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Design of Neural Network Controller for Active Vibration control of Cantilever plate with piezo-patch as sensor /actuator

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ABSTRACT: *The purpose of this work is to control the vibration of the plate with the help of neural network controller. Using augmented equations, a finite element model of a two-dimensional cantilever plate instrumented with a piezoelectric patch sensor-actuator pair is derived. The contribution of piezoelectric sensor and actuator layers on the mass and stiffness of the plate is considered. As mesh size (8x8) is found best for the future modeling and analysis of the plate has been taken.LQR controller tuning has been designed with the help of Neural Network training. It is observed that neural network controller has found suitable and gave effective control to suppress the first three modes of vibration of cantilever plate. With the help of MATLAB simulation results are presented.*

Nomenclature

$\{D\}$	electric displacement vector	ω_m	mth modal frequency
$\{E\}$	electric field vector	$[e]$	piezoelectric stress coefficient matrix
$\{\varepsilon\}$	strain vector	$[\in]$	permittivity constant matrix
$\{\sigma\}$	stress vector	$\in_0$	absolute permittivity
$[d]$	piezoelectric strain coefficient matrix	q	charge applied on piezoelectric material
$[c]$	elasticity matrix	v	voltage generated in piezo electric patch
Y	Young's modulus of elasticity	ζ_m	mth Modal damping ratio
μ	Poisson's ratio	f_m	mth Modal force vector
ρ	Density	$\{s\}$	state variable
$\{p\}$	pyroelectric constant vector	$[A]$	system state matrix
$\{\alpha\}$	coefficient of thermal expansion vector	$[B]$	control matrix
u,v,w	displacements along, respectively x, y and z-axis	$[C]$	output matrix
$\alpha_2^*\alpha_1^*$	coefficient associated with Kinetic energy and Strain energy	$[M]$	mass matrix
$\{F^e\}$	external force vector on an element	$[K]$	stiffness matrix
{x}	displacement vector	$[C]$	damping matrix
		A	area
η_m	mth modal state vector	d	thickness of piezoelectric patch
$[N]$	Hermite's interpolation function	T_e	kinetic energy of element
V_e	potential energy of element	W_{elect}	Electric energy of element
$[m_s^e]$	substrate element mass matrix	*Superscripts*	
$[m_P^e]$	piezoelectric element mass matrix	T	transpose
G	noise influence matrix	*Subscripts*	
K_e	Kalman filter gain	s	substrate
		p	piezoelectric
		i	in the ith direction

Key words: *Smart structure, Finite element model, Active vibration control, Neural Network Controller*

I. INTRODUCTION

Vibration control is the strategy in which an external source of energy is used to control structural vibrations is called active vibration control (AVC). It essentially consists of sensors to capture the structural dynamics, a processor to manipulate the sensor signals, actuators to obey the order of processor and a source of energy to actuate the actuators. Such a structure is known as a 'smart structure'. Piezoelectric materials possess excellent electromechanical properties viz. fast response, easy fabrication, design flexibility, low weight, low cost, large operating bandwidth, low power consumption, generation of no magnetic field while converting electrical energy into mechanical energy, etc. So, they are extensively used as sensors and actuators in AVC [12].

Damble, Lashlee, Rao and Kern [1] studied an integrated approach to design and implement robust controllers for smart structures. Jha and Jacob Rower [2] purposed neural networks for identification and control of smart structures is investigated experimentally. Piezoelectric actuators are employed to suppress the vibrations of a cantilevered plate subject to impulse, sine wave and band-limited white noise disturbances. The neural networks used are multilayer perceptron trained with error back propagation. Jha and Chengli He [3] purposed a neural-network-based adaptive predictive controller is developed and validated experimentally. On-line nonlinear plant identification is performed using a multilayer perceptron neural network with tapped delay inputs. Q. Song, J. C. Spall and Y.C. Soh [4] studied robust neural network tracking controller using simultaneous perturbation stochastic approximation. They consider the problem of robust tracking controller design for a nonlinear plant in which the neural network is used in the closed-loop system to estimate the nonlinear system function. Liu, Lin and Lee [5] proposed a novel neural network approach for the identification and control of a thin simply supported plate. The motion behaviour of a two dimensional model of piezoelectric materials bounded to the surface of the plate is analytically investigated.

