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Neural networks-based damage detection for bridges considering errors in baseline finite element models

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Abstract

Structural health monitoring has become an important research topic in conjunction with damage assessment and safety evaluation of structures. The use of system identification approaches for damage detection has been expanded in recent years owing to the advancements in signal analysis and information processing techniques. Soft computing techniques such as neural networks and genetic algorithm have been utilized increasingly for this end due to their excellent pattern recognition capability. In this study, a neural networks-based damage detection method using the modal properties is presented, which can effectively consider the modelling errors in the baseline finite element model from which the training patterns are to be generated. The differences or the ratios of the mode shape components between before and after damage are used as the input to the neural networks in this method, since they are found to be less sensitive to the modelling errors than the mode shapes themselves. Two numerical example analyses on a simple beam and a multi-girder bridge are presented to demonstrate the effectiveness of the proposed method. Results of laboratory test on a simply supported bridge model and field test on a bridge with multiple girders confirm the applicability of the present method.

1. Introduction

Civil infra-structures are exposed to various external loads such as earthquakes, gusts, traffic, and wave loads during their lifetime. The structures may get deteriorated and degraded with time in an unexpected way, which may lead to structural failures causing costly repair and/or heavy

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loss of human lives. Consequently, structural health monitoring has become an important research topic in conjunction with damage assessment and safety evaluation of structures [1–3]. The use of system identification approaches for damage detection has been expanded in recent years owing to the improvement of structural modelling techniques incorporating response measurements and the advancements in signal analysis and information processing capabilities.

Damage estimation methods based on the vibration data can be classified into two groups according to the dependence on the structural model: i.e., signal- and model-based methods [2,3]. Signal-based methods detect damages by comparing the structural responses before and after damages, not using the information on the structural model. Damages are defined by damage indices, which may be determined using the results of the experimental modal analysis [4–8] or the time–frequency domain analysis [9–12]. Signal-based damage estimation methods are generally appropriate for detection of damage locations, whereas not effective for estimation of damage severities. On the other hand, model-based methods can estimate the damage locations and severities by improving the mathematical model of the structure using experimental data, since the structural damages result in changes of the dynamic characteristics [13–16]. Various techniques have been developed for estimating the stiffness changes due to damages from the identified modal parameters. Recently, soft computing techniques such as the neural networks and genetic algorithm have been utilized increasingly owing to their excellent pattern recognition capability [17–33].

In this study, the neural networks (NN) technique using the estimated modal parameters is studied as a model-based method for element-level damage detection. The process of the model-based damage detection using the modal data eventually reduces to a pattern recognition problem. Neural networks technique can generally provide an efficient tool for this pattern recognition problem. Many researchers have studied the NN approaches for the damage estimation of a structure owing to the versatility in dealing with various types of input and output and the quick computational capability. Wu et al. applied the back propagation neural networks technique to recognize the locations and the extent of individual member damage of a simple three-story frame [17]. Szewczyk and Hajela developed a modified counterpropagation neural networks approach for the inverse mapping between the stiffness of individual structural elements and the global static displacements under a testing load [24]. Yun and Bahng proposed a substructural identification method for complex structure using multilayer perceptron [25]. Lee et al. applied the NN technique using the modal data to health monitoring of bridges [26]. Ni et al. applied the probabilistic neural networks technique to identify the damages in the cable-stayed Ting Kau Bridge from the simulation data [31].

Several problems still remain to be resolved before the NN approach using the estimated modal parameters becomes a truly viable method for structural health monitoring and damage assessment. They are the effects of the errors in the input modal parameters and the errors in the intact baseline finite element (FE) model. The effect of the input errors may be reduced by the noise injection learning [26–29]. The error in the baseline FE model can be very critical, since modal properties are to be generated for various perturbed cases around the baseline model and used as the training patterns for the neural networks. If the effects of the modelling errors exceed the modal sensitivity to damage, accurate damage estimation may not be carried out. Updating of the baseline model using the measured data will be helpful to improve the estimation accuracy as demonstrated for a simple structure by the present authors [26]. However, the updating process is still difficult, since lots of measurement information are needed for a large and complex structure. Moreover, it may not guarantee to obtain an adequate updated model applicable to the damage detection. Ni et al. suggested a method using differences in the estimated element-level stiffness between before and after damage to deal with the effect of the modelling error [33].

In this study, a neural networks-based damage detection technique using the modal data is proposed, which employs the input parameters less sensitive to the modelling errors. They are the differences and the ratios of the mode shapes before and after damages instead of the mode shapes. As a practical application, a procedure for damage estimation of bridge structures is presented using ambient vibration data caused by traffic loadings. It may generally consist of identification of the modal parameters, updating of the baseline FE model, and assessment of the damage locations and severities based on the changes of modal properties [26]. However, in this study, updating of the baseline FE model is intentionally skipped to demonstrate the effectiveness of the present method. The natural frequencies can be measured more accurately than the mode shapes. However, it is well known that the natural frequencies change very sensitively to the environmental effects such as temperature, while the mode shapes vary less sensitively [34,35]. In real structures, the temperature effects on the natural frequencies can be much larger than the effects of damages, which may make the damage detection for real structures difficult. Hence, in this study, the information on the natural frequencies is excluded to reduce the environmental and operational effects such as temperature, humidity, traffic volume, etc. The mode shape properties alone may not be sufficient to identify the structural damages spread almost evenly to the whole structure. However, such type of damage is not considered in this study.

Two numerical verifications were performed to investigate the effectiveness of the proposed method. Then, laboratory test and field test were carried out on bridge structures. The results indicate that the proposed NN-based damage estimation method using the differences or the ratios of the mode shapes gives good estimations for the damage locations and severities.

2. Theoretical background

2.1. Modal parameters less-sensitive to modelling errors

For the effective neural networks-based damage detection using the modal parameters, it is very important to choose the input data which is less sensitive to the errors in the baseline FE model, since the training patterns for the networks are to be generated from the FE model. In the previous work by the present authors [26], the natural frequencies and the mode shapes were used as the input to the NN. However, it has been found that the natural frequencies vary significantly with temperature changes and the establishment of an accurate baseline FE model is very difficult for large structures. The effect of the modelling error on the mode shapes may exceed the modal sensitivity to the damage. In this study, the modal sensitivity is investigated based on the modal perturbation equations.

The characteristic equations for a structure before and after damage can be written as

$$[K_0]\{\phi_0\} = \lambda_0[M]\{\phi_0\}, \tag{1a}$$

$$[K_0 + \Delta K_d]\{\phi_0 + \Delta\phi_d\} = (\lambda_0 + \Delta\lambda_d)[M]\{\phi_0 + \Delta\phi_d\}, \tag{1b}$$

where K is the stiffness matrix, M is the mass matrix , λ is the eigenvalue which is a square of the natural frequency, and ϕ is the mode shape. Subscripts 0 and d denote intact and damaged cases, respectively. Assuming the mass remains the same after structural damage, the first order modal perturbation equation for the stiffness change associated with the damage ΔK_d can be obtained as

$$[\Delta K_d]\{\phi_0\} + [K_0]\{\Delta\phi_d\} = \lambda_0[M]\{\Delta\phi_d\} + \Delta\lambda_d[M]\{\phi_0\}. \tag{2}$$

Similar modal perturbation equations for the same stiffness change ΔK_d but for a case with modelling error $\Delta\tilde{K}$ can be written as

$$[K_0 + \Delta\tilde{K}]\{\phi_0 + \Delta\tilde{\phi}\} = (\lambda_0 + \Delta\tilde{\lambda})[M]\{\phi_0 + \Delta\tilde{\phi}\}, \tag{3a}$$

$$[K_0 + \Delta\tilde{K} + \Delta K_d]\{\phi_0 + \Delta\tilde{\phi} + \Delta\tilde{\phi}_d\} = (\lambda_0 + \Delta\tilde{\lambda} + \Delta\tilde{\lambda}_d)[M]\{\phi_0 + \Delta\tilde{\phi} + \Delta\tilde{\phi}_d\}, \tag{3b}$$

where the symbol ~ denotes the quantities associated with the modelling errors $\Delta\tilde{K}$. Then the first order modal perturbation equation for ΔK_d can be obtained as

$$[\Delta K_d]\{\phi_0\} + [K_0]\{\Delta\tilde{\phi}_d\} = \lambda_0[M]\{\Delta\tilde{\phi}_d\} + \Delta\tilde{\lambda}_d[M]\{\phi_0\}. \tag{4}$$

