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ART-2 UNSUPERVISED NEURAL NETWORK FOR DAMAGE CLASSIFICATION IN STRUCTURAL HEALTH MONITORING IMPEDANCE-BASED

Stanley Washington Ferreira de Rezende

stanley-washington@hotmail.com

Bruno Pereira Barella

brunobarella@hotmail.com

Renan Garcia Rosa

renangarcia@gmail.com

Robson Medrado de Oliveira

robsommedradooli@gmail.com

José dos Reis Vieira de Moura Júnior

zereis@ufg.br

Mathematics and Technology Institute – Federal University of Goiás

Abstract. *This work aims to present the use of the ART-2 Neural Network in the intelligent diagnosis of structural failures. For this, the technique of impedance-based structural health monitoring is used in order to inspect a hydraulic pipeline composed of PVC pipes. A simulated damage by mass addition was inserted near the influence range of the PZT patch, and subsequently data processing techniques as temperature compensation were applied to impedance signatures (baseline and damage) in order to identify possible misdiagnosis. After applying the ART-2 Neural Network, it can be observed that it was able to efficiently delineate the different states of pipeline integrity, being applicable to the monitoring of structural integrity.*

Keywords: *Impedance-based Structural Health Monitoring, ART-2 Neural Network, Smart Diagnostics.*

1. INTRODUCTION

The technique of the impedance-based structural health monitoring is grounded on the analysis of vibration at high frequencies. This method, initially proposed by Liang, Sun and Rogers (1997), has the ability to detect minor changes in the physical properties of a mechanical system, which may suggest the presence of damages.

Structural damage to mechanical systems can often pose major financial, human life and environmental damage. Especially, when these systems are considered critical such as pipeline system in petrochemical companies. Among the many problems generated by cracks in pipelines systems, we can mention the event that occurred in the Keystone pipeline in South Dakota, in which there was a rupture caused by its poor installation. This breakdown eventually worsened over time, leading to the critical system crash on November 16, 2017 near Amherst (JWN, 2017).

About thousands of gallons of oil have been spilled into the environment, causing significant financial and environmental damage. One way to avoid such an event would be the continuous monitoring of the entire structure through the electromechanical impedance technique, since it could help in the diagnosis of structural integrity thus avoiding the critical failure through the use of predictive maintenance (Moura Júnior, 2008).

The basic concept of the technique consists of monitoring the mechanical impedance of some structure, and for that, the variation of the electrical impedance of a transducer coupled it is evaluated. Changes in the mechanical impedance values of a structure can be caused by changes in mass, stiffness or damping parameters.

Aiming to perform the monitoring step, the technique usually uses piezoelectric materials (PZT patch) in which it is possible to emphasize its direct and inverse effect. When the piezoelectric material is subjected to a mechanical strain, it will generate a potential difference between its poles (direct effect) thus allowing its use as a sensor. However, when the piezoelectric material is subjected to a potential difference, it will strain causing a vibration in the structure (inverse effect) that allows the use of the transducer as an actuator (Leucas, 2009).

In order to collect the impedance signatures, the direct and inverse effects of the piezoelectric materials must be used simultaneously. That is, an alternating potential difference over a certain frequency range must be applied for excitation of the structure in order to obtain its frequency response function (FRF). This is then stored and used for future quantitative and qualitative assessments (Farrar *et al.*, 2003).

An appropriate structure-transducer coupling and by using the studies of Liang, Sun and Rogers (1997) on the admittance equation, it is possible to identify the presence of damage by varying the dynamic parameters of the system. The admittance equation formulated by Liang, Sun and Rogers (1997) can be expressed as Eq. (1)

$$Y(\omega) = i\omega a \left(\left(\epsilon_{33}^T (1 - i\delta) \right) - \left(\frac{Z_s(\omega)}{Z_s(\omega) - Z_a(\omega)} * \hat{Y}_{xx}^E * (d_{3x})^2 \right) \right) \quad (1)$$

where $Y(\omega)$ is the electrical admittance of the PZT transducer, $Z_a(\omega)$ and $Z_s(\omega)$ are the mechanical impedance values of the PZT patch and the structure respectively, \hat{Y}_{xx}^E is the Young's modulus for an electric field E , d_{3x} is the piezoelectric coupling constant in the direction of strain x , a is the geometric constant of the transducer, ϵ_{33}^T is the complex dielectric constant of PZT and δ is the dielectric loss tangent.

