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CHARACTERIZATION OF DAMAGE IN CERAMIC MATRIX COMPOSITE MATERIAL USING RESONANT TESTING AND ARTIFICIAL NEURAL NETWORK

Bruno Arrais Bezerra, brunobezerraufsj@gmail.com
Alexandre Carlos Eduardo, alexandrecarloseduardo@ufsj.edu.br
Fidelis Borges Santos Ferreira, fidelis.borges@hotmail.com
Túlio Hallak Panzera, tuliopanzera@ufsj.edu.br

Federal University of São João del Rei – UFSJ
Praça Frei Orlando, 170, Centro, São João del-Rei – MG, Brazil

Abstract. *The article deals with of an experimental/numerical investigation focused on methods of Resonant Frequency Testing (RFT) and Artificial Neural Network (ANN) for detection of material structure integrity damage in Ceramic Matrix Composite (CMC) with crack. The crack present in any material structure influence its vibrational behavior like its frequency and resonance. In the present study there were analyzed undamaged specimens and also specimens containing defects of cracks type. Intact specimen measurement results proved that non-homogeneity of ceramic material is not source of nonlinear effects accompanying elastic waves propagation. The results experimental are compared with the results numerically obtained. The simulations were performed using Matlab® software. Then by using Feed-forward, back propagation neural network the relationship between the location and the depth of the crack as input and the structural eigen frequencies as output are studied. At the end by performing both the computational analysis it is proved that the presence of cracks affects the natural frequency and the mode shapes of the structure. Other parameters can affect the dynamic modulus like moisture content, temperature and mix proportions need to be investigated.*

words: *ceramic matrix composite, resonant testing, artificial neural network.*

1. INTRODUCTION

The study of materials characterization is important in knowing more about the behavior of the materials so that the utilization of the materials could be varied and used to the utmost potential. Knowledge of materials characterization is widely applied in the area of failure analysis to prevent engineering breakdown especially the very much undesirable catastrophic and cascading ones. In the area where safety, reliability and quality control are highly considered, the continuous development of analysis technique and measurement technology for materials characterization becomes inevitable. The worldwide trend in this segment has been the development and application of advanced methods to detect damage, estimating the useful life of the structure due to this damage, applying effective methods to slow the spread of cracks.

Early damage detection and eventual estimation of damage is an important problem for any decision regarding structural repair and prevention of disaters. Damage in engineering is defined as intentional ou unintentional changes to the material and/or geometric properties of these systems, including changes to the boundary conditions and system connectivity, which adversely affect the current or future performance of that of that system (Farrar et al., 2005).

One prominent aspect of materials characterization is the determination of elastic properties for materials by investigating the corresponding elastic constants namely Young's Modulus (E), and Poisson's ratio (v). As meticulously reviewed in Pagnotta (2008), various techniques have been developed for characterizing materials by their elastic properties. These variations of techniques could be classified into two major methods: static and dynamic.

Static methods are based on determination of specimen's stress and strain during standard mechanical testing. The specimens need to conform to certain specific shape and size for testing. Meanwhile, dynamic methods are nondestructive methods allowing variation in specimens' shapes and dimensions. Materials could be repeatedly tested through range of temperatures and conditions. There are two types of dynamic methods namely ultrasonic method and resonant method.

Ultrasonic method involves the quantification of transit time of wave propagation through materials while resonant method involves the measurement of natural frequencies and the associated modal shapes to acquire the desired elastic constants. The resonant method or modal vibration testing has been widely favored as the method of testing due to the fact that it is easy to be implemented and does not require expensive equipments. ASTM E 1876-09(2009) provided the procedures for determining elastic properties from the measured impulse excitation of vibration.

In this paper ANN was used for mapping damage in ceramic matrix composite material (the Portland cement and the clay sintering). ANN has emerged as a promising tool for characterization of properties material with crack. The ceramic matrices investigated in this experiment are: Clay and Portland cement. Note that the processing of clay is

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through the burning process (sintering) and cement through the hydration process, to give strength to the product. In this study a feed-forward back-propagation neural network is used to learn the input (the location and depth of a crack)-output (the structural eigen frequencies) relation of the structural system. A neural network for the cracked structure is trained to approximate the response of the structure by the data set prepared for various crack sizes and locations.

