Research Article

Active Vibration Control of the Smart Plate Using Artificial Neural Network Controller

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The active vibration control (AVC) of a rectangular plate with single input and single output approach is investigated using artificial neural network. The cantilever plate of finite length, breadth, and thickness having piezoelectric patches as sensors/actuators fixed at the upper and lower surface of the metal plate is considered for examination. The finite element model of the cantilever plate is utilized to formulate the whole strategy. The compact RIO and MATLAB simulation software are exercised to get the appropriate results. The cantilever plate is subjected to impulse input and uniform white noise disturbance. The neural network is trained offline and tuned with LQR controller. The various training algorithms to tune the neural network are exercised. The best efficient algorithm is finally considered to tune the neural network controller designed for active vibration control of the smart plate.

1. Introduction

In the present time, the research on the control of noise and vibration of the flexible structure is increasing remarkably. It is also very important because the flexible structures show possessions of vibration when they are subjected to disturbance forces, leading to component and structural damage. The active vibration control cause of advantages in reducing weight and cost of the system is utilized by the industries to reduce the vibrations. An idea/principle of suppressing the vibration in these structures is crucial to be known before implementing. The controllers have grown up to a very large extent over the past few years. The controllers are used specifically to act upon a particular input and control the action of the system. They have got tremendous significance and application potential in a smart/intelligent system. The classical controllers have also been used by researchers to control noise and structural vibrations like proportional, proportional derivative, proportional integral derivative, and so forth. But these are not as efficient as intelligent controllers. Active vibration control (AVC) is one of the applications of smart structure. Leug (1936), founder of AVC, gives the concept for reducing sound in

a channel. In AVC, an external energy source is used to control vibration produce in the structure. The idea consists of detectors to see these structural dynamics/vibrations, a controller to collect the detectors/sensors signals and give a suitable signal to the actuators, and the actuators to do its job according to the controller. Such an arrangement is known as a “smart structure.” Fuzzy controller, neural network controller, ANFIS controller, and so forth come under the category of adaptive/intelligent controllers. These can be used as an identifier/estimator when it is calculating the whole system response even for that position where sensor is not placed. Xia and Ghasempoor [1] introduce a neural network controller which generates a control signal by detecting noisy sinusoidal vibration factor of a cantilever plate to stop the vibration. The multilayer feedforward ANN is utilized in which one hidden layer and one output layer are present. The hidden layer contains log sigmoid neurons and one output layer has three log sigmoid neurons. Many uncertainties are introduced: first to push the shaker against the beam and second to filter the continuous input signal with band pass filter characteristics from detector to provide a voltage to the higher frequency harmonics. Such system helps in eliminating the time delay sensitivity. Snyder and Tanaka

[2] uses the feedforward neural network control system to control sound and vibration by making a control signal which is the result consequent from a pure tone reference signal containing some level of harmonics. The algorithm is also having a filter based controller which is using gradient decent type algorithm. The limitation of the system is that only linear signal with respect to the reference signal can be surely evaluated and performed. There is a need of continuous updating of the FIR filter weights so that a robust system can be formed. Jha and Rower [3] formed a neural network controller which is controlling harmonics of the inputs sine wave and impulse; white noise provided the offline training. An error backpropagation technique for multilayer perceptron neural network model is utilized by them. Neural Network Identifier is also used simultaneously with neural network controller to predict the system response to the input and depend on response neural network controller generating the control signal to suppress the vibrations. Qiu et al. [4] made a vision feedback based active vibration control system for flexible manipulator by using radial basis function neural networks. The end side image processing methods are given by them. PD control algorithm output is used to train the radial basis neural network. In Bianchi et al. [5], exertion on active noise and vibration neural network controller for a rectangle flat aluminum plate was based on diagonal recurrent neural networks to reduce electromechanical harmonics with the help of software platform of RT-LINUX. A diagonal recurrent artificial neural network is implemented containing one input layer, one recursive hidden layer, and a single output layer. The least mean square algorithm is utilized to train both the estimator and director. Bhowmik [6] worked on semiactive control strategy for rotary type magnetorheological damper based on neural network on a base excited shear frame structure. Training data is taken from hysteresis loop and force displacement trajectory. Magnetorheological damper which is semiactive device is utilized as a sensor and actuator damper changing the frictional force with respect to changing current and vice versa. Youn et al. [7] found the results and variations of sudden delamination of the composite beam with the help of neuroadaptive controller. Pedro et al. [8] presented an adaptive neural network-based feedback linearization slip control scheme for antilock braking system (ABS) to reduce vehicle braking distance. The multilayer perceptron neural network model is used to represent ABS. Levenberg-Marquardt algorithm is employed to train the neural network with genetic algorithm optimized controlled gain signal. The difference between the speeds of the wheels of a car or a four-wheeler in which we are applying brakes is sensed and it is provided to the controller and the braking pressure is controlled by the neural network controller. In this way, braking distance is reduced. The designing of the system is having a lot of the problems though it is having a number of challenges like nonlinearities in the suspension system and uncertainties like road conditions and road surface and so forth. The neural network based feedback linearization controller demonstrated robustness to both model and parametric uncertainties related to control of suspension. Ku and Lee [9] presented diagonal recurrent ANN which is actually recurrent ANN having an unseen

layer and this layer is made of self-recurrent neurons. The researchers used a system in which they are using two DRNNs (diagonal recurrent neurocontrollers) which is the type of neural network controllers. One of them is used for identification purpose and the other for a controlling purpose. Based on the working of these, they are named as diagonal recurrent neuroidentification (DRNI) and as diagonal recurrent neurocontroller (DRNC). The system is identified by DRNI and provides signal to the DRNC. DRNC is used to derive unknown dynamics to minimize error between desired and the plant output. A generalized backpropagation method is used to train both DRNI and DRNC. Lyapunov function is used to calculate the adaptive learning rates for the DRNN. Different cases were studied like bound input bound output nonlinear plant control, tolerance to vibrations, the non-BIBO (bound input bound output) nonlinear plant, and the control system which has interpolation ability of DRNN. It is better than fully connected recurrent neural network in terms of fewer weights required for training in it and mapping characteristics. It is tested for online adaptive ability, recovering ability from disturbance, and interpolation ability. Erkaya [10] investigated the effect of joint clearance on bearing vibrations of the mechanical system. He utilized the neural network to predict and estimate the vibration characteristics of the mechanism for different range of speeds and clearance sizes. Generalized regression neural network (GRNN) and RBF network both are used by him. He found the RBF network superior to the others for this purpose of identifying and analyzing a mechanical system. Result of the experiment shows that the clearance size is directly proportional to the bearing amplitude. Feedforward RBF with only one hidden layer, 1 input layer with five linear neurons, 1 output layer with 3 linear neurons, and 1 hidden layer with 10 nonlinear neurons are used. Zhou et al. [11] investigated active vibration control of an aluminum plate with backpropagation neural network which uses error filtering technique. The comparison between FEBPNN and FXBPNN is done in which FEBPNN is faster than FXBPNN in terms of speed. A digital signal processor is used to implement backpropagation neural network and filtered-x least mean square based controller. The proposed controller is proved to be efficient for nonlinear control problem to eliminate the vibration of the system. Jha and He [12] present a comparison between ANN and predictive adaptive controllers for controlling vibrations of time varying and nonlinear construction. The ANN utilizes nonlinear neural network autoregressive plant model taking exterior input whereas the other neural network uses linear autoregressive plant model. The neural adjustable prognostic controller was observed to be more efficient than adaptive generalized predictive controller. The controllers show a great adaptability to change in plant dynamics and external disturbance applied to cantilever plate. The ANN controllers can be used as controllers as well as identifier in variety of applications. Some researchers are convinced to use it as controller for active vibration control, while some use it as estimator for various randomly changing structural and environment situations. In both of the situations, it serves with very high precision and shows a great performance. The ANN controllers are

