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ADAPTIVE NEURO FUZZY CONTROL FOR VIBRATION SUPPRESSION OF A SMART BUILT-IN PLATE WITH EMBEDED PIEZOELECTRIC SENSORS AND ACTUATORS

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Abstract. *One of the most important problems in engineering is, among others, the vibration suppression of smart composite structures, i.e. the reduction of the oscillations, which in turn are caused by external dynamic loadings. Embedded sensors and actuators, made of piezoelectric materials, along with a suitable control system provide intelligent behavior to the smart structures. Vibration suppression can be achieved using fuzzy controllers. Fine-tuning of the involved parameters may become necessary and can be achieved either by using the trial and error method, or via global optimization, such as genetic algorithms (GAs), particle swarm optimization (PSO), differential evolution (DE) etc. In this case the results are usually very satisfactory, however, the computational cost increases. On the other hand, adaptive, optimized neuro fuzzy controllers, like the ones which are presented here, can be even more effective in the design and application of smooth robust controllers. These smart controllers are able to follow a training procedure, and thus to increase their robustness, i.e. their adaptivity under several -and some times completely different- conditions. The modeling of neuro fuzzy controllers is quite similar to other system identification techniques. The first step is the construction of the control system and subsequently a set of training data is necessary for configuration. These data will be used for the tuning of the control parameters until an error criterion is met. In other words, the controllers are first designed, based on the dynamic characteristics of the modeled structures, and then an optimization process, which is based on adaptive neural fuzzy techniques, i.e. on neural networks, is applied. Some good results in this direction have already been presented in previous investigations of the authors [1, 2, 3]. An important feature of these controllers lies to the fact that they can achieve significant suppression of the oscillations without knowledge of the full state-space (measurements) of the problem and without the application of any classical optimization method. Recent developments and applications mostly on linear smart structures are presented here. More specifically, several plate models with different support scenarios and loadings are modeled and studied, in order to prove the robustness and the efficiency of the control.*

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1 INTRODUCTION

One of the most important problems in engineering is the suppression of the vibrations of structures due to external excitation factors, i.e. wind or seismic loadings. Moreover, in smart structures, a significant degree of uncertainty is always present, due to potential imperfections and errors of both the control mechanisms and the model itself. Especially in multilayer structures, several failures, such as delamination between the different layers, fatigue or other damages, may appear. In laminated materials, such as the ones used in laminated structures, the repeated applied stresses, impact the layers of the structures and can lead them to separate. This phenomenon can form a less tough structure. Prediction of failure in composite laminates can be accomplished using computational methods based on material strength and fracture toughness, as it is presented in [4].

Classic monitoring tools and control techniques often encounter several limitations to the study of such problems. For this reason, the use of intelligent fuzzy and neuro-fuzzy control techniques is suggested. An introductory survey of fuzzy control has been conducted in [5]. Indeed, to maximize the efficiency of the proposed controllers, their characteristics can be subjected to a fine-tuning process either using global optimization algorithms [6, 7] or artificial neural networks [2, 3]. Artificial neural networks provide better solutions to some problems due to their capability of parallelism and learning. More specifically, the use of neural networks in control is considered as a natural step in the evolution of control methodology. A short review on neural networks for control systems is done in [8].

A well-established implementation of the adaptive neuro-fuzzy system is the adaptive neuro fuzzy inference system (ANFIS) of MATLAB®, as presented in [9]. The procedure followed, may be summarized in several steps as follows. Firstly, a detailed mechanical model of the total system is constructed. Subsequently, the dynamics of the system are calculated and saved. These data are used for the optimization and training of the neuro-fuzzy controller by using the ANFIS procedure. The resulting controller can be used for the control of the total system. The numerical results indicate the efficiency of the proposed control scheme for the vibration suppression on a cantilever beam under sinusoidal and ramp-type excitations. The control is not only efficient, but smooth as well.

The objective is the development of an intelligent, reliable and robust control system, as well as the establishment of a proper connection with numerical integration algorithms for the study of dynamic systems. For the development of such controllers at the present investigation, fuzzy inference tools, as well as artificial neural networks techniques are used. More specifically, the controllers are first designed and subsequently they are subjected to an optimization process, by using either adaptive neural fuzzy techniques. The proposed methods for control and optimization are proved to be very efficient and robust as well.

