PAPER REF: 4028

LOCATING AND QUANTIFYING DAMAGES IN 3-D FRAME USING RESIDUAL ERROR METHOD AND NEURAL NETWORKS

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RESUMO

Two methods were used for damage identification in 3-D frames models. The first step was to locate such faults by the Residual Error method, which is based on changes in the dynamic properties of structural models. In the second part of this work the technique of Artificial Neural Networks trained with Backpropagation algorithm was used in order to quantify the damages located at first step. The numerical analysis showed that both methods presented satisfactory results since they allowed locating and quantifying the damages present in the structural models.

Keywords: Dynamic Characteristics, Damage, Residual Error Method, Artificial Neural Network.

INTRODUCTION

With the evolution in the techniques of structural design and the use of lighter and more resistant materials, the structures are being more required both in the aspects of comfort and safety as well as the best use of places. Such factors generate the search for more slender and flexible structures, what turns them more susceptible to the actions of static and dynamic character which may cause deterioration, excessive vibrations or even being the cause of the structural collapse.

In consequence of those factors, studies have begun in order to search adequate ways to do structural monitoring including to locate and to quantify damages. At first, there were techniques of ray-X, ultrasonic and magnetic resonance, however these were onerous practices and, in a certain way, with a big demand of time. Besides that, these methods do not always supply satisfactory results.

Developing faster methods with low costs and applicability to structure in general in order to structural health monitoring are desirable. Among such methods, those based on study of the dynamic characteristics (natural frequencies, mode shapes and modal damping values) should be mentioned.

As it is known damage causes a stiffness reduction in the structures, so the methods based on the dynamic properties consider this fact (Adams *et al.* 1978). In this way such methods use the alterations the dynamic parameters caused by damages.

Some works has been developed in this sense, such as:

Adams *et al*. (1978) proposed a method based on the changes in dynamic characteristics to identify damage in structures. The authors showed how vibration measurements made at a single location in the structure could be used, in conjunction with a theoretical model, to indicate both the location and magnitude of the damage.

Allemang and Brown (1982), and Lieven and Ewins (1988) proposed the indexes MAC (Modal Assurance Criterion) e COMAC (Coordinate Modal Assurance Criterion) capable to analyze changes between mode shapes of the intact and damaged structures. The COMAC compares mode shapes in a point-wise manner giving the possibility of locating damage in a structure. The MAC is a global index of damage detection.

Pandey *et al*. (1991) also used the changes in mode shapes produced by damage. They formulated a method which uses the difference in the curvature mode shapes between the intact and damaged case to detect the location of damage in a structure.

Hearn and Testa (1991), observed that normally the damage present in a structure are characterized by a local loss of stiffness and mass but the effect of stiffness in an extent is much greater than the mass. The loss of stiffness can be expressed as a reduction in the geometrical and/or physical properties of the structural component. The latter may be caused by chemical processes implying in the reduction of the Young's Modulus.

Wu *et al*. (1992) used the Artificial Neural Network (ANN) technique for the identification of damages in the structure. The net Backpropagation was trained with numeric data of accelerations, to the which FFT was applied. They were supplied, as data of entrance of the net, the accelerations in the domain of the frequency and the exits were the identifications of the damages. After the stage of generalization of the net, the study showed that the net got to learn the structural behavior as for the presence of damages, however, in more complex cases, they should be made alterations in the data of entrance of the net.

Elkordy *et al*. (1993) used a neural network to diagnose damage. In this work the authors used an analytical model and experimental vibration for answers. They used three backpropagation networks, which have as input data in the training process, the percentage differences between the frequencies of structures with different damage states. The networks were tested with data from experimental model and showed good results, so they were able to correctly identify the damage.

Based on Adams *et a.l.* `conclusion (1978) that the stiffness loss caused by damage in the structure produces alterations in the natural frequencies and in their respective mode shapes, Genovese (2000) proposed a method to locate and quantify damages in structures based on the error in the movement equation of the intact structure where this error was produced by the mode shapes and natural frequencies of the damage structure. This method named the Residual Error Method (REM) was extended to other types of structures by Brasiliano (2001) and Marcy *et al*. (2012).

Gomes (2004) used the ANN technique with Functions of Radial Base to obtain information of possible damages in a simple supported beam. Still making use of ANNs, Genovese (2005) proposed an hybrid method, which combines the REM (Genovese, 2000, Brasiliano *et al*., 2004) with ANNs so that they can be located and quantified damages in structures. That technique consists of the use of the Method of the Residual Error for locating and of the ANNs for quantifying the damages.

In this work, the REM, proposed by Genovese in 2000, was extended to be applied in order the localize damages in 3D-frame models. From the results obtained by the REM, the Artificial Neural Network technique was used to quantify the damages previously located.

RESIDUAL ERROR METHOD

The Residual Error Method - REM (Genovese, 2000) is used to identify damage present in a structure. This method is based on the alteration, produced by damage, in the dynamic properties of structures.

The identification is done in two steps, the location and quantification of the damage. The location is done by observing the error present in the modal equation (Equation 1).

$$\mathbf{E} = \boldsymbol{K\phi'} - \boldsymbol{\Lambda' M \Phi'} \tag{1}$$

$\boldsymbol{M}$ →Mass matrix of the structure intact;
$\boldsymbol{K}$ →Stiffness matrix of the structure intact;
$\boldsymbol{\Phi'}$→Matrix of damaged mode shapes;
$\boldsymbol{\Lambda'}$→Diagonal matrix of natural frequencies of the damaged structure;
E→Matrix in which values represent the error produced by damage in the movement equation.

$$\mathbf{E} = [\boldsymbol{e}_1 \boldsymbol{e}_2 \boldsymbol{e}_3 \dots \boldsymbol{e}_n]_{(Nxn)} \tag{2}$$

$$\boldsymbol{\Phi'} = \left[\boldsymbol{\phi'}_1 \boldsymbol{\phi'}_2 \boldsymbol{\phi'}_3 \cdots \boldsymbol{\phi'}_{\boldsymbol{n}}\right]_{(Nxn)} \tag{3}$$

$$\boldsymbol{\Lambda'} = \begin{bmatrix} \omega_1'^2 & 0 & 0 & \dots & 0 \\ 0 & \omega_2'^2 & 0 & \dots & 0 \\ 0 & 0 & \omega_3'^2 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & \omega_n'^2 \end{bmatrix} \tag{4}$$

Where N is the number of spatial test points n is the number of identified modes and $\boldsymbol{\phi'}_i$ is the ith mode shape vector of damaged structure.

Each column of matrix **E** is a vector corresponding to one mode shape, Equation (2). Each value of this vector represents the error that occurs in some positions of the structure. Then, the highest error value will indicate the damage position to a mode shape.

The damage quantification consists in looking for the minimum error in the modal equation by an iterative process, however, in this study the damage quantification was done by Artificial Neural Networks.

ARTIFICIAL NEURAL NETWORK

Artificial Neural Network (ANN) are computational tools inspired in the human brain and nervous system functioning. The great capacity of the biological neural system to perform complex tasks has been attributed to the parallel and distributed processing nature of the biological neurons. ANN imitates such structures where the calculus is processed through simple unities, called artificial neurons, which are interconnected to form a network.

In this work, the ANN used was the Multilayer Perceptron (MLP). The typical structure of this ANN is shown in Figure 1.