Although the SHM technique for electromechanical impedance has proved to be efficient in the structural integrity studies, some disadvantages can still be observed depending on the types of equipment used in its implementation. The sampled signals can be influenced by noise arising from poor connection of the wires used for coupling of the transducers, as well as by temperature variations during the experimentation stage (Bastani *et al.*, 2012).

Temperature changes can influence the diagnosis of structural failures, making the system false-positive. Diagnosis correspond to positive indications of damage, even if there is no structural failure in the monitored system. Thus, filtering and temperature compensation processes are indispensable practices for obtaining reliable diagnoses (Rabelo, 2014).

Diagnostics of structural failures using the electromechanical impedance technique are commonly based on quantitative and qualitative analysis the vibration signatures. In order to obtain a qualitative analysis, the displacements of the resonance peaks are commonly observed (Rabelo, 2014).

Displacements at the structural resonance peaks are due to the increase of punctual rigidity in the structure, which may originate from the presence of damage. In order to obtain a quantitative analysis, the so-called damage metrics are commonly applied. These, aiming to facilitate the distinction between the integrity states of the system are commonly presented in the form of a boxplot graph.

Among the main metric types used efficiently in the literature, the main is called Root Mean Square Deviation (RSMD) (Palomino, 2008). This is expressed as Eq. (2)

$$RSMD_i = \sum_{i=1}^n \sqrt{\left(\frac{[Re(Z_{r,i}) - Re(Z_{t,i})]^2}{[Re(Z_{r,i})]^2} \right)} \quad (2)$$

where $Re(Z_{r,i})$ is the real part of the reference signature (baseline) and $Re(Z_{t,i})$ is the real part of the test signature (Sun *et al.*, 1997). However, when the metric values are dimensionally very close, the separability of these can become a complex task, requiring the application of techniques capable of intelligently distinguishing statistical results.

Among artificial intelligence (AI) techniques widely used in the recognition and classification of statistical data are those based on artificial neural networks (ANNs). The present contribution has the objective of demonstrating the use of the ART-2 type neural network supported by the impedance-based structural health monitoring (Gomes, 2017).

Such a network architecture has been shown to be of particular interest in classification and dimensionality reduction research such as (Barszcz *et al.*, 2014), mainly due to their capacity for self-organization and their dynamic learning form.

Thus, a PVC pipeline system is instrumented to simulate different conditions of damage close to the area the PZT patch influence. Signatures of electromechanical impedance are then gathered and treated by filtering and temperature compensation techniques, since these were damaged by natural or experimental factors (Huynh and Kim, 2016).

After the treatment step, the RMSD damage metric was applied aiming to generate statistical values for recognition, training and simulation of the neural network ART-2. The results show the application potentiality of the method.

2. ART-2 NEURAL NETWORK

The neural networks based on the Adaptive Resonance Theory (ART) are unsupervised learning models capable of decoding and recognizing stable patterns in real time. For this, a process of incremental self-organization of their synaptic weights is performed, in response to random sequential data obtained at various moments of the training and simulation phase (Gomes, 2017).

The ART networks were developed in order to overcome the problems of stability and plasticity of classical ANNs. That is, to enable a network's ability to learn new values as they are presented to it, without the knowledge already acquired in previous stages (training) being forgotten (Nachev and Hill, 2010).

The architecture of the network is composed of two fields of n neurons, one of recognition (also called attention subsystem) and one of comparison (called orientation subsystem), a parameter ρ of surveillance and a module θ of redefinition (Barszcz *et. al.*, 2014). Figure 1 shows a diagram of the network topology of type ART-2.

