

## An Investigation into the Capabilities of Artificial Neural Networks(ANN) in Predicting the Location and Depth of Crack on Beam

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**Abstract:** This paper investigates the capabilities of Artificial Neural Networks (ANN) in predicting the crack location and depth on I-section beam under the clamp boundary condition. Several finite element analyzes have been carried out for the training and testing of the ANN model using MODAL analysis in ANSYS software. The I-section beam is modelled in solid structural beam. The natural frequencies were found through analyzes made using finite element analysis (FEA) software. The ANN model was developed using the algorithm Cascade-forward Back Propagation (CFBP). The validity of the method designed is verified by the determination coefficient (R). It was found that the R<sup>2</sup> (R: coefficient of determination) values are 0.998 for train and test data, respectively. The result showed that the backpropagation training algorithm was capable of predicting the crack depth and location of solid I-section beam. To evaluate the capability and efficiency of the developed ANN model, the results predicted by ANN are in excellent agreement with the results of the finite element analysis (FEA). This study is useful and contributes significance knowledge to understand the prediction of crack location and depth of I-beam using the ANN model.

**Keywords:** Crack detections, Finite Element Analysis, Artificial Neural networks.

### 1. Introduction

Cracks are among some of the principal causes of structural failure. They develop in the structures due to various reasons such as fatigue, temperature variation, excessive load, cyclic load, environmental effects, impact loading, etc. Thus, structural health monitoring is necessary to avoid risks, damages, and failures. So, to avoid a major failure or accident, the early prognosis of structural cracking is required. Visual inspection and some non-destructive testing (NDT) methods for detecting crack are difficult as it requires time, expenses and are quite inefficient. So the alternative methods are motivated to be developed. Damage detections have gained more attention among scientific and engineering communities to ensure structural safety and integrity. Several crack detections had been presented in vibration-based or guided wave-based damage detection techniques. For example, the method for crack detection in beam structures using the concept of defect mode of phononic crystals (Chuang, K.-C et al., 2020). Nigam, R., & Singh, S. K.(2020) carried out the A wavelet-based crack detection method to identify the beam's crack location. The effect of measurement noise on the crack detection with simulated cracked beam responses was studied. Other than that, the crack identification of beams made of functionally graded materials (FGMs) using the wavelet analysis (Zhu, L.-F. et al.,2018), methods of strain energy, and spatial wavelet transform (Ramesh, L., & Srinivasa Rao, P., 2018). The vibration signals analysis based on

FFT averaged bands and statistical quantities applied to the time signals and wavelet approximations (Abu-Mahfouz, I., & Banerjee, A., 2017).

ANNs are a powerful technique used in solving many real-life issues. When applied mostly in the field of structural dynamics, ANNs seems to be a potent tool. Its composition is almost the same as the cells' structural type in the human brain. It comprises various layers such as input, hidden, and output layers. Each layer includes different neurons, and input layer neurons reflect the raw data that fed to the system. Through certain weights, the hidden layer is associated with the input and output layer. However to date, there is a lack of study related to the prediction of the crack of a beam using Artificial Neural Networks (ANN). Banerjee. A et al.(2017) presented the prediction of the location and depth of a crack using Cascade Forward Back Propagation (CFBP) artificial neural network and Adaptive Neuro-Fuzzy Inference Systems (ANFIS). The predictions of crack location and depth by ANN and GA were verified with experimentation results (M.S. Mhaske & S.N. Shelke,2015). Abin Paul & Jobil Varghese (2017) used Feed-forward multi-layer neural networks trained by back-propagation to predict the location and depth of a crack of beams, and the results were compared with ANSYS results. Also, the prediction of failure rectangular beam using ANN(P. Behera,2015) and S.Li et al. (2019) proposed an image-based crack detection of the concrete method using a deep convolutional neural network (CNN). Based on the literature reviewed, it is clear that the predicting failure of the beam using ANN is still not well understand. This is the first time to predict the crack location and crack depth of the I-section beam using ANN due to vibration analysis. Moreover, the new technique and data and generated in this study could be used by other researchers for validation, comparison, or reference.

