DAMAGE DETECTION IN BEAMS

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By

A. Karthik Subhash

Roll No-212ce2042

Department of Civil Engineering

National Institute of Technology Rourkela

Rourkela-769008,

Orissa, India

May, 2014

DEPARTMENT OF CIVIL ENGINEERING
NATIONAL INSTITUTE OF TECHNOLOGY,
ROURKELA, ORISSA-769008, INDIA

CERTIFICATE

This is to certify that the Thesis Report entitled "***Damage detention in beams***", submitted by ***Mr.AttlutikarthiksubhashRoll no.212CE2042*** in partial fulfilment of the requirements for the award of **Master of a Technology in civil Engineering** with specialization in "**structural Engineering**" during session 2012-2014 at National Institute of technology, Rourkela is Anauthentic work carried out by him under my supervision and guidance.

To The best of my knowledge, the matter embodied in the thesis has not been submitted to Any other university/institute for the award of any degree or diploma

Place: Rourkela

Date: - 26thMay, 2014

Prof.U.K.Misra
Dept. of Civil Engineering
National Institute of Technology
Rourkela – 769008

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I bow to the Devine power, who led me all through.

A. Karthik Subhash

ABSTRACT

Identification of crack location and depth in structural elements such as beams, columns, and slabs, etc., subjected to time varying loads will help them to retrofit before failure thereby its life and structural capabilities can be greatly improved. It is not always possible to detect the initial cracks by visual inspection.

Laboratory test results of isotropic simply supported beam and Cantilever beams with different crack location and crack depths data are collected from literatures as in terms of system natural frequencies and crack locations for single crack and multi cracks. Different models are developed for crack detention using Natural frequencies as Input and Crack Depth and locations as Output.

At first an attempt made for simply supported beam having a Single crack detection using Artificial Neural Network (ANN) Model. Different ANN models are developed using different training functions and found Levenberg-Marquartd (LM) fits best among others which is evaluated in terms of R-square value. The Comparison has been made between developed ANN models and regression models. It shows that the ANN models can perform well than regression models. Further the simple equation has been presented for evaluation of crack depth based on the performance of the models developed.

Secondly, the problem involves detection of multi crack damage in a Cantilever beam using ANN Model and Response Surface Method (RSM). To achieve better results in RSM higher degree equation is used. Thefinal performances of each model are evaluated in terms of R-value. And, it is found that ANN fits the equation reasonably good. Crack Depth and Crack location can be detected using ANN approaches which may be helpful in retrofitting the structures.

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NOMENCLATURE

a_1	Depth of first crack
a_2	Depth of Second crack
A	Area of cross section of beam
ANN	Artificial neural network
CLR	Crack length ratio
CDR	Crack depth ratio
F1	First natural Frequency
F2	Second natural Frequency
F3	Third natural Frequency
FE	Finite Element
FEA	Finite element analysis
h	Depth of beam
I	Moment of inertia
L	Length of beam
L1	Length of first crack position
L2	Length of second crack position
LM	Levenberg-Marquartd
R	Correlation coefficient
RSM	Response Surface Method
RMSE	Root mean square error
ω	Natural frequency of intact beam
ω_c	Natural frequency of cracked beam

CHAPTER-1

INTRODUCTION

1.1 Background and Motivation

Engineering structures play akey role within the lives of a modern community.They are usually designed to possess longer life period. The failure or poor performance of engineering structures may cause disruption of facility or might result in loss of human lives and property. It is therefore, very important to ensure that the structural members perform safely

Many techniques are used within the past for damage identification. Some of these are visual (e.g. dye penetrant method) and different use sensors to find local damages (e.g. acoustic emission, magnetic flux, eddy current, radiographs and thermal fields). These ways are time consuming and cannot find that a structure is damage free without testing the complete structure in minute details. Moreover, if a crack is buried deep inside the structure it may not be detectable by these localized methods. Based on the changes within the modal parameters researchers have developed several prediction techniques like Artificial Neural Network (ANN), response surface method etc. most of them are for damage identification. The techniques are designed with an aim for faster and correct estimation of damage present within the structures.

1.2 Focus of the thesis

The process of observance and identifying damage is great importance in civil engineering. The structures related to, civil should be free from cracks and make sure it is safe. Cracks in buildings or any engineering systems may lead to catastrophic failure and should be detected early.The effects of damage on structural members are changes in frequencies, mode shapes and damping of structures. So it is very easy measurement of natural frequencies is simpler than that of structural damping, damage will be find from dynamic analysis of the structure using natural frequencies.

the prime importance is that dynamic characteristics of cracked structures in structural health monitoring and non-destructive damage testing because the identified vibration data will be used to observe, quantify, and locations extent of the cracks or damages in a every structure member.The cracks present within the system are also considered to develop the analytical model to review the impact of cracks on the modal response of the system. But large no of attempts has been created to find whether structural element damage has occurred because of the positionor extent of any such damage. In the present scenario increasing interests within the use of artificial neural networks (ANNs) for the health monitoring and damage detections.

The usefulness of neural networks in finding the damage has been improved due to their ability to deal with the analysis of the structural damage with intensive a computation.The most desirable feature of the approach is that it's ready to detect damage with previous information (Natural frequencies)about a model of the structure. It may effectively cope with qualitative and incomplete information, making it extremely promising for detecting structural damage (Kao and hung 2003). Therefore, a well-designed neural network is ready to serve as a real time computing machine for structural health monitoring.

The current analysis aims at the development of a single crack and multi crack identification for intelligent condition monitoring of structures using the change in modal parameters of the structural member.For this purpose, data have been collected for simply supported and cantilever for single crack and multi crack prediction respectively.Comparison has been made between ANN and regression methods for single crack, ANN and Response surface methods for multi crack.

1.3 Organization of the thesis

After the brief introduction concerning damage detection using ANN technique, a thorough review of earlier works and present works relating prediction of damage are mentioned in Chapter-2 to reach the data are collected for single crack and multi cracks from available literatures.

Chapter-3 shows the current methodology adopted for ANN commonly used Levenberg-Marquartd neural network,regression, response surface method. Further to its modelling

Chapter-4 Results and developed modelsfor ANN, Regression and response surface method. Finally a comparison study is formed in terms of statistical parameters a like Correlation Coefficient (R), and Root Mean Square Error (RMSE). Equations given for the most effective fit.

In Chapter-5, the major conclusions emerged from the studies are reported and the future scope of work is indicated.

CHAPTER-2

LITERATURE REVIEW

2.1 Single and multi cracks

A modified neural network which is counter propagation was developed by Szewczyk and Hajelaused (1994) to carry out the inverse mapping among a vector of the stiffness of individual structural elements and the vector of the global static displacements under a testing load. The sample data was generated using a finite element program. It shows that the network function which is an associative memory device is capable of satisfactory diagnostics even in the presence of noisy or incomplete measurements.

Sureshetal.[2004]haspresentedamethodconsideringtheflexuralvibrationina cantilever beam having transverse crack. They computed model frequency parameters analytically for various crack locations and depths and these parameters are used to train the neural network to identify the damage location and size. Here, they have made a study of the comparison of performance of two widely used neural network i.e.multi- layer perception (MLP) network, radial basis function (RBF) network and shown the variation of actual output with the network output. Finally, they stated that the radial basis function network performance is superior to multi-layer perception network.

Masri et al. (1996) made a feed forward neural network for detecting the changes in the characteristics of structure-unknown systems. The approach is based on the use of vibration measurements from a "healthy" system for training a neural network for identification purposes. Subsequently, the trained network was fed comparable vibration measurements from the same structure under different episodes of response in order to monitor the health of the structure.

Zhao and Ivan (1998)used a neural network which is counter propagation to locate structural damage for a beam, frame and support movements of a beam in its axial direction. They considered a variety of diagnostic parameters including static displacements, natural frequencies, mode shapes and other parameters based on mode shapes. The method first demonstrated a plane frame, based on static displacements then applied to continuous beams using dynamic properties of structures. The required data were obtained through computer simulation by finite element analysis.

