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VIBRATION-BASED DAMAGE DETECTION OF SLAB STRUCTURE USING ARTIFICIAL NEURAL NETWORK

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Abstract. This paper investigates the effectiveness of artificial neural network (ANN) in identifying damages in structures. Global (natural frequencies) and local (mode shapes) vibration-based data has been used as the input to ANN for location and severity prediction of damages in a slab-like structure. A finite element analysis has been used to obtain the dynamic characteristics of intact and damaged structure to train the neural network model. Different damage scenarios have been introduced by reducing the local stiffness of the selected elements at different locations along the structure. Several combinations of input variables in different modes have been used in order to obtain a reliable ANN model. The trained ANN model is validated using laboratory test data. The results show that ANN is capable of providing acceptable result on damage prediction of tested slab structure.

Keywords: Structural damage detection, artificial neural network

Abstrak. Kertas kerja ini memaparkan kajian berkenaan keberkesanan *Artificial Neural Network (ANN)* dalam mengenal pasti kerosakan di dalam struktur. Data dari getaran seperti frekuensi semula jadi dan mod bentuk digunakan sebagai data masukan bagi ANN untuk meramalkan lokasi dan tahap kerosakan bagi struktur lantai. Analisis unsur terhingga *(Finite Element Analysis)* telah digunakan untuk memperoleh ciri-ciri dinamik bagi struktur-struktur rosak dan tidak rosak untuk 'melatih' model '*neural network*'. Senario kerosakan yang berbeza disimulasikan dengan mengurangkan kekukuhan elemen pada lokasi yang berbeza sepanjang struktur tersebut. Berbagai kombinasi data masukan bagi mod yang berbeza telah digunakan untuk memperolehi model ANN yang terbaik. Hasil kajian ini menunjukkan ANN mampu memberikan keputusan yang baik dalam meramal kerosakan pada struktur lantai tersebut.

Kata kunci: Ramalan kerosakan struktur, *Artificial Neural Network*

1.0 INTRODUCTION

Much research effort has been spent on various structural health monitoring techniques in order to develop a reliable, efficient and economical approach to increase the safety and reduce the maintenance cost of civil structures. Many different techniques have been proposed and investigated ranging from application of electrical impedance techniques to structural dynamics approaches. Among these techniques, structural dynamics approach has been extensively explored by many researchers due to the reason that it can provide information on potential failure

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mechanisms that are unforeseen. Since the earliest work by Crawley and Adams [1], there has been numerous research utilising modal parameters in damage identification, most of them reported that modal parameters is capable of addressing the existence and location of the damages. Dynamic parameters such as natural frequencies, mode shapes and structural damping are functions of some selected structural parameters, where any degradation of structural properties would result in the changes in those dynamics parameters.

According to a review by Salawu [2], although changes of natural frequencies is a useful parameter to indicate the existence of damage in structure, it is not sufficient to locate the damage. Therefore, extra information such as mode shape is needed to overcome this weakness. Additionally, multiple modes are often needed to provide better estimation of damage severities and locations. Since damage detection is a non-linear and an inverse process, application of such algorithm is usually very complicated and sometimes not feasible. An approach based on artificial intelligence system such as neural network (ANN) would be the methods of choice due to its capability in adaptive learning, self-organization and its suitability for real-time operations [3]. There has been quite large amount of ANN applications for damage identification purpose, most of them focused towards using different vibration-based analysis data directly or indirectly as the input variables [4-8], process mapping [5, 9-11] and different types of algorithm [12-14].

Most of the previous works using ANN techniques to detect structural damage are purely numerical based, i.e. the structural damage and the associated changes in vibration properties were simulated numerically [9, 15, 16]. Application of ANN model to detect both real and laboratory structural damage is quite limited.

The primary objective of this work is to demonstrate the ability of ANN models, which are trained using numerically simulated damage data, to detect damage location and severity of laboratory tested RC slab. Unlike numerically simulated damage data, which are noise free, the measured vibration data from real or laboratory structures inevitably contain noises. Therefore, the accuracy of a trained ANN model with numerical data in detecting real structural damage needs to be proven.

2.0 METHODOLOGY

There are 3 main parts in this work: i) numerical analysis, ii) experiment and iii) application of ANN in detection of damage severity and location using experimental data.