The paper is organized as follows. Section 2 describes brief review of techniques for characterization (Resonant Method and Artificial Neural Network). In section 3 a methodology using data experimental and ANN is presented. In section 4 experimental procedures is presented. Results and discussions are presented in section 5. Conclusions and recommendations follow in section 6.

2. BRIEF REVIEW OF TECHNIQUES FOR CHARACTERIZATION

2.1 Resonant Method

This test method covers the determination of the elastic properties of ceramic whitewares materials. Specimens of these materials possess specific mechanical resonance frequencies which are defined by the elastic module, density, and geometry of the test specimen. Therefore the elastic properties of a material can be computed if the geometry, density, and mechanical resonance frequencies of a suitable test specimen of that material can be measured. Young's modulus is determined using the resonance frequency in the flexural mode of vibration (Morrel, 2006).

The shear modulus, or modulus of rigidity, is found using torsional resonance vibrations. Young's modulus and shear modulus are used to compute Poisson's ratio, the factor of lateral contraction (ASTM E 1876-09, 2009).

2.1.1 Determination of the dynamic modulus of elasticity longitudinal

The dynamic modulus of elasticity can also be computed from the fundamental longitudinal frequency of vibration of a specimen, according to the following equation:

$$E_{dl} = 4N^2L^2\rho * (10)^{-12} \qquad MN/m^2 \tag{1}$$

where: L = length of the specimen, mm; N = fundamental longitudinal frequency Hz, Hz; ρ = density, Kg/mm^3

The most accurate method for determining density is to weigh the specimen in air and suspended water.

$$\rho = \frac{W_A}{W_A - W_\omega} \tag{2}$$

where: W_A = weight of specimen in air; W_ω = weight of specimen in water.

2.1.2 Determination of the dynamic modulus of elasticity flexural

$$E_{df} = CWN^2 * (10^{-2}) \qquad MN/mm^2 \tag{3}$$

where: W = weight of specimen in kg; N = fundamental flexural frequency in Hz

$$C = \frac{0.164L^3T}{d^4} \qquad s^2/m^2(cilinder)$$
$$= \frac{0.0966L^3T}{bt^3} \qquad s^2/m^2(prism)$$

L = length of specimen in mm; d = diameter of cylinder in mm; t, b = dimensions of cross section of prism in mm, t, being the direction in which it is driven; T = a correction factor dependent upon the ratio of the radius of gyration K, to length L, and on the Poisson's ratio (table). For a cylinder, K= d/4. For a prism, K= t/3.464.

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2.1.3 Determination of the dynamic modulus of elasticity torsional

$$G_d = 4t^2 L^2 \rho F * 10^{-12} \qquad MN/m^2 \tag{4}$$

where: L = length of specimen in mm; t = fundamental torsional frequency; ρ = density in kg/ m2; F = a form factor
= 1 for a circular cylinder
= 1.183 for a square cross section prism.
The Poisson's ratio is calculated by,

$$v_d = \left(\frac{E_d}{2G_d} - 1 \right) \tag{5}$$

where: υ_d = dynamic Poisson's ratio; E_d = dynamic modulus of elasticity; G_d = dynamic modulus of rigidity;

2.1.4 Determination of factor ou damping coeficient

The factor of damping is calculated by the resonant frequencies of sample and frequencies either side.

$$Q = \frac{f_r}{f_2 - f_1} \tag{6}$$

where : f_r = resonant frequency (Hz); f_1 and f_2 = the frequencies either side of f_r at which the vibration amplitude drops to 0.707 of that at f_r .

These parameters can be directly estimated using the technique artificial neural network as described section 2.2.