Assuming small damage ΔK_d and small modelling error $\Delta\tilde{K}$, $\Delta\lambda_d$ and $\Delta\tilde{\lambda}_d$ in Eqs. (2) and (4), which are the variations of λ due to the same damage ΔK_d for two FE models without and with the modelling error $\Delta\tilde{K}$, may be approximated as $\Delta\lambda_d \approx \Delta\tilde{\lambda}_d$. Verification of the approximation is given numerically for an example structure in Section 3.1. Then following equation can be obtained from Eqs. (2) and (4):

$$[K_0 - \lambda_0 M]\{\Delta\phi_d - \Delta\tilde{\phi}_d\} = 0. \tag{5}$$

The solution for Eq. (5) can be obtained as

$$\{\Delta\phi_d\} = \{\Delta\tilde{\phi}_d\} \tag{6a}$$

or

$$\{\Delta\phi_d - \Delta\tilde{\phi}_d\} = \alpha\{\phi_0\}. \tag{6b}$$

Eq. (6a) means that the mode shape changes due to the damage in a system without modelling errors are same as those in a system with the modelling error, which indicates that the changes of mode shapes are less sensitive to the modelling errors than the mode shapes themselves. Eq. (6b) means that the difference between the mode shape changes due to the damage in a system without the modelling error and those with the modelling error is proportional to a mode shape of the intact system without the modelling error. To investigate the existence of the proportional constant α not equal to zero, Eq. (6b) is pre-multiplied by $\{\phi_0\}^{\mathrm{T}}$ as

$$\{\phi_0\}^{\mathrm{T}}\{\Delta\phi_d - \Delta\tilde{\phi}_d\} = \alpha\{\phi_0\}^{\mathrm{T}}\{\phi_0\}. \tag{7}$$

If the mode shapes are normalized as

$$\begin{aligned} &\|\phi_0\|_2 = \phi_0^{\mathrm{T}}\phi_0 = 1, \quad \|\phi_d\|_2 = \|\phi_0 + \Delta\phi_d\|_2 = 1, \\ &\|\tilde{\phi}\|_2 = \|\phi_0 + \Delta\tilde{\phi}\|_2 = 1, \quad \|\tilde{\phi}_d\|_2 = \|\phi_0 + \Delta\tilde{\phi} + \Delta\tilde{\phi}_d\|_2 = 1 \end{aligned} \tag{8}$$

the following approximate relationships can be obtained as

$$\phi_0^{\mathrm{T}}\Delta\phi_d \approx 0, \quad \phi_0^{\mathrm{T}}\Delta\tilde{\phi} \approx 0, \quad \phi_0^{\mathrm{T}}\Delta\tilde{\phi}_d \approx 0. \tag{9}$$

Then the left-hand side of Eq. (7) vanishes and α becomes zero, which means Eq. (6a) is the only viable solution for Eq. (5).

Based on the assumption of a small modelling error $\Delta\tilde{K}$, the following approximate relationship can be obtained from Eq. (6a) for the mode shape ratios before and after damage for the cases with and without the modelling error as

$$\frac{\phi^i_{dj}}{\phi^i_{0j}} \approx \frac{\tilde{\phi}^i_{dj}}{\tilde{\phi}^i_{0j}} \quad \text{for } \forall i,j \text{ where } \phi^i_{0j}, \tilde{\phi}^i_{0j} \neq 0. \tag{10}$$

In this study, the differences or the ratios of the mode shapes between before and after damage are proposed to be used as the input for the NN-based damage estimation, since they are less sensitive to the modelling error in the baseline FE model than the mode shape themselves.

2.2. Neural networks for damage detection

Standard back-propagation algorithm [25–29] is employed in this study. The networks consist of an input layer, two hidden layers, and an output layer as shown in Fig. 1. Sigmoid functions are utilized as non-linear activation functions for all layers. The input layer contains the measured mode shape properties (i.e., the mode shape differences or the mode shape ratios before and after damages), and the output layer consists of the element-level stiffness indices to be identified as

$$S_i = k_{i,d}/k_{i,0}, \tag{11}$$

where i denotes the element number. The information on the natural frequencies is not induced in the input layer, since they may vary significantly with the environmental and operation conditions. In this study, the element-level damage severity is defined as

$$\alpha_i = 1 - S_i. \tag{12}$$

The input/output relationship of the NN can be non-linear as well as linear, and its characteristics are determined by the synaptic weights assigned to the connections between the

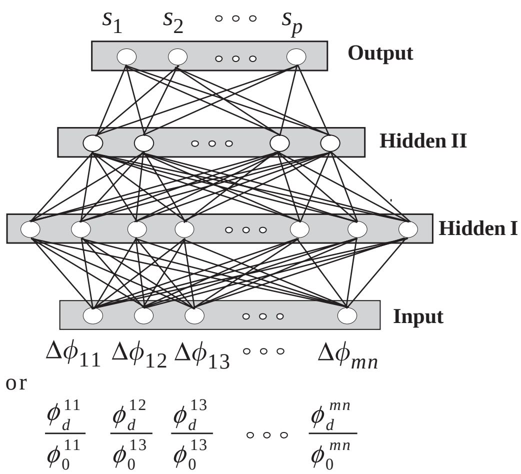


Fig. 1. Multilayer perceptrons.

Table 1
Information used in the networks for damage detections

Information in the networks	Damage detection case			
	Simple beam	Multi-girders	Model bridge	Real bridge
No. of modes used	4	3	4	3
No. of training patterns	4000	80 000	5000	100 000
No. of input nodes	20	98	24	80
No. of 1st hidden nodes	20	60	24	60
No. of 2nd hidden nodes	8	40	8	60
No. of output nodes	8	40	8	40

neurons in two adjacent layers. The differences or the ratios of the mode shapes between before and after damage were used as input to the NN to reduce the effect of errors in the baseline FE model of the structure. Training patterns for the NN were generated using the initial baseline FE model, which may have modelling errors of considerable size. The noise injection learning technique [27,28] is employed to reduce the effects of the measurement error in the input mode shape data.

The effect of the measurement errors in the mode shapes near the support and/or the node points may be severer than at the other locations. Hence, selective information excluding the mode shape data near the node points is utilized as the input to the NN in this study. The activation level for the mode shape is determined by the magnitude of the normalized of mode shape: i.e., the mode shape components of which magnitudes are larger than 10% of the maximum value are used. The number of training patterns is chosen considering the Vapnik–Chervonenkis dimension (VCdim) criterion, so the total number of the training patterns are taken as 5–10 times of the number of the synaptic weights in the networks [36,37]. Training patterns are generated using the Latin hypercube technique [38], so that the whole sample space may be represented effectively with a limited number of the samples. The damage severity range assumed for each element in the training patterns is 0.5–1.5 with a step size of 0.05 for the first three cases and 0.2–1.8 with the same size for the real bridge case. The structure of networks was determined based on the trends of the learning curves evaluated for various cases of the NN structure. Details of information of the networks for damage detections in each case were listed in Table 1.

3. Numerical verification examples

3.1. A simple beam

A numerical example analysis was performed on a simple beam model to investigate the effectiveness of the present NN-based damage detection method. Fig. 2 shows the simple beam model, which consists of 8 beam elements with equal element length ($L^{EL} = 1.25\,\mathrm{m}$) and originally with uniform bending rigidity ($EI = 7.75 \times 10^4\,\mathrm{kN\,m^2}$). The modelling errors were introduced to each of the structural members as random variables. To investigate the effectiveness of the various input quantities to the NN under the modelling errors in the baseline FE model, 100 FE models

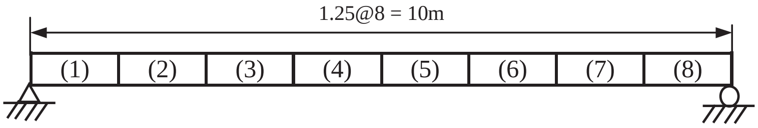


Fig. 2. A simple beam model and element numbers.

Table 2
Natural frequencies of a simple beam model (intact case)

Modes	True	Models with 5% modelling error					Models with 10% modelling error				
		5-A	5-B	5-C	5-D	5-E	10-A	10-B	10-C	10-D	10-E
1	7.268	7.251	7.341	7.236	7.246	7.276	7.249	7.251	7.072	7.133	7.269
2	28.80	28.56	29.01	28.66	28.97	28.80	28.86	28.85	28.36	29.25	28.45
3	63.62	63.63	63.88	64.01	63.73	63.91	62.99	62.85	63.66	62.88	63.89
4	109.7	109.5	109.5	109.6	109.5	109.5	109.3	109.3	109.4	109.2	109.1

with 5% and 10% modelling errors in RMS-level were generated by perturbing the bending rigidities of the beam elements.