The numerical analysis concentrates on generation of training data using dynamic analysis based on finite element analysis (FEA). Different damage scenarios at different damage extents and locations were generated by varying modulus of elasticity (E) to represent the stiffness reduction at different locations on the slab. The output of FEA are natural frequencies and corresponding mode shapes. They were used as the ANN input parameters.

The experimental work was carried out to obtain the on-site modal data whereby a reinforced concrete slab was tested progressively to failure. Natural frequencies and mode shape values of the slab at three different damage states were recorded. They were used as the input data to predict the failure condition of the slab.

The ANN model in this study was developed using MATLAB's neural network toolbox. The model was trained using the data from intact and damage cases produced by FEA. To study the efficiency and accuracy of the ANN model, it was trained with different levels of data availability, varying from only natural frequencies to the combination of natural frequencies and mode shapes. The trained model was then applied to detect damage locations and severity of laboratory tested RC slab-like structure using measured vibration data of different damage states.

3.0 EXPERIMENT DATA AND FINITE ELEMENT MODEL

The experimental data was obtained from Nguyen [17] and the specimen used was a two-span reinforced concrete slab with a dimension of 6400 mm $\times$ 800 mm $\times$ 100 mm. The concrete grade is 32 and the mass density is 2.55×10^3 kg/m^3. The slab rested on wooden planks placed over three steel UB sections.

The slab was loaded by applying two point loads at the middle of both spans using two hydraulic jacks. Each of the loads was positioned at the middle of each span. Three types of increment loads were applied to produce 3 damage states i.e. 23.4 kN (working load), 37.2 kN (ultimate load) and beyond the ultimate load until the slab failed. Vibration tests were performed at the intact level and after each increment load. Working and ultimate damage states modal data were used as the input to predict the failure condition. The outcome was then verified by the slab failure pattern obtained after the slab was loaded beyond ultimate load.

A 5.4 kg impact hammer, 16 accelerometers and a 16-channel input acquisition system were used for vibration test. There were a total of 27 measured points on the slab to extract both bending and torsional modes. However, in this study, only vertical bending mode shapes of the middle slab were taken as the input of ANNs. Figure 1(a-b) shows the dimension of the slab and the location of accelerometers. DIAMOND software which runs on MATLAB platform was used to post-process the data to obtain natural frequencies and mode shapes. The measured 3 modes of frequencies for different damage states are given in Table 1.

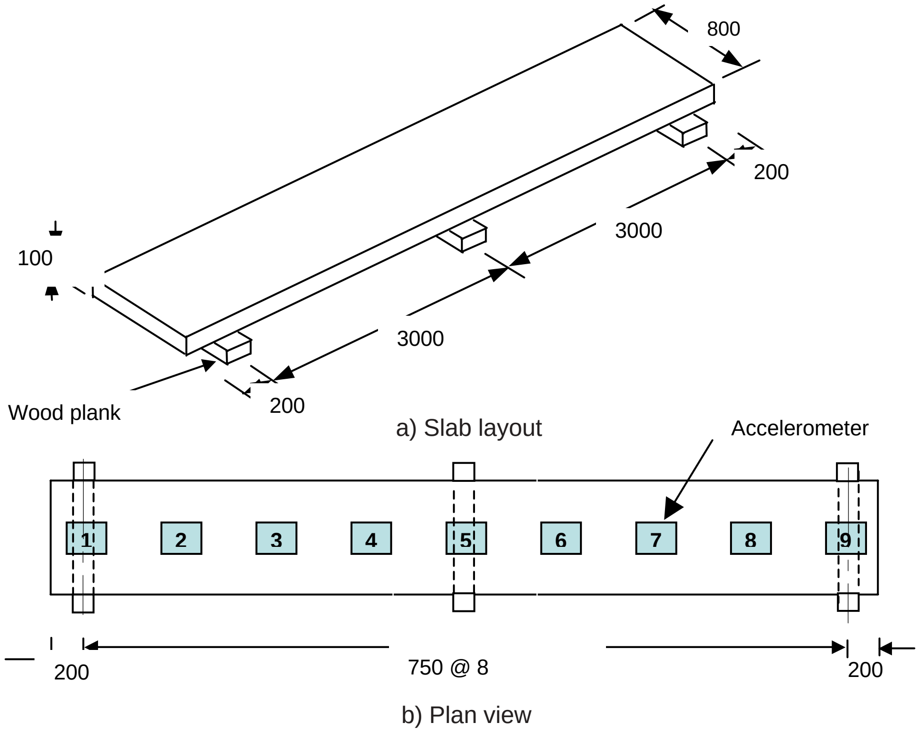


Figure 1 The dimension of the slab (mm) and the location of accelerometers

Table 1 Frequencies (Hz) of the slab at different load levels

Load (kN)	Mode 1	Mode 2	Mode 3
Undamaged (0 kN)	18.530	24.608	68.187
Working (23.4 kN)	16.127	20.712	60.827
Ultimate (37.2 kN)	10.442	15.718	49.861

