate greater than 25% and less than 50%;
- Medium Severity Level: median rate greater than 50% and less than 75%;
- Severity Level very high; median rate greater than 75%.

These percentages of the Median Ratio, respective to each level, are based on the refinement of parameters associated with the theoretical foundation established in the Structural Analysis. Based on the General Deviation and the Failure Signal Deviation, the Failure rate was set by:

- Very Low Failure Level: Deviation rate less than 25%;
- Low Failure Level: Deviation rate greater than 25% and less than 50%;
- Average Failure Level: Deviation rate greater than 50% and less than 75%;
- Very High Failure Level; established by a Deviation rate greater than 75%.

5. Experimental Methodology

The experimental methodology aimed to collect the structural dynamic parameters against the excitation developed by the shake table, for the analysis of the global and local prognosis of the structure.

Structural dynamics was the parameter determined in the monitoring due to its close relationship with the spatial parameters. Structural modifications, such as damage, interfere in the dynamic responses of the structure, enabling the differentiation of a normal structure and a structure with damage and/or structural failure [18].

For this reason, excited the building model with the shake table determined by the excitation type EI center, represented by the Kanai-Tajimi stochastic earthquake model (Wg), defined, according to Kanai [19], by:

$$WgS = \frac{\sqrt{S_o}\,(2\zeta_g\omega_g + \omega_g{}^2)}{s^2 + 2\zeta_g\omega_g + \omega_g{}^2} \tag{5}$$

Any structure is excited by different frequencies, coming from different sources of excitation, such as the action of wind, the action of vehicle movement, the structural load, among others. Therefore, the choice of a seismic excitation, which in this case, by presenting a small-time and power, does not present structural risk to the building model and allows complete monitoring of the structure against the various sources and frequencies of excitation that exist in a real building structure.

Respecting a non-destructive test, and based on the dynamic sensitivity concerning structural spatial parameters, the structural failure was determined by the addition of masses on the floors of the structure, as shown in Fig. (**8**).
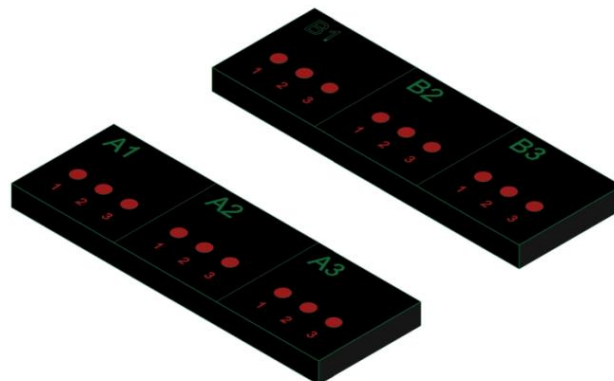
Figure 8: Configuration of the mass addition in the structure. **Source**: Elaborated by the author.

As can be seen in Fig. (**8**) above, in each influence zone there were mass increases represented by the red dots. Thus, there were three types of failure in each sensor loop:

- Fault 1: adding a mass in position 1;
- Fault 2: adding two masses in positions 1 and 2;
- Fault 3: adding three masses in positions 1, 2, and 3.

Thus, with increasing sums of mass, it is possible to evaluate the severity of the damage, where one mass would represent a low severity case and three masses would represent the most severe case.

Having seen all this, the normal signal comes from the capture of the vibrational parameters of the structure without the addition of mass, which represents the structure in a healthy state.

After capturing the signals, the Fourier Transform was applied. Switching to the frequency spectrum allows a peak-to-peak analysis of the structural response amplitude.

6. Results and Discussions

Based on the methodology used, we arrived at a database with 24 signals representative of structural normality and 432 signals representative of damage in the building model. These signals are detailed in Table **1**, according to the location of the sensors.

Table 1:   Discretion of signals according to location.

Sensor Position	Quantity			
	Fault 1	Fault 2	Fault 3	Regular
A1	24	24	24	4
A2	24	24	24	4
A3	24	24	24	4
B1	24	24	24	4
B2	24	24	24	4
B3	24	24	24	4

Source: Elaborated by the author.

Through this database, the Negative Selection Algorithm was applied to analyze the structural state and from this, if there is failure locate and quantify its structural impact.

6.1. Structural State Analysis

Following the implementation of the algorithm, the results shown in Table **2** were obtained for the initial structural state analysis step.

Table 2:   Result of the analysis of the structural state through the signals of the structure.

Signal Type	Signal Input	Signal Detection	Percentage of Accuracy
Regular	24	24	100%
Fault	432	432	100%

Source: Elaborated by the author.

As one can denote from the table there was a 100% crossover matching in the structural state analysis, correctly separating the normal signals from the fault signals. This success of the structural state detection had been observed in a work of Moro [6] and shows that the evolution of the algorithm did not affect the efficiency of this initial step of the NSA when compared to the one in the cited work [6].

6.2. Location of Representative Fault Signals

According to the experimental procedure, the algorithm should localize 72 fault signals on each floor and 24 fault signals in each influence zone for fault localization.

After the analysis step, we arrived at the result established in the tables below referring, respectively, to the location result for each floor, represented by Table **3**, and the location result for each failure zone, represented by Table **4**.

Table 3:   Table of results obtained in the localization.

