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Finite element analysis of vessels to study changes in natural frequencies due to cracks

A. Choubey, D.K. Sehgal, N. Tandon *

ITMME Centre, Indian Institute of Technology, Hauz Khas, New Delhi 110 016, India

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Abstract

When significant damage occurs in structures, there is a change in stiffness, which in turn affects the natural frequency. To study this, a study was conducted to analyse the effect of cracks on natural frequencies in two vessel structures. Finite element analysis has been used to obtain the dynamic characteristics of intact and damaged vessels for the first eight modes of these structures. Two kinds of vessel, boilers and storage tanks, were chosen and through-thickness cracks were analysed. Different cases were examined by changing the size and locations of cracks with the help of a FEM (Finite element model). Natural frequencies and mode shapes were analysed. The natural frequencies for different modes have been used as input pattern of ANN (artificial neural network) model. The output of the ANN model is a crack size for a particular location. It was found that as the crack size increased, natural frequency changed to a large extent, but the frequency was not reduced in the same manner for every position of damage for the same size of crack. It was also found that the reduction in natural frequencies depends upon the mode shapes of the structures.

Keywords: Natural frequency; FEM; Mode shape; Artificial neural network; Vessels; Crack

1. Introduction

Pressure vessels are needed in the oil, chemical, nuclear power and many other industries. In the process industries, application for such vessels includes paper and pulp mills, caustic soda plants, bleaching, water purification, sewage treatment, refineries, anti-freeze components, fertilizers, insecticides and refrigerants plants. The primary requirement of these vessels is to be leak proof, so it is important to detect cracks in pressure vessels and storage tanks before use. NDT techniques can be used to detect a flaw in the pressure vessel.

The existence of a crack causes changes in natural frequencies, mode shapes and structural damping. Since, the measurement of natural frequencies is easier than that of changes in structural damping, damage can be detected from dynamic analysis using natural frequencies and mode shapes. Examination of the change in natural frequencies allows an estimation of both the location and size of the crack [1–3]. The dynamic characteristics like mode shapes and natural frequencies can be estimated by both experimental and numerical methods [4,5]. Several researchers [6–8] used this fact for damage detection. As damage detection is an inverse, non-linear and non-unique problem, that generally does not have a feasible algorithmic solution or for which an algorithmic solution is too complicated to be found and handled, a different approach is required. Therefore, artificial neural networks (ANNs) [9,10], are used for automation of defect identification and tracking [11].

In the present work, boiler and cylindrical storage tanks were chosen as test structures. A FEM (finite element model) has been used to determine the dynamic characteristics of the intact and damaged structures up to eight modes of the structures. Different damage scenarios were obtained by changing the size of the defect at different locations. Natural frequencies and corresponding mode shapes were obtained by FEM. Different cases with different location and size of cracks were studied to see for which location the reductions in natural frequencies were significant. Natural frequencies corresponding to different crack sizes for a particular location were used as input patterns to an artificial neural network. The output of the ANN is a crack parameter (crack size).

* Corresponding author. Tel.: +91 11 26591276; fax: +91 11 26596222.
E-mail address: ntandon@itmmec.iitd.ernet.in (N. Tandon).

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Nomenclature

a	size of crack	h	height of storage tank
c	distance of crack on cylindrical shell from bottom	l	effective length of boiler
C	distance of crack on boiler from right end	w,k	weights in neural network

2. Finite element modeling

In model dependent vibration-based analysis, it is important to have an accurate numerical model. For numerical analysis the models of intact and damaged structures of vessels were created using ANSYS software [12].

2.1. FEM of boiler with hemispherical ends

The specifications of the structure are as follows.

Internal diameter is 5 m, length is 18 m (cylindrical portion), thickness is 0.0254 m, effective length is 23 m, saddle width is 0.3048 m, and distance between two saddles is 14.3424 m. Effective length is the distance between two extreme ends of the boiler taking into account both the hemispherical and cylindrical portions. Material properties taken for the boiler structure are—modulus of elasticity: 210×10^9 N/m^2, Poisson's ratio: 0.28 and density: 7840 kg/m^3. Boundary conditions: all nodes at the area where saddles are attached were fixed.