## **2. Methodology**

The finite element analysis and simulation were performed using the commercially available FE software package, (Ansys Student 2019 R3) with built-in failure criteria functions. ANSYS was used owing to its simplicity, and its ability to provide all the necessary functions for structural analysis of layered composite structures and Artificial Neural Network using model ANN package in MATLAB Software. The present studies were systematically divided into two stages which perform FEA simulation using ANSYS, and design Artificial Neural Network (ANN) using MATLAB.

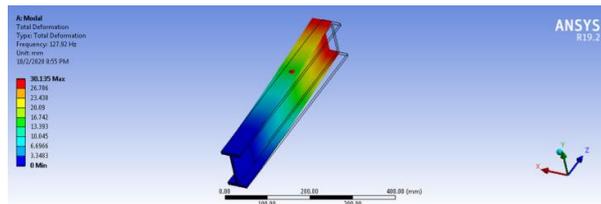
### **2.1 Finite Elements Simulations**

In this stage, the simulation had perform to collect the data of modes shape of vibration for each cases with varies the crack locations and depth of crack. Table 1 shows the dimension of the beam that has been used to train and test the data, the length, width, flange thickness, web thickness and height is modelled using a computer added design (CAD), for the young modulus and density is the parameters for material structural steel.

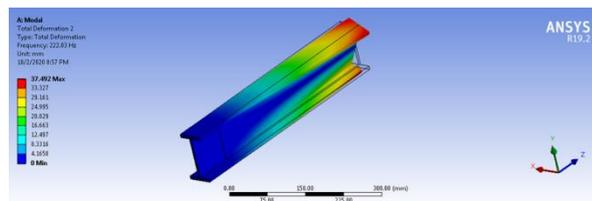
**Table 1. Technical Properties of I-Beam**

Properties	Value
Length (mm)	100
Width (mm)	25
Flange thickness (mm)	3.5
Web thickness (mm)	2.5
Height (mm)	50
Young modulus (Mpa)	$2 \times 10^5$
Density (Kg/m <sup>3</sup> )	7850

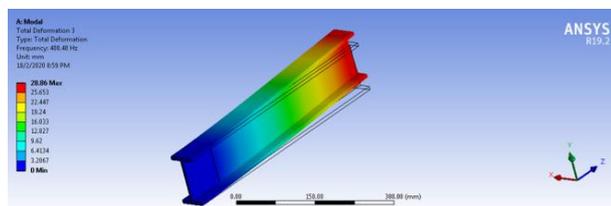
Fig. 1 until Fig. 5 shows the mode shape of vibrations of the beam had been used to predict the location and depth of the crack. The crack location is at 0.5 mm from the boundary condition that had been fixed. The crack depth is 5 mm, 10 mm, 16 mm, 20 mm, and 25 mm. The crack location is from 5 mm until 90 mm from the boundary condition.



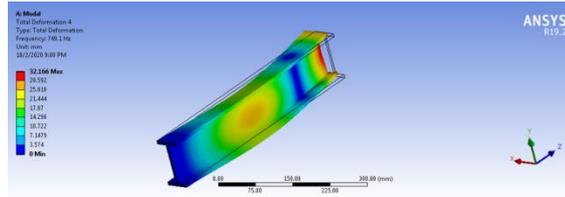
**Fig 1. First mode (bending first order in x-direction)**



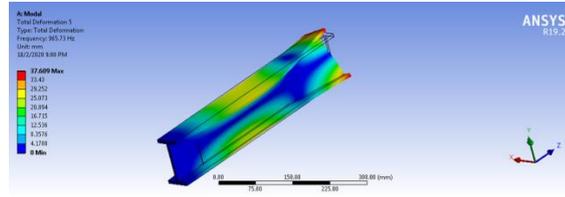
**Fig 2. Second mode (twisting first order)**