used as an active vibration suppressor for various shapes like cantilever beam cantilever plate, inverted L shape structure, and so forth. In all these cases, robust characteristics of the ANN controllers are experienced significantly. Smyser and Chandrashekhara [13] worked on robust neural network controller on composite beam which has configuration of sensor and actuator layers in between the beam plates. The output of the Linear Quadratic Gaussian (LQG) controller is provided to the neural network controller for training sample data offline using backpropagation algorithm. With the changing initial parameters like forces, inputs and neural network controller are more efficient than Linear Quadratic Gaussian (LQG). In some experiments, they are utilized as a powerful device to control jerks to a building type structure which shows that it can be used in the prevention of earthquake and volcano-like natural disaster. Chen [14] developed a genetic algorithm based neural classifier controller to stop building structure shaking freely and forcefully. In this way, it is an active mass damper system in which neural classifier controller is trained by genetic algorithm which is three layers of feedforward neural network excited with sigmoid nonlinearities. Based on the classification of system input output measurements, a response signal is generated proportional to this to stop disturbances. Liu et al. [15] proposed a backpropagation algorithm to reduce vibration of the structures under earthquake having semiactive control devices (e.g., magnetorheological fluid damper). In aviation industries, there is need for light weight of the device to reduce power consumption for noise and vibration mitigation of flexible spacecraft. It can serve as a power efficient and less weight device. Liu et al. [16] control the low frequency noise radiation by combining ANN identifier and ANN controller. Yildirim and Eski [17] worked on reducing the vibration of the space truss structure with the help of neural network. In automotive industries, efficiency of vehicle suspension system can be dramatically changed by use of the ANN controllers, providing customer a luxurious experience. Bosse et al. [18] did their work to suppress the vibration of a car suspension system having a 200 kg metal plate. The very frequently used backpropagation ANN and radial basis ANN controller are utilized by them. Radial basis neural network controller is found to be better automotive vehicle suspension system than the back-propagation neural network controller suspension system after testing them. It can be used to find the natural frequency of any moving or vibrating body. Kumar et al. [19] examined Linear Vector Quantisation (LVQ) neural network for reducing vibrations of an inverted L shape structure for the first three natural frequencies. It overcomes the drawback of LQR controller as it cannot bear up with system parameters changing very rapidly like pay loads and position. The artificial neural network controllers can also be used as identifier and estimator of evaluating output of the portion of the body where sensor is not placed. Hence the solution converges to be fully satisfied with the material coordinates. Islam and Craig [20] made a backpropagation ANN based damage detection system for composite structure. The ANN is trained with the frequency values of the first five natural frequencies of the composite beam structure in both the damage condition and the healthy condition. The stiffness

parameter of the beam is continuously observed because it is directly proportional to active response of the formation. After a sufficient training to the neural network estimator, the location and intensity of damage can be evaluated easily. It can predict exactly the strength of damage and the location on which damage to a body occurs. Zheng et al. [21] performed the RBF (radial basis function) ANN for structural health supervising of composite cantilever beams optimized with the combination of genetic algorithm and fuzzy logic. In the growing electronic industries robots and manipulators are being developed in which precision or accuracy in movement is very important. These robots have a number of revolving motors and degree of freedom. ANN is showing dramatic results for controlling movements of robots and manipulator link. Li et al. [22] worked on the elimination of the pulsation of the modular robot having nine degrees of freedom by backpropagation neural network based on genetic algorithm. Genetic algorithm with backpropagation removes many shortcomings of the traditional methods; also it optimizes the different factors of the neural network. An efficient controlling system is designed which can predict the controlling action to stop vibration of the cantilever plate.

2. Methodology

2.1. Block Diagram of the Active Vibration Control. The basic block diagram of the active vibration control which is used by us during our research is shown in Figure 1. It is having a cantilever plate, a sensor, an actuator, a charge amplifier, a voltage amplifier, a cRIO based controller, and input and output data acquisition cards.

2.2. Finite Element and State Space Formulation

2.2.1. Finite Element Discretization. The plate is formulated according to Kirchhoff assumption (thin plate) and accordingly the piezoelectric layers are completely united together and formulated with linear elastic activities (small displacement and the strains). The small displacements fields are represented by u , v , and w which are present along the horizontal axis x , vertical axis y , and a third axis z which is perpendicular to both previous axes x and y . These can be expressed by the Kirchhoff hypotheses as shown in Figure 2 and the dynamic response of the smart element by Lagrangian method for a finite structure and applying Hamilton principle is given by

$$\int_{t_1}^{t_2} \{ \delta q_k \}^T \cdot \left[[M_{qq}^e] \{ \ddot{q}_k \} + [K_{qq}^e] \{ q_k \} + [K_{q\Phi}^e] \{ \Phi \} - \{ \bar{f} \} \right] + \{ \delta \Phi \} \left[[K_{\Phi q}^e] \{ q_k \} + [K_{\Phi\Phi}^e] \{ \Phi \} + \{ Q_a \} \right] dt = 0, \quad (1)$$

where

$$[M_{qq}^e] = \rho \int_V [X]^{-T} [L_M] [H]^T [H] [L_M] [X]^{-1} dV,$$

$$[K_{qq}^e] = [X]^{-T} \int_V Z^2 [L_K]^T [D] [L_K] [X]^{-1} dV,$$

FIGURE 1: Vibration controlling system of a cantilever plate.

