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Multi crack detection in structures using artificial neural network

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Abstract. Cracks are one of the main causes of structural failure. The detection of cracks is broadly carried out using NDT methods, vibration-based methods, and various mathematical models. The detection of single crack has been widely and importantly studied in recent years. However, the diagnosis of multiple cracks is minimal. In this paper, an alternative way for detecting multiple cracks used is Artificial Neural Networks (ANN) based modeling which is a subfield of artificial intelligence. The evolutions in the ANN have brought up various new potential in the arena of complex problems. In ANN modeling, networks can be built directly from experimental data using its self-organizing capabilities which is the main advantage of using ANN. This paper tries to predict multiple cracks in cantilever beam using soft computing technique. The crack location and crack depth of two cracks are the output parameters and the first three relative natural frequencies are the input parameters to the neural network. The result sets obtained from the finite element analysis (FEA) are used to train the network and the simulated results are obtained. It has been found that the maximum error percentage between the analytical and the ANN outputs is very less which shows that the ANN can well build to predict the characteristics of the multiple crack. This paper proposes a good approach for multiple damage detection in cantilever beam.

1. Introduction

Mechanical failure can be occurred due to various reasons like loading and stress, environment, poor quality design, defects in materials etc [1]. The accumulation of damage in structures would reduce its safety and can even lead to structural failure which is unavoidable [2]. Cracks in structures are one of the main causes of structural failure. The research on the diagnosis of single crack is universally carried out in recent years using NDT methods, vibration-based methods, and various mathematical models. Thus, study, research, and investigation of multiple cracks seem necessary to avoid structural failures.

The ANN approach can be used to a greater extent to predict the damage detection. Artificial neural networks are the mathematical model of human nerve system. A neural network contains input, hidden and output layers. The input layer is connected to hidden nodes through some connecting weights and forms a relationship and in turn, hidden one is connected to output layer through some weights. The neurons in the input layer represent the input raw data which are processed and the output layer neurons represent the desired output information. Artificial Neural Networks (ANN) is used to predict damage in a beam-like structure with good accuracy [3]. The major studies concerned with the damage detection are considered for the case of single crack. In the survey of Dimarogonas [4] the crack prognosis problem in structures has been broadly carried out and several techniques and process were presented due to its practical and theoretical importance. Nasiri et al. [1] had presented a review paper on the use of Artificial Intelligence (AI) methods for mechanical fault detection. There are various studies on detection of depth and location of the single crack using Neural based controller [3, 5-6]. Multiple cracks effects and its identification is well archived in a review paper by Sekhar [7]. Mehdi Behzad et al. [8] has used Linear Elastic Fracture Mechanics and vibration based algorithm to identify depth, location and crack type of multiple crack in a beam. Finite element method and Newton Raphson method has been used in the prognosis in multi-cracked beam using modal natural frequencies and vibration amplitudes by Jinhee Lee [9-10]. The value of natural frequencies and estimation of the undamaged mode shapes are used for localizing and detecting multiple cracks and Rayleigh-Ritz method to minimize the complexity by Maghsoodi et al. [11]. Teidj et al. [12] had used the measurement of the changes in the beam frequencies and observed their variations which enable to detect the crack defect characteristics. Boundary element and finite element method with the use of sensitivity analysis was used to predict the multiple cracks by Jinhee Lee [13]. Mehrjoo et al. [14] provided a method to diagnose the cracks of joints in truss through artificial neural network.

2. Neural Network Model

The specimen considered here is a cantilever beam having length (L) = 300 mm and thickness (h) = 5 mm with two cracks. The geometry of a cantilever beam with double crack is shown in Figure 1. The parameters are as follows:
Relative crack depth of 1st crack (cd_1) = a / h, Relative crack depth of 2nd crack (cd_2) = b / h
Relative crack location of 1st crack (cl_1) = x / L, Relative crack location of 2nd crack (cl_2) = y / L

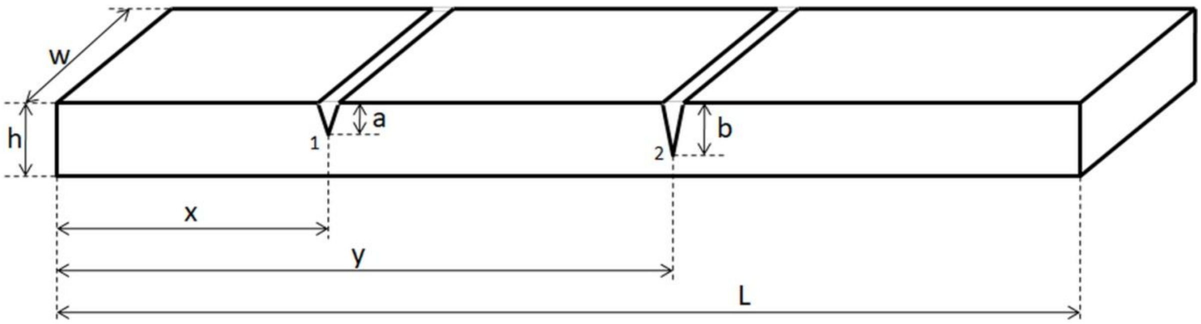

Figure 1. Multi-cracked cantilever beam

The first three modal natural frequencies of the cracked and uncracked beam were calculated through ANSYS. The first three natural frequencies of the uncracked beam are as follows:
F_1 = 45.67 Hz, F_2 = 285.9 Hz, F_3 = 799.3 Hz

