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Crack Detection in Simply Supported Beam by Artificial Neural Network Using Bayesian Regularization Algorithm

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ABSTRACT

Civil engineering structures are prone to damage and deterioration during their service period. So damage assessment plays a vital role in structural operation. This paper presents a novel approach to detect damage in a simply supported beam by Artificial Neural Network (ANN). ANN models are developed by considering first three mode natural frequency ratio as input parameters and crack depth ratio as the output parameter. A back propagation feed forward neural network with two different training algorithms i.e. Bayesian Regularization and Levenberg-Marquartd (LM) algorithm have been used and their results are compared. The performances of the ANN model are presented based on statistical parameters like correlation coefficient, coefficient of efficiency, root mean square error and over fitting ratio. The results show that the ANN approach can be used as a cost effective and structural health monitoring tool for predicting damage in beams and Bayesian Regularization Neural Network (BRNN) model gives better generalization as compared to Levenberg-Marquartd Neural Network (LMNN) model.

Keywords *: ANN, back propagation neural network , Bayesian regularization, Correlation coefficient, Coefficient of efficiency, Over fitting ratio, Levenberg- Marquartd , Natural frequency, Root mean square error.*

1. INTRODUCTION :

Basically cracks are the main cause for failure of structure.Cracks represents a threat to the reliable behaviour of the part of the structural element. So structural health monitoring plays a vital role now days. Beams are the most common used structures in civil engineering. Mostlydamage in beams occurs due to long-term service, collision, impact, etc. The formation of cracks can result in catastrophic failure. Therefore, early crack detection is very important for the safe operation of plants, machinery and high integrity structures.

Generally conventional damage assessment methods are direct process methods, proceeding linearly from cause to effect. In these methods, a mathematical model is constructed and the behaviour of the structure is studied by using that model. Though the conventional methods have many attractive features but there are many uncertainties arises during the model updating such as FE modelling errors and measurement of noise which are mainly due to inaccurate parameters, non-ideal boundary conditions and structural non-linear properties. And also the damage assessment algorithms which are commonly adopted are generally complex and inappropriate where measured data are incomplete [12]. However large no of attempts has been made to determine structural damage.

REVIEW OF LITERATURE:

Recently, the use of Artificial Neural Network (ANN) has attained a lot of interest for structural health monitoring and damage detection. It's because ANN has the ability to detect damage without going for computation. In this approach, the measured dynamic responses from the intact and damaged structures can be used directly without resorting to the modelling procedures. The important feature of this method is it can able to detect damage without prior knowledge of the model of the structure. Therefore, a well-designed neural network is able to serve as a real time data processor for structural health monitoring.

Szewczyk and Hajelaused[1] developed a counter propagation neural network and the data was generated by finite element program. They showed that ANN model is capable of satisfactory diagnostics even in the presence of noisy or incomplete measurements. Masri et al. [2] used a feed forward neural network to detect the changes in the characteristics of structure-unknown systems. For damage identification purpose they used the vibration measurements from a "healthy" system to train the neural network. A counter propagation neural network was developed by Zhao and Ivan [3] to locate structural damage in a beam, frame and support movements of a beam in its axial direction. Static displacements, natural frequencies, mode shapes data were used as the input parameters for the model. Chang et al.[4] presented a ANN model to detect damage in which a modified back-propagation learning algorithm i.e. an improved steepest descent algorithm was proposed. By which it can overcome possible saturation of the sigmoid function and speed up the training process. ABP neural network proposed by Zang and Imregun[5]for structural

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damage detection using measured frequency response functions (FRFs) as input data. Kao and Hung [6] proposed an approach to detect structural damage in which L-BFGS learning algorithm was used for the model. Maity and Saha[7]proposed a Back -propagation neural network to study the behaviour of the undamaged structure as well as of the structure with various possible damaged states. They have used a Gradient Descent as training algorithm for the model. The detection of damage was studied on a simple cantilever beam using the model. Fang et al. [8] Proposed a back -propagation neural network (BPNN) to detect damage on a cantilever beam using frequency response functions (FRFs) as input data. The data were generated experimentally. Haryanto et al. showed ABPNN method with [9]Lavenberg Merquardt as training algorithm. They used this method to estimate the existence, location and extent of stiffness reduction in a fixed end beam, which was indicated by the changes of the structural static parameters such as deflection and strain. A back propagation ANN was studied by Li and Yang [10]to identify damage in beam. They used Lavenberg Merquardt as training algorithm and changes of variances of structural response as input vector and damage status as output.FEA model was used to generate the data for the neural network.

