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Artificial Intelligence Applied in the Detection and Fault Localization in Dynamic Systems

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ABSTRACT

A methodology using artificial intelligence for diagnosing structures and predicting failures in mechanical systems is presented. An Artificial Immune System (AIS) able to identify and locate faults with good predictability was developed, having its op eration based on the Negative Selection Algorithm (NSA). The Negative Selection Algorithm is divided into two steps: Censor phase and Monitoring. In the first step, the algorithm can learn about the normal operation of the system and created a baseline. In the second step, the algorithm evaluates the system data and becomes able to identify patterns different from what has been learned, in other words, a possible failure. The algorithm developed was optimized with the Clonal Selection Algorithm (ClonalG), aiming at fewer data in training. The results obtained suggest that the AIS can learn about the normal system operation using 5% of the available data, being able to diagnose with an excellent safety margin the predictability of a failure and inform where it is located. With the optimization by ClonalG the need for training data is reduced by 50% and the deviation adopted by 70%, without jeop- ardizing the algorithm hit rate. Thus, the algorithm optimized by ClonalG proved to be an excellent tool in the prevention of failures and accidents, presenting general hit rates above 99.90%. The differentials of this work are the high hit rate presented by the AIS, which performs few misclassifications, and the fact that modeling is not necessary. The system is able to learn by itself about the behavior of the data.

Keywords: structural health monitoring; artificial immune system; negative selection algorithm; clonalg; fault detection.

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I. INTRODUCTION

The current and important line of research called Structural Health Monitoring (SHM) aims to detect failures in the initial states, intervening in the propagation of the failure and consequently preventing disasters and accidents occur causing the stopping or damaging the structure. As highlighted in Hall (1999), an SHM must have the following requirements:

- data acquisition and processing;
- validation and analysis of signals;
- identification and characterization of failures;
- interpretation of adverse changes in a structure;
- assist decision making.

In the literature, many works addressing the monitoring and diagnosis of failures have been identified and some are presented with a focus on the application of computational intelligence techniques such as: artificial neural networks Pandey and Barai (1995); Zheng, Wang, and Liu (2004), genetics algorithms Chen et al. (2007); Merizio, Chavarette, Moro, and Outa (2020), neural networks and wavelet transform Santi- ago et al. (2004), an electrical impedance technique combined with artificial neural networks Lopes Jr, Turra, Mu¨ller, Brunzel, and Inman (2001), electrical impedance technique with genetic algorithms Tebaldi (2004), piezoelectric sensors and actuators in artificial neural networks Giurgiutiu and Cuc (2005), PZTs Flynn and Todd (2010), Fuzzy logic Chandrashekhar and Ganguli (2009), electromechanical impedance technique Pita, Turra, and Vieira Filho (2013), wavelet transform Abreu, Chavarette, Villarreal, Duarte, and Lima (2014); Qiu, Lee, Lin, and Yu (2006) , artificial immunological algorithms F. Lima,

Lotufo, and Minussi (2013), intelligent hybrid algorithms Parra dos Anjos Lima, Chavarette, dos Santos e Souza, Silva Frutuoso de Souza, and Martins Lopes (2014), among others.

It is important to emphasize that the monitoring and identification of structural failures is a complex problem and is much-discussed in the literature. Thus, it is important to develop new tools to contribute with new alternatives, even innovative alternatives to solve this type of problem.

The choice of using the AIS through the negative selection algorithm is essentially justified due to it is ability to learn and recognize patterns and to present excellent performance in other types of pattern recognition and diagnosis problems, as high - lighted by the authors em F. P. Lima, Chavarette, Souza, and Lopes (2017); Merizio, Chavarette, and Outa (2019).

The ClonalG algorithm works in 8 steps, starting with the selection of a specific population of antibodies that are cloned and hypermutated for further evaluation of the affinity between these and the antigens. Followed by the re-selection process, the best clones are selected to be evaluated and mutated in order to obtain the best possible combination of antigen and antibody De Castro and Von Zuben (2000). ClonalG is commonly applied in domains of optimization and pattern recognition, being therefore chosen.

