# Optimization of structural parameters using artificial neural network for vibration reduction in beams

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By:

**PRADEEP KUMAR**

**107ME061**

Under the guidance of:

**Prof. S C Mohanty.**

Department of Mechanical Engineering

**Department of Mechanical Engineering.**

**National Institute Of Technology, Rourkela**

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**NATIONAL INSTITUTE OF TECHNOLOGY, ROURKELA**

# CERTIFICATE

This is to certify that the project entitled "optimization of structural parameters using artificial neural network for vibration reduction in beams" submitted by Pradeep Kumar in partial fulfillment of the requirements for the awards of Bachelor of Technology, NIT Rourkela (Deemed university) is an authentic work carried out by him under my supervision and guidance. To the best of my knowledge the matter embodied in the project has not been submitted to any Institute/University for the award of any degree or diploma.

Date: 10.05.2011.

Prof. S C Mohanty

Department of Mechanical Engineering,

National Institute of Technology, Rourkela

**NATIONAL INSTITUTE OF TECHNOLOGY, ROURKELA**

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Finally, we deem it a great pleasure to thank one and all those who helped us carry out this project.

PRADEEP KUMAR (107ME061)
MECHANICAL ENGINEERING DEPARTMENT
NATIONAL INSTITUTE OF TECHNOLOGY, ROURKELA

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# ABSTRACT:

Recently optimization of structural parameters like stiffness coefficient and damping coefficient, using artificial neural network for vibration reduction in beam has become a major application in aerodynamics and many other fields. By placing the PVC dampers of different cross sectional area at different locations along a beam, we have to minimize the response and the response time of the beam due to vibrations. Measuring factor of damping (reduction in vibration) is the LOSS FACTOR (Ω) for the system. Along the beam, where the loss factor is more, it gives us an optimal position for placing the damper. It also gives stability to the structure. The stability of the beam enhances due to increase in core loss factor also.

# LITERATURE REVIEW:

Articles of Nakra[1-3] have widely treated the quality of vibration control with the visco-elastic materials. Briseghella et al. [4] studied the energetic stability troubles of the beams and frames by using finite element process. Kerwin [5] was the first to perform a quantitative study of the damping effectiveness of the constrained viscoelastic layer and he derived an expression to guess the loss factor. Ungar [6] derived general expressions for the loss factor of homogeneous linear composites in conditions of the properties of the constituting materials. Di Taranto [7] proposed a theory to estimate natural frequencies, loss factors for the finite length sandwich beam. Jones et al.[8] theoretically and experimentally calculated the damping capacity of a sandwich beam with the visco-elastic core. Asnani and Nakra [9] compared multilayer simply supported sandwich beams and projected loss factors and displacement response effectiveness for beams of different amount of layers. Chatterjee and Baumgarten[10] obtained for the simply supported sandwich beam, the damped natural frequencies and logarithmic decrement for the basic mode of vibration. They also conducted the experiments to verify their theoretical consequences. Nakra and Grootenhuis [11] studied tentatively as well as experimentally, the vibration characteristics of the asymmetric dual core sandwich beams. They did not comprise the rotary and longitudinal inertia terms in their study. Later Rao [12] integrated both these effects in his analysis. Asnani and Nakra [13] studied the outcome of number of layers and thickness ratio on the system loss factors for the simply supported multilayer beam. Rao [14] checked the influence of pre-twist on resonant frequency and loss factor for the symmetric pre-twisted simply supported sandwich beam and initiate that pre-twisting reduces loss factor and very soft thick cored beam is particularly sensitive to even little changes of pre twist. Rao and Stuhler [15] analyzed the damping effectiveness of the tapered sandwich beam with simply supported and clamped free end circumstances. Rao [16] investigated the free vibration of the short sandwich beam considering the higher order effects, such as inertia, extension and shear of all the layers. He found that if these parameters are neglected for short sandwich beam, there is an error as high as 45% in calculation of the loss factor and frequencies. Rubayi and Charoenree [17] carried theoretical and experimental investigations to attain the natural frequencies of the cantilever sandwich beams subjected to the gravity force only. Rao [18] on a different work obtained graphs and equations to approximate frequencies and loss factor for the sandwich beam under various boundary conditions. Johnson and his teammates [19-20] used the finite element method to calculate frequencies and loss factors for beams and plates with the constrained visco-elastic layer. Vaswani et al.[21] derived the equations of motion for a multilayer curved sandwich beam forced to harmonic excitation. Lall et al.[22] observed the partially covered sandwich beams using three unlike methods and found that method by Markus [23] shows modal loss factors only, whereas Rayleigh-Ritz and classical investigation method give both loss factor and resonant frequencies. Dewa et al.[24] calculated the damping effectiveness of incompletely covered sandwich beams. They also found out that partially covered beams have a better damping capacity as compared to fully covered beams. He also validated his theoretical readings through some experiments. Imaino and Harrison [25] used the modal strain energy method and finite element techniques to verify damping of first and second bending resonances of the sandwiched beam with forced damping layer.

He and Rao [26] developed an analytical method to compare the parameter study of a coupled flexural and longitudinal vibration of the curved sandwiched beam. Effects of parameters like curvature, core width and shear modulus over the system loss factor and the resonant frequency were verified. Same authors [27], in another work observed the vibration of multi span beams with the arbitrary boundary conditions. Effects of parameter like position of intermediate supports and the adhesive thickness on the resonant frequencies and loss factors were checked. Bhimaraddi[28] computed both the resonant frequencies and the loss factors for a simply supported beam with constrained layer damping, using a representation which projected the link of displacements and transverse shear stresses, across the interfaces of the layers. Sakiyama et al.[29] anticipated an analytical method for free vibration analysis of a three layer continuous sandwich beam and also studied the outcome of shear factor and the core thickness on the resonant frequencies and loss factors. Fasana and Marchesiello [30] computed the mode shapes, frequencies and loss factors for the sandwich beams by Rayleigh-Ritz method. They took polynomials which suited the geometric boundary conditions as acceptable function. Banerjee[31] studied the free vibrations of the three layer sandwich beam using dynamic stiffness matrix method. He computed the natural frequencies and mode shapes. In a recent work, Nayfeh[32] conducted experiment to get resonant frequencies and loss factors and compared with values predicted by his developed model, for vibrations parallel to the plane of lamination of a symmetric elastic visco-elastic sandwich beam.