2 STRUCTURAL MODEL OF THE BUILT-IN PLATE

The structural model of the present investigation consists of a smart laminated plate with integrated piezoelectric sensors and actuators, which is based on the First-order Shear Deformation Theory for laminated composite plates (FSDT) or Mindlin theory. This is an extension to the widely used Mindlin-Reissner theory. The FSDT which was proposed by Reissner and Mindlin, takes into consideration shear deformation effects by the way of linear variation of in-plane displacements through the thickness.

In the model considered here, two piezoelectric layers are symmetrically bonded perfectly on the top and bottom surface of the host composite plate. The top layer acts like an actuator, while the bottom one is used as a sensor. The poling direction of the piezoelectric actuator is assumed to be along the z-axis.

2.1 Structural dynamics

To derive the equations of motion for the laminated composite plate with surface bonded sensor and actuator layers, Hamilton's principle is used:

$$\int_0^T \left(\delta T - \delta U + \delta W\right) dt = 0 \tag{1}$$

The kinetic energy *T*, the potential energy *U* and the total work done due to virtual displacements δu are given as follows:

$$\begin{aligned} &\delta T = -\int_V \rho \{\ddot{u}\}^T \{\delta u\}\, dV \qquad \delta U = \int_V \left(\{\sigma\}^T \{\delta\varepsilon\} - \{D\}^T \{\delta E\}\right) dV \\ &\delta W = \{\delta u\}^T \{F_c\} + \int_S \{\delta u\}^T \{f_S\}\, dS + \int_V \{\delta u\}^T \{f_V\}\, dV - \int_{S_p} \{\delta E\}^T \{q\}\, dS \end{aligned} \tag{2}$$

where $\{F_c\}$ is the concentrated force vector, $\{f_S\}$ is the surface force vector, $\{f_V\}$ is the body force vector, $\{q\}$ is the surface charge vector, *S* is the surface area where external force is acting, and S_p is the surface area of piezoelectric layer where applied electric charge is acting.

Substituting relations (2) in Hamilton's principle (1), we obtain:

$$\begin{aligned} \int_0^T \Bigg\{ &\int_V \left(\{\ddot{u}\}^T \{\delta u\} + \{\sigma\}^T \{\delta\varepsilon\} - \{D\}^T \{\delta E\} - \{\delta u\}^T \{f_V\}\right) dV \\ &- \{\delta u\}^T \{F_c\} - \int_S \{\delta u\}^T \{f_S\}\, dS + \int_{S_p} \{\delta E\}^T \{q\}\, dS \Bigg\} dt = 0 \end{aligned} \tag{3}$$

Equation (3) is a good starting point for finite element approximations using independent variables *{u}* and ϕ^p.

2.2 Finite element formulation

For the discretization of the composite plate the finite element method is used. Namely, four-node rectangular bilinear isoparametric elements with five degrees of freedom per node, i.e. $\{u_0, v_0, w_0, \theta_x, \theta_y\}$, are used. The first three degrees of freedom of each node correspond to the displacements in directions x, y and z respectively, while the last two the rotations around the axes x and y.

The governing equations of an element can be written as:

$$\begin{aligned} \left[M\right]_e \{\ddot{d}_e\} + \left[K_{uu}\right]_e \{d_e\} + \left[K_{u\phi}\right]_e \{\phi\}_e &= \{F_{(m)}\}_e \\ \left[K_{\phi u}\right]_e^T \{d_e\} - \left[K_{\phi\phi}\right]_e \{\phi\}_e &= \{F_{(q)}\}_e \end{aligned} \tag{4}$$

where the element mass matrix $\left[M\right]_e$, the element elastic stiffness matrix $\left[K_{uu}\right]_e$ and the element mechanical load vector $\{F_m\}_e$ are given by:

$$[M]_e = \sum_{k=1}^{nplies} \int_{-1}^{1}\int_{-1}^{1} \rho_k [N]^T \left[\int_{z_k}^{z_{k+1}} [L_Z]^T [L_Z] dz\right] [N] |J| d\xi d\eta$$

$$[K_{uu}]_e = \sum_{k=1}^{nplies} \int_{-1}^{1}\int_{-1}^{1} \left[\int_{z_k}^{z_{k+1}} [B]^T [\bar{Q}]_k [B] dz\right] |J| d\xi d\eta$$

$$\{F_m\}_e = \int_{V_e} [N]^T \{f_V\}_e dV + \int_{S_e} [N]^T \{f_S\}_e dS + [N]^T \{F_c\}_e$$

