Visual Abstract

Damage assessment in beam-like structures by correlation of spectrum using machine learning

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ABSTRACT. Damage assessment in the actual operating process of the structure is a modern and exciting problem of construction engineering due to several practical knowledge about the current condition of the inspected structures. However, the problem faced is the difficulty in controlling the excitation in structures. Therefore, the output-based structural damage identification method is becoming attractive because of its potential to be applied to an actual application without being constrained by the collection of the information excitation source. An approach of damage assessment based on supervised Machine Learning is introduced in this study by using the correlation of spectral signal as an input feature for artificial neural network (ANN) and decision tree. The output of machine learning algorithms consists of the appearance of new cuts, the level of cutting and the cutting position. A supported beam model was constructed as an experiment to determine if the method is reasonable for engineering structures. Different machine learning algorithms have been applied to check the relevance of the proposed feature from vibration data. This study contributes a standard in the damage identification problem based on spectral correlation.

KEYWORDS. Damage identification; Artificial neural network (ANN); Decision Tree; Spectral correlation, beam-like structure.

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INTRODUCTION

Structural health monitoring (SHM) plays a vital role in ensuring the safety and entirety of the structures by assessing the damage development and predicting the remaining life cycle of the structural and mechanical systems such as buildings, bridges and machines, etc. It is a process in the experimental data as vibration response can be used to detect and evaluate structural damage degrees appropriately. SHM process can be categorised into five levels [1]: (1) presenting damage, (2) localising damage, (3) categorising damage, (4) quantifying damage, and (5) predicting the development of damage. As the basic technique of SHM, structural damage detection has been intensively investigated for decades. Vibration signals are a big data source exploited popularly for the damage detection of structures [2, 3]. These signals contain features that indicate sensitivity to structural damage. In the literature, vibration-based damage identification (VBDI) methods were investigated and applied in structures such as beams, trusses, plates and frames [4]. Moreover, the beam is one of the useful elements in many large constructions. Therefore, the damage evaluation in the beams is also chosen in many studies about VBDI.
The traditional VBDI methods extensively use modal properties extracted from Fourier transform (FT) of response signals as naturals frequencies, mode shape and damping [5]. Fourier transform is usually used to analyse signals in the time domain to Power spectral density (PSD) in the frequency domain. PSDs are also widely used in Structural Health Monitoring (SHM) [6-9]. Thus, the vibration features extracted in the frequency domain through the Fourier transform can be used for damage detection. However, these features are extracted from original vibrations. The types of vibration can influence each other and create deviations in properties. Or, specific properties will be hidden by other vibration mode properties. This may cause the monitoring and evaluation process to be inaccurate. Some inherent characteristics of the FT can affect damage detection accuracy. The FT loses the temporal information of the signals and cannot capture the evolutionary features in signals measured from naturally excited structures [10]. This makes FT challenging to detect damage and SHM.
In addition, a predictive model using Machine learning algorithms in the problem of damage identification is proposed in this study. The proposed features will be used to train machine learning with neural network pattern recognition (NNPR). This machine learning serves the damage detection process in beams [11-15] or conditional assessment in bridges [3, 16, 17]. Analytical models are made when measurements are time-consuming and costly. Although many different models have been used in many specific applications, a few models do not accurately predict because they depend on the particular problem, and no single model is suitable for all damage detection levels. The current situation is that the learning algorithms may fail or provide low accuracy on different data sets [18].

METHODOLOGY

Power spectral density of vibration

According to Euler–Bernoulli beam theory, the governing differential equation of beams is as follows:

$$\frac{\partial^2}{\partial x^2}\left[EJ(x)\frac{\partial^2 w(x,t)}{\partial x^2}\right]+\rho\frac{\partial w^2(x,t)}{\partial t^2}+c\frac{\partial w(x,t)}{\partial t}=f(s,t) \tag{1}$$

Where $w(x,t)$ is the displacement response of beam in location at time EJ is bending rigidity, ρ is linear density, c is damping coefficient, and $f(s,t)$ is the external force in location s at time t. Boundary and initial conditions are shown as follows:

$$\begin{aligned} &w(0,t)=0 \quad ; \quad w(l,t)=0,\\ &\left.\frac{\partial^2 w(x,t)}{\partial x^2}\right|_{x=0}=0; \quad \left.\frac{\partial^2 w(x,t)}{\partial x^2}\right|_{x=l}=0\\ &w(x,0)=0 \quad ; \quad \left.\frac{\partial w(x,t)}{\partial t}\right|_{t=0}=0; \end{aligned} \tag{2}$$

The solution of the governing equation of beams with length L can be found in general forms as follows:

$$w(x,t)=\sum_{r=1}^{\infty}\phi_r(x)w_r(t) \tag{3}$$

in which $\phi_r(x)$ and $w_r(t)$ are r^{th} mode shape and r^{th} generalised displacement of the beam, respectively.
From Eq. (1) and Eq. (3), the differential equation of the beam in each generalised coordinate is shown as:

$$\ddot{w}_r(t)+2\xi_r\omega_{nr}\dot{w}_r(t)+\omega_{nr}^2 w_r(t)=f_r(t) \tag{4}$$

with ω_{nr}, ξ_r and $f_r(t)$ are natural frequency, damping ratio and generalised force of r^{th} mode shape, respectively. This parameter is defined as

$$\rho\omega_{nr}^2\phi_r(x) = \frac{\partial^2}{\partial x^2}\left[EJ(x)\frac{\partial\phi_r(x)}{\partial x^2}\right] \tag{5}$$

$$\int_0^L \rho\phi_r(x)\phi_k(x)\,\mathrm{d}\,x = \mu_r\delta_{rk} \tag{6}$$

$$\int_0^L c\phi_r(x)\phi_k(x)\,\mathrm{d}\,x = 2\mu_r\omega_{nr}\xi_r\delta_{rk} \tag{7}$$

$$f_r(t) = \frac{1}{\mu_r}\int_0^L \phi_r(x)\,f(x,t)dx \tag{8}$$

With $H_r(\omega)$ is the frequency response function (FRF)of r^{th} mode shape, the solution of Eq. (4) can be found in the form as follows:

$$q_r(t) = \int_{-\infty}^{\infty} H_r(\omega)\,\mathrm{F}_r(\omega)\,\mathrm{e}^{i\omega t}\,d\omega \tag{9}$$

where $Fj(\omega)$ is the Fourier transform of force $fj(t)$. The FRF of the beam-like system at coordinate x by excitation at coordinates is determined as follows [19]:

$$H(x,s,\omega) = \sum_{j=1}^{\infty}\phi_r(x)H_r(\omega)\phi_r(\mathrm{s}) \tag{10}$$

With $S_f(s,\omega)$ is the PSD of excitation at coordinate s, the PSD of the vibration response S_w is calculated as follows:

$$S_w(x,\omega) = S_f(\mathrm{s},\omega)\left|\sum_{r=1}^{\infty}\frac{\phi_r(x)\phi_r(\mathrm{s})}{(\omega_{nr}^2-\omega^2)+2i\xi_r\omega_{nr}\omega}\right|^2 \tag{11}$$

In General, PSD of response depends not only on material properties (natural frequency ω_n and damping ratio ξ) but also boundary conditions (mode shape ϕ). Doebling et al. [19] defined "damage" as the changes in a mechanical system's material characteristics or geometrical conditions. Therefore, PSD of response will be variable by the presence and development of damage. According to S. Beskhyroun and T. Oshima [20, 21], a structural damage identification algorithm based on changes in the curvature of power spectral density is proposed and performed in a laboratory's numerical and experimental bridge models under fixed excitation. Then, dynamic measurements of a reinforced concrete beam have confirmed that the algorithm is effective when it relies on changes in the peak amplitude of PSD between undamaged and damaged beams [22]. The results illustrate that these methods increased the sensitivity of PSD in diagnosing and identifying damages. Nonetheless, they should be considered to apply for real bridges because of random moving load. A damage index extracted from PSD of vibration response under traffic vehicles called Loss Factor Function is used to monitoring material deterioration of bridge [23, 24].