The data (X_1, X_2, …, X_n) are introduced in the input layer and the network progressively processes such data through subsequent layers, producing a result (Y_1, Y_2, …, Y_k) in the output layer. The input neurons are linked to those in the intermediate layer through α_{ji} weights and the neurons in the intermediate layer are linked to those in the output layer through ω_{kj} weights. The network maps out the relation between the input data and the output variables based on the nonlinear activation functions.

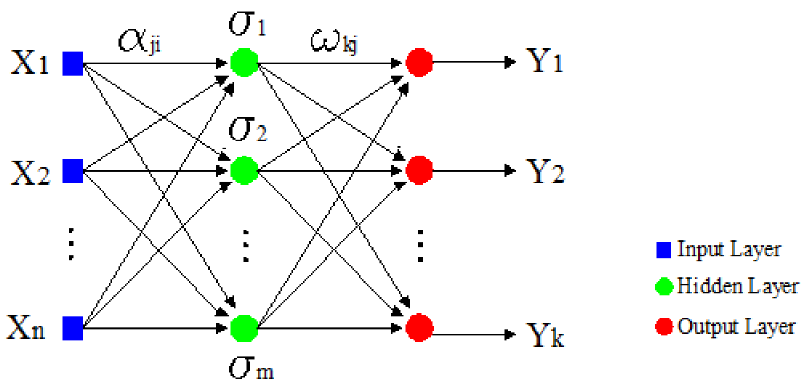

Fig. 1 MLP network one intermediate layer

Between the input and the output layers, multiple intermediate layers may be included. In theory, the increase in the number of intermediate layers improves the mapping capacity of the network. On the other hand, it significantly increases the processing time and the necessity of memory for storage due to the great quantity of weights. Works have demonstrated the use of a single intermediate layer is sufficient for an ANN to approximate any complex nonlinear function. For this reason, this was the setting used (Figure 1). The explicit correlation for the output values is given by:

$$Y_k = f_1\left(\sum_{j=1}^{S} \omega_{kj} \cdot f_2\left(\sum_{j=1}^{S} \alpha_{ji} X_i + \theta_j\right) + \theta_k\right) \tag{5}$$

in which α_{ji} is the weight connecting the ith neuron in the input layer and the jth neuron in the hidden layer, ω_{kj} is the weight connecting the kth neuron in the output layer and the jth neuron in the hidden layer, θ_j is the bias for the jth hidden neuron, θ_k is the bias for the kth output neuron, f_2 is the activation function of the nodes in the hidden layer, and f_1 is the activation function of the nodes in the output layer.

Activation functions are necessary for relating inputs and outputs of artificial neural networks. In the Figure 1 was used f_2 function for the hidden neurons and f_1 for the output layer neuron.

The determination of the ANN weights is made through a procedure called training, in which several input-output examples are presented to the ANN and its weights are iteratively modified until ANN reaches an acceptable mapping capacity, which is defined by the user. The training is performed by a back-propagation algorithm which has been successfully applied to water resources systems as well.

In this approach, the Levenberg-Marquardt (LM) algorithm was used for the back-propagation training. The LM algorithm is designed to approach second-order training speed and accuracy without having to compute the Hessian matrix. Second-order nonlinear optimization techniques are usually faster and more reliable. Nowadays, the Levenberg-Marquardt algorithm is, admittedly, the fastest for ANN training with moderate size, even requiring a superior amount of memory compared to other algorithms.

NUMERICAL ANALYSIS

This work was made in the program called MATLAB (MathWorks, R2009b) because this software has a high performance in numerical analyses, besides it provides an environment of easy utilization in the elaboration of computational codes.

In the stage concerning to the use of the Residual Error Method, computational routines were developed based on previous programs and using the equations 1 to 4 (Figure 2). The process begins with the input data including the intact and damaged discretized models. Starting from these, the dynamics properties are obtained and compared, arriving to the unbalance of the model movement equation, the called Residual Error.

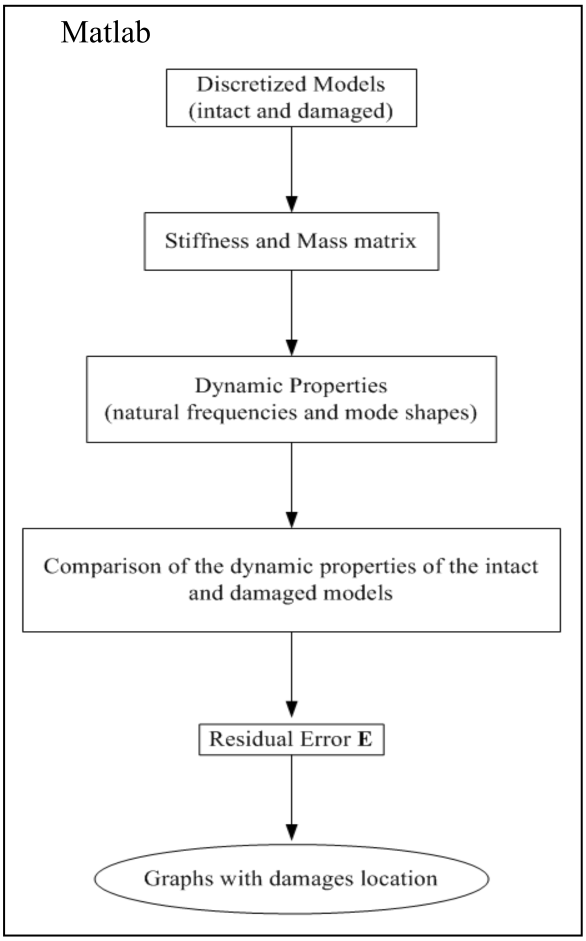

Fig. 2. Damage localization by REM.

The quantification stage, in which the ANNs were used, was also performed in the environment of Matlab, more specifically the Neural Network Toolbox package. This toolbox contains the Back-propagation algorithm, besides that it has a great reach in what concerns to the ANNs variations.

The damage quantification stage (Fig. 3) starts with the simulation of damage cases for the network training. Possessing these cases, all the previously described stages are performed for obtaining the REM errors, and used like this, together with their outputs (severity of the respective damages), as data for ANN'S training.

In this stage, the activation functions are defined as well as the neurons number of the hidden layer, in a way that it is obtained the best of ANNs acting. At the end of the training and of the validation, the process errors are known. In case of satisfactory results (good learning), the net goes to the generalization stage. In this stage, it is supplied to the net the data of the problem that has to be solved, that is, the REM errors generated by the damaged elements, of which it is being looked for the severity.