Table 2 shows the first 4 natural frequencies calculated for 5 sample cases of the FE models with 5% and 10% modelling errors along with those obtained from the correct model. Verification of the approximation $\Delta\lambda_d \approx \Delta\tilde{\lambda}_d$ in Section 2.1 is carried out for six damage cases described in Table 3. Fig. 3 shows that the natural frequency changes due to damage in the system without modelling error are found to be almost same to those with the modelling error. The difference between $\Delta\lambda_d$ and $\Delta\tilde{\lambda}_d$ is less than 0.2% in both cases of Model 5-A and 10-E.

Fig. 4 illustrates the influence of the modelling errors on the first mode shape. The differences in the mode shapes between the true intact case and a baseline FE model with 10% modelling error (Model 10-E) are found to be much larger than those due to damage. Obviously, the mode shape data cannot be effectively used for damage detection, if the effect of the error in the baseline FE model is more significant than the change in the mode shape caused by damage.

Damage estimation was performed for the six damage scenarios shown in Table 3. Three different modal quantities were used as input to the NN. They are the mode shapes themselves, the mode shape differences between before and after damage, and the mode shape ratios for the first four modes. To investigate the effectiveness of the three input quantities under the modelling errors in the baseline FE model, 100 baseline FE models were generated for each case with 5% and 10% modelling errors. Accordingly 100 neural networks were constructed for this investigation. Figs. 5 and 6 show the mean and standard deviation of the estimated damage indices (100 cases) along with the assumed exact values. It can be observed that all assumed damages were estimated very successfully, if the mode shape differences or the mode shape ratios were used. The mean values of damage indices are fairly close to the assumed exact values and the standard deviations are very small. However, if the mode shapes were utilized as the input to the NN, the mean values of damage indices still remain reasonable, but the variances become very large for all elements. This indicates the accurate damage detection cannot be guaranteed by using mode shape themselves, if the baseline FE model contains significant level of the modelling error.

Table 3
Damage scenarios for a simple beam model (loss of bending rigidity)

	Element number							
	1	2	3	4	5	6	7	8
Case 1	—	—	10%	—	—	—	—	—
Case 2	—	15%	—	—	—	—	—	—
Case 3	—	—	—	10%	—	—	15%	—
Case 4	—	—	15%	10%	—	—	—	—
Case 5	—	10%	15%	—	—	10%	—	—
Case 6	10%	—	—	15%	—	—	15%	—

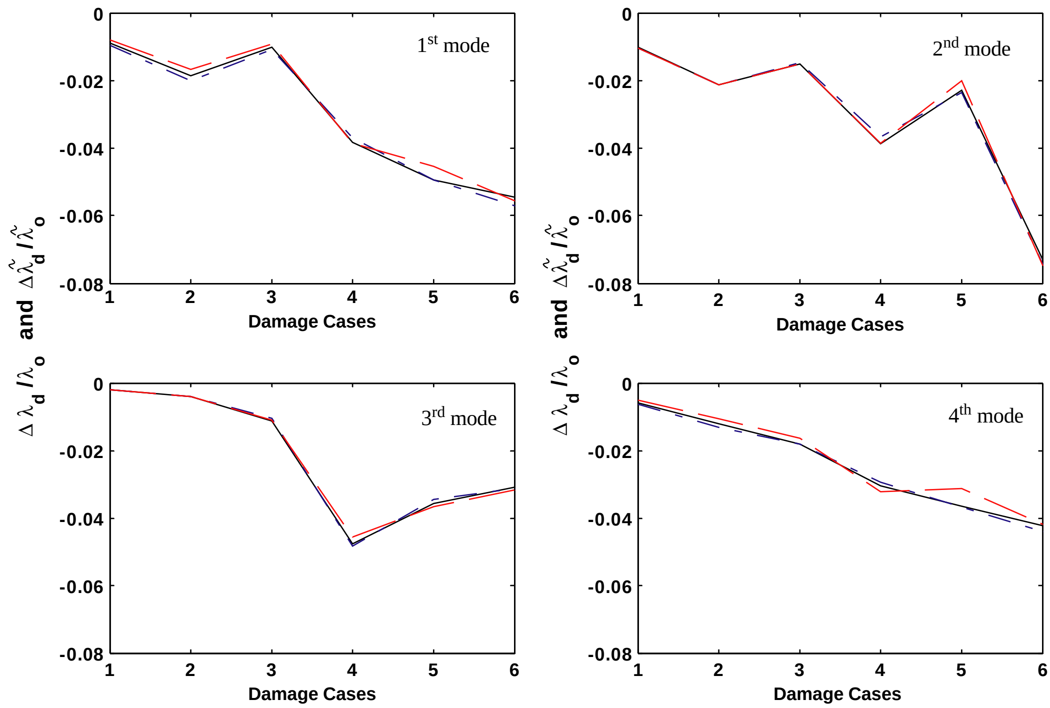
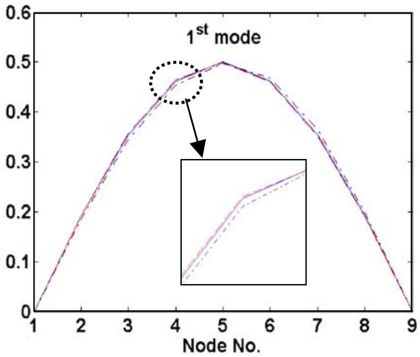


Fig. 3. Numerical verification for $\Delta\lambda_d \approx \Delta\tilde{\lambda}_d$ (——: $\Delta\lambda_d/\lambda_0$ without modelling error, - - -: $\Delta\tilde{\lambda}_d/\tilde{\lambda}_0$ with 5% modelling error (5-A), -·-·: $\Delta\tilde{\lambda}_d/\tilde{\lambda}_0$ with 10% modelling error (10-E)).

From these results, it can be concluded that the differences or the ratios of the mode shapes between before and after damages can be used more effectively as the input to the NN to reduce the effect of the modelling errors in the baseline FE model.

3.2. A bridge with multiple girders

A more realistic example analysis was performed on a single span bridge with multiple girders. The bridge, which consists of 5 girders, diaphragms and slabs, is modelled using beam elements



Modal values of first mode			
Node No.	True intact	True damaged (10% at EL. 3)	Model 10-E Intact
2	0 .1913	0.1926	0.1865
3	0 .3535	0.3566	0.3454
4	0 .4620	0.4643	0.4542
5	0 .5000	0.4994	0.4975
6	0 .4620	0.4598	0.4688
7	0 .3535	0.3512	0.3649
8	0 .1913	0.1899	0.1979

Fig. 4. Variations of first mode shape due to damages and modelling errors (––: true intact, - - -: true damaged (10% at El. 3), - · - · : model 10-E intact).

for the girders and diaphragms and shell elements for the slabs as shown in Fig. 7. The first three modes were calculated for the intact case using SAP2000 program, and the results are shown in Fig. 8 and Table 4. Various cases of the baseline FE model with different modelling errors of 10% and 20% rms-levels were generated as in the previous example.

Damage estimations were carried out for six damage scenarios described in Table 5 and the results of two example cases are shown in Figs. 9 and 10. If the mode shape differences or ratios were used as the input to the NN, the accuracy of the damage estimation has been found to be fairly good for all the damage cases, even though there were modelling errors as large as 20% in rms-level. However, if the mode shapes were used, lots of false alarm occurred and the damage detection failed as in Figs. 9a and 10a. Similar trends were observed for the cases with different modelling errors. From these results, it can be concluded that the present NN-based damage detection method using the mode shape differences or the mode shape ratios as the input parameters can be effectively used even for complex structures to reduce the effect of the modelling errors.

4. Laboratory test on a bridge model

In the previous work by the present authors [26], a method for health monitoring of a bridge structure was presented using ambient vibration data caused by traffic loadings. A laboratory test was carried out for damage assessment of a bridge model subjected to vehicle loadings using a NN technique. As input to the NN, the ratios of the resonant frequencies between before and after damages and the mode shapes after the damages were used in the study. The frequency ratios were employed to reduce the mass effect of the vehicles on the frequencies. An initial FE model was updated using the inverse modal perturbation technique [14] to get a better FE model for an intact condition before applying the process of damage estimation. More details are explained in the full script [26].