The recognition field consists of three or more layers of resonant or adaptive neurons, of which the synaptic weights associated with the interconnections of the last two layers are called *bottom-up* and *top-down* (Muchoney and Williamson, 2001). Bottom-up weights are associated with non-recurrent feedforward interconnects, while top-down weights are associated with backpropagation of information for the compensation of synaptic weights.

Both types of these weights relate to the network's ability to store information for a long term (Long Term Memory - LTM). However, the activity patterns developed internally in each of the layers of the ART network are related to the Short Term Memory (STM) of this network (Senger and Gouveia, 2010).

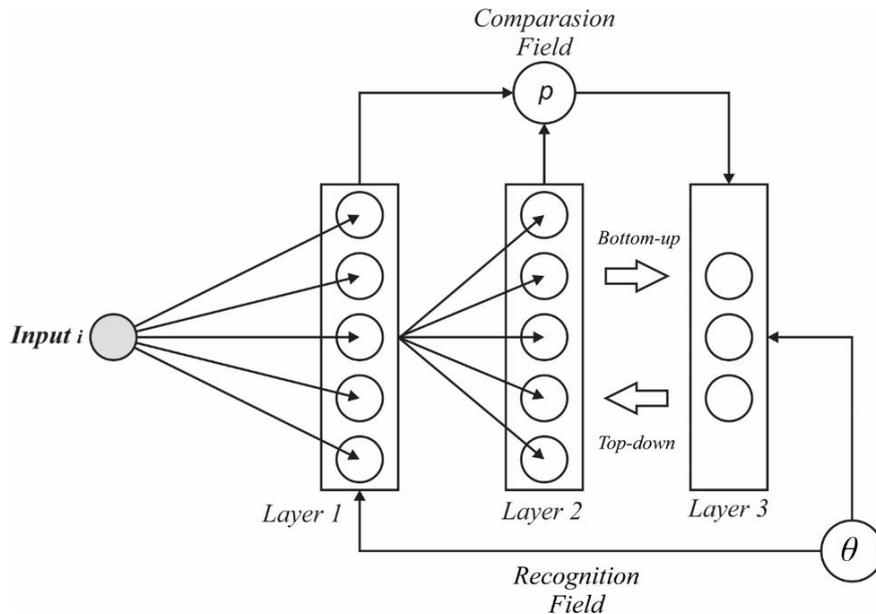


Figure 1. ART-2 neural network architecture.

Once new input values are sampled to the comparison field, it rates them according to the closest proximity neuron, i.e., the *best match unit* (BMU). For this, the Euclidean distance between the input vector and each neuron of the evaluated layer is commonly used (Carpenter, Grossberg and Reynolds, 1991).

After the classification phase, the module θ compares the acceptance intensity of each neuron with the vigilance parameter. If the intensity is greater, a new training step is performed and the neighboring neuron weights are updated (Carpenter and Grossberg, 1987).

If the intensity is lower, it is inhibited and a step of searching for a new winning neuron is performed. Finally, the iterations are concluded with the activation of a randomly chosen neuron, when none of the neurons are larger than the ρ parameter (Matias and Neto, 2018; Gomes, 2017).

In general, the ART architecture delimits different output vectors whose dimensions are the same as those of the input patterns, and each response vector will represent a new grouping of the input data, that is, a new cluster (Senger and Gouveia, 2010; Müller, 2018). This possibility of automatic creation of clusters during the training phase is what distinguishes type ART-2 networks from other self-organizing architectures present in the literature, such as Kohonen maps and Hopfield networks (Affonso, 2011).

3. EXPERIMENTAL PROCEDURE

The experimental procedure was performed in order to identify different integrity conditions of a PVC pipeline (3/4" diameter) coupled to a hydraulic pump. For the simulation of failure conditions, a strategic section of the pipeline was instrumented in order to simulate the possible states of the structure.

Initially, a pristine pipeline condition was monitored to be as a baseline for subsequent statistical tests. Then, three other distinct integrity conditions of the structure were equally evaluated.