**Fig 3. Third mode (bending first order in Y-direction)**



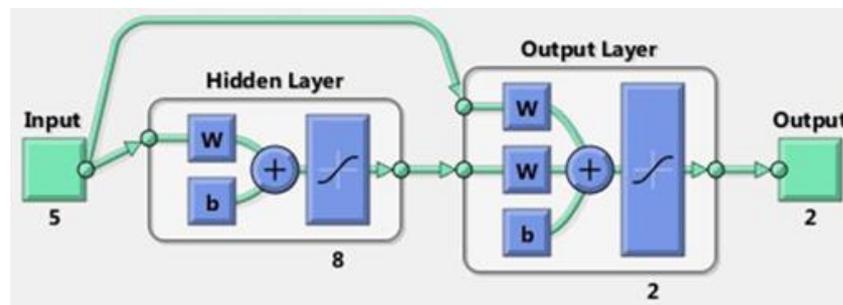
**Fig 4.** Forth mode (bending second order in x-direction)



**Fig 5.** Fifth mode (twisting second order)

## 2.2 Artificial Neural Network Modeling

Artificial neural networking (ANN) in MATLAB is used to analyze and predict the crack's depth and position in the beam and data obtained for the training and validation process in ANN. In MATLAB, the desired inputs and outputs or targets are imported in the workspace, and using “nntool” network is created using inputs and targets. Here, a typical three-layered Cascade-Forward Back Propagation (CFBP) neural network consists of three neurons in the input layer, nine neurons in the hidden layer, and two neurons in the output layer. The first until five modes shape of vibrations (f1, f2, f3, f4 and f5) were taken as an input parameter; relative crack location (l) and relative depth crack (dl) were defined as output parameters. The various functions used are Levenberg Marquardt (trainlm) is taken as Training function, and LEARNGDM had been chosen as learning adaption method, Mean square error (MSE) taken as performance function and Sigmoid function (tansig) as transfer function. Fig. 6 shows the neural network architecture of Cascade-forward backpropagation. It contains five inputs and two outputs with eight number of the hidden neuron.



**Fig 6.** Neural network architecture

### 3. Results and Discussion

In neural networks, the training and learning function is used to modify the network's weights and biases. The training function applies an algorithm on all weights and biases in networks, but the learning function deals with individual weights and biases in networks. In this study, the different training and learning functions to find the best training and learning function.

#### 3.1 Training and Validation of ANN

A layer that connects the input layer to the output layer is called the hidden layer. The number of hidden layers in the network should be chosen randomly because there is no specific method to calculate how many hidden layers need one network. In each network, the changing of the number of hidden layers and neurons of each layer to find the best result. Improve generalization capacity by increase the number of the hidden layer. Most of the time, one or two hidden layers are enough to reach a good result. This paper uses one and two hidden layers with different neurons and compares them with each other. Table 2 is the training parameters for modeling the ANN. The input layer is the Natural frequency of the beam with and for the output layers is the crack depth and crack location.

**Table 2.** ANN training parameters

The number of data	300 data : 237 training data, 63 testing
Input layer	Natural frequency of beam
The number of Neuron in hidden layer	5,8
Output layer	Crack depth and crack location
Network type	Cascade forward back propagation
Training function	Trainlm
Learning function	LEARNGDM
Output transfer function	Tangent sigmoid
Hidden transfer function	Tangent sigmoid
Performance function	MSE

Table 3 is showing the MSE and R2 to compare the performance function of the various train function and learn functions. There are many ways to evaluate network performance; one of the methods is Mean Square Error (MSE). To get the maximum performance, the MSE should be the minimum amount. For assessing our created networks in this paper, the MSE measurement is used to determine the best network. Table 4 shows that the training function and learn function were chosen based on performance validation. The

