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Research Paper

Damage detection of structural based on indirect vibration measurement results combined with Artificial Neural Network

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In Structural Health Monitoring (SHM), damage detection and maintenance are among the most critical factors. For surface damage, damage detection is simple and easy to perform. However, detecting and repairing is difficult for damage hidden deep in the structure. Using the structure's dynamic features, damage can be detected and repaired in time. With the development of sensor technology, indirect vibration measurement solutions give accurate results, minimizing errors by infinitely increasing the number of measurements. This solution offers a great opportunity to reduce the cost of structural health monitoring. Based on the large amount of data obtained from indirect monitoring, artificial intelligence technologies can be used to obtain a more comprehensive model of SHM. In this paper, the dynamic responses of the structure will be extracted and determined through a vehicle crossing the bridge. Based on the results of structural dynamic response, a finite element model is built and updated so that this model can represent the real structure. Damage cases will be analyzed and evaluated as input to train the Artificial neural network. The trained network can detect damage through regular health monitoring by indirect methods.

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1 Introduction

The indirect monitoring technique is based on the dynamic response collected by sensors installed on the vehicle during movement. This method brings more benefits than the traditional method, so has been interested and developed by many researchers. Many authors have studied the feasibility and data processing of indirect monitoring [1-3]. Yang et al. [4, 5]first

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proposed to use dynamic data extracted from vehicles crossing the bridge structure to determine the natural frequency of the structure. By collecting vehicle data multiple times over the bridge, some damage was detected. Yang et al found this data can be used to detect structural damage. McGetrick et al [6, 7] used a number of sensors fixed on the vehicle over the bridge. Thereby, the natural frequencies of the bridge structure are determined. Although there are many problems with accuracy, this can be compensated for by performing multiple monitoring, with lots of data. The detection of damage of the structure will be detected if there is a large difference between many measurements. At the same time, this helps to reduce the cost of monitoring equipment installed directly on the constructions without being used on other buildings. This indirect method is capable of commercializing and attracting investment for many projects. With just one equipment investment, it can be used for many different projects.

Today, with the great development of information technology, especially in the field of artificial intelligence and the success of artificial neural networks in intellectual training for computers, there have been many studies incorporating artificial intelligence in predicting and diagnosing events[8, 9]. It can be said that artificial intelligence has opened a new era of development for industries, including structural health monitoring. In this article, by using indirect vibration measurement results combined with artificial neural networks; the authors propose a new approach to detecting structural damage.

2 Research methods and approach

2.1 Indirect monitoring

In indirect monitoring techniques, the vehicle can be considered as both exciter and receiver (Fig. 1)[10]:

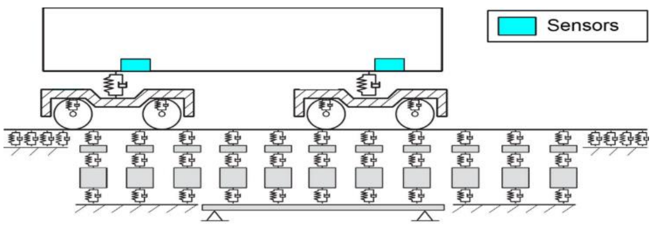


Fig. 1 – Indirect monitoring of a railway bridge

The interaction between the bridge and vehicle leads to a second order differential equation. This equation is written in matrix form as follows:

$$[M].\{\ddot{q}\}+[C].\{\dot{q}\}+[K]\{q\}=[F] \tag{1}$$

$[M]$ is the mass matrix, $[C]$ is the damping matrix; $[K]$ represent the stiffness matrix, $\{q\}$ is the displacement vector and $[F]$ denotes the external force vector. In the road bridge, because it is greatly affected by the flatness of the road surface, indirect monitoring has not proved effective. However, for railway bridges, the dynamic responses of the structure can be easily extracted through the dynamic response collected from the train crossing the bridge. This comes from the fact that the railway bridge is not affected much by the contact surface. At the same time, the operating speed of the train is relatively stable, there is not much fluctuation like that of road vehicles. One of the important data that can be extracted from the dynamic response of the train when crossing the bridge is the frequency of the structure and the displacement at the sensor mounting position over time.

2.2 Artificial neural network

An Artificial Neural Network (ANN) (Fig. 2) is a network (include many components) inspired by the Human nervous system. ANN is one of the breakthroughs in artificial intelligence thanks to its ability to learn from experience and improve itself by creating different paths to connect the neurons of the network. Applications of ANN include classification, pattern recognition, control systems, and image processing. ANN consists of the input, hidden, and output layers. Each layer consists of neurons that contain information and are linked by training parameters (weight and bias). At each neuron, a processing element will be built and connected with other synapses based on the number of neurons in front of it.