FIGURE 2: Coordinate scheme of a coated finite element with incorporated piezoelectric substance.

$$\begin{aligned} [K_{q\Phi}^e] &= [K_{\Phi q}^e]^T = -[X]^{-T} \int_V z [L_K]^T [e]^T B_Z dV, \\ [K_{\Phi\Phi}^e] &= - \int_V B_Z^T [\xi^T] B_Z dV, \\ \{\bar{f}\} &= \int_V \{f_b\} dV + \int_A \{f_A\} dA, \\ \{Q_a\} &= \int_A \sigma_q dA. \end{aligned} \quad (2)$$

Allowing arbitrary variations of $\{q_k\}$ and $\{\Phi\}$, two equilibrium equations written in generalized coordinates are now obtained for the k th element:

$$\begin{aligned} [M_{qq}^e] \{\ddot{q}_k\} + [K_{qq}^e] \{q_k\} + [K_{q\Phi}^e] \{\Phi\} - \{\bar{f}\} &= 0, \\ [K_{\Phi q}^e] \{q_k\} + [K_{\Phi\Phi}^e] \{\Phi\} + \{Q_a\} &= 0, \end{aligned} \quad (3)$$

where $[K^e]$, $[M_{qq}^e]$ are the matrixes for extended element stiffness and element mass.

Integrating matrix $[K_{qq}^e]$ which is referring to the mechanical stiffness in the z direction yields

$$[K_{qq}^e] = \sum_{i=1}^3 h_i [X]^{-T} \int_A [L_K^T] [D_i] [L_K] dA [X]^{-1}, \quad (4)$$

where h_i is given by

$$h_1 = h_a \left(\frac{h_p}{2} + \frac{h_a}{2} \right)^2 + \frac{h_a^3}{12}, \quad (5)$$

$$h_2 = \frac{h_p^3}{12}, \quad (6)$$

$$h_3 = h_s \left(\frac{h_p}{2} + \frac{h_s}{2} \right)^2 + \frac{h_s^3}{12}, \quad (7)$$

and $[D_i]$ or $[D_a]$, $[D_p]$, and $[D_s]$, for $i = 1, 2, 3$, can be calculated by $[D]$ matrix in the following equation for

piezoelectric and plate material properties, respectively, and dA is equal to $dx dy$:

$$[D] = \frac{E}{1-\nu^2} \begin{bmatrix} 1 & \nu & 0 \\ \nu & 1 & 0 \\ 0 & 0 & \frac{(1-\nu)}{2} \end{bmatrix}. \quad (8)$$

Integrating the matrix which is denoting element mass in the z direction results in

$$[M_{qq}^e] = \sum_{i=1}^3 \rho_i [X]^{-T} \int_A [L_M]^T [H_i] [L_M] dA [X]^{-1}, \quad (9)$$

where $\rho_1 = \rho_a$, $\rho_2 = \rho_p$, $\rho_3 = \rho_s$, and $[H_i]$ (for $i = 1, 2, 3$) are

$$\begin{aligned} [H_1] &= [H_a] = \begin{bmatrix} h_a & 0 & 0 \\ 0 & h_1 & 0 \\ 0 & 0 & h_1 \end{bmatrix}, \\ [H_2] &= [H_p] = \begin{bmatrix} h_p & 0 & 0 \\ 0 & h_2 & 0 \\ 0 & 0 & h_2 \end{bmatrix}, \\ [H_3] &= [H_s] = \begin{bmatrix} h_s & 0 & 0 \\ 0 & h_3 & 0 \\ 0 & 0 & h_3 \end{bmatrix}. \end{aligned} \quad (10)$$

The matrix $[K_{q\Phi}^e]$ and matrix $[K_{\Phi\Phi}^e]$ are integrated in the z direction with respect to the thickness of each piezoelectric layer (where $dV = dV_a$ and $dV = dV_s$), which results in

$$\begin{aligned} [K_{q\Phi}^e]_a &= -\frac{1}{2} (h_p h_a + h_a^2) [X]^{-T} \int_A [L_K]^T [e]_a^T B_Z dA, \end{aligned} \quad (11)$$

$$[K_{\Phi\Phi}^e]_a = -\frac{4ab [\xi_a^S]}{h_a}, \quad (12)$$

$$[K_{q\Phi}^e]_s = \frac{1}{2} (h_p h_s + h_s^2) [X]^{-T} \int_A [L_K]^T [e]_s^T B_Z dA, \quad (13)$$

$$[K_{\Phi\Phi}^e]_s = -\frac{4ab [\beta \xi_s^S]}{h_s}. \quad (14)$$

Equations (6), (9), (11), and (13) are integrated numerically by using the Gauss-quadrature integration method:

$$\begin{aligned} [K_{qq}^e] &= \sum_{i=1}^3 h_i [X]^{-T} \sum_{\eta} \sum_{\xi} [L_K]^T [D_i] [L_K] W_{\xi} W_{\eta} [X]^{-1}, \\ [M_{qq}^e] &= \sum_{i=1}^3 \rho_i [X]^{-T} \sum_{\eta} \sum_{\xi} [L_M]^T [H_i] [L_M] W_{\xi} W_{\eta} [X]^{-1}, \\ [M_{q\Phi}^e]_a &= -\frac{1}{2} (h_p h_a + h_a^2) \\ &\quad \cdot \sum [X]^{-T} \sum_{\eta} \sum_{\xi} [L_K]^T [e]_a^T [L_M] W_{\xi} W_{\eta} B_z, \\ [K_{q\Phi}^e]_s &= \frac{1}{2} (h_p h_s + h_s^2) \\ &\quad \cdot \sum [X]^{-T} \sum_{\eta} \sum_{\xi} [L_K]^T [e]_s^T W_{\xi} W_{\eta} B_z, \end{aligned} \quad (15)$$

where W_{ξ} , W_{η} are the weight factors and (ξ, η) Gaussian integration point coordinates.