2.2. Crack analysis of boiler

A finite element model is created with the specification of the original structure and meshing is done using eight noded shell elements. The number of elements is 1268. Two locations are chosen for creating cracks one at 11.5 m from both ends and the other 7 m from the right end. At each location, the size of the crack varies with the ratio of crack size to the effective length of the boiler (a/l) as 0.1, 0.2, 0.3, 0.35. Hence, a total of eight cases were analysed. Fig. 1 shows the finite element mesh of the boiler with a crack.

2.3. FEM of oil storage tank

The specification of the structure is as follows:

Internal diameter of cylinder: 5 m, thickness: 0.04 m, and height of the tank: 10 m.

Boundary conditions: cylindrical tank has its top portion and bottom portion closed and all degree of freedom at the bottom area have been made zero. The material properties taken were the same as in the case of the boiler.

Elements used are eight node shell elements and the number of elements is 588.

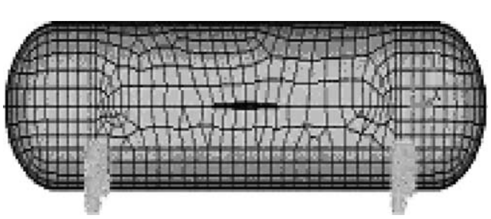

Fig. 1. FEM of boiler with a crack.

2.4. Crack analysis of storage tank

Through cracks were created vertically along the height. Three locations have been chosen—2.5, 5 and 7.5 m for creating cracks. For each location, the size of the vertical crack varies as the ratio of crack length to the height of the cylinder (a/h) varies as 0.1, 0.2, 0.3 and 0.4. A FEM of a storage tank with a crack is shown in Fig. 2.

3. Neural networks

A neural network is a powerful data modeling tool that is able to capture and represent complex input/output relationships [9,10]. The motivation for the development of neural network technology stemmed from the desire to develop an artificial system that could perform 'intelligent' tasks. A neural network acquires knowledge through learning and its knowledge is stored within inter-neuron connection strengths known as synaptic weights.

The true power and advantage of neural networks lies in their ability to represent both linear and non-linear relationships and in their ability to learn these relationships directly

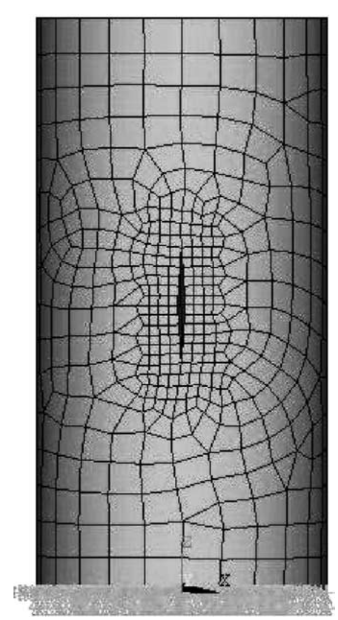

Fig. 2. FEM of storage tank with crack.

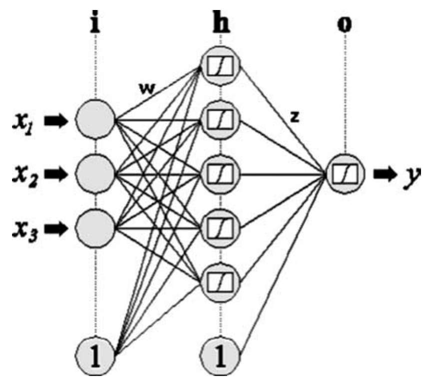

Fig. 3. Simple neural network.

from the data being modeled. Traditional linear models are simply inadequate when it comes to modeling data that contain non-linear characteristics. The most common neural network model is the multilayer perceptron (MLP). This is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown. The MLP and many other neural networks learn using an algorithm called error back-propagation. An error back-propagation neural network consists of several layers of nodes somehow analogous to neurons: an input layer (i), one or more hidden layers (h) and an output layer (o) (Fig. 3). Each node in a layer receives its input from the output of the previous layer nodes or from the network input. The connections between nodes are associated to synaptic weights (w, z) that are adjusted iteratively during the training process. An additional node with a constant output (usually 1) is often added to the input and hidden layers. These nodes are known as bias nodes. Their role in neural networks is very similar to that of the constant term in multiple regression.