In comparison with the works of F. P. Lima et al. (2017); Oliveira, Chavarette, and Lopes (2019), the differential of this work is the optimization using genetic algorithm; the clonal selection algorithm. In this case, approximately 50% less data is needed in the training phase than the algorithm without optimization. In addition, the system is capable of identifying and any type of failure, due to the capacity for continuous learning. A failure never before presented to the system can be identified as a new failure pattern, for future identification and localization.

Compared to the work published by Chouidira, Khodja, and Chakroune (2019), this work differs in that it does not require any pre-modeling of the system, being able to adapt to different situations and systems. For example, this same algorithm was applied in the detection of faults in pipes by acoustic means, with few modifications, by the authors Merizio, Chavarette, Moro, Outa, and Mishra (2021).

Compared to the article published by Eren (2017), which uses the same database as this research, this article differs in terms of the method used. AIS are more efficient in detecting and locating faults for this type of application, as the results suggest, requiring less data in training and presenting more satisfactory results than in the article by the mentioned authors.

II. MATERIALS AND METHODS

Pattern recognition, studied by authors such as Hunt, Timmis, Cooke, Neal, and King (1999), Forrest, Javornik, Smith, and Perelson (1993) and Dasgupta and Forrest (1999), is one among several applications of Artificial Immune Systems (AIS). This computationally elaborated tool is based on the ability of the biological immune system to identify antigens and antibodies and decide how to perform the interaction between them.

The AIS and the Clonal Selection Algorithm are composed of intelligent methodologies, inspired by the biological immune system, for solving real world problems Dasgupta and Nino (2008).

In the development of genetically inspired algorithms it is not appropriate to attempt partial or total reconstruction of the immune system. It is more appropriate to use the path of developing pragmatic models inspired by the immune system, preserving the primary biological characteristics that are amenable to computational implementation and effective in the development of engineering tools Castro, De Castro, and Timmis (2002a); Hunt et al. (1999).

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 Forrest, Perelson, Allen, and Cherukuri (1994), 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's technique is based on the pattern recognition exerted by the biological immune system in the recognition of T lymphocytes that occurs in the thymus

F. P. Lima, Lopes, Lotufo, and Minussi (2016); Merizio et al. (2020). The diagnostic system of the algorithm consists of two phases: The Censor phase and Monitoring; as illustrated and shown by Fig. 1.

In the Censor phase, sets of detectors are created. This set of vectors will constitute the baseline, which stores the normal operating data of the system and will be used later by the AIS to detect failures in real time comparing it with the rotor data, discriminating own/non-own signals, in the Monitoring. 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 Castro et al. (2002a); F. P. Lima et al. (2016).

In the censorship module, as shown on the left in Fig. 1, a signal is chosen at random and has its correspondence checked with the baseline. If the affinity between these is higher than the calculated affinity rate, the signal is rejected and a new signal is analyzed, otherwise the signal is stored at the set of damage detectors F. P. Lima et al. (2016); Outa et al. (2020).