Yu and Jinde Cao [6] studied robust control of uncertain stochastic recurrent neural networks with time varying delay. They consider a novel control method which is given by using the Lyapunov Functional method and linear matrix inequality (LMI) approach. Chun-Fei Hsu [7] proposed an adaptive recurrent neural network control (ARNNC) system with structure adaptation algorithm for the uncertain nonlinear systems. The developed ARNNC system is composed of a neural controller and a robust controller. Roy and chakraborty [8] purposed genetic algorithm (GA) based linear quadratic regulator (LQR) control scheme has been proposed for active vibration control of smart Fiber Reinforced Polymer (FRP) composite shell structures under combined mechanical and thermal loading.

Mei, Wu and Jiang [9] purposed a neural network robust adaptive control for a class of time delay uncertain nonlinear systems. They describe a robust adaptive control scheme based on neural network is proposed for a class of time delay uncertain nonlinear system. M. Adhyaru, I. N. Kar, M. Gopal [10] studied bounded robust control of nonlinear systems using neural network–based HJB solution. They use Hamilton–Jacobi–Bellman (HJB) equation–based optimal control algorithm for robust controller design is proposed for nonlinear systems. J. F .de Canete, Perez Saz-Orozco and I. Garcia-Moral [11] studied robust stability in multivariable neural network control using harmonic analysis. In the research they describe robust stability and performance are the two most basic features of feedback control systems. Gupta, Sharma, Thakur and S P singh [12] A new scheme for active structural vibration control using piezoelectric patches at elevated temperatures is analytically derived and experimentally verified. A control law is derived using augmented piezoelectric constitutive equations which include the temperature dependence of piezoelectric stress coefficient and permittivity.

In this paper, the design of a Neural Network controller is to be done. Here two inputs and six outputs are taken with the help of LQR controller to design the Neural Network controller. The two inputs of LQR controller are the coefficient associated with Kinetic energy and Strain energy and six outputs are taken as Control Gain to control first three modes of vibration.

II. METHODOLOGY

2.1 Plate

An isotropic elastic rectangular plate of homogenous material is considered with its dimensions length L, breadth B, and thickness H. The plate is simply supported at two opposite sides and is subjected to vibrations. The vibration of the boundaries will be uniform and synchronous, i.e., the amplitude will be constant along the sides and all points along the boundaries will be vibrating in-phase. The remaining degrees of freedom along the sides of the structure will be locked. The plate is discretised into some finite number of smaller elements of identical shapes and sizes. The structure will be modeled by means of the FEM. It is supposed that the pair of piezoelectric patches can be added to the structure as sensor and actuator in piece coinciding with the surface area of each element.

Considering M is the number of elements along the length of the plate and N are the number of elements along the breadth. Each element is considered to be rectangular in shape with nodes i, j, l and m; and with dimensions length 2a and breadth 2b and thickness h.

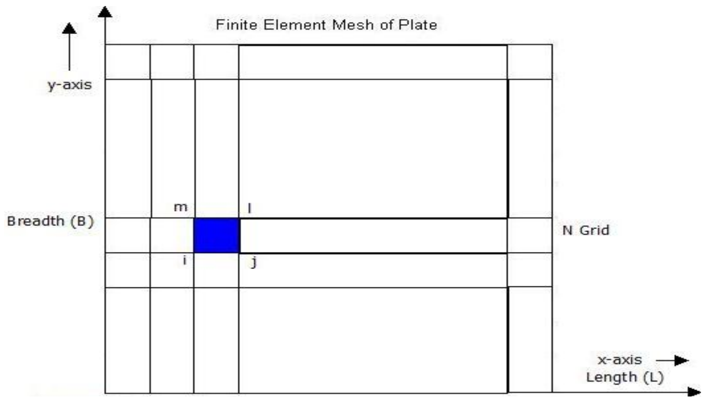

Fig. 1: Finite Element Mesh of Plate

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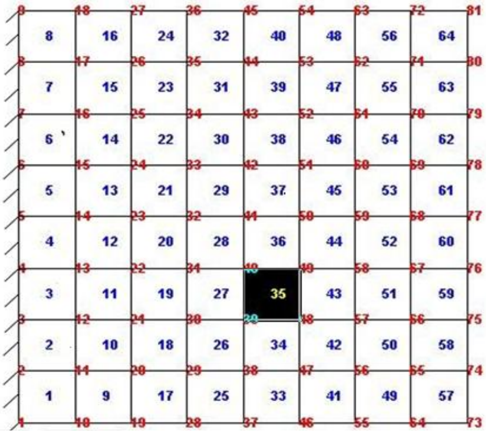

Fig. 2: Smart piezoplate structure divided into 64 finite elements with 81 nodes.