At the p^{th} piezoelectric layer, the electromechanical coupling matrix and the permittivity matrix are given by:

$$\left[K_{u\phi}\right]_e = \int_{V_p} [B]^T [\bar{e}] \left[B_\phi\right] dV = \left[K_{\phi u}\right]_e^T$$

$$\left[K_{\phi\phi}\right]_e = \int_{V_p} \left[B_\phi\right]^T \left[\bar{\xi}\right]_k \left[B_\phi\right] dV$$

The global equations can be obtained by assembling the elemental equations (4) as:

$$\begin{aligned} [M]\{\ddot{d}\} + [K_{uu}]\{d\} + \left[K_{u\phi}\right]\{\phi\} &= \{F_m\} \\ \left[K_{\phi u}\right]\{d\} + \left[K_{\phi\phi}\right]\{\phi\} &= \left\{F_q\right\} \end{aligned} \tag{5}$$

where $\{d\}$ and $\{\phi\}$ are the global mechanical and electrical DoFs vectors, $[M]$ is the global mass matrix, $[K_{uu}]$, $\left[K_{u\phi}\right] = \left[K_{u\phi}\right]^T$ and $\left[K_{\phi\phi}\right]$ are the global mechanical stiffness, mechanical–electrical coupling stiffness and dielectric stiffness matrices respectively. $\{F_m\}$ and $\left\{F_q\right\}$ are the respective global mechanical and electrical loads vectors.

Next we assume that the electrical DoFs vector in Equation (5) can be divided into the actuating and sensing DoFs, $\{\phi\}_e = \{\phi_a, \phi_s\}^T$, where the subscripts 'a' and 's' denote the actuating and sensing capabilities. Hence, considering open-circuit electrodes, and in that case $\left\{F_q\right\}$ = {0}, the non-specified potential differences in Equation (5) can be statically condensed and the equations of motion and charge equilibrium become:

$$\begin{aligned} [M]\{\ddot{d}\} + [K_{uu}]\{d\} &= \{F_m\} - \left[K_{u\phi}\right]_a \{\phi\}_a \\ \{\phi\}_s &= -\left[K_{\phi\phi}\right]_s^{-1} \left[K_{\phi u}\right]_s \{d\} \end{aligned} \tag{6}$$

where $\left[K_{uu}^*\right] = \left[K_{uu}\right] - \left[K_{u\phi}\right]_s \left[K_{\phi\phi}\right]_s^{-1} \left[K_{\phi u}\right]_s$.

Equations

(6) are the final equations of motion and can be used in smart structures applications such as vibration control.

3 NEURO FUZZY CONTROL

The adaptive neuro-fuzzy control scheme which is used at the present investigation is based on Sugeno inference, thus it is a Sugeno-type controller, which is capable of training via neural networks, and namely, the back-propagation method. The control system takes two inputs (the displacement and the velocity) and returns a single output (control force), thus is a multiple input – single output (MISO) controller.

The inputs of the controller are described by Gaussian membership functions, while the output take constant values, due to the limitations of Sugeno inference. Optimization is achieved via a training process. Namely, the characteristics of the fuzzy system of this controller are tuned using artificial neural networks, and more specifically, a well-chosen set of training data, which is used in order to adjust the system parameters. For the compilation of these data, the model is first simulated without any control mechanism attached, in order to collect the necessary vibration data. Subsequently, these data are used for the training of the Sugeno controller. It is worth mentioning that the training of this controller has been performed based on data provided by a simpler beam model as it was presented in [3]. The fact that the same controller functions well also in other models proves its robustness.