Sahin M. et al.[33] presented a damage detection algorithm, by using the combination of global (Variations in the natural frequencies) and local (curvature mode shapes) vibration-based analysis data as input in artificial neural networks (ANNs) for location and strict prediction of damage in beam-like structures. Material damage shows changes in the structural parameters, e.g. the stiffness of a structural part or a substructure and its damping coefficient. These changes will alter the dynamic characteristics like the natural frequency and mode shape of the structure. With the current innovations in the computer technology for data collection, signal handling and analysis, the parameters of a structure can be known from the measuring responses and excitations of the structure by using system identification methods as an inverse problem. These identification strategies use mathematical models to illustrate the structural behavior and set up the relationship between a specific damage condition and its corresponding changes in structural reaction or Eigen-value. These mathematical recognition methods can be sub divided into time-domain approach by the use of response in time series and frequency-domain approach based on Eigen-value study [34]. Neural networks have drawn a considerable focus in the civil engineering field because of their ability to fairly precise an random continuous function and mapping. Indeed, framing a linear or nonlinear structural system with a neural network has been progressively documented as one of the system identification paradigms [35]. By establishing a neural network model which is capable of learning and forecasting the functional mappings between input and output, a structure that is linear or non-linear discrete- time multivariable dynamic system can be framed in a nonparametric form [36]. The data acquired by a neural network is placed in its connecting weight and bias. Among various neural networks with different topology structures, multi-layer neural network is the generally used in structural identification and control [37]. Yun and Bahng (2000) presented a method for estimating the stiffness parameters of a complex structural system by using a back-propagation neural network with natural frequencies and mode shapes as inputs. Wu et al. (2002) formulated a decentralized stiffness identification method with neural networks made between the restoring force and the displacement/velocity of a multi-degree-of- freedom (MDOF) structure. First neural model was given by McCulloch and Pitts in 1943. ANN which learns using the Back propagation algorithm was given by Rumelhart and McCulland in 1986.

# INTRODUCTION:

Sandwiched structures are getting much significance particularly in the aerospace as well as other applications due to their outstanding vibration damping capacities. In an earlier work, Mead and Markus found out the forced vibration characteristics of a three layer damped sandwich beam with random boundary conditions. Asnani and Nakra studied the vibration damping properties of a multilayer sandwich beam. Rubayi and Charoenree estimated the natural frequencies of a cantilever sandwich beam for a wide range of system parameters. Rao and Stuhler studied the damping effectiveness of the tapered symmetric sandwich beams for some clamped-free and hinged-hinged boundary conditions. Rao in his later works calculated the frequency and loss factors of sandwich beams with unlike boundary conditions and presented his findings in the shape of graphs and formulae. Rao also investigated the vibration properties of pre-twisted sandwich beams. He also found out the forced vibration characteristics of a damped sandwiched beam subjected to varying forces. Sharma and Rao studied static deflection and stresses in the sandwich beams under various boundary conditions. Bauld determined the instability regions of simply supported sandwich column subjected to pulsating compressive load. Chonan studied the firmness of two layered cantilever beam with imperfect elastic bonding and forced to constant horizontal and

tangential compressive forces.

The purpose of the current work is to study the dynamic stability of a three layered symmetric sandwiched beam, subjected to end periodic axial forces. Equations of motion are formulated using the finite element methods. The areas of instability of the simple and combined resonances are made by using modified Hsu's methods proposed by Saito and Otomi

# FORMULATION OF THE PROBLEM

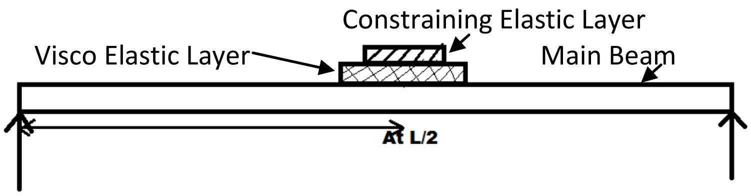



*Fig1: Beam with Constraining Layer*

Figure 1 shows a beam of length L with a constraining layer. The finite element model made is based on some of the following assumptions:

(1) The transverse displacement *w* is identical to all the three layers.

(2) The values of rotary inertia and shear deformations in a constrained layer are considered nil.

(3) We use linear theories of elasticity and visco-elasticity.

(4) There is no slip between the layers and also there is a perfect continuity at the interfaces.

(5) Young's modulus of a visco-elastic material is considered negligible as compared to the elastic material.

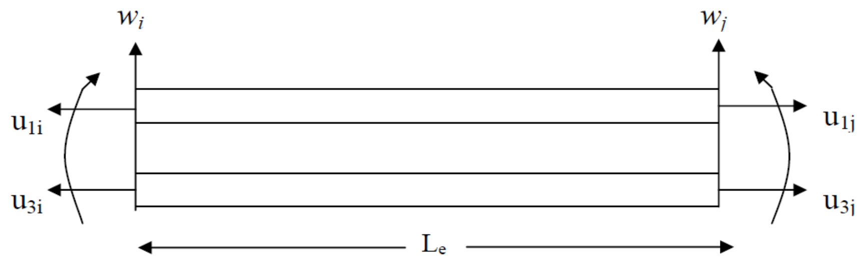



*Fig2: element of sandwiched beam*

As shown in figure 2, the element model presented here comprises of two nodes and every node has four degrees of freedom. Nodal displacements are represented by

$$\{ \Delta^e \} = \{ u_{1i}\ u_{3i}\ w_i\ \Phi_i\ u_{1j}\ u_{3j}\ w_j\ \Phi_j \}$$

Where i and j represent elemental nodal numbers.