In the experiment, the supports were not restrained vertically, thus the mode shapes obtained in the experiment were proportionally shifted to resemble the restraint condition. Figure 2 shows the shifted mode shapes for undamaged, working and ultimate damage states.

It was found that the accelerometer at location 4 was not functioning correctly and those at locations 1, 5 and 9 always provide 0 values in every mode, hence only 5 mode shape values (l2, 3, 6, 7, 8) were taken as the input for ANN.

Figure 3 shows the failure occurred after loading beyond ultimate load. The crack took place at the centre support and at the middle of first span. There was no crack observed in the second span.

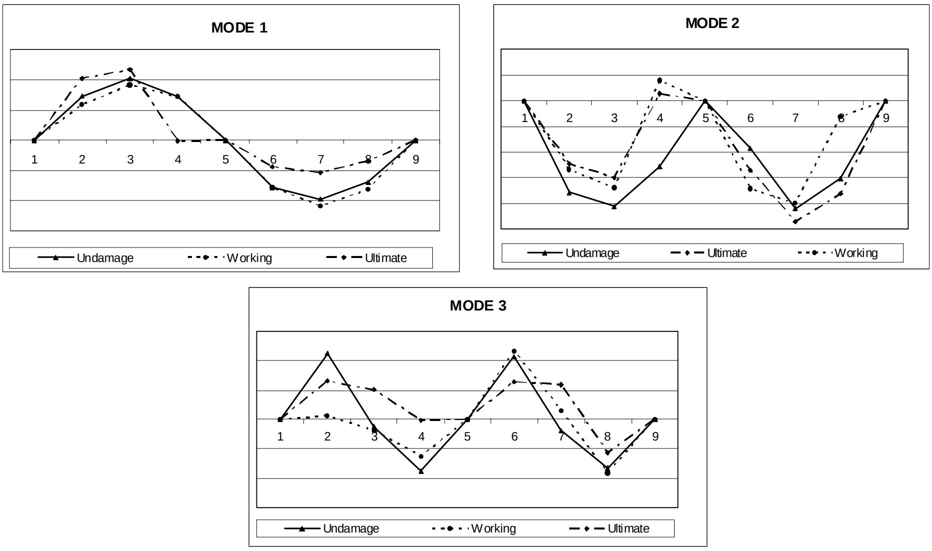
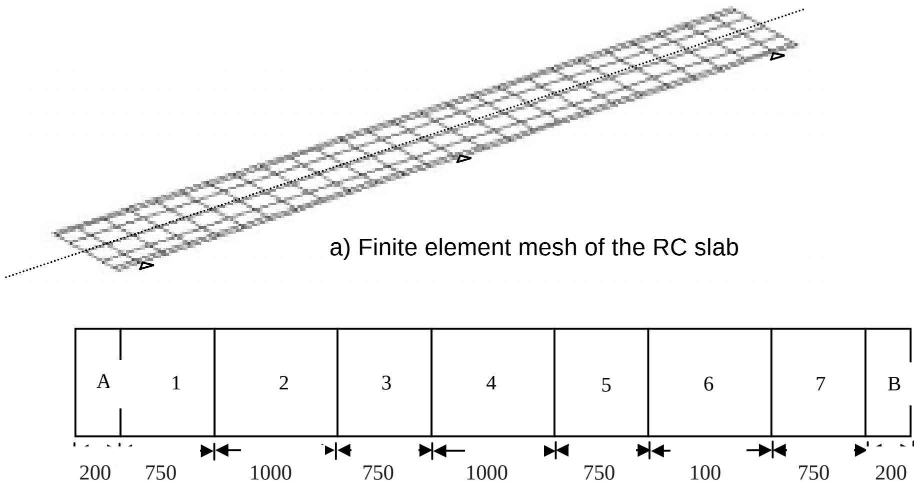