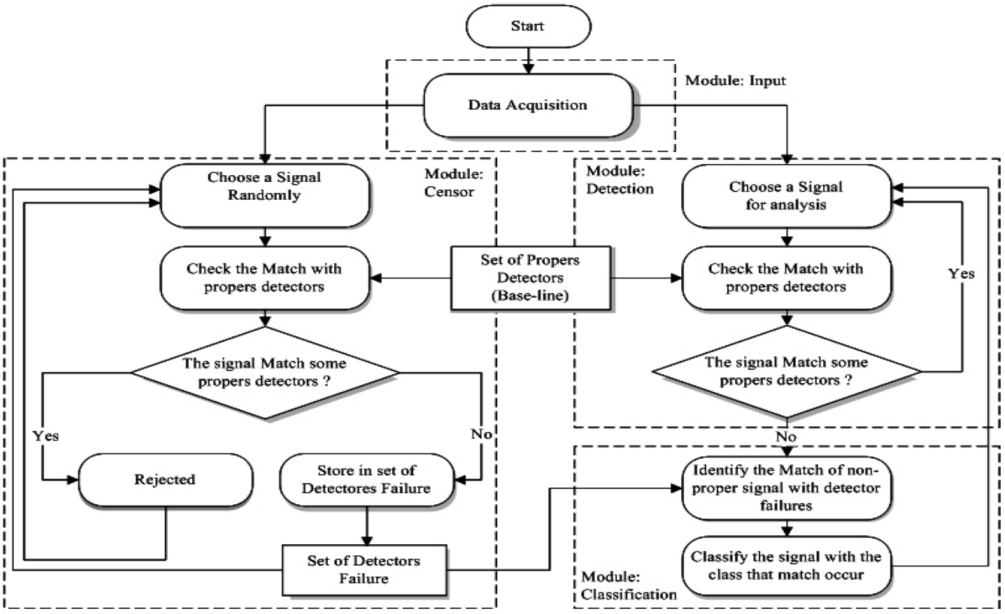

Figure 1: Flowchart of the censo phase and monitoring of the NSA. From Parra dos Anjos Lima, Chavarette, Silva Frutuoso de Souza, et al. (2014)

In this work, ClonalG was applied precisely in the Censoring Module stage, generating new signals based on those provided for the analysis, in order to insert greater diversity into the system. That is, the baseline is not exactly composed by the structure's signals, but by the antibodies generated by ClonalG that have better affinities with the antigens provided by the NSA in the first stage.

To the right of the Fig. 1, after the acquisition of the signals, the detection module is executed, where the signals being analyzed are compared with the own detectors, performing to analyze the marriage between the signals. If the signal is close enough to the baseline (affinity higher than the calculated affinity rate), the system skips to the next signal. Otherwise, an abnormal situation is detected and this signal will go to the classification module F. P. Lima et al. (2017); Merizio et al. (2020).

Finally, in the classification module, the signals selected in the previous step are compared with the damage detectors, in order to perform the signal classification F. P. Lima et al. (2017).

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 Oliveira et al. (2019); Outa et al. (2020):

$$TAf = \frac{An}{At} * 100 \quad (1)$$

Where:

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

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

A partial match occurs when a predetermined amount of positions between signals has the same value. This amount is called the affinity rate. A perfect match occurs when all signal positions have the same values, is both are perfectly equal Merizio et al. (2019).

In this work was use the partial marriage criterion proposed by Bradley and Tyrrell (2002) and a 12% deviation in the proper detectors.

2.2 Clonal Selection Algorithm

The adaptive immune response is the base of the Clonal Selection Algorithm (ClonalG), originally proposed by De Castro and Von Zuben (2000). The affinity maturation process and the principle of clonal selection proportional to affinity are the pillars of ClonalG's work.

When a human with non-defective adaptive immunity is exposed to an antigen, some his cells subpopulations, derived from bone marrow, called B lymphocytes, respond by producing antibodies (Ab). Each cell secretes only one type of antibody, which is specific for the antigen. The antigen connects with the B lymphocyte receptor and, after a second signal from accessor cells (such as the TH cell), the antigen stimulates the B cell to divide and turn into terminal cells of the type secretory of antibodies, called plasma cells De Castro and Von Zuben (2000); De Oliveira, Chavarette, and dos Anjos Lima (2020).

As De Castro and Von Zuben (2000) says, in ClonalG the maintenance of memory cells works independently of the repertoire. With the most stimulated cells, selection and repro- duction (cloning) occurs. For the least stimulated cells, only death. Then, with clones with higher antigenic affinities, affinity maturation and hypermutation proportional to cell affinity occur. After this process, these clones are re-selected and re-added to the initial group, on condition that 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. 2.2 Castro, De Castro, and Timmis (2002b); De Oliveira et al. (2020); F. P. Lima et al. (2016):

1. *Initiation:* Is randomly generated the population of antibodies (Ab) composed of Ab = Ab{m} + Ab{r} with N lymphocytes for each of the antigens (Agj), where N is the sum of M plus R;
2. *Affinity rating:* Is determined an affinity vector between each (Agj) and the lym- phocytes in the population (Ab).
3. *Selection:* Aiming to compose a subpopulation Abj {n} ulation Ab the n antibodies with greater affinities;, are removed from the population *Ab* the *n* antibodies with greater affinities;
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 (Agj);