Analyzed Floor	Signal Fault 1	Percentage of Accuracy	Signal Fault 1	Percentage of Accuracy	Signal Fault 1	Percentage of Accuracy
First	72	100%	72	100%	72	100%
Second	72	100%	72	100%	72	100%

Source: Elaborated by the author.

Table 4:   Table of results obtained in the Localization phase by zone of influence.

| Analyzed Floor	Signal Fault 1	Percentage of Accuracy	Signal Fault 1	Percentage of Accuracy	Signal Fault 1	Percentage of Accuracy
A1	24	100%	24	100%	24	100%
A2	24	100%	24	100%	24	100%
A3	24	100%	24	100%	24	100%
B1	24	100%	24	100%	24	100%
B2	24	100%	24	100%	24	100%
A3	24	100%	24	100%	24	100%

Source: Elaborated by the author.

As presented by Tables **3** and **4**, there was an average crossover matching of 100% denoting maximum efficiency in NSA decision-making

6.3. Quantification of Damage

Observing that the quantification of damage is correlated to location, the results of the severity level and failure level for the two-story building model will present 100% accuracy. That is, this logical step of the Negative Selection Algorithm will demonstrate the influence of each failure mode on the overall structure.

The result of the damage quantification shown in Fig. (**9**) was obtained for the First Failure Mode, which was established by the addition of a mass.
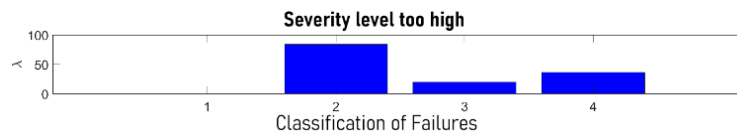
Figure 9: Quantification of damage to Fault 1. **Source**: Elaborated by the author.

As one can denote the 144 signals of the first failure mode, 143 signals are established with a very high degree of Severity, that is, they present a vibration level much higher than the normal signals. Of these signals with the maximum severity, 62% present moderate failure, 11% high failure and 27% present an imminent risk of structural collapse.

This shows that even with a smaller failure mode the structure presents a high risk of failure. This is due to the structural sensitivity that minor damage can cause to collapse, necessitating structural over-dimensioning for works that do not present an SHM. The result of the damage quantification shown in Fig. (**10**) was obtained for the second failure mode, which was established by the addition of two masses:
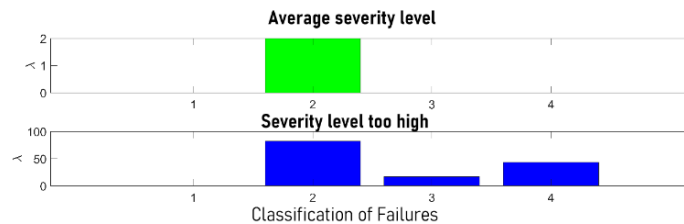
Figure 10: Quantification of damage to Fault 2. **Source**: Elaborated by the author.

As one can denote the 144 signals of the second failure mode, 142 signals are established with a very high degree of Severity. Of these signals with the maximum severity, 58% present moderate failure, 12% high failure, and 30% present imminent risk of structural collapse.

The damage quantification result shown in Fig. (**11**) was obtained for the third failure scenario, which was produced by adding three masses.
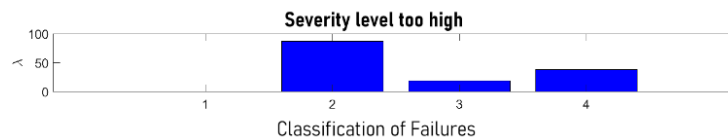
Figure11: Quantification of damage to the Fault 3. **Source**: Elaborated by the author.

As can be denoted from the 144 signals of the third failure mode, all signals are established with a very high degree of Severity. Of these signals with the maximum severity, 60% present moderate failure, 13% high failure, and 27% present imminent risk of structural collapse.

Thus, it can be seen that the increase of the failure mode provides the increase of the severity degree and, therefore, this structure presented a lower survival curve, since the accumulated failure rate increased as established in a work of Xenos [20]. This proves the veracity of the results obtained after the implementation of the Negative Selection Algorithm.

7. Conclusion

This work had the objective of constituting a new Structural Integrity Monitoring System that meets the philosophy/requirements of the Cyber-Physical model and the social needs, established not only in the detection of the damage but also, in the capacity of locating and quantifying it against the structural constitution.

Looking at the final results associated with the experimental procedure, the CEM proved to be efficient, robust, and economically feasible, having a high performance and overcoming the shortcomings of traditional techniques.

This high performance is due to the use of the Artificial Immune System that enabled the evolution of the SHM and presented fault detection and localization with 100% accuracy and a damage quantification that meets the theoretical basis, as represented in the results.

Its limitations are defined by the need for further technological developments in the field of sensors as well as increased computational capacity for data processing. The growing complexity of the structure necessitates more demands on these components, limiting the capacity of the new Structural Integrity Monitoring System.

Observing this work, it is clear that the AI has the ability to diagnose, locate, and quantify structural failures in an SHM structure; however, for this research to be a complete tool, the direction of evolution will be the continuous learning of machines for data processing and the ability to make decision-making prognostic regarding the structure analyzed. Therefore, observing the total work, this Structural Integrity Monitoring System associated with the Artificial Immune System and applied to the building model, characterizes a revolution to the structural branch, because it transforms the main structural determinant into a "human body, i.e., in a complex and perfect machine with all its parts working in sync and without potential failures.

Acknowledgements

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