Figure 2 Mode shapes for undamaged, working and ultimate damage states for the first 3 modes

Figure 3 Cracks occurred on the slab after being loaded beyond ultimate load

The RC slab was modelled using Finite Element Modeling (FEM) in which the deck and bottomside of the slab were considered as shell elements. It was supported with 3 supports, which were assumed as hinge supports. Figure 4(a) shows the finite element mesh of the structure having 189 nodes and 156 elements. For the purpose of damage location, the slab was divided into 9 sections from end to end as shown in Figure 4(b). It is assumed that every element within the same section has the same material properties. The material properties used are: Modulus of elasticity (E) = 3.3 Mpa, density (ρ) = 2.45×10^3 kg/m^3, Poisson's ratio (ν) = 0.2.



a) Finite element mesh of the RC slab

b) Sections on the slab (mm)

Figure 4 (a) – (b) Finite element mesh and sections on the slab

Modal analysis using FEM was carried out to generate input and output data for ANN training and testing.

4.0 MODEL UPDATING

The purpose of model updating is to tune the finite element model. Modulus of elasticity (E) values have been chosen as the updating parameter. The measured vibration frequencies of the undamaged slab were used as target parameters for model updating.

A 18:64:9 multilayer perceptron ANN with backpropogation algorithm was used for updating purpose. Natural frequencies and mode shapes for 3 bending modes were used as the input parameters, while the output was represented by the divided sections. Table 2 shows the vibration frequencies before and after updating, and the experimental natural frequencies. Figure 5 shows the updated mode shapes as compared with the experimental mode shapes.

The updated vibration frequency and the mode shape are not exactly the same as measured data. This is probably due to the idealised hinge support conditions used in the finite element model, which is not the same as the actual support conditions. The support parameters are not included in the current updated process. However, a further study is underway that also includes the support conditions as updating parameters, from which improved results are expected. The E values are as listed in Table 3.

Table 2 Comparison of measured frequencies and vibration frequencies before and after model updating

Model	**Mode 1**	**Mode 2**	**Mode 3**
Initial	18.497	29.023	73.931
Updated	18.234	27.835	71.962
Experimental	18.306	25.301	69.267

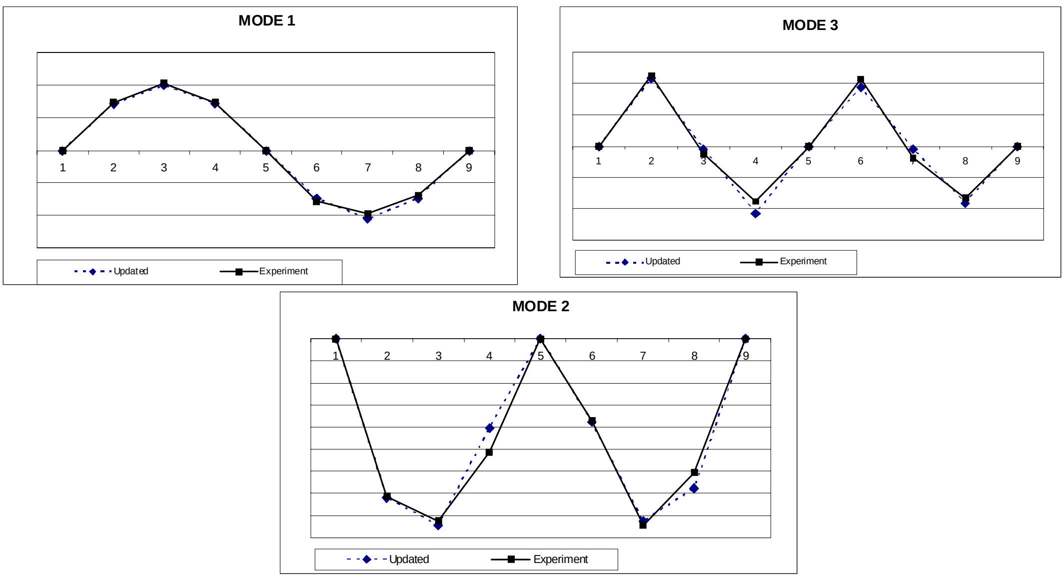


Figure 5 Comparison between the experimental and updated mode shapes

Table 3 Updated values of Modulus of Elasticity (E)