2.2.2. Obtaining the Global Matrices. The element matrices are assembled into global matrices. The assemblage process to obtain the global matrices is written as

$$\begin{aligned} [M] &= \sum_{k=1}^N [T_k]^T [M_{qq}^e] [T_k], \\ [K_{qq}] &= \sum_{k=1}^N [T_k]^T [K_{qq}^e] [T_k], \end{aligned} \quad (16)$$

where N is the number of finite elements and $[T_k]$ is the distribution matrix defined by

$$T_k(i, j) = \begin{cases} 0 & \text{if } j \neq m_k(i) \\ 1 & \text{if } j = m_k(i) \end{cases} \quad (17)$$

for $i = 1, 2, \dots, 12$, $j = 1, 2, \dots, n$,

where n_{dof} is the number of degrees of freedom of the whole construction and m_k stands for the index vector including the degrees of freedom (3 dof) of the n th node (1, 2, 3, or 4—see Figure 1) in the k th finite element given by

$$m_k = \{3n_k - 2 \quad 3n_k - 1 \quad 3n_k\}. \quad (18)$$

Considering that n_a actuators and n_s sensors are distributed in the plate, (4) and (5) can be written in the global form:

$$[M] \{\ddot{\zeta}\} + [K_{qq}] \{\zeta\} + \sum_{k=1}^{n_{e_i}} [T_k]_i^T [K_{q\Phi}]_i \{\Phi\} - \{F\} = 0, \quad (19)$$

$$\sum_{k=1}^{n_{e_i}} ([K_{\Phi q}]_i [T_k]_i \{\zeta\} + [K_{\Phi\Phi}]_i \{\Phi\} + Q_a) = 0, \quad (20)$$

where $[T_k]_i$ is the distribution matrix (Equation (17)) which explains the position of the k th element in the plate configuration by using zero-one inputs, where the zero input means that piezoelectric actuator/sensor is not there and one input means that there is only one actuator/sensor in that specific element position, n_{e_i} is the number of finite elements of the i th piezoelectric actuator/sensor, and $\{\zeta\}$ is the nodal displacement vector of the global configuration.

In the piezoelectric sensor, there is no voltage applied to the corresponding element ($Q = 0$), so that the electrical potential generated (sensor equation) is calculated by using a standard equation which is written below

$$\{\Phi_s\} = - \sum_{k=1}^{n_{e_i}} [K_{\Phi\Phi}]_{si}^{-1} [K_{\Phi q}]_{si} [T_k]_i \{\zeta\} \quad (21)$$

for $i = 1, 2, \dots, n_s$.

The total voltage $\{\Phi\}$ is sum of the voltage $\{\Phi_s\}$ that is sensed by the sensor, the voltage $\{\Phi_{sa}\}$ that is detected by the actuator (see (21)), and the applied voltage $\{\Phi_a\}$. Then, $\{\Phi\}$ can be expressed by the following equation:

$$\{\Phi\} = \{\Phi_s\} + \{\Phi_{sa}\} + \{\Phi_a\}. \quad (22)$$

The global dynamic equation can be formed by substituting (21) into (22) and then into (19). The sum of the forces due to actuator and mechanical forces comes to the right hand side of the final equation which gives

$$[M] \{\ddot{\zeta}\} + [K_{qq}^*] \{\zeta\} = \{F\} + \{F_{el}\}_j, \quad (23)$$

where $[K_{qq}^*]$ and $\{F_{el}\}$ (electrical force) are given by, respectively,

$$[K_{qq}^*] = [K_{qq}] - [K_{el}], \quad (24)$$

$$\{F_{el}\}_j = \sum_{k=1}^{n_{e_j}} [T_k]_j^T [K_{q\Phi}]_{aj} \Phi_{aj}, \quad \text{for } j = 1, 2, \dots, n_a, \quad (25)$$

where $[K_{el}]$ is the electric stiffness written as

$$\begin{aligned} [K_{el}] &= \sum_{k=1}^{n_{e_i}} \sum_{j=1}^{n_a} [T_k]_i^T [K_{q\Phi}]_{si} [K_{\Phi\Phi}]_{si}^{-1} [K_{\Phi q}]_{si} [T_k]_i \\ &\quad + \sum_{j=1}^{n_a} \sum_{k=1}^{n_{e_j}} [T_k]_j^T [K_{q\Phi}]_{aj} [K_{\Phi\Phi}]_{aj}^{-1} [K_{\Phi q}]_{aj} [T_k]_j. \end{aligned} \quad (26)$$

2.2.3. Full State Feedback Modal Control. Full state feedback modal control is explained by S. L. Schulz as follows.

For the full state feedback modal control, relationship between electric charges and modal state variables is given by the following expression:

$$\{q\} = [\Phi] \{\eta\}. \quad (27)$$

Then,

$$\begin{Bmatrix} \{q\} \\ \{\dot{q}\} \end{Bmatrix} = \begin{bmatrix} [\Phi] & [0] \\ [0] & [\Phi] \end{bmatrix} \begin{Bmatrix} \{\eta\} \\ \{\dot{\eta}\} \end{Bmatrix}, \quad (28)$$

$$\{x\} = [\Phi] \{x_m\},$$

where $\{x_m\}$ is the vector of the state space variables composed by the modal variable vector $\{\eta\} = \{\eta_1, \eta_2, \dots, \eta_n\}^T$ and the respective time derivatives $\{\dot{\eta}\} = \{\dot{\eta}_1, \dot{\eta}_2, \dots, \dot{\eta}_n\}^T$. $[\Phi]$ is a matrix, which is organized in such a way that each column contains an eigenvector, obtained from the eigenvalue-eigenvector problem

$$[[K] - [\Omega] [M]] [\Phi] = \{0\}, \quad (29)$$

where $[\Omega]$ is a diagonal matrix:

$$[\Omega] = \text{diag}(\omega_1^2, \omega_2^2, \dots, \omega_n^2), \quad (30)$$

where $(\omega_1^2, \omega_2^2, \dots, \omega_n^2)$ are the square values of circular frequencies, and the matrix $[\Phi] = [\{\Phi_1\}, \{\Phi_2\}, \dots, \{\Phi_n\}]$ contains in each column $[\Phi_i] = [\{\Phi_1\}, \{\Phi_2\}, \dots, \{\Phi_n\}]^T$, the eigenvector corresponding to the eigenvalue ω_i^2 . Taking (11) into account, the following equation of motion is obtained:

$$\begin{aligned} [I] \{\ddot{\eta}\} + [\Lambda] \{\dot{\eta}\} + [\Omega] \{\eta\} \\ = [[\Phi]^T [M] [\Phi]]^{-1} [\Phi]^T [F] \{u\}, \end{aligned} \quad (31)$$

where $[I]$ is the identity matrix and $[\Lambda]$ a diagonal matrix with the diagonal terms defined as $\{2\xi_1\omega_1, 2\xi_2\omega_2, 2\xi_3\omega_3, \dots, 2\xi_n\omega_n\}$, where ξ_i is the damping ratio of the i th mode shape. The equations, in the state space form, become

$$\begin{aligned} \{\ddot{x}_m\} &= [A_m] \{x_m\} + [B_{u_m}] \{u\} + [B_{u_m}^*] \{v\}, \\ \{y\} &= [C_m] \{x_m\} + [D_m] \{u\}, \end{aligned} \quad (32)$$

FIGURE 3: A neural network.

where matrices $[A_m]$, $[B_{u_m}]$, $[C_m]$, $[D_m]$, and $[B_{u_m}^*]$ are defined as follows:

$$\begin{aligned} [A_m] &= \begin{bmatrix} [0] & [I] \\ -[\Omega] & -[\Lambda] \end{bmatrix}; \\ [B_{u_m}] &= \begin{bmatrix} [0] \\ [[\Phi^T] [M] [\Phi]]^{-1} [\Phi^T] [F] \end{bmatrix}; \\ [C_m] &= [-[\Omega] \quad -[\Lambda]]; \\ [D_m] &= 0, \\ [B_{u_m}^*] &= \begin{bmatrix} [0] \\ [[\Phi^T] [M] [\Phi]]^{-1} [\Phi^T] [F] [K_{u0}] [K_{00}]^{-1} [K_p] \end{bmatrix}, \end{aligned} \quad (33)$$

where $[C_m]$ and $[D_m]$ can be defined according to the desired output variables (modal state space variables, control forces, acceleration, etc.).