A way of choosing the patterns representing the characteristics of the structure, which are to be used as the input to neural networks, is one of the most important subjects in this approach. The natural frequencies and modes of a structure are used as the input patterns in this study. The choice has been made based on the following advantages: (1) the natural frequencies represent global behaviour, while the mode vectors represent local characteristics; and (2) they can be obtained from the measurements of structural behaviour.

A neural network works best if all its synaptic weights have been properly adjusted. The error back-propagation algorithm is a way to compute these weights. A perceptron is defined parametrically by its weights $\{w,k\}$ where w is a column vector of length equal to the dimension of the input vector x and k is a scalar. The weights $\{w,k\}$ are obtained by iteratively training the perceptron with a known data set containing input–output pairs, one input vector in each row of a matrix x, and one output in each row of a matrix y.

Hence, the basic strategy for developing a neural network-based approach to identify a structural system is to train the back-propagation neural network to recognize the element-level structural parameters from the measurement data on the structural behaviour, such as natural frequencies and mode shapes. Since, the neural network-based structural identification is highly dependent on the training patterns, it is very important to prepare well-examined data sets. The number of training patterns must be large enough to represent the structural system properly. In the present work, a single output (crack size) is taken from the ANN.

4. Results and discussions

4.1. FEM results

Natural frequencies for the first eight modes of the boiler and the storage tank as obtained by ANSYS are given in Tables 1 and 2, respectively. The first four mode shapes of the boiler and the tank are shown in Figs. 4 and 5, respectively.

The natural frequencies obtained by finite element analysis for the boiler with a crack at different locations are given in Tables 3 and 4. Reductions in natural frequencies due to cracks at different locations were computed and are plotted for the first four modes in Fig. 6.

Fig. 6 shows that in mode 1, as the crack moves towards the middle from the right end, the percentage reduction in natural frequency decreases up to $a/l = 0.3$. In this mode, the boiler is vibrating with respect to the supports (fixed areas) so the surface that is near the support is under tension. This may be the reason for decreasing the percentage reduction in natural frequencies as the crack moves towards the middle portion of the boiler. In mode 2, the deformation shape is completely different. The surface at the middle of the boiler is trying to vibrate and it is more in compression than the surface near the support. Therefore, as the crack moves towards the middle portion of the boiler, the percentage reduction in natural frequency increases. Also, in this mode, the reduction is more compared to the reduction in mode 1. In mode 3, the percentage reduction is less than in mode 2. As the crack moves towards the middle of the boiler, the percentage reduction in natural frequency increases. In this mode, the surface where the crack is present is under expansion and the boiler surface at the middle just above the location where the centre crack is present is vibrating more, so this may be the reason that here the reduction is more. But here, the surface where the crack is

Table 1
Natural frequencies of boiler in Hz

Mode 1	Mode 2	Mode 3	Mode 4	Mode 5	Mode 6	Mode 7	Mode 8
7.545	10.552	10.876	14.718	16.706	19.942	21.326	21.788

Table 2
Natural frequencies of storage tank in Hz

Mode 1	Mode 2	Mode 3	Mode 4	Mode 5	Mode 6	Mode 7	Mode 8
14.585	29.534	29.536	30.128	30.142	30.661	30.662	32.020

