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SHUNT CONTROL ON CANTILEVER BEAM BY NEURAL NETWORK : OBJECTIVE FUNCTION

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Abstract. Piezoelectric materials have been extensively studied in recent years for the development of electromechanical harvesting devices. Usually connected to a structure, these kinds of materials convert kinetic energy into electric energy, and your electronic parameters interact directly to the vibrations of the system they are coupled on. Therefore, this work aims at comparing the use of genetic algorithms and artificial neural network techniques in the implement of shunt control in a structural set of a cantilever beam coupled to a piezoelectric layer in the piezo-beam configuration. For the architecture of the genetic algorithm and the neural network, was used a software with finite element model implemented and the comparisons were made analyzing the computational demand of the algorithms and their respective responses when both of them were defined on the task of finding the best combination between the parameters of resistance and inductance of the piezoelectric patch that result in the best damping to the structure. The comparison between the techniques had a focus on the use of the objective function of the system by them, parameter used as a metric to gauge the aggregate computational demand, and the damping provided with the respective configurations suggested by the two techniques. The results show that the neural network after training completes your execution in order of 102 seconds, much faster than the genetic algorithm, presenting a response with an average gain in damping of 23,24dB, but, even though faster, this technique demands much more iterations than the genetic algorithm, due to its nature of parallel computations, and additional care for the input data, that need a pre-processing not seen in the genetic algorithm technique.

Keywords: Shunt Control, Neural Network, Genetic Algorithm, Objective Function, Smart Structures.

INTRODUCTION

The field of smart structures, or structures with integrated sensors and actuators, has arisen to offer improved vibration control in applications where passive techniques are either insufficient or impractical. The introduction of these materials with small volume, low weight and ease of structural integration, made piezoelectric sensors and actuators has been the overwhelming transducer of choice for smart structures.(Aphale, 2007). It is well known that there are a number of difficulties associated with the control of flexible structures, the foremost of which are: variable resonance frequencies; high system order; and highly resonant dynamics. Traditional control system design techniques such as LQG, H2 and H∞ commonly appear in research works and have been well documented. Unfortunately, the direct application of such techniques has the tendency to produce control systems of high order and possibly poor stability margins.

The design of controllers for smart structures is a challenging problem due to the presence of non-linearities in the structural system and actuators, the limited availability of control force, and the non-availability of accurate mathematical models.(Rao, Damie, Tebble, Kern, [11]). In this scenario, vibration control of smart structures using neural networks has thus been receiving attention for their advantages in self-learning, fault tolerance, and parallel processing.

Works in this area has become common. We can cited some few example, as the study of Finite element analysis and design of actively controlled piezoelectric smart structures(Xu SX, Koko [17]), the proposition of a fuzzy-logic algorithm to the vibration suppression of a clamp-free beam with piezoelectric sensor/actuator. (Zeinoun, Khorrami [20]), or the developed of a nonlinear feed forward controller for smart structures, that showed that the neural network is essentially a transversal filter with a nonlinear hidden layer between the input and output. (Snyder, Tanaka [13]).

Therefore, this work aims to compare the usage of neural network technique with genetic algorithm techniques, focusing on the recurrence number of the objective function of both codes, measured by the amount of iterations performed, as well as their execution time.

Equation of Motion for Beam Structure

For the study of the structure was adopted the classic beam model (piezoceramic-host).(Santos [12]). In this case was considered only the presence of deflection, disregarding the shear, thus Bernoulli Euler theory can be developed the equation of motion for the structure. With the applied theory of the Bernoulli can be developed the equation of motion for the structure, this form the structure-patches-circuits coupled equations of motion can be written as

$$\begin{bmatrix} M & 0 \\ 0 & M_q \end{bmatrix} \begin{Bmatrix} \ddot{u} \\ \ddot{D}_p \end{Bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & C_q \end{bmatrix} \begin{Bmatrix} \dot{u} \\ \dot{D}_p \end{Bmatrix} + \begin{bmatrix} K_m & -\bar{K}_{me} \\ -\bar{K}_{me}^t & \bar{K}_e \end{bmatrix} \begin{Bmatrix} u \\ D_p \end{Bmatrix} = \begin{Bmatrix} F \\ F_q \end{Bmatrix}, \tag{1}$$

where M_q is the inertial vector due to the presence of resistance and inductance, u and D_p are the vectors global mechanical displacement and electric displacement dofs. M, K_m, $\bar{K}_{me}$, $\bar{K}$ are the mass and mechanical, piezoelectric and dielectric stiffness matrices and F is the mechanical excitation force vector. C_q and F_q are the matrix of the damping and the vector of force dues the presence of resistance and inductance, but how in this work is studded only the output mechanical the value of the vector of electric voltage is equal zero.