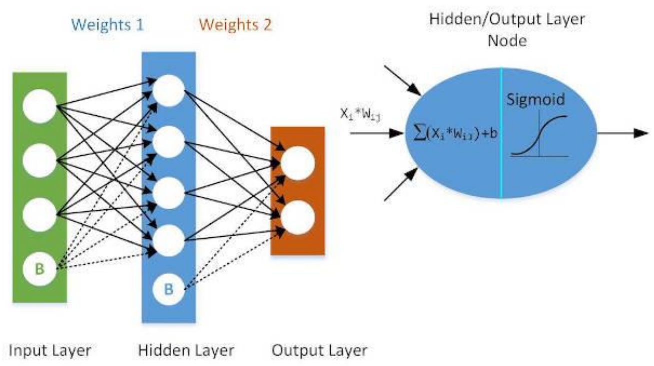


Fig. 2 – Artificial neural network architecture [11]

In this paper, based on indirect monitoring results, the finite element model is built and updated. This model has the same behaviour with real bridge structure. Then, damage data will be generated corresponding to the data that can be obtained from indirect monitoring data (here, natural frequency and displacement at a certain position). Finally, these data are used to train the network.

3 Case study

3.1 Cat Linh – Ha Dong railway bridge

Cat Linh-Ha Dong is an urban railway line belonging to the Hanoi Urban Railway network connecting Cat Linh and Ha Dong (Fig. 3). The total length of the route is 13021.48m, the whole route is designed on high. The span structure of the line is a combination of simple spans. The span length is one of 18.5, 20, 26, 29, 30, 32m. Span structure with box cross section (Fig. 4)

Fig. 3 – Cat Linh-Ha Dong railway bridge

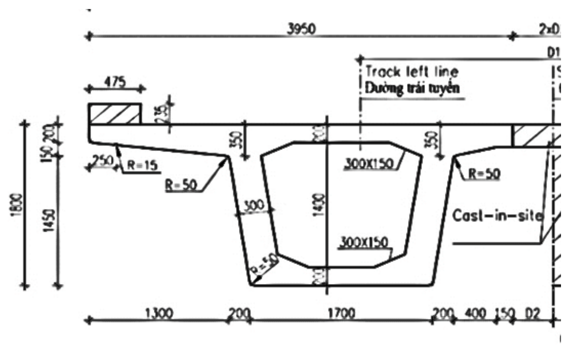


Fig. 4 – Cross section of span

3.2 Indirect monitoring of Cat Linh Ha Dong railway bridge

Using 4accelerometer sensors installed vertically and horizontally of the bridge. The sensors are mounted on the deck of the train, at the position corresponding to the 4 wheels (Fig. 5).