However ANN is a "black box" system, it unable to explain the input-output relationship. It also deals with the problem of over fitting or poor generalization i.e. when the model subjected to new (test) data set it shows poor results. The review of the present study as cited in the literature indicates that most of the investigations have been carried out using back propagation ANN with gradient descent and LM as training algorithm and most of the data are theoretical, experimental data are quite less. In this present study experimental data has been used for detection of crack in a simply supported beam. Here two different ANN models have been developed using Bayesian regularization and Lavenberg Merquardt as the training algorithm. The performance of the ANN models for assessing damage has been compared based on statistical parameter.

3. ARTIFICIALNEURAL NETWORK (ANN):

ANNs are parallel information processing system inspired by human biological brain, whereby they capture the brainy function manipulation to approach a specific problem by using certain rules to achieve suitable results. It is composed of a large number of highly interconnected processing elements (neurones) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurones. This is true of ANNs as well

3.1 Model of an artificial neuron

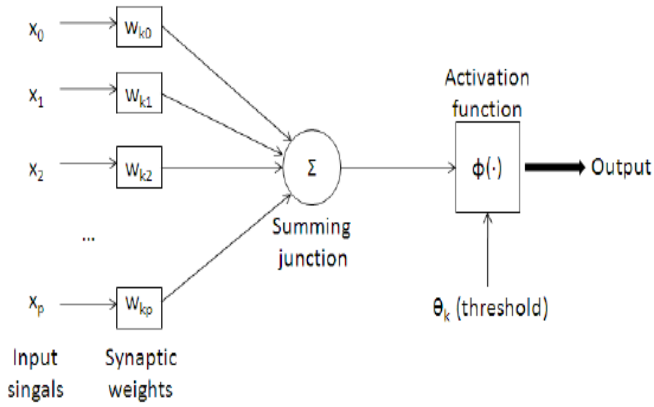

Fig-1: Artificial (Mathematical) model of a neuron

The above fig shows the simple model of an artificial neuron. X_0, X_1, X2…X_p are the inputs to the artificial neuron. W_{k0}, W_{k1}, Wkp are the weights attached to the input links. The weights are multiplicative factors of the inputs to account for the strength of the synapse. Hence the total input received by the soma of the artificial neuron is

$$\text{Total Input (I)} = W_{k0}X_0 + W_{k1}X_{2+} \ldots\ldots\ldots W_{kp}X_p$$

$$= \sum W_{ki} X_i \qquad (1)$$

To generate the final output, the sum is passed through a non-linear activation function or transfer function which releases the output.i.e= ϕ (I)

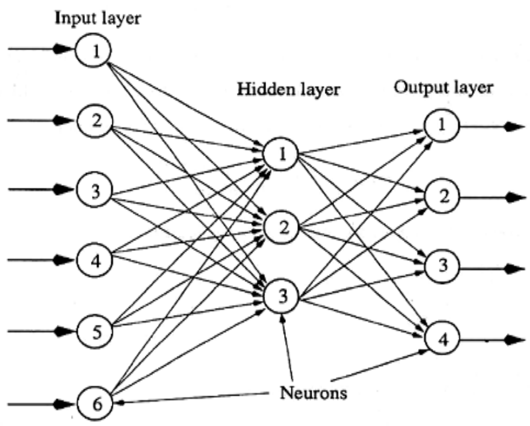

Fig-2: Typical architecture of a neural network

The neural network structure consists of an input layer, an output layer, and at least one hidden layer. Input signals are received at the input layer, pass through the hidden layer and arrive at the output layer of ANN. All neurons are linked to the neurons in the next layer through their connectivity weights. The most commonly used neural network is feed forward back-propagation neural network which follows the supervised learning process. It is mainly suited for prediction type problem. .