In the case of optimal control, the following Lyapunov quadratic function, to be minimized, is defined as

$$\begin{aligned} J_m &= \left(\frac{1}{2} \right) \int_0^\infty (\{X_m\}^T [Q_m] \{X_m\} + \{u^T\} [R_m] \{u\}) dt. \end{aligned} \quad (34)$$

Then, the following equations hold:

$$\begin{aligned} \{X_m\} &= [\Phi]^{-1} \{X\}, \\ \begin{Bmatrix} \{\eta\} \\ \{\dot{\eta}\} \end{Bmatrix} &= \begin{bmatrix} [\Phi]^{-1} & 0 \\ 0 & [\Phi]^{-1} \end{bmatrix} \begin{Bmatrix} \{q\} \\ \{\dot{q}\} \end{Bmatrix}. \end{aligned} \quad (35)$$

Modal weighting matrices $[Q_m]$ and $[R_m]$ are related to the well-known traditional weighting matrices $[Q]$ and $[R]$, respectively, by

$$\begin{aligned} [Q_m] &= [[\Phi]^{-T} [Q] [\Phi]^{-1}], \\ [R_m] &= [[\Phi]^{-T} [R] [\Phi]^{-1}]. \end{aligned} \quad (36)$$

The input forces are defined by the relation

$$\{u\} = -[K_m] \{X_m\} = -[K_m] \begin{Bmatrix} \{\eta\} \\ \{\dot{\eta}\} \end{Bmatrix}, \quad (37)$$

where $[K_m]$, the modal gain matrix, is given by $[K_m] = [[R_m]^{-1} [B_{u_m}]^T [S_m]]$ and obtained solving the following Riccati equation in the modal state space:

$$\begin{aligned} [S_m] [A_m] + [A_m]^T [S_m] &- [S_m] [B_{u_m}] [R_m]^{-1} [B_{u_m}]^T [S_m] + [Q_m] \\ &= [0]. \end{aligned} \quad (38)$$

2.3. Neural Network Control. Now we will train neural network according to some input and corresponding output gain of the LQR controller as is shown in Figure 4 and neural network will predict the output in response to any data in the future. An artificial neural network (ANN) is a very basic and replicate model of biological nerve cell system present in our brains. An ANN system is having processing entities which computes the outputs from inputs with some bias values. These are called neurons. A single neural network is shown in Figure 3. The equation of the processing unit in the output of the ANN system having n inputs and neuron j is

$$\begin{aligned} y_j &= \varphi_j(v_j), \text{ where} \\ v_j &= \left(\sum_{i=1}^m w_{ji} x_i + b_j \right), \end{aligned} \quad (39)$$

x_i : input signals, w_{ji} : weights, b_j is bias.

In this way, we design ANN controller for controlling vibrations of a cantilever plate bonded with piezopatches as sensor and actuator. For a given set of inputs (length, breadth, thickness piezopatch location, etc.) to the ANN, outputs are calculated from the first level neurons and fed to the next level of neurons in the ANN which is named as hidden level of ANN. The electrical output transmits from a level to another level till the final level output is computed which gives a response gain to reduce the trembling voltage. The input weights and bias values remain constant during the process of “forward pass” of the value from input level to the next level of computing the output.

The output response of the ANN is compared with the target value (t_j). The error is calculated by taking difference between target value and output response:

$$e_j = t_j - y_j. \quad (40)$$

FIGURE 4: Showing the training process of ANN controller for AVC.

The total error value can be expressed by the following equation, where c is the total number of neurons in the output layer of the ANN:

$$E = \frac{1}{2} \sum_{j=1}^c e_j^2. \quad (41)$$

The error E is used to find out the cost function, and the input weights and bias values should be changed to minimize it. The sensitivity is got by taking partial derivatives of error represented by $\partial E / \partial w_{ji}$ which can be used to resolve the search direction to update the weight value w_{ji} as

$$w_{ji}(k+1) = w_{ji}(k) - \eta \frac{\partial E(k)}{\partial w_{ji}(k)}, \quad (42)$$

where k is the present instant and $(k+1)$ is the next instant in the above equation. The above method is refined using a “momentum term” which stabilizes outcome of the backpropagation algorithm. The training of the ANN is complete when the error (or change in the error) lessens to a little quantity. ANN is robust controller. It can work even in the condition when environmental condition changes like temperature and pressure. When the NN controller is trained with inputs and outputs with very less errors, then we will get the same output as before changing condition. It is also useful in the conditions like when initial conditions are changing and forces are changing.

The flow chart of ANN is shown in Figure 5.

3. Experimental Setup with Results and Discussion

Figure 6 is picture of the experimental setup used by the authors and their mentors for performing experiments to control the vibration of a smart structure.

Figure 7 is showing the real time controller provided by NI Instruments Company.

cRIO controller is the latest controller provided by the NI Instruments. This is the controller which can be used with

the computer as well as individually. It has its own memory and it can use computer memory on the user desire. When we want our project to work devoid of attaching to computer, then we can use it individually also. Using application button on it, we can use this facility. It has many parts of it. These are chassis, power supply, and DAQ cards. The chassis is connected to controller and it is used to hold DAQ cards within it so that they can be properly fitted and fixed with controller. The power supply is used to give 12-volt power supply to controller. In our cRIO controller, we can use 4 input and output DAQ cards simultaneously. The DAQ 9263 card is used to give output to the particular actuator and so forth. Basically it is an output DAQ card. It is used to produce that amount of output voltage in the range of -10 volts to $+10$ volts. It is amplified by the voltage amplifier attached to it and given to the piezoactuator. We are using DAQ 9234 and DAQ 9263 in our experiment provided by NI Instruments. The DAQ card stands for data acquisition card. It basically deals with the data used in the experiment. The DAQ 9234 is input data card; it is receiving data from the piezosensor as is shown in Figure 8 and providing to the cRIO controller for processing. In between sensor and DAQ, we are using charge amplifier to enhance the charge received from sensor so that it can be in the specified range of DAQ to collect properly. The plate is fixed at an end with a fixed point and piezosensors and actuators are placed on the particular location of the plate. They are then connected to input and output DAQ cards. The response of sensor taking from DAQ 9234 is shown present in Figure 9.