Damage sensitive feature

Correlation analysis has been a rarely-studied approach for damage identification because it concentrates on the relationship between two signals in the time domain. The Pearson correlation coefficient, developed by Karl Pearson (1880s) [25], is generally applied in the time domain and has a value between -1 and 1. If the two signals have a linear relationship, it is +1, and if the two signals have inverse linearisation, it is -1. A few studies used this coefficient to identify damage. For instance, the Pearson correlation coefficient is one of three techniques to analyse the relationship between the surface waveform for testing fatigue damage of reinforced concrete structural elements in Ref [26]. Two Pearson correlation coefficient-based algorithms were used for evaluating the laser-generated ultrasonic wave to detect the interfacial damage of the coat-substrate structure [27]. A novel damage index based on the Pearson correlation coefficient is utilised ultrasonic guided wave to detect damage in plate-like structures [28]. In addition, this coefficient was also used for correlation analysis together with transmissibility in the frequency domain between damage states and the baseline to detect damage to the benchmark structure [29]. In this study, the correlation between signals in the frequency domain as PSD of response at different positions in the mechanical system in the same condition is investigated changes of PSD when the system deteriorated. A measure of the similarity of two spectral signals based on the Pearson correlation coefficient called the Power spectral correlation factor (PSCF) is defined as follows:

$$R_{S_iS_j} = \frac{\mathrm{cov}(S_i, S_j)}{\sigma_{S_i}\sigma_{S_j}} \tag{12}$$

where $\mathrm{cov}(S_i,S_j)$ is the covariance between PSD $S_w(x_i,\omega)$ and PSD $S_w(x_j,\omega)$, σ_{Si} and σ_{Sj} are standard deviations of PSD signal. Due to the positive-value characteristic of PSD, PSCF only takes values from 0 to 1.

Machine learning using neural network pattern recognition

Machine learning technology has been employed to verify the applicability of SHM, such as classification, regression, prediction and clustering. This study uses a machine learning method applied Artificial Neural Networks (ANNs) to classify damage. An ANN structure consists of several connected nodes (artificial neurons) arranged in different layers (Figure 1). The first and last layers are input x and output y, respectively. The layers between the input and output layers are called the hidden layers.

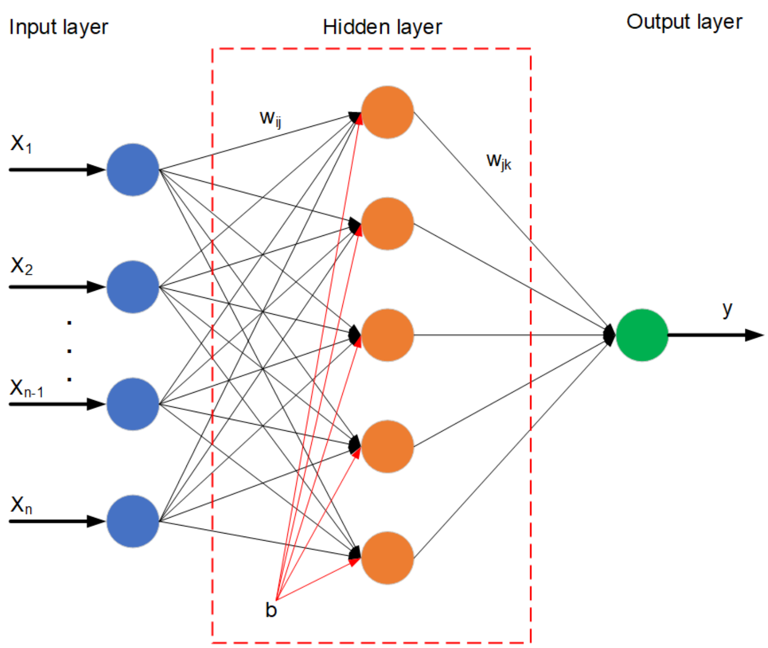

Figure 1: Simple neural network pattern recognition

ANN is trained for damage identification in classification problems [30] and regression problems [31]. Using a non-parametric method, the recognition process allows the slightest possible error to exist. The training process improves performance (minimising errors) using the back-propagation method to adjust the connection weights (w). In this neural network, the active function is a function of $u_k = \sum w_{ki}x_i + b_k$, where k is the kth neural order, and ith is the order of the ith input. Accordingly, the output of a neuron can be determined as follows:

$$o_k = f_k(u_k) = f_k\left(\sum w_{ki}x_i + b_k\right) \tag{13}$$

At the hidden layer, the value b_k (bias) is the regular selection to initialise the active function's value at each neuron due to the largest derivative of the error function. This makes the process of minimising errors occur fast. The default error function of feed-forward networks is the average squared error (MSE). The MSE between the network output $o_k = f_k(u_k)$ and the target output $y_k(x)$ is defined as follows:

$$MSE = \sum_{k=1}^{N} \frac{(y_k - o_k)^2}{N} \tag{14}$$

Thus, the MSE is also a function dependent on u_k, and the rate of error improvement will be a derivative. Therefore, bringing u_k o the value whose derivative of the error function has the largest value makes the process of reducing errors faster because the rate of improvement of the error (the derivative of the error function) is initialised with the most significant value.

Machine learning using Decision Tree algorithm

In machine learning, classification and regression are two-step processes consisting of learning and prediction steps. The learning step involves developing a model based on training data, and the prediction step consists in using the model to predict data response. Decision trees (Figure 2) are a popular machine-learning algorithm for classification and regression tasks [32, 33]. They allow complex relationships between input features and output targets to be modelled in an easy-to-use but assertive manner.

A hierarchical tree structure consists of root nodes, branches, internal nodes, and leaf nodes. In a decision tree, each node represents a decision, and branches that emanate from the root node are fed into internal nodes called decision nodes. At the end of each branch, terminal or leaf nodes represent the predicted outcome of the decision process. The algorithm constructs the decision tree based on a training dataset by selecting the most relevant features. Feature selection begins at the root node and moves down the tree, then select the next feature with the most excellent predictive power. Depending on the selected features, the algorithm recursively splits the data into smaller subsets until all or most records can be classified.

One of the decision tree types is the bagged decision tree algorithm, also known as bootstrap aggregating, which is an ensemble learning method that combines multiple decision trees to improve the accuracy and stability of predictions [34]. In the algorithm, the training data is randomly sampled with replacement to create multiple bootstrap samples, and each is used to grow a separate decision tree [35]. The algorithm aims to improve the performance and accuracy of decision trees by reducing the variance and overfitting. After aggregating the predictions of each decision tree, the ensemble's final prediction is determined.

The bagged decision tree works as follows:

- Bootstrapping.
- Decision Tree Construction.
- Prediction Aggregation.

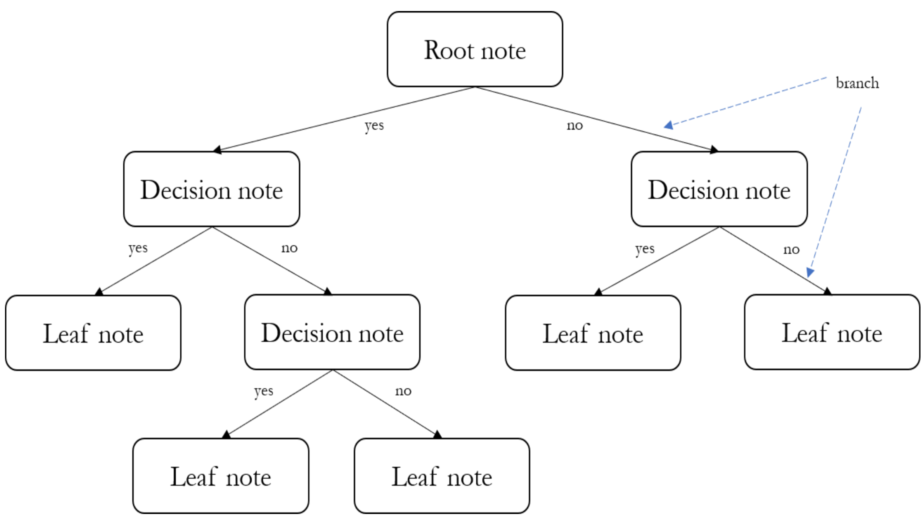

Figure 2: The decision tree diagram.

Proposed method

Damage identification is a multi-level problem: detecting, locating, assessing damage, etc. The first stage uses methods for qualitative exists of damage in the structure. This level can be performed without previous information on the system response when it is damaged. These methods are called novelty detection [36]. Later-stage damage detection methods provide information on the probable location and an assessment of the damage. The pattern recognition approach can be used if there are large amounts of data in both computational and experimental investigations. Training a neural network pattern recognition for damage identification makes tracking the vibration signal simpler. To achieve the best recognition process features sensitive to damage are used as the inputs of ANN. These features are exploited by analysing changes in the PSD corresponding to the weakening of the structure. For promising results in applying SHM [31, 37-39], Matlab software with many training algorithms available in Neural Network Toolbox is used in this paper to map features as PSCFs to damage levels. The Levenberg-Marquardt back-propagation algorithm is chosen because of its good performance on function fitting (nonlinear regression) problems [31, 40]. Additionally, we implement a decision tree algorithm to classify the level of cuts through the reworked PSCFs.