A structural damage detection method was studied by Chang et al. (2000) in which a modified back-propagation learning algorithm i.e. an improved steepest descent algorithm was proposed which overcomes the possible saturation ofthe sigmoid function and speeds up the training process. The concept of orthogonal array adopted here significantly reduces the number of training data while maintaining the data completeness. The NN model was first trained off-line using training data which was initially collected that contains various damage cases, as outputs and their corresponding dynamic characteristics, which include natural frequencies and first mode shape curvature, calculated from the finite element (FE) model as inputs.

Zang and Imregun(2001) proposed BP neural network for structural damage detection using measured frequency response functions (FRFs) input data. Even if the training time and convergence-related problems could be overcome by parallel processing on fast CPU arrays, network over fitting would still remain a major obstacle. When the number of variables is much greater than the number of training samples, neural networks can focus on local details of individual training samples which may well be meaningless in a global context would still remain a major obstacle. A principal component analysis (PCA)-based data reduction technique was applied here to the measured FRFs for data reduction. The methodology above was validated using simple numerical test cases based on Finite element models of beam and plate structures

A novel neural network-based approach was developed by Kao and Hung (2003) for detecting structural damage. The proposed approach involves two steps. The first step, system identification, uses neural system identification networks (NSINs) to identify the undamaged and damaged states of a structural system. The second step, structural damage detection, uses the aforementioned trained NSINs to generate free vibration responses with the same initial condition or impulsive force. Comparing the periods and amplitudes of the free vibration responses of the damaged and undamaged states allows the extent of changes to be assessed. They have used a more effective adaptive L-BFGS learning algorithm for the model. To demonstrate the feasibility of using the proposed approach it was applied both on a numerical example and experimental example.

A Back -propagation neural network has been proposed by Maity and Saha (2004) to recognize the behaviour of the undamaged structure as well as of the structure with various possible damaged states. They have used Gradient Descent as training algorithm for the model. The model was applied on a simple cantilever beam. A FEM was used to calculate strain and displacement were used as possible candidates for damage identification .The superiority of strain over displacement for identification of damage has been observed in this study.

Fang et al. (2005) showed structural damage detection on a cantilevered beam using frequency response functions (FRFs) as input data to the back-propagation neural network (BPNN). The data were generated by experimentally. A tunable steepest descent (TSD) algorithm using heuristics is investigated. It improves the convergence speed significantly without sacrificing the algorithm simplicity and the computational effort.

Jeyasehal and Sumangala (2006)proposed an artificial neural network (ANN) based approach for the assessment of damage in pre-stressed concrete (PSC) beams. To generate the training and test data for the ANN an experimental program has been carried out. It has been demonstrated that it is possible to assess the damage with reasonable accuracy by the ANN learning by a back propagation algorithm with stiffness and natural frequency as test inputs

A BPNN method was developed by Haryanto et al. (2007) for estimating the existence, location and extent of stiffness reduction in structure, which is indicated by the changes of the structural static parameters such as deflection and strain. LavenbergMerquardt algorithm was applied as training algorithm. The proposed techniques were applied to detect damage in a fixed end beam. The structural response of strain and displacement due to specific loading was obtained by FEM.

Li and Yang (2008) presented a novel method of damage identification for beam using artificial neural network (ANN) based on statistical property of structural response**.** Back-propagation ANN with Lavenberg Merquardt algorithm as training algorithm has been used here and the changes of variances of structural response as input vector and damage status (location and extent) as output was adopted for identifying the damage in beam. A FEA model was developed to generate the data.

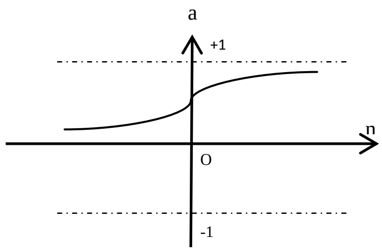
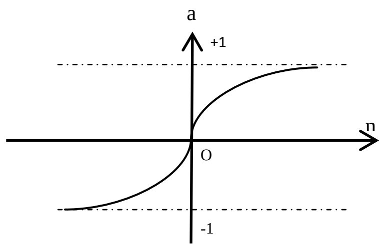
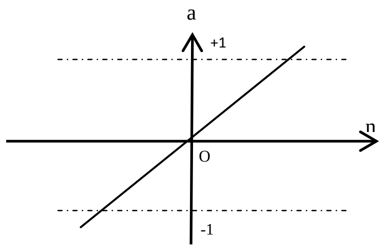
Mehrjoo et al. (2008) have presented a damage detection inverse algorithmic program to estimate the damage intensities of joints in bridge structure using back propagation neural network methodology.

Agosto et al. (2008) have applied the neural network methodology with a combination of vibration and thermal damage detection signatures to develop a damage defection tool. They need applied the developed technique on sandwich composite for the aim of crack detection.

Saravanan et al. (2010) have prohibited the strength of an artificial neural network, wavelet and proximal support vector machine supported damage detention Methodology for a beam.

The activation functions used by researchers in designing of artificial neural network are presented below in the table.

Table 2.1: Examples of Activation Functions used in ANN

Name	Transfer function	Symbols
Log-sigmoid	$\log sig(n) = \dfrac{1}{(1+e^{-n})}$	
Tangent-Sigmoid	$\tan sig(n) = \dfrac{2}{(1+e^{(-2\cdot n)})} - 1$	
Purlin	$purelin \cdot (n) = n$	

2.2 Data collection

2.2.1 Single crack

The data are has collected from the literature Owolabi et al. (2003) shown in Table below .The problem involves determination of damage extent for a simply supported aluminium beam using ANN by taking input parameters as natural frequency (1st mode, 2nd mode & 3rd mode) and depth of crack ratio as output parameters. The acceleration frequency responses were noted at seven totally different points on the beam model through an experiment by using a dual channel frequency analyser. The cracks were generated as single open transverse cracks with a thickness of 0.4 mm approximately.

Table 2.2: Properties of the beam:

Beam width	25.4 mm
Beam depth	25.4 mm
Beam length	650 mm
Young's modulus of the beam	$0.70x10^{11}$ N/m^2
Poisson's Ratio	0.35
Density	2696 kg/m^3

The data of Natural Frequencies for simply supported beam with or without cracks are taken Owolabi et al. (2003)

2.2.2 Multi crack

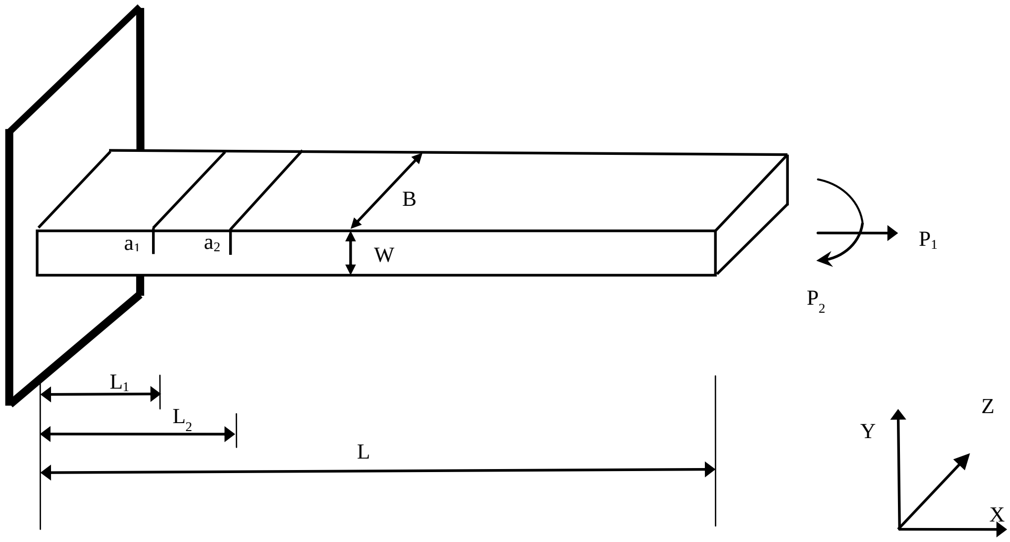


Fig 2.1:Cantiliver beam with multi crack

Beam width	0.050m
Beam depth	0.0060 m
Beam length	0.80m
Yong's modulus of the beam	0.724×10^{11} N/m^2
Poisson's Ratio	0.334
Density	2713 kg/m^3

For the preparation of the model analysis crack depths a_1=a_2=0.0003, ..., 0.003m (difference of every depths=0.0003m) are imported at the 17crack locations L_1=0.04... 0.68m (difference of every length =0.04m) and L_2=0.08... 0.72m (difference of every length =0.04m).Totally a hundred and seventy casesfor 10 depths and seventeen crack locations are used for the primary 3 natural frequencies. The patterns that include a hundred and seventy sets of information are used

Natural Frequencies for cantilever beams with multi cracks are taken from the literature Mogal Shyamal (2009).

