IDENTIFICATION OF DAMAGE IN STEEL BEAM BY NATURAL FREQUENCY USING ANNS MODELS

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ABSTRACTS: Beams have played a significant role in engineering applications and they have been commonly used for modelling civil problems. In fact, different models and methods have been developed to identify the damage to the beams. In this paper, the artificial neural network (ANN) model was developed to predict the location, width and depth of the saw-cut of steel beams by the change of natural frequencies. The natural frequencies of a steel beam in different scenarios were identified by the Finite Element Method (FEM). In order to validate the accuracy of FEM model, the natural frequencies of the steel beam in the case of no saw-cut determined by this model were compared with those determined by the Frequency Domain Decomposition (FDD) method. The results indicated that, the combination of FEM method, FDD method and ANN model would have great significance in structure health monitoring.

KEYWORDS: Crack prediction, ANN, natural frequency, Frequency Domain Decomposition, FEM dynamic analysis.

1. INTRODUCTION

Beams have played a significant role in engineering applications and they have been commonly used for modelling civil problems. In fact, different models and methods have been developed to identify the damage to the beams. Yang XF [1] applied the Galerkin's and energy method to identify the crack in vibrating beams. Swamidas ASJ [2] used Timoshenko and Euler formulation to determine the cracks in the beam. Gillich Gilbert-Rainer and Zhou Yun-Lai [3-5] detected the damage crack based on the vibration measurement. Zhou Yun-Lai [6] also studied the forced vibration of the cracked beam. The results of these studies demonstrated a good performance in structural damage detection.

In recent years, Artificial Neural Networks (ANNs) are becoming an efficient tool for predicting the damage within the structure. Lee Jong-Won [7] developed a technique to detect location and size of a through-the-thickness crack in straight thin-walled pipe subjected to bending using the modal properties and ANN. Samir K [8] addressed the damage identification problem by means of a Genetic Algorithm (GA) approach based on the change of the natural frequency. Gowd B Prakruthi [9] proposed two algorithms of crack detection one using fuzzy logic (FL) and the other artificial neural networks (ANN). The artificial neural networks (ANN) and adaptive neuro-fuzzy inference systems (ANFIS) were also used to predict the size of the crack and its location based on the natural frequencies and frequency response functions [10]. The natural frequencies used as inputs for ANN were also presented by Nazari F and Baghalian [11] and Rao Putti Srinivasa [12]. However, these studies almost have not mentioned the prediction of crack width and the position of the crack to be investigated has been evenly spaced.

The use of eXtended Finite Element (XFEM) and eXtended IsoGeometric Analysis (XIGA) coupled with PSO and Jaya algorithm for predicting crack position and length in plates was presented by Khatir Samir [13]. Khatir Samir also [14] developed a two-stages approach based on normalized Modal Strain Energy Damage Indicator (nMSEDI). The result indicated that the Teaching Learning Based Optimization (TLBO) - Artificial Neural Network (ANN) - Particle Swarm Optimization (PSO) combined to IsoGeometric Analysis (IGA) could be used to determine correctly the severity of damage in beam structures. The ANN combined with PSO (ANN-PSO) was also investigated to predict the crack depth in pipeline structure based on modal analysis technique using Finite Element Method (FEM) [15]. Mortazavi SNS [16] developed a radial basis function artificial neural network (RBF-ANN) model to predict the fatigue crack growth, including the short and long crack regimes. The predictions showed that the RBF-ANN model has a good interpolation capability to predict the nonlinearity of both short and long crack growth behavior. However, these studies almost have not mentioned the prediction of crack width and the position of the crack to be investigated is also evenly spaced. However, the width of the crack has not also been mentioned and the input data of these models were stress intensity factor range, stress ratio etc, these data are difficult quantities to measure in structure.

In this paper, the ANN model is developed to predict the location, width and depth of the saw-cut of steel beams by the change of natural frequencies. The natural frequencies of a steel beam in different scenarios are identified by the FEM model. In order to validate the accuracy of FEM model, the natural frequencies of the steel beam in the case of no saw-cut determined by this model are compared with those determined by the Frequency Domain Decomposition (FDD) method. Finally, conclusions are presented.