A good SHM process must be able to evaluate all damage levels. However, damage identification is only possible when the damage's presence and severity change the structural responses. Therefore, in this study, the appearance and the severity of damage are the targets of the network. The stiffness of the damaged section shows the severity of the damage. A two-level VBDI process (Figure 3) is proposed to signal the presence of damage and assess severity. All input parameters for the network are calculated based on scenarios of damage levels. However, the study trained two machine learning algorithms for damage location and seversity estimation to recognise samples obtained from slightly damaged models in the laboratory.

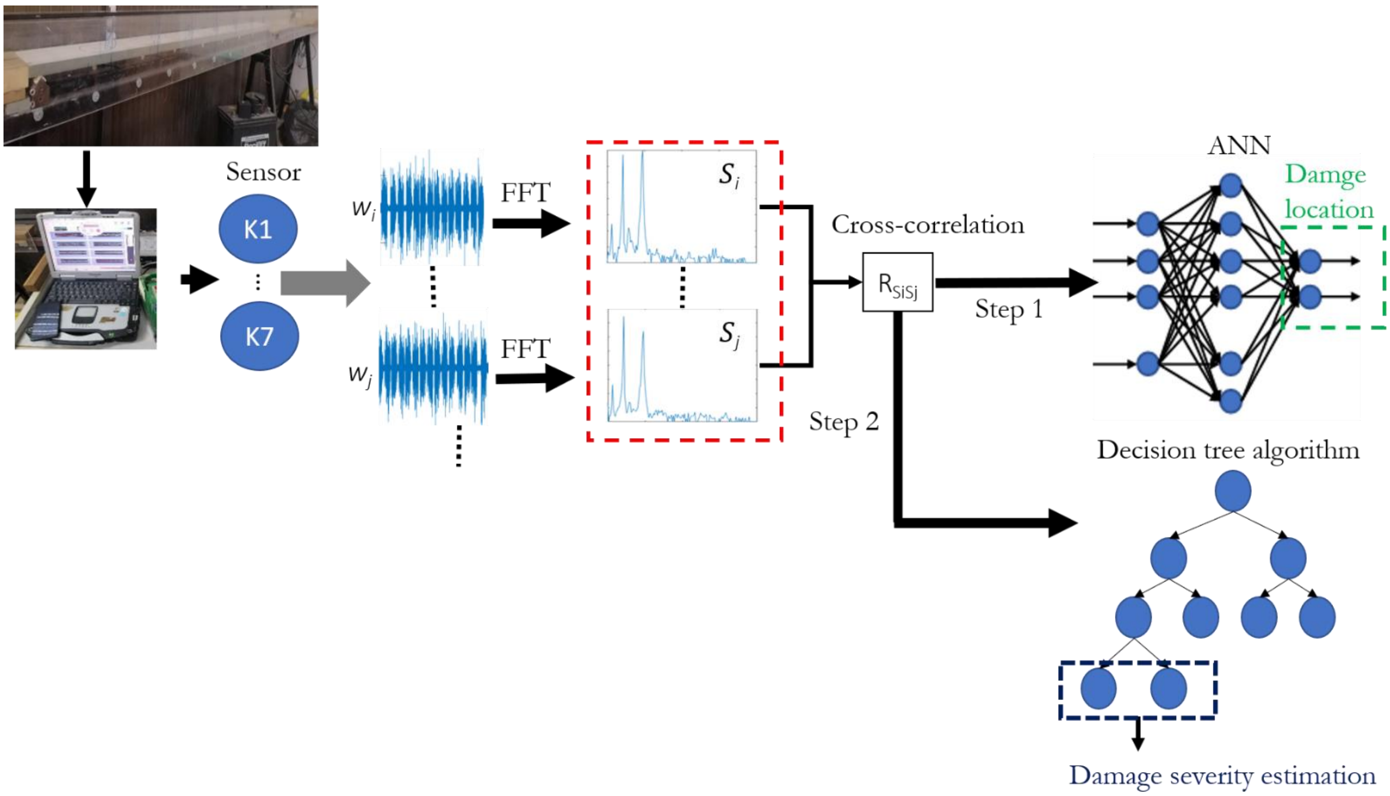

Figure 3: Schematic representation of proposed methodology.

FFT is applied to convert the acceleration signal into an amplitude-frequency spectrum, and then features suitable for damage identification are calculated from the measurement of the vibration signals at scenarios. After that, the first-level identification is performed by the 1st ANN trained for novelty damage detection. If the presence of damage occurs, the second-level identification will be carried out using the decision tree trained to assess the level of the damage. The resulting output vector will evaluate the extent of the damage.

RESULT AND DISCUSSION

Experiment model

The study experimented with a wooden beam supporting two ends as a model for an actual bridge girder. Wooden beams have a set of dimensions length × width × thickness of 1.2 m × 0.1 m × 0.017 m. The load moving on the beam is implemented to collect a large number of vibration signals of the beam through different beam states for evaluation. This test applies a moving load to a wooden beam by a motor driving a moving load of 3 kg. The inverter controls the vehicle's speed in the frequency range from 20Hz to 50Hz, equivalent to 37.7cm/s to 94.25 cm/s. According to the frequency values of the inverter, we denote these velocities as V1 to V16, as shown in Table 1. This experiment then uses seven accelerometers (K1, K2, K3, K4, K5, K6, K7) to measure the acceleration at seven positions: 1/8, 2/8, 3/8, 4/ 8, 5/8, 6/8, and 7/8, along the beam length.

There are twelve scenarios for the structural condition of beams: intact (undamaged) and eleven damaged states with different damage locations. Initially, we measured the vibration of the intact beam. We then make a cut near the 4th sensor position (K4) and continue to perform vibrations to capture data. Then we continue to increase the depth of the cut by three more cases. Cuts were made at positions near the 1st sensor (K1) and the 7th sensor (K7), respectively. Cuts are made with a constant width of 0.006 m, a depth which is increased to 0.003 m, 0.006 m, 0.009 m, and 0.011 m, respectively, extending the entire beam width. Seven accelerometers are installed under the beam along the length of the beam to collect the signal. Each accelerometer sensor records continuously for 400 seconds under each speed state during a recording period of 10 s with a sampling frequency of 2000. Data is recorded 12 times for 12 different beam scenarios. We used speeds from V1 to V16, shown in Table 1, to create a data bank. Its test model and actual implementation are illustrated in Figure 4 and Figure 6, and the shape of the cuts is shown in Figure 5. The 12 damage situations are listed in Table 2, and the accelerometer sensor specifications are shown in Table 3. Finally, some measured acceleration signals of structural conditions are presented in Figure 7.

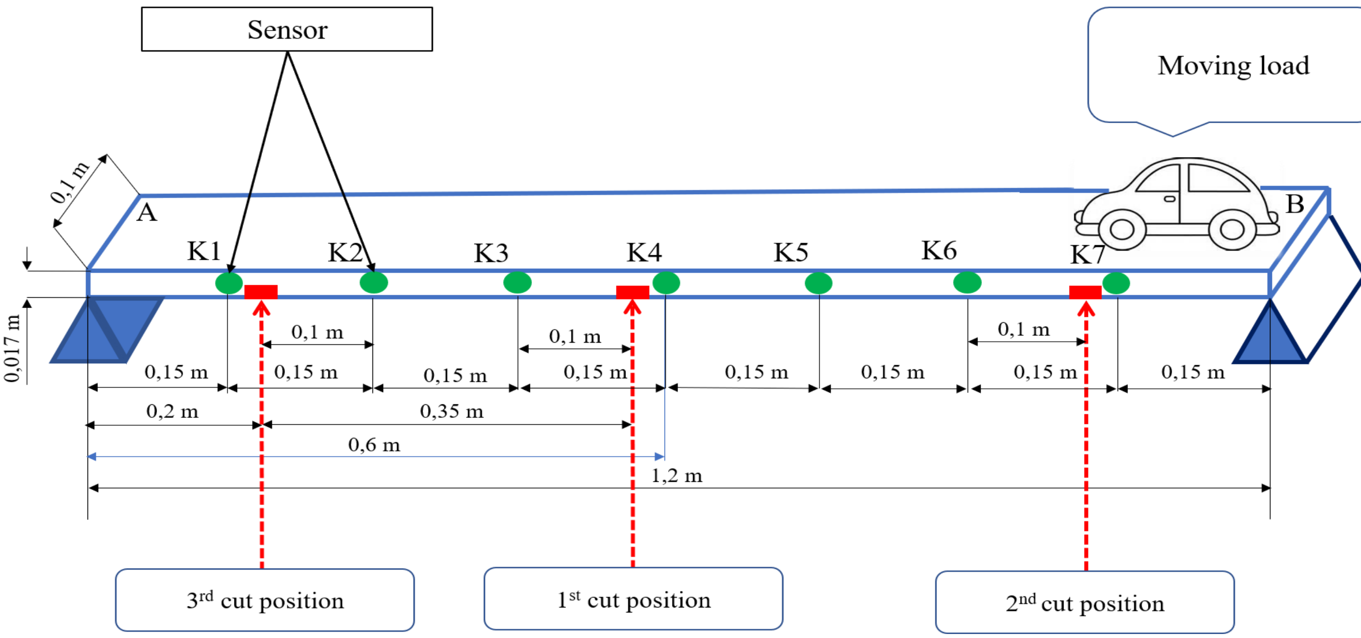

Figure 4: Illustrate the experiment model.