The resulting form of the membership functions (clusters) of the inputs i.e. the displacement (in1) and the velocity (out2), after the initialization process are shown in Figure 1 and Figure 2 respectively. Namely, four clusters of Gaussian form for each input occurred from the subtractive clustering process.

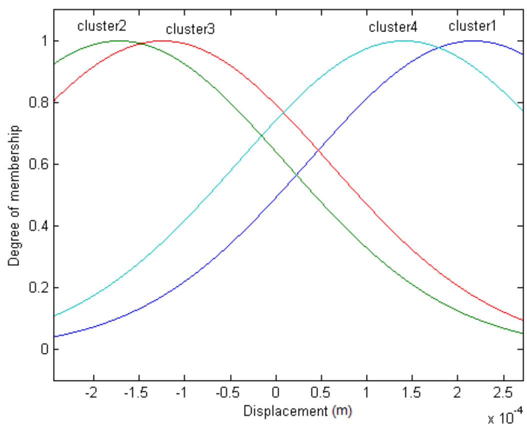


Figure 1: Membership function of the displacement

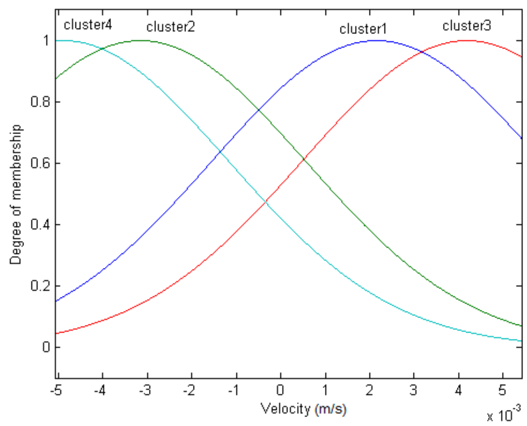


Figure 2: Membership function of the velocity

The output variable, i.e. the control force (out1), can take either constant values or linear functions taking values within the range [-1 1].

The if-then verbal rules which describe the emerging system are given in detail in Table 1. For example: if Displacement is in cluster 1 and velocity is in cluster 1 then the control force is out1.

	Displ. Cluster 1	Displ. Cluster 2	Displ. Cluster 3	Displ. Cluster 4
Vel. Cluster 1	Out1	-	-	-
Vel. Cluster 2	-	Out2	-	-
Vel. Cluster 3	-	-	Out3	-
Vel. Cluster 4	-	-	-	Out4

Table 1: Fuzzy rules of the ANFIS controller (Displ=displacement, Vel=velocity)

For the structure of rules in ANFIS see Figure 3. The visualization of the rules is shown in Figure 4.