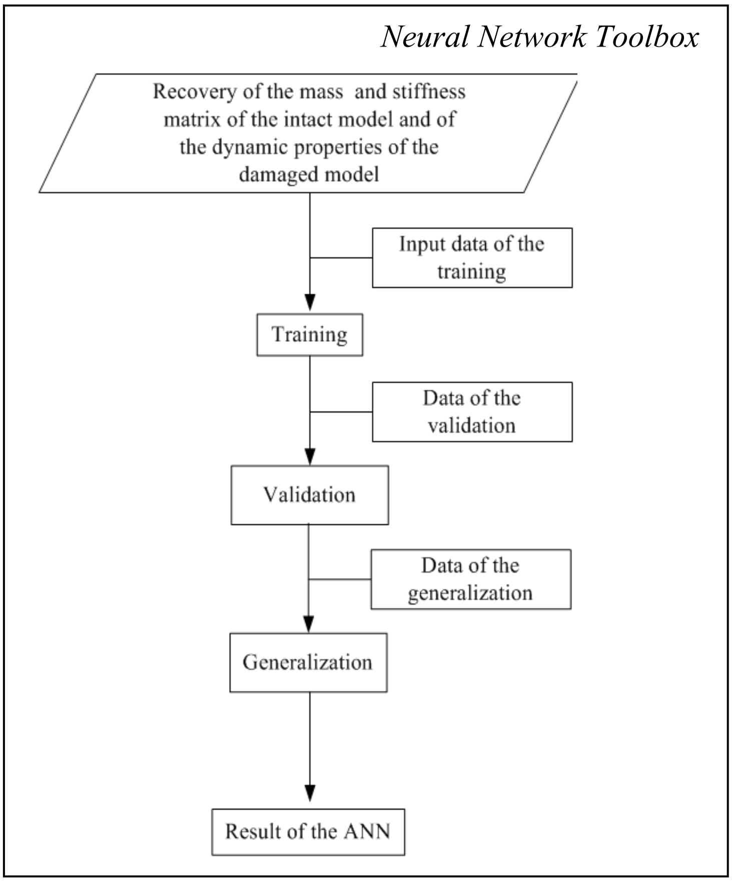

Fig. 3 Quantification stage by ANN

THE MODEL

The two methods Residual Error Method and Artificial Neural Network were applied to identification damage in 3D frame (Fig 4) with a rectangular cross-section of 0.3m x 0.3m. This frame was discretized with 1170 of 0.1m in length. Every node has six degrees of freedom (Fig 5). The properties of the 3D-frame are: cross-sectional area A=0.09m^2; moments of inertia I_x= 0.00168m^4, I_y=0.000675m^4 and I_y=0.000675m^4; Young's modulus 2.5x1010N/m²; Poisson's ratio ν=0.2; density ρ = 2500 Kg/m^3. The stiffness matrix (Gere and Weaver, 1987) and mass matrix (J. S. Przemieniecki, 1968) are defined by equations 6 and 7, respectively.

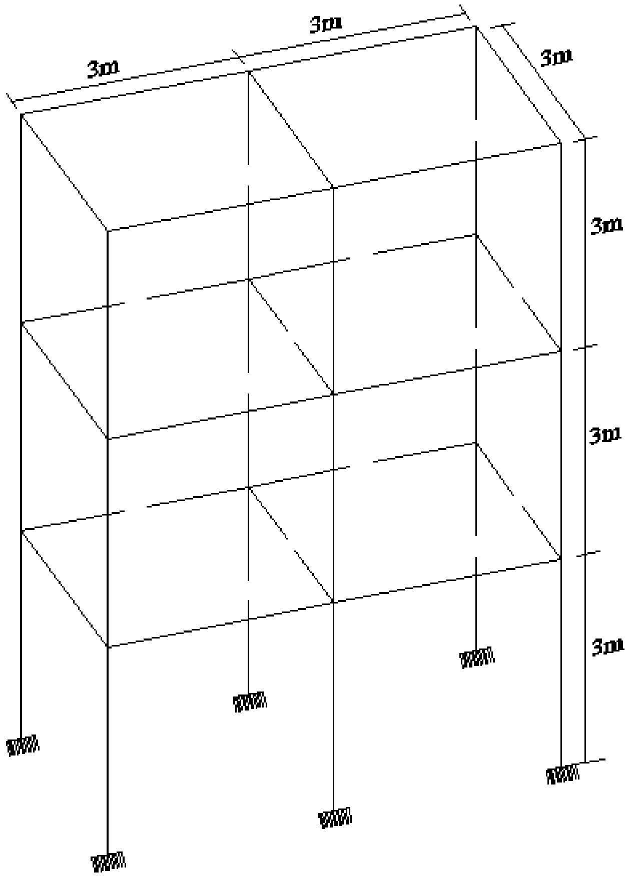

Fig. 4 – Strucutral model used

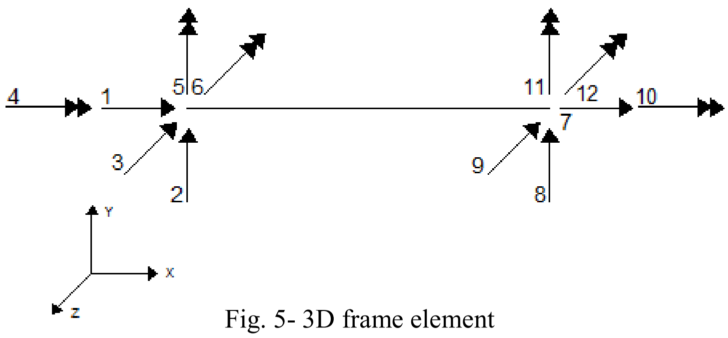

Fig. 5- 3D frame element

$$\boldsymbol{M} = \rho LA \begin{bmatrix}
\frac{1}{3} & 0 & 0 & 0 & 0 & 0 & \frac{1}{6} & 0 & 0 & 0 & 0 & 0 \\
0 & \frac{13}{35}+\frac{6I_Z}{5AL^2} & 0 & 0 & 0 & \frac{11L}{210}+\frac{I_Z}{10AL} & 0 & \frac{9}{70}-\frac{6I_Z}{5AL^2} & 0 & 0 & 0 & -\frac{13L}{420}+\frac{I_Z}{10AL} \\
0 & 0 & \frac{13}{35}+\frac{6I_Y}{5AL^2} & 0 & -\frac{11L}{210}-\frac{I_Y}{10AL} & 0 & 0 & 0 & \frac{9}{70}-\frac{6I_Y}{5AL^2} & 0 & \frac{13L}{420}-\frac{I_Y}{10AL} & 0 \\
0 & 0 & 0 & \frac{I_X}{3A} & 0 & 0 & 0 & 0 & 0 & \frac{I_X}{6A} & 0 & 0 \\
0 & 0 & -\frac{11L}{210}-\frac{I_Y}{10AL} & 0 & \frac{L^2}{105}+\frac{2I_Y}{15A} & 0 & 0 & 0 & -\frac{13L}{420}+\frac{I_Y}{10AL} & 0 & -\frac{L^2}{140}-\frac{I_Y}{30A} & 0 \\
0 & \frac{11L}{210}+\frac{I_Z}{10AL} & 0 & 0 & 0 & \frac{L^2}{105}+\frac{2I_Z}{15A} & 0 & \frac{13L}{420}-\frac{I_Z}{10AL} & 0 & 0 & 0 & -\frac{L^2}{140}-\frac{I_Z}{30A} \\
\frac{1}{6} & 0 & 0 & 0 & 0 & 0 & \frac{1}{3} & 0 & 0 & 0 & 0 & 0 \\
0 & \frac{9}{70}-\frac{6I_Z}{5AL^2} & 0 & 0 & 0 & \frac{13L}{420}-\frac{I_Z}{10AL} & 0 & \frac{13}{35}+\frac{6I_Z}{5AL^2} & 0 & 0 & 0 & -\frac{11L}{210}-\frac{I_Z}{10AL} \\
0 & 0 & \frac{9}{70}-\frac{6I_Y}{5AL^2} & 0 & -\frac{13L}{420}+\frac{I_Y}{10AL} & 0 & 0 & 0 & \frac{13}{35}+\frac{6I_Y}{5AL^2} & 0 & \frac{11L}{210}+\frac{I_Y}{10AL} & 0 \\
0 & 0 & 0 & \frac{I_X}{6A} & 0 & 0 & 0 & 0 & 0 & \frac{I_X}{3A} & 0 & 0 \\
0 & 0 & \frac{13L}{420}+\frac{I_Y}{10AL} & 0 & -\frac{L^2}{140}-\frac{I_Y}{30A} & 0 & 0 & 0 & \frac{11L}{210}+\frac{I_Y}{10AL} & 0 & \frac{L^2}{105}+\frac{2I_Y}{15A} & 0 \\
0 & -\frac{13L}{420}+\frac{I_Z}{10AL} & 0 & 0 & 0 & -\frac{L^2}{140}-\frac{I_Z}{30A} & 0 & -\frac{11L}{210}-\frac{I_Z}{10AL} & 0 & 0 & 0 & \frac{L^2}{105}+\frac{2I_Z}{15A}
\end{bmatrix} \quad (6)$$