In the present study, the proposed NN-based damage detection technique using the mode shape differences or the mode shape ratios are applied to the same bridge model. Updating of the

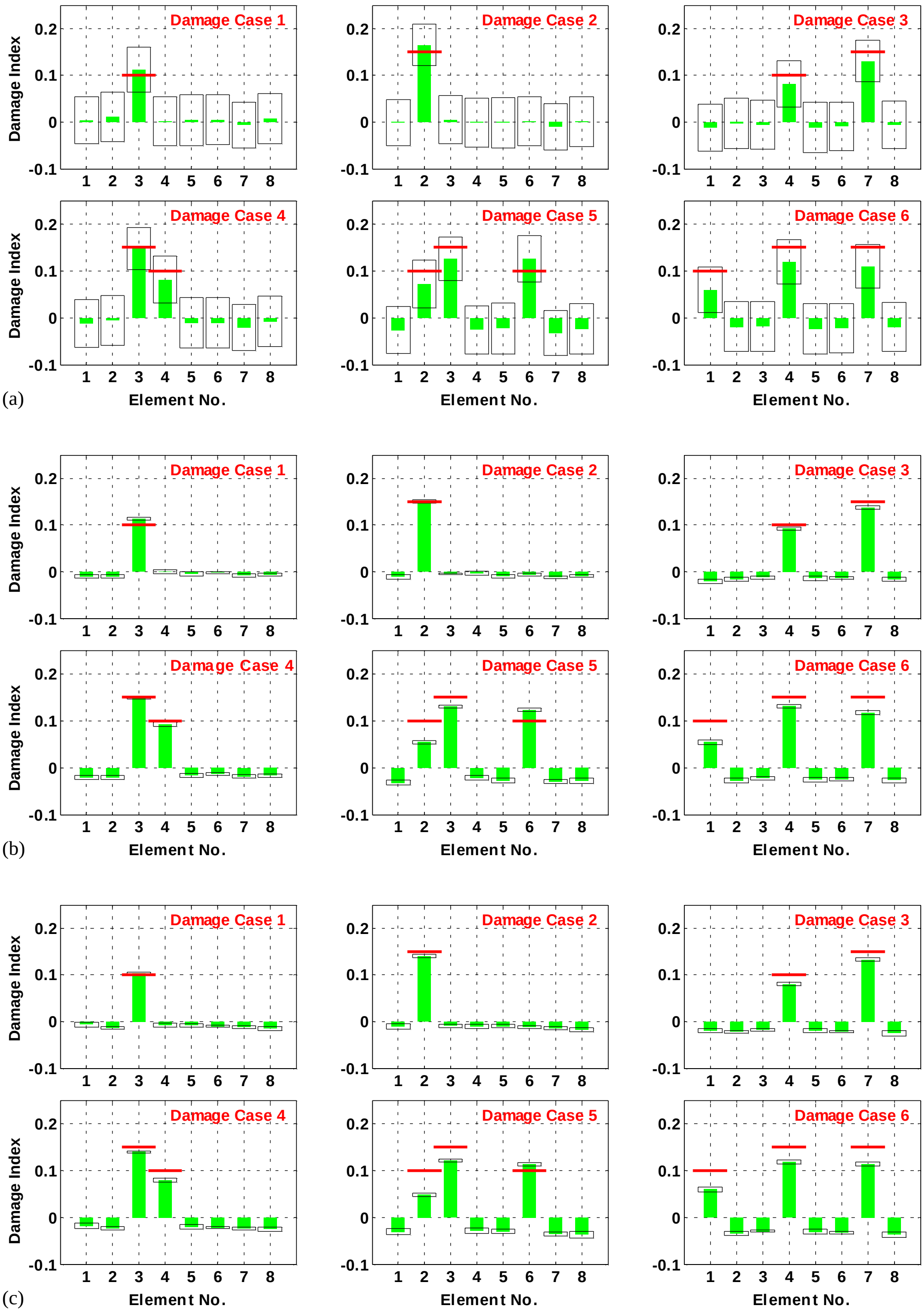


Fig. 5. Damage detection results for a simple beam with 5% modelling error (▬ assumed exact, ▓: mean, □: mean ± σ). (a) Using mode shapes, (b) using mode shape differences, (c) using mode shape ratios.

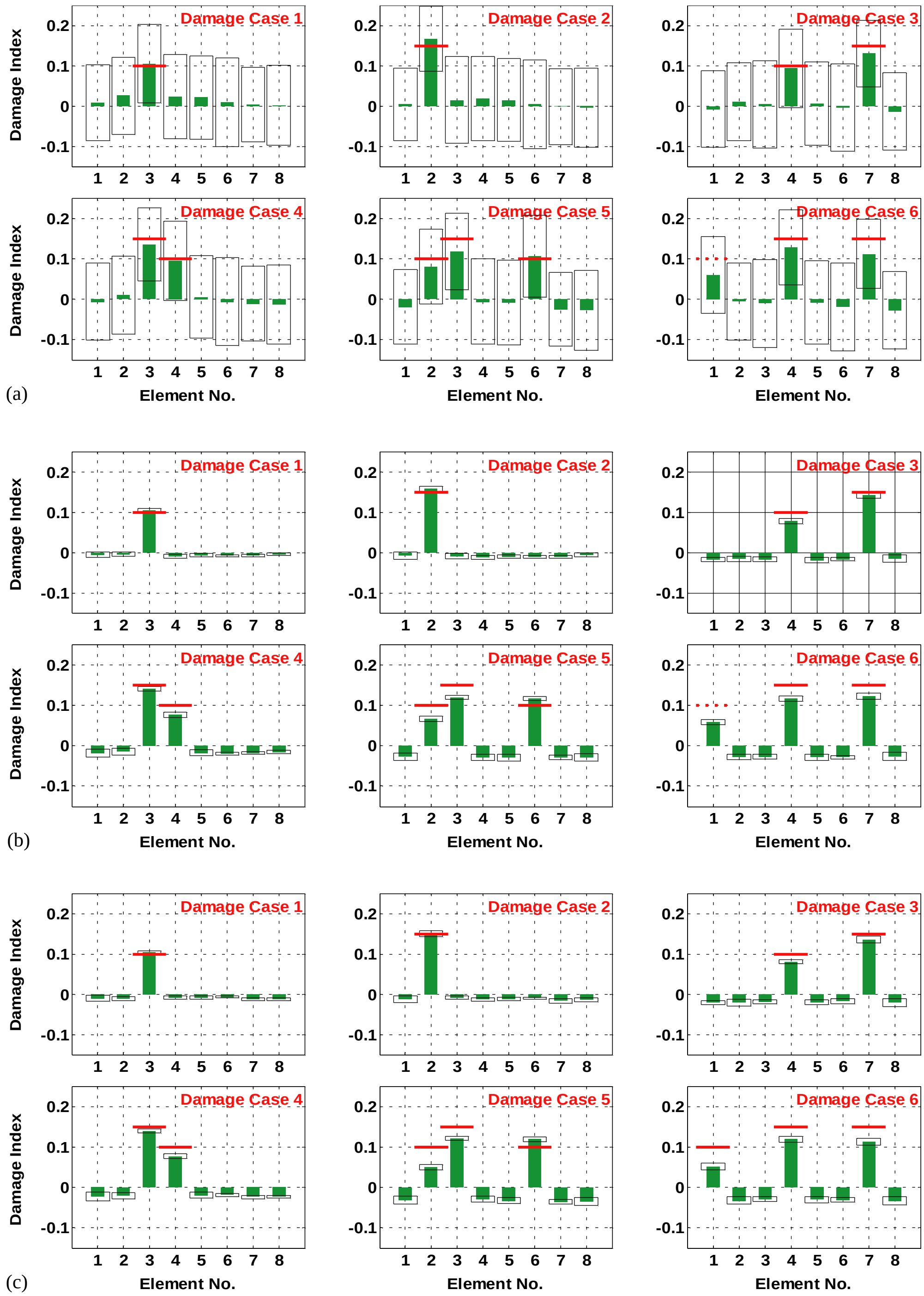


Fig. 6. Damage detection results for a simple beam with 10% modelling error (▬ assumed exact, ▒: mean, □: mean ± σ). (a) Using mode shapes, (b) using mode shape differences, (c) using mode shape ratios.

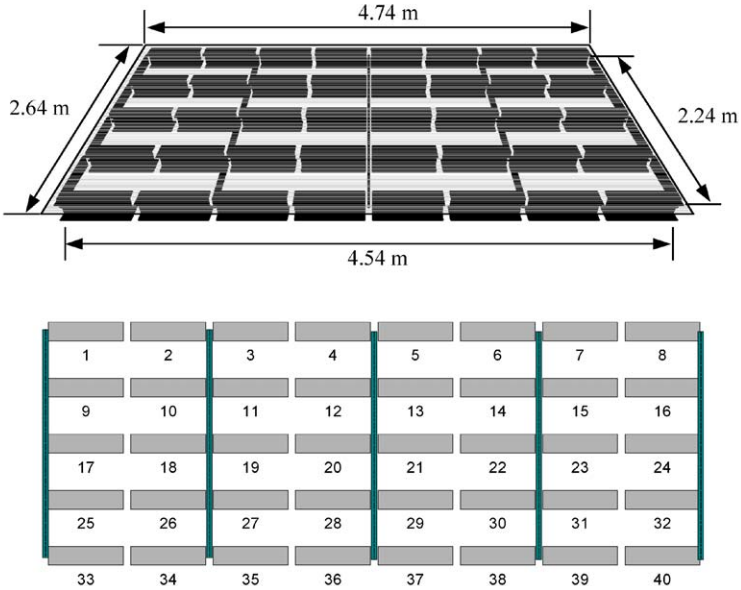


Fig. 7. A bridge with multiple girders and element numbers.