2. IDENTIFICATION OF NATURAL FREQUENCIES BY FREQUENCY DOMAIN DECOMPOSITION (FDD) AND FINITE ELEMENT (FEM) METHOD

2.1. Identification of natural frequencies of the steel beam by Frequency Domain Decomposition (FDD)

Frequency domain decomposition is proposed by Brinker et al. [17]. This method decomposes the spectral density matrix at each frequency into singularity values and singularity vectors by the singular value decomposition (SVD). Frequency domain decomposition is an extension of the basic frequency domain technique or commonly known as the Pick Peaking technique, in which natural frequencies is identified by finding peaks in the spectral density matrix.

The relationship between unknown input x(t) and measured response output y(t) can be expressed as follows:

$$[G_{yy}(\omega)] = [H(\omega)]^{*}[G_{xx}(\omega)][H(\omega)]^{T} \quad (1)$$

Where:

$[G_{xx}(\omega)]$ is the Power Spectral Density (PSD) matrix of the input;

$[G_{yy}(\omega)]$ is the PSD matrix of the responses;

$[H(\omega)]^{*}$ is the complex conjugate matrix of Frequency Response Function (FRF);

$[H(\omega)]^{T}$ is the transpose matrix of FRF.

The FRF can be written in prutial fraction:

$$\left[H(\omega)\right] = \sum_{1}^{N} \frac{[\mathrm{R}_k]}{j\omega - \lambda_k} + \frac{[\mathrm{R}_k]^{*}}{j\omega - \lambda_k^{*}} \quad (2)$$

$$\lambda_k = -\sigma_k + j\omega_{dk} \quad (3)$$

Where: n is the number of modes, λ_k is the pole of the k^{th} mode shape, σ_k is minus the real part of the pole and ω_{dk} is the damped natural frequencies of the k^{th} mode shape.

$[\mathrm{R}_k]$ is the residue expressed as follows.

$$[\mathrm{R}_k] = \phi_k . \gamma_k^{T} \quad (4)$$

Where: ϕ_k is the mode shape vector, γ_k the modal participation vector.

Suppose the input is white noise, its power spectral density is constant or

$[G_{xx}(\omega)]$ = C, (C is constant). Formula is rewritten as follows:

$$[G_{yy}(\omega)] = \sum_{1}^{N}\sum_{1}^{N}\left[\frac{[\mathrm{R}_k]}{j\omega - \lambda_k} + \frac{[\mathrm{R}_k]^{*}}{j\omega - \lambda_k^{*}}\right] \times C \times \left[\frac{[\mathrm{R}_k]}{j\omega - \lambda_k} + \frac{[\mathrm{R}_k]^{*}}{j\omega - \lambda_k^{*}}\right]^{T} \quad (5)$$

Multiplying the two partial fraction factors and making use of the Heaviside partial fraction theorem, after some mathematical manipulations, the output PSD can be reduced to a pole/residue form as follows:

$$[G_{yy}(\omega)] = \sum_{1}^{N} \frac{[A_k]}{j\omega - \lambda_k} + \frac{[A_k^{*}]}{j\omega - \lambda_k^{*}} + \frac{[B_k]}{-j\omega - \lambda_k} + \frac{[B_k^{*}]}{-j\omega - \lambda_k^{*}} \quad (6)$$

Where: $[A_k]$ is the k^{th} residue matrix of the output PSD.

At a certain frequency ω only a limited number of modes will contribute significantly, typically one or two modes. Thus, in the case of a lightly damped structure, the response spectral density can always be written:

$$[G_{yy}(\omega)] = \sum_{k \in Sub(\omega)} \frac{d_k \phi_k \phi_k^{T}}{j\omega - \lambda_k} + \frac{d_k^{*} \phi_k^{*} \phi_k^{*T}}{j\omega - \lambda_k^{*}} \quad (7)$$

Where: $k \in$ Sub(ω) is the set of modes be denoted at a specific frequency, ϕ_k is the mode shape vector and λ_k is the pole of the k^{th} mode shape.