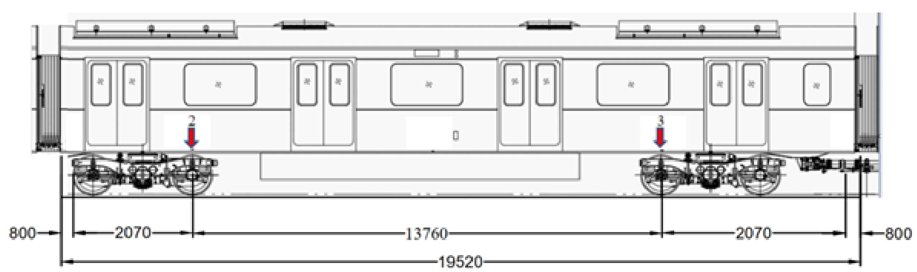


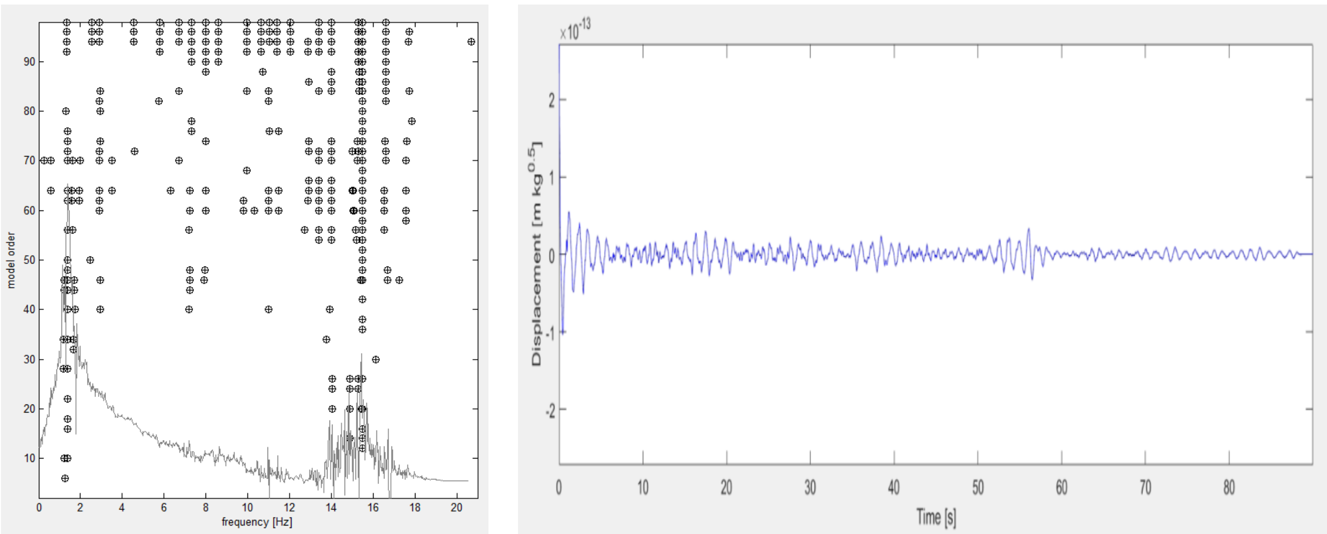
Fig. 5 – Sensor installation diagram

For this field investigation, monitoring was carried out by collecting the data from train through bridge structure. During the bridge traverse, the time was recorded and marked the timestamp when crossing the spans of the bridge. Based on the marking times, the data will be broken down, extracting the data of the structure to be monitored, other data was discarded. CompactDAQ Chassis (cDAQ-9178) is a signal transmitter to a computer. The data received from the sensor will go through the Chassis and store on the computer (Fig. 6).The data is considered and analyzed for a 32m.

Fig. 6 – Indirect monitoring data collection

All data was stored in the laptop for processing using MACEC toolbox [12]. Data is processed in steps to ensure accuracy. The Fast Fourier Transform (FFT) was employed to convert the obtained dynamic signal from the time domain to a representation in the frequency domain. The frequency range of interest was limited to an interval 0-12Hz, to reduce analysis and identification time. The dynamic characteristics are estimated by a stabilization diagram. Simultaneously, by integrating twice the accelerometer data from the accelerometer, the sensor displacement data on the wheel is recorded. The frequency and displacement plot in time are shown in the Fig. 7.

After processing vibration measurement data in the time domain by parametric method through the program to identify vibration characteristics by MACEC tool. The natural frequency results are f1=1.371, f2=15.5Hz. Displacement plot shows the vertical displacement of the sensor. This is also the displacement of the wheel and the span structure. Based on these two results, perform model update and generate data to train the network



a. b.

Fig. 7–Result of indirect monitoring: a. Stabilization diagram; b measuring point displacement

3.3 Build a finite element (FE) model and update the model

With the bridge structure considered, a FE model of the bridge is constructed. The built model consists of 64 beam elements. Each element node contains 6 degrees of freedom (DOF) corresponding to translational and rotational displacements in the X, Y and Z axes.

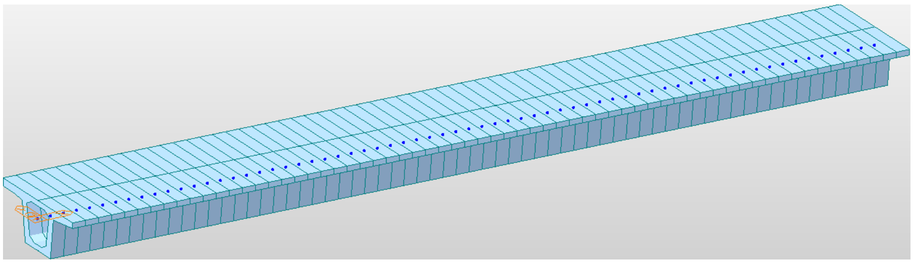


Fig. 8–FE model of span 32m

The train specifications are also shown in the figure below:

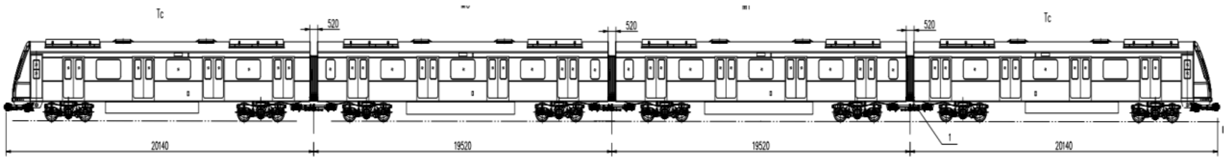


Fig. 9 –Train specifications

Accurate determination of material parameters requires many experiments; moreover, the results will also give a range of values that are not exactly a specific number. Similar to the case under consideration, the parameters for concrete have not been determined at all, but only available studies have been used to determine the limits of values of these parameters, parameters of the material, the stiffness of the bearing also need to be considered. In order for the FEM model to have the same behavior with the real structure, it is necessary to select the value of uncertainty parameters so that the difference between the experimentally measured values and the model results is minimum. An objective function based on the natural frequency and the displacement is used to evaluate the similarity of the FEM model and the real structure. After updating, the uncertain parameters are optimized and presented in Table 1:

Table 1-Uncertain parameters

No	**Uncertain parameters**	**Upper bound**	**Lower bound**	**Initial value**	**Updated value**
1	Young's modulus of concrete - E (GPa)	40.00	45.00	42.00	43.45
2	Weight density of concrete - ρ *(kg/m3)*	2500	2800	2500	2651.8
3	Stiffness of bearing- *k (N/m)*	1×10^{10}	4×10^{10}	1×10^{10}	1.568×10^{8}

3.4 Generate data and train the ANN model

In this study, the architecture of ANN includes 1 input layer, 1 hidden layer, and 1output layer. Input data used in training the network includes natural frequencies and displacements with different damage scenarios. The output data used is the level of damage of the considering structure. Modal analysis of updated model is performed to to generate input and output data for the ANN. The stiffness of the elements is gradually reduced to create damage in the structure. Consider failures from 0-100% of the cases. The stiffness of the elements considered will decrease from 0-100% with a step of 1%. The load model (train) is simulated as for real train specifications. The total number of samples used to train the network is 6400 samples.