Table 1: Speed and mass of the moving load

Load mass	*Symbol*	*Velocity (cm/s)*
3 Kg	V1	37.7
	V2	41.47
	V3	45.24
	V4	49.01
	V5	52.78
	V6	56.55
	V7	60.32
	V8	64.09
	V9	67.86
	V10	71.63
	V11	75.4
	V12	79.17

V13	82.94
V14	86.71
V15	90.48
V16	94.25

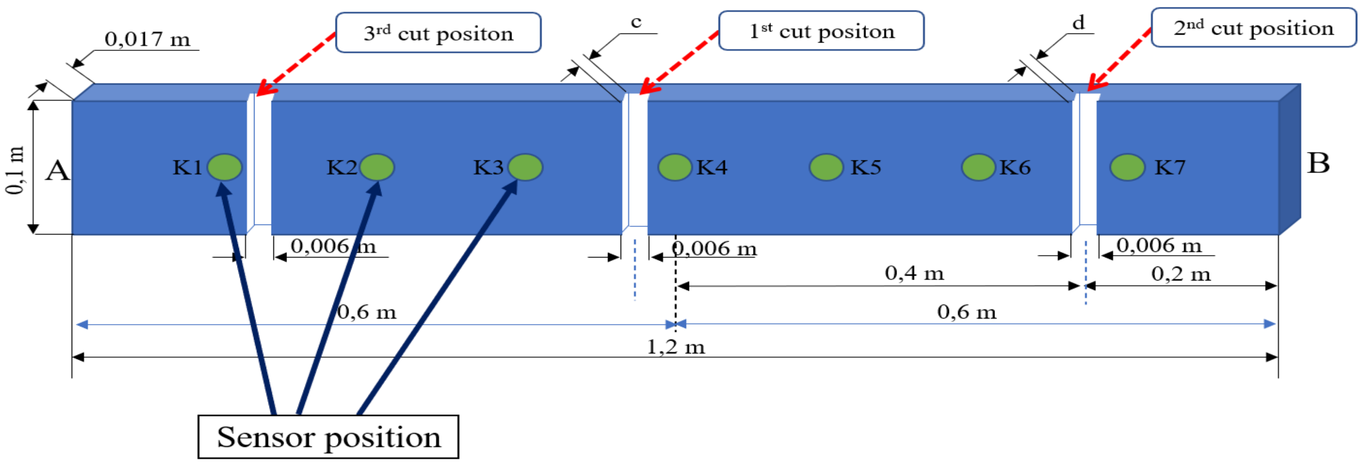

Figure 5: The shape of the cuts.

Table 2: Scenarios of structural condition

Damage state (symbol)	Quantity of damage	Location of damage		
		1st Cut (depth)	2nd Cut (depth)	3rd Cut (depth)
H00 (Intact Beam)	0	-	-	-
H01	1	Nearly K4 (3mm)	-	-
H02	1	Nearly K4 (6mm)	-	-
H03	1	Nearly K4 (9mm)	-	-
H04	1	Nearly K4 (11mm)	-	-
H05	2	Nearly K4 (11mm)	Nearly K7 (3mm)	-
H06	2	Nearly K4 (11mm)	Nearly K7 (6mm)	-
H07	2	Nearly K4 (11mm)	Nearly K7 (9mm)	-
H08	2	Nearly K4 (11mm)	Nearly K7 (11mm)	-
H09	3	Nearly K4 (11mm)	Nearly K7 (11mm)	Nearly K1 (6mm)
H10	3	Nearly K4 (11mm)	Nearly K7 (11mm)	Nearly K1 (9mm)
H12	3	Nearly K4 (11mm)	Nearly K7 (11mm)	Nearly K1 (11mm)

Table 3: Specifications of accelerometers

Parameter	Magnitude
Rated capacity	$\pm$ 19.61 m/s^2 ($\pm$ 2G)
Nonlinearity	Within $\pm$ 1% RO
Hysteresis	Within $\pm$ 1% RO
Rated output	0.5 mV/V (1000×10^{-6} strain) or more

Safe temperature	-15 to 65°C
Safe excitation	6V AC or DC
Recommended excitation	1 to 3V AC or DC
Input resistance	121Ω ± 1.7%
Output resistance	121Ω ± 1.7%
Cable	4-conductor (0.08mm²) vinyl shielded cable, 3.2mm diameter by 5m long
Safe overload	300%
Frequency response	DC to 60Hz ± 5%
Transverse sensitivity	4% RO or less
Weight	Approx. 25g (excluding cable)