For the coupling of the PZT patch in the structure used, a connector in PLA material was made by 3D printing and subsequently this was affixed in sections of the PVC pipes by means of Nylon clamps. The acquisition system for the collection of impedance signatures was composed of an Eval AD5933EBZ card and a PZT patch buzzer type (0.22x0.06mm).

The acquisition card used has internally the CI AD5933, of which the board is able to gather both the magnitude and the phase of the electromechanical impedance signatures. The board communicates with the computer through a USB connection, and this communication is performed through the software "AD5933 Evaluation Board Software Rev. B".

Figure 2 a) and b) illustrate, respectively, the structure and the acquisition system (PLA connector, PZT patch and Eval AD5933EBZ card) adopted in the experimental procedure of this contribution.

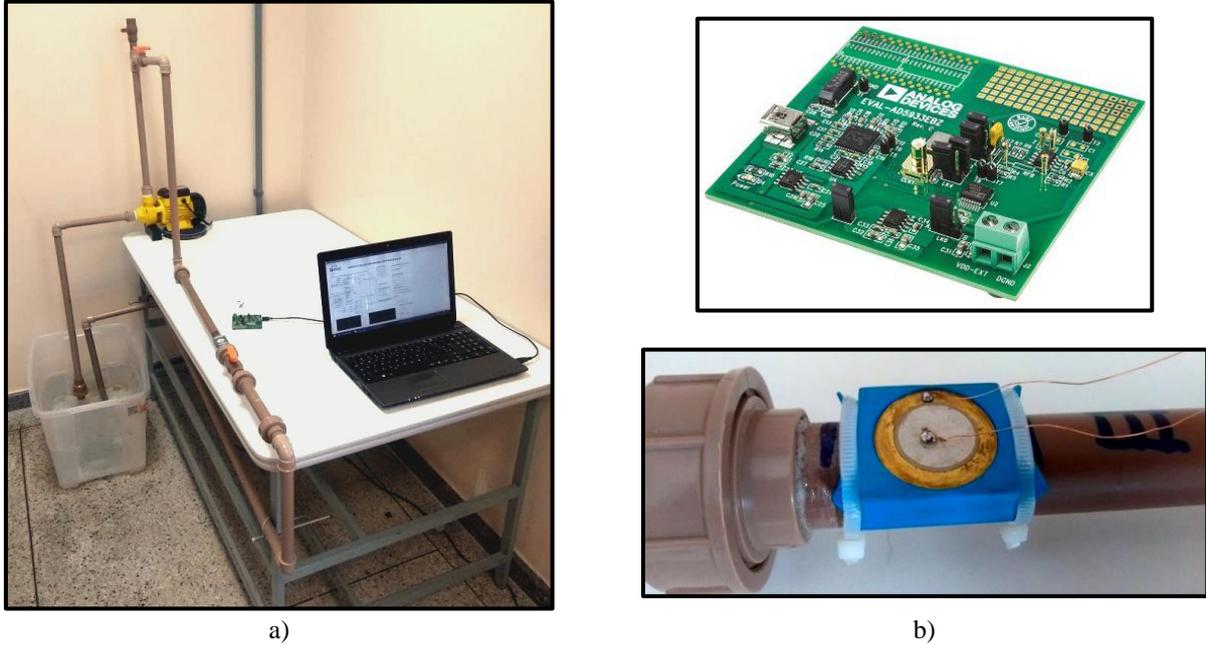


Figure 2. Pipeline structure (a) and acquisition system (b) used in the experimental procedure.

For the simulation of failures, three identical sections of PVC pipes (550mm length by $\frac{3}{4}$ " diameter) were used in order to define different conditions of integrity to the system. The first damage condition is characterized by uneven wear of the inner wall of the sampled tube.

The second and third failure conditions are characterized by the addition of mass to the system in order to simulate two possible clogging situations. Condition 2 considered adding 8g of Durepoxi to the pipe sample while Condition 3 considered the addition of a tissue filter, located at the junction of the pipe near the PZT patch.