CHAPTER-3

PREDICTION METHODS

3.1 Artificial Neural Networks (ANN)

Neural Networks that are simplified models of the biological neuron system, may be a massively parallel distributed processing system created from extremely interconnected process elements known as neurons that have the flexibility to be told and thereby acquire knowledge and make it available for use (Rajsekaran et al. 2008).

3.1.1 Biotic model of a neuron

The neuron (cell) forms the interconnected element in the biological nervous system. That unit is a straightforward process receiving and processing theinput from one neuron to other through its input path known as dendrites. An activity associate all of a neuron is or non-process. If the mixedinput sign is robust enough, it create the input signal to its output path is known as axons that branch up and joints to totally different neuron's input through a junction called as synapses. Thequantity of input sign transferred is governed by the junction strength which is synthetic naturally. This junction strength is found to be changedall out the learning process of the brain. Therefore this is a remembrance unit of each linkage (Das, 2005).

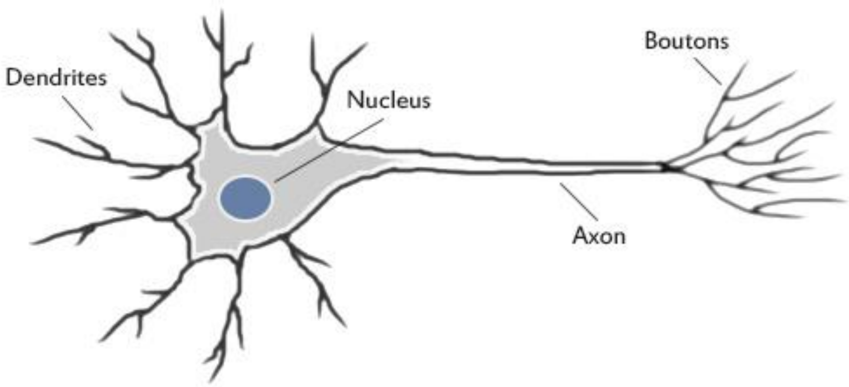


Fig 3.1: Biological Neural Network (Ref: www.the projectspot.com)

3.1.2 Model of an artificial neuron

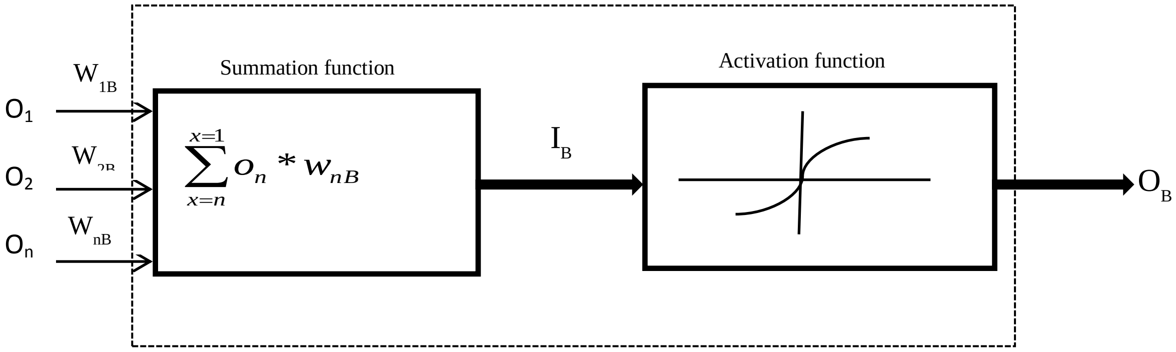


Fig 3.2 Artificial (Mathematical) model of a neuron

The on top of fig shows the simple model of an artificial neuron. Here O_1, O_2….On are being the inputs to the artificial neuron. W_{1B}, W_{2B}, W_{nB} is the weights hooked up to the input links. The weights are increasing trend of the inputs to accomplish for the strength of the union. Thus the entire input IB received by the some of the artificial neuron is

$$i_{\mathbf{B}} = W_{1B}O_1 + W_{2B}O_2 + ... + W_{nB}O_n$$

$$= \sum_{i=1}^{n} W_{iB}O_x \qquad (3.1)$$

To develop the output OB, the summation is passed to a mathematical filter called activation function or transfer function that gives the output i.e. $O_B = f\ (I_B)$

3.1.3 Architecture of an artificial neural network

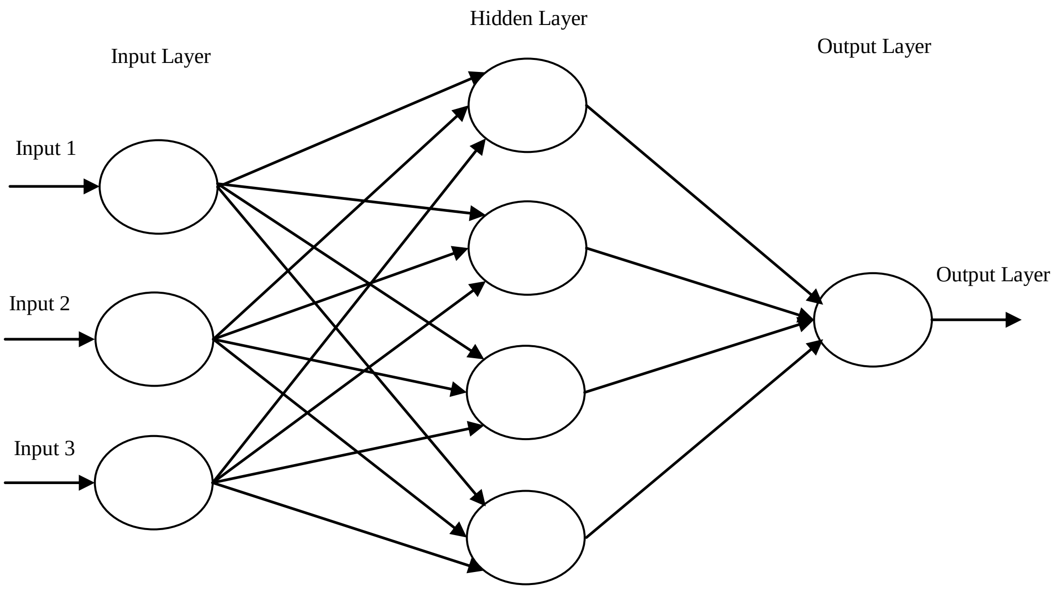


Fig 3.3: Typical model of a neural network

The neurons are termed as interconnected dealing out elements or nodes in a calculated model of the artificial neural network. The networks consistsaccomplice input vector of elements x $_l$ (l = 1, 2…, N_i) is relay through a relation that's high tended by weight w $_{jl}$ to gives the hidden unit z $_j$ (j = 1… N $_h$)

$$z_j = \sum_{l=1}^{Ni} w_{jl} x_l + b_{j0} \tag{3.2}$$

Where N_i is the number of input unitsand$N_h$is the increasedhidden units.The weighted input and a bias b_{j0}make up the hidden layer or units. An error weight that plays as a constant joined to the weight is a bias. This input goes through a layer of activation function (f) which gives

$$r_j = \sum_{l=1}^{Ni} w_{jl} x_l + b_{j0} \tag{3.3}$$

The transfer functions are created because of the nonlinearity in the relationships with input output. The commonly used transfer functions are hyperbolic tangent sigmoid,sigmoid and logistic sigmoid functions given below.