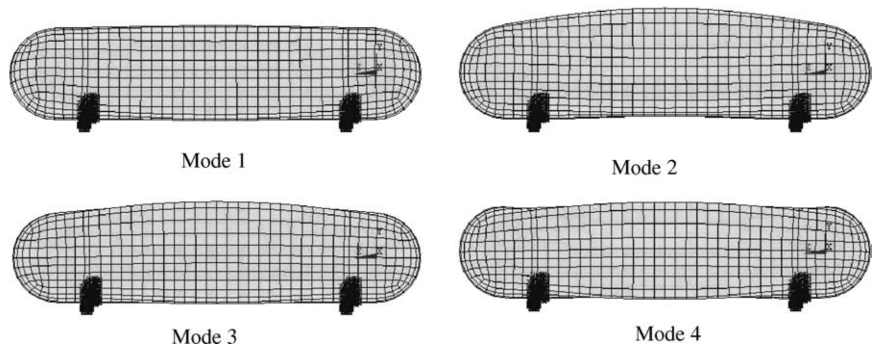

Fig. 4. Mode shapes of boiler.

present is not vibrating as much as it was vibrating in mode 2, so in this mode the percentage reduction reduces. The percentage reduction in natural frequency in mode 4 is higher than that observed in the previous three modes. In this mode, the boiler surface is vibrating at the top and also at the front. The surface where the crack is present is under compression and this compression increases as the crack moves from the right end towards middle portion. This could be the reason that the percentage reduction in natural frequency increases as the crack moves from the right end toward the middle portion.

Natural frequencies obtained from finite element analysis for the storage tank with a crack at different locations are given in Tables 5–7. Percentage reduction in natural frequencies due to a crack at different locations for the first four modes are shown in Fig. 7.

In the first mode, the upper plate covering the cylinder is vibrating, so it is not possible to set up a trend for a crack on the cylindrical portion of the vessel in this mode. Fig. 7 shows that in mode 2, the percentage reduction in the natural frequency is greater near the fixed end compared to the percentage reduction near the free end. As in this particular mode the cylinder is compressed more at the middle portion the percentage reduction is more. As the crack moves away from the middle portion this compression reduces, this may be the reason for the decrease in percentage reduction in natural frequency. In mode 3, the percentage reduction in natural frequency is greater near the free end than near the fixed end. The maximum reduction is at the middle portion. The cylinder is deforming at the middle and this deformation reduces as we move away from the middle portion. As the cylinder is deforming more near the free end compared to the fixed end, the percentage reduction in natural frequency is more near the free end compared to that near the fixed end. In mode 4, the percentage reduction in natural frequency reduces compared to modes 2 and 3. In this mode, the top plate covering the cylindrical tank is vibrating. This may be the reason that the percentage reduction in natural frequency is much less in this mode. The deformation shape for this particular mode shows that the cylinder is also vibrating like a cantilever. This may be the reason that the percentage reduction in natural frequency is more near the fixed end (the location where the bending moment is maximum) and is a minimum near the free end (the location of minimum bending moment).

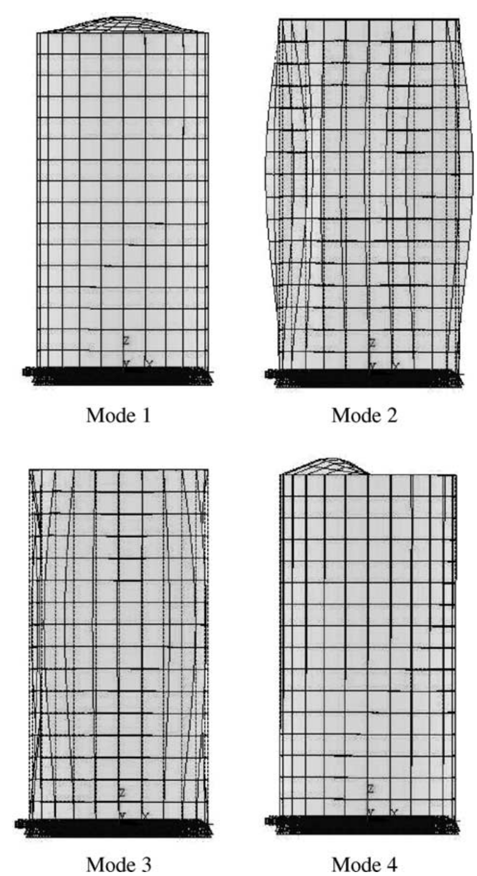

Fig. 5. Mode shapes of storage tank.