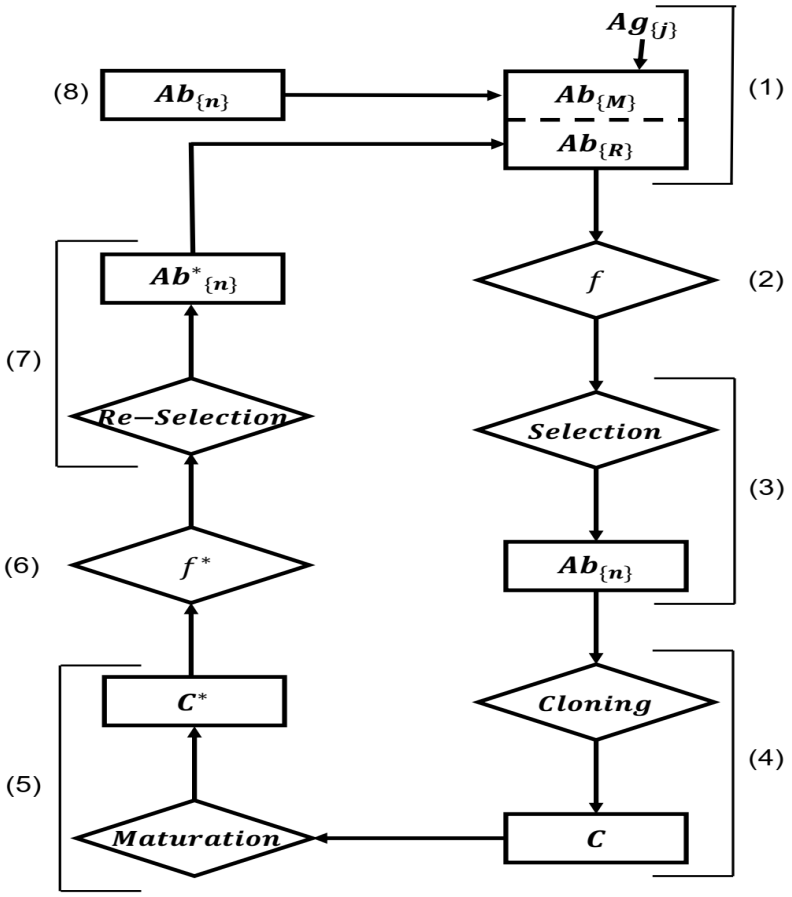

Figure 2: Flowchart of the Clonal Selection Algorithm for the pattern recognition problem

7. *Re-selection:* From this mature population C*, re-select the n best antibodies, the subset Ab{n}, in order to be candidates for entering the memory set Ab{m}. 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:* D of the antibodies with lower affinities of R are chosen to be replaced by D new individuals, inducing diversity in the repertoire.

The process from steps 2 to 8 is repeated until the stop criterion is reached.

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

Clonal G was implemented in the NSA censorship module after the signals be selected randomly in the initial phase, with (Agj) antigens entering in the ClonalG. What the NSA receives from ClonalG to make the classification is precisely the population of Ab antibodies.

II. DESCRIPTION OF THE TEST RIG SETUP

The database used was collected by the NSF I/URC Center for Intelli- gent Maintenance Systems (IMS – www.imscenter.net) and is available on the NASA website (https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/) entitled Bearing Data Set.

The experimental table consists of a shaft connected to an AC motor with constant speed (2000 RPM) where 4 oil-lubricated double roller bearings (Rexnord ZA-2115) are installed. On the 2 central bearings a radial load of 6000 lbs is applied by a spring mechanism. Four highly sensitive accelerometers are used for data set. In Fig. 3 it is possible to see the diagram of the rotor.