.

$$f(z) = \frac{1}{1+e^{-z}} \tag{3.4}$$

$$f(z) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}} \tag{3.5}$$

The summation outputs pass through another layer of filters

$$V_k = \sum_{j=1}^{Nh} W_{kj} r_j + b_{ko} = \sum_{j=1}^{Nh} w_{kj} f \left[\sum_{l=1}^{Ni} w_{jl} x_l + b_{j0} \right] + b_{ko} \tag{3.6}$$

And another transfer function F to give output y (k = 1… N_0)

$$y_k = F(v_K) = F\left[\sum_{j=1}^{Nh} w_{ki} f\left[\sum_{l=1}^{Nl} w_{jl} x_l + b_{j0} \right] + b_{k0} \right] \tag{3.7}$$

This way it continues based upon hidden and output layers. This hidden layer and output layer gives unknown parameters in relation of weights when nonlinear activation function produces to a highly nonlinear function.

3.1.4 Learning / Training Process

The learning techniques in artificial neural network noticeto the strength of the network to learn from their nature and upgrade the performances. The weights are adjustable for each run of the network and are found from a set of information through the process of trainingor learning . The learning method could be split into two maindivisions.

1) Unsupervised learning.

2) Supervised learning.

Supervised Learning input pattern used to train the network is related to an output pattern, which is the target or desired output. A coach is assumed to be present throughout the learning process; once a comparison is made between the networks computed output and the correct expected output to determine the error (Rajsekaran and Vijayalakshmi 2008).

The weights and the thresholds arethe network parameters are updated during the training procedure to reduce the sum of squares of the residuals among the measured and predicted output. In unsupervised learning target output is not given to the network. The weights are adjusted based on other criteria called Kohonen learning rule

The main objective is to minimize the error between actual to predicted output.

$$E(W,U) = \sum_{l=1}^{N_s} \sum_{k=l}^{N_0} \left(y_{lk}(x_l) - y_{lk} \right)^2 \tag{3.8}$$

Where N_s is the number of samples, N_o is the number of outputs, U and W are the weights of the output and hidden layer, respectively, and the predicted output from inputs x isy(x).

The most normally used neural network is feed forward back-propagation neural network that follows the supervised learning process. It's in the main suited for the prediction type problem.The Figure shows typical architecture of a back propagation algorithm. Here the technique is processed forward from given input to actual output layer errors are calculated following back in another controlthe obtained changed weights with higher work. In back-propagationlearning technique, the connected weights are at random selected. Depends up on the initial weights and bias the error propagated is reduces throughback propagation algorithm(Das, 2005)(Eq. 3.8).

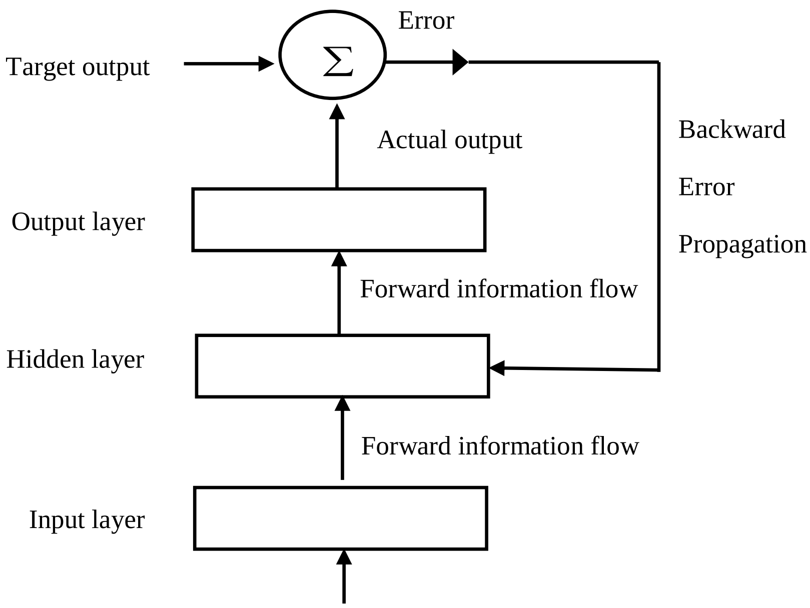


Fig 3.4: Typical back propagation neural network

In every initial training result the weight vector is adjusted towardsthe control of maximum decrease of E that is scaled by alambda (λ) learningrate. Methodically, a weights and bias is renewing to different value(Eq. 3.9).

$$w_{new} = w_{old} - \lambda \nabla E, \tag{3.9}$$

$$\text{Here}\, \nabla E = \left(\frac{dE}{dw_1}, \frac{dE}{dw_2}, \ldots\ldots, \frac{dE}{dw_n} \right)$$

One,properequity of sigmoid transfer function is that

$$\frac{d\, f(x)}{dx} = f(x)(1 - f(x)) \tag{3.10}$$

The gradient of sigmoidal function is calculated by subtraction and the subtraction operator. This givesthe reduced new weights from starting irregular values. Back-propagation training functions mostly use the supervised learning. However, once hiddennumber of layers and therefore the data point and the number of variables will rise in learning process. Time taking for the neural network learning and training will be slow as increase with the problem size. Newly, it reachesa local minimum in weight space if it may be a gradient based algorithm,

That problem increasing the speed of the algorithm can be solved by growing the step size and to avoid the local minima a momentum factor to be used.

3.1.5 Testing of network

At the end of the training part, the associated trained weights of the neurons are stored in the ANN memory. In the next part, testing part, the trained network is fed a new set of data. The ANN predictions (using the trained weight) are compared to the target output values to assess the ability of the network to produce (generalize) correct response to the testing patterns that only broadly speaking resembles the data in the training part. Once the training and testing gives the fine results for the predicted output are found to be successful, the corresponding NN can be place to use in employment (Das et al., 2005).

3.1.6 Choice of inputs

Artificial neural network is a knowledge driven approach. Through input and output data the model parameters are developed and also the model is relevant for that problem. Model inputs are important in the data driven approach.so, in artificial neural network the selection of the inputs should choose correct. Presenting an all variety of inputs to neural networks usually will be size increasing and that infusing the decreasing the model speed. So, there is a use of the proper selection of the inputs in this technique (Guyon and Elisseeff, 2003, Olden et al., 2004).

The choice of input variable is based on a previous data on causal variables in conjunction with inspection of plots of potential inputs and outputs. If the relationship to be model is less understood, analytical techniques like cross-correlation analysis or principal component analysis are used.in separate networks the stepwise approach can also be used for training for each variable. The results are adding for every training and network is working at its best separately assumed. This will be adding unless the new extra variable end still the performance should be improved. This method has the advantages of being unable to take the certain mixture of variables can be pointless on their own (Guyon and Elisseeff, 2003).

3.1.7 Division of data and pre-processing

In neural network models to know the generalization it is required to divide the information into sub-sets which is a trained set and an independent tested set. A group of data based on amount of data points is preferred as a validation set which avoids over fitting. Also training, testing and validation sets represent data set. ANNs do not require extrapolating i.e. not use to determine the correlations for information values, beyond the range those had been trained.

After division of information into training, testing and validation set, pre-process of data to an appropriate type before application of ANNs is required. To avoid the dimensional dissimilarities in input parameters, pre-processing is required. The variables need to be scaled in such a manner to commensurate with the limits of activation function used for output layer. Example: If the output of logistic functions are in between 1 to 1, the data are scaled between 1 to 0.9 or 0 .2 to 0 (Maity and Saha, 2004). In case of hyperbolic tangent sigmoid function, data is scaled between [-1, 1]. If the transfers function within the output layer is linear (unbounded), scaling is not essential. However, for effective application of ANNs scaling to a uniform range is adopted.