Table 3
Natural frequencies of boiler in Hertz (case 1: crack at front side, at a distance (C) 7 m from the right end of the boiler)

a/l	Modes							
	1	2	3	4	5	6	7	8
0.1	7.5317	10.554	10.835	14.618	16.676	19.887	21.206	21.746
0.2	7.5028	10.465	10.716	14.369	15.730	18.804	19.994	20.478
0.3	7.4360	9.9146	10.5	12.658	13.712	15.839	17.399	19.220
0.35	7.4070	9.3805	10.486	11.897	12.798	15.040	17.128	18.751

Table 4
Natural frequencies of boiler in Hz (case 2: crack at front side, at a distance (C) 11.5 m from right end of the boiler)

a/l	Modes							
	1	2	3	4	5	6	7	8
0.1	7.541	10.564	10.841	14.624	16.696	19.852	21.329	21.807
0.2	7.5117	10.403	10.685	14.172	15.356	19.178	20.435	21.052
0.3	7.4330	9.725	10.481	12.077	13.663	16.906	18.231	19.464
0.35	7.355	9.1307	10.199	11.208	13.361	15.616	17.533	18.368

4.2. Neural network results

In order to find the most effective ANN that uses vibration based analysis data for the crack length prediction, the MATLAB neural network toolbox was used. Different combinations of input and output pairs were then introduced to these supervised feed-forward back-propagation ANNs for training and validation. Here, frequencies for all eight modes were used as input and crack length ratio as output.

4.2.1. Training for boiler for crack at a distance 7 m from right end

Input: $f=7.4070$, 9.3805, 10.486, 11.897, 12.798, 15.040, 17.128, 18.751.

Output: $a/l=0.3442$; actual value $=0.35$; error $=1.6\%$.

4.2.2. Training for boiler for crack at a distance 11.5 m from right end

Input: $f=7.355$, 9.1307, 10.199, 11.208, 13.361, 15.616, 17.533, 18.368.

Table 5
Natural frequencies of storage tank in Hz (case 1: crack at a distance (c) 2.5 m from fixed (bottom) end of storage tank)

a/h	Modes							
	1	2	3	4	5	6	7	8
0.1	14.594	29.543	29.559	30.121	30.206	30.604	30.655	31.956
0.2	14.594	29.307	29.399	30.067	30.176	30.342	30.585	31.744
0.3	14.594	28.192	29.114	29.822	30.146	30.250	30.388	31.550
0.4	14.594	25.476	27.651	29.463	29.960	30.152	30.238	31.323

Table 6
Natural frequencies of storage tank in Hz (case 2: crack at a distance (c) 5 m from fixed (bottom) end of storage tank)

a/h	Modes							
	1	2	3	4	5	6	7	8
0.1	14.594	29.392	29.530	30.123	30.208	30.618	30.646	31.968
0.2	14.604	29.105	29.407	30.102	30.226	30.494	30.607	31.757
0.3	14.6	27.866	28.229	30.021	30.134	30.221	30.428	31.351
0.4	14.595	24.723	25.696	29.556	29.670	30.172	30.321	30.870

Table 7
Natural frequencies of storage tank in Hz (case 3: crack at a distance (c) 7.5 m from fixed (bottom) end of storage tank)

a/h	Modes							
	1	2	3	4	5	6	7	8
0.1	14.601	29.443	29.533	30.140	30.211	30.629	30.648	31.999
0.2	14.599	29.138	29.383	30.118	30.212	30.518	30.571	31.892
0.3	14.596	28.488	28.645	30.078	30.145	30.290	30.427	31.675
0.4	14.596	25.655	26.376	29.672	29.921	30.201	30.296	31.183