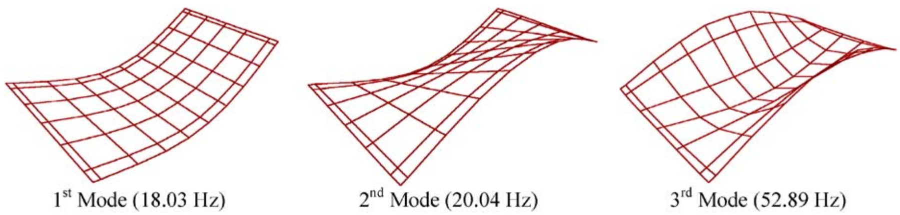


Fig. 8. First three mode shapes of a bridge with multiple girders.

Table 4
Natural frequencies of a bridge with multiple girders (intact case)

Modes	True	With 10% modeling error	With 20% modeling error
1	18.03	17.86	17.68
2	20.04	19.88	19.81
3	52.89	52.82	52.82

Table 5
Damage scenarios for a bridge with multiple girders (loss of bending rigidity)

El. no.	Case 1 (%)	Case 2 (%)	Case 3 (%)	Case 4 (%)	Case 5 (%)	Case 6 (%)
7	—	20	20	—	30	30
11	20	20	20	30	30	30
28	—	—	20	—	—	30

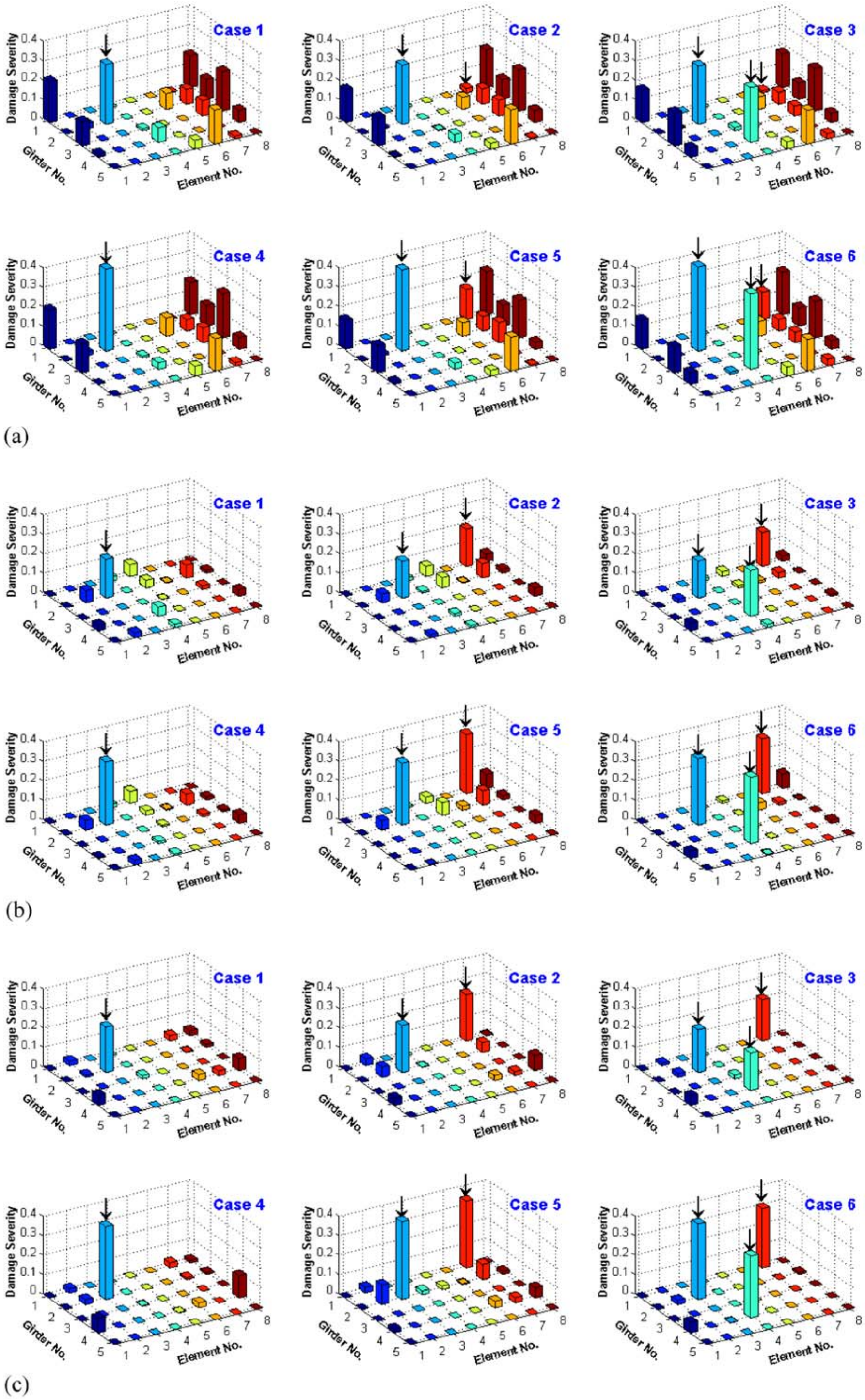


Fig. 9. Estimated damages for a multi-girder bridge with 10% modelling error (the exact locations of damages are marked with arrows(↓)). (a) Using mode shapes, (b) using mode shape differences, (c) using mode shape ratios.

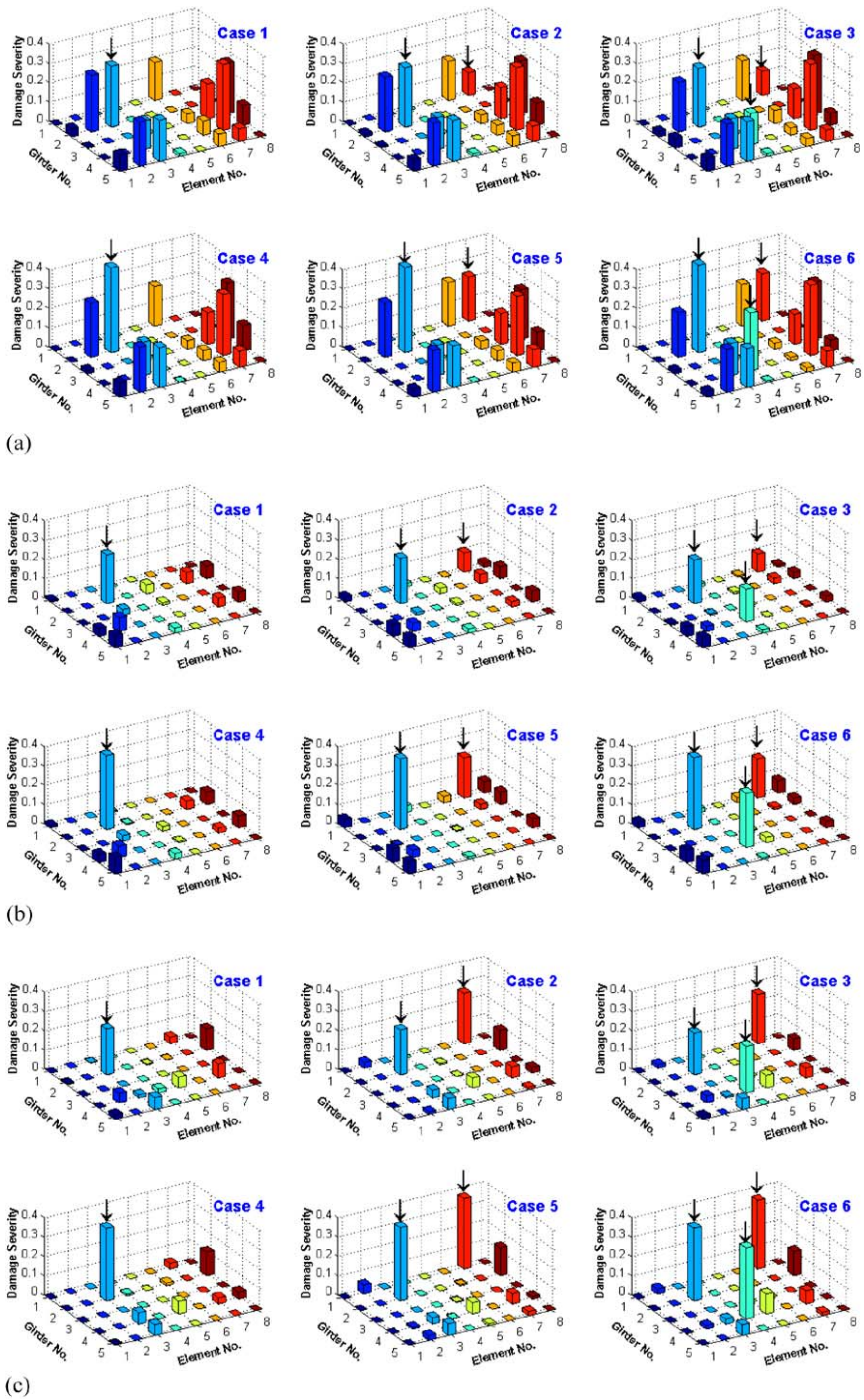


Fig. 10. Estimated damages for a multi-girder bridge with 20% modelling error (the exact locations of damages are marked with arrows(↓)). (a) Using mode shapes, (b) using mode shape differences, (c) using mode shape ratios.