Figure 3 shows the relation between PVC pipe samples and simulated damage conditions in the experimental phase.

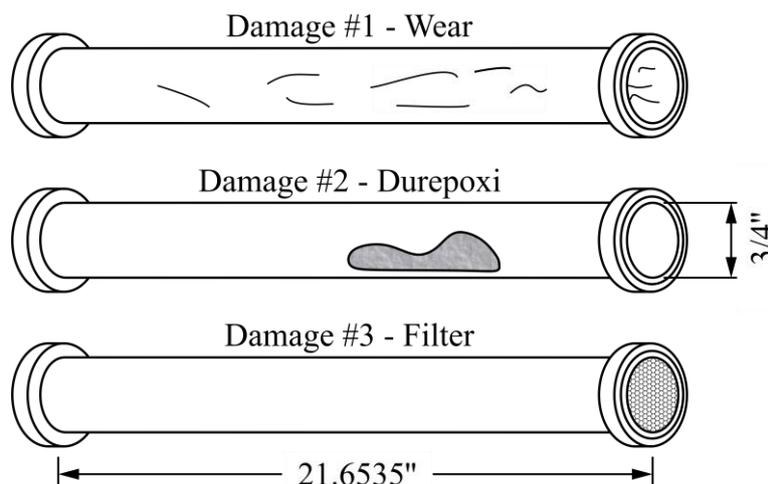


Figure 3. Relation between the pipe samples and the simulated integrity conditions.

The impedance signatures were monitored in a frequency range of 10-100 kHz with a step of 19.57 Hz and a total of 4608 sampling points. For these collections, the direct and inverse effects of the PZT patch was used simultaneously, where an alternating voltage of 2 V_{pp} was applied on the PZT patch and then the dynamic response is collected by the acquisition system.

In all, 10 signatures were collected for each level of severity, baseline and three damage conditions, thus totaling a set of 40 impedance samples. After the collection step, the signatures were treated by filtering techniques (low pass filter) and temperature compensation (Rabelo, 2014) in order to minimize possible errors of analysis.

The filtering method employed in this contribution is the application of a fourth order Butterworth digital filter, which achieves an excellent approximation of the passband as opposed to a wide transition range. The Butterworth filter type is low pass filter with a cutoff frequency of 0.3, according to the Nyquist rate. The implementation of the filter followed the steps described in (MathWorks, 2019).

For temperature compensation, the Effective Frequency Displacement by Correlation Analysis method was used, which has the ability to compensate for impedance signatures both vertically and horizontally. For this, the method aims to maximize the correlation coefficient between a fixed signal and a signal to be compensated, making in each iteration a relative displacement in the impedance signatures (Rabelo, 2014).

After data preprocessing, the damage metric was calculated for each sample. Then, an ART-2 neural network was implemented computationally in Matlab® in order to intelligently identify and classify the different states of the structure.

Aiming to create a non-biased computational classifier, an ART-2 type neural network was trained with eight metric values of each severity level (80% of samples), and these were chosen at random. After the creation and training steps of the network, it was then simulated with the two remaining metrics (samples 2 and 9) and with a surveillance ρ value of 0.90.

4. RESULTS AND DISCUSSION

After applying the filtering and temperature compensation techniques on the samples data, it can be observed that the impedance signatures and damage metric indices became more normalized, thus avoiding possible diagnostic errors due to natural factors and noises. Figure 4 shows the means of the samples of each severity level before and after the filter and compensation steps, as well as their respective metric sets.