So, the relative frequency (f_1, f_2, f_3) = frequency of cracked beam/frequency of uncracked beam. The following Table I show the relative first three natural frequencies at given depth and location. The data in Table 1 are the training data of the neural network. Around 44 out of 60 data sets were considered as training data sets and 16 data sets are presented to the network as testing data sets.

Table 1. Training data to the neural network

S.no	f1	f2	f3	cd1	cd2	cl1	cl2
2	0.9519	0.9577	0.954	0.4	0.4	0.0066	0.333
3	0.9562	0.9459	0.9657	0.4	0.4	0.0066	0.5
4	0.96	0.9518	0.9486	0.4	0.4	0.0066	0.666
5	0.9611	0.9617	0.9573	0.4	0.4	0.0066	0.833
7	0.9715	0.9761	0.9955	0.4	0.4	0.1666	0.5
8	0.9695	0.9809	0.9759	0.4	0.4	0.1666	0.666

9	0.972	0.9916	0.9835	0.4	0.4	0.1666	0.833
11	0.9844	0.9784	0.9633	0.4	0.4	0.333	0.666
12	0.9871	0.9894	0.9732	0.4	0.4	0.333	0.833
14	0.9932	0.974	0.9866	0.4	0.4	0.5	0.833
15	0.9974	0.9798	0.9659	0.4	0.4	0.666	0.833
17	0.9175	0.9349	0.9149	0.4	0.8	0.0066	0.333
18	0.923	0.8264	0.9649	0.4	0.8	0.0066	0.5
19	0.9472	0.8711	0.8551	0.4	0.8	0.0066	0.666
20	0.9562	0.947	0.9057	0.4	0.8	0.0066	0.833
22	0.9417	0.8803	0.9953	0.4	0.8	0.1666	0.5
23	0.9647	0.9034	0.8917	0.4	0.8	0.1666	0.666
24	0.9723	0.9741	0.902	0.4	0.8	0.1666	0.833
26	0.9805	0.9171	0.8927	0.4	0.8	0.333	0.666
27	0.9875	0.9764	0.9137	0.4	0.8	0.333	0.833
29	0.9933	0.9604	0.9217	0.4	0.8	0.5	0.833
30	0.9982	0.9706	0.9172	0.4	0.8	0.666	0.833
32	0.7951	0.8476	0.8787	0.8	0.4	0.0066	0.333
33	0.8018	0.8429	0.8879	0.8	0.4	0.0066	0.5
34	0.8553	0.8762	0.8879	0.8	0.4	0.0066	0.666
35	0.8024	0.8561	0.8815	0.8	0.4	0.0066	0.833
37	0.8507	0.9672	0.9877	0.8	0.4	0.1666	0.5
38	0.8531	0.9711	0.9685	0.8	0.4	0.1666	0.666
39	0.9747	0.9858	0.9521	0.8	0.4	0.1666	0.833
41	0.9365	0.955	0.9117	0.8	0.4	0.333	0.666
42	0.9128	0.9513	0.8996	0.8	0.4	0.333	0.833
44	0.9682	0.8882	0.9886	0.8	0.4	0.5	0.833
45	0.9886	0.882	0.8685	0.8	0.4	0.666	0.833
47	0.6891	0.7251	0.7885	0.8	0.8	0.0066	0.333
48	0.7692	0.6897	0.8782	0.8	0.8	0.0066	0.5
49	0.7936	0.7799	0.7759	0.8	0.8	0.0066	0.666
50	0.7948	0.9148	0.8212	0.8	0.8	0.0066	0.833
52	0.7404	0.7769	0.9815	0.8	0.8	0.1666	0.5
53	0.7628	0.821	0.8375	0.8	0.8	0.1666	0.666
54	0.8544	0.9706	0.9224	0.8	0.8	0.1666	0.833
56	0.903	0.8838	0.8032	0.8	0.8	0.333	0.666
57	0.9049	0.9382	0.8471	0.8	0.8	0.333	0.833
59	0.9659	0.8721	0.9265	0.8	0.8	0.5	0.833
60	0.9917	0.8963	0.854	0.8	0.8	0.666	0.833

Thus the data number 1, 6, 10, 13, 16, 21, 25, 28, 31, 36, 40, 43, 46, 51, 55, 58 are used for testing ANN. In this study, a typical three-layered Feed Forward Back Propagation (FFBP) neural network is considered consisting of an input layer with three input nodes, a hidden layer with nine neurons and an output layer with four output nodes as shown in Fig. 2.