$$\boldsymbol{K}=\begin{bmatrix}
\frac{EA}{L} & 0 & 0 & 0 & 0 & 0 & -\frac{EA}{L} & 0 & 0 & 0 & 0 & 0\\
0 & \frac{12EI_Z}{L^3} & 0 & 0 & 0 & \frac{6EI_Z}{L^2} & 0 & -\frac{12EI_Z}{L^3} & 0 & 0 & 0 & \frac{6EI_Z}{L^2}\\
0 & 0 & \frac{12EI_Y}{L^3} & 0 & -\frac{6EI_Y}{L^2} & 0 & 0 & 0 & -\frac{12EI_Y}{L^3} & 0 & \frac{6EI_Y}{L^2} & 0\\
0 & 0 & 0 & \frac{GI_X}{L} & 0 & 0 & 0 & 0 & 0 & -\frac{GI_X}{L} & 0 & 0\\
0 & 0 & -\frac{6EI_Y}{L^2} & 0 & \frac{4EI_Y}{L} & 0 & 0 & 0 & \frac{6EI_Y}{L^2} & 0 & \frac{2EI_Y}{L} & 0\\
0 & \frac{6EI_Z}{L^2} & 0 & 0 & 0 & \frac{4EI_Z}{L} & 0 & -\frac{6EI_Z}{L^2} & 0 & 0 & 0 & \frac{2EI_Z}{L}\\
-\frac{EA}{L} & 0 & 0 & 0 & 0 & 0 & \frac{EA}{L} & 0 & 0 & 0 & 0 & 0\\
0 & -\frac{12EI_Z}{L^3} & 0 & 0 & 0 & -\frac{6EI_Z}{L^2} & 0 & \frac{12EI_Z}{L^3} & 0 & 0 & 0 & -\frac{6EI_Z}{L^2}\\
0 & 0 & -\frac{12EI_Y}{L^3} & 0 & \frac{6EI_Y}{L^2} & 0 & 0 & 0 & \frac{12EI_Y}{L^3} & 0 & \frac{6EI_Y}{L^2} & 0\\
0 & 0 & 0 & -\frac{GI_X}{L} & 0 & 0 & 0 & 0 & 0 & \frac{GI_X}{L} & 0 & 0\\
0 & 0 & -\frac{6EI_Y}{L^2} & 0 & \frac{2EI_Y}{L} & 0 & 0 & 0 & \frac{6EI_Y}{L^2} & 0 & \frac{4EI_Y}{L^2} & 0\\
0 & \frac{6EI_Z}{L^2} & 0 & 0 & 0 & \frac{2EI_Z}{L} & 0 & -\frac{6EI_Z}{L^2} & 0 & 0 & 0 & \frac{4EI_Z}{L}
\end{bmatrix} \tag{7}$$

Table 1 Physical properties of the model

Youg's modulus	E=2.5x10^{10}N/m^2
Density	ρ = 2500 Kg/m^3
Poisson's ratio	ν = 0.2

Three damaged cases were analyzed with only one damaged element. The damages were introduced by a reduction in the area of the elements. In the first case (Fig 6(a)) the element 91 (located between nodes 61 and 92) had reduction of area of 20% in the section, which equates to loss of 38%, 49% and 20% of moments of inertia I_x, I_y and I_z. In the second case (Fig 6(b)) was considered a reduction of area of 40% in the section of element 870 (located between nodes 449 and 861), which equates to a loss of 68%, 79% e 40% of moments of inertia.

Table 2 Damage cases

Case	Damage element	Area reduction (%)
1	91	20
2	870	40
3	1141	10

In the third damaged case (Fig 6(c)) the element 1141 (located between nodes 1127 and 1097) had a reduction of 10% in the cross-section which corresponds to a loss of 68%, 79% and 40% in the moments of inertia x, y and z respectively.