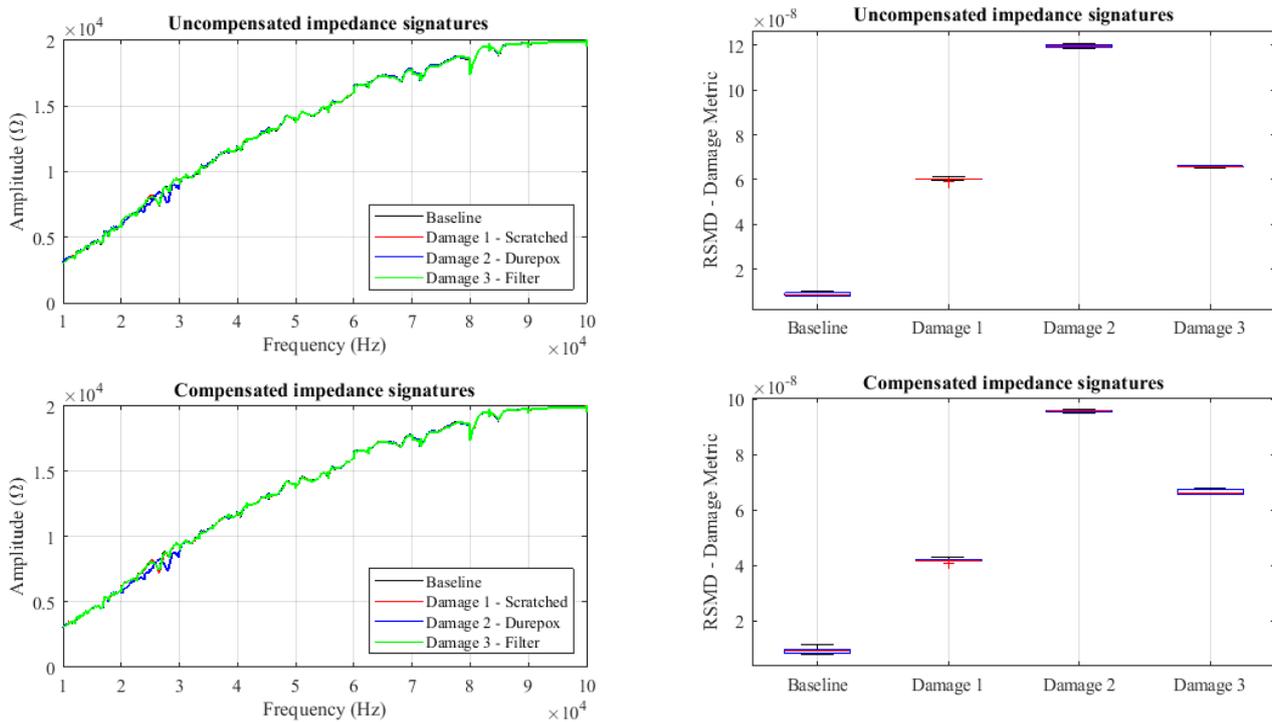


Figure 4. Means and metric values of the data sets sampled in their respective acquisition groups.

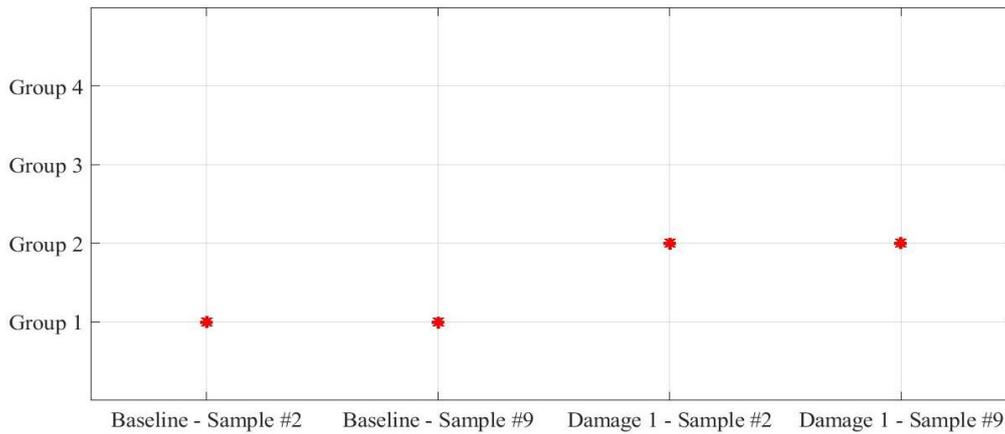
Figure 4 also shows that the electromechanical impedance technique allows for the identification and qualitative classification of the states of the structure, since the occurrence of displacement of the resonance peaks as well as the linear separability of the metric sets sampled.