2.2 Finite Element Formulation

Consider a flexible elastic plate structure (fig.1). The plate is instrumented with piezo-patches collocated sensor–actuator pair polarized in the thickness direction. The top and bottom surface of each piezo-patch is covered by electrodes. At the piezo location, the structure is composite in the thickness direction with two piezo-patches and one elastic layer. The plate is modeled using the finite element method. It is divided into discrete finite elements where 'ζ' and 'η' are the natural coordinates of the finite element and they are related to global coordinates *(x, y)* as:

$$\zeta = \frac{x}{a} \tag{1}$$

$$\eta = \frac{y}{b} \tag{2}$$

Each finite element has four nodes and each node has three degrees of freedom: one translational w and two rotational θ_x and θ_y . If $\{u_e\}$ is the displacement vector of an element then displacement in the *z*-direction can be interpolated as:

$$w = [N]_{1\times12}\{u_e\}_{12\times1} \tag{3}$$

Where $[N]_{1\times12}$ is Hermite's interpolation function.

Ignoring shear deformations in the plate and using Kirchhoff's classical plate theory, strains developing in the plate can be written as:

$$\{\varepsilon\} = \{\frac{\partial u}{\partial x}\ \frac{\partial v'}{\partial y}\ \frac{\partial v'}{\partial x} + \frac{\partial u}{\partial x}\}^T \tag{4}$$

Where $u = -z\frac{\partial\omega}{\partial x}$ and $v' = -z\frac{\partial\omega}{\partial y}$

After substituting values of 'u' and 'v'' in the above equation, we get:

$$\{\varepsilon\}_{3\times1} = z[B_u]_{3\times12}\{u_e\}_{12\times1} \tag{5}$$

Where $[B_u]_{3\times12} = [-\frac{z\partial^2}{\partial x^2} - \frac{z\partial^2}{\partial y^2} - \frac{2z\partial^2}{\partial x\partial y}]^T_{3\times1}[N]_{1\times12}$

Kinetic energy of one finite element: $$T_e = \frac{1}{2}\int_s \rho_s\omega^2 d\tau + \frac{1}{2}\int_p \rho_p\omega^2 d\tau \tag{6}$$

Potential energy of one finite element:

$$V_e = \frac{1}{2}\int_s \{\varepsilon\}^T\{\sigma\}d\tau + \frac{1}{2}\int_v \{\varepsilon\}^T\{\sigma\}d\tau \tag{7}$$

Electric energy stored in one finite element:

$$W_{elect} = \frac{1}{2}\int_P \{E\}^T\{D\}d\tau \tag{8}$$

External surface traction or a point force can act on a smart structure. These forces would do work on the smart structure and as a result, energy stored per element is:

$$W_{ext\,(1)} = \int_{A_s}\{w\}^T\{f_s^e\}dA_s \tag{9}$$

Work required to apply external charge on the surface of a piezoelectric is:

$$W_{ext\,(11)} = -\int_{A_p} qv dA_P \tag{10}$$

Now, the Lagrangian for one finite element of the smart structure can be obtained as:

$$L = T_e - V_e + \left(W_{elect} + W_{ext\,(1)} + W_{ext\,(11)}\right) \tag{11}$$

The Lagrangian can be calculated using finite element relations and augmented constitutive equations. The equation of motion of one finite element is derived using Hamilton's principle:

$$\delta\int_{t1}^{t2} L dt = 0 \tag{12}$$

The resulting variational contains two variables namely '$\{u_e\}$' and 'v'. Taking variation with respect to $\{u_e\}$, we get:

$$([m_s^e] + [m_P^e])\{\ddot{u}_e\} + ([k_s^e] + [k_P^e])\{u_e\} + [k_{uv}^e]v = \{F_S^E\} \tag{13}$$

And taking variation with respect to 'v', we get:

$$[k_{vu}^e]\{u_e\} - [k_{vv}^e]v = 0 \tag{14}$$

$$v = [k_{vv}^e]^{-1}[k_{vu}^e]\{u_e\} \tag{15}$$

Where $[m_s^e] = \int_s \rho_s[N]^T[N]d\boldsymbol{\tau}$

$[m_P^e] = \int_P \rho_P [N]^T [N] d\boldsymbol{\tau}$

$[k_S^e] = \int_s z^2 [B_u]^T [c_s][B_u] d\boldsymbol{\tau}$

is the substrate element stiffness matrix,

$[k_P^e] = \int_P z^2 [B_u]^T [c_s][B_u] d\boldsymbol{\tau}$

is the piezoelectric element stiffness matrix,

$[k_{uv}^e] = [k_{uv}^e]^T = \int_P z\{B_u\}^T [e^t][B_v] d\tau$ is the electromechanical interaction matrix.