The Frequency domain decomposition technique is based on the singular value decomposition of the Hermitian response spectral density matrix.

$$[G_{yy}(\omega)] = [\mathrm{U}][S][\mathrm{U}]^{H} \quad (8)$$

Where: $[S]$ is a diagonal matrix holding the scalar singular values, $[U]$ is a unitary matrix holding the singular vectors and $[U]^H$ is a Hermitian matrix.

From vibration measurement data of the structure (acceleration), we calculate the spectral density matrix $[G_{yy}(\omega)]$ and decompose the singular value according to formula (8) to determine the natural frequencies of the structure.

The test to obtain dynamic responses (acceleration) of steel beam structures at nodes over time. The result of vibration measurement is used to identify the natural frequencies of the structure. The physical parameters of the structure are shown in Table 1. The equipment used in the test are NIcDAQ-9137 and two accelerameter (PCB 352C68, PCB 353B33). Two accelerometer sensors to measure the vibration of the beam (Figure 2), the NIcDAQ-9137 connected with accelerometer sensors and display (Figure 1). Accelerometer measurements are collected and displayed through the NI Signal Express software pre-installed. Proceed with the installation and install parameters for measuring equipment, create vibration for the structure by any stimulus is large enough for the structure to work in the elastic stage. The measured data are recorded as the value of the acceleration over time at the location where the acceleration is mounted.

After measuring the vibration of the structure, acceleration at the nodes on the steel girder structure

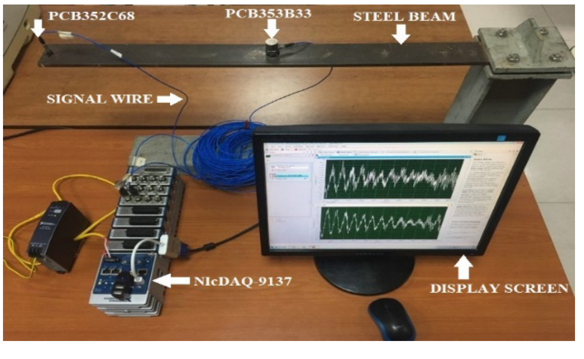

Figure 1. Experiment setup of the real structure

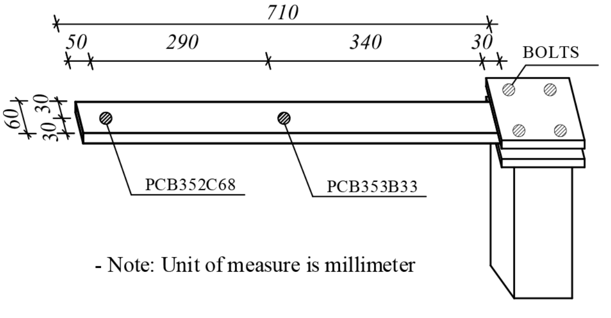

Figure 2. The position of the sensors

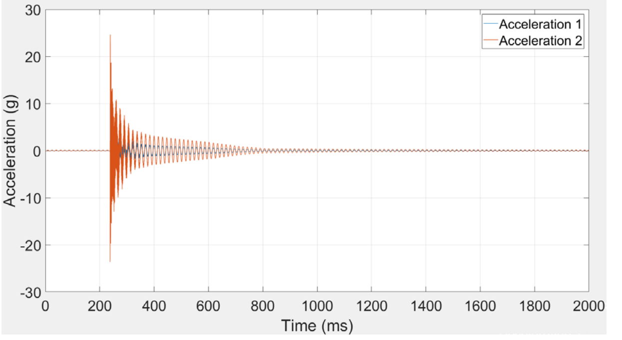

Figure 3. Results of acceleration of the beam

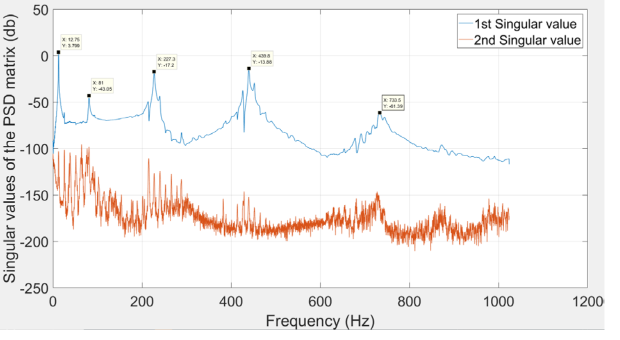

Figure 4. Power spectral density (PSD)