In the real time software, a program is designed to get the frequency response of the plate. The modes of frequency give the information about the different natural frequency on which the plate is vibrating. The block diagram is used to find out the frequency response of the cantilever plate in the Labview as shown in Figure 10.

AI2 is the DAQ card input which is the electrical output of piezopatch, spectra showing the frequency response. The natural frequency is found in the software because on the base of it we can be sure that what finite element model we have taken is correct to the exact natural model. We can say

FIGURE 5: Flow chart of ANN controller.

that if the natural frequency and the calculated frequency are same, then we will be able to predict that the FEM model we have used to calculate frequency is correct and it can be used for further experiments. The spectrum graph showing the natural frequency in Labview is shown in Figure 11.

The natural frequency values found are the same as the theoretical value shown in Table 1.

The LQR control is performed for various changing initial conditions like length, breadth, thickness, piezopatch location, and force applied. These initial and final ranges of these parameters are found out. A set of the values is formed

TABLE 1: Different natural frequency of plate.

Mode	Frequency in hertz (radians/seconds)
1	8.6325
2	14.4408
3	32.7073

with the help of Design of Expert software. Now these values are used as input to LQR controller. These are presented in Table 2.

TABLE 2: Data to train ANN controller.

Set number	Length	Breadth	Thickness	Piezopatch location	Force applied
1	6.715359	0.014	0.0028	33	0.06
2	0.01	0.01	0.0006	1	0.02
3	0.018	0.01	0.005	1	0.1
4	0.014	0.014	0.0028	33	0.06
5	0.014	0.014	0.0068	33	0.06
6	0.014	0.0067	0.0028	33	0.06
7	0.014	0.014	0.0028	64	0.06
8	0.014	0.014	0.0028	33	0.06
9	0.018	0.018	0.0006	64	0.02
10	0.014	0.001	0.0028	33	0.06
11	0.01	0.018	0.005	1	0.1
12	0.0213	0.014	0.0028	33	0.06
13	0.014	0.014	0.0028	33	0.14
14	0.018	0.001	0.005	64	0.02
15	0.01	0.018	0.005	64	0.02
16	0.014	0.014	0.00121	33	0.06
17	0.014	0.014	0.006	33	0.06
18	0.01	0.01	0.005	64	0.1
19	0.001	0.014	0.0028	33	0.06
20	0.18	0.01	0.0006	64	0.1
21	0.018	0.018	0.0006	1	0.1
22	0.018	0.018	0.005	1	0.02
23	0.014	0.0218	0.0028	33	0.06
24	0.014	0.014	0.0028	25	0.06
25	0.014	0.014	0.0028	33	0.01
26	0.001	0.018	0.0006	64	0.1

FIGURE 6: Experimental setup.

The gain which is provided by the LQR controller after putting the parameters in Table 2 one by one is tabulated in Table 3.

FIGURE 7: Compact RIO controller.

The graphs shown in Figures 12 to 23 show the LQR controller controlled responses with the uncontrolled response of the vibrating plate with respect to change in the value of length, breadth, thickness, piezolocation, and force applied at the edge of plate. Figure 12 shows the LQR controller controlled responses with the uncontrolled response of the vibrating plate when length is 6.715359, breadth is 0.014, thickness is 0.0028, piezopatch location is 33, and force applied is 0.06.

TABLE 3: Gain provided by LQR controller.

Set number	Gain 1	Gain 2	Gain 3	Gain 4	Gain 5	Gain 6
1	-5.34384	1.266311	-15.1422	59.98446	-13.4177	-163.402
2	-30.8317	117.2606	-481.423	201.1786	-435.037	-689.654
3	-204.382	-3946.77	7223.789	340.018	697.8009	805.0139
4	20.75024	-210.9	176.3011	-97.6276	176.2581	762.439
5	34.14729	-323.238	266.4356	-86.2691	139.8064	722.9445
6	10.3685	-1095.87	436.9909	-76.9095	242.5998	699.5781
7	-470.418	913.6222	5164.082	392.6117	-683.974	848.1237
8	20.75024	-210.9	176.3011	-97.6276	176.2581	762.439
9	-0.00634	0.011947	0.27167	7.604772	-90.5553	49.28556
10	2.011603	-193.098	1123.937	-40.1914	507.2924	598.6292
11	-1778.76	387.7702	7583.986	323.2583	-545.455	637.7004
12	-16.2142	-523.256	308.2623	128.1226	323.8691	809.923
13	20.75024	-210.9	176.3011	-97.6276	176.2581	762.439
14	0.016217	-1.04014	11.76462	-1.33537	179.4479	42.1376
15	1.71758	-21.0888	-48.7158	-9.31947	106.7416	-189.156
16	-4.78286	-60.3665	-51.1621	69.58895	155.9016	-712.945
17	20.75024	-210.9	176.3011	762.439	176.2581	762.439
18	-0.13753	0.20259	-6.30982	3.276641	-110.084	-25.9889
19	13.66055	-0.85689	-40.1233	-27.3118	-0.04933	-11.3715
20	-0.00034	-0.01026	-0.16178	2.148319	94.3725	-20.768
21	-37.6283	-88.9394	-451.119	335.1834	608.4086	-810.857
22	587.0237	-1039.23	6229.23	-413.116	703.4352	857.2671
23	9.664285	16.1104	50.39208	-111.78	-94.5749	420.801
24	-26.3016	-50.1253	-102.178	155.1931	49.32188	-745.871
25	20.75024	-210.9	176.3011	-97.6276	176.2581	762.439
26	0.067735	-0.18187	-0.62975	-14.268	53.55698	-86.1095

FIGURE 8: Fixed plate with a piezopatch at its top surface.

FIGURE 9: Signal received from the piezosensor.

Figure 13 shows the LQR controller controlled responses with the uncontrolled response of the vibrating plate when length is 0.01, breadth is 0.01, thickness is 0.0006, piezopatch location is 1, and force applied is 0.02.

Figure 14 shows the LQR controller controlled responses with the uncontrolled response of the vibrating plate when length is 0.018, breadth is 0.01, thickness is 0.005, piezopatch location is 1, and force applied is 0.1.