Put the value of v from eqation (14), in the equation, we get the equation of motion of one finite element of the smart plate structure as:

$$[M_e]\{\ddot{u}_e\} + [K_e]\{u_e\} = \{F_e\} \quad (16)$$

Where $[M_e]$, $[K_e]$ and $\{F_e\}$ are elemental mass matrix, elemental stiffness matrix and total force on the finite element respectively.

Applying assembly procedure and boundary conditions, the global equation of motion of the smart cantilevered plate structure is obtained as:

$$[M]\{\ddot{x}\} + [C]\{\dot{x}\} + [K]\{\dot{x}\} = \{F\} \quad (17)$$

Where the damping term $[C] = \alpha[M] + \beta[K]$. '$\alpha$' and '$\beta$' are Rayleigh mass and stiffness damping coefficients respectively. This is the equation of motion of a two dimensional smart cantilevered plate instrumented with one collocated piezoelectric sensor–actuator pair.

2.3 LQR Controller

LQR optimal control theory is used to determine the active control gain. The following quadratic cost function is minimized

$$j = \frac{1}{2}\int_0^\infty (x^T Q x + u^T R u) dt \quad (18)$$

Q and R represent weights on the different states and control channels and their elements are selected to provide suitable performance. They are the main design parameters. J represents the weighted sum of energy of the state and control. Assuming full state feedback, the control law is given by

$$u=-kx \quad (19)$$

With constant control gain,

$$k = R^{-1} B^T S \quad (20)$$

Matrix S can be obtained by the solution of the Riccati equation, given by

$$A^T S + SA + Q - SBR^{-1}B^T S = 0 \quad (21)$$

The closed loop system dynamics with state feedback control is given by

$$\dot{x} = (A - Bk)x + Er(t) \quad (22)$$

2.3 Determination of weighting matrices

Weighting matrices $[Q]$ and $[R]$ are important components of the LQR optimization process. The compositions of $[Q]$ and $[R]$ elements influence the system's performance. Ang. *et al* [13] proposed that weighting matrices could be determined, considering the weighted energy of the system, as follows

$$[Q] = \begin{bmatrix} \alpha_2^*[\psi]^T[K][\psi] & [0] \\ [0] & \alpha_1^*[\psi]^T[M][\psi] \end{bmatrix} \quad (23)$$

$$[R] = 1 \quad (24)$$

A vast research have been done so far for neural network controller but in this research the neural network controller training used for tuning LQR controller which gave the minimum settling time and gave effective control to suppress the first three modes of vibration of cantilever plate.

Table 1: Input and Output of LQR controller

S No.	α_2^*	α_1^*	k1	k2	k3	k4	k5	k6
1	10	20	0.068194	13.01451	5.832724	-2.2212	-49.4622	2033.436
2	20.14	30.14	0.137404	26.16566	11.727	-3.34731	-74.4928	2714.578
3	32.25	42.25	0.24224	46.02262	20.62714	-4.69217	-104.345	3408.725
4	44.45	54.45	0.368897	69.93655	31.34608	-6.047	-134.375	4022.424
5	55.5	65.5	0.499835	94.58898	42.39643	-7.27409	-161.535	4525.661
6	75.6	85.6	0.773395	145.9095	65.40166	-9.50611	-210.845	5348.572
7	95.1	105.1	1.078137	202.8389	90.9225	-11.6714	-258.568	6063.211
8	106.14	116.14	1.266419	237.9043	106.6426	-12.8973	-285.537	6439.785
9	117.15	127.15	1.464863	274.7825	123.1758	-14.1198	-312.397	6798.588
10	128.2	138.2	1.674296	313.6208	140.5882	-15.3467	-339.318	7143.947
11	139.4	149.4	1.896662	354.772	159.038	-16.5903	-366.569	7480.639
12	150	160	2.116142	395.3081	177.2125	-17.7672	-392.325	7788.21
13	161.24	171.24	2.358146	439.9166	197.2134	-19.0151	-419.602	8103.736
14	172.7	182.7	2.614407	487.0587	218.3508	-20.2875	-447.375	8415.236
15	180	190	2.782525	517.9356	232.1956	-21.0979	-465.046	8608.718
16	190	200	3.01884	561.2733	251.6279	-22.2081	-489.229	8867.974