Finite Element Model of Piezoelectric Beams

The structure is a fixed beam of the aluminum of dimension 220 mm in length, width of 25mm and thickness of 3 mm, the piezoelectric has a variable length, width of 25mm and thickness of 0.5 mm, as we can see in the Figure 1. The extension piezoceramics are made of PZT-5H material whose properties are: $\bar{C}_{11}^{D} = 97.767$ GPa, $\rho = 7500Kg.m^3$, piezoelectric coupling constants $\bar{h}_{31} = 1.3520x10^9$ N.C^1, and dielectric constants $\bar{\beta}_{33}^{\varepsilon} = 57.830x10^6 m.F^1$. For the beam has: $\rho = 2700Kg.m^{-3}$ and $E = 70x10^9 MPa$. (Santos, [12]).

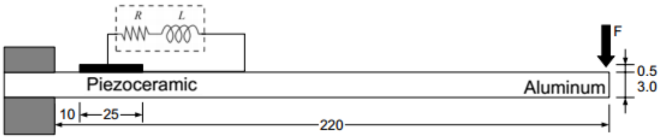

Figure 1. Representation of cantilever beam with bonded extension piezoceramic patch.

The optimization had the focus in resistance and inductance values of the circuit, wherever the resistance (R) is responsible in damping by means of Joule effect and the inductance (L) is responsible to control resonant frequency of the structure, this form had use a shunt circuit, the representation for this system can be seen in Figure 2.

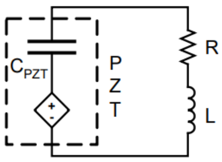

Figure 2. Configuration of the RLC circuit together with the piezoelectric.

Analysis of the equations for harmonic vibrations

For analysis of harmonic vibration, the proposed model (Santos [12]) is used to evaluate the mobility (velocity/force) frequency response function of the base structure. The resistive (R) or resonant (RL) shunt circuit affects both the passive control performance. In this way, it became necessary to use the circuit that will dissipate the energy or to storage for later use.

How this work analyze a purely mechanical excitation, such as $\underline{F}_q = 0$ and F = $bfe^{j\omega t}$, the amplitude of a displacement output y = c_pu can be written as $y = G\,(\omega)\,f$, where the FRF $G(\omega)$ is

$$G(\omega) = c_p\{(-\omega^2 M + K_m - \bar{K}_{me}(\omega^2 M_q + i\omega C_q + \bar{K}_e)^{-1}\bar{K}_{me}^{t})\}^{-1} b \tag{2}$$

Analyzing the equation 2 it can be noted that the resistance and the inductance have the capacity to change the rigidity properties of the piezoelectric material, in this way it will be applied to the case types i) open-circuit when R_c tending to infinity and ii) short-circuit when $Lc = Rc = 0$. For the open circuit it has

$$G^{oc}(\omega) = c_p\{-\omega^2 M + K_m\}^{-1} b \tag{3}$$

To the closed circuit

$$G^{sc}(\omega) = c_p\{-\omega^2 M + [K_m - \bar{K}_{me}\bar{K}_e^{-1}\bar{K}_{me}^{t}]\}^{-1} b \tag{4}$$

You may note that no structural modification is observed in the open circuit box, whereas in the case of a short circuit, the rigidity of the piezoelectric patches is reduced.

Vibration Control using piezoelectric actuators and state feedback

This way is necessary to rewrite the motion equations in the form of state space, containing the displacements and modal velocities of the piezoelectric patches and their derivatives of time.

$$\dot{z} = \hat{A}z + \hat{B}V_c + \hat{B}_f f \;,\; y = \hat{C}_y z, \tag{5}$$

where

$$z = \begin{bmatrix} \alpha \\ q_p \\ \dot{\alpha} \\ \dot{q}_p \end{bmatrix}, \hat{A} = \begin{bmatrix} 0 & 0 & I & 0 \\ 0 & 0 & 0 & I \\ -\Omega^2 & K_p & -\Lambda & 0 \\ L_c^{-1}K_p^t & -\Omega_e^2 & 0 & -\Lambda_e \end{bmatrix}, \quad \hat{B} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ L_c^{-1} \end{bmatrix}, \hat{B}_f = \begin{bmatrix} 0 \\ 0 \\ b_\phi \\ 0 \end{bmatrix}, \hat{C}_y = \begin{bmatrix} c_\phi & 0 & 0 & 0 \end{bmatrix}. \quad (6)$$