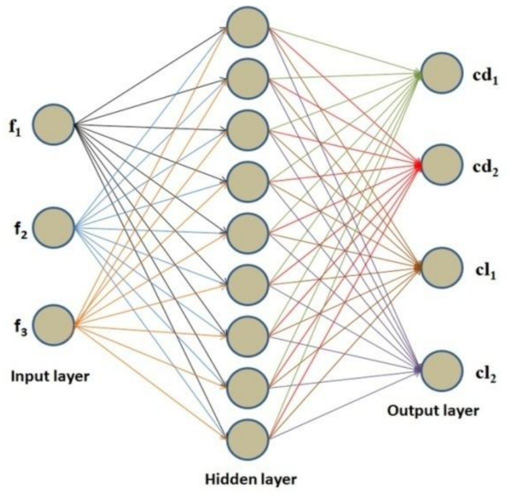

Figure 2. Architecture of three-layered FFBP network

Here an organized network is considered, which is feed-forward network trained with back propagation, which uses a set of input data and a set of analogous desired output data called target data. Here, input data is the first three relative natural frequencies and the target data is the crack location from fixed end and crack depth of crack 1 and crack 2. The various functions used in this network are – Transfer function: Sigmoid function, Training function: TRAINLM (Levenberg-Marquardt), Adaption learning function: LEARNGDM, Performance function: MSE (Mean Square Error). The input parameters required for the training of data are provided as shown in Table 2.

Table 2. Input parameters for training

S.no	Input Parameters for Training	Values
1.	Goal	1e-06
2.	Learning rate	0.1
3.	Momentum parameter	0.001
4.	Number of epochs	10000
5.	Number of nodes in input layer	3
6.	Number of neuron in hidden layer	9
7.	Number of nodes in output layer	4

3. Validation with Analytical Results

The data from the Table I are trained in the neural network and the outputs are predicted. The outputs of both the analytical and predicted data (through ANN) are compared as shown in Table 3.

4. Results and discussions

In order to avoid an extensive failure or accident, the early prognosis of crack in structures is necessary. The multiple cracks are dangerous for early failure of the structures. So their diagnosis is much important to avoid structural failures. Here, the data are trained in the neural network and outputs are obtained. From Table III, it is been seen that the maximum error percentage between the analytical and the ANN outputs is less than 5% which shows that the ANN can well build to predict the characteristics which are location and severity of the multi cracks in the structures.

A comparison graph between analytical and ANN outputs for the three-layered network for relative crack depth and relative crack location of crack 1 and crack 2 has been shown in Figure 3(a) & 3(b) respectively. So it can be seen that the depth and the location of multiple cracks can be detected through ANN with error percentage of less than 5% which shows that analytical and the predicted outputs are in good agreement with each other.

Table 3. Comparison between analytical (anyl.) and ANN outputs

S.no	cd_1			cd_2			cl_1			cl_2		
	Anyl.	ANN	Error % wrt anyl.	Anyl.	ANN	Error % wrt anyl.	Anyl.	ANN	Error % wrt anyl.	Anyl.	ANN	Error % wrt anyl.
1	0.4	0.4	**0**	0.4	0.4	**0**	0.006	0.006	**0**	0.166	0.166	**0**
6	0.4	0.417	**4.2**	0.4	0.417	**4.27**	0.166	0.165	**0.168**	0.333	0.332	**0.249**
10	0.4	0.4	**0**	0.4	0.4	**0**	0.333	0.333	**0**	0.5	0.5	**0**
13	0.4	0.4	**0**	0.4	0.4	**0**	0.5	0.5	**0**	0.666	0.666	**0**
16	0.4	0.399	**0.25**	0.8	0.812	**1.56**	0.006	0.006	**0**	0.166	0.166	**0**
21	0.4	0.412	**3**	0.8	0.8	**0**	0.166	0.166	**0**	0.333	0.333	**0**
25	0.4	0.4	**0**	0.8	0.8	**0**	0.333	0.333	**0**	0.5	0.5	**0**
28	0.4	0.391	**2.23**	0.8	0.791	**1.115**	0.5	0.505	**1.082**	0.666	0.666	**0**
31	0.8	0.8	**0**	0.4	0.4	**0**	0.006	0.006	**0**	0.166	0.166	**0**
36	0.8	0.77	**3.75**	0.4	0.398	**0.5**	0.166	0.166	**0**	0.333	0.333	**0**
40	0.8	0.8	**0**	0.4	0.4	**0**	0.333	0.333	**0**	0.5	0.5	**0**
43	0.8	0.791	**1.115**	0.4	0.387	**3.16**	0.5	0.505	**1.082**	0.666	0.666	**0**
46	0.8	0.8	**0**	0.8	0.8	**0**	0.006	0.006	**0**	0.166	0.166	**0**
51	0.8	0.8	**0**	0.8	0.8	**0**	0.166	0.166	**0**	0.333	0.333	**0**
55	0.8	0.794	**0.65**	0.8	0.795	**0.578**	0.333	0.333	**0.108**	0.5	0.504	**0.864**
58	0.8	0.8	**0**	0.8	0.8	**0**	0.5	0.5	**0**	0.666	0.666	**0**