2.2 Artificial Neural Network (ANN)

There is a distinct difference in the frequencies across different part thickness and compositions. This difference cannot be effectively tacked with a simple rule based system based simply on the frequencies of resonance. The complete and accurate knowledge of the composite part's composition is almost impossible in real-life scenario making the accurate prediction of the resonance frequencies very difficult. An ANN based approach assumes no knowledge of the composition or thickness of the parts. Moreover an on-site train and use approach is more attractive to a good characterization, which would need to conduct an in-depth study each time it changed its parameters, if it were to rely on rule based methods (Bishop CM., 1995).

Various architectures were tried out with two different types of classifiers, the Multi Layer Perceptron (MLP) and the Radial Basis Function (RBF) based neural networks. These were chosen since they are the two most commonly used classifiers and also the fastest. They were trained with various source vectors, all in the frequency domain.

The general role of Neural Network applied a structure multi-layer perceptron is illustrated in Fig.1,

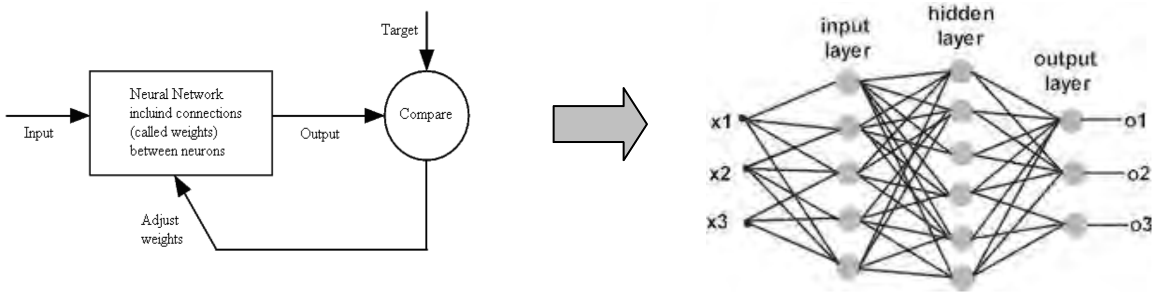

Figure 1 - General role of Neural Network applied a structure multi-layer perceptron

Setting up an ideal artificial neural network involves extensive planning of the network topology-number of input, hidden and output nodes to implement and the training sets used in the process. An important task with setting up the system is interfacing the neural network with the "outside" world. Designing a functional neural network for any given power system would involve five major design parameters that ought to be considered during implementation: choosing network topology; unit characteristics of each unit in the system; training procedures and methods; training Sets/variables; input/output representations and post-processing.

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The network is a generic full-connected multi-layer perceptron with backpropagation. Its neurons are basically McCulloch-Pitts neurons having evaluation functions and the network itself is the same network introduced by Frank Rosenblatt. The characteristics of such a network can be listed as its evaluation function, its weight updating rule, its error function and so on. These characteristics are defined accordingly:

For the ith neuron of the jth layer, the firing function is:

$$V_{ji} = f\left(\sum_{k=1}^{N(j-1)} V(j-1)iW_{jik}\right) \tag{7}$$

where

$$f(x) = \tanh(x) \tag{8}$$

The standard error of ith neuron of the jth layer in a multi-layer perceptron is:

$\delta_{ji} = f'(V_{ji})(exp_i - V_{ji})$ if it is the output layer,

$\delta_{ji} = f'(V_{ji})(\sum_{k=1}^{N(j+1)} \delta_{(j+1)k} W_{(j+1)ki})$ otherwise;

where

$f'(x) = 1 - \tanh^2(x)$, V is the value fired by the neuron and W are the connection weights.

Weight updating rule is:

$$W_{ji}(n) = W_{ji}(n-1) + \Delta W_{ji}(n) \tag{9}$$

Where

$$\Delta W_{ji}(n) = \mu \Delta W_{ji}(n-1) + ß\delta_{ji}(n)V_i(n) \tag{10}$$

Here μ represents momentum coefficient whereas β represents the beta parameter.

The redefined error is:

$$E_{ref} = E_{std} + \sum_{i,j} (W_{ij})^2 \tag{11}$$

The Root Mean Square Error (RMSE) (also called the root mean square deviation, RMSD) is a frequently used measure of the difference between values predicted by a model and the values actually observed from the environment that is being modeled.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (X_{obs,i} - X_{model,i})^2}{n}} \tag{12}$$

where X_{obs} is observed values and X_{model} is modelled values at time/place i.