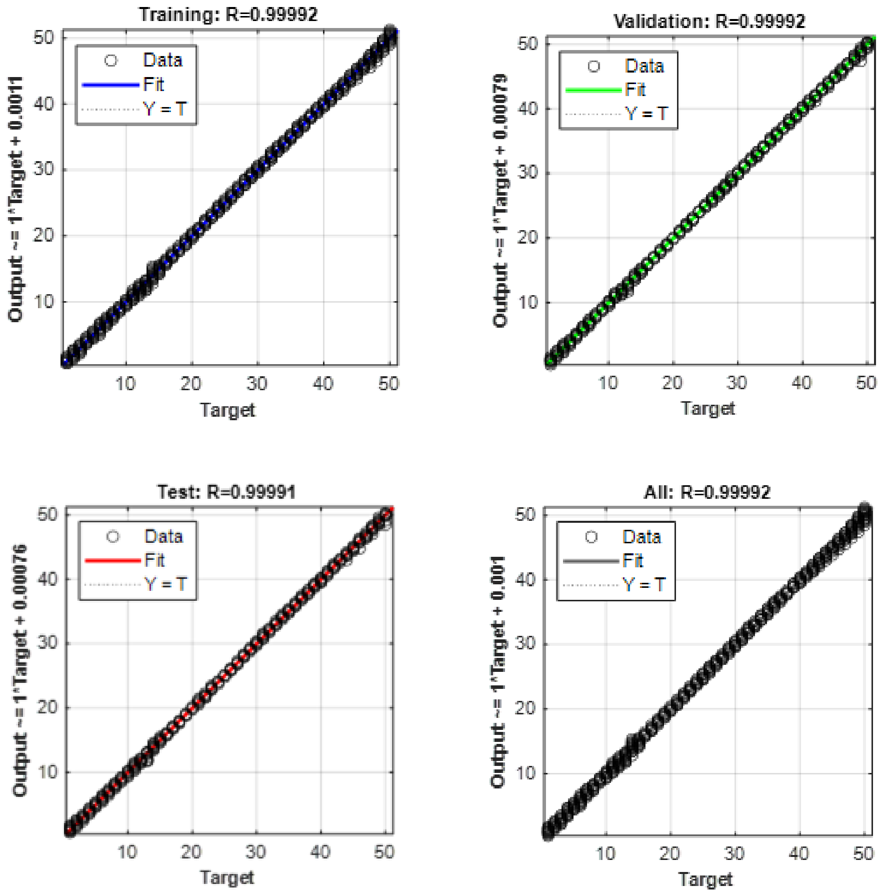


Fig. 10 –Regression values of ANN

After generating the data, the ANN is set to the parameters for training the network. A loop is performed to select the most suitable number of hidden layers. Setting the number of hidden layers that will be looped within the value range from 1 to 50. To ensure accuracy, some noise effects are also added to the input data with a noise level of 2%.ANN employs the Levenberg-Marquardt back propagation algorithm to train the network. Data split in the training process 70%-15%-15% is used for damage identification. The maximum number of epochs is set to 1000.

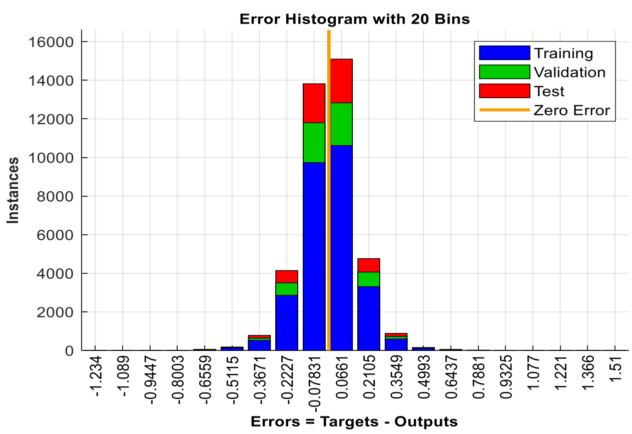


Fig. 11 – Error histogram of ANN

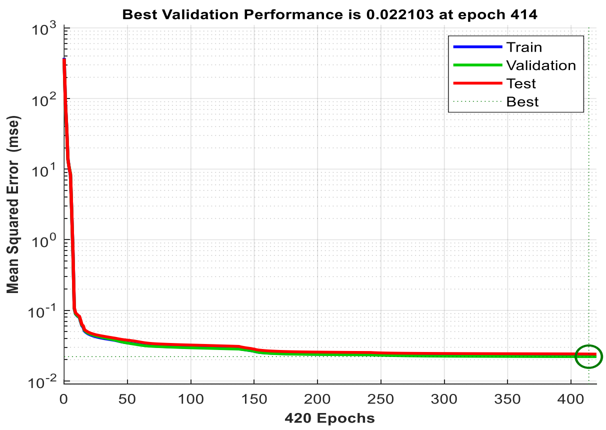


Fig. 12 –Tolerance of network

Fig. 10, Fig. 11, Fig. 12, present the regression values of training value set, validation value set and test value set. All of the training cases are higher 0.99. The training dataset, validation dataset and test dataset are stick to the target line (45degree line). This shows that the predicted value and the actual value are almost similar. The calculated regression value (R) in the above training case is close to the value 1, which represents a high match between the predicted results and the target results. Fig. 11 shows the error distribution between the predicted and target values. The difference between the target and the output is very small. The network tolerance is very low, which shows that the network is working fine, the values in the sets are not overfitting. Through the above results, it is possible to use indirect vibration measurement results in combination with artificial neural networks to detect structural damage.

4 Conclusions

Through the combined approach of indirect monitoring and artificial intelligence network, this study presents a new solution for structural damage detection. The method is practically applied at the Cat Linh - Ha Dong railway project, with positive results. The main conclusions drawn are as follows:

The indirect monitoring method has potential in structural health monitoring, especially in the field of railway bridges. By collecting data during mining, it is possible to predict structural health. This method allows large amounts of data to be collected by allowing an infinite number of measurements during service operation, and it is not necessary to stop serving during data collection.

The combination of indirect monitoring and artificial intelligence network can accurately predict the location of damage on the structure. In this paper, using indirect measurement results, a FE model is updated and data generated. From the generated data, the artificial neural network model is trained and makes future predictions

The values of the trained artificial neural network are achieved at very high (greater than 0.99).The model using indirect monitoring data is successfully trained. In further studies, research is needed to increase training performance and network training speed

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