is obtained over time. The data of one measurement is shown in Figure 4 and Figure 5. With the acceleration data obtained from the experiment, calculate and estimate the power spectral density according to Welch's estimation method and resolve the singularity values by SVD algorithm according to formula (8). We determine the natural frequencies of the structure corresponding to the positions of the maximum power spectral density function. Results of identifying the five natural frequencies are shown in Figure 3.

Test structure is a steel beam. The physical parameters of the structure are shown in Table 1.

Table 1. The physical parameters of the test structure

No	Parameter	Value	Unit
1	Length	710	mm
2	Density weight	7850	Kg/m^3
3	Modulus of elasticity	2.03x10^5	Mpa
4	Width	60	mm
5	Height	8	mm

After measuring the vibration of the structure, acceleration at the nodes on the steel girder structure is obtained over time. The data of measurements are shown in Figure 4.

With the acceleration data obtained from the experiment, calculate and estimate the power spectral density according to Welch's estimation method and resolve the singularity values by SVD algorithm according to formula (8). We determine the natural frequencies of the structure corresponding to the positions of the maximum power spectral density function. Results of identifying the five natural frequencies are shown in Figure 5.

Comparing the natural frequencies obtained by the FDD method and the results of the calculation of the natural frequencies by the experimental modal analysis (EMA) method are shown in the Table 2.

Table 2. Comparison of natural frequencies between methods

No	Mode	FDD (Hz)	EMA (Hz)	Error (%)	Theory (Hz)	Error (%)
1	1	12.75	12.8	0.4	12.9	1.2
2	2	81.0	79.8	1.5	80.9	0.1
3	3	227.3	228.6	0.6	226.6	0.3
4	4	439.5	446.1	1.5	444	1.01
5	5	733.5	735.6	0.3	734	0.07

2.2. Identification of natural frequencies of the steel beam by Finite Element Method (FEM)

A finite element model is generated in Abaqus using three-dimensional elastic beam elements (Figure 5). The beam is discretised into 34080 elements. The model is showed close agreement with the measured responses (Table 3).

In order to simulate the damage in the beam, the elements corresponding to the saw-cut are removed (Figure 6). The 219 damage scenarios are envisaged. In which, 214 scenarios (No. 1 to No.214) are used

Figure 5. Finite element model of beam

Table 3. The physical parameters of the test structure

No	Frequency Domain Decomposition (Hz)	Finite element method (Hz)	Error (%)
1	12.75	12.99	1.91
2	81	81.4	0.50
3	227.3	227.83	0.23