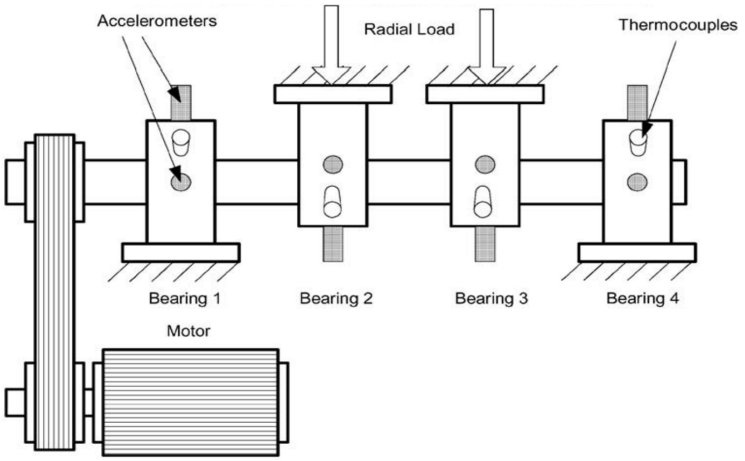

Figure 3: Bearing test rig and sensor placement illustration. From Qiu et al. (2006)

The data set was collected using PCB 353B33 High Sensitivity Quartz ICP accelerometers installed one on each bearing. The failures are expected after exceeding the life of the bearing project, with more than 100 million revolutions. Data collection was facilitated by NI DAQ Card 6062E Qiu et al. (2006).

Data were collected from an experimental table. The experiment was run until one of the bearings failed, which occurred after approximately 44 days. The vibration data is collected at 20 kHz for a second from accelerometers installed on each bearing housing once every twenty minutes. The data has 20,480 points at each recording with sampling rate of 20 kHz. The proposed bearing failure detection algorithm is applied to the collected data. The failure occurred in bearing 3, which develops an outer race defect.

The choice of applying the algorithm to the data collected from the lubricated bearings is due to this being a classic and well-known dynamic vibrational set, which further enables the ability to generate the system for more specific dynamic applications.

IV. RESULTS

4.1 AIS without optimization

From the application of the AIS in the database for fault detection, the following results were obtained: Of the 6321 experimental collections, the rotor was detected in a normal situation in 6076 of them. 6066 is the right number of normal signals. The signs identified as failure were: 6002, 6068 to 6107, 6109 to 6128, 6130 to 6134,6136, 6137 and 6144 to 6319. Of these, 1 is the number of false positives and 11 the number of false negatives. That is, the system issued a fault alert on signal 6002, which should be classified as a normal signal, and 11 fault signals were classified as normal. The hit rate of the AIS was 99.922%, using a affinity rate calculated of 95.98%. 5.0% of normal signals were used to compose the baseline, with 2.0% deviation over each signal; as explained by Bradley and Tyrrell (2002); F. P. Lima et al. (2016) the proposed deviation is adopted in order to make the process more dynamic and efficient. In contrast, the higher the deviation, the higher the risk adopted. Deviations between 0.5% and 10% are commonly adopted.

The catastrophic system failure occurred on March 17 at 8 pm and 22 minutes, and the first failure alert was issued at signal 6068 (on March 16 at 8 am and 2 minutes), followed by 39 other alerts (more that 6 consecutive hours of alert), in other words: The first real fault alert was issued more than 36 hours before the system stopped. The first ”false failure” signal was issued 17 hours before detection by AIS.

The Tab. 1 table shows the percentages of affinity between each signal and the baseline. Signals 1000 to 1001 are an example of AIS's behavior in classifying normal signals, while signs from 6068 to 6072 are examples of classification that AIS detected as a failure and from 6289 onwards the catastrophic failure occurred.

Table 1 shows how high the affinities are, and higher than the affinity rate, in normal signals, and the affinity reduction behavior the closer the fault is.

4.2 AIS with ClonalG optimization

ClonalG was developed and applied in the NSA Censor phase. As stated in Section 2, the ClonalG algorithm finds the lymphocytes that are closest to the antigens provided by the system. In other words, ClonalG identifies the curves as close as possible to the structure data under normal conditions.

Figure 4.2 presents the convergence graph of ClonalG in the NSA Censor phase, where it can be seen that after 25 iterations, there are no major changes in convergence (absolute distance between the antibodies and the antigens presented).

The application of ClonalG to optimize the NSA generated the following results: From the universe of 6321 data collections, the rotor was detected in a normal situation in 6077. Faults were detected between signals: 6068 to 6081, 6083 to 6119, 6121 to 6131, 6133 to 6137 and 6144 to 6319. Of the signs mentioned, there were no false positives and there were 11 false negatives. As a final result, the fault detection accuracy increased to 99.928%.