The modal displacements are such that $u = \phi\alpha$ and, for mass normalized vibration modes, $\Omega^2 = \phi^t K_m \phi$ and $\Lambda = \phi^t C\phi$. Ω is a diagonal matrix which elements are the undamped natural frequencies of the structure with piezoelectric patches in open-circuit. $\Omega_e^2 = L_c^{-1}\bar{K}_e$ and $\Lambda_e = L_c^{-1}R_c$ are both diagonal matrices which elements stand, respectively, for the squared natural frequencies of the electric circuits and the ratio between the resistances and inductances. The electromechanical coupling stiffness matrix projected in the undamped modal basis is defined as $K_p = \phi^t \bar{K}_{me}$. Input b and output c_y distribution vectors are also defined, with modal projections $b_\phi = \phi^t b$ and $c_\phi = c_y\phi$, and f is a vector of the amplitudes of each mechanical force applied to the structure (Santos [12]).
A linear state feedback for the applied voltages V_c is assumed such that $V_c = -gz = -g_{dm}\alpha - g_{de}q_p - g_{vm}\dot{\alpha} - g_{ve}\dot{q}_p$, where g is a matrix of control gains for each state variable. Therefore, the state space equation (5) becomes

$$\dot{z} = (\hat{A} - \hat{B}g)z + \hat{B}_f f \ , \ y = \hat{C}_y z. \quad (7)$$

For a single-input mechanical excitation f, the closed-loop or controlled amplitude of a single displacement output y can be written such that $\tilde{y} = G_h(\omega)\tilde{f}$, where the FRF $G_h(\omega)$ is

$$G_h(\omega) = \hat{C}_y(j\omega I - \hat{A} + \hat{B}g)^{-1}\hat{B}_f, \quad (8)$$

which can also be derived from the second order equations of motion projected into the undamped modal basis leading to

$$G_h(\omega) = c_\phi\left\{-\omega^2 I + j\omega(\Lambda + K_p \underline{D}_{cc}^{-1} g_{vm}) + [\Omega^2 + K_p D_{cc}^{-1}(g_{dm} - K_p^t)]\right\}^{-1} b_\phi, \quad (9)$$

where the closed-loop dynamic stiffness of the electric circuit $\underline{D}_{cc}$ is

$$D_{cc} = -\omega^2 L_c + j\omega(R_c + g_{ve}) + (\bar{K}_e + g_{de}). \quad (10)$$

In this work, the control gain $\underline{g}$ is calculated using the standard optimal LQR control theory applied to a single-input/single-output case, that is with only one active-passive patch-circuit pair for the control to minimize the vibration amplitude at one specific location of the structure, such that the following objective function is minimized

$$J = \frac{1}{2}\int_0^\infty \left(\dot{y}^2 + rV_c^2\right) \underset{.}{t}, \quad (11)$$

where $\dot{y}$ is the velocity at one location of interest and V_c is the control voltage applied to the active-passive shunt circuit in all cases following an iterative routine proposed in (Trindade, Benjeddou and Ohayon [3]).

Control Methods

Once even a minimal vibration is capable cause large destruction in mechanical systems, techniques to suppress or establish control over the systems vibration is widely researched.

These researches generally presents two categories, the passive controls, as presented by the model used for passive control of the vibration and Sound radiation from submerged shells (Oh, Ruzzene, Baz [9]), and active controls, where we have structural active vibration control using active mass damper by block pulse functions(Younespour, Ghaffarzadeh [19]), work that describe the concept of the using of a secondary system to absorbs the mechanical energy of the first one and consequently your vibration amplitude.

Also is known the possibility of systems of control that merge these two categories of techniques, creating passive-active systems as its seen with the application of H∞ control technique in modeling and H∞ control of active-passive vibration isolation for floating raft system (Yang, Hu, Zhang [18]).

Inside the concept of a additional system designed for damping, stands out the usage of piezoeletrics as secondary system for vibration absorption as were made in experiments on optimal vibration control of a flexible beam containing piezoelectric sensors and actuators (Abreu, Ribeiro, Steffen Jr [1]), where instead of transform the mechanical absorved energy into the range of motion, the scructure transform mechanical energy into electrial and dispereses it.

A similar structure was adopted to this work, generally referenced as shunt control.

Shunt Control

The main idea of shunt control comes from the principle of energy conservation that establish that the total quantity of energy in a isolated system remains constant, concept associated with a large number of scientists along the years, since Thales of Miletus until James Prescott Joule, been even correlated with Newton. Starting from this principle, once you used the amount of energy in a isolated system, it has no longer driving source to realize any movement, therefore, in a vibration control, design a secondary system that consume the internal energy of the primary one, as the energy coming from any external excitement, results in your stabilization. The basic way of use the energy of a system is converting this energy into movement, heat, electricity or any other energetic state.