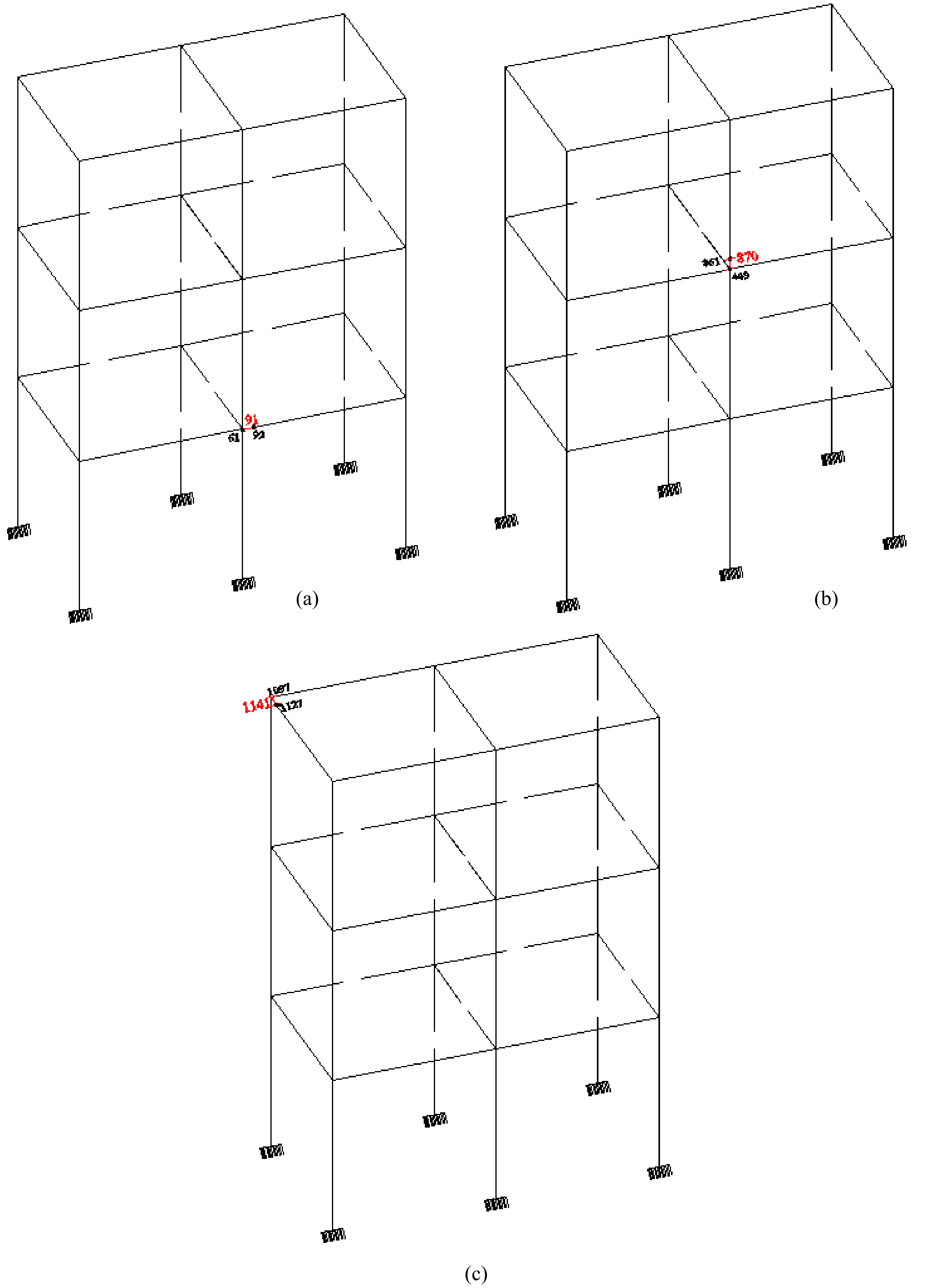

Fig. 6 Damaged Cases.

RESULTS

Table 3 shows the first five natural frequencies of the intact and damaged models corresponding to the three scenes of damage considered in this study. Figure 7 presents the respective natural mode shapes from the intact model.

Table 3. First five natural frequencies from the intact and damaged models.

Frequencies	Intact Model (Hz)	Damage Case 1 (Hz)	Damage Case 2 (Hz)	Damage Case 3 (Hz)
1ª	2.1828	2.1823	2.1828	2.1829
2ª	2.6498	2.6471	2.6481	2.6493
3ª	5.8514	5.8506	5.8509	5.8508
4ª	7.1029	7.0987	7.0985	7.1024
5ª	7.4549	7.4555	7.4311	7.4447

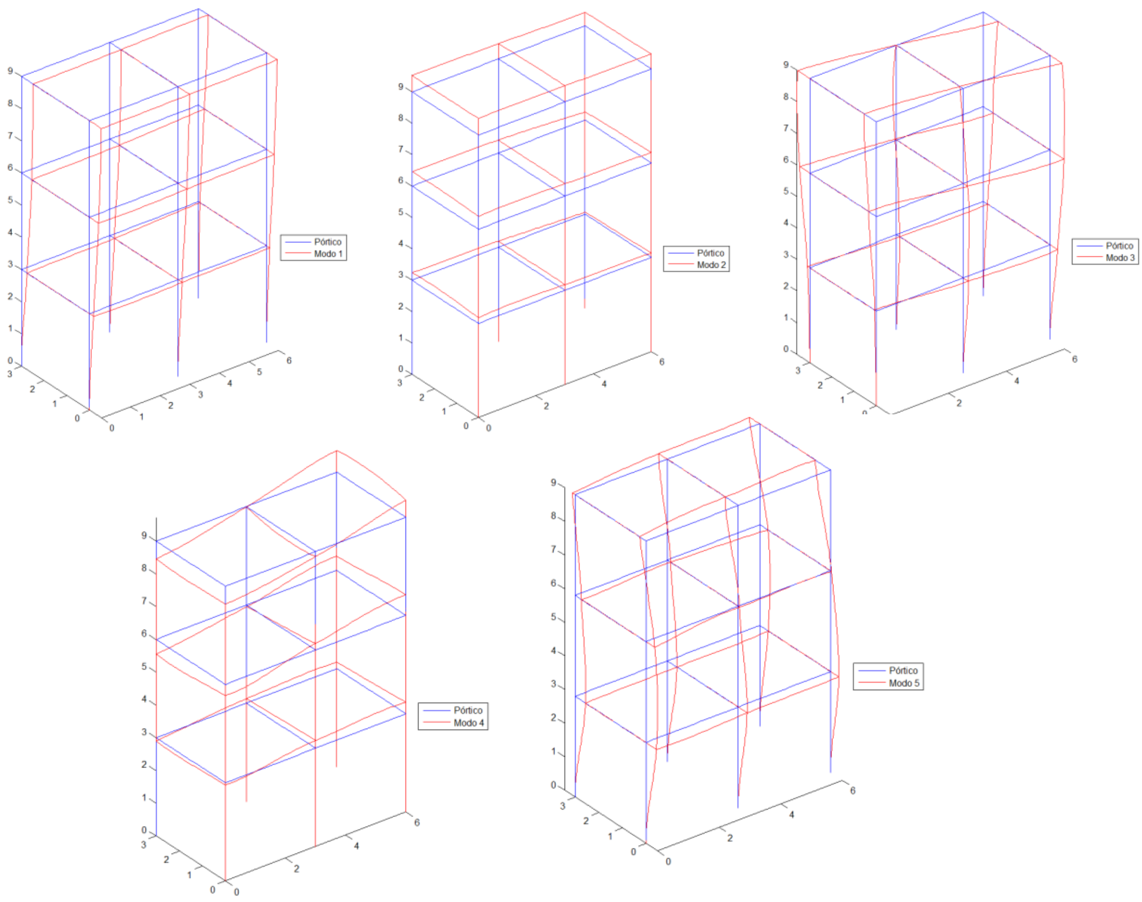

Fig. 7. First five natural mode shapes of the intact model.

The REM was applied to the identified dynamic properties in order to locate the damaged regions represented by the elements 91, 870 and 1141. The quantification of the damages was done by the ANN method. Figures 8, 9 and 10 show the results corresponding to the localization of the damaged elements.

The results present in the Figure 9 represent the case 1 which corresponds to the initial reduction of area of 20% in the section of the element 91. This element is located between nodes 61 and 92. Observing the Figure 9 it is possible to verify that peaks of the residual error in the movement equation appears at nodes 61 and 92 which define the damaged element 91. It happens for the all natural mode shapes considered.

Figure 10 shows the results obtained from the application of the REM for the damage case 2 which correspond to an area reduction of 40% in the section of the element 870. This element is defined by the nodes 449 and 861. The same pattern is repeated for this case. The peaks of the residual error in the movement equation appear at nodes 449 and 861 which define the damaged element in this case.