Section	**A**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**B**
E ($\times 10^{10}$) (Mpa)	3.10	2.65	3.54	3.12	2.65	3.25	3.25	3.02	3.1

5.0 TRAINING ANN MODEL

In order to find the most effective ANN model that utilises modal data to predict damage severity and location, several ANN models was developed. Multilayer perceptron with backpropogation algorithm ANN with one hidden layer was utilized. The most suitable ANN model was determined using trial and error process by applying various numbers of hidden neurons incrementally. The lower and upper bound of number of hidden neurons were set based on Kalmorogov's and Lippmann [18] approach. The formula is as shown below:

$$\text{Lower bound of neurons in hidden layer: } 2N+1 \tag{1}$$

$$\text{Upper bound of neurons in hidden layer: } OP*(N+1) \tag{2}$$

where N is the number of input neurons and OP is the number of output neurons.

The numbers of neurons of input and output were the same as the number of input and output variables respectively. The ANN was trained using 7000 epoch by maintaining learning rate at 0.05. Sigmoid function was used at both layers.

In training process, ANN was required to perform two tasks: i) reproduce the pattern it was trained on (training performance) and ii) predict the output of given pattern it had not seen before (testing performance). The best ANN model was chosen based on the best testing performance on the basis of minimum mean square error (MSE). Once the best model had been determined, validation process was conducted by introducing a new set of damage scenario produced by FEM. This was followed by application of experimental data to predict the corresponding E values (E') at different levels.

The training samples should cover all possible damage cases which involve the location and the extent of damages. Since the total number of damages such as the number of cracks is very large even for simple structure, Latin hypercube sampling [19] was used to obtain the well distributed damage in terms of damage severity and location, thus the whole sample may be represented effectively with limited number of data. The damage severities were modelled in terms of Young's modulus reduction, applied for each element and ranged between 0 to 0.9. The total number of data set was 1801, out of which 320 sets were taken randomly for testing purpose and the rest were used for training including one with no damage. The data was normalised between the range of 0 to 1 to ensure that all the data contributed evenly and to fulfill the criteria of the transfer function.

To evaluate the effect of different input parameters to ANN performance, 4 different input combinations were used for training and testing, as follows:

(i) Natural frequencies of 3 vibration modes (3FREQ)
(ii) Natural frequencies and mode shape value of 1 vibration mode (1FREQ & 1MSHP)

(iii) Natural frequencies and mode shape value of 2 vibration modes (2FREQ & 2MSHP)
(iv) Natural frequencies and mode shape value of 3 vibration modes (3FREQ & 3MSHP)

Due to the very minimum effect of 2 elements at both ends, only 7 elements between the end supports of the slab were taken as the output.

Table 4 shows the result of ANN training and testing performance for different input combination and the corresponding ANN model architecture.

Table 4 ANN performance for different input combinations

Input	Training performance (MSE)	Testing performance (MSE)	Model
3 FREQ	0.045664	0.047967	3-18-7
1FREQ & 1MSHP	0.023211	0.025361	6-44-7
2FREQ & 2MSHP	0.015081	0.016244	12-73-7
3FREQ & 3MSHP	0.012844	0.014673	18-114-7

It is observed that the testing and testing performance increased when higher numbers of mode data are used as the input for training. ANN model results in larger error when only natural frequencies are used as the diagnostic parameter. This indicates that the combination of global and local vibration parameters provides better outcome than using global parameter only. Figure 6 provides the results of the damage severity predicted by ANN for validation purpose for different input combinations. Damage severities are addressed using elemental Stiffness Reduction Factor (SRF), which indicates that the higher SRF, the higher the severity. The equation is as follows:

$$SRF = 1 - \frac{E'}{E} \tag{3}$$

The result above shows that in most cases, ANN is able to provide good prediction. The combination of natural frequencies and modes shapes at higher mode is able to produce higher accuracy, while higher error is observed when ANN is only trained using natural frequencies.