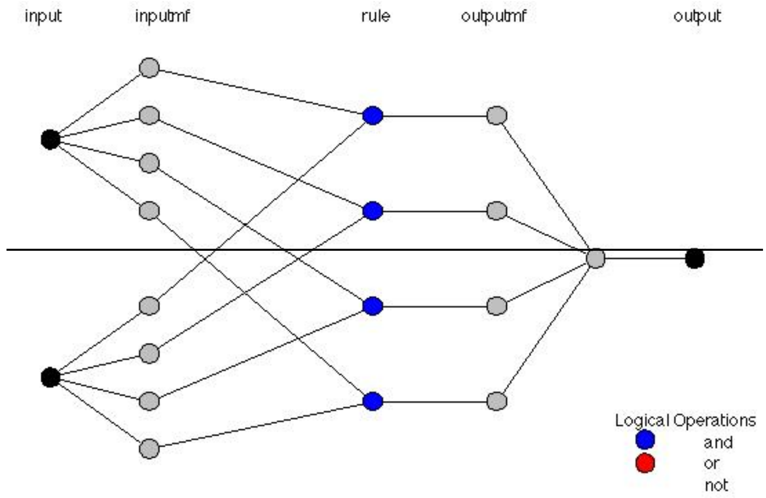


Figure 3: The structure of rules in ANFIS

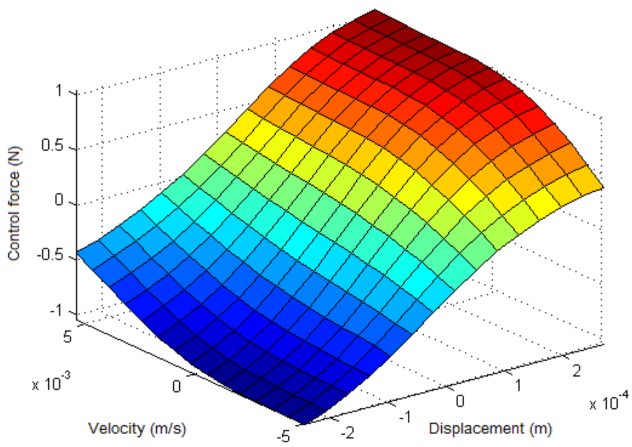


Figure 4: Graphic representation of the fuzzy rules of controller 3

The “and” method has been set to prod (product), while the “or” method has been set to probor (probabilistic or). The implication and the aggregation method have been set to min and max respectively. As defuzzification method the weighted average (wtaver) method is chosen.

It is worth mentioning that the characteristics of this controller (membership functions, rules, etc.) came through a training process, unlike the ones of fuzzy controllers which have been set based on experience.

4 NUMERICAL RESULTS

4.1 Plate model

The plate model which is considered in this investigation consists of a quadratic built-in plate fixed at two opposite edges. The dimensions of the host structure measure 0.8 m × 0.8 m, while thet material properties are given in detail in Table 2 [10].

Property	T300/976 graphite-epoxy composite	G1195N PZT
E_1 (GPa)	150	63
$E_2= E_3$ (GPa)	9.0	63
G_{12} (GPa)	7.1	24.2
$G_{23}= G_{13}$ (GPa)	2.5	24.2
$\nu_{12} = \nu_{13} = \nu_{23}$	0.3	0.3
ρ (kg/m^3)	1600	7600
$d_{13}= d_{23}$ (m/V)	-	$254\cdot10^{-12}$
$d_{42}= d_{51}$ (m/V)	-	$584\cdot10^{-12}$
Ply thickness (mm)	0.25	0.1

Table 2: Material properties

The plate is discretized in 144 quadratic finite elements, which yield to a system with 169 nodes with 5 degrees of freedom per node. The first three degrees indicate the displacement at the x, y and z axes respectively, while the other two denote the rotation around the x and y axes respectively. In the present paper, we consider the vertical displacement at the z axis. The plate is fixed at two opposite edges as shown in Figure 5.

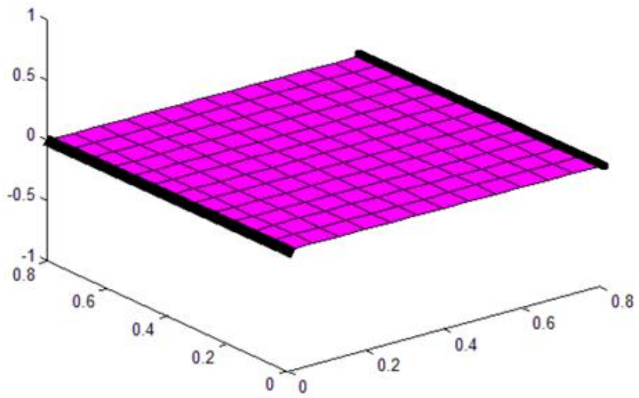


Figure 5: The built-in plate

The counting of the nodes and of the elements of the structure are shown in Figure 6 and Figure 7 respectively.