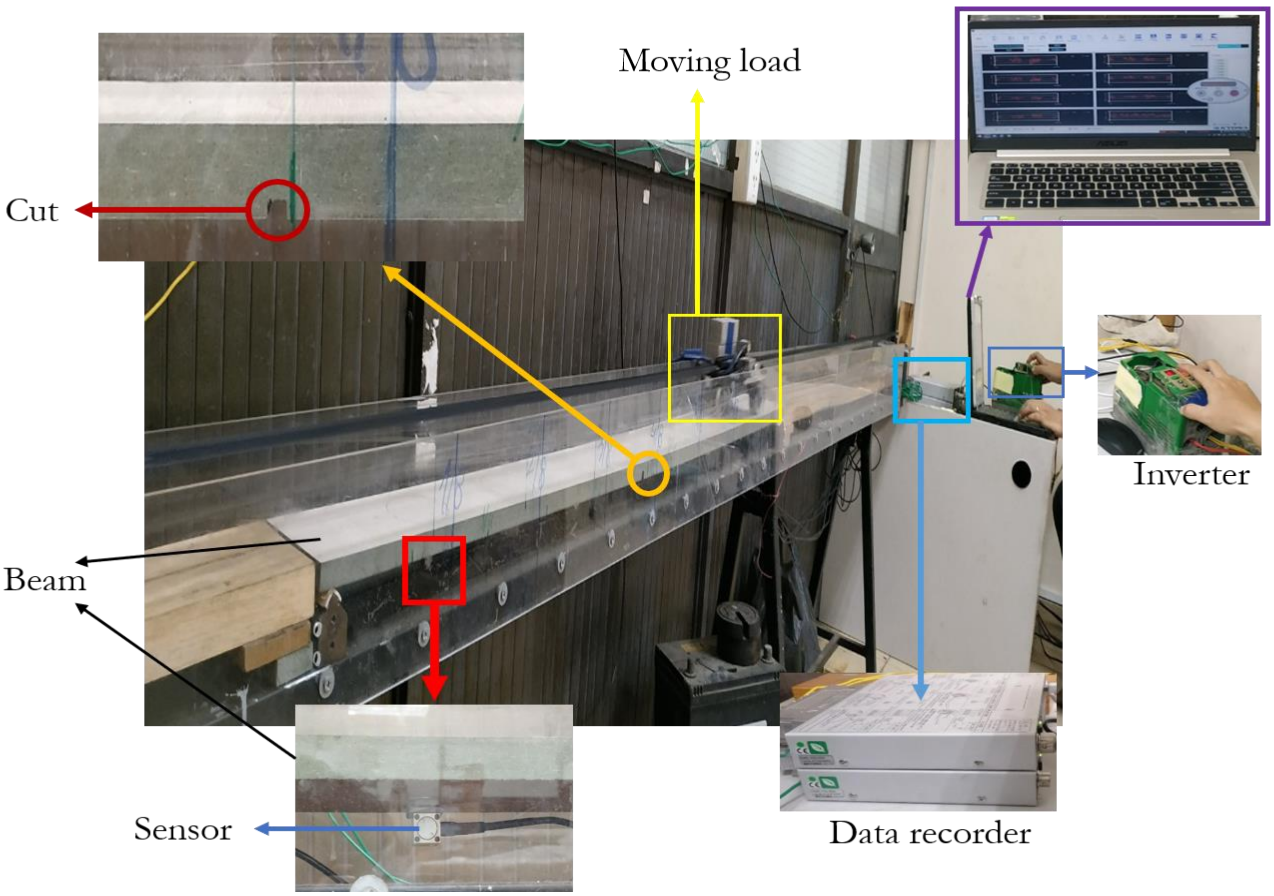

Figure 6: Deployment in laboratory

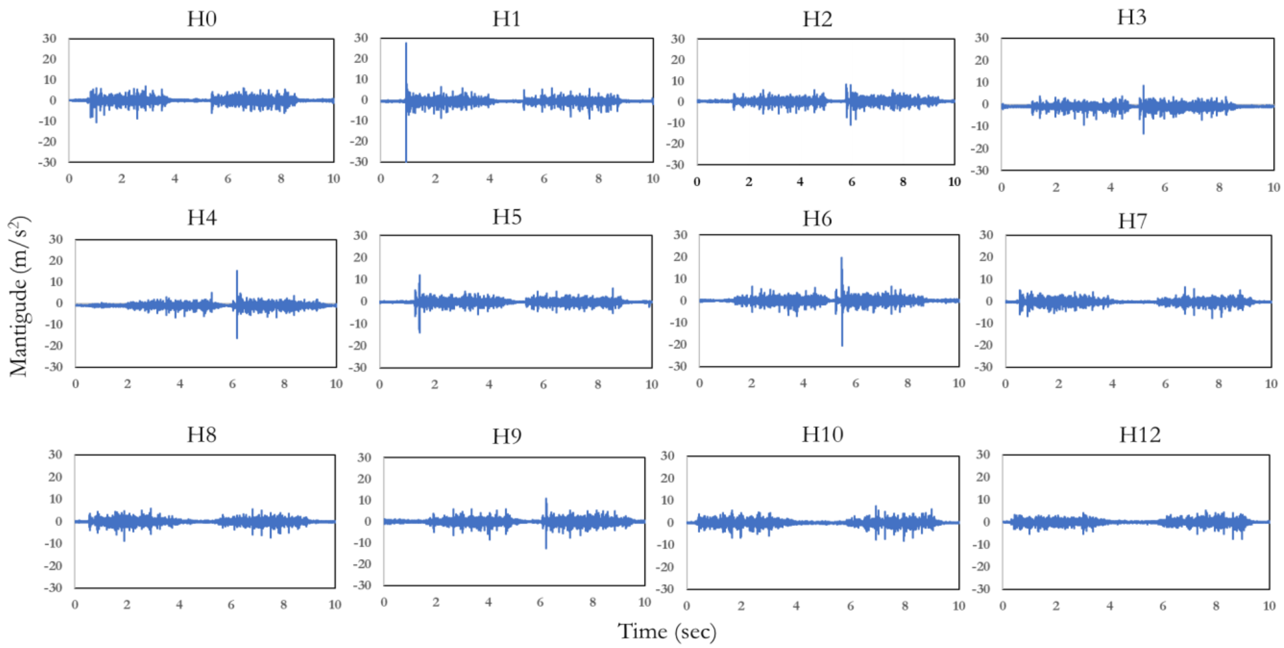

Figure 7: Original signal of twelve states.

Feature extraction

Using vibration signal analysis, researchers can study the frequency components of a mechanical system by measuring its vibration response to external stimuli or internal forces. The spectrum of a vibration signal provides valuable information about the mechanical behaviour of the system, including its natural frequencies, damping ratios, and mode shapes. Spectrum analysis is a powerful tool in signal processing that allows us to understand a signal's sinusoidal components at different frequencies. By performing a Fourier transform on a signal, it is possible to determine its spectrum. The spectrum can provide insights into the underlying physical processes that generate the signal.

Additionally, the spectral analysis of the vibration signal can identify anomalies or defects in the system by analysing the frequency response number of a structure for external forces. Furthermore, researchers can obtain information about its stiffness and damping properties to evaluate structures' performance and safety. Therefore, we use the spectrum in this study to look for the sensitive feature.

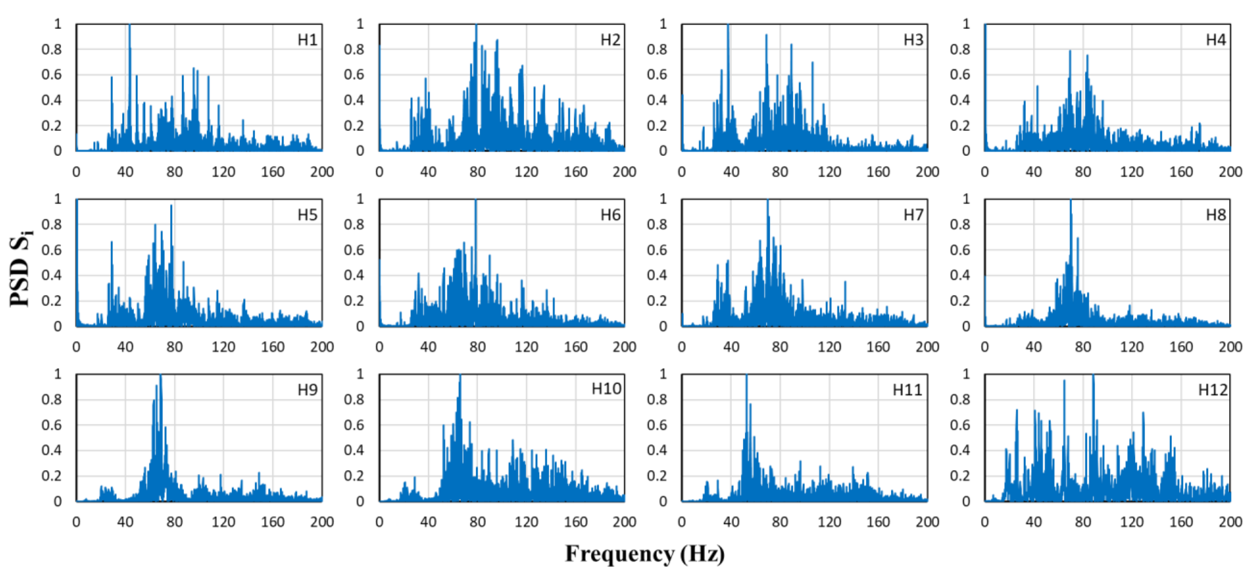

Figure 8: The spectrums of twelve states.

Specifically, each acceleration signal (in 10s) will be converted into a separate amplitude-frequency spectrum for feature extraction, as shown in Figure 8. Several studies have indicated that exploiting damage-sensitive features in the frequency domain will accurately describe the system's properties. Consequently, tracking natural frequency changes is recommended in many studies for damage diagnosis. This study uses the correlation coefficient according to Eq. (12) to evaluate spectra evolution through different scenarios.

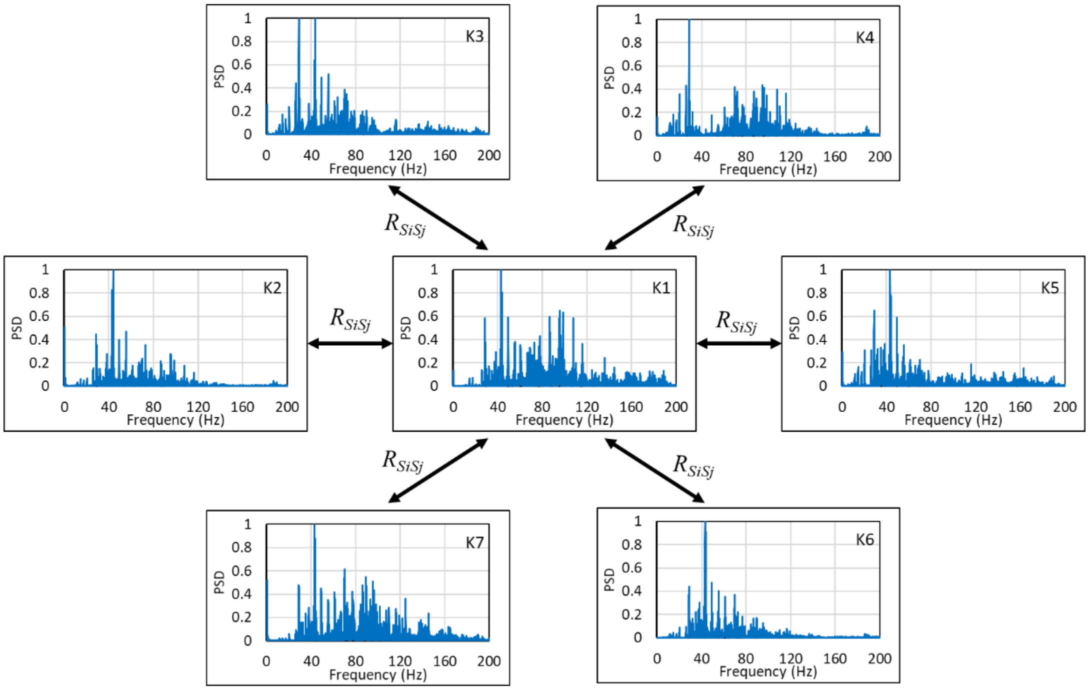

Figure 9: Spectra of measurement locations(sensors) and the procedure for calculating correlation values.