The most common way of conversion of energy is from work to thermal energy. A wide range of devices does this conversion accidentally, either by mechanical friction, joule effect or any other disturbances, using only part of their potential to perform its work, what is defined by his efficiency, losing the rest by this conversion. Another devices, on the other hand, produce this heat energy intentionally for multiples usages. A conversion that still has no much highlight, but is increasingly applicable is the conversion from work to electrical energy, for this scenario piezoeletrics stands out.

Ceramics piezoelectric are described as a ceramic set that has a natural dipole present on your structure. This dipole makes the structure deform in the presence of a electrical field or produce a electrical dislocation with a mechanical deformation. This singular characteristic makes these ceramics a interesting alternative to conversion of energy without the need of dealing with punctual heat that could be harmful to the parts of the system exposed to it, once the heat can weaken or even force a change of phase in its structure.

The application of ceramics piezoelectric as shunt circuits are present in a large scale of systems that used the concept of shunt control, as it's seen in the work of structure control by a hybrid system in extension and shear(Santos, 2008 [12]), the similar idea was applied to reduce the error of the measure of high speed nano-scale positioners that present a dominant first mode of vibration due harmonics of a input signal. (Aphale, Fleming, Moheimani [2]).

The usage of a piezoelectric for shunt with a parallel R-L circuit for structural damping (Wu [16]) was an attractive model that we adopted for this work. The main idea of our research is demonstrate how efficient techniques of neural network are to determine the resistance (R) and inductance (L) parameters for theses circuits when we compare with genetic algorithm techniques, aiming a best optimization.

Optimization

Optimize is the act of creation the more favorable conditions for the development of something. When it is spoken in optimization of a circuit, we are looking for the best configuration of your passive elements to guarantee that this circuit do the best way what it was made to do, in case of a shunt circuit, we search for the best configuration to provide dispersion of energy and, consequently, damping of a structure.

Once we are looking for this dispersion of energy using a R-L parallel circuit, we are looking for the best configuration of resistance and inductance of this circuit to provide the minor mechanical or the bigger electricity response for the system, since these concepts are linked, as demonstrated previously.
Artificial intelligence has been widely exploited in recent years to aid in the solution of engineering problems, the mostly used techniques are the genetic algorithm and the artificial neural network, used in a similar research for shunt active power filter control. (M Qasim, V Khadkikar, [10])

Genetic Algorithm

The Genetic Algorithm (GA) can be described as a family of computational models that are inspired by the evolution of species for problem solving. They incorporate potential solutions to a problem in species of chromosomes, or population, that pass through segregation and data crossing, applying a selection nature that seeks to filter the results that best match the solution of the problem, selecting them positively for future crossings and penalizing those that flee the possible solution of the problem, thus forcing the structure to converge to a single value that meets the nature of the formulation.
This model has been recently adopted to solve a large scale of engineering problems of optimization in several areas as the optimization of laminate stacking sequence for buckling load maximization (Rifte, Haftka, 1996) or even the structural optimization of Lennard-Jones clusters. (Deaven, Tit, Morris, Ho [4])

A genetic algorithm works in defined space of possible results, in this way, it is necessary to establish boundaries for the code, such boundaries have been defined through the use of a parallel work of structural vibration control using piezoelectric (Santos [12]), which provides us a equation to reach the resistance and inductance values considered optimal to the piezoelectric circuit, these values were defined in the algorithm as the expected average results and the boundaries were a made to restrain a thousand of possible results, called as population, centered in these optimal values. The optimal values used were resistance of *208.96 Ohm* and inductance of *121.71 H*. In order of fair comparison with Neural Network, the same space of average results were used for both structures. A flow chart for this model it's seen in Figure 3.