The axial displacement of a constraining layer, the transverse displacement and the rotational angle, can be represented in terms of nodal displacements and finite element shape functions.

$$u_1 = [N_1]\{\Delta^e\},\ u_3 = [N_3]\{\Delta^e\},\ w = [N_w]\{\Delta^e\},\ \Phi = [N_w]'\{\Delta^e\}$$

Where prime represents the differentiation w.r.t. axial co-ordinate x and hence the shape functions are given as

$$[N_1] = [1\text{-}\xi\ 0\ 0\ 0\ \xi\ 0\ 0\ 0\ ]$$

$$[N_3] = [0\ 1\text{-}\xi\ 0\ 0\ 0\ \xi\ 0\ 0\ ]$$

And

$$[N_w] = [0\ 0\ (1-3\xi^2+2\xi^3)\ (\xi-2\xi^2+\xi^3)L_e\ 0\ 0\ 3\xi^2-2\xi^3\ (-\xi^2+\xi^3)\ L_e]$$

Where $\xi = x/L_e$ and $L_e$ is the element's length.

**CONSTRAINING LAYERS**

The constraining layer has its potential energy given as

$$U_k^{(e)} = \frac{1}{2}\int_0^{L_e} E_k I_k \left(\frac{d^2 w}{d x^2}\right)^2 dx + \frac{1}{2}\int_0^{L_e} E_k A_k \left(\frac{du}{dx}\right)^2 dx \qquad k = 1,3$$

Where E= Young's modulus, A= cross-sectional and I = moment of inertia

The citations 1 and 3 represent the upper and lower constraining layers respectively.

Also the kinetic energy of the constraining layers is observed as

$$T_k^{(e)} = \frac{1}{2}\int_0^{L_e} \rho_k A_k \left(\frac{dw}{dt}\right)^2 dx + \frac{1}{2}\int_0^{L_e} \rho_k A_k \left(\frac{du}{dt}\right)^2 dx \qquad k = 1,3$$

Where ρ = mass density.

By substituting the values from above equations, we have the element potential energy and the Kinetic energy of the constraining layers given as

$$U_k^{(e)} = \frac{1}{2}\left\{\Delta^{(e)}\right\}\left(\left[K_{ku}^{(e)}\right]+\left[K_{kw}^{(e)}\right]\right)\left\{\Delta^{(e)}\right\} \qquad k = 1,3$$

And

$$T_k^{(e)} = \frac{1}{2}\left\{\Delta^{(e)}\right\}\left(\left[M_{ku}^{(e)}\right]+\left[M_{kw}^{(e)}\right]\right)\left\{\Delta^{(e)}\right\} \quad k = 1,3$$

Where

$$\left[K_{ku}^{(e)}\right] = \left[K_{1u}^{(e)}\right]+\left[K_{3u}^{(e)}\right] = E_1 A_1 \int_0^{L_e} \left[N_1\right]^T \left[N_1\right] dx + E_3 A_3 \int_0^{L_e} \left[N_3\right]^T \left[N_3\right] dx$$

$$\left[K_{kw}^{(e)}\right] = \left[K_{1w}^{(e)}\right]+\left[K_{3w}^{(e)}\right] = E_1 I_1 \int_0^{L_e} \left[N_w\right]^T \left[N_w\right] dx + E_3 I_3 \int_0^{L_e} \left[N_w\right]^T \left[N_w\right] dx$$

$$\left[M_{ku}^{(e)}\right] = \left[M_{1u}^{(e)}\right]+\left[M_{3u}^{(e)}\right] = \rho_1 A_1 \int_0^{L_e} \left[N_1\right]^T \left[N_1\right] dx + \rho_3 A_3 \int_0^{L_e} \left[N_3\right]^T \left[N_3\right] dx$$

$$\left[M_{kw}^{(e)}\right] = \left[M_{1w}^{(e)}\right]+\left[M_{3w}^{(e)}\right] = \rho_1 A_1 \int_0^{L_e} \left[N_w\right]^T \left[N_w\right] dx + \rho_3 A_3 \int_0^{L_e} \left[N_w\right]^T \left[N_3\right] dx$$

## VISCOELASTIC LAYER

According to Mead and Markus, the axial displacement $u_v$ and shear strain $\gamma_v$ of a visco-elastic layer are calculated from the kinematic relationships between the constraining layers. They are given as:

$$u_v = \frac{u_1 + u_3}{2} + \frac{(t_1 - t_3)}{4}\frac{\partial w}{\partial x}$$

$$.\ \gamma_v = \frac{\partial w}{\partial x}\left[\frac{2t_2 + t_1 + t_3}{2t_2}\right] + (u_1 - u_3)$$

From the above we can see that $\gamma_v$ and $u_v$ can be represented in terms of the nodal displacements and the element shape functions:

$$u_v = (N_v)\left\{\Delta^{(e)}\right\}$$

$$\gamma_v = (N_\gamma)\left\{\Delta^{(e)}\right\}$$

Where

$$(N_v) = \frac{1}{2}\left((N_1) + (N_3)\right)\frac{(t_1 - t_3)}{4}(N_w)$$

$$(N_\gamma) = \frac{1}{2}\frac{\left((N_1) - (N_3)\right)}{t_2} + \frac{(t_1 + 2t_2 + t_3)}{t_2}(N_w)$$

The potential energy of a visco-elastic layer due to its shear deformation is predicted as

$$U_v^{(e)} = \frac{1}{2}\int_0^{L_e} G_v A_v \gamma_v{}^2 dx$$

Where $A_v$ = cross-sectional area

$G_v$ = complex shear modulus of visco-elastic layer.