There is no stopping criterion defined. The training ends when the maximum number of loops is reached. I did not implement a stopping criterion because of practical reasons. In almost every case the training made successful adjustments in a very small number of loops and this made it unnecessary to define a stopping criterion.

When a neuron is disabled its connections to the upper layers are disabled. When 'Direct Input Connection' is selected new connections from input neurons to output neurons are added. For both of the tasks the inputs are either 1 or -1; so as the output values. It is basically a design issue in order to specify a correspondence between the neurons and the evaluation function tanh which has a range of [-1,1]. Initial weights are randomized between [0,1]. Data separation specified with 'Training/Data' parameter for training and test phases is randomized too. This means, in each training the data given to the training and test phases will be different (Haykin, 1998). This paper multi-layer perceptrons (MLP) are neural nets used to as function approximators (Fig. 2).

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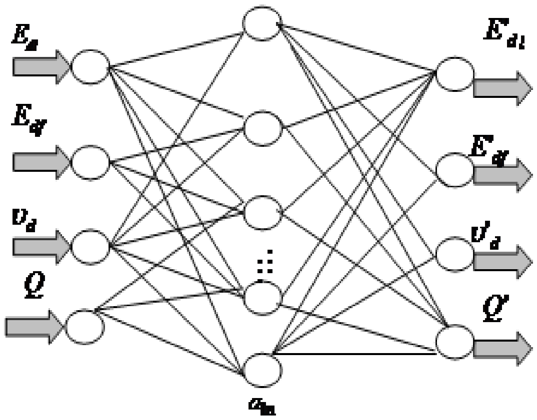

Figure 2- Network architecture of a multilayer perceptron neural network for the prediction of release properties.

The topology utilized:

- one input layer (the inputs of the network - elastic properties, E_{dl}, E_{df}, v_d and $Q \rightarrow$ *parameters elastic non-damage*;
- one hidden layer;
- one output layer (the outputs of the network - E'_{dl}, E'_{df}, v'_d and $Q' \rightarrow$ *parameters elastic with damage*.

3. METHODOLOGY USING EXPERIMENTAL DATA AND ARTIFICIAL NEURAL NETWORK (ANN)

The experimental data was obtained and the neural nets as described was trained. The output of the net from the damage condition was compared to one without damage. The Fig. 3 illustrate the methodology for characterization of damage in ceramic matrix composite material utilized.

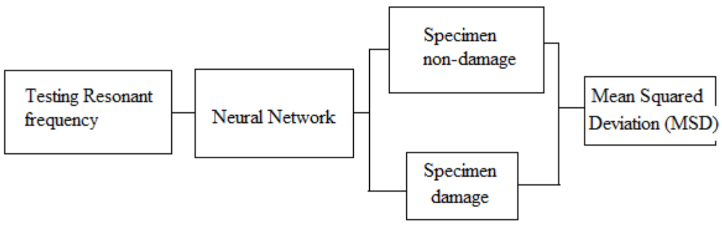

Figure 3 - Methodology for characterization of damage in ceramic matrix composite material.

To compare the outputs it was used a Mean Squared Deviation (MSD) between the functions.

4. EXPERIMENTAL PROCEDURES

4.1 Materials and Specimens

The particulate composites can be classified as a material containing two main phases, the dispersive phase of particles and the matrix phase, continuous and responsible for loading distribution. The matrix phase used in this experiment was the Portland cement ARI PLUS (ASTM Type III). The dispersive phase of clay sintered is investigated for two levels of sintering temperature, 900°C and 1200°C.

4.2 Experimental Setup

Acoustic tests was conducted on cylindrical specimens of each variety determining the resonance frequency of the acoustic waves in these pieces. The longitudinal wave velocity was determined by means of a resonance-based method using an Erudite MK3 test device of working frequency range 1 Hz to 100 kHz, with EMAT vibrator and piezoelectric receiver (Fig. 4).