3.2 Levenberg-Marquardt algorithm:

It provides a numerical solution to the problem of minimizing a function. The LevenbergMarquardt algorithm (LMA) interpolates between the Gauss- Newton algorithms (GNA) and method of Gradient descent. In LMA method, the change in weights is obtained by solving the following equation.

$$\sum_{j=1}^{n} \alpha_{ij} \nabla w_j = -\frac{1}{2}\frac{dE}{dw_i} \qquad (2)$$

Where n is the no of adoptive weights of the network, E is the mean squared error. Elements of the α matrix are given by

$$\alpha_{ij} = \left(1 + \lambda \nabla wi_j\right) \sum_{k=1}^{N} \frac{dy(x_k)}{dw_i} \cdot \frac{dy(x_k)}{dw_j} \qquad (3)$$

Where N is the no of examples and y (x_k) is the network output corresponding to the example x_k. λ Variable is an adjustable parameter. If λ is very small, the α matrix becomes the Hessian and if λ greater than or equal to 1, the method is analogues to Steepest Descent.

3.3. Bayesian Regularization Neural Network (BRNN)

The most commonly used error function is the mean squared error (MSE) function. In Back Propagation Neural Network, over fitting is due to unbounded values of weights (parameters) during minimization of the error function, mean square error (MSE). The training function used BRNN updates the weight and bias values according to Levenberg-Marquardt optimization. It minimizes a combination of squared errors and weights by modifying the performance function, and then determines the correct combination so as to produce a network that generalizes well. The process is called Bayesian regularization.

$$MSEREG = \gamma MSE + (1-\gamma) MSW \qquad (4)$$

Where MSE is the mean square error of the network, γ is the performance ratio and

$$MSW = \frac{1}{n}\sum_{j=1}^{n} w_j^{\,2} \qquad (5)$$

This performance function will cause the network to have smaller weights and biases there by forcing networks less likely to be overfit. The above combination works best when the inputs and targets are scaled in the range [-1, 1].

4. PROBLEM IDENTIFICATION:

The problem involves determination of damage extent for a simply supported aluminium beam using ANN by considering changes in natural frequency ratio (1^{st} mode, 2nd mode & 3^{rd} mode) as the input parameter and depth of crack ratio as output parameter. The experimental data are collected from the literature Owolabi *et al.* [12] shown in Table- 1. In this paper the acceleration frequency responses were obtained at seven different locations on the beam model experimentally by using a dual channel frequency analyzer. The cracks were generated as single open transverse cracks with a thickness of 0.4 mm approximately.

Properties of the beam

Width of the beam = 25.4 mm

Depth of the beam = 25.4 mm

Length of the beam = 650 mm

Elastic modulus of the beam = 70 GPa

Poisson's Ratio = 0.35

Density = 2.696 gm/cm^3

TABLE-1: Natural Frequency ratios for simply supported beam with or without cracks (Owolabi et al. [12])

Sl no	Crack Location	Crack depth ratio (a/h)	Fundamental natural Frequency ratio (ω_c/ω)		
			1st mode	2nd mode	3^{rd} mode
1	0.0625	0	1	1	1
2		0.1	1	1	1
3		0.2	1	0.9991	0.9915
4		0.3	1	0.9963	0.9915
5		0.4	0.9995	0.9817	0.9829
6		0.5	0.9974	0.9848	0.9658
7		0.6	0.993	0.9714	0.9573
8		0.7	0.9848	0.9544	0.9402
9	0.1875	0	1	1	1
10		0.1	0.998	0.9962	1

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		0.2	0.9956	0.9889	1
12		0.3	0.9881	0.9712	0.9828
13		0.4	0.9781	0.9481	0.9741
14		0.5	0.9664	0.9232	0.9569
15		0.6	0.9371	0.8818	0.9483
16		0.7	0.8756	0.8175	0.931
17		0	1	1	1
18		0.1	0.9923	0.9967	1
19		0.2	0.9892	0.9903	1
20	0.3125	0.3	0.9758	0.9767	1
21		0.4	0.9507	0.9524	1
22		0.6	0.868	0.8902	1
23		0.7	0.7896	0.8424	1
24		0	1	1	1
25	0.4375	0.1	0.996	0.9994	1
26		0.2	0.9849	0.9976	0.9915
27		0.3	0.9686	0.9952	0.9829
28		0.4	0.9418	0.9918	0.9744
29	0.4375	0.5	0.8961	0.9861	0.9402
30		0.6	0.8318	0.9811	0.8547
31		0.7	0.7065	0.9704	0.8245
32		0	1	1	1
33		0.1	0.994	0.9999	1
34		0.2	0.997	0.9998	0.9915
35	0.5	0.3	0.9535	0.9995	0.9744
36		0.4	0.9234	0.9995	0.9573
37		0.5	0.8724	0.9995	0.9402
38		0.6	0.8119	0.999	0.9145
39		0.7	0.7085	0.9986	0.8014
40		0	1	1	1
41		0.1	0.998	0.9979	1
42		0.2	0.9968	0.9889	1
43	0.6875	0.3	0.9797	0.9774	0.9915
44		0.4	0.9617	0.9613	0.9915
45		0.5	0.9225	0.9337	0.9915
46		0.6	0.8546	0.8988	0.9915
47		0.7	0.7713	0.8693	0.9915
48		0	1	1	1
49		0.1	0.9994	0.9994	1
50		0.2	0.999	0.9975	1
51	0.875	0.3	0.9978	0.9936	1
52		0.4	0.9971	0.9905	0.9914
53		0.5	0.9945	0.9824	0.9828
54		0.6	0.9893	0.9696	0.9483
55		0.7	0.9829	0.9578	0.931