To create a feature by correlation of spectral value, we calculate the value of spectral correlation between measurement locations. Specifically, as shown in Figure 9, we calculate the correlation of the spectral value of sensor K1 with other spectral values (K2, K3, K4, K5, K6, K7). Similarly, implementing the calculation for all measurement locations, we obtain a 7×7 matrix, including the correlation values shown in Table 4.

Table 4: Correlation coefficient of the spectrum between measurement sites

	K1	K2	K3	K4	K5	K6	K7
K1	1	0.62213	0.66153	0.68644	0.65229	0.56469	0.63889
K2	0.62213	1	0.98656	0.95169	0.98866	0.10808	0.99479
K3	0.66153	0.98656	1	0.96307	0.98438	0.18497	0.98252
K4	0.68644	0.95169	0.96307	1	0.95504	0.13951	0.95849
K5	0.65229	0.98866	0.98438	0.95504	1	0.20295	0.98748
K6	0.56469	0.10808	0.18497	0.13951	0.20295	1	0.14909
K7	0.63889	0.99479	0.98252	0.95849	0.98748	0.14909	1

To reduce the number of inputs to the ANN, we remove the duplicate or similar correlation coefficient values and only take the distinct values for training. Therefore, the remaining input data is 21 values, as shown in Figure 10.

	K1	K2	K3	K4	K5	K6	K7
K1	1	0.62213	0.66153	0.68644	0.65229	0.56469	0.63889
K2	0.62213	1	0.98656	0.95169	0.98866	0.10808	0.99479
K3	0.66153	0.98656	1	0.96307	0.98438	0.18497	0.98252
K4	0.68644	0.95169	0.96307	1	0.95504	0.13951	0.95849
K5	0.65229	0.98866	0.98438	0.95504	1	0.20295	0.98748
K6	0.56469	0.10808	0.18497	0.13951	0.20295	1	0.14909
K7	0.63889	0.99479	0.98252	0.95849	0.98748	0.14909	1

0.62213	0.66153	0.68644
0.65229	0.56469	0.63889
0.98656	0.95169	0.98866
0.10808	0.99479	0.96307
0.98438	0.18497	0.98252
0.95504	0.13951	0.95849
0.20295	0.98748	0.14909

Figure 10: Feature extraction from correlation values.

Since the signal is received continuously for 400s, we will have 40 amplitude-frequency spectrums with the same velocity. Therefore, with 16 speeds and 12 damage scenarios, we will have 16×40×12=7680 spectrums. Finally, we obtain a data bank of 7680 samples, each including 21 spectral correlation values.

ANN structure and applying ANN for damage detection

ANN structure and training process

The mechanical properties of the structure change due to the appearance of damage or weakening of the structure, and the vibration spectral characteristics can provide valuable information about the properties and behaviour of the structure through the change of spectrum. As conventional methods are labour-intensive, machine learning methods are superior in assessing these related changes. Therefore, machine learning methods are nominated in this paper. We use an ANN to detect and locate the cut, then use the decision tree algorithm to evaluate the level of the cuts. Due to machine learning tools, identifying and locating the appearance of damage or cuts becomes more straightforward and more precise. However, feature extraction is essential in achieving ANN or decision tree with high accuracy and generalisation ability. This study extracts damage-related sensitive features from spectral correlations between measurement locations to identify damage-related sensitive features.

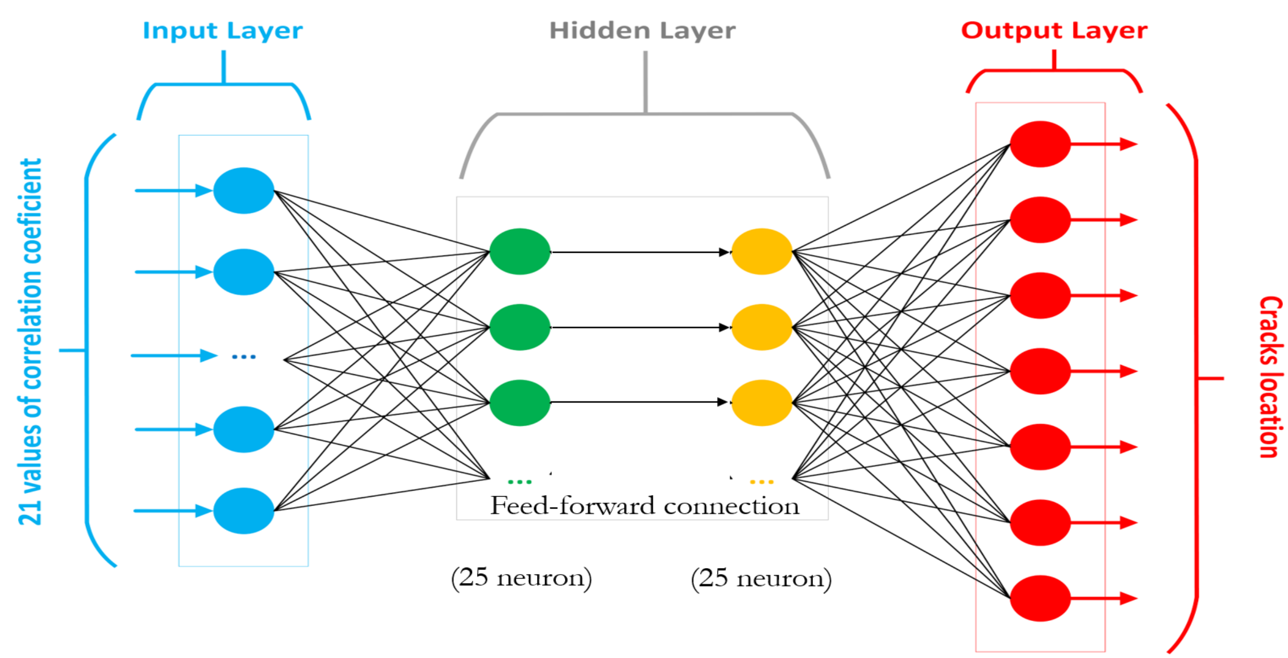

Figure 11: Architecture of the proposed feed-forward neural network

The proposed ANN has one input layer, two hidden layers and one output layer (Figure 11). The input layer is the spectral correlation values, totalling 21 features. These features are then fed into two layers, with 25 neurons in each layer. These classes use a log-sigmoid transfer function (logsig), whose expression is as follows:

$$\text{logsig}(n) = \frac{1}{1+e^{-n}} \tag{15}$$

Terminally, the output layer consists of 7 neurons with values 0 to 1 for damage detection. The activation function in the output layer is a hyperbolic tangent sigmoid transfer function (tansig) with the following formula:

$$\text{tansig}(n) = \frac{2}{1+e^{-2n}} - 1 \tag{16}$$

These outputs will have a value from 0 to 1 to indicate the presence or absence of damage. We assume that the beam has damage (a cut or more) when the output value is approximately 1 and no damage when the output is around 0. Additionally, these seven values correspond to the sensors K1 to K7 along the beam length to determine the damage location. To interpret the ANN model's results, we analysed each neuron's output values to determine the most likely type of damage. If the first neuron has a value of around 1 and all other neurons have nearly 0, we conclude there is damage at the first sensor site (K1). If there is more than one damage, the value approximately equal to 1 of the ANN's output will be increased. In general, by analysing the output values of 7 neurons in our ANN model, we can interpret the probability of appearance and location of damage in different damage scenarios.

The databank from the experiment, which contains 6912 samples (90% of the data bank) for eleven damage and integrity scenarios, is employed to train the proposed ANN architecture. This databank is split into three fractions for training, validation, and testing with ratios of 80%, 10%, and 10%, respectively. The maximum number of epochs for training is set up to 100. However, a validation criterion also comes into effect to stop the training process when the number of consecutive failures is 6 in the validation. The training process employs the Levenberg-Marquardt back-propagation to update the weights and biases. The training process of the ANN was finished at the 47th epoch because it met the validation criterion. The best validation performance is attained at the 41th epoch, as shown in Figure 12.