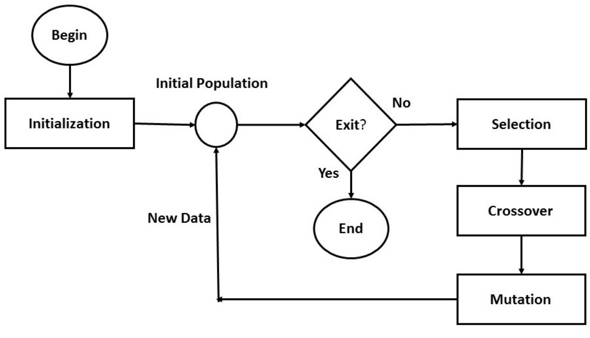

Figure 3. GA's Flow Chart

Artificial Neural Network

Artificial Neural Networks (ANN) are a set of computational techniques to obtain answers that present a mathematical model corresponding to the neural structure of living organisms, being able to learn and to improve their results with multiples trainings and applications.Neural networks have a large number of highly interconnected processing elements (nodes) that demonstrate the ability to learn and generalize from training patterns or data. They, like humans, can perform pattern-matching tasks, while traditional computer architecture, however, is inefficient at these tasks. On the contrary, the latter is faster at algorithmic computational tasks. Neural networks, like fuzzy logic control/decision systems, are excellent at developing human-made systems that can perform the same type of information processing than our brain performs.(Lin [8]).

There are three typical steps for building this model; the input of data, in general is used arrays to organize this data. Learning, the step where multiple data are crossed and analyzed according to stipulated conditions, producing increasingly accurate and close answers to the mathematical ideal, and data output.

This model provides a lot of works in the area of optimization and structure control as the adaptive control in smart structures (Rao, Damie, Tebbe, Kern, [11]) or the identification and control of dynamic systems using recurrent fuzzy neural networks (Lee, Teng [6]), can be also cited your usage for system identification and control on a smart structure (Lee [7]).

For this paper, to create the Target data, the values of Resistance and Inductance were randomly by a normal distribution centered on analytical optimal values in order to produce individuals for the Training. The difference between the max amplitude answers of the complete system with these values, of resistance and inductance, and the respective values for both open and short circuit were saved as the Input data. The choice of the size of the vectors were think aims to balance aspects of precision and execution time of the network, focusing on the converging line of the code.

The training function of the network updates weight and bias values according to Levenberg-Marquardt optimization. The choose was due the high speed answer of this function and the reliability associated with this back propagation algorithm, working in a maximum of 1000 epochs. The error function used were the difference between of the peak amplitude frequency of first vibration mode for both open and short circuit. The code objective were minimize this difference. With this minimization, we find a R-L configuration for the circuit that presents the same natural frequency of the structure it was coupled to in the max resistance(open circuit) and in the zero resistance(short circuit) condition, having thus your max excitation in the same frequency that the beam for both extreme configuration.

The choice of optimize the shunt circuit using these two referential condition was due the fact that these condition produce the max mechanical and consequently the minimal electrical response on the beam, having the same maximal amplitude, thus we are always dealing with the worst condition that the system can be exposed to. This way, since the damping were effective in these conditions it will be to any other.

Once the shunt circuit absorb the energy coming from excitation, having a configuration that ensures the beam with the circuit has the same natural frequency of the both open and short conditions, ensures in the same way that this circuit provides a best damping for the system in the excitation the beam would had your max vibration, showing itself a great choice for a structural damping. A flow chart for this model it's seen in Figure 4.

Results

The results of the configuration of resistance and inductance, in Figure 1 suggested by the Artificial Neural Network and the Genetic Algorithm are shown in a comparison of frequency responses with both short circuit, $R = L = 0$ and open circuit $R = \infty$ and $L = 0$, in the Figure 5. Verifying the results presented, can be observed an alteration of stiffness, no affecting the other vibration modes. The suggested configuration of resistance and inductance shows no effect on the another frequencies of the structure, keeping

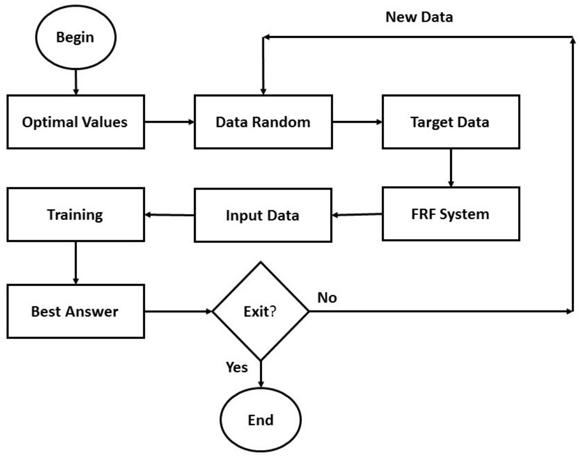

Figure 4. ANN's Flow Chart

restricted to the control we arbitrate. This condition demonstrates a precision control of damping by both adopted methods once only the first vibration mode was chosen for damping.