That is, an improvement of less than 0.01%. However, the use of ClonalG allows important changes in the NSA parameters, for example: There was a 50% reduction in the percentage of normal signals used to compose the base-line, previously 5% of normal signals were used, 2.5% are now used. Besides that, there was 70% reduction in the deviation used, before it was 2% and now the percentage has been reduced to 0.6%. Physically, the use of less data by the NSA directly means greater robustness of the AIS, and the use of a smaller deviation provides greater security in operations.

The cost of this greater reliability is the need more processing power and available memory, and the algorithm optimized with ClonalG can take up to 68% more time than the previous one to complete the processing on the same hardware.

Table 2 shows the affinities between signal and the lymphocytes indicated by Clon- alG in the Censor phase of the NSA.

Comparing Tab. 2 with Tab. 1, it can be verified that there were practically no changes between the two cases. This is justified due to the size of the data set and the ratio of normal signals to the number of total signals be high. When using better data set, the affinities found by the optimized system are slightly higher than before.

Table 1: Affinities calculated by AIS for each signal in relation to baseline

Signal number	Position 1 (%)	Position 2 (%)	Position 3 (%)	Position 4 (%)
1000	99.80	99.12	99.41	99.51
1001	99.61	99.61	99.90	99.41
1002	99.80	99.32	99.32	99.80
1003	99.80	99.02	99.61	99.12
1004	98.63	99.51	99.32	99.32
1005	98.04	99.12	98.83	98.73
1006	99.22	99.32	99.71	99.80
1007	99.80	99.90	99.80	99.41
1008	99.90	99.71	99.71	99.32
1009	99.41	99.90	99.51	99.12
6068	99.71	99.02	94.33	95.99
6069	99.61	99.12	95.11	97.65
6070	99.12	99.12	93.55	96.48
6071	99.41	99.12	95.11	96.38
6072	99.51	99.61	95.01	96.48
6289	99.02	95.60	79.08	98.14
6290	99.61	98.44	74.68	94.04
6291	95.70	85.43	61.39	69.89
6292	88.37	87.00	37.73	88.37
6293	86.31	86.02	35.48	87.59

4.3 Failure location by AIS

The fault location was performed using the minimum deviation method. The median of standard deviations was calculated, which was calculated from the failure signals detected in relation to the baseline.

Table 3 shows the respective calculation for each sensor.

The higher the result, the higher the distance between the values of the signals from that position in relation to the values in the same position of the baseline and the closer the fault accelerometer is. AIS correctly identified the location of the failure in the case presented in position 3. When applying the same method to others data set with others fault positions, AIS has always identified the location of the failure with an excellent safety margin.

As an example of that described, Tab. 4 presents the results of the fault location for another data set of a rotor also with 4 bearings and 4 accelerometers, where the fault is in position 1. Being correctly identified by the AIS.