Hence the kinetic energy of visco-elastic layer is

$$T_v^{(e)} = \frac{1}{2}\int_0^{L_e} \rho_v A_v \left\{\left(\frac{dw}{dt}\right)^2 + \left(\frac{du_v}{dt}\right)^2\right\} dx$$

From the above formulated equations, the potential energy and the kinetic energy of visco-elastic material layer are given as

$$U_v^{(e)} = \frac{1}{2}\left\{\Delta^{(e)}\right\}\left(\left[K_v^{(e)}\right]\right)\left\{\Delta^{(e)}\right\}$$

$$T_v(e) = \frac{1}{2}\left\{\dot{\Delta}^{(e)}\right\}\left(\left[M_v^{(e)}\right]\right)\left\{\dot{\Delta}^{(e)}\right\}$$

Where

$$\left[K_v^{(e)}\right] = G_v A_v \int_0^{L_e} \left[N_\gamma\right]^T \left[N_\gamma\right] dx$$

$$\left[M_v^{(e)}\right] = \rho_v A_v \int_0^{L_e} \left[N_v\right]^T \left[N_v\right] dx + \rho_v A_v \int_0^{L_e} \left[N_w\right]^T \left[N_w\right] dx$$

Where dot denotes its differentiation w.r.t. time *t*.

**EQUATION OF MOTION**

According to the Hamilton's principle, we have

$$\delta \int_{t_1}^{t_2} \left(T^{(e)} - U^{(e)}\right) dt = 0$$

By substituting the strain energy, kinetic energy, and the work done by the load force into the Hamilton's principle, the governing equation for the sandwich plate element is obtained as Follows

$$\left[M^{(e)}\right]\left\{\ddot{\Delta}^{(e)}\right\} + \left[K^{(e)}\right]\left\{\Delta^{(e)}\right\} = 0$$

Assembling mass, elastic stiffness and geometric stiffness matrices of individual element, the equation of motion for the sandwich plate is written as

$$[M]\{\ddot{\Delta}\} + [K]\{\Delta\} = 0$$

Where $\{\Delta\}$ is the global displacement matrix

# <u>ARTIFICIAL NEURAL NETWORK</u>:

## INTRODUCTION

Studies on neural networks have been forced to follow the way that the brain operates. A network is basically described in the terms of individual neurons, network connectivity, weights associated with various links between the neurons and the activation function for each neuron. The network maps an input vector from one space to another. The mapping is not specified, but is trained. The network is represented with a specified set of inputs and their respective outputs. The learning process is used to set up proper interconnection weights and the network is trained to make suitable associations between the inputs and their following outputs. Once trained, the network provides rapid mapping of a given input into the preferred output quantities. This, in turn, can be used to modify the efficiency of the design process. Artificial neural systems are that physical cellular systems which acquire, store and utilize experimental information. Powerful learning algorithm and self-organizing rule allow ANN to self adapt as per the requirements in continually varying environment (adaptability property). The ANN architecture is a multilayer, feed forward backpropogation architecture. Multilayer perception (MLP) has an input layer, output layer and hidden layer. Input vector is incident on input layer and then to hidden layer and subsequently to final layer/output layer via. weighted connections. Each neuron operates by taking the sum of its weighted inputs and passing the results through a non-linear activation function ( transfer function ). Generally sigmoid function is chosen as the non-linear activation function.

# BACK PROPOGATION:

Back propagation is an overview of the Widrow-Hoff's learning law to multiple-layer networks and nonlinear differentiable transfer functions. Here the Input vectors and their corresponding target vectors are used to train a network until it is able to fairly precise a function, associate input vectors with some specific output vectors, or classify input vectors according to an appropriate route defined by the operator. Networks with biases, a sigmoid layer and a linear output layer are capable of representing any function with a fixed amount of discontinuities. Standard back propagation is a gradient descent algorithm, same as that of the Widrow-Hoff's learning rule, in which the network weights are forced along the negative of the side of the performance function. The term back propagation represents the way in which gradient is computed for nonlinear multilayer networks. There are various numbers of variations on the fundamental algorithms that are based on different standard optimization techniques, like conjugate gradient and Newton method. Suitably trained back propagation networks are likely to give reasonable answers, when given with inputs that they had never encountered. A new input leads to an output which is analogous to the correct output for respective input vectors used in training that are similar to the new inputs being given. This overview makes it feasible to train a network on a resembling set of input/target pairs and achieve good results without training the network on all the possible input/output pairs.

# NEURON MODEL (LOGSIG, TANSIG, PURELIN)

An elementary neuron with *R* inputs is shown underneath. Each input has an appropriate weightage *w*. The input to the transfer function *f* is the sum of the weighted inputs and the bias. To generate the outputs, neurons can utilize any differentiable transfer function *f*.

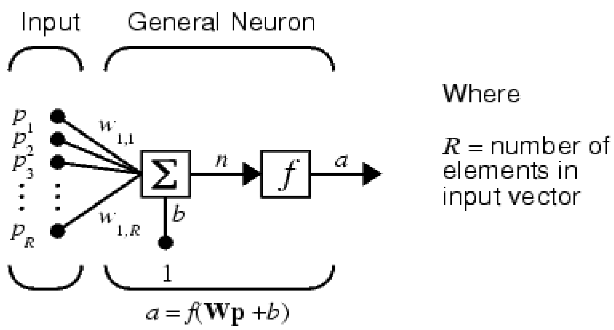



Fig 3: Neural network structure

Multilayer networks generally use a log-sigmoid transfer function known as *logsig*.

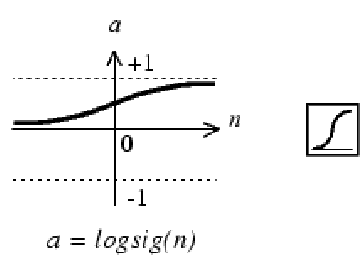



Fig 4: Log-Sigmoid Transfer Function

The function *logsig* produces outputs between 0 and 1 while the neuron's total input goes from negative to positive infinity.