2.4 Design of Neural Network Controller

The design of Neural Network controller is based on simple human reasoning. The design of the neural network controller (NNC) is based on the inversion of the plant model (Neural Network Identifier). The NNC (figure) has five hidden neurons and a single output neuron, which gives the controller voltages. The inputs consist of excitation signals, control signals and time-delayed target values. There are many practical applications, where the disturbance is known or measurable. A neural network (also known as 'artificial neural network') is a massively parallel interconnection of simple processors or neurons that has the ability to learn from its environment and store the acquired knowledge for future use. Properly formulated and trained NNs are capable of approximating any linear or nonlinear function to the desired degree of accuracy. The neural networks used in the current research are known as multilayer perceptron (MLP). The MLPs comprise a layer of input signals, one or more hidden layers of neurons, and an output layer of neurons. A layer consists of a single or multiple neurons. Differences between the desired outputs (targets) and the network outputs give the errors. The connection strengths ('weights') and 'biases' are updated during training (or learning) such that the network produces the desired output for the given input.

Mathematically, neuron *j* having *m* inputs is described as follows:

$$y_j = \varphi_j(v_j) \tag{24}$$

Where $v_j = \left(\sum_{i=1}^{m} w_{ji}\, x_i + b_j\right)$

$x_i - input\ signals, w_{ji} - weights\ and\ b_j\ is\ bias$

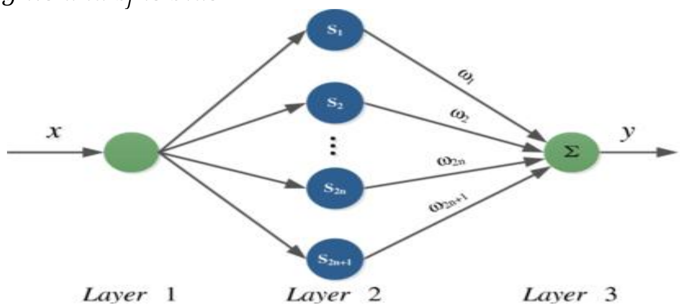

Fig. 3 Neural Network Controller

For a given set of inputs to the network, outputs are computed for each neuron in the first layer and forwarded to the next layer. The signals propagate on a layer-by-layer basis until the output layer is reached. The weights and biases remain unchanged during the 'forward pass'. The output of the network is compared with the desired value (t_j) and difference gives the error.

$$e_j = t_j - y_j \tag{25}$$

The total error is defined by equation (28), where *c* is the number of neurons in the output layer.

$$E = \frac{1}{2}\sum_{j=1}^{c} e_j^2 \tag{26}$$

The error *E* represents the cost function, and the weights and biases are updated to minimize it.

The computed partial derivatives (sensitivity) $\partial E/\partial w_{ji}$ determine the search direction for updating the weights w_{ji} as

$$w_{ji}(k+1) = w_{ji}(k) - \eta\frac{\partial E(k)}{\partial w_{ji}(k)} \tag{27}$$

k is the current time and (*k* + 1) is the next time step. The above update formula is refined using a 'momentum term' that has a stabilizing effect on the back-propagation algorithm. The training of the NN is complete when the error (or change in the error) reduces to a predetermined small value.