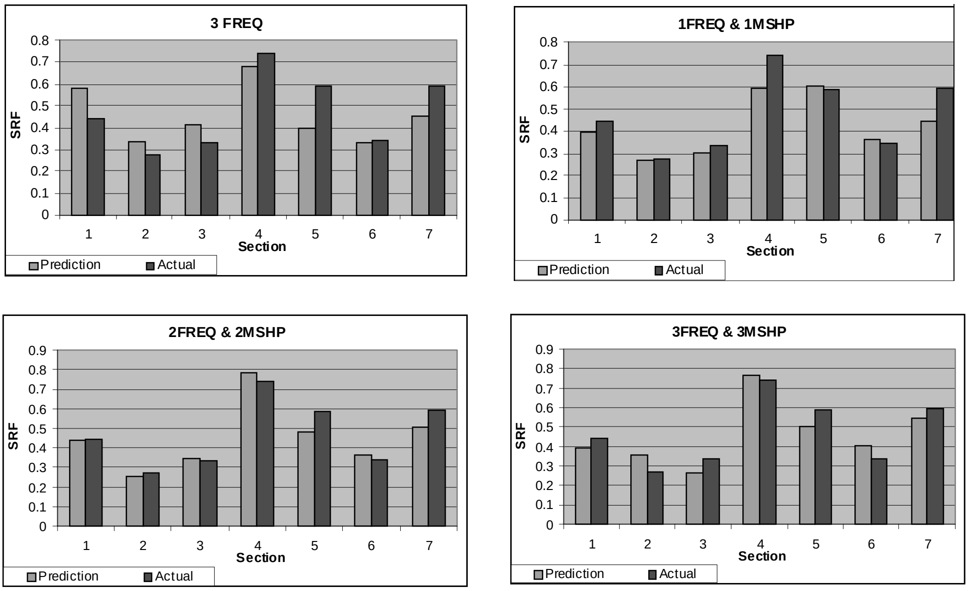


Figure 6 ANN damage prediction using numerical data

6.0 DAMAGE IDENTIFICATION USING THE TRAINED ANN MODEL

To detect the damage occurred on the slab for real case, experimental data was applied to the trained ANN to predict the damage occurred on the slab for working and ultimate damage states. The prediction results are shown in Figure 7.

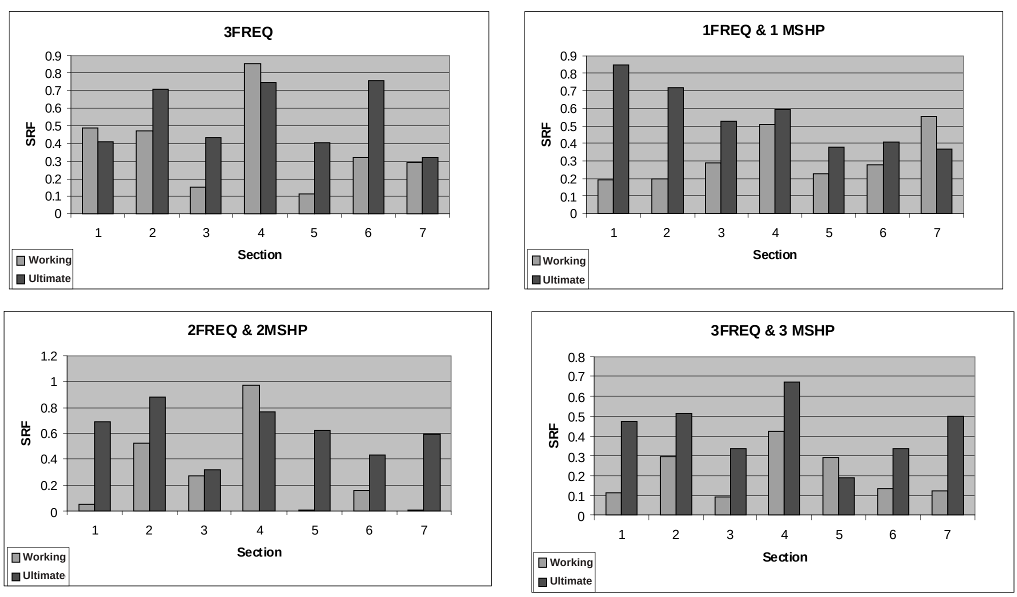


Figure 7 ANN prediction using experimental data

Based on the results above, at working damage states, ANN was unable to provide correct failure pattern using the model trained with natural frequencies only and combination of first mode natural frequencies and mode shapes. However, the cracks at Section 2 and 4 were correctly located using ANN model that was trained using combination of natural frequencies and mode shapes at higher modes. At ultimate damage state, all ANN models were unable to predict accurate damage pattern. To verify the results, the measured frequencies of experiment (NFexp) were compared with natural frequencies calculated by FE using E' values (NF'). Tables 5 (a)-(d) show the comparison.