Figure 15 shows the LQR controller controlled responses with the uncontrolled response of the vibrating plate

when length is 0.014, breadth is 0.014, thickness is 0.0028, piezopatch location is 33, and force applied is 0.06.

Figure 16 shows the LQR controller controlled responses with the uncontrolled response of the vibrating plate when length is 0.014, breadth is 0.014, thickness is 0.0068, piezopatch location is 33, and force applied is 0.06.

FIGURE 10: Power spectrum of the input signal.

FIGURE 11: Frequency spectrum of the cantilever plate.

FIGURE 12: Controlled and uncontrolled response of the LQR controller at length = 6.715359, breadth = 0.014, thickness = 0.0028, piezopatch location = 33, and force applied = 0.06.

Figure 17 shows the LQR controller controlled responses with the uncontrolled response of the vibrating plate when length is 0.014, breadth is 0.0067, thickness is 0.0028, piezopatch location is 33, and force applied is 0.06.

Figure 18 shows the LQR controller controlled responses with the uncontrolled response of the vibrating plate when length is 0.014, breadth is 0.014, thickness is 0.0028, piezopatch location is 64, and force applied is 0.06.

Figure 19 shows the LQR controller controlled responses with the uncontrolled response of the vibrating plate when length is 0.0213, breadth is 0.014, thickness is 0.0028, piezopatch location is 33, and force applied is 0.06.

Figure 20 shows the LQR controller controlled responses with the uncontrolled response of the vibrating plate when length is 0.018, breadth is 0.001, thickness is 0.002, piezopatch location is 64, and force applied is 0.02.

Figure 21 shows the LQR controller controlled responses with the uncontrolled response of the vibrating plate when length is 0.01, breadth is 0.01, thickness is 0.005, piezopatch location is 64, and force applied is 0.1.

Figure 22 shows the LQR controller controlled responses with the uncontrolled response of the vibrating plate when length is 0.018, breadth is 0.018, thickness is 0.0006, piezopatch location is 1, and force applied is 0.1.

Figure 23 shows the LQR controller controlled responses with the uncontrolled response of the vibrating plate when

FIGURE 13: Controlled and uncontrolled response of the LQR controller at length = 0.01, breadth = 0.01, thickness = 0.0006, piezopatch location = 1, and force applied = 0.02.

FIGURE 15: Controlled and uncontrolled response of the LQR controller at length = 0.014, breadth = 0.014, thickness = 0.0028, piezopatch location = 33, and force applied = 0.06.

FIGURE 14: Controlled and uncontrolled response of the LQR controller at length = 0.018, breadth = 0.01, thickness = 0.005, piezopatch location = 1, and force applied = 0.1.

FIGURE 16: Controlled and uncontrolled response of the LQR controller at length = 0.014, breadth = 0.014, thickness = 0.0068, piezopatch location = 33, and force applied = 0.06.

length is 0.014, breadth is 0.0218, thickness is 0.0028, piezopatch location is 33, and force applied is 0.06.

The artificial neural network is trained according to the inputs and output gain of the LQR controller. We have performed many training methods to get the maximum efficiency. Table 4 shows the different training algorithm and corresponding training efficiency.

After analyzing all functions in Table 4, we have come to a solution that if we trained the neural network with trainbr training algorithm then we got the maximum training efficiency of 99.4%. Therefore we will take this training algorithm for the further considerations. The neural network utilized by us in this process is shown in Figure 24.

There is input matrix of 26×5 and 26×6 output matrix in the training process. The input matrix is calculated

by the DOE software. The output matrix is calculated by the running program in MATLAB which is having length, breadth, thickness, piezopatch location, and tip displacement force as an input. LQR controller after giving values of Q and R and applying impulse input provides us with the value of output gain which is further utilized by the neural network controller to predict the output response. The training process is shown in the Figure 25. Then after training of the neural network which is having 5 input neurons in the input layer and 6 output neurons in the output layer according to the input and output matrix, there are 10 hidden neurons in the hidden layer which is decided by us during the training process. The regression plot of the ann which we can see when we finished training of the neural network is shown in Figure 26. We can increase and decrease these neurons

TABLE 4: Different efficiency of training functions.

Training methods	Full form of the functions	Training efficiency
Train	Train neural network	36.3
Trainb	Batch training with weight and bias learning rules	0.13
Trainbfg	BFGS quasi-Newton backpropagation	34.9
Trainbfgc	BFGS quasi-Newton backpropagation for use with NN model reference adaptive controller	86.13
Trainbr	Bayesian regularization	99.4
Traincgb	Powell-Beale conjugate gradient backpropagation	42.14
Traincgf	Fletcher-Powell conjugate gradient backpropagation	79.86
Traincgp	Polak-Ribière conjugate gradient backpropagation	77.16
Traingd	Gradient descent backpropagation	58.192
Trainгда	Gradient descent with adaptive learning rule backpropagation	47.11
Traingdm	Gradient descent with momentum backpropagation	23.28
Traingdx	Gradient descent with momentum and adaptive learning rule backpropagation	40.9
Trainlm	Levenberg-Marquardt backpropagation	72.48
Trainoss	One-step secant backpropagation	83.09

FIGURE 17: Controlled and uncontrolled response of the LQR controller at length = 0.014, breadth = 0.0067, thickness = 0.0028, piezopatch location = 33, and force applied = 0.06.

FIGURE 19: Controlled and uncontrolled response of the LQR controller at length = 0.0213, breadth = 0.014, thickness = 0.0028, piezopatch location = 33, and force applied = 0.06.

FIGURE 18: Controlled and uncontrolled response of the LQR controller at length = 0.014, breadth = 0.014, thickness = 0.0028, piezopatch location = 64, and force applied = 0.06.

according to our desire. But training process becomes slow if we increase the number of neurons in the hidden layer.

After training of the neural network, we have to make ANN controller; we have to save the desired training algorithm script in advance script option in MATLAB. Then load this script in the ANN controller program and ANN controller is ready to predict the output according to any input which is not even given in the training data. The performance diagram of the trained neural network is shown in Figure 27. The best training performance comes at epoch 349.

Figure 28 shows the training state diagram of the trained neural network.

The error histogram diagram of the trained neural network is shown in Figure 29.

Figure 30 is showing the control action of the neural network controller for reducing the vibration of the plate after giving some vibration. The blue line is showing

FIGURE 20: Controlled and uncontrolled response of the LQR controller at length = 0.018, breadth = 0.001, thickness = 0.002, piezopatch location = 64, and force applied = 0.02.

FIGURE 22: Controlled and uncontrolled response of the LQR controller at length = 0.018, breadth = 0.018, thickness = 0.0006, piezopatch location = 1, and force applied = 0.1.