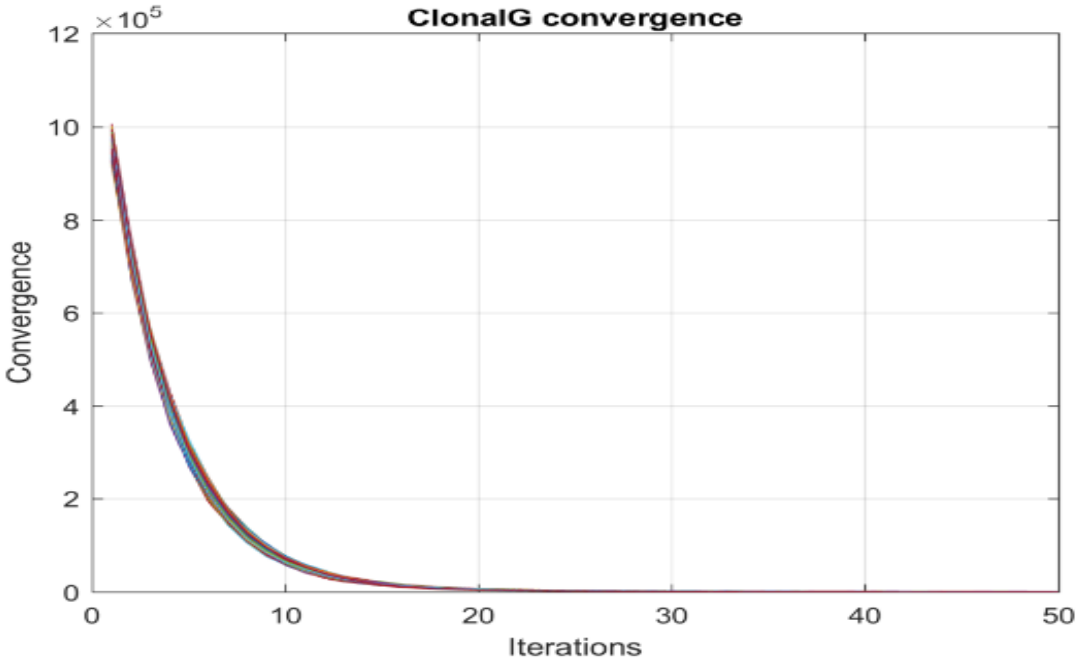

Figure 4: ClonalG convergence graph

V. CONCLUSIONS

The failure detection performed by the AIS based on the NSA was able to predict the occurrence of the failures with a good safety margin. The application of this type of technique in the monitoring of the health of instrumented dynamic systems allows a greater use of the useful life, indicating what is the best time to carry out the replacement without accidents occurring.

The AIS obtained a hit rate of 99.992%, issuing 1 false positive and 11 false neg- atives, of a total of 6321 signals. The predictability of the failure occurring started more than 36 hours before the system stopped. In the case of optimized AIS, the hit rate increased by less than 0.01%, due to the non-detection of the false positive.

Although there are no relevant changes in the overall success rate of the AIS, it can be considered that with the optimization of the SHM by ClonalG interesting results were obtained, in the sense of there a 50 % reduction in the need for training data. Before, the system needed to know 5.0% of the normal signals in the Censor phase and, after the optimization, this number increased to 2.5%. As well as a reduction of 70% in the deviations used, being considerable reductions, which show a good optimization by the Clonal selection mechanism.

The fault location by the method of minimum deviations was successful, with more than 75% reliability in all cases analyzed (considering the distance between the deviations of the accelerometers with and without failure).

Genetic algorithms proved to be an interesting tool in the monitoring of structures used in Mechanical Engineering, being a robust and reliable method for the detection and localization of failures.

Table 2: Affinities calculated by AIS for each signal in relation to the lymphocytes selected by ClonalG

Signal number	Position 1 (%)	Position 2 (%)	Position 3 (%)	Position 4 (%)
1000	99.90	99.71	99.71	99.90
1001	99.71	99.61	99.71	99.80
1002	99.80	99.51	99.51	99.71
1003	99.71	99.90	99.71	99.71
1004	99.90	99.71	99.61	99.90
1005	99.80	99.12	99.41	99.61
1006	99.71	99.80	99.90	99.32
1007	99.61	99.80	99.51	99.12
1008	98.83	99.51	98.83	99.41
1009	99.90	99.12	98.83	98.83
6068	99.22	99.22	94.92	96.68
6069	99.80	99.41	95.01	97.65
6070	99.32	99.02	93.84	96.87
6071	99.51	99.02	94.92	96.58
6072	99.71	99.51	95.01	95.21
6289	98.92	96.29	79.86	98.44
6290	99.61	98.63	75.17	94.13
6291	96.19	89.35	64.42	73.22
6292	91.30	91.40	43.60	91.79
6293	87.39	88.47	37.24	89.54

Table 3: Fault location using the minimum deviations method

Position 1 (%)	Position 2 (%)	Position 3 (%)	Position 4 (%)
68.230	95.571	437.560	104.516

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Disclosure statement

The authors declare that they have no conflict of interest.

Table 4: Fault location performed in another data set

Position 1 (%)	Position 2 (%)	Position 3 (%)	Position 4 (%)
292.497	51.211	59.476	38.194

Data availability statement

The data used are available at:https://ti.arc.nasa.gov/tech/dash/groups/ pcoe/prognostic-data-repository/.

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