3.1.8 Generalization

Training minimizes the error, use to get optimized weight vectors. Also, reducing it may create overtraining as the whole error in the network once new knowledge is given to the trained network. Over fitting happens if numbers of training points in coaching set are insufficient. The error in the network drives to a very less value (Das, 2005).

The network required to be equally efficient for new data throughout testing or validation i.e. generalization. It is an important aspect for efficient implementation of ANN. There are many ways for generalization as early stopping or cross validation and Bayesian regularization. In the early one the error in validation or testing set is controlled by training process. Validation error may decrease in initial phase of training, as well as training set error. If the network over fit the data, error in validation set rises. The training is stopped, if validation error increases for a number of iterations thus weights and biases at minimum validation error are returned. An independent set is preferred to assess the performance of the model at different learning stages. The available information is divided into three subsets: training, testing and validation set i.e. data intensive. This is not suitable if the data set size is small and the response obtained in early stopping is not extremely smooth compared to Bayesian regularization as it do not require validation data set that is separated out of the training data and it uses all of the data.

3.2 Regression

When we are examining the relationship between a quantitative outcome and a single quantitative input explanatory variable, simple linear regression is the most commonly considered analysis methods (The “simple" part tells us we are only considering a single explanatory variable.) In multiple regressions we usually have many different values of the explanatory input variable, and we usually assume that values between the observed values of the explanatory variables are also possible values of the explanatory variables. We postulate a linear relationship between the outcome and the value of the explanatory input variable.

3.2.1 Regression Analysis

It is a statistical technique for considering linear and non-linear relations.Below it is showing the general form in equation (3.11)

$$Y=b_0 + b_1X_{1i} + b_2X_{2i}+ \varepsilon \quad (3.11)$$

Where, ‘Y’ is the secondary variable, and $X_{1i, \ldots,} X_{ki}$ are the independent variables. Finally, ‘ε’is the residual term, which represents the composite effect

The result of a regression is a set of estimates of the regression constants $b_o,b_1,.,b_k$.These values are finding for the coefficients by making the residue is ‘0’and the standard deviation errors are small that can neglect. The result is outlined in the obtained equation:

$$Y_{pred} = b_0 + b_1X_{1i} + b_2X_{2i} \quad (3.12)$$

3.2.2 Multiple Regressions

Multiple regressions are an expansion of linear regression having only one dependent variable(Y) and more than independent variables(X).The sum of squared deviations of the observed and predicted Y is a minimum when predicted value of Y is a linear transformation of the X variables. The calculations are more complicated as the relationships among all the weights assigned to the variables. The reading of the results is more complex for the same reason.This conversion is simplein the case of linear conversion of two variables. The "b" values are called regression weights and are computed in a way that minimizes the sum of squared deviations

$$\sum_{i=1}^{N}(Y_i - Y_i^{'})^2 \quad (3.13)$$

The variation is only the intercept (b_0) and slope (b_1) in the case of linear were estimated, while in multiple regression case, three weightswere estimated (b_0, b_1, and b_2).

3.3 Response Surface Methodology (RSM)

Response surface methodology (RSM) is a collection of mathematical and statistical techniques for prediction. The main objective is to identify the damage (output variable) which is influenced by several independent variables (input variables). An experiment is a series of tests, called runs, in which changes are made in the input variables in order to identify the reasons for changes in the output response.

Originally, the RSM was developed to model experimental responses (Box and Draper, 1987), and then migrated into the modelling of numerical experiments. The difference is in the type of error generated by the response. In physical experiments, inaccuracy can be due, to measurement errors while, in computer experiments, numerical noise is a result of incomplete convergence of iterative processes, round-off errors or the discrete representation of continuous physical phenomena (Giunta et al., 1996; van Campen et al., 1990, Toropov et al., 1996). In RSM, the errors are assumed to be random.

This involves performance original system with a similar, more computationally tractable system model. This similar equation typically takes the form of a first order to n^th^ order polynomial; the typical equation is shown in equation (3.14)

$$G(x) = G(x_{1,....,}x_n) \approx a_0 + a_1 x_1 + ... + a_n x_n + ...$$

$$+ a_{n+1} x_1^2 + ... + a_{2n} x_n^2 + a_{2n+1} x_1 x_2 + ... \quad (3.14)$$

Finding the constants through the linear regressionis easy.It should be noted that not all response methods require a polynomial function as an approximation and the response function is not required to be linear in the parameters. Typical function is shown in Eq. 3.15.

$$G(a_n, b_n) = A_c - a_n[0.01694 - 0.01353\exp\left(\frac{-0.4158}{b_n}\right) \qquad (3.15)$$

By trying the two variables as input, the following input data matrix can be constructed

$$X^* = \begin{bmatrix} a_1 & b_1 \\ a_2 & b_2 \\ \cdot & \cdot \\ \cdot & \cdot \\ \cdot & \cdot \\ a_n & b_n \end{bmatrix}$$

Where,*n* corresponds to the number of observations in rows. The response of the system can find by using the above made inputs shown in Eq. 3.16

$$Z = [O_1 \quad O_2 \quad O_3 \ . \ . \ . \ O_n]^T \qquad (3.16)$$

The first otder is not fits best then we will go for the second order polynomial the matris is defined

$$X = \begin{pmatrix} 1 & x_{11} & x_{12} & x_{11}^2 & x_{12}^2 & x_{11}x_{12} \\ 1 & x_{21} & x_{22} & x_{21}^2 & x_{22}^2 & x_{21}x_{22} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ 1 & x_{n1} & x_{n2} & \dots & & x_{n1}x_{n2} \end{pmatrix}$$

Where *n* is the number observations. Six is the minimum number of observations to give the best second order polynomial, only the first two columns are needed for this example. In general $X=[1:X^*]$

The normal equationshown in Eq. 3.17can be solved for the constants

$$a = (X^T X)^{-1} X^T Z \qquad (3.17)$$

The performanceof the system

$$G(x) \approx G'(x) = C_1 - C_2 a_n + C_3 b_n \qquad (3.18)$$

These response can be graphically represented,three dimensional space or count plot to see the response through visual . Response drawn in the below fig(3.5) x_i , $x_j$and by keping all other variables constant.

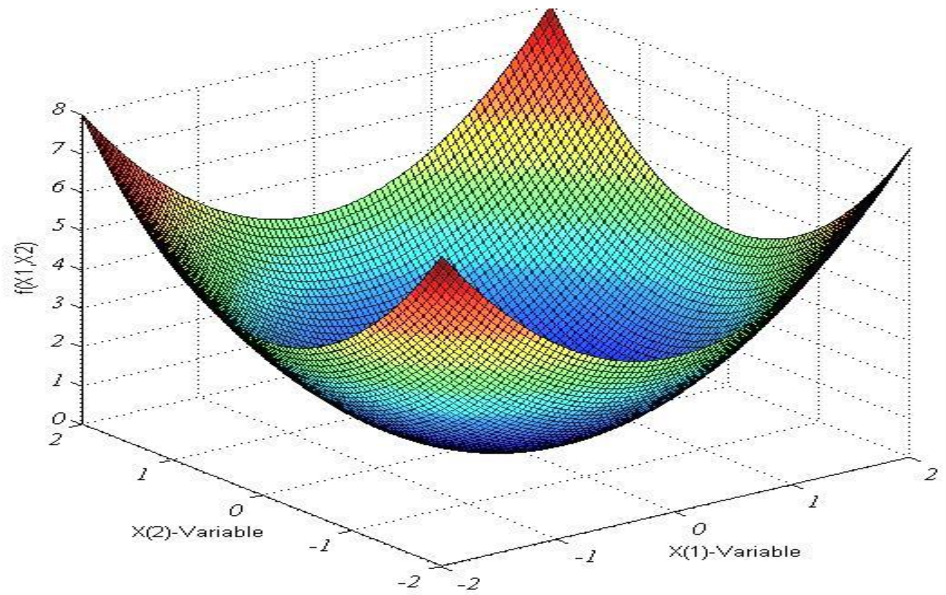


Fig 3.5: 3D Response surface plots

3.4 Modelling

3.4.1 Network Data Preparation

In the present analysis ANN models are developed by taking input parameters as changes in the natural frequency ratio (1st mode, 2nd mode & 3rd mode) and crack depth ratio (CDR) and crack location ratio (CLR) as output parameters. The minimum and maximum values of inputs and outputs are given in Table 1 and the properties of the material tested are given in Table 3.1.