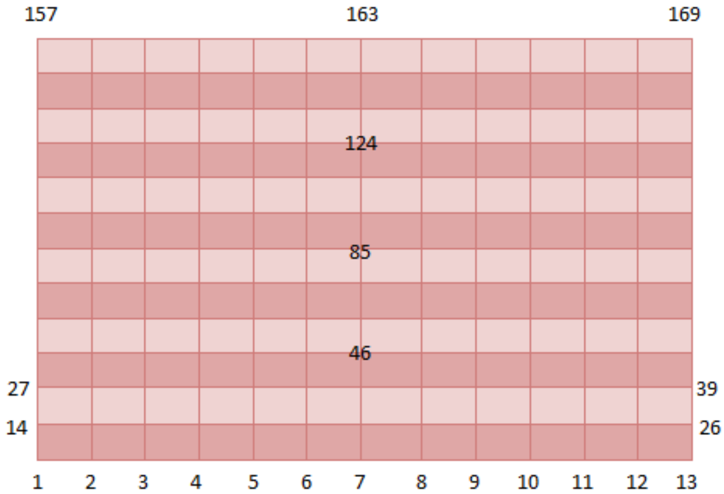


Figure 6: Counting of nodes

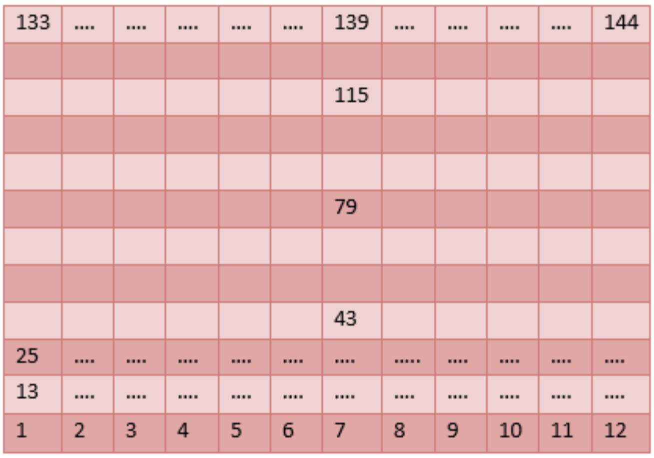


Figure 7: Counting of elements

4.2 Numerical results

The plate is excited through an external loading of sinusoidal form. We consider two different loading scenarios. In the first scenario, the external loading is applied to three different points at node 7, 85 and 163, while the control force is applied at node 85. The loading which is applied to each node is given as:

$$P = \frac{1}{3} sin(20t) \ \text{(N)} \tag{7}$$

For the second scenario, the loading is applied at five different nodes, namely at node 7, 46, 85, 124 and 163. The control force is again applied at node 85. The loading which is applied to each node in this case is given as:

$$P = \frac{1}{5} sin(20t) \ \text{(N)} \tag{8}$$

The results regarding the suppression which is achieved from the use of the neuro-fuzzy controller regarding the displacement, the velocity and the acceleration, along with the forces for the two different scenarios are presented in Figure 8 and in Figure 9 respectively.