baseline finite element model is intentionally skipped to demonstrate the effectiveness of the present method. A schematic of the experimental setup is shown in Fig. 11a and the FE model used in this study is shown in Fig. 11b. Modal parameters were obtained using the frequency domain decomposition technique [38,39]. The resonant frequencies and the mode shapes were obtained from the vertical accelerations at seven equally spaced locations along the girders of the bridge model, and the results for several cases are shown in Fig. 12 and Table 6. The natural

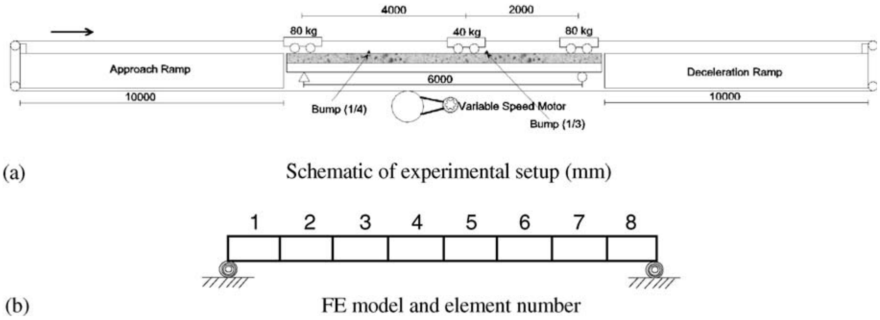


Fig. 11. Experimental setup for a bridge model.

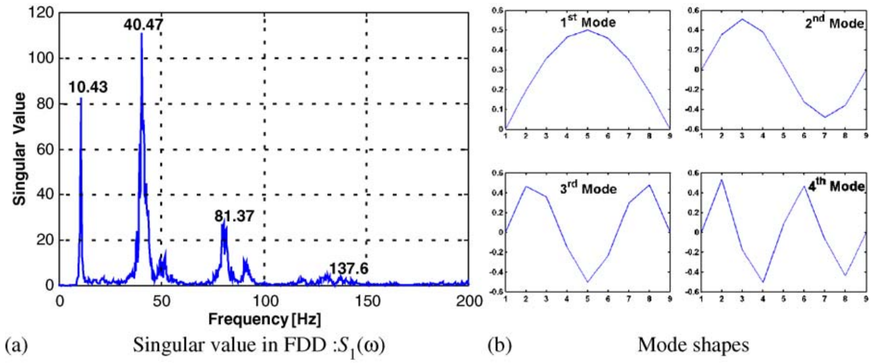


Fig. 12. Identified modal parameters of a bridge model using FDD (Intact w/vehicles).

Table 6
Resonant frequencies of a bridge model for intact and several damage cases

Modes	Intact FE models		Tests				
	Initial	Updated	Intact (w/Impact)	Intact (w/vehicles)	Damage Case 1	Damage Case 4	Damage Case 8
1	9.23	11.45	11.40	10.43	10.10	9.63	8.57
2	36.87	40.09	41.00	40.47	40.20	38.50	34.90
3	82.69	84.13	81.80	81.37	79.70	77.83	67.80
4	145.9	146.7	137.4	137.6	136.0	134.1	130.1

Note: Natural frequencies for the intact FE models and the impact test are without the vehicle masses and the others are with the vehicle masses.

Table 7
Damage scenarios for a bridge model (loss of bending rigidity)

El. no.	Case 1 (%)	Case 2 (%)	Case 3 (%)	Case 4 (%)	Case 5 (%)	Case 6 (%)	Case 7 (%)	Case 8 (%)
2	—	—	—	—	−15.8	−15.8	−22.1	−32.1
4	−16.6	−16.6	−16.6	−16.6	−16.6	−31.0	−31.0	−31.0
6	—	−9.5	−16.9	−25.4	−25.4	−25.4	−25.4	−25.4

frequencies computed from the intact FE model differ significantly from the measured values, since the effect of the moving mass of test vehicles was not considered in the analysis. Therefore, the initial FE model was updated using the impact test data in which the mass effect was excluded in the previous study. Damage estimation was carried out using three different types of modal quantities as the input to the NN as in the previous numerical example cases. The information on the natural frequencies was not included to verify the effectiveness of the present methods using the mode shape information only.

Eight damage cases described in Table 7 were analyzed. In each case, damages were imposed by cutting out parts of the bottom flanges in the girder segments. Fig. 13 shows the estimated damage severities along with the inflicted values. Most locations of the inflicted damages are detected fairly successfully, if the mode shapes generated around the updated finite element model were utilized during the training of the NN. However there were a number of cases with false alarms. On the other hand, if the NN was trained using the mode shape differences or the ratios generated around the initial FE model, the estimated results are found to be much better than those using the NN trained by the mode shapes from the updated FE model. The above results confirm the effectiveness of using the differences or the ratios of the mode shapes for damage estimation under the modelling errors in the initial FE model.

In Fig. 13, the estimated damage indices using the mode shapes and the differences in the estimated element stiffness between before and after damage (i.e.: Ni's approach [33]) are also shown for the purpose of comparison. It has been found that good estimates can be also obtained by using the differences in the estimated element stiffness if the NN was trained using the mode shapes generated from the updated FE model. However further analyses showed that the estimated results became poor if the training patterns were generated from the initial FE model with larger modelling errors.

5. Field test on Hannam Grand Bridge

Field tests on damage estimation were performed on the northern-most span of old Hannam Grand Bridge over Han River in Seoul, Korea (Fig. 14), which is to be replaced during bridge renovation. It is simply supported, and the length of the span is 22.7 m. It consists of nine steel plate girders and a concrete slab. Originally it had 10 girders, but the 10th girder was removed during the construction of the newly built bridge next to it. Ambient vibration tests were carried out for vertical acceleration on the bridge deck. The vibration was mainly induced by the traffic loads on the adjacent new bridge and the train loads under the test bridge. Eight sets of