Table 3.1:Minimum and Maximum values of data set

Inputs			Outputs	
Fundamental Natural Frequency Ratio (ω_c/ω)			Crack Length Ratio (L_1/L)	Crack Depth Ratio (A/H)
1st Mode (f_1)	2nd Mode (f_2)	3rd Mode (f_3)		
0.7065	0.8175	0.8014	0.0625	0
1	1	1	0.875	0.7

Pre-processing of data helps in generalization of ANN models. Hence all data in the set has been scaled in the range of -1 to +1 by a simple linear normalization function.

$$X = 2\left(\frac{X_n - X_{\min}}{X_{\max} - X_{\min}}\right) - 1 \qquad (3.19)$$

Where,X_n, X_{max} and X_{min} are the normalized, maximum and minimum values of data in vector. Properties of the beam tested had already shown above

3.4.2Development of ANN Models

An Artificial Neural Network (ANN) consists of a set of interconnected elements called neurons that provide a response or output from a series of inputs. In the present study ANN models are developed using Levenberg- Marquardt training algorithm as this algorithm is often the fastest back propagation algorithm in MATLAB Neural Network Toolbox and is highly recommended as a first choice supervised algorithm. First nine models for prediction of crack depth ratio (CDR) and next nine for crack length ratio (CLR).

The details network basic structure of ANN models developed and activation function used are given in Table 4.1the number of hidden neurons depends primarily on the nature of the data. However, there are no strict rules for choosing the number of hidden layers and the number of neurons in each hidden layer. Most back-propagation neural networks will have one or two hidden layers, with the number of neurons in the hidden layers usually falling somewhere between the total number of input and output neurons. In our approach, the number of hidden layers and the corresponding neurons were decided by the corresponding learning performance of the neural network during the training and testing of network.In this case, a network having one hidden layer with maximum of 3 neurons is used. Therefore, the basic structure of the back propagation neural network adopted here is 3–1–1. It has been checked to have the best performance by varying the numbers of hidden layers and neurons. In the training phase, 80% inputs from training set along with corresponding desired outputs used to train the network.

The weights in the neural network were changed iteratively according to the generalized delta rule. 15% of total set were used for testing and 5% data are used for validation. The data's are randomly selected for model training, testing and validation. A major difference between training and testing is that in the test case, the weights in the network are not updated. Since the earliest work by dynamics parameters such as natural frequencies and mode shapes have been widely applied for damage detection, as the modal parameters are functions of structural properties. This implies that any degradation of the structural properties results in changes of the modal parameters. The general mathematical equation relating the input variables and the output can be written as,

$$CDRn = f_{out}\left\{b_0 + \sum_{k=1}^{h}\left[w_k \times f\left(b_{hk} + \sum_{i=1}^{m} w_{ik} X_i\right)\right]\right\} \quad (3.20)$$

3.4.3 Development of Regression Models

The multiple linear regression models has been developed which is extension of a simple linear regression model to incorporate three explanatory variables such as Fundamental natural Frequency ratio (1^{st} mode, 2^{nd} mode, and 3^{rd} mode). Multiple regression modelling is now a mainstay of statistical analysis in most fields because of its power and flexibility. The predicted and actual values for both CDR and CLR are shown in Figure 4.1. The general form of multiple linear regressions is shown below,

$$y = b_0 + b_1 \cdot x_1 + b_2 \cdot x_2 + ... + b_n \cdot x_n \quad (3.21)$$

Where Y is output, b_0,b_1,..,b_n are constants and x_1,x_2,….,x_n are the explanatory variables.

3.4.3 Development of RSMModels

The first, second and Third order models has been developed to incorporate three input variables such as Fundamental natural Frequency (1^{st} mode, 2^{nd} mode, and 3^{rd} mode). It is most advantageous for than others mostly it is used for the optimization.The predicted equations for both CDR and CLR are shown in equation 4.6 & 4.7. The general form of response surface method is shown below,

$$G(x) = G(x_{1,....,}x_n) \approx a_0 + a_1x_1 + ... + a_nx_n +$$

$$a_{n+1}x_1^2 + ... + a_{2n}x_n^2 + a_{2n+1}x_1x_2 + ... \quad (3.22)$$

CHAPTER-4

RESULTS AND DISCUISSIONS

4.1 Results for single crack

Table 4.1: shows the performance of various model created for prediction of both CDR and CLR. It is found that the network structure of 3-1-1 with log sigmoid activation function can better predict the CDR value with a testing R-value of 0.967. Comparison of RMSE of various developed ANN models for CDR prediction is given in Figure 4.1 shows that the ANN model with tansig activation function gives lesser RMSE values than others. However considering overall R-values of all models the one with tansig gives higher value as shown in table 4.1 with increase of hidden neuron. For the sake of simplicity a simple equation (4.1) is presented for prediction of CDR.

Table4.1: Performance Of ANN Model Developed for CDR and CLR prediction

R- Values for CDR predictive models									
Network structure	Tansig			Logsig			Purelin		
	Training	Testing	Validation	Training	Testing	Validation	Training	Testing	Validation
3-1-1	0.965	0.968	0.95	**0.963**	**0.967**	**0.961**	0.865	0.929	0.83
3-2-1	0.962	0.966	0.979	0.959	0.989	0.874	0.856	0.948	0.965
3-3-1	**0.989**	**0.980**	0.963	0.975	0.966	0.891	**0.847**	**0.961**	**0.985**
R- values for CLR predictive models									
3-1-1	**0.369**	**0.561**	**0.729**	0.352	0.596	0.32	**0.307**	**0.699**	**0.223**
3-2-1	0.28	0.56	0.542	0.29	0.586	0.22	0.129	0.58	0.377
3-3-1	0.463	0.674	0.2316	0.256	0.846	0.6	0.183	0.528	0.044

Best fitting

RMSE of CDR predictive models							Regression
Network structure	Tansig		Logsig		Purelin		
	Training	Testing	Training	Testing	Training	Testing	
3-1-1	0.170	0.203	**0.195**	**0.173**	0.339	0.381	0.335
3-2-1	0.175	0.200	0.190	0.178	0.335	0.372	
3-3-1	**0.094**	**0.142**	0.148	0.196	**0.355**	**0.347**	
RMSE Of CLR predictive models							
3-1-1	0.68	0.59	0.68	0.56	0.63	0.65	
3-2-1	0.59	0.96	0.64	0.62	0.67	0.44	0.7674
3-3-1	0.62	0.80	0.67	0.51	0.67	0.63	