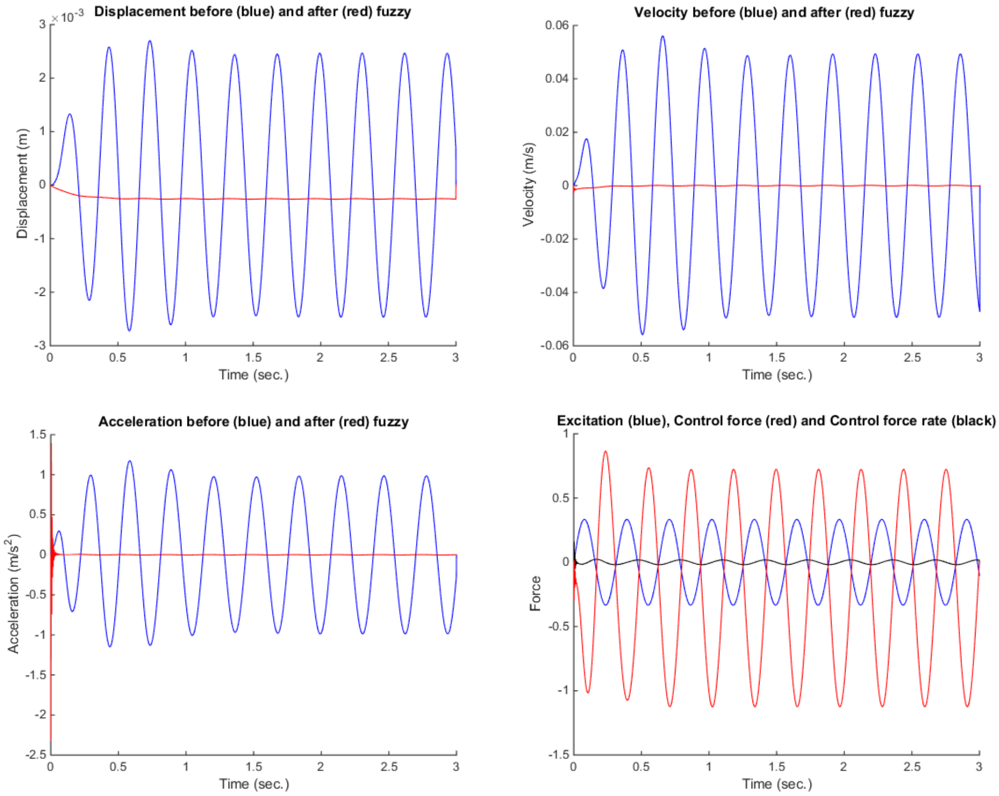
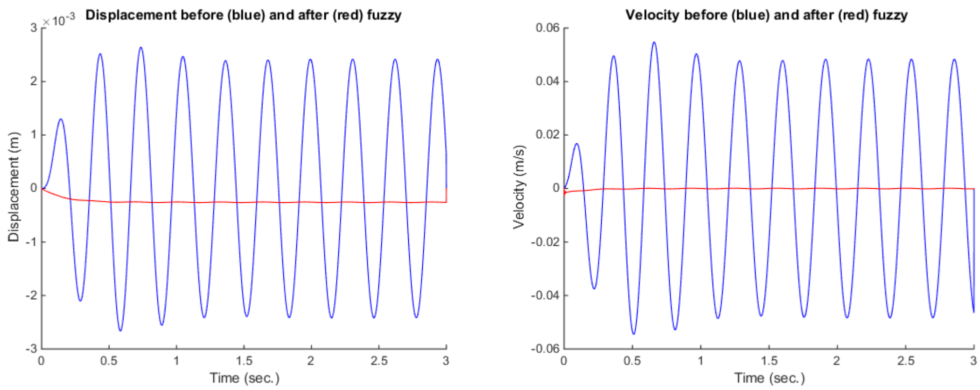


Figure 8: Displacement, velocity, acceleration and forces at node 85 for three point loading



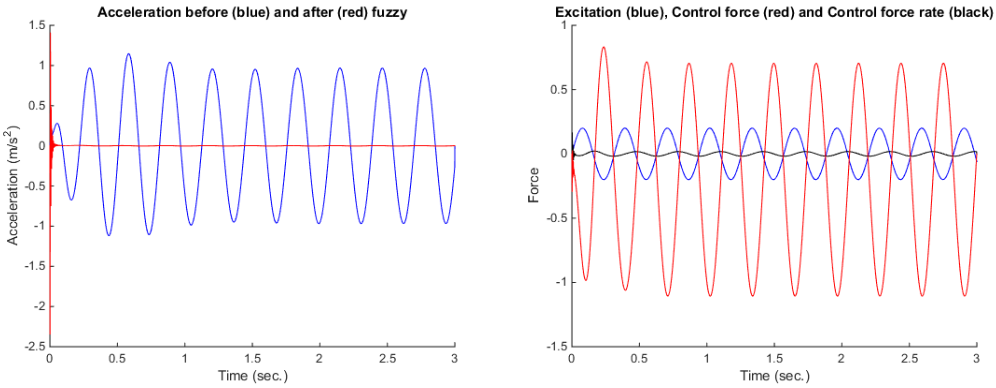


Figure 9: Displacement, velocity, acceleration and forces at node 85 for five point loading

In the first three diagrams of each figure with blue color is denoted each measure before the application of the control, while with red color is shown the corresponding measure after control. As for the forces, with blue color is shown the external loading, with red color is denoted the control force which came out of the neuro-fuzzy system and with black color is given the control force rate.

The numerical results for the two different loading scenarios are presented in Table 3 and Table 4 respectively.