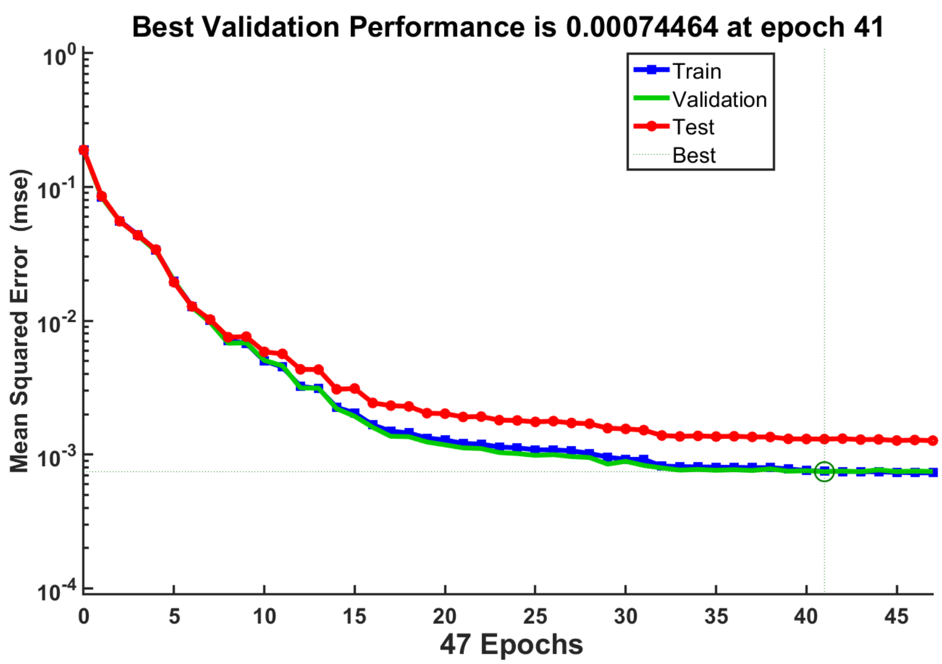

Figure 12: Training performance of the proposed neural network.

ANN testing

In order to confirm the generality of trained ANNs, this study uses 764 samples to test. These samples are extracted from the experimental data (10% of the data bank) and not used for training. Because of the large number of samples used for testing, we present the test results with 10 representative samples for each damage state, as shown in Figure 13.

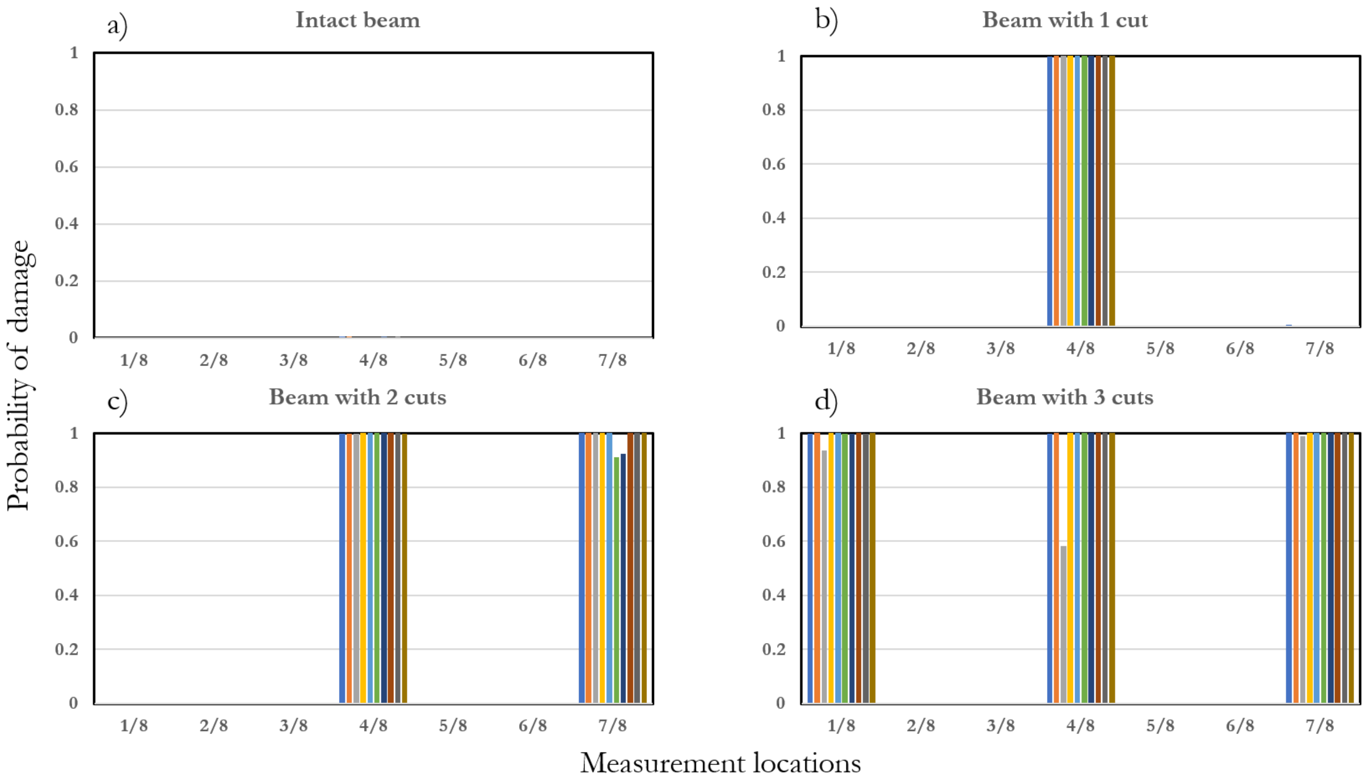

Figure 13: Output of the proposed ANN for damaged locations:
a) Intact beam
b) Beam with one cut at 4/8 position
c) Beam with two cuts at 4/8 and 7/8 position
d) Beam with three cuts at 1/8; 4/8 and 7/8 position.

As observed in Figure 13, all predictions of ANN for 10 samples are correct in different states. Although some samples of beams with cuts give a value not close to 1, their probability is still greater than 0.5. The results show that the trained ANN reaches remarkable generalizability. With ten samples for each damage scenario, most of the predictions of the proposed ANN are correct. Only some did not achieve the desired value when predicting the location of the second and third cuts. The proposed method is highly feasible for potential applications based on these results.

Application of the decision tree method to assess the extent of the cuts

In structural health monitoring, detecting and locating damage is essential, and determining the extent of damage is equally important. Therefore, in this paper, we propose to use a decision tree to evaluate the damage level based on the spectral correlation coefficient.

The bagged decision tree algorithm is a machine learning technique that has gained popularity due to its advantages over ANN. The algorithm produces decision trees that are easy to interpret and explain. Tree structures can be used to visualise decision trees, making it easier to understand how the model arrived at specific predictions. In addition, a major advantage of the algorithm is that it can be parallelised, so multiple decision trees can be trained simultaneously, significantly reducing the training time compared to an ANN algorithm. Therefore, we choose the bagged decision tree algorithm despite ANN to assess the extent of the cuts.

This study used TreeBagger's supervised machine learning function in Matlab software to analyse and model the extracted feature data. In this implementation, we use a dataset including 6338 samples and train a TreeBagger model with 50 trees. Figure 14 shows a decision tree made up of the training dataset. We then compute the model's out-of-bag (OBB) error, which estimates the classification error on new data. We use 702 samples, including 11 damage scenarios, to test the reliability of the decision tree. The results are represented by the confusion matrix shown in Figure 15.

The confusion matrix is a table with rows representing the true class labels and columns representing the predicted class labels. The four outcomes of classification problem are:

- True positive (TP): the model correctly predicted the positive class.
- False positive (FP): the model incorrectly predicted the positive class.
- True negative (TN): the model correctly predicted the negative class.
- False negative (FN): the model incorrectly predicted the negative class.