Table 5(a) Comparison of NFexp and NF' for 3FREQ

	Working			Ultimate		
Mode	NFexp	NF'	Δ (%)	NFexp	NF'	Δ (%)
1	16.127	13.970	13.380	10.442	10.613	1.638
2	20.712	18.402	11.153	15.718	15.533	1.177
3	60.827	49.102	11.725	49.861	46.096	7.550
Average error (%)			12.086	**Average error (%)**		3.297

Table 5(b) Comparison of NFexp and NF' for 1FREQ & 1MSHP

	Working			Ultimate		
Mode	NFexp	NF'	Δ (%)	NFexp	NF'	Δ (%)
1	16.127	15.476	4.030	10.442	11.266	7.891

Table 5(c) Comparison of NFexp and NF' for 2FREQ & 2MSHP

	Working			Ultimate		
Mode	NFexp	NF'	Δ (%)	NFexp	NF'	Δ (%)
1	16.127	14.756	8.500	10.442	10.613	9.106
2	20.712	20.857	0.700	15.718	15.533	16.939
Average error (%)			4.600	**Average error (%)**		13.023

Table 5(d) Comparison of NFexp and NF’ for 3FREQ & 3MSHP

	Working			Ultimate		
Mode	NFexp	NF’	Δ (%)	NFexp	NF’	Δ (%)
1	16.127	16.170	0.267	10.442	13.932	33.422
2	20.712	23.693	14.393	15.718	19.474	23.896
3	60.827	63.713	4.744	49.861	53.074	6.440
Average error (%)			6.468	**Average error (%)**		21.254

Tables 5(a)-(d) show that ANN trained using natural frequencies only (3FREQ) produced highest error compared to the other cases. For the cases using combination of natural frequencies and mode shapes, a higher error was observed when ANN model was trained using higher modes. This is probably due the noise in the measured signal, which might lead to the error in input data. By comparing the ANN prediction between working and ultimate damage states, the natural frequencies predicted by ANN using data from ultimate damage state produced higher error compared to the working damage states. By referring to the mode shape of ultimate damage state (Figure 2), it is suspected that the existence of errors at second span particularly at 3rd mode shape has contributed to this outcome.

The results of this study show that, in theory, more modal data will give better predictions on structural damage when the data is free from error. This is evidenced when ANN is able to provide reliable prediction when the data produced by FEA is applied. However, in actual application of the method to identify structural damage, because of the inevitable errors in vibration measurements, and uncertainties in structural model, a well-trained ANN model using error free data does not necessarily give reliable prediction of structural damage. Moreover, since more measured data will introduce more possible errors in the trained model, using more data is not necessarily beneficial in terms of damage identification. Therefore, although an ANN model in theory can predict structural damage, as demonstrated in this paper, and in many publications by other researchers using error-free numerical simulations, in order to reliably use it, accurate measurement and FE modeling are needed. It is also very important to include possible uncertainties in the model training.

7.0 CONCLUSION

In this study, a slab-like structure with two damage states was studied for the application of ANN to detect damage and severity after load application. Damages were simulated by reducing the values of modulus of elasticity. All the required data were generated using finite element analysis. Global (natural frequencies) and local (mode shape) dynamic parameters were utilised in this study. The following conclusions have been made based on the results obtained.

(i) ANN is capable of establishing the relationship between causes and effects of damage if the data is free from error. The result shows that ANN produced good performance when tested using the data produced by finite element.

(ii) Higher mode of dynamic parameters provides better performance for training and testing. However, for practical purpose, higher mode provides higher error, thus reduces the efficiency of ANN.

(iii) In this application, it is assumed that the FE model is precise enough to represent the vibration properties of the structure. However in practice, there are many uncertainties during the model updating procedure such as the FE modelling error and measurement noise. To improve the result, the existence of uncertainties should be taken into account.

(iv) Gradient descent algorithm such as backpropagation algorithm still unable to provide high level convergence rate. This is evidence from Table 4, where the existence of error during training needs to be improved in order to reduce the error in prediction. Moreover, this type of algorithm suffers from slow convergence and sometimes falls to local minima which leads to inaccuracy in prediction.

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