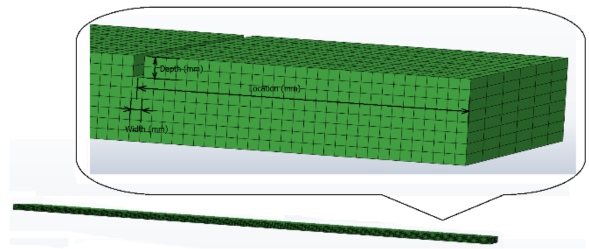

Figure 6. Finite element model of saw – cut beam

Table 4. Database developed by FEA

No	Location (mm)	Width (mm)	Depth (mm)	Natural frequencies			
				Mode 1 (Hz)	Mode 2 (Hz)	Mode 3 (Hz)	Mode 4 (Hz)
1	710.5	1	1	12.957	81.141	95.883	227.09
2	700.5	1	1	12.933	81.03	95.828	226.86
3	690.5	1	1	12.936	81.081	95.832	227.08
4	680.5	1	1	12.938	81.129	95.839	227.27
5	670.5	1	1	12.941	81.172	95.846	227.43
…	…	…	…	…	…	…	…
72	710.5	1	2	12.866	80.586	95.569	225.57
73	700.5	1	2	12.783	80.19	95.33	224.76
74	690.5	1	2	12.791	80.355	95.328	225.45
75	680.5	1	2	12.800	80.508	95.349	226.05
76	670.5	1	2	12.808	80.649	95.374	226.56
…	…	…	…	…	…	…	…
143	710	2	1	12.939	81.034	95.844	226.8
144	700	2	1	12.916	80.938	95.781	226.64
145	690	2	1	12.92	81.002	95.785	226.91
146	680	2	1	12.923	81.061	95.794	227.14
147	670	2	1	12.926	81.115	95.803	227.34
…	…	…	…	…	…	…	…
215	75.5	1	1	13.002	81.407	96.043	227.75
216	75.5	1	2	13.005	81.403	96.068	227.57
217	76	2	1	13.005	81.413	96.068	227.74
218	405.5	1	1	12.987	81.245	95.984	227.69
219	602.5	1	1	12.956	81.369	95.892	227.82

as training and validation data to build ANN model. The other 5 scenarios are used as testing data. Table 4 shows the damage scenario identification and the corresponding natural frequencies, which are developed by FEM. The additional appearance of Mode 3 in Table 4 is due to the fact that the FEM analysis model is three-dimensional, while in this experiment, we utilized a two-dimensional FDD model. However, in practice, it is possible to use

FDD to obtain all modes, similar to the FEM model. Table 5 shows ranges of variables in the database. These ranges are very important for prediction due to they imply the boundaries of the models.

Table 5. Ranges of variables in the database

No.	Variable	unit	count	min	max
1	Location	mm	219	0	710.5
2	width	mm	219	0	2
3	depth	mm	219	0	2
4	Mode 1	Hz	219	12.783	13.008
5	Mode 2	Hz	219	80.19	81.455
6	Mode 3	Hz	219	95.328	96.084
7	Mode 4	Hz	219	224.76	227.95

3. DEVELOPMENT OF THE ANN MODEL

The artificial neural network (ANN) models in this study have been developed with the aid of the software package PYTHON Version 3.11.0. Monitoring data includes natural frequencies and mode shapes; however, the mode shapes are not the number, so it is hard to normalize thus, the natural frequencies of four modes are chosen as input variables and the location, width, the depth of the saw - cut are selected as output variables.

3.1. Data division and preprocessing

The data have been divided into three subsets, training set for model calibration, validation set for model verification, and testing set. The testing set is completely random. The ratio of validation data to training data is 20%. It is consistent with the recommendation of author [18].

To make sure that all variables get equal attention during training, the preprocessing is conducted by scaling the input and output variables between 0.0 and 1.0. The scaled value of each variable is calculated as follows:

$$x_n = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{9}$$

Where x_{max} and x_{min} are the maximum and minimum values of each variable x.

3.2. Model architecture, weight optimization and stopping criterion

The model geometry (i.e., the number of hidden layers, the number of hidden nodes in each layer) and weight optimization (i.e., learning rate and momentum term) are very important to the development of the ANN models.

Hornik, Stinchcombe [19] suggested that a network with one hidden layer can approximate