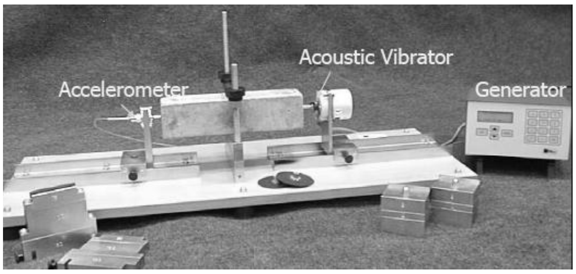

Figure 4 - ERUDITE determines the resonant frequency of Ceramic matrix composite Specimens in cylindrical specimens (Erudite MkIV, CNS, 2004).

This test method measures the resonance frequencies of test bars of suitable geometry by exciting them at continuously variable frequencies. Mechanical excitation of the specimen is provided through use of a transducer that transforms an initial electrical signal into a mechanical vibration. Another transducer senses the resulting mechanical vibrations of the specimen and transforms them into an electrical signal that can be displayed on the screen of an oscilloscope to detect resonance.

The resonance frequencies, the dimensions, and the mass of the specimen are used to calculate Young's modulus and the shear modulus.

5. RESULTS AND DISCUSSION

In order to demonstrate the applicability of the proposed approach a standard neural artificial test was performed on the percentages of correctly classified records as a function of the training iteration number.

The percentages of correct classifications (0% up to 20 iterations), first increased very slowly up to about 100 iterations (Fig. 5) and then climbed very quickly to reach 100% for 180 iterations with the training set and 92% with the test set.

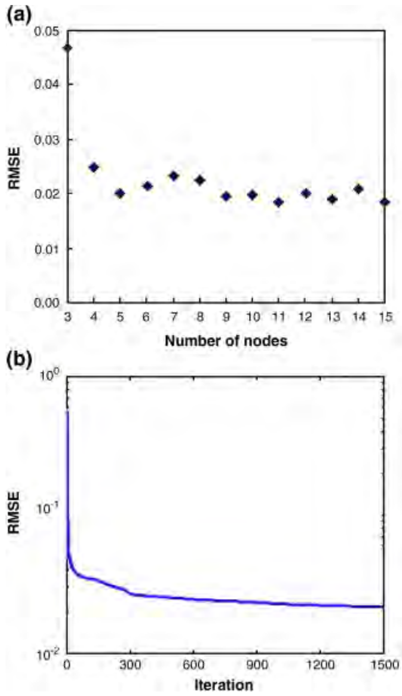

Figure 5 - Neural network training: (a) Change in RMSE (Root Mean Square Error) in the training set) with increasing numbers of hidden nodes; (b) Change in RMSE with increasing number of iterations (the 6-11-5 network model).

The number of hidden units used in this application was determined through experimental simulations: Fig. 5a shows the variation of RMSE values at convergence as a function of the number of hidden nodes. The experiments were performed with a maximum number of iterations of 1500 and the final RMSE was between 0.17 and 0.27 with the number of hidden nodes being 4 or higher. The minimum RMSE with the smallest number of nodes was attained adopting architecture with 11 hidden nodes. This was the architecture finally adopted, given the small change in the

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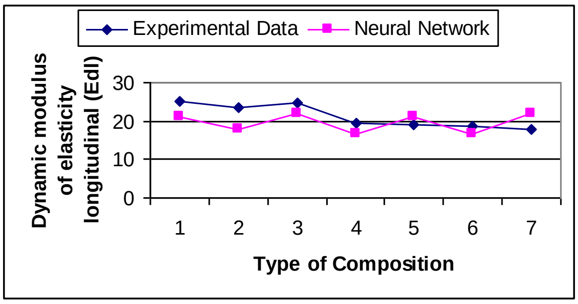
converged RMSE with a further increase of the number of hidden nodes. Fig. 5b shows the training accuracy of the network model used (6-11-5) as a function of the training iterations. The RMSE decreased less than 0.005 when increasing the number of iterations from 1000 to 1500. The maximum number of iterations in the learning process was thus set to 1000. Another set of experiments was performed with 11 hidden nodes and 1000 maximum iterations to evaluate the impact of the random initialization of biases and weights of the input nodes. The impact was negligible, possibly because of the large number of iterations.