The data are divided randomly into training and testing set. The training data is considered as 70% of the total data i.e. 39 data set and rest 30 % data i.e. 16 set data are taken testing data. Once the data have been divided it is important to pre-process the data to a suitable form before applying ANNs .The variables have to be scaled in such a way as to be commensurate with the limits of the activation function used in the output layer. So here all the training and testing sets are scaled in the range [-1, 1] before training as follows.

$$X_n = 2\frac{(X - X_{min})}{(X_{max} - X_{min})} - 1 \qquad (6)$$

$$Y_n = 2\frac{(Y - Y_{min})}{(Y_{max} - Y_{min})} - 1 \qquad (7)$$

Where X_n, Xmax, X_{min} are the normalized, maximum and minimum values of inputs and Y_n, Ymax, Y_{min} are the normalized, maximum and minimum values of outputs respectively.

5. Design of ANNs

In this study a neural network with one hidden layer is designed by using MATLAB 7.0 neural network toolbox. The number of hidden layer neurons is determined through a trial- and-error process and the smallest number of neurons that yield satisfactory results (based on performances criteria) is used. The network consists of 3 nodes in the hidden layer and 1 node in the output layer for determination of extent of crack.ANN models are developed using, Levenberg- Marquardt, Bayesian regularization algorithm for the training process. The transfer function which used here is hyperbolic tangent sigmoid function.

6. Results and Discussions

The results of ANN model trained Bayesian regularization method (BRNN) are compared with the commonly used Levenberg-Maqruardt trained neural networks (LMNN) to discuss the prediction efficiency of the ANNs. The correlation coefficient (R) and root means square errors (RMSE) are mostly used statistical performance criteria for evaluation of ANN models. It is recommended that there exists a strong correlation between observed and predicted when R is greater than 0.8. Here the training and testing result of BRNN and LMNN model are shown in the following graphs where T and A represents the target and actual output.