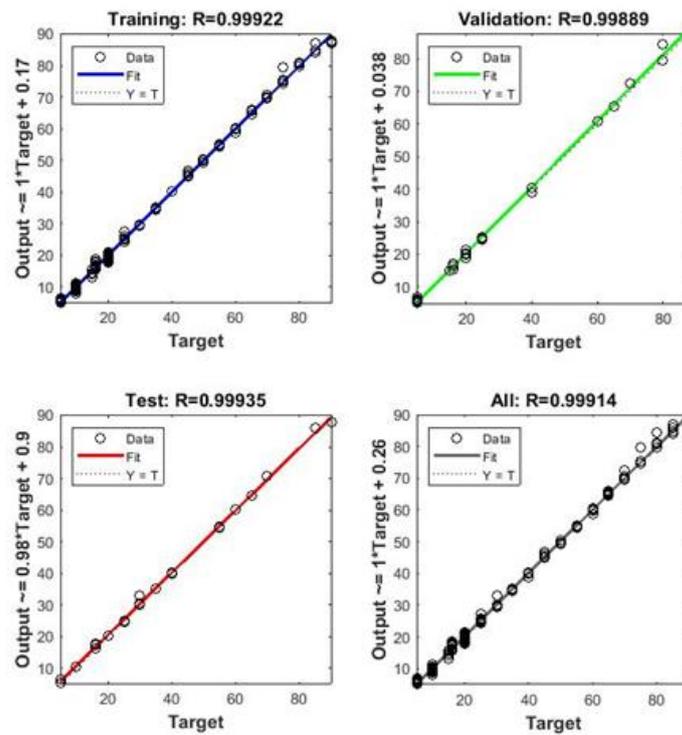
hidden neuron has been choosing based on the formula that the minimum amount of hidden neuron is required to optimize the performance of ANN. Fig. 7 shows the regression analysis obtained from the training data. The  $R^2$  is required approaching to 1 to get the best result of the analysis

**Table 3.** various training function and learning function

Train function	Learn function	Transfer function	MSE & $R^2$	The number of neuron in hidden layer			
				5		8	
				Train	Test	Train	Test
Trainlm	Learngd	Purelin	MSE	62.12	95.27	80.47	64.02
			$R^2$	0.94295	0.9208	0.93487	0.95172
		Tansig	MSE	3.195	11.75	0.1385	77.92
			$R^2$	0.99758	0.98991	0.99988	0.94367
	Learngdm	Purelin	MSE	62.19	64.67	65.62	108.3
			$R^2$	0.94767	0.94266	0.94253	0.93848
		Tansig	MSE	7.976	10.45	0.1555	4.235
			$R^2$	0.99908	0.99837	0.99937	0.99715
trainbr	Learngd	Purelin	MSE	71.49	63.51	90.54	55.53
			$R^2$	0.94487	0.92897	0.94185	0.95572
		Tansig	MSE	1.594	3.49	0.5858	73.41
			$R^2$	0.99866	0.99693	0.99864	0.99949
	Learngdm	Purelin	MSE	67.58	106.9	73.72	82.52
			$R^2$	0.94121	0.93038	0.93951	0.95894
		Tansig	MSE	0.7875	21.95	0.2275	4.057
			$R^2$	0.9984	0.99764	0.99805	0.9993

**Table 4.** MSE and R<sup>2</sup>

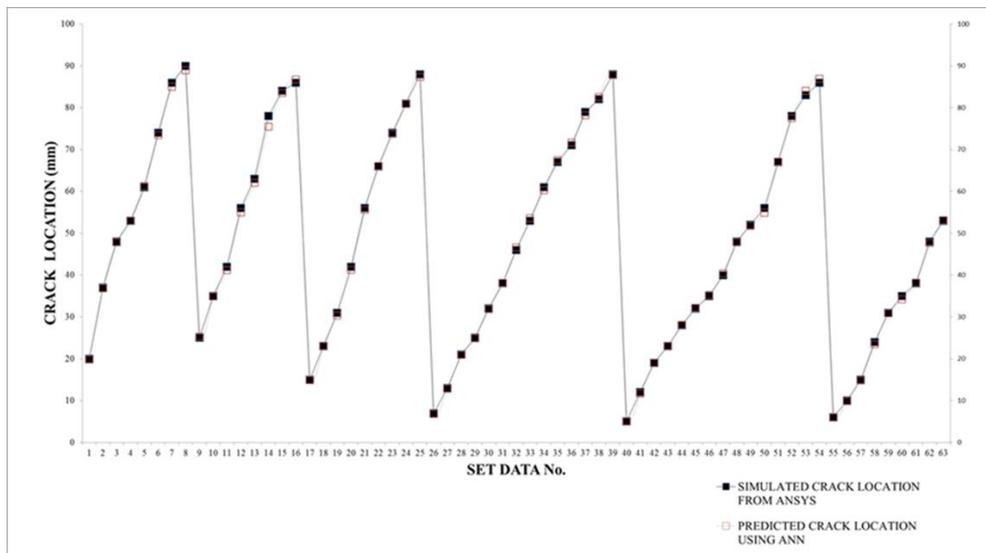
Neuron in hidden layer	Training and learning function :TRAINLM and LEARNGDM				Hidden layer transfer function
	R <sup>2</sup>			Training MSE	
	Training	validation	testing		
5	0.94646	0.94893	0.94449	60.6	Purelin
	0.99873	0.99748	0.99766	0.892	Tansig
8	0.94113	0.94374	0.9505	61.4	Purelin
	0.99922	0.99889	0.99935	0.166	Tansig