5.1 Performances of the parameters elastic matrix composite material

In Fig. 6(a), the dependence of the dynamic modulus of elasticity longitudinal on type composition of the Ceramic Matrix Composite material is illustrated. The experimental data is compared with performance of the neural network trained. In Fig. 6(b), the error between experimental data and neural network.



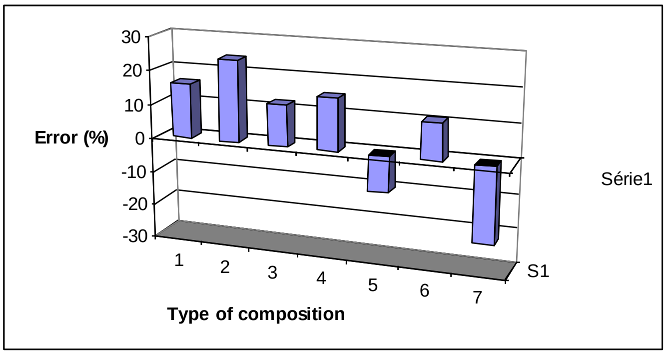
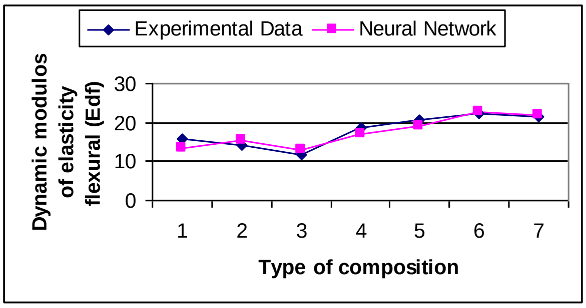


Figure 6-(a) Performance Dynamic modulus of elasticity longitudinal; 6-(b) Error by performance dynamic modulus of elasticity longitudinal.

From these results the followings are discussed:

- Fig. 6-(a) shows the variations experimental data for dynamic of elasticity longitudinal (E_{dl}) and the mapping response of neural network. We see that decreasing these parameter elastic. Decrease of dynamic modulus of elasticity is associated with internal damping and energy dissipation in material because ceramic matrix with type composition is more elastic than without.
- Fig. 6-(b) shows the variations of error percentual for type de composition of the ceramic matrix. The average dynamic modulus of elasticity longitudinal (E_{dl}) was found of the 6,46 %. The value found may be considered a little above that found for the experimental conditions / computer. Usually 3% error is a reference. Several variables consider that are present in the process, influencing the final result: material composition, suitable job resonance methods and artificial neural networks, among others.

In Fig. 7(a), the dependence of the dynamic modulus of elasticity flexural on type composition of the Ceramic Matrix Composite material is illustrated. The experimental data is compared with performance of the neural network trained. In Fig. 7(b), the error between experimental data and neural network is illustrated.



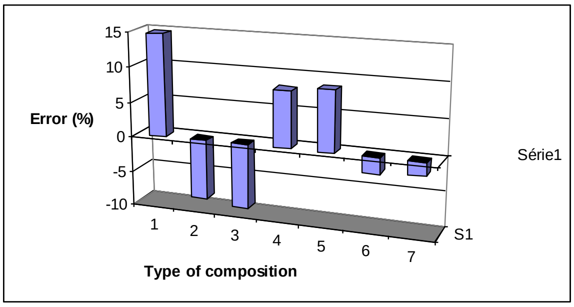


Figure 7-a) Performance Dynamic modulus of elasticity flexural; 6-b) Error by performance dynamic modulus of elasticity flexural.

In the Figure 7(b) shows the variations of error percentual for type de composition of the ceramic matrix. The average dynamic modulus of elasticity flexural (E_{df}) was found of the 1,36 %. It can be considered an excellent value for the conditions presented.