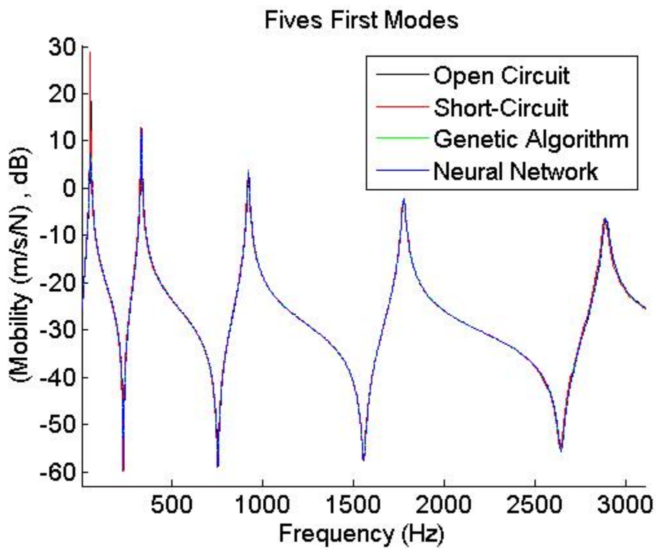

Figure 5. Frequency Responses for Five First Modes of Resonance of Cantilever Beam

The Figure 6 shows the frequency response for the first mode of vibration. On that, can be seen an average damping gain of *23.24dB* for the ANN and *24.27dB* for the GA, between open circuit and controlled structure. Although close in amplitude, ANN and GA shows a little larger difference of results when we compare the time of executions and the iterations demanded to provide the configurations.

The results for the time of execution of the Genetic Algorithm method proceed, in the Figure 7, where its seen the times for GA's execution, in seconds, for the ten experimentally tests. The values for this method shows up a wide range, having its minimum in 1397.63s and maximum in 1693.20s, with a global variation of 295.57s average, or 5 minutes.

The results for the Neural Network, Figure 8, shows up a more behaved range. The values for the minimum and maximum are, respectively, 54.18s and 49.92s, keeping restricted to a global variation of 4.26s, much smaller than the one presented by the genetic algorithm, proving to be more reliable.

The Figure 9 and 10 shows, respectively, the values of iterations demanded for both techniques to provide the configuration of Resistance and Inductance for the beam. Once again, a better behavior is seen for the Artificial Neural Network, demonstrating both a smaller number of iterations, averaging

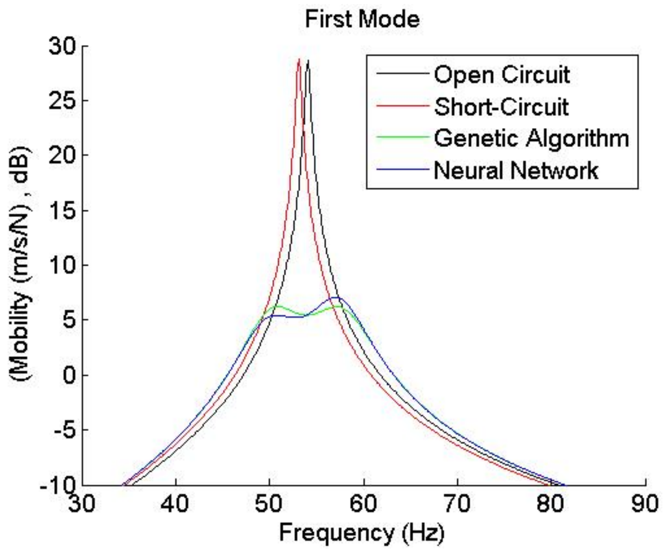

Figure 6. Comparison of Frequency Responses for First Mode of Resonance of Cantilever Beam