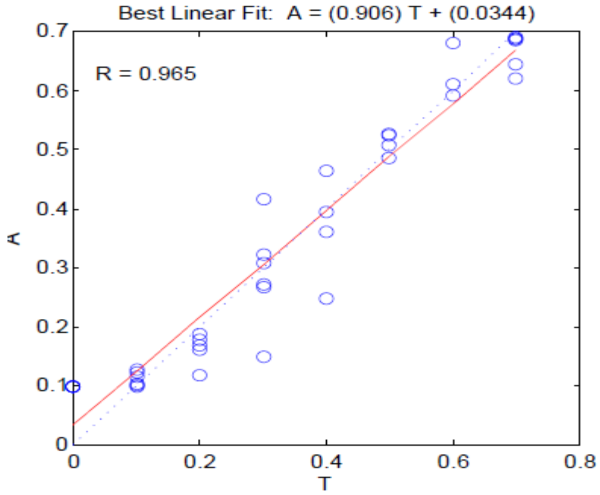

Fig-3: Training result of BRNN model

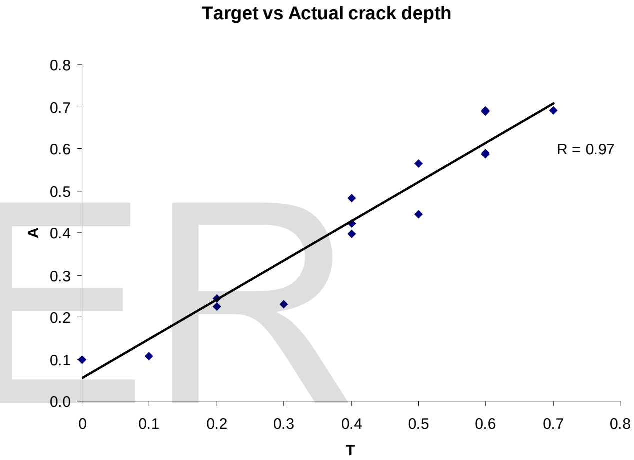

Fig-4: Testing result of BRNN model

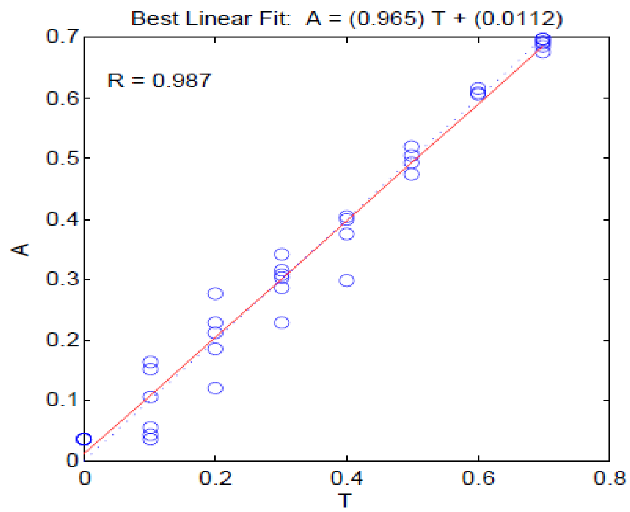

Fig-5: Training result of LMNN model

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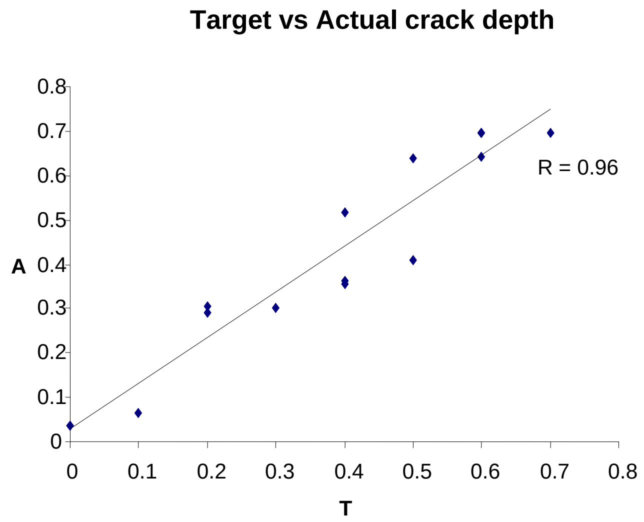

Fig-6: Testing result of LMNN model

However, R is a biased parameter and sometimes, higher values of R may not necessarily indicate better performance of the model. So coefficient of efficiency (E) is also considered.

The E value compares the target and actual values of the variable and evaluates how far the network is able to explain total variance in the data set. In addition to this over fitting ratio has also been determined to know the generalization behaviour of the two models. The over fitting ratio close to 1.0 shows good generalization. The performance of neural network models based on all the statistical parameter has been shown in Table 2.

Table-2: Performance of neural network models during training and testing phase

ANN models	Training data			Testing data			Over fitting ratio
	R	E	RMSE	R	E	RMSE	
BRNN	0.965	0.931	0.061	0.97	0.924	0.06	0.982
LMNN	0.987	0.973	0.038	0.96	0.875	0.077	2.03

It is observed from Table-2 that during training phase, LMNN shows good predictions based on R value i.e. 0.987; however it shows a bit poor prediction for testing data signified by high over fitting ratio (2.03) as compared with BRNN model. Here BRNN model gives good predictions and better generalization with an over fitting ratio of 0.982 which is nearly equal to 1. So BRNN model is found to be the best model as compared to LMNN model.

7. CONCLUSIONS:

This paper presents the effectiveness of ANN for damage assessment in beams using different training algorithms. It can be observed that ANN trained with natural frequencies ratios efficiently predicts the damage extent with reasonable accuracy. The proposed BRNN model presents good predictions compared to LMNN model in detecting damage extent based on all statistical parameters. Therefore ANN approach can be used as a cost effective and structural health monitoring tool for predicting damage in beam like structures.

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