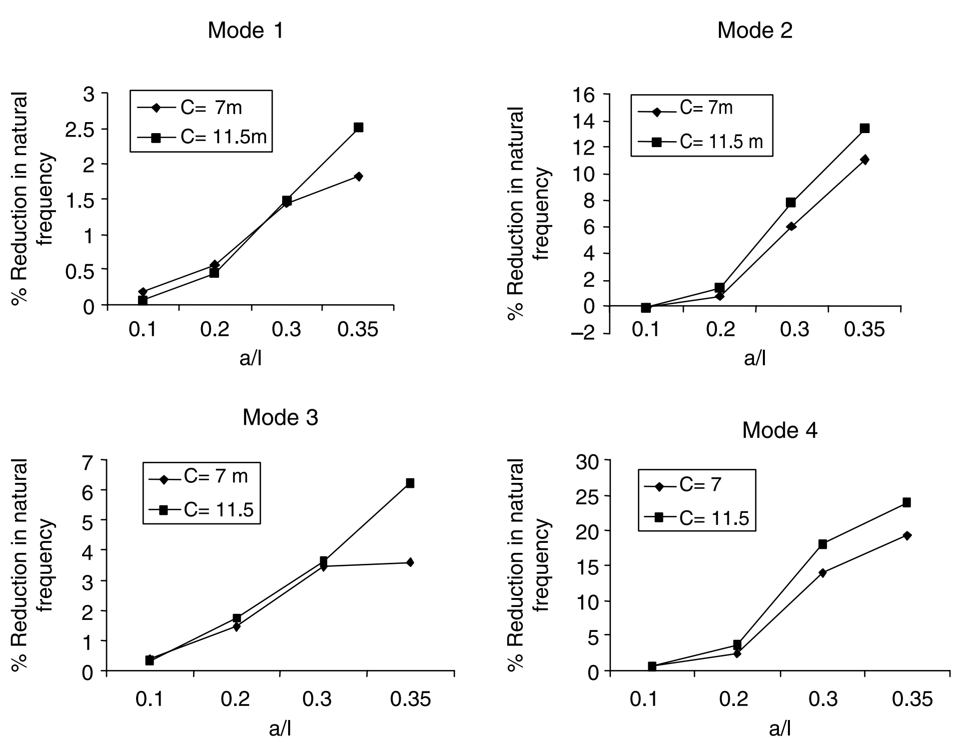

Fig. 6. Reduction in natural frequencies of boiler as crack location changes from its right end.