Several performance metrics are calculated from these four results to show the performance of the decision tree:

– Accuracy: The proportion of correctly classified samples in the data set. It is calculated as follows:

$$\text{accuracy}=\frac{\text{TP+TN}}{(\text{TP+TN+FP+FN})} \tag{17}$$

– Recall (also known as sensitivity): This metric indicates how well a classifier can predict a correct classification. It is calculated as follows:

$$\text{recall}=\frac{\text{TP}}{(\text{TP+FN})} \tag{18}$$

– Precision: Precision is another important performance metric used to evaluate the performance of a classification model. Precision focuses on the proportion of correct positive predictions. It is calculated as:

$$\text{precision}=\frac{\text{TP}}{(\text{TP+FP})} \tag{19}$$

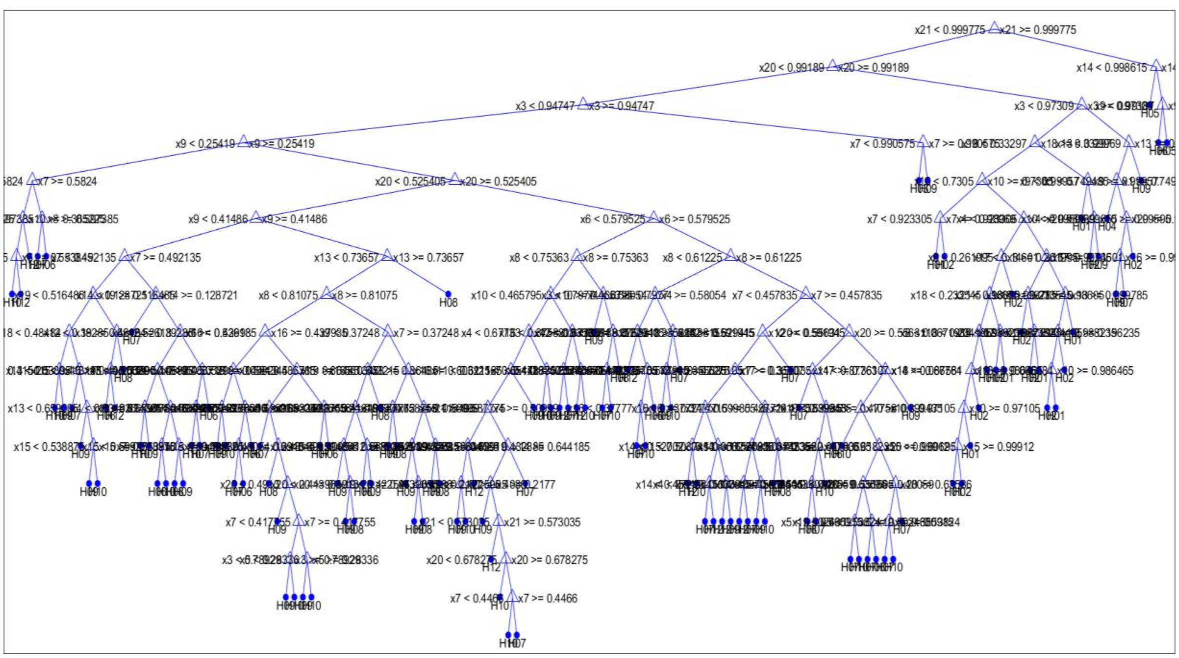

Figure 14: Decision tree model.

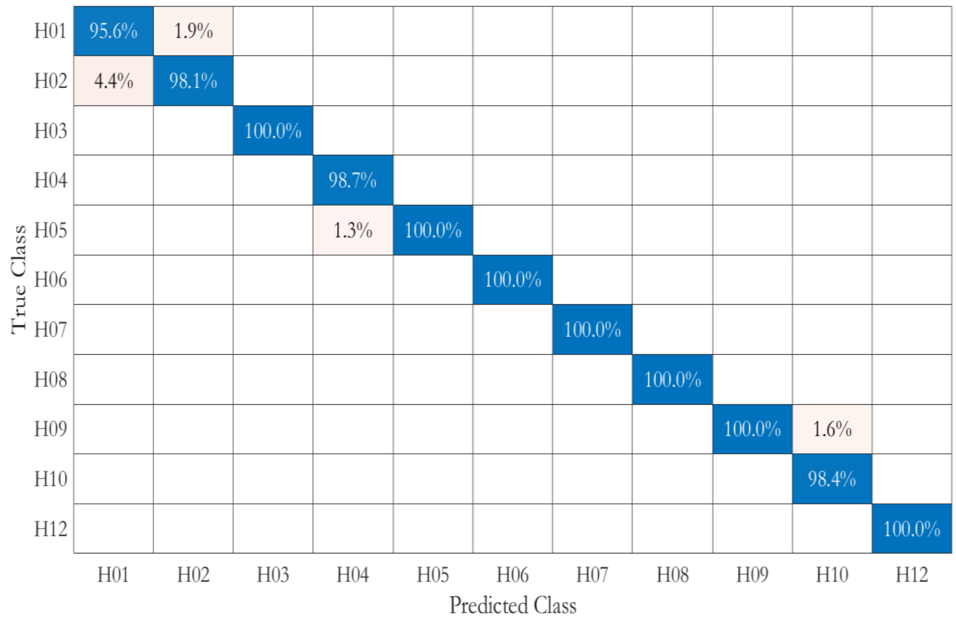

Figure 15: The performance of classification models.

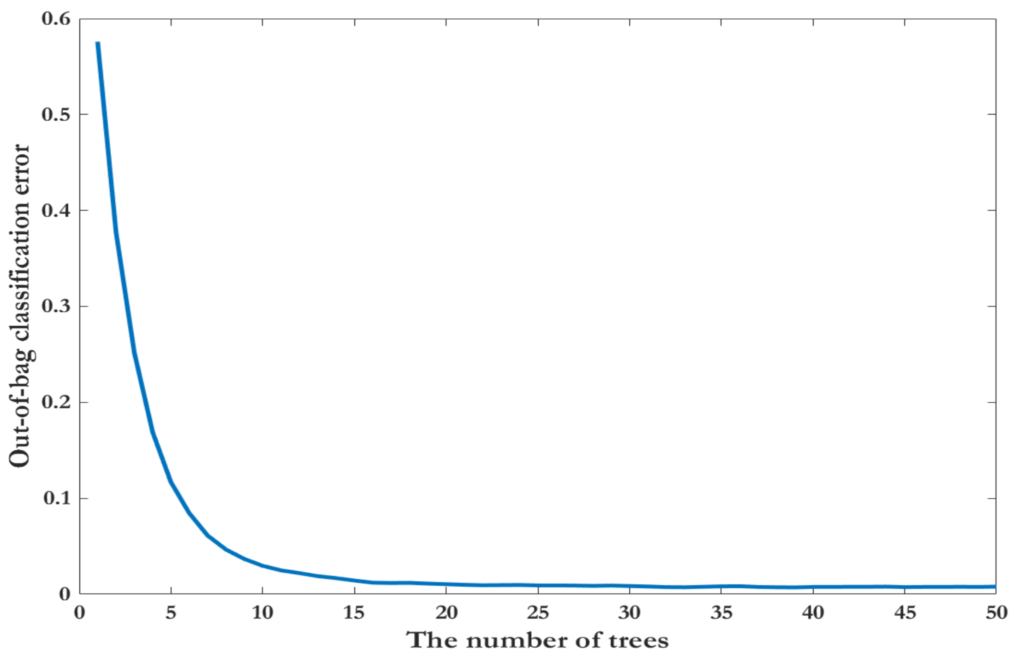

Figure 16: Out-of-bag error versus the number of trees

According to the results shown in Figure 16, the model's out-of-bag error tends to approach zero starting from Tree 20. The overall classification error is calculated by averaging the out-of-bag error values, which is approximately 0.043, that the model's performance is good.

Table 5: Several performance metrics for classification.

	Accuracy	**Recall**	**Precision**
Value	99.15%	94.55%	98.11%

Based on Table 5, we achieved high accuracy of 99.15%, indicating that many instances were correctly classified. Furthermore, 98.11% of the optimistic predictions made by the model were accurate, indicating a high degree of precision.

However, some positive instances were incorrectly classified as negatives due to the recall rate of 94.55%. Overall, these results demonstrate the effectiveness of our classification model in accurately predicting the target variable.

CONCLUSION

This article proposes a two-step diagnostic method using power spectral correlation values combined with machine learning algorithms to detect damages on the beam. The spectrum is computed from the acceleration response at various locations on the beam using an FFT algorithm capable of feature extraction in the frequency domain. Based on the measurement of beam vibration data under different moving load speeds, the method is verified as a viable method to model the vibration state of a bridge deck under traffic loads. The extracted features are correlation coefficients of spectral value between measurement locations. In the first step, the spectral correlation matrix at different locations is combined with an Artificial Neural Network (ANN) to identify the location and appearance of damages. Then the spectral correlation vector is used as input to the decision tree (treebagger) algorithm to assess the level of damage in second step. As a result, the proposed approach can be implemented in four stages: damage detection, damage localisation, damage type recognition, and damage severity estimation.

In the proposed ANN, the factors serve as inputs and demonstrate remarkable precision. The generalizability of the ANN is confirmed based on noteworthy testing process results with an accuracy of 99.93%. Besides, the decision tree algorithm also exhibits extremely accurate classification with 99.15%. However, this study must use two machine learning methods to achieve the desired results. Further research is needed to optimise the damage recognition algorithm. In addition, it is possible to create more complex damage scenarios to test the algorithm and apply it to the actual structures.

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