	Maximum displacement (m)	Maximum velocity (m/s)	Maximum acceleration (m/s^2)	Maximum acceleration after t=0.3 sec.
Without control	0.0054	0.1119	2.3213	2.3213
With control	2.6355×10^{-4}	0.0027	3.7102	0.0198
Fluctuation percentage	-95.14%	-97.55%	+59.83%	-99.15%

Table 3: Numerical results at node 85 for the case of the three-point external loading

	Maximum displacement (m)	Maximum velocity (m/s)	Maximum acceleration (m/s^2)	Maximum acceleration after t=0.3 sec.
Without control	0.0053	0.1093	2.2643	2.2643
With control	2.6343×10^{-4}	0.0028	3.7592	0.0200
Fluctuation percentage	-95.03%	-97.47%	+66.00%	-99.11%

Table 4: Numerical results at node 85 for the case of the three-point external loading

The results for the suppression of the displacement and the velocity are very satisfactory. Regarding the acceleration one may observe that there is an increase of the vibrations, which could be a burden for the material and/or the sensors and the actuators. However, this problem occurs at the beginning of the simulation and it is vanished after less than half a second.

5 CONCLUSIONS

Taking into account the numerical results, as well as the results of other investigations of our team [2, 3, 9], one can observe that the intelligent neuro-fuzzy control scheme which is proposed and tested here is not only very efficient, but and very robust as well. This conclusion comes out from the proved ability of the proposed controller to function perfectly not only for different models, but also under several conditions. This may include different support scenarios, application of different external loadings, etc.

It is also shown that the proposed control system has the ability to handle non-linearities, and to function well, even if it was not trained for the specific model which was studied in the present paper, i.e. the built-in plate, but instead for a simpler one, i.e. a cantilever beam.

REFERENCES

[1] G.K. Tairidis, G.E. Stavroulakis, D. Marinova, E. Zacharenakis, Classical and soft robust active control of smart beams. M. Papadrakaikis, D.C. Charmpis, Y. Tsompanakis, N. D. Lagaros eds. *Computational Structural Dynamics and Earthquake Engineering*, CRC Press - Taylor & Francis Group, London, UK, Chapter 11, 165-178, 2009

[2] G.E. Stavroulakis, I. Papachristou, S. Salonikidis, I. Papalaios, G.K. Tairidis, Neurofuzzy Control for Smart Structures. Y. Tsompanakis, B.H.V. Topping eds. *Soft Computing Methods for Civil and Structural Engineering,* Saxe-Coburg Publications, Stirlingshire, UK, Chapter 7, 149-172, 2011

[3] G.K. Tairidis, I. Papachristou, M. Katagas and G.E. Stavroulakis, Neuro - fuzzy control of smart structures, *10th HSTAM International Congress on Mechanics*, Chania, Crete, Greece, May 25-27, 2013

[4] C.G. Dávila, P.P. Camanho, C.A. Rose, Failure criteria for FRP laminates. *J Compos Mater,* 39, 323-345, 2005

[5] M. Sugeno, An Introductory Survey of Fuzzy Control, *Inform Sciences,* 36, 59-83, 1985

[6] G.K. Tairidis, G. Foutsitzi, P. Koutsianitis, G.E. Stavroulakis, Fine tuning of a Fuzzy Controller for Vibration Suppression of Smart Plates using Genetic Algorithms. *Adv Eng Softw,* 101, C, 123-135, 2016

[7] G.K. Tairidis, G. Foutsitzi, P. Koutsianitis, G.E. Stavroulakis, Fine tuning of Fuzzy Controllers for Vibration Suppression of Smart Plates using Particle Swarm Optimization, *8th GRACM International Congress on Computational Mechanics*, Volos, Greece, July 12-15, 2015

[8] P. Antsaklis, Neural Networks for Control Systems, *IEEE T Neural Networ,* 1(2), 242-244, 1990

[9] G.E. Stavroulakis, I. Papachristou, S. Salonikidis, I. Papalaios, G.K. Tairidis, Neurofuzzy Control for Smart Structures. Y. Tsompanakis, B. Topping eds. *Soft Computing Methods for Civil and Structural Engineering*. Stirlingshire: Saxe-Coburg Publications, 149-172, 2011

[10] K.Y. Lam, X.Q. Peng,G.R. Liu, J.N. Reddy, A finite-element model for piezoelectric composite laminates, *Smart Mater Struct*, 6, 583-591, 1997