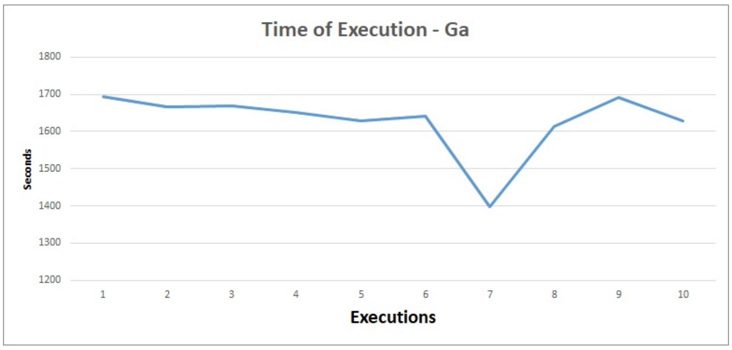

Figure 7. Comparison of Time Execution - GA

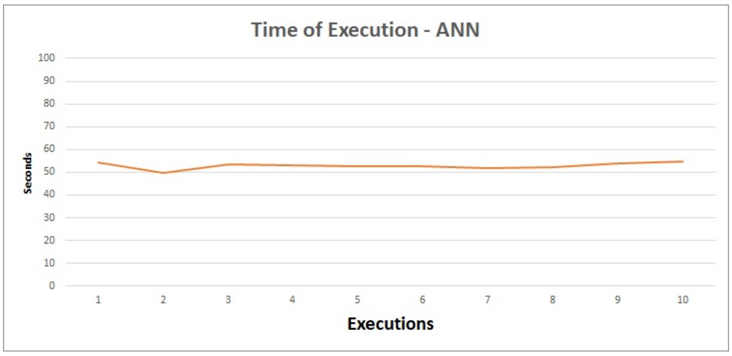

Figure 8. Comparison of Time Execution - ANN

1330 iterations, and a smaller range of iterations ranging from 1587 to 1125 total iterations to achieve the desired configuration. The Genetic Algorithm presents an average number of iterations of 61122, almost 45 times the demanded for the ANN, with the global variation of 8016 iterations. The Figures 11 and 12 presents the range of values between the two techniques punctually for the ten experiments, so as to visually presents the discrepancy between time and number of iterations used, respectively.

Thus we notice a relative advantage for the Artificial Neural Network technique, with an average execution time of 52.81s in contrast to 1646.43s of the Genetic Algorithm, however this scenario is reversed when comparing the damping range produced by both techniques.

The Figure 13 shows the frequency response of the beam for the ten configurations suggested by both techniques, on that its seen, even with less predictable behavior, the Genetic Algorithm presents a

Figure 9. Comparison of Iterations Demanded - GA

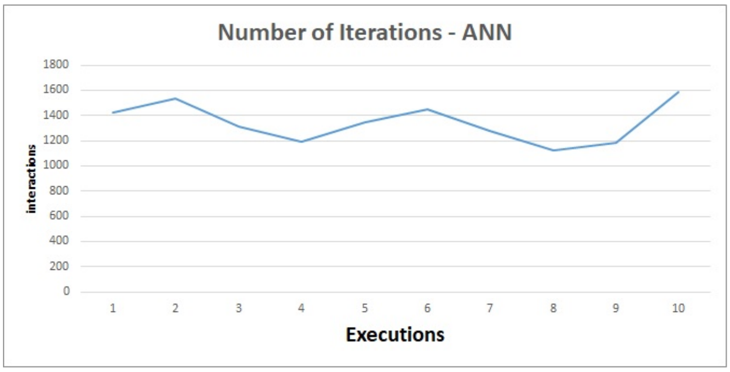

Figure 10. Comparison of Iterations Demanded - ANN

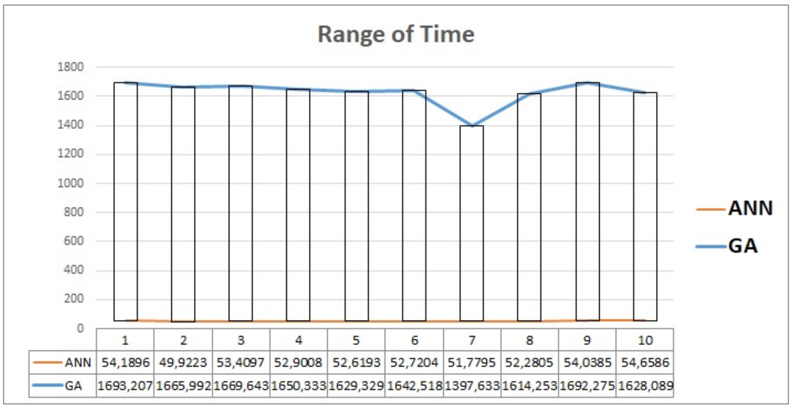

Figure 11. Range of Time Execution

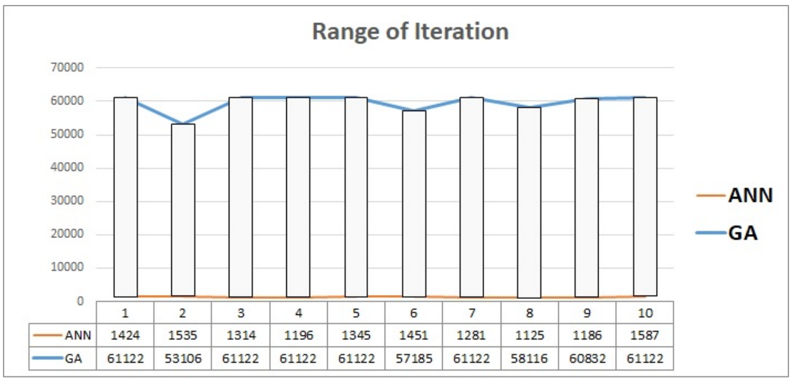

Figure 12. Range of Iterations

better global damping than the Neural Network, with 25,23dB against 23,3dB. Comparing both configurations, can be observed a same nature of control for the structure and the average damping for ANN and GA were, respectively, 23,24dB and 23,64dB. The range of values for the codes was plotted in Figure 14 in order to provide a visual conference of the distinction of responses that both structures presents.