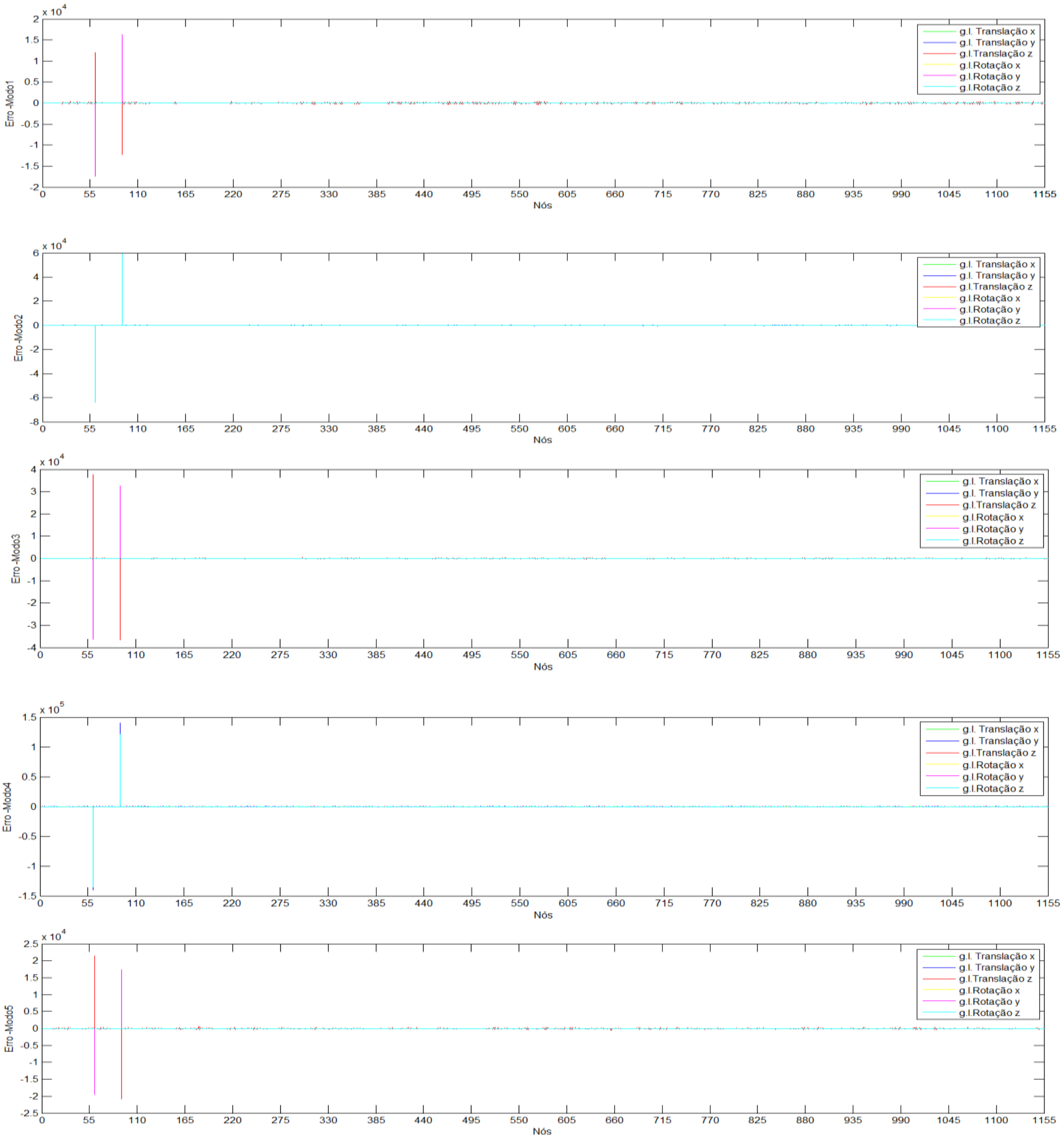

Fig. 8 Residual Error Function for the first five natural mode shapes – Case 1.

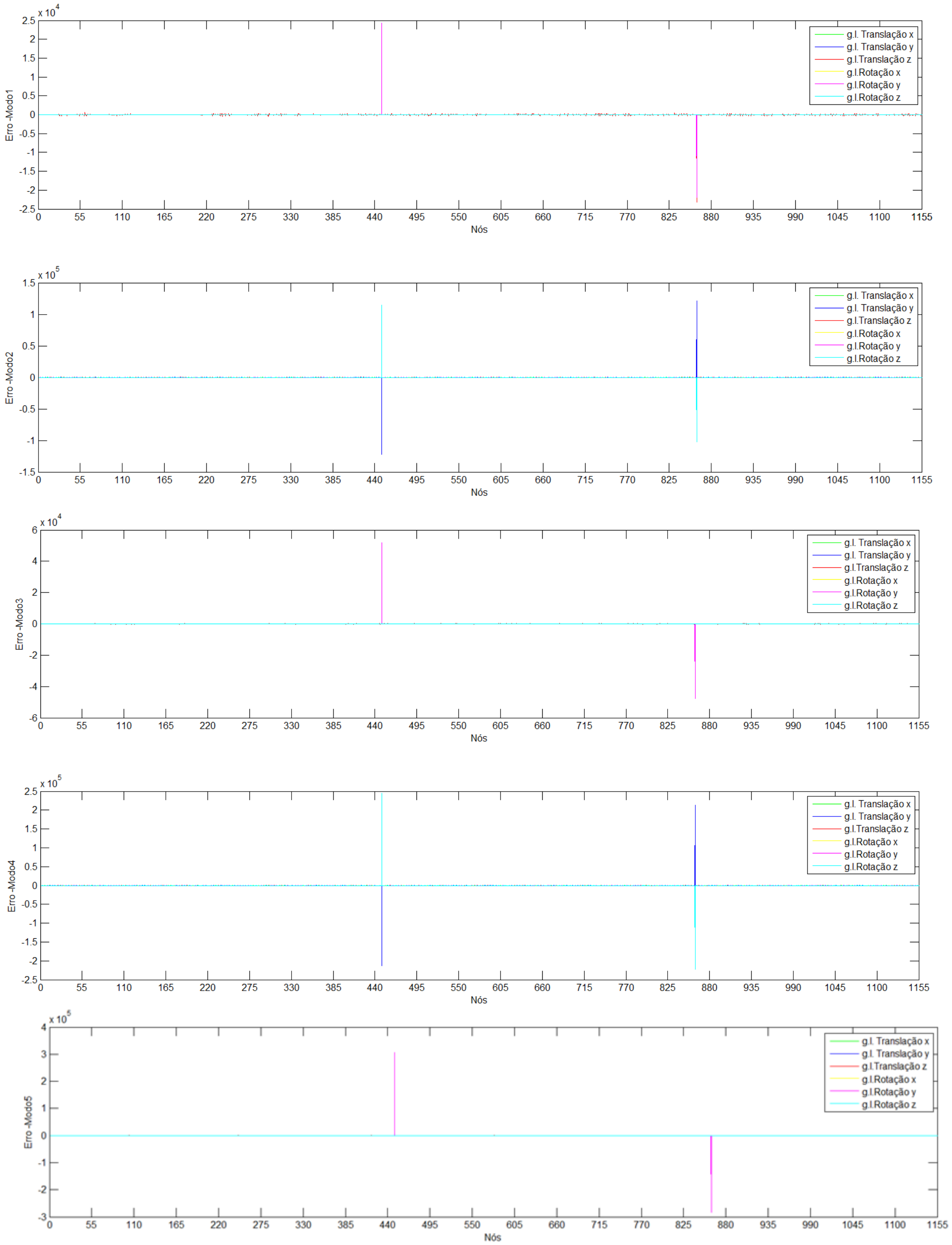

Fig. 9 Residual Error Function for the first five natural mode shapes – Case 2.