FIGURE 21: Controlled and uncontrolled response of the LQR controller at length = 0.01, breadth = 0.01, thickness = 0.005, piezopatch location = 64, and force applied = 0.1.

FIGURE 23: Controlled and uncontrolled response of the LQR controller at length = 0.014, breadth = 0.0218, thickness = 0.0028, piezopatch location = 33, and force applied = 0.06.

the uncontrolled vibrations taken by the plate and the green one is showing the controlled action established by the controller. The vertical axis is the tip displacement which we give to the plate initially to produce vibration, and horizontal axis is showing the time. At that time the length of plate is 0.16 m, breadth is 0.16 m, thickness is 0.0006 m, piezoelectric patch location is 8, and 2 mm displacement is given to the plate.

Now we have tested the neural network for various changing values for examining its robustness.

In Figure 31, the length of the plate is changed (0.016 m) and the rest of the parameters are kept the same; the ANN shows the appropriate results.

In Figure 32, the length of the plate is changed (0.048 m) and the rest of the parameters are kept the same; the ANN shows the suitable controlled action.

In Figure 33, the breadth of the plate is changed (0.240 m) and the rest of the parameters are kept the same; the ANN shows the proper results as there is no effect on the controlling action of ANN.

In Figure 34, the thickness of the plate is changed (0.0008 m) and the rest of the parameters are kept the same; the ANN shows the desired results.

In Figure 35, the thickness of the plate is changed (0.001 m) and the rest of the parameters are kept the same; the ANN shows the correct results as there is no effect on the controlling action.

FIGURE 24: ANN controller during designing process.

FIGURE 25: Training of the neural network in MATLAB.

FIGURE 27: Performance graph of trained ANN.

FIGURE 26: Regression plot of the ANN comes after training.

FIGURE 28: Training state of the trained neural network.

In Figure 36, the piezopatch location is changed at the 14th element and the rest of the parameters are kept the same; the ANN shows the good results. In this way we observe the robustness of the ANN.

In Figure 37, the piezopatch location is changed at the 4th element and the rest of the parameters are kept the same; the ANN shows the suitable results according to our desire.

In Figure 38, the initial displacement is changed to 6 mm from 2 mm and the rest of the parameters are kept the same; the ANN shows the appropriate results and there is no change on the working of ANN.

In Figure 39, the initial displacement is changed to 10 mm from 2 mm and the rest of the parameters are kept the same and the ANN shows the excellent results.

FIGURE 29: Error histogram of trained ANN.

FIGURE 30: Uncontrolled and controlled responses (ANN) at the edge of plate.

FIGURE 31: Uncontrolled and controlled responses (ANN) at the edge of plate when length is 0.016 m.

FIGURE 32: Uncontrolled and controlled responses (ANN) at the edge of plate when length is 0.048 m.

FIGURE 33: Uncontrolled and controlled responses (ANN) at the edge of plate when breadth is 0.240 m.

FIGURE 34: Uncontrolled and controlled responses (ANN) at the edge of plate when thickness is 0.0008 m.

FIGURE 35: Uncontrolled and controlled responses (ANN) at the edge of plate when thickness is 0.001 m.

FIGURE 38: Uncontrolled and controlled responses (ANN) at the edge of plate at 6 mm displacement.

FIGURE 36: Uncontrolled and controlled responses (ANN) at the edge of plate at the 14th piezolocation.

FIGURE 39: Uncontrolled and controlled responses (ANN) at the edge of plate at 10 mm displacement.

FIGURE 37: Uncontrolled and controlled responses (ANN) at the edge of plate at the 4th piezolocation.

In Figure 40, the initial displacement is changed to 0.02 m from 2 mm and the rest of the parameters are kept the same; the ANN shows the very good results.

In Figure 41, the initial displacement is changed to 0.03 m from 2 mm and the rest of the parameters are kept the same; the ANN shows the correct results.

In Figure 42, the initial displacement is provided 20 times from initial displacement and the rest of the parameters are kept the same; the ANN shows the right results.

4. Conclusion

An intelligent controller (artificial neural network controller) is designed for controlling the vibration of a smart plate (metallic rectangular plate integrated with piezoelectric patches) structure having finite length, breadth, and thickness for single input and single output approach tuned with output

FIGURE 40: Uncontrolled and controlled responses (ANN) at the edge of plate at 0.02 m displacement.

FIGURE 42: Uncontrolled and controlled responses (ANN) at the edge of plate at 2 mm $\times$ 20 = 40 mm displacement.

FIGURE 41: Uncontrolled and controlled responses (ANN) at the edge of plate at 0.03 m displacement.

of LQR controller. Although various types of training algorithms are used to train this ANN controller for eliminating the vibrations of the smart plate, yet Bayesian regularization training method is found to be the best. It trained the neural network 99.4% which is very good to train any neural network to understand the desired response. The trained neural network controller is tested or verified for various changing input values and it is performing well in these values which are not even provided in the training data. Hence the designed artificial neural network controller is able to suppress the structural vibration effectively of a smart structure subjected to impulse force and a disturbance of white noise.

Nomenclature

a : Half length of the finite element in x direction, m
 A : Relative to surface area

b : Half length of the finite element in y direction, m
 C : Elastic constant, N/m²
 C_s : Piezoelectric sensor capacitance, F
 D : Electric displacement vector, C/m²
 e : Piezoelectric stress coefficient, C/m²
 E : Young's modulus, N/m²
 f : Force, N
 h : Thickness, m
 K : Stiffness matrix
 M : Mass matrix
 q : Displacement field vector
 q_i : Nodal displacement field, m
 T : Kinetic energy, J
 u : Displacement field in x direction, m
 U : Potential energy, J
 v : Displacement field in y direction, m
 V : Volume, m³
 w : Displacement field in z direction, m
 W : Work, J.

Greek Symbols

ε : Strain field
 σ : Stress, N/m
 ν : Poisson ratio
 θ_u : Rotation about u -axis
 ξ : Dielectric tensor
 ζ : Nodal displacement vector
 Φ : Electric potential, volts
 ω : Frequency, rad/s
 ρ : Material density, kg/m³.

Subscripts

a : The actuator
 b : Relative to the body
 p : Relative to the plate structure

s: Relative to the sensor
 sa: Relative to the sensed voltage in the actuator
 x: Relative to x direction
 y: Relative to y direction
 qq: Relative to the stiffness
 $q\Phi$: Relative to the piezoelectric stiffness
 $\Phi\Phi$: Relative to the dielectric stiffness.

Superscripts

e : Relative to the element
 S: Relative to constant strain
 T: Matrix transpose.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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