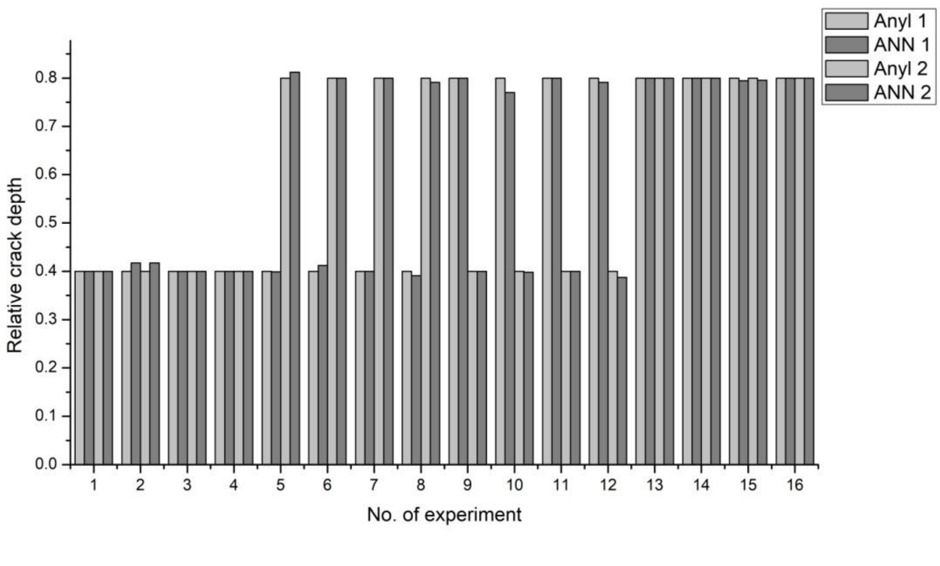

Figure 3(a). Comparison graph of relative crack depth of crack 1 and 2

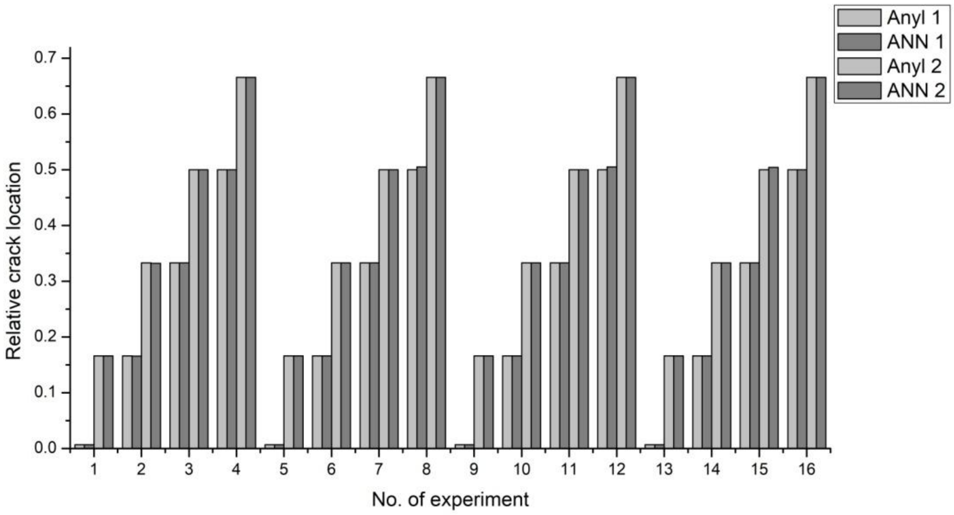

Figure 3(b). Comparison graph of relative crack location of crack 1 and 2

5. Conclusion

The purpose of this study is to summarize the use of ANN in the detection of multiple structural damages. From the result, it is concluded that in this approach ANN can be used to predict multiple cracks and their location and severity in a cantilever beam with good accuracy. The average error percentage of the testing data is approximately 0.5% which shows that the current method used can be applied for detection of multiple damages in structures. Using Feed Forward Back Propagation network is enough for detection of crack depth and location in structures. This ANN controller will provide us the damage information accurately.

6. References

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