Using neural network fitting tool the inputs (coefficient associated with Kinetic energy and strain energy) and output (control gain) are given in the form of matrix i.e. of 16X2 and 16X6 in the range of 0 to 200 with training 70%, validation 15% and testing 15%. The hidden neurons are taken as 10. Network has been trained with the help of Levenberg-Marquardt back propagation algorithm which gave the regression plot for the neural network controller (Fig 4)

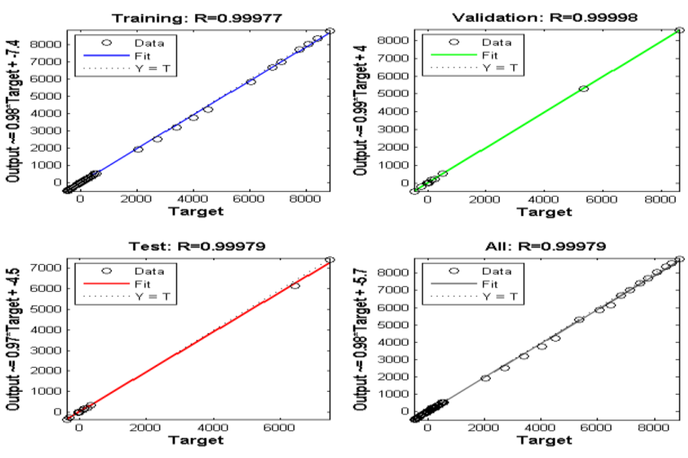

Fig 4 Regression Plot of Neural Network Controller

III. RESULT

Settling time for each patch placed in the 8X8 mesh under various control laws are as shown in the table2:

Table 2: Input parameters (Piezolocation, α_2^*, α_1^*) and settling time obtained using neural network controller

Sr. No.	Piezolocation	coefficient associated with Kinetic energy (α_2^*)	coefficient associated with Strain energy (α_1^*)	Settling Time
1	60	10	20	3.84
2	55	20.14	30.14	8.14
3	35	55.5	65.5	1.34
4	64	44.45	54.45	8.38
5	20	117.15	127.15	4.99
6	15	139.4	149.4	7.56
7	18	172.7	182.7	7.52
8	9	20.14	30.14	4.99
9	25	95.1	105.1	7.65
10	30	32.25	42.25	1.91
11	30	10	20	2.45
12	45	180	190	7.98
13	11	190	200	7.55
14	50	75.6	85.6	8.17
15	39	20.14	30.14	2
16	28	32.25	42.25	1.91

The Neural Network Controller is designed based on simple human reasoning. Using Neural Network Fitting tool input and output has been given in the form of matrix with 10 hidden neurons. Network has been train with the help of Levenberg-Marquardt back propagation algorithm. Input to the controller consists of coefficient associated with Kinetic energy and Strain energy of the structure and output of the controller are the gains applied to the actuator. Neural Network is used in such a way that voltage given to the actuator within breakdown voltage limits and provides stability to the system. The proposed neural network controller is tested for active vibration control of a cantilever plate to suppress first three modes of vibrations. A finite element model of 2D cantilever plate instrumented with a piezoelectric patch as sensor/actuator has been taken. While controlling first three modes simultaneously with a single sensor/actuator pair, effective control is observed with present approach. The position of sensor/actuator has been varied 1 to 64 positions which are available on finite element plate. The value of the coefficient associated with Kinetic energy and Strain energy has also been varied from 0 to 200. Thus by varying the sensor/actuator location and value of coefficient associated with Kinetic energy and strain energy, we found out the minimum settling time using Neural Network Controller. Table2. shows the settling time of using Neural Network Controller at various locations and values of coefficient associated with Kinetic energy and strain energy. The settling time are calculated by changing various position of piezo-patches and both coefficient associated with Kinetic energy and strain energy on MATLAB software. Some settling time figures are shown below. The best time settling is obtained at 35th piezo-patches and co-efficient associated with Kinetic energy and strain energy positions are 55.5 and 65.5 respectively. Figure 5 shows controlled and uncontrolled coefficient of kinetic energy (32.25) and strain energy (42.25) when piezoactuator is placed at 28th position. Figure 6 shows controlled and uncontrolled coefficient of kinetic energy (32.25) and strain energy (42.25) when piezoactuator is placed at 30th position. Figure 7 shows controlled and uncontrolled coefficient of kinetic energy (55.5) and strain energy (65.5) when piezoactuator is placed at 35th position. Figure 8 shows controlled and uncontrolled coefficient of kinetic energy (10) and strain energy (20) when piezoactuator is placed at 60th position.