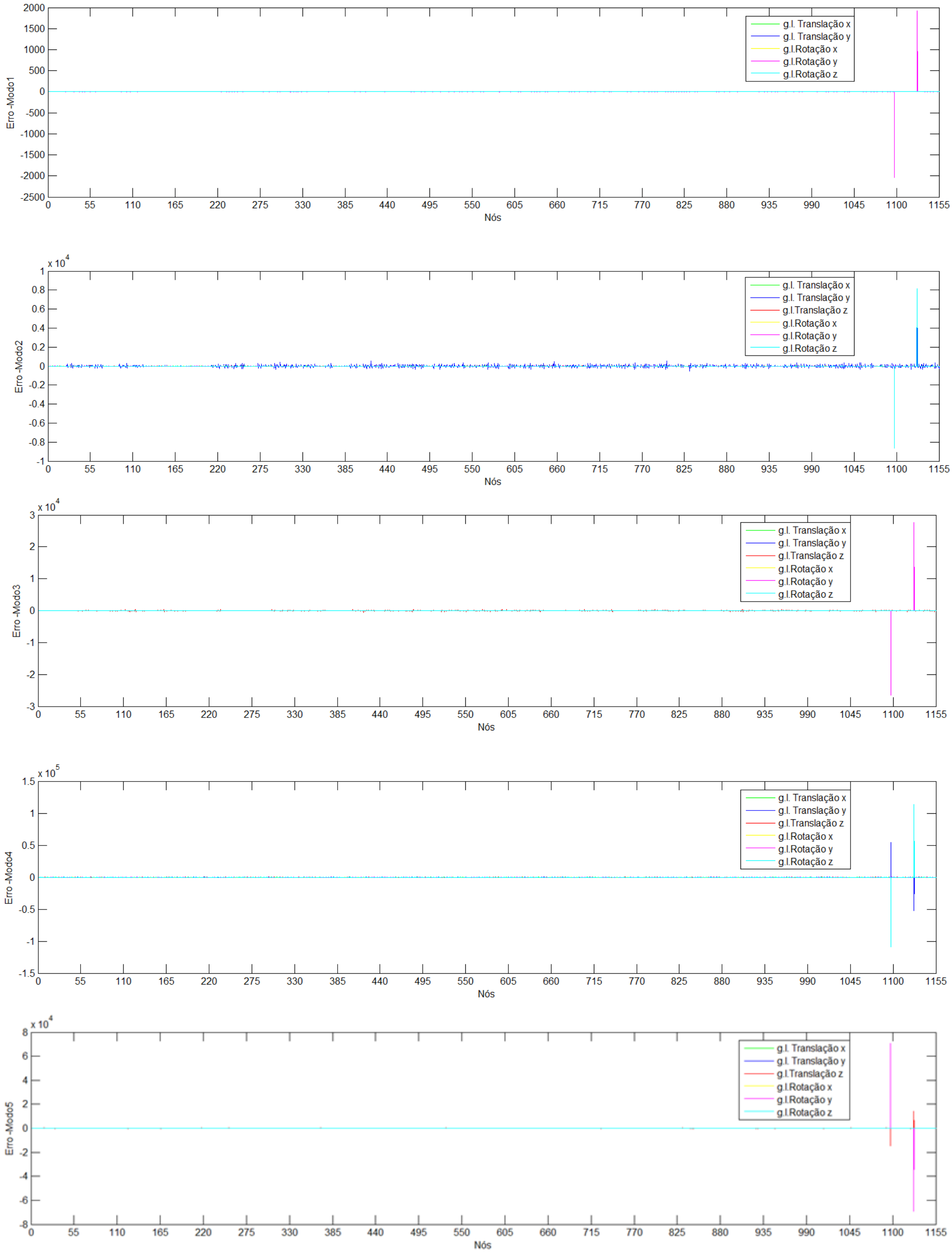

Fig. 10 Residual Error Function for the first five natural mode shapes – Case 3.

The third case of damage corresponds to an initial area reduction of 10% in the section of the element 1141 which is located between nodes 1097 and 1127. As in the other two cases considered, the results present in Figure 11 show that the damaged element could also be identified by the REM.

As mentioned previously, the damage quantification step was done by ANN technique. A network with three layers (input layer, intermediate or hidden layer and output layer – Figure 11) was created in order to solve the problem of damage quantification. The input layer was formed by five neurons which were fed by the errors found applying the REM (Equation 4).

The hidden layer was composed by nine neurons. Such number of neurons was chosen because it allowed a better performance of the network. The output of the network must be the quantification of the damage, so the correspondent layer was formed by only one neuron. As can be seen in Figure 11, the three layers were related in order to process only one result.

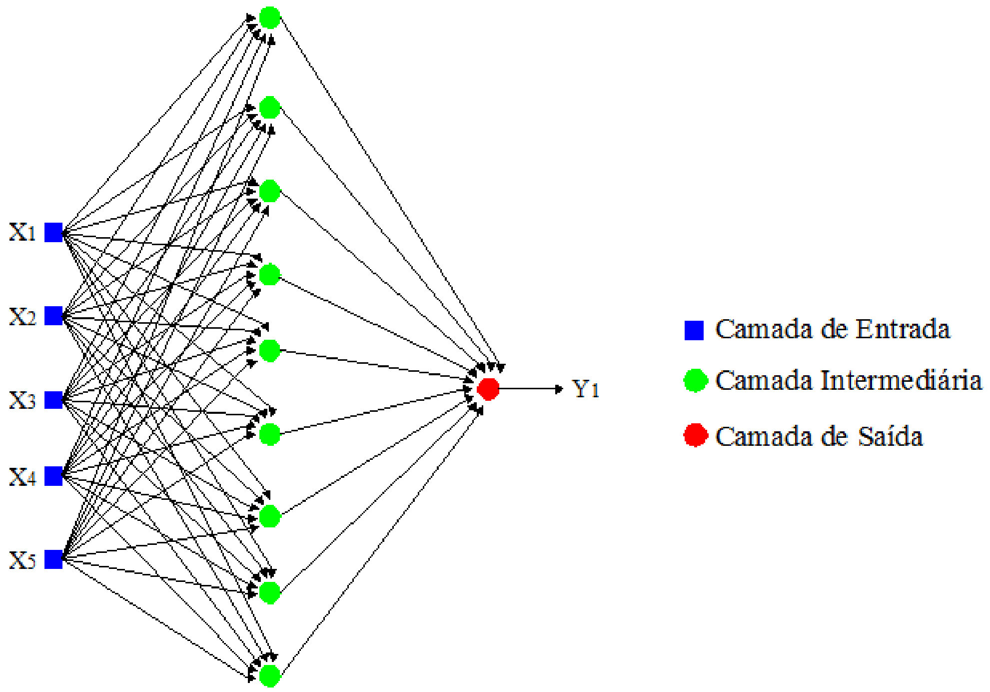

Fig. 11 Artificial Neural Network applied to quantify the damages in the considered model.

Between the input and the hidden layers the Tansing function was used. The Satlins function was used between the hidden and the output layers. Such functions were randomly chosen in order to obtain a better performance of the network. The Tansing (*Hyperbolic tangent sigmoid*) and the Satlins (*Symmetric saturating linear*) functions are represented in the figures 12 (a) and (b), respectively. Figure 13 shows a schematic illustration of the network structure.