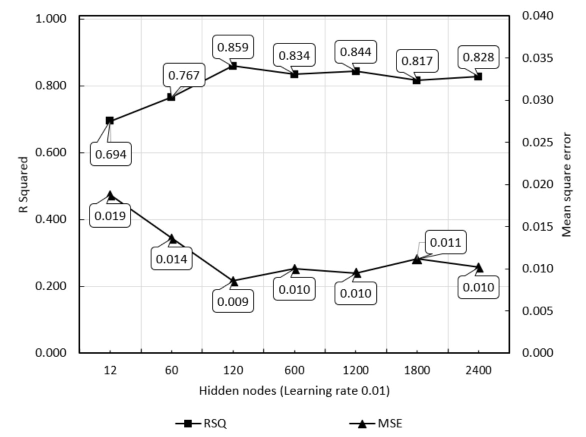

Figure 7. Effect of number of hidden layer nodes on performance of ANN model

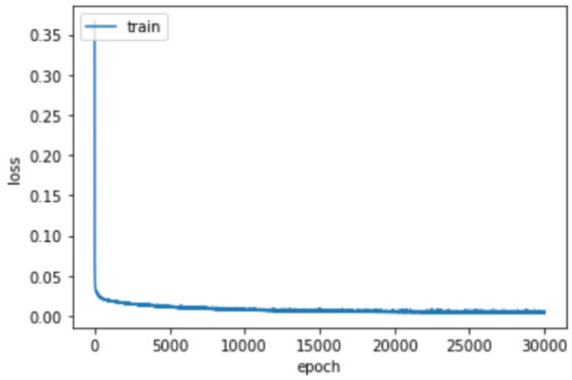

Figure 8. Variation of loss against epoch

any continuous function provided that sufficient connection weights are used. Thus, one hidden layer is used in this ANN model.

Transfer functions in the hidden and output layers are ReLU and Tanh, respectively. The 30000 epochs (training cycles) are selected to terminate the training process. This number basically satisfies the requirement that the training loss at the end of the training process does not fluctuate and does not increase (Figure 8).

Figure 7 shows the effect of the number of hidden nodes on the performance of model. The model with 120 hidden nodes indicates the lowest prediction error (the lowest value of the mean square error and the highest value of the R squared). The number of hidden nodes using for ANN model in this paper is much more than the number of hidden nodes recommended by Caudill [20] before.

The learning rate is a tuning parameter in an optimization algorithm that determines the step size at each iteration while moving toward a minimum of a loss function [21]. Figure 9 depicts the effect of the learning rate on the performance of ANN models. It can be seen that the lowest prediction error comes up with the learning rate of 0.0012. Adam optimizer is chosen for the gradient descent optimization algorithm. It already incorporates something like momentum; thus, the momentum term is not examined.

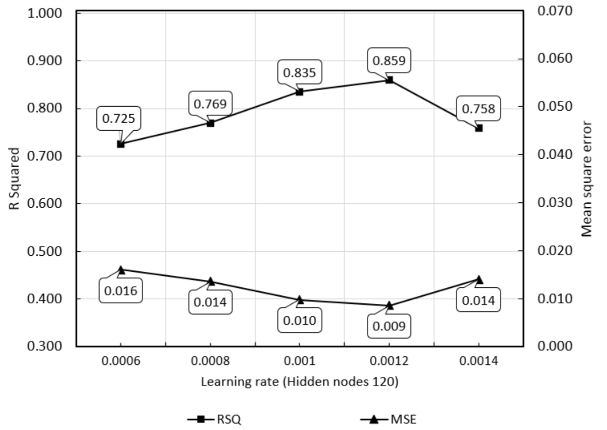

Figure 9. Effect of learning rate on performance of ANN model

3.3. Model validation and testing

After training, ANN model will be verified by the validation set. In the validation process, the R squared value, R^2, is 0.8385, and the mean