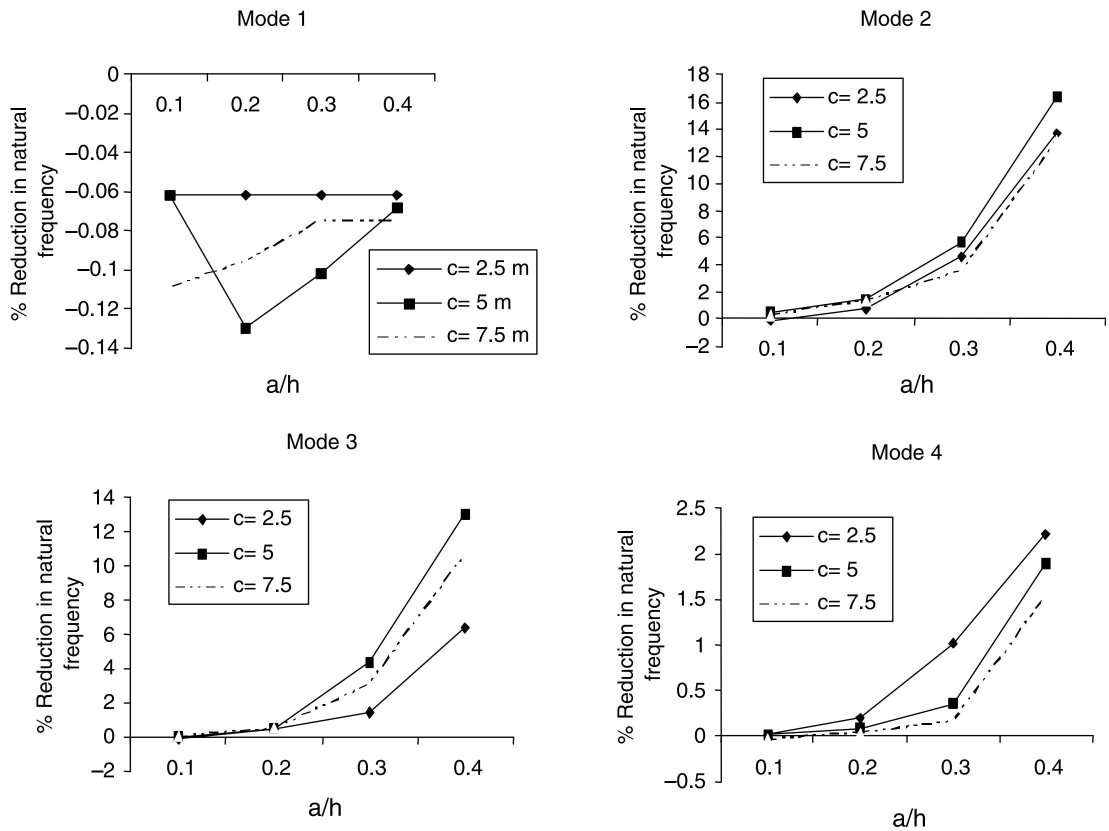

Fig. 7. Reduction in natural frequencies of storage tank as crack location changes from fixed end to upwards.

Output: $a/l=0.3445$; actual value $=0.35$; error $=1.57\%$.

4.2.3. Training for storage tank for a crack at 2.5 m from bottom

Input: $f=14.594$, 25.476, 27.651, 29.463, 29.960, 30.152, 30.238, 31.323.

Output: $a/h=0.405$; actual value $=0.4$; error $=1.25\%$.

4.2.4. Training for storage tank for crack at a 5 m from bottom

Input: $f=14.595$, 24.723, 25.696, 29.556, 29.670, 30.172, 30.321, 30.870.

Output: $a/h=0.408$; actual $=0.4$; error $=2\%$.

4.2.5. Training for storage tank for crack at 7.5 m from bottom

Input: $f=14.596$, 25.655, 26.376, 29.672, 29.921, 30.201, 30.296, 31.183.

Output: $a/h=0.4044$; actual $=0.4$; error $=1.1\%$.

The values of frequencies shown in Sections 4.2.1–4.2.5 have been taken from the corresponding Tables 3–7of Section 4.1. The values corresponding to a particular *a/l* or *a/h* ratio in these tables were used for testing or validation and the values of the remaining ratios were used for training the neural network. A two layer network, one input layer and one output layer was used. There was no hidden layer. The input layer had eight neurons and ‘tansig’ as activation function whereas the output layer had one neuron and ‘purelin’ as activation function. ANNs can learn about the behaviour of damaged and undamaged structure. The ANN model was first trained with the sample of data that contained crack parameter (crack size ratio) and resulting frequencies from the FEM. This trained ANN model was then used to reconstruct the crack parameter by feeding in the measured frequencies. The reconstructed crack parameter is further examined by checking whether or not calculated values satisfactorily match the measured ones. If not the ANN model would have another round of retraining until a satisfactory match is reached. Training of ANN has been done with 1000 number of epochs and TRAINLM training algorithm was used.

5. Conclusions

FEM results show that if the crack size increases, a frequency reduction takes place. The change in frequencies due to the presence of a defect is a function of the crack length and its location and it also depends upon the mode shapes of the structure. The location of damage affects different modes of vibration differently. A neural network was used to predict the size of damage at a particular location. In the FEM, crack dimensions and locations were given as input and natural frequencies were obtained as output. In the neural network frequencies were used as input and crack size as output. So the neural network is an inverse damage detection technique and can be used as a tool in condition monitoring. It is a promising tool for damage detection and output from the ANN model improves with the increase in retraining process.

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