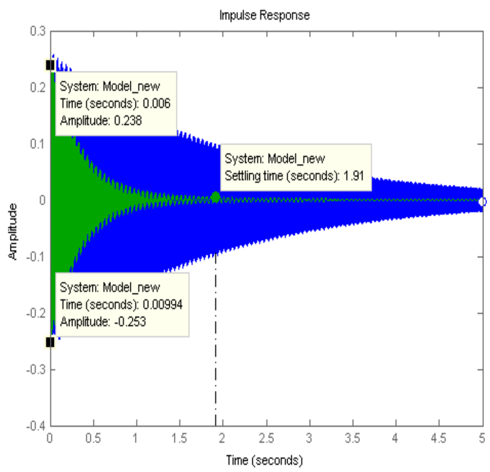

Fig 5 Controlled and Uncontrolled coefficient of Kinetic energy and strain energy When piezoactuator placed at 28th position (al=32.25 and bet=42.25)

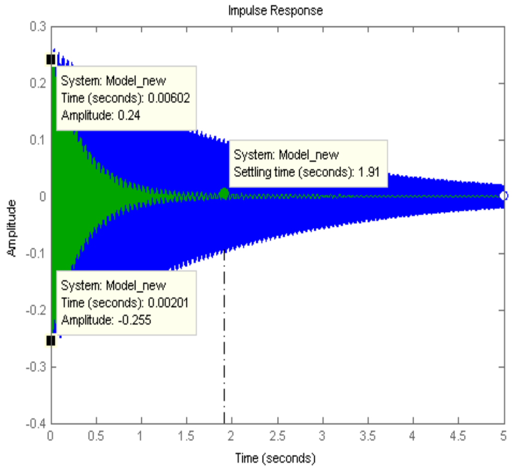

Fig 6 Controlled and Uncontrolled coefficient of Kinetic energy and strain energy When piezoactuator placed at 30th position (al=32.25 and bet=42.25)

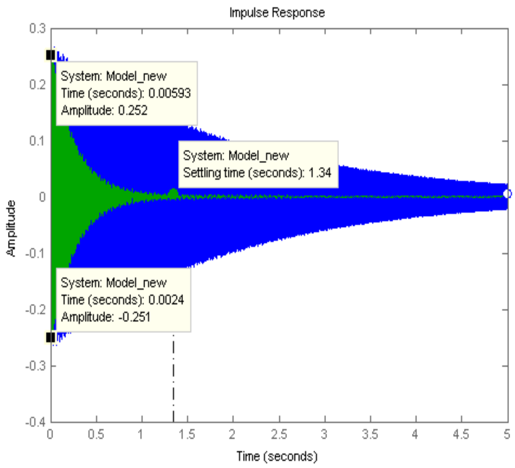

Fig 7 Controlled Uncontrolled coefficient of Kinetic energy and strain energy When piezoactuator placed at 35th position (al=55.5 and bet=65.5)

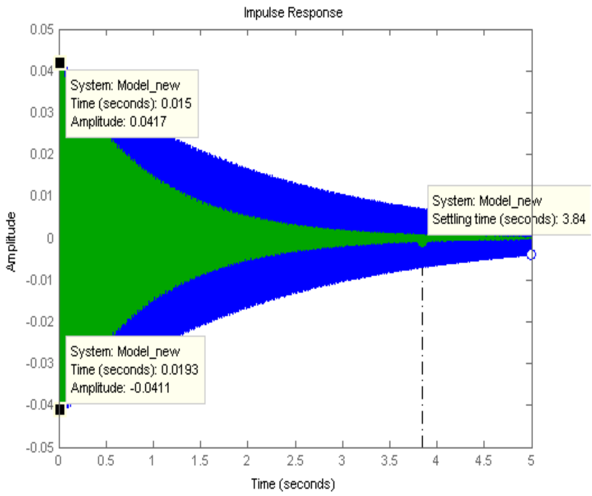

Fig 8 Controlled and Uncontrolled coefficient of Kinetic energy and strain energy When piezoactuator placed at 60th position (al=10 and bet=20)

IV. CONCLUSION

This work shows the basic techniques for analysis of active vibration control using piezoelectric sensor and actuator. A general scheme of analyzing and designing piezoelectric smart cantilever plate with Neural Network control tuned with LQR controller is successfully developed in the study. The two inputs of LQR controller are taken as coefficient associated with Kinetic energy and Strain energy to determine the weighing matrices Q & R and six outputs are taken as

Control Gain to control first three modes of vibration. The present scheme has flexibility of designing the collocated and non-collocated system. The best location of sensor/actuator pair is 35^{th} which gives the minimum settling time i.e.1.34 sec and the concern coefficient of Kinetic energy and strain energy are 55.5 and 65.5 respectively.

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