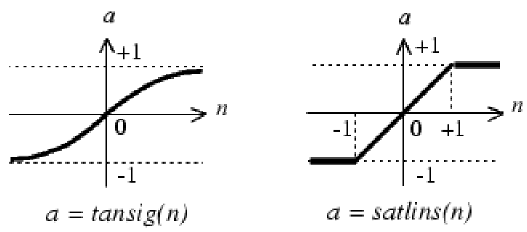

Fig. 12 Activation functions used in the Artificial Neural Network. (a) Tansing Function; (b) Satlins Function. (MathWorks, R2009b)

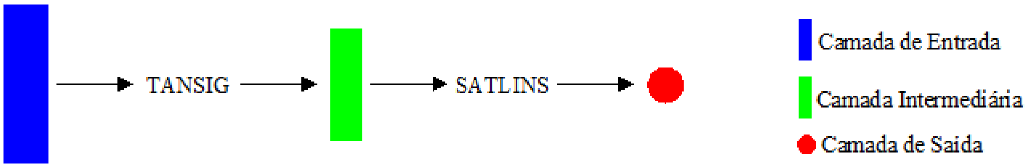

Fig. 13 Schematic illustration of the Artificial Neural Network used to damage quantification.

For the network training and validation, different damaged cases were simulated. These cases are shown in tables 4 and 5 and Figure 14. In a first step the REM were applied to damaged cases considered in order to provide the inputs and outputs of the neural network.

Table 4 Damaged cases used in the neural network training.

Damaged Cases	Damaged Elements	Damage (%)
6	60	1
7	60	5
8	60	10
9	31	20
10	31	25
11	30	30
12	30	40

Table 5 Damaged cases used in the validation of the neural network.

Damaged Case	Damaged Element	Damage (%)
13	391	45

Once training and validation data were provided, the network was applied and the errors obtained during the training iterations were about 10^{-25}. So, it can be verified that the network found the relation between the input (residual errors from the Residual Error Method) and output (quantification of the damage) data.

After the training and validation, the network, with ajusted weights, is now on the stage of generalization. In this fase, it was provided to ANN the data about the localization of the damages of the damage cases 1 (20% damage on element 91), 2 (40% damage on element 870) and 3 (10% damage on element 1141), data obtained through the Residual Error Method.

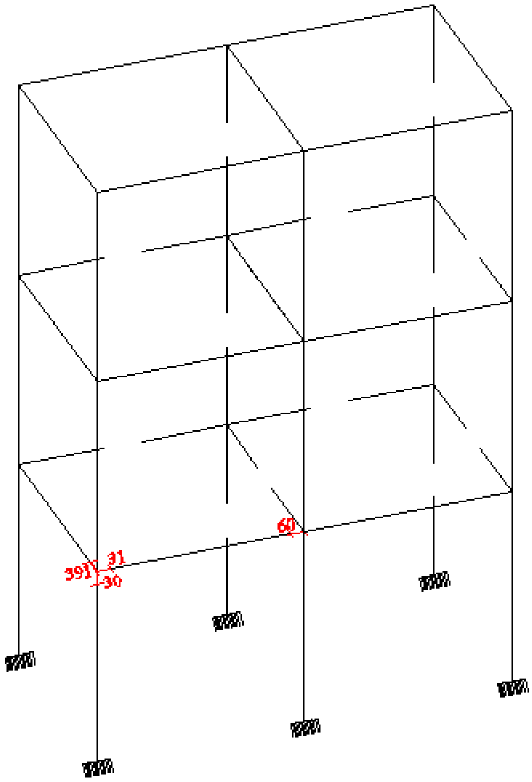

Fig. 14 Locations of the damages used in the training of the Artificial Neural Network.

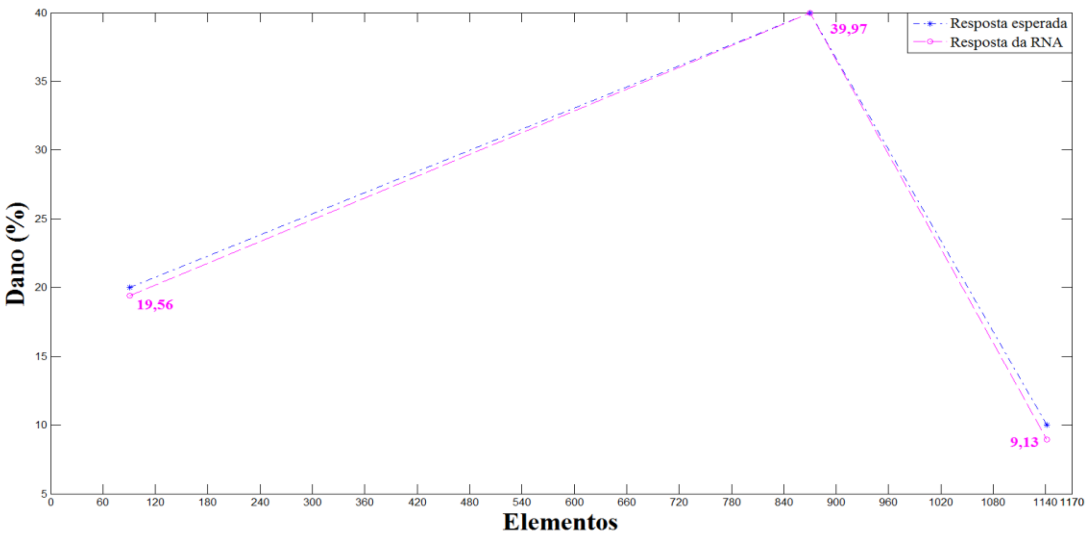

Fig. 15 Damage quantification by the Artificial Neural Network.

The five highest values of the errors used on the localization of damages where selected, and transmitted to the network as input data. The latter was simulated and provided as a result the quantification of the referred damages (Fig 15).

Figure 15 shows the results for the damage quantification from the cases 1, 2 and 3 considered. The presence of three points can be noticed at the Figure 15. These points represent the values of the magnitude of damages in cases 1, 2 and 3 obtained by the Artificial Neural Network technique (values in pink). Values in blue represent those which were expected.

For the damaged case 1, the network identified a damage of magnitude 19.56% in the element 91. The expected value was 20%, so the technique provided a very satisfactory result. The same comments can be done for the other two points: the neural network identified a damage of 39.97% in the element 870, and a damage of 9.13% for the element 1141. The expected values of damages were 40% and 10% respectively, as can be observed in the Figure 15.

CONCLUSIONS

Based on previous studies, the Residual Method Error (REM) was extended in order to identify, from the alterations in the dynamic characteristics, the damages present in the 3-D frames models. By the other side the Artificial Neural Network was applied to quantify the damages located by the REM.

The application of the two methods had a very good performance by observing the obtained results. Both methods has shown that they could be an important alternative in Structural Health Monitoring once they allowed to locate and quantify with satisfactory precision the damages introduced initially in the structural models considered.

More studies must be done in order to obtain a better evaluation of the studied methods once they had been applied only to numerical models without any level of noise.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the funding by CAPES (Coordenação de Aperfeiçoamento de Pessoal de Nível Superior) – Brazil.

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