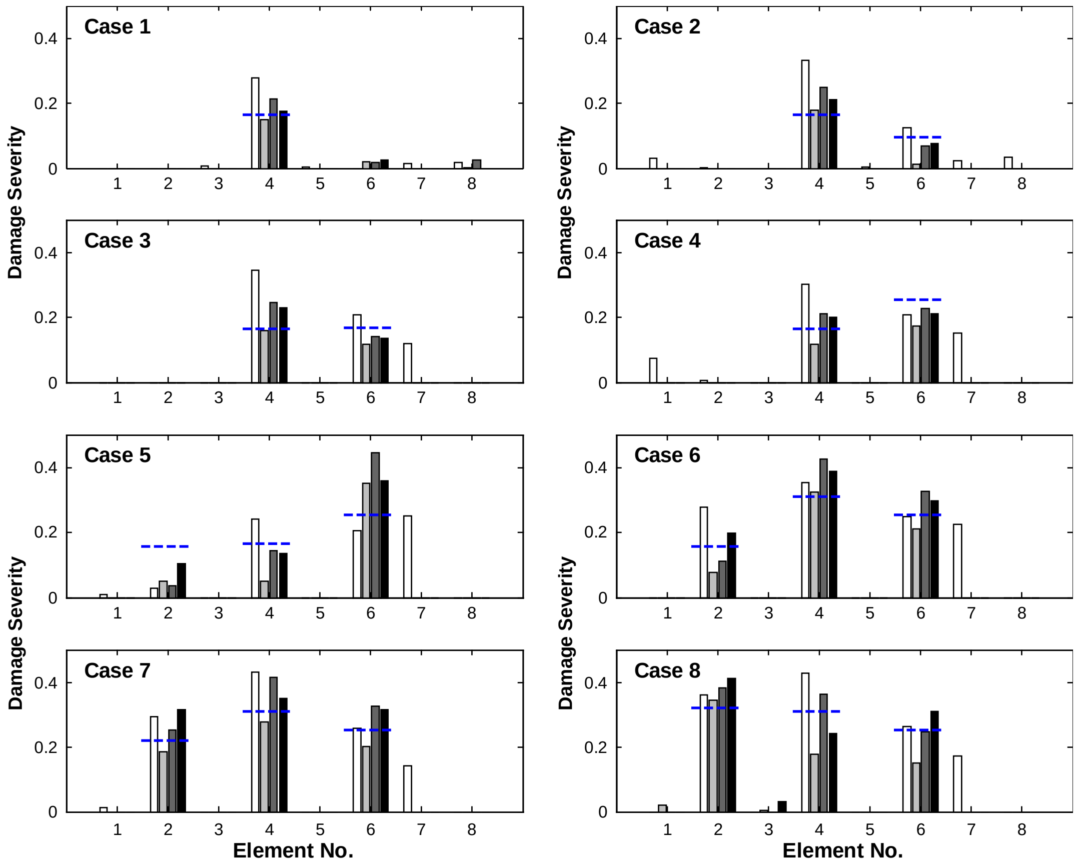
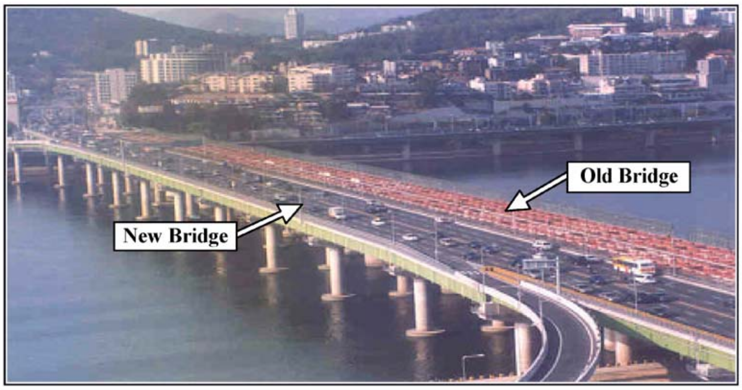


Fig. 13. Estimated damages of a bridge model using various input data (- - -: inflicted values, □: using mode shapes (trained using updated model), ▭: using mode shapes and stiffness index differences (trained using updated model), ▭: using mode shape differences (trained using initial model), ▬: using mode shape ratios (trained using initial model)).

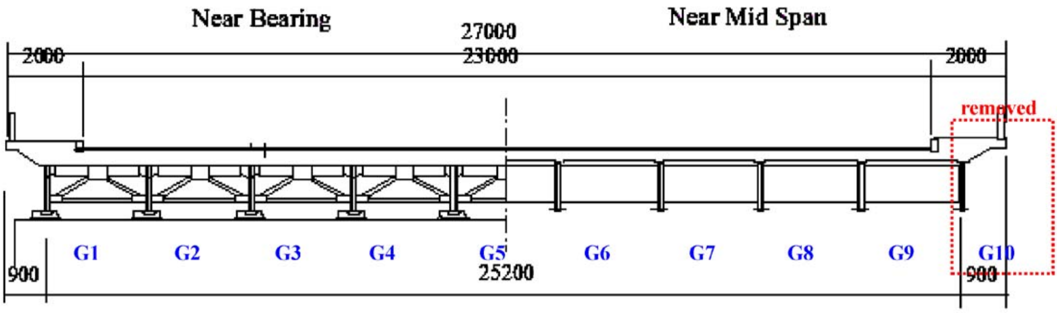
measurements were carried out on Girders 1–8 as shown in Fig. 15. For each set, vertical accelerations were measured at 11 equally spaced points on the slab just above each girder. Reference signals to correlate each experimental set were obtained at eight points (R1–R8). Fig. 16 shows an typical case of acceleration time history obtained from ambient vibration test.

Fig. 17 shows the inflicted damage scenarios imposed by torch cuts on the main girders of the bridge for the present damage detection study. The damages were imposed locally, unlike in the bridge model for the laboratory test. Modal parameters for each damage state were identified using the frequency domain decomposition method. An initial FE model for the bridge was constructed based on the drawings using beam elements for the girders and diaphragms and shell elements for the slab. The modal analysis was performed using SAP 2000 program. Table 8 shows the modal properties calculated from the initial FE model and those estimated from the experiments for each damage case. It can be observed that the measured first natural frequency increases slightly rather than decreases, as the damage becomes more severe. This indicates the



(a) Overview of old and new bridges

(b) Northern-most span of old bridge (span = 22.7m)



(c) Section view of old bridge

Fig. 14. View of Hannam Grand Bridge in Seoul, Korea.

difficulty in using resonant frequencies as damage indicators for large civil engineering structures, where the environmental effects on the resonant frequencies such as temperature, humidity, etc. may not be ignored. Besides of the environmental effects, the support conditions may cause significant variations of the natural frequencies. Accordingly, the natural frequency information was not used in the damage detection procedure. In Table 8, the modal assurance criteria (MAC) values are also shown, which represent the closeness between the calculated and the experimental mode shapes. The first three modes gave close results to the test results: i.e., above 97% in MAC value. Therefore, the first three mode shapes were used as inputs for the damage estimation. In

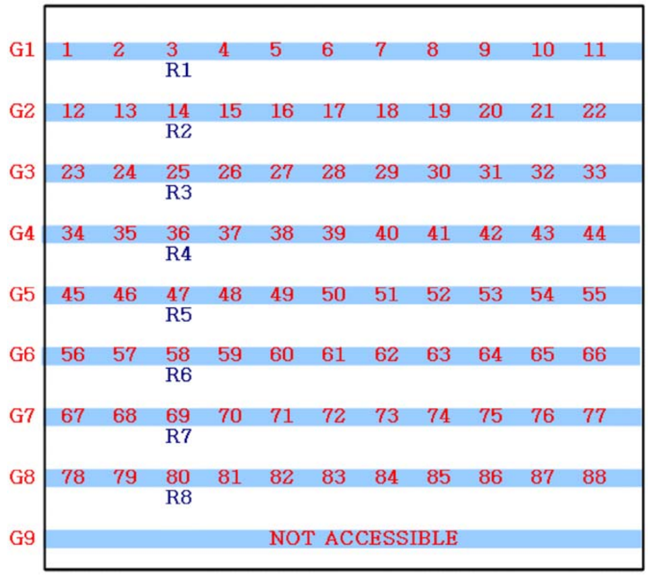


Fig. 15. Measurement locations for vertical acceleration (1–88: roving sensors, R1–R8: reference sensors).

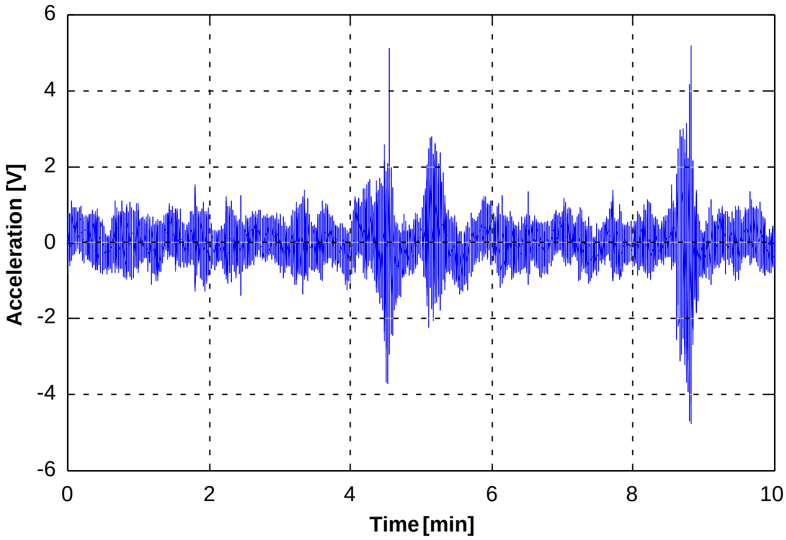


Fig. 16. Acceleration time history (at sensor 39).

general, the mode shapes estimated from the measurement contain more error than the natural frequencies. However, the lower modes can be estimated with good accuracy, as the measurement and signal processing techniques have improved remarkably.