Best fitting R-Square

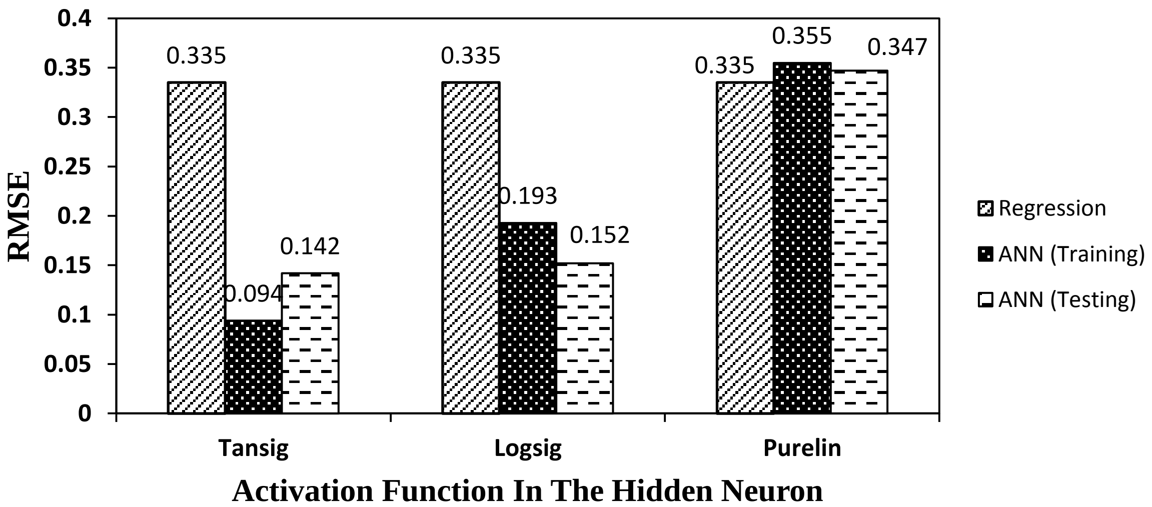


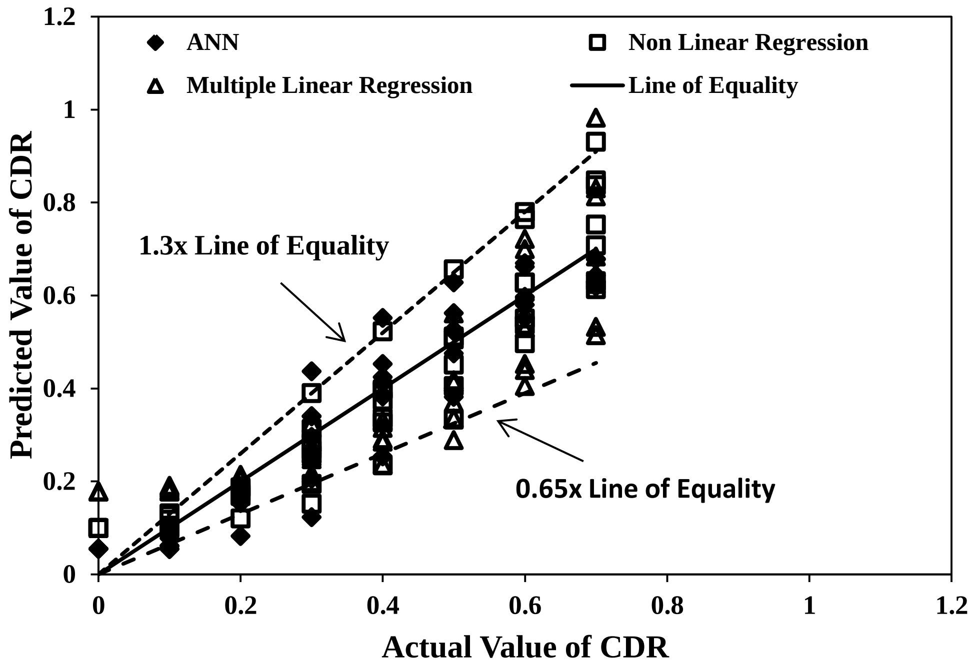
Fig 4.1: Comparison of RMSE of various developed ANN models for CDR prediction

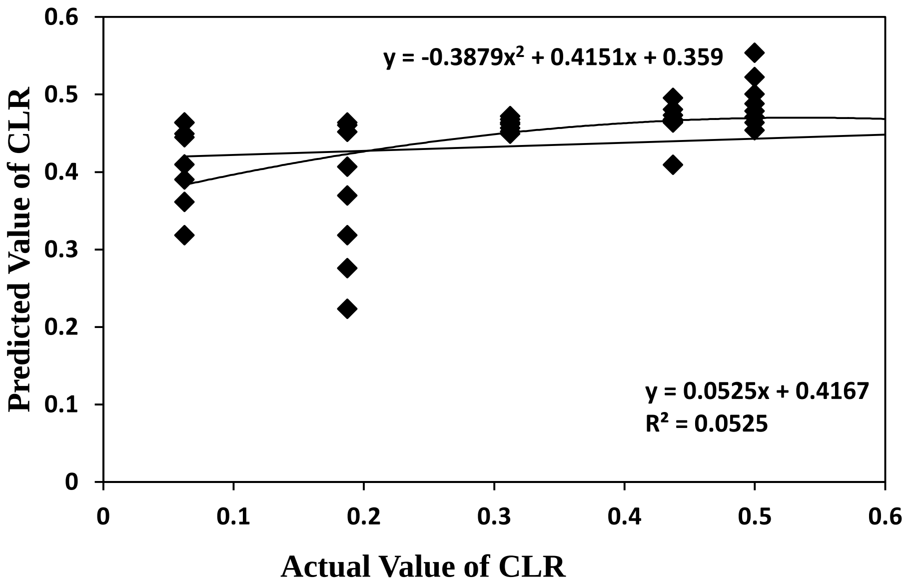
The ANN model for prediction of CDR as follows,

$$CDR = \frac{-868.231}{1+e^{-n}} + 0.6837 \qquad (4.1)$$

Where $n = -0.6104 \times f_1 + 18.179 \times f_2 + 24.2973 \times f_3 - 49.0953$

The above equation gives R-value of 0.967.


ANN
Non Linear Regression
Multiple Linear Regression
Line of Equality
1.3x Line of Equality
0.65x Line of Equality
Predicted Value of CDR
Actual Value of CDR
0
0.2
0.4
0.6
0.8
1
1.2


y = -0.3879x² + 0.4151x + 0.359
y = 0.0525x + 0.4167
R² = 0.0525
Predicted Value of CLR
Actual Value of CLR
0
0.1
0.2
0.3
0.4
0.5
0.6

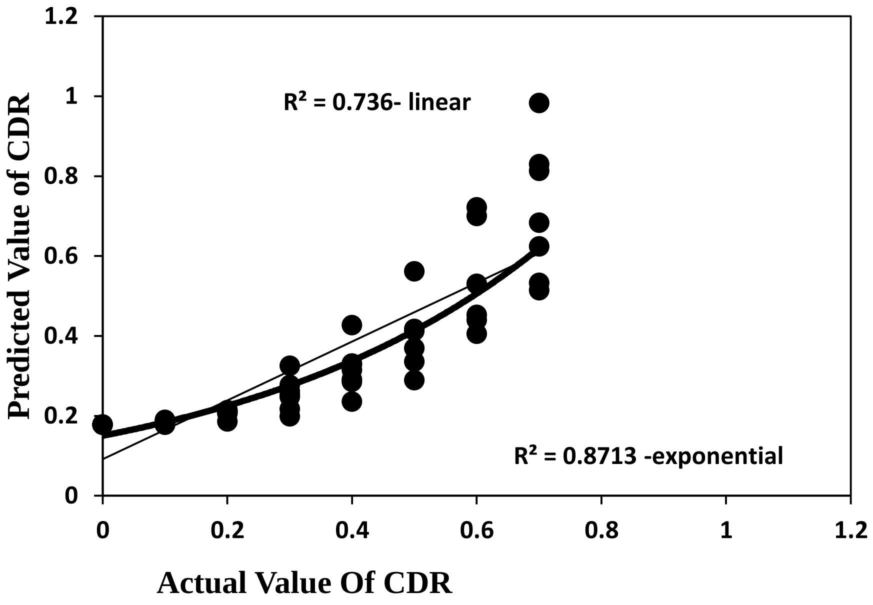


Figure 4.2: Actual And Predicted Values Of CLR And CDR (regression)

The non linear regression equation has been presented for the prediction of CDR having R-value of 0.933 as follows,

$$\text{Where}, CDR = \frac{\ln(0.044 \times f_1 - 21.344 \times f_2 - 21.119 \times f_3 + 43.641)}{2.022} \qquad (4.2)$$

f_1, f_2 and f_3 are the frequency ratios (1st mode, 2nd mode, and 3rd mode).