Alternatively, a tan-sigmoid transfer function *tansig* can be used by multilayer networks.

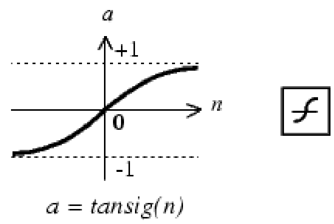



Fig 5: Tan-Sigmoid Transfer Function

Sometimes a linear transfer function *purelin* is used in the back propagation networks.

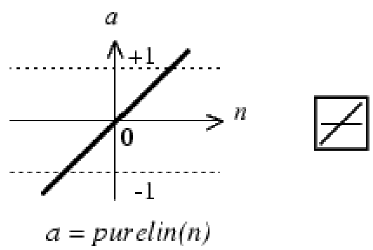



Fig 6: Linear Transfer Function

The outputs of the network are restricted to a small range, if the final layer of a multilayer network has the sigmoid neurons. The network outputs can take on any value if the linear output neurons are used.

In back propagation it is essential to calculate the derivatives of any transfer functions used in the process. Each of the transfer functions as above, *logsig*, *tansig*, and *purelin*, can be recalled to calculate their own derivatives.

Call the transfer function with the string 'dn to calculate a transfer function's derivative.

Where dn = tansig('dn',n,a)

The transfer functions described above are the most usually used transfer functions for back propagation, but other differentiable transfer functions can be generated and used with back propagation if preferred.

# CREATING A NETWORK:

The first step in the training of a feed forward network is to create a network object. The function *newff* generates a feed forward network. Basically it requires three arguments and returns it to the network object. The first argument consists of a matrix of sample R-element input vectors. The second argument consists of a matrix of sample S-element target vectors. The sample inputs and outputs are then used to set up network's input and output dimensions and parameters. The third argument consists of an array containing the sizes of individual hidden layer. (The size of output layer is determined from the targets.)

We can provide more optional arguments. For example, the fourth argument consists of a cell array comprising the names of the transfer functions that are to be used in each and every layer. The fifth argument consists of the name of the training function to be used. If just three arguments are provided, then the default transfer function for hidden layers is *tansig* and for the output layer is *purelin*. The default training function is called *trainlm*.

## TRAINING:

Once the network weights and biases are initialized, the network is ready for its training. We can train the network for function estimation (nonlinear regression), its pattern association and classification. During a training process we need a set of examples of proper network behavior for network inputs *p* and target outputs *t*. Also the weights and biases of the network are iteratively familiarized to reduce the network's performance function *net.performFcn*. Mean square error, *mse* is the principle performance function for the feed forward networks which is also defined as the average square error between the outputs *a* and the target outputs *t* of the network.

All such algorithms employ a slope of the performance function to decide how to adjust the weights so as to minimize the performance. The gradient is hence calculated by using a technique called back propagation that involves performing backward computations for the network. The back propagation computation is generally derived from the chain rules of calculus.

There are usually four steps in the training process:

1. Assemble the training data.
2. Create the network object.
3. Train the network.
4. Simulate the network response to new inputs.

# BACKPROPOGATION ALGORITHM

The simplest execution of back propagation learning is updating the network weights and biases in the directions where the performance function decreases rapidly, towards the negative of the slope. An iteration of this algorithm can be written

$$X_{k+1} = \mathbf{X}_k - (\boldsymbol{\alpha}_k \text{ X } g_k)$$

Where $X_k$ = vector of current weights and biases,

$g_k$ = current gradient ; $\boldsymbol{\alpha_k}$ = learning rate.

There are two very different ways in which the gradient descent algorithm can be used, the incremental mode and batch mode.

In the incremental mode, the gradient is estimated and the weights are updated after all the inputs are applied to the network individually. In the batch mode, all inputs are fed to the network before the weights are updated.

**Batch Gradient Descent (*traingd*):**

The batch steepest descent training function is termed as *traingd*. Here the weights and biases are updated in the direction of the negative slope of the performance function. When we have to train a network using batch steepest descent, we must change the network from *trainFcn* to *traingd*, and then call the function train. There can be only one training function related with a given network.

There are seven training parameters that are linked with *traingd*:

- *epochs*
- *show*
- *goal*
- *time*
- *min_grad*
- *max_fail*
- *lr*

The learning rate *lr* is multiple times of the negative of the gradient to demonstrate the changes to the weights and biases. The greater the learning rate, the larger the step. If the learning rate is made too big, the algorithm turns to uneven. When the learning rate is set too small, the algorithm takes a long time to congregate.

The training condition is displayed for every show of algorithmic iterations (If show is set to *NaN*, then the training status is not shown). The other parameters reveal when the training will stop. The training will terminate

- When the no. of iterations exceeds *epochs*
- When the performance function drops below *goal*
- When the gradient's magnitude is less than *mingrad*
- When the training time is more than the time in seconds. *max_fail*.

# OBSERVATION:

After analysis, we got:

For 1$^{st}$ mode of vibration:

Table 1: Core loss factors for different location in 1$^{st}$ mode of vibration

| Location | Core loss factor |
|---|---|
| l/4 | 0.0023 |
| l/2 | 0.0052 |
| 3l/4 | 0.0024 |

For 2$^{nd}$ mode of vibration:

Table 2: Core loss factors for different location in 2$^{nd}$ mode of vibration

| Location | Core loss factor |
|---|---|
| l/4 | 0.0048 |
| l/2 | 0.0001 |
| 3l/4 | 0.0051 |

By fixing the input vector and target output, we can predict the core loss factor at different locations along the beam.

Assuming L equal to 100 units. The locations where the loss factor will be more, that location will b optimal for vibration reduction.