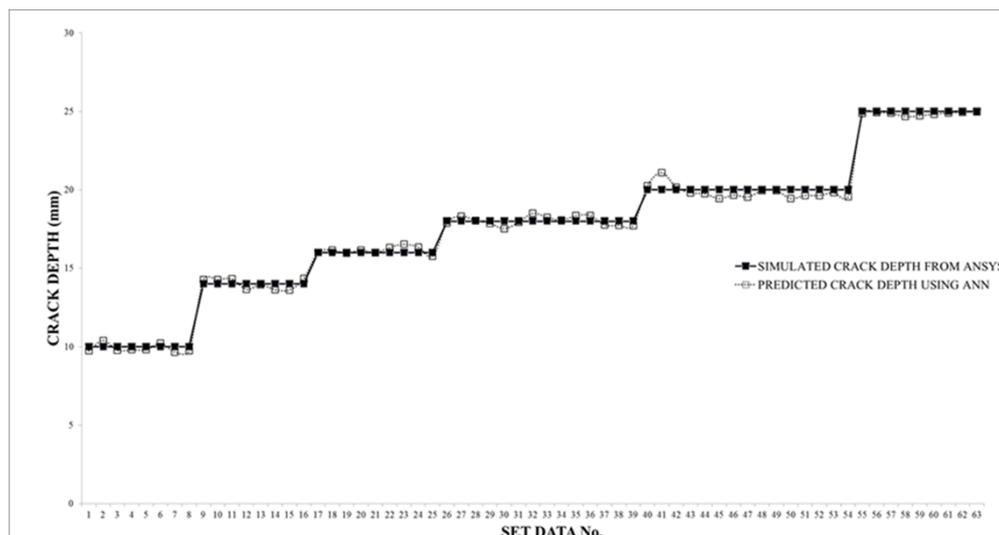
**Fig 7.** Regression analysis

### 3.2 Prediction Simulation Results

The ANN predicted results are in very good agreement with numerical simulation results, and the network can be used for testing. Hence the test data sets are applied to the network, which were never used in the training process. I-Beams' data sets with multi-crack depths vary from 5 mm to 25 mm. Fig. 8 shows the results of predicted using ANN between numerical simulation using ANSYS for crack depths. It observed that the error between prediction results with simulation results from Finite Element Analysis is lower than 5%. It shows the comparison data crack location (CL) using ANSYS and ANN, the data shown to prove that the ANN can predict the location of crack quite accurately. In multi-crack locations varies from 5 mm to 90 mm. Form Fig. 9, it is observed that the error between prediction results with simulation results from Finite Element Analysis is lower than 3%.



**Fig 8.** Prediction Results compared with simulation results of Crack Depth



**Fig 9.** Prediction Results compared with simulation results of Crack Locations

#### 4. Conclusion

This paper presents the investigation into the capabilities of Artificial Neural Networks (ANN) in predicting the crack location and depth on the I-section beam under clamp boundary conditions. The existence of crack has a distinct influence on the structure's natural frequency. Another cause is that the natural frequency variations are strongly affected by the crack and crack location size. The crack presence and location can be determined through the correlation of the simple modes between the fractured beams. The cracked cantilever beam frequency decreases throughout all vibration modes with an increase in the crack depth. The ANN modeling has significantly given good predictions of CD and CL using MATLAB software. The difference error between prediction and numerical simulation has below 5% error. The ANN model's good things provide the choices to select the refile learning and adaptive learning suitable for the problem statement. Due to this finding, it can conclude that the current study is useful and has contributed knowledge about understanding the capabilities of Artificial Neural Networks (ANN) in predicting the crack location and depth on I-section beam.

#### 5. Acknowledgement

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