Comparing the mode shapes along Girders 2 and 3 where the actual damages were introduced for damage cases II and III (Fig. 18), the discrepancies between the modes calculated from the

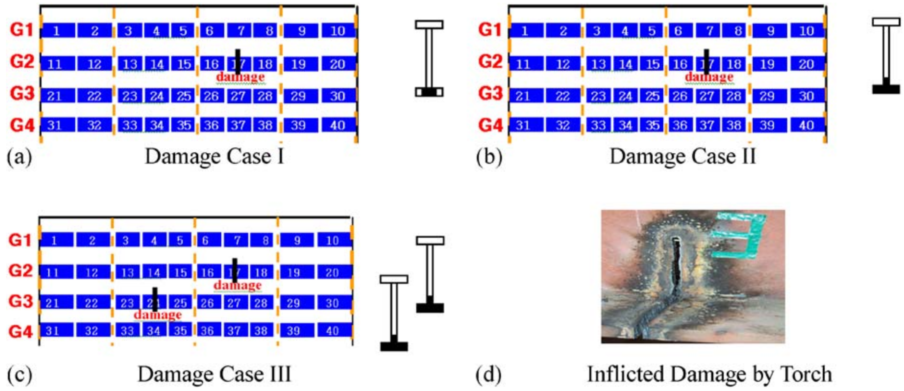
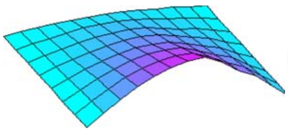
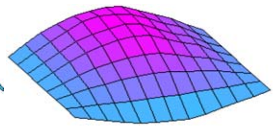
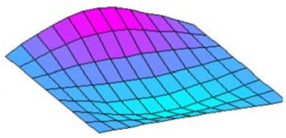


Fig. 17. Damage scenarios for Hannam Grand Bridge.

Table 8
Natural frequencies and modes of Hannam Grand Bridge for various damage cases

Modes	1st mode	2nd mode	3rd mode
Calculated (Intact)	4.071 Hz	4.452 Hz	5.626 Hz
Measured			
Intact	4.247 Hz (99.79)	4.876 Hz (97.86)	5.771 Hz (99.71)
Damage I	4.188 Hz (99.38)	4.903 Hz (99.45)	5.823 Hz (99.64)
Damage II	4.196 Hz (99.90)	4.780 Hz (99.35)	5.778 Hz (99.57)
Damage III	4.218 Hz (99.51)	4.757 Hz (99.56)	5.799 Hz (99.73)
Measured mode shapes (Intact case)			

Note: values in parentheses are the MAC values (%).

intact FE model and those measured from the intact structure are found to be much larger than those between the measured intact and damage cases. This implies that the mode shapes generated around the intact FE model may be used to train the NN for damage estimation. In such case, the model updating process can be used to obtain a better FE model which can represent real behaviors of the structure more closely. The more refined the analytical model is, the more effective the damage estimation is. However, element-level model updating is generally very difficult for large and complex civil structures, and it may not guarantee a successful model for the element-level damage estimation. These problems can be overcome by using the mode shape difference or the mode shape ratios instead of the mode shapes themselves as in the previous examples.

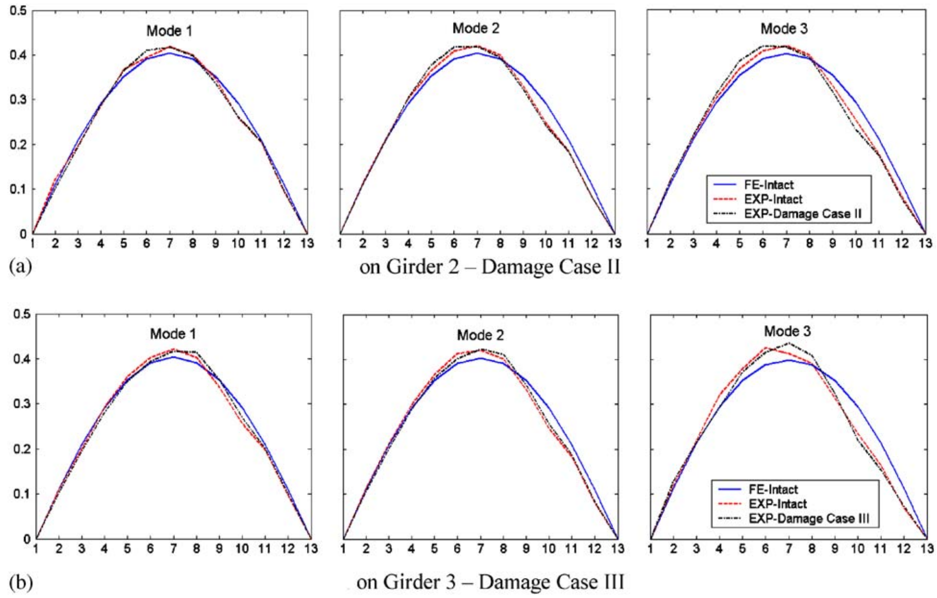


Fig. 18. Mode shapes along girders 2 and 3 for damage cases II and III.

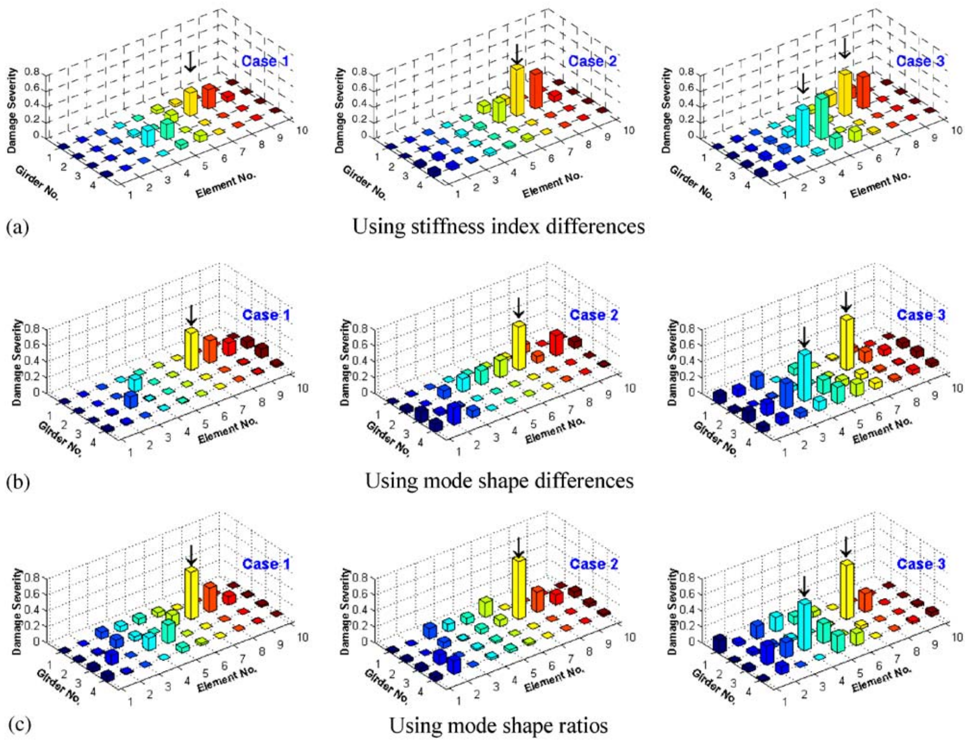


Fig. 19. Estimated damages for Hannam Grand Bridge (the exact locations of damages are marked with arrows (↓)).

Damage estimation was performed on a substructure composed of four girders shown in Fig. 17 using the first three modes which are judged to be relatively accurate. The differences and the ratios of the mode shapes between before and after damages were, respectively, used as the inputs to the neural networks. The damage detection was performed using selective information excluding the mode data near the node points. The frequency information was not used. Fig. 19 shows that the damage locations are identified with good accuracy for all the cases, whereas the estimated results contain false alarms with small magnitudes at several locations. But it can be found that the estimated damage indices have dominant values at the locations of actual damages. The approach using the mode shapes and the differences in the estimated element stiffness [33] were also used for the purpose of comparison and the results are also shown in Fig. 19. It has been found that all the damage locations were identified reasonably for all the cases, however the estimated results contain false alarms with fairly large magnitudes at several locations.

6. Concluding remarks

A neural networks-based technique is presented for element-level damage assessments of structures using the modal properties. The mode shape differences or the mode shape ratios between before and after damage are used as the input to the NN to reduce the effect of the modelling errors in the baseline FE model, from which the training patterns are to be generated.

From two numerical example analyses on a simple beam and a multi-girder bridge, the effectiveness and the applicability of the proposed method using the mode shape differences or ratios are demonstrated. From laboratory tests on a bridge model, it has been found that the present neural networks technique can be effectively used for damage detection of the bridges under traffic loadings considering the modelling errors. Most of the inflicted damages have been detected very successfully for various damage cases. For an experimental study on a real bridge with multiple girders, the damage estimation was performed on a substructure using selective information excluding the mode shape data near the nodal points. The damage locations were identified with good accuracy for all the damage cases, whereas the estimated damage severities contained minor false alarms at several locations.

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