Multiple linear regressions for prediction of both CDR and CLR have been carried out and the actual and predicted response is shown in figure 4.1. It is noted that the predicted response of CDR to actual CDR showing high correlation coefficient of 0.731 when fitted with linear model. Using a simple nonlinear function, the linear model has been transformed, model giving high correlation coefficient of 0.871 when fitted with exponential function. The nonlinear regression equation is presented in equation (4.2). The predicted values of CDR through all model with actual value is presented in figure 4.2. This shows that the ANN model with network structure of 3-1-1 can predict the CDR value in more realistic than other models followed by nonlinear regression model.

4.2 ANN Results for multi crack

The performance of various ANN models for prediction of crack depth, location of first crack and second crack is shown in below.

Table 4.2:shows it is found that the network structure of 3-1-1 with tan sigmoid activation function will predict the crack depth value with a testing R-value of 0.99. Shows,the ANN models with logsig activation functions provide lesser R-value than others. But considering overall R-values of all models the one with tansig provides higher value as shown in table 4.1. For the sake of simplicity a straightforward equation (4.3) is presented for prediction of crack depth.

Table 4.2:R-values for crack depth predictive models

Network structure	Logsig			Purelin			Tansig		
	testing	training	validation	testing	training	validation	testing	training	validation
3-1-1	0.99	0.89	0.89	0.99	0.88	0.92	**0.99**	**0.91**	**0.97**

Best fitting R-Square

Predicted equation or crack depth (d) $= \dfrac{e^{2B}-1}{e^{2B}+1}$ (4.3)

$$B = 2.6117\frac{e^{A}}{e^{A}+1} - 1.2175$$

$$A = 5.5824 f_1 + 2.1247 f_2 + 4.2573 f_3 - 0.1068$$

Table 4.3shows prediction forfirst crack location. It is found that the network structure of 3-1-1 with tan sigmoid activation function can better predict the first crack location value with a testing R-value of 0.99. Shows the ANN model with logsig activation function gives lesser R-value than others. However considering overall R-values of all models the one with tansig gives higher value as shown in table 4.4. For the sake of simplicity a simple equation (4.4) is presented for prediction of crack depth.

Table 4.3:R-values for first crack length(L1) predictive models

Network Structure	Logsig			Purelin			Tansig		
	testing	training	validation	testing	training	validation	testing	training	validation
3-1-1	0.98	0.89	0.91	0.97	0.91	0.91	**0.99**	**0.89**	**0.95**

Predicted equation for first crack (L1) $= \dfrac{e^{2B_1}-1}{e^{2B_1}+1}$ (4.4)

$$B_1 = 0.8130\frac{e^{2A_1}-1}{e^{2A_1}+1} - 0.085$$

$$A_1 = 18.2326 f_1 - 0.864 f_2 - 3.738 f_3 + 9.478$$

Table 4.4shows prediction forsecond crack location. It is found that the network structure of 3-1-1 with tan sigmoid activation function can better predict the secondcrack location value with a testing R-value of 0.98. Showsthe ANN model with purelin activation function gives lesser R-value than others. However considering overall R-values of all models the one with tansig gives higher value as shown in table 4.5. For the sake of simplicity a simple equation (4.5) is presented for prediction of crack depth.

Table 4.4:R-values for second crack length(L2) predictive models

network structure	logsig			purelin			tansig		
	testing	training	validation	testing	training	validation	testing	training	validation
3-1-1	0.96	0.93	0.93	0.90	0.91	0.96	**0.98**	**0.92**	**0.97**

Predicted equation for Second crack (L2) $= \dfrac{e^{2B_2}-1}{e^{2B_2}+1}$ (4.5)

$$B_2 = -2.52 A_2 + 0.579$$

$$A_2 = -3.256 f_1 + 0.100 f_2 - 0.611 f_3 - 1.402$$

4.3 RSM Resultsfor multi crack

Table 4.5Response surface methodsfor prediction of both crack depth (d)and crack lengths (L1&L2) have been carried out and predicted response is shown in figure 4.5. It is noted that the predicted response to actual showing high correlation coefficient when fitted with 3rd order equation. Using a 3rd degree equation, the 1st degree equation has been transformed, model giving high correlation coefficient of 0.92, 0.94 and 0.96 for respective depth, first crack and second crack locations.when comparing the both the ANN model with network structure of 3-1-1 can predict the best results in terms of the R-value in more realistic than other models followed by response surface method.

The 3rd order equation for crack depth and both lengths is presented below (4.6&4.7).

Table 4.5:R-values in RSM predictive models

Polynomial degree	Crackdepth(d)	First crack length(L1)	Second crack length(L2)
1st degree eq.	0.77	0.93	0.94
2nd degree eq.	0.89	0.94	0.95
3rd degree eq.	**0.92**	**0.95**	**0.96**

Equation Predicted for crack depth(d) $= -0.548 f_1^2 - 0.073 f_2^2 + 0.002 f_3^2 + 0.650 f_1$

$$f_2 + 0.016 f_2 f_3 - 0.166 f_3 f_1 + 0.025 f_1^3$$

$$-0.017 f_1^2 f_2 + 0.006 f_1^2 f_3 + 0.001 f_2^2$$

$$+ f_3 + 0.001 f_3^2 f_1 - 0.003 f_1 f_2 f_3 - 3.787 \quad (4.6)$$

Equation Predicted forboth cracks (L1&L2)

$$= -2219.23 f_1^2 - 30.157 f_2^2 - 4.236 f_3^2 + 330.380 f_1$$

$$+ f_2 + 2.727 f_2 f_3 + 131.358 f_3 f_1 + 103.292 f_1^3$$

$$+ 0.022 f_3^3 - 2.628 f_1^2 f_2 - 0.253 f_1^2 f_3$$

$$-1.013 f_2^2 f_1 + 0.279 f_2^2 f_3 - 0.215 f_3^2 f_1$$

$$-0.069 f_3^2 f_2 - 1.398 f_1 f_2 f_3 + 662.466 \quad (4.7)$$

CHAPTER-5

CONCLUSION AND SCOPE FOR FUTURE WORK

5.1Conclusion

The effectiveness for damage assessment in beams has been presented using different prediction techniques. In these thesis damage detection problems for single crack and multi crack has been considered for beams having different boundary conditions namely simply supported beam and Cantilever beam.

At first, different models (ANN and regression) considering frequencies as inputs for prediction of damages (crack depth and crack location) for a simply supported beam is developed. The performance of developed model is accessed by R-value and RMSE. Comparison between ANN and regression model has been made. This developed ANN models perform better than other developed models. Simple equations have been presented for prediction of CDR with relatively high R-value which is discussed in Chapter-4.

The second problem presents damage assessment for multi crack in Cantilever beams using data from literature. The performances of different ANN models have been accessed considering the statistical parameters R. Later, the same is predicted using Response Surface Method (RSM) and corresponding error is found using R value.

From the present study the following conclusions can be made.

(1) Equation is developed for the both the ANN and Regression analysis among the both neural network gives good result in terms of correlation coefficient (R)

(2) In case of multi crack the response surface method in 3rd order equation give the R= 0.96 and equation is given

(3) Neural network gives best fit for multi crack, when it is compared with RSM

(4) It can be observed that the damage extent can be found out using ANN models trained with only natural frequencies with reasonable accuracy.

(5) This developed model can also be used for different varied applications of engineering, given the predefined values as input to the system. The networks here produced reasonable performances for the identification of cracks.

5.2 Scope for future work

In the present study, damage extent has been acknowledged in simply supported beam and Cantilever beam with single and multi-open cracks. However,it’s absolutely difficult to find out damage of the beam without any information. Therefore, using natural frequencies as input data then it is easyfind the location of damage. The end of the day scope of the present investigation will be expressed as follows.

(1) ANN model for detecting crack and location of cracks in cantilever or fixed end beam with totally different materials.

(2) ANN model for detecting damage in beam with multi cracks with totally different boundary conditions.

(3) Crack detection in beam using hybrid neuro fuzzy technique.

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