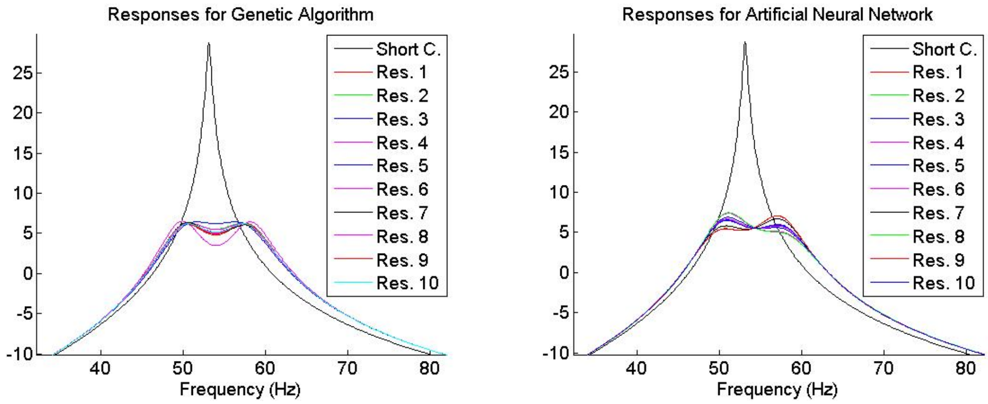

Figure 13. Response of Frequency (a) Genetic Algorithm (b) Artificial Neural Network

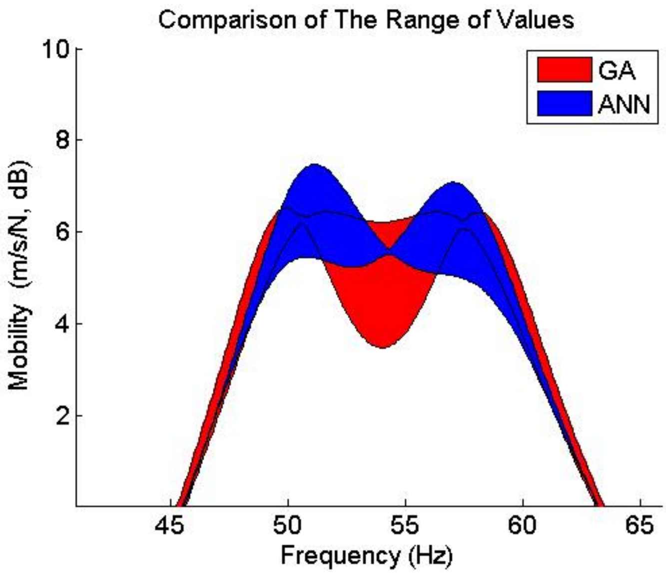

Figure 14. Comparison of The Range of Values

Conclusion

The results shows that both adopted techniques provided optimized configurations for the structure in a order of damping superior of *20dB*, demonstrating the usage of any of these techniques are a interesting alternative for setup of a shunt control system, being the main difference the computational demand associated to each of them, measured by the time execution of the codes, and the number of iterations needed to get the result.

An analysis of performance, with focus in time of processing and attenuation of the amplitude for frequency tuned, shows a better performance for Neural Network compared with Genetic Algorithm, since the ANN presents a damping gain very close to that of GA, working in a much lower computational demand.

The ANN shows up a better choice for the shunt control of smart structures, once this technique demonstrates the answers in order of 50 seconds and has a time of execution less of a tenth than GA's, besides this technique presents a relevant difference between the number of iterations required, demanding almost 50000 iterations fewer than the genetic algorithm to provide close configurations of resistance and inductance, and damping for the beam, what means the ANN is much more adaptive, and justifies the time contrasts.

An additional advantage of this technique is your adaptive learning characteristic, that allows your structure go through complex changes without demand additional computational cost to adapt to the new conditions, being recommended for active vibration control systems or any kind of control that need a quick answer from the controller.

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