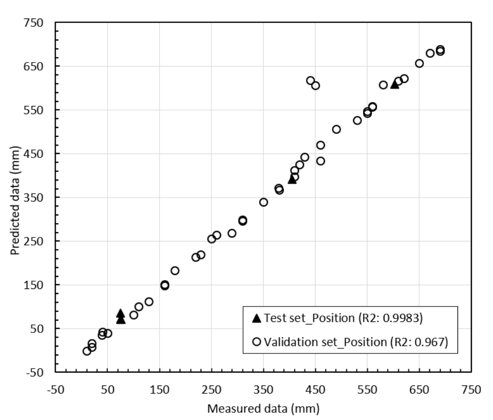

Figure 10. Scatter plots of predicted versus measured data for the position

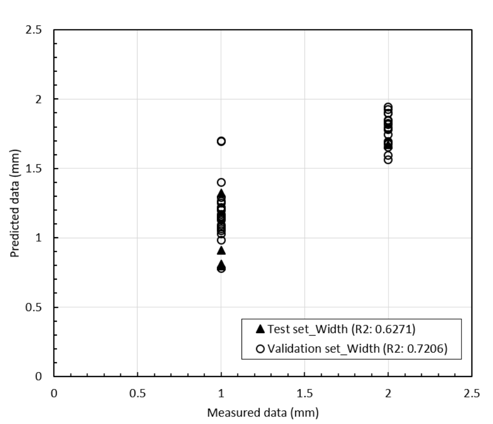

Figure 11. Scatter plots of predicted versus measured data for the width

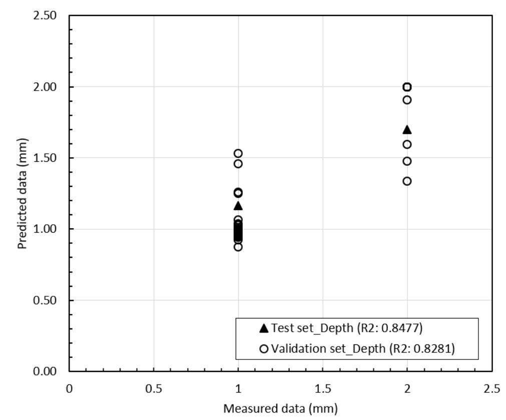

Figure 12. Scatter plots of predicted versus measured data for the depth.

Table 6. Accuracy in predicting the saw - cut location of the model

Predetermined value (mm)			Predicted value (mm)			Deviation (%)		
Location	Width	Depth	Location	Width	Depth	Location	Width	Depth
75.5	1	1	70.25	0.91	0.95	-6.96	-8.91	-4.83
75.5	1	2	85.68	1.32	1.70	13.48	32.42	-15.16
76	2	1	71.60	1.67	1.16	-5.79	-16.38	16.49
405.5	1	1	390.83	0.81	0.99	-3.62	-19.14	-1.36
602.5	1	1	608.77	0.80	0.98	1.04	-20.31	-1.51

squared errors value, MSE, is 0.0097. These values basically are better than that during testing. In the testing process, the R squared value, R^2, is 0.8244, and the mean squared errors value, MSE, is 0.0071. The explanation is that the data for validation are considered more principle than those used for testing process.

Figure 10 to Figure 12 show the performance of the ANN model for the location, the width and the depth of the saw - cut, respectively. It may be seen that the performance of the model for the position is the highest accuracy. The predicted values of the location of saw - cut have minimum scatter around the best fit line. It is possible that the training value of the location has better coverage than the rest. The value of the width and depth of the saw - cut is only 1mm or 2mm, so it could be confusing in the learning process of the model.

Table 6 shows the accuracy in predicting the location, the width and the depth of the saw - cut. The deviation between the measured value and the predicted value of the saw - cut location is the smallest. The biggest deviation of location is 13.48% while the biggest deviation of width and depth is 32.42% and 16.49%. This is also demonstrated by the R squared value. The R squared value for the location prediction of testing set is 0.9983. This value is bigger than the R squared value for the width and depth prediction (Figure 11, Figure 12). However, the model's accuracy is not very high. This could be due to the fact that the test data is arbitrary and entirely new. To increase the model's accuracy, we may need more training data or additional reliable independent variables.

4. CONCLUSIONS

After presenting how to determine natural frequency by frequency domain decomposition (FDD), using FEM method to generate data for ANN model and using ANN model to predict the location, the width and of the saw - cut of steel beams by the natural frequency, the main findings of this study were the following.

- The natural frequencies determined by the FDD method were consistent with those determined by the FEM method. Therefore, the natural frequencies of the structure over time could be exactly determined and reliably used as input parameters for ANN model to detect the damage saw - cut.

- The ANN model was capable of predicting the location, width, and depth of saw - cut in the beam by natural frequencies. The model predicted saw - cut location better than the other two values. However, the accuracy of the model was not so high. In order to increase the accuracy of the model, it may be needed more training data or more input reliable independent variables.

- The FEM method can be used to create a learning dataset at first or in the case of not enough monitoring data set. The combination of FEM method, FDD method and ANN model will have great significance in structure health monitoring.

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