In Fig. 8, the dependence of the dynamic modulus of rigidity (Gd) on type composition of the Ceramic Matrix Composite material is illustrated. The experimental data is compared with performance of the neural network trained.

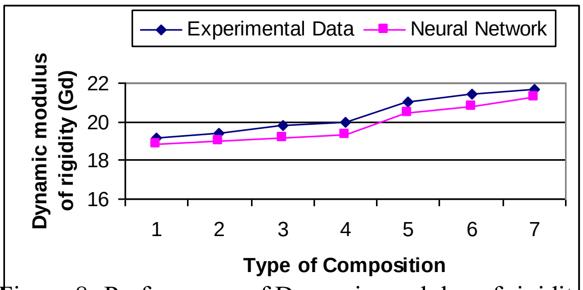


Figure 8- Performance of Dynamic modulus of rigidity.

- Fig. 8 shows the variations experimental data for dynamic modulus of rigidity (Gd) and the mapping response of neural network. We see that increasing these parameter elastic. Increase of dynamic modulus of rigidity is associated increase in fundamental torsional frequency of system.

In Fig. 9, the dependence of the Factor or damping coefficient (Q) on type composition of the Ceramic Matrix Composite material is illustrated. The experimental data is compared with performance of the neural network trained.

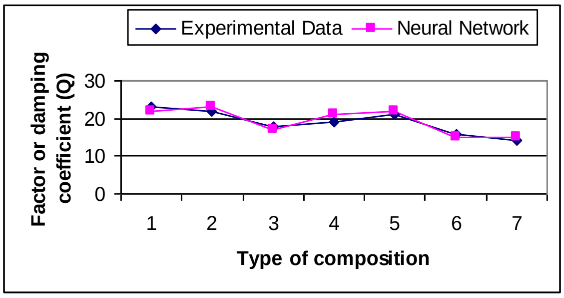


Figure 9- Performance of Factor coefficient

In Fig. 9 shows the variations experimental data for Factor or damping coefficient (Q) and the mapping response of neural network. We see that decreasing these parameter elastic. Decrease of Factor or damping coefficient is associated with decreasing of resonance frequency

6. CONCLUSION AND RECOMMENDATIONS

In this work, a method of Characterization of Damage in Ceramic Matrix Composite material was developed, using the association of Resonant Testing and Artificial Neural Network. In the considered method, is intended primarily for detecting significant changes in the dynamic modulus of elasticity of laboratory or field test specimens that are undergoing exposure to weathering or other types of potentially deteriorating influences. The conditions of manufacture, the moisture content, and other characteristics of the test specimens materially influence the results obtained.

Although the basic equipment and testing procedures associated with the resonant frequency techniques have been standardized in various countries, and commercial testing equipment is easily available, the usefulness of the tests is seriously limited for the following reason: generally, these tests are carried out on small-sized specimens in a laboratory rather than on structural members in the field because resonant frequency is affected considerably by boundary conditions and the properties of ceramic matrix composite

7. REFERENCES

Alfano, M., Pagnotta, L., 2006. “Determining the elastic properties of isotropic materials by modal vibration testing of rectangular thin plates,” Journal of Sound and Vibration, Vol. 293, , pp. 426-439.

ASTM Standard E1876-09, 2009. “Standard test method for dynamic Young’s modulus, shear modulus, and Poisson’s ratio by impulse excitation of vibration,” ASTM International, West Conshohocken, PA, DOI: 10.1520/E1876-09, www.astm.org.

Bishop CM., 1995. Neural networks for pattern recognition. Oxford: Oxford University Press.

Erudite MkIV, CNS, 2004. Farnell Limited, Commercial folder, Hertfordshire, England.

Haykin SS., 1998. Neural networks: a comprehensive foundation. 2nd ed. Prentice Hall.

Morrel, R., 2006. NPL measurement good practice guide No. 98 - Elastic module measurement, UK National Physical Laboratory Report.

Pagnotta, L., 2008. “Recent progress in identification methods for the elastic characterization of materials,” International Journal of Mechanics, Vol. 2, n. 4, pp. 129-140.

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