After the impedance signatures preprocessing step and the RSM-D metric were performed for each sample, 8 metric values of each severity level were randomly chosen in order to use them for the training process. The metric values chosen for the network training phase are shown in the white cells in Table 1.

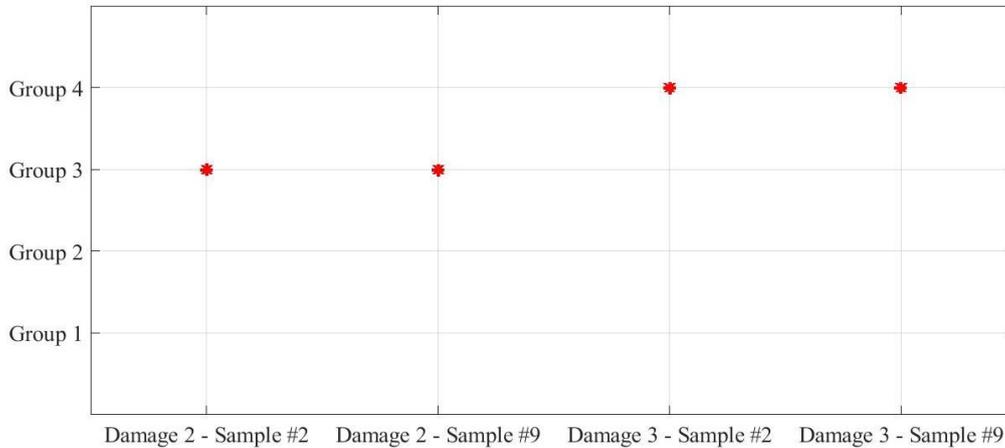
Table 1. RMSD metric values used to build ART-2 neural network.

	Samples									
	1	2	3	4	5	6	7	8	9	10
Baseline	0,1116	0,1142	0,0890	0,0816	0,0830	0,0823	0,0877	0,0980	0,0995	0,0948
Damage #1	0,4167	0,4168	0,4072	0,4181	0,4220	0,4298	0,4199	0,4272	0,4227	0,4189
Damage #2	0,9580	0,9608	0,9616	0,9614	0,9576	0,9539	0,9591	0,9510	0,9491	0,9573
Damage #3	0,6770	0,6668	0,6803	0,6790	0,6653	0,6571	0,6608	0,6598	0,6550	0,6563

In order to verify the network classification potentiality in the structural integrity analysis, the remaining metrics values (samples 2 and 9) were used for the simulation phase, which are presented in the gray cells in Table 1. Figure 5 a) and b) presents the results of the classification obtained after the simulation of the ART-2 network.



a) Set 1 - Baseline and Damage 1



b) Set 2 - Damage 2 and Damage 3

Figure 5. Result of the ART-2 network simulation step for randomly selected samples from each state (Samples two and nine of each set).

The network used in this work classified the different metric values in their respective groups. In this way, it can be seen that it was able to distinguish the different integrity conditions of the structure under study. In addition, it is noticed that during the simulation and training step of the ART-2 network, it begins to create new classes of grouping as new categories of data are presented to it.

Such functionality enables not only the classification of data at specific levels, but also the identification of possible outliers. Therefore, the technique presented in this contribution evidences the applicability of the ART-2 type neural network in the monitoring of structural integrity during the evaluation phases.

5. CONCLUSION

From the network simulation made with real metric values, It can be observed that the ART-2 neural network was able to efficiently delineate the different states of pipeline system integrity, being applicable to the structural health monitoring under the presented conditions.

6. ACKNOWLEDGEMENTS

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