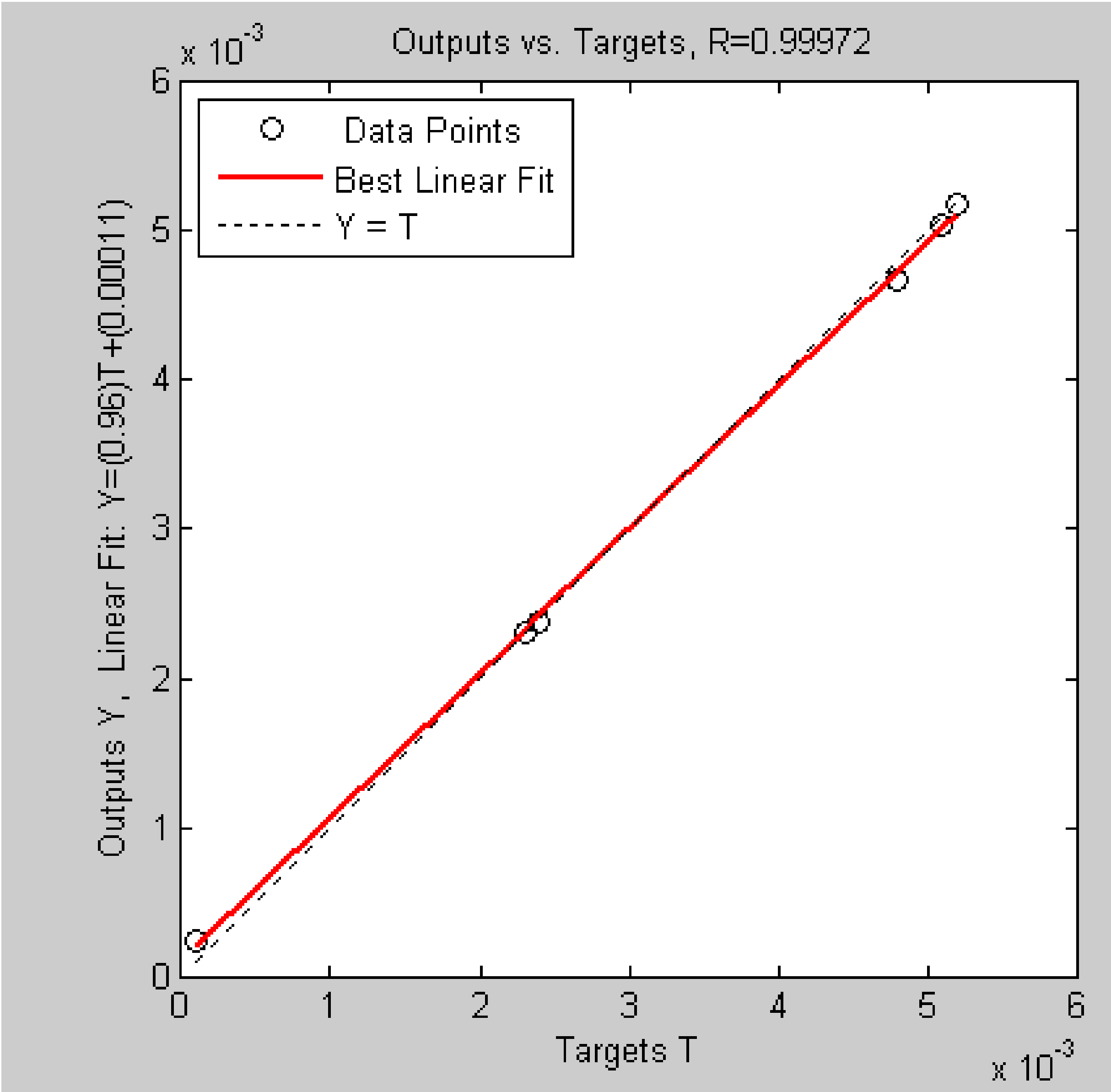
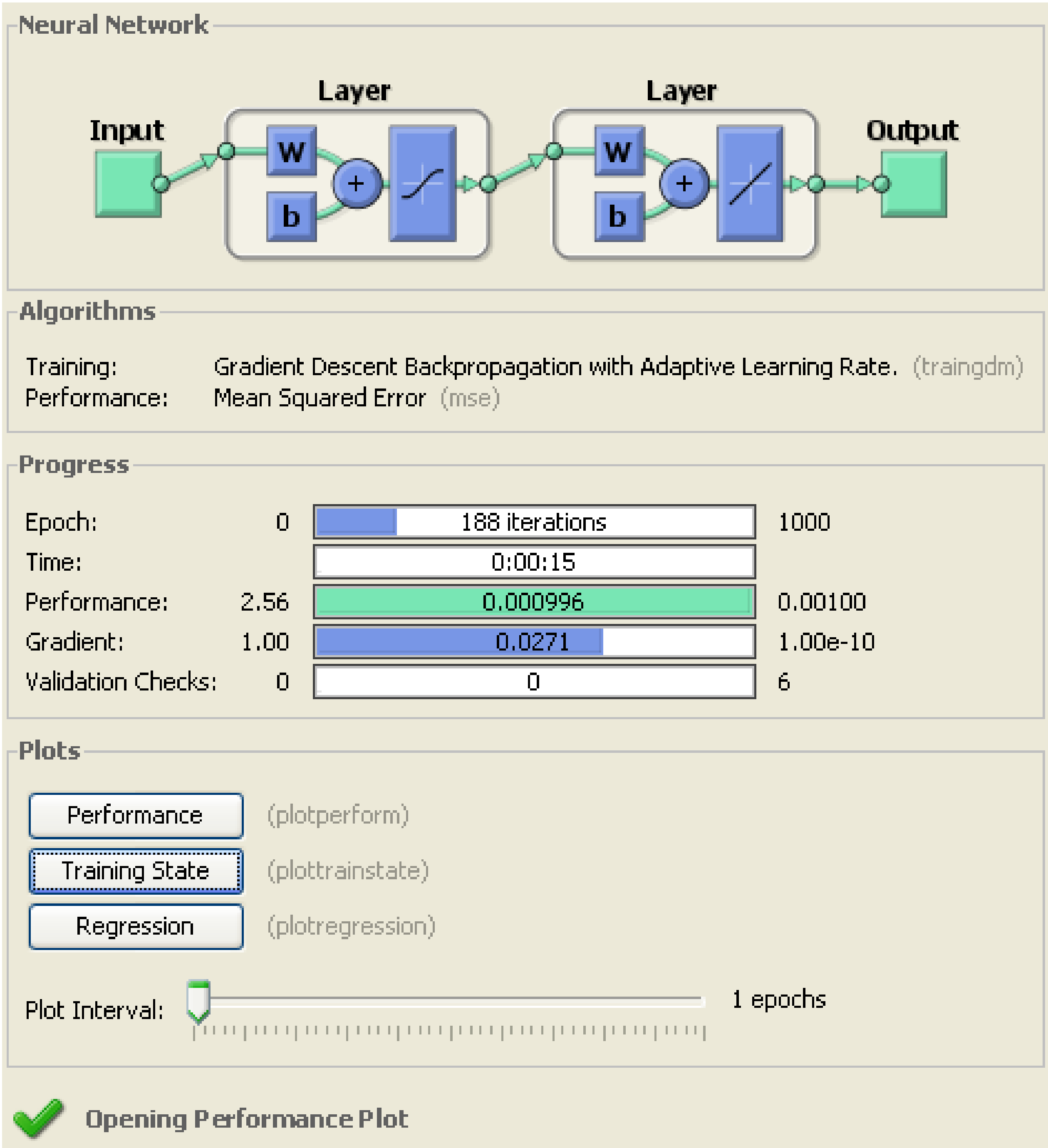



Fig 7:Regression plot




<u>Fig 8: Architecture</u>

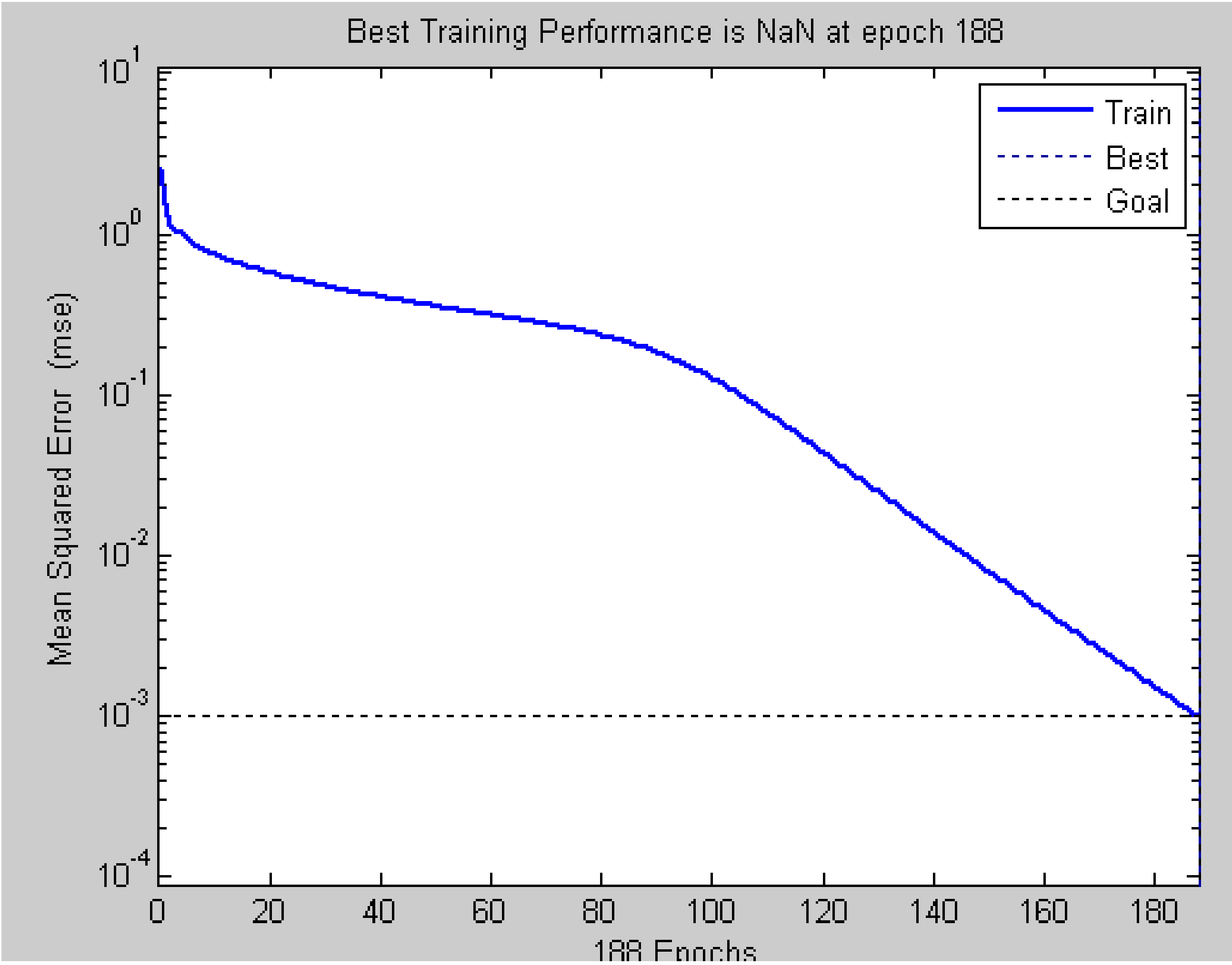



Fig 9: Performance

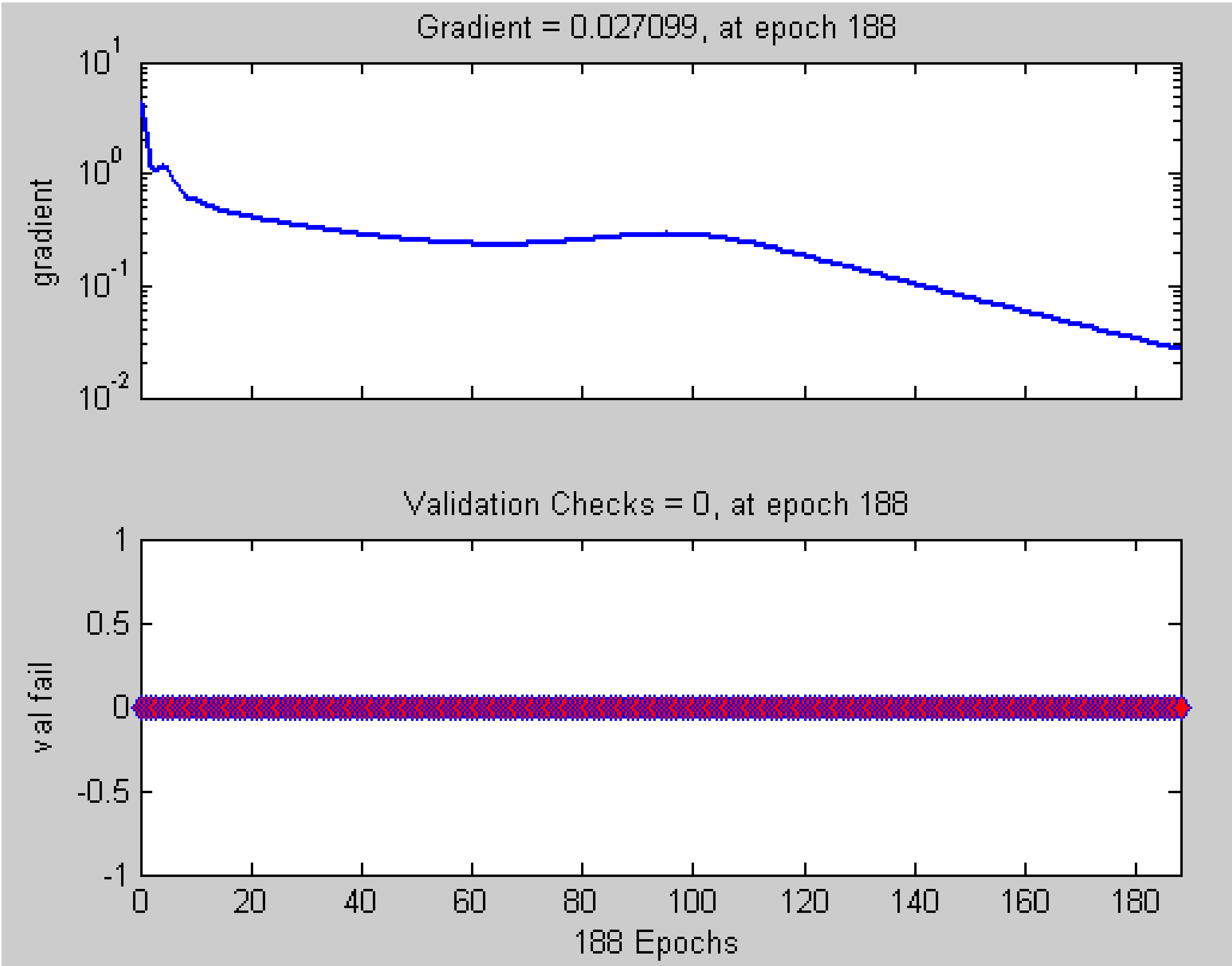



Fig 10: Training state

# RESULT:

Table 3: Prediction values of core loss factor for different Input locations for different modes of vibration

| SL No. | Mode of vibration | Input (location) | Prediction |
|---|---|---|---|
| 1 | 1st | 10 | 0.0040 |
| 2 | | 15 | 0.0039 |
| 3 | | 20 | 0.0035 |
| 4 | | 25 | 0.0023 |
| 5 | | 30 | 0.0007 |
| 6 | | 35 | 0.0003 |
| 7 | | 40 | 0.0017 |
| 8 | | 45 | 0.0038 |
| 9 | | 50 | 0.0052 |
| 10 | | 55 | 0.0054 |
| 11 | | 60 | 0.0048 |
| 12 | | 65 | 0.0038 |
| 13 | | 70 | 0.0029 |
| 14 | | 75 | 0.0024 |
| 15 | | 80 | 0.0022 |
| 16 | | 85 | 0.0021 |
| 17 | | 90 | 0.0021 |
| 18 | | 95 | 0.0021 |
| 19 | | 100 | 0.0021 |
| 1 | 2nd | 10 | 0.0045 |
| 2 | | 15 | 0.0046 |
| 3 | | 20 | 0.0047 |
| 4 | | 25 | 0.0047 |
| 5 | | 30 | 0.0044 |
| 6 | | 35 | 0.0035 |
| 7 | | 40 | 0.0018 |
| 8 | | 45 | 0.0006 |
| 9 | | 50 | 0.0002 |
| 10 | | 55 | 0.0003 |
| 11 | | 60 | 0.0006 |
| 12 | | 65 | 0.0015 |
| 13 | | 70 | 0.0032 |
| 14 | | 75 | 0.0050 |
| 15 | | 80 | 0.0060 |
| 16 | | 85 | 0.0064 |
| 17 | | 90 | 0.0067 |
| 18 | | 95 | 0.0069 |
| 19 | | 100 | 0.0072 |

# CONCLUSION

Therefore for $1^{st}$ mode, 11L/20 ie, 55 unit away from origin will be the optimal location for vibration reduction. For $2^{nd}$ mode, L ie. 100 units away from origin will be the optimal location for vibration reduction. .

# FUTURE WORK

The following works may be carried out as an extension of the present work.

1. Beams with constraining layer and with different boundary conditions.

2. Plates with constraining layer and with different boundary conditions..

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