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INFLUENCE OF MEASUREMENT ERRORS ON STRUCTURAL DAMAGE IDENTIFICATION USING ARTIFICIAL NEURAL NETWORKS*

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Abstract: The effect of measurement errors on structural damage identification using artificial neural networks (ANN) was investigated in this study. By using back-propagation (BP) networks with proper input vectors, numerical simulation tests for damage detection on a six-storey frame were conducted with measurement errors in deterministic as well as probabilistic senses. The identifiability using ANN for damage location and extent was studied for the cases of measurement errors with different degrees. The results showed that there exists a critical level of measurement error beyond which the probability of correct identification is sharply decreased. The identifiability using the neural networks in the presence of modeling and measurement errors is finally verified using experimental data on a two-storey steel frame.

Key words: structural damage identification, artificial neural network, measurement error
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INTRODUCTION

From the viewpoint of serviceability and safety of structures, the detection of structural damage is an important issue for civil engineers. In the past two decades, many efforts have been made to monitor structural integrity using changes in modal parameters through vibration measurements. With the use of structural identification concepts, measurements of the modal characteristics of a structure can be used to detect the location and severity of the damage. A state-of-the-art review on various vibration-based damage identification methods and their merits and demerits is available (H.K.P.U., 1998). Among the methods are artificial neural networks which have recently received considerable attention in damage detection studies (Wu et al., 1992; Elkordy et al., 1993; Szewczyk and Hajela, 1994; Tsou and Shen, 1994; Barai and Pandey, 1995; Rhim and Lee, 1995; Masri et al., 1996; Garcia et al., 1997; Worden, 1997, Xu et al., 1997; Zhao et al., 1998).

The primary sources of difficulties in structural damage detection include measurement noise, modeling error, uncertainty of ambient conditions and incompleteness of measured data. While most of the damage identification methods work successfully when noise-free simulated data are used, presence of the uncertainties due to modeling and measurement errors causes many of the methods to fail. It is generally acknowledged that neural networks tend to be robust in the presence of noise and can distinguish between these random errors and the desired systematic outputs (Levin and Lieven, 1998). It is hoped this property can be used for damage detection. Up to date, however, there is lack of exploratory study focusing on the influence of modeling and measurement errors on structural damage detection using ANN.

Uncertainties arising from measurement noise have been treated in damage detection using other nondestructive methods. Beck and Katafygiotis (1992, 1998) presented a general Bayesian statistical approach to infer structural stiffness changes from observed changes in the modal parameters. Within the probabilistic framework, they explicitly treated the uncertainties that arise from measurement noise, modeling error and possible non-uniqueness in the problem of updating the stiffness distribution. Introducing a branch-and-bound search scheme, Sohn and Law (1997) extended this approach to identifying

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multiple damage locations of frame structures considering both modeling and noise errors. Ricles and Kosmatka (1992) presented a methodology for detecting structural damage in elastic structures by non-destructive means. The test measurement error was treated as a normally distributed random variable with zero mean and specified covariance. Hassiotis and Jeong (1993) developed a method for estimation of structural damage using measured changes in natural frequencies. Numerical tests were performed on a beam and a frame. By using exact or noise-polluted natural frequency data, reduction in the stiffness of up to 40% at single or multiple sites was detected. The measurement noise was simulated by a normally distributed random variable with zero mean and given deviation. The test results indicated that when random noise corrupted the data, light damage was not identified well because the change in the eigenvalues due to damage was sometimes less than the change due to noise. On the other hand, a small amount of random noise in the data did not alter the results in the identification of severe damage of most elements. Ferregut et al. (1995) studied the effects of experimental uncertainties on detectability of structural damage using a frequency sensitivity method through simulating a number of NDE inspections on a cantilever beam subjected to a single damage at several locations using the Monte Carlo technique.

Masri et al. (1996) studied measurement noise effects using ANN for detection of changes in structural parameters. Two simulations were carried out. At first, noise was added only to the data in the training stage. In the second test, noise was added only to the data in the detection stage. It was concluded that, while the presence of noise pollution lessened the discrimination capabilities for detecting small perturbations in the structural characteristics, the approach was still capable of identifying relatively small changes in the dominant structural system parameters. Worden (1997) studied the method of novelty detection of damage in a simple simulated lumped-parameter mechanical system. Two simulations, which added low (RMS 0.01) noise and high (RMS 0.05) noise, were carried out to investigate how the sensitivity of the novelty index depended on the noise level.

The authors used input parameters, called Combined Parameters, as input vectors to BP networks for structural damage identification (Ni et al., 1999, Wang et al., 2000). Since the Combined Parameters were computed with several modal frequencies and the modal components at a few selected points, the problem of incompleteness of modal measurement could be overcome. Numerical simulation and experimental verification proved that the performance of BP networks in which the Combined Parameters were used as the input vectors was satisfactory. The influence of modeling error on structural damage identification using ANN with improved BP algorithm had also been studied through theoretical analysis, numerical simulation and experimental verification (Wang et al., 2000). The influence of measurement error alone, and that of both modeling and measurement error are further discussed.

NUMERICAL SIMULATION

A mathematical model of a six-storey planar frame constructed of standard 152 × 152 × 23-UC columns and 203 × 133 × 25-UB beams was used for numerical simulation tests. The column-base and beam-column connections of the frame are treated as semi-rigid joints with rotational stiffness. The study focuses on the detection of structural connection damage which is practically meaningful for buildings and bridges. An inspection of 60 000 buildings in Los Angeles after the 1994 Northridge earthquake showed that a common type of damage in this earthquake was connection failure (Todd, 1994). Beams and columns remained intact, but the joints were severely damaged and moment connections were reduced to nearly simple hinges. Quantitative assessment of such damage is necessary for reanalyzing the structural behavior of a building damaged by earthquake.

As shown in Fig. 1, the frame is modeled by 54 two-dimensional beam elements with semi-rigid joints and is composed of 50 nodes. Damage is simulated by reducing the rotational stiffness of spring elements at column-base connections and beam-column connections. So a total of 14 single-damage scenarios will be studied in each damage detection test. The natural frequencies of the first ten modes and the horizontal modal components of the first mode at six DOFs (Fig. 1) are chosen to generate the input vectors to ANN. For identifying damage location, only one level of the damage extent, i.e. 50% reduction in the rotational stiffness is applied to each connection respectively to train ANN. Six levels of the damage extent (1%, 5%, 10%, 20%, 30% and 50% reduction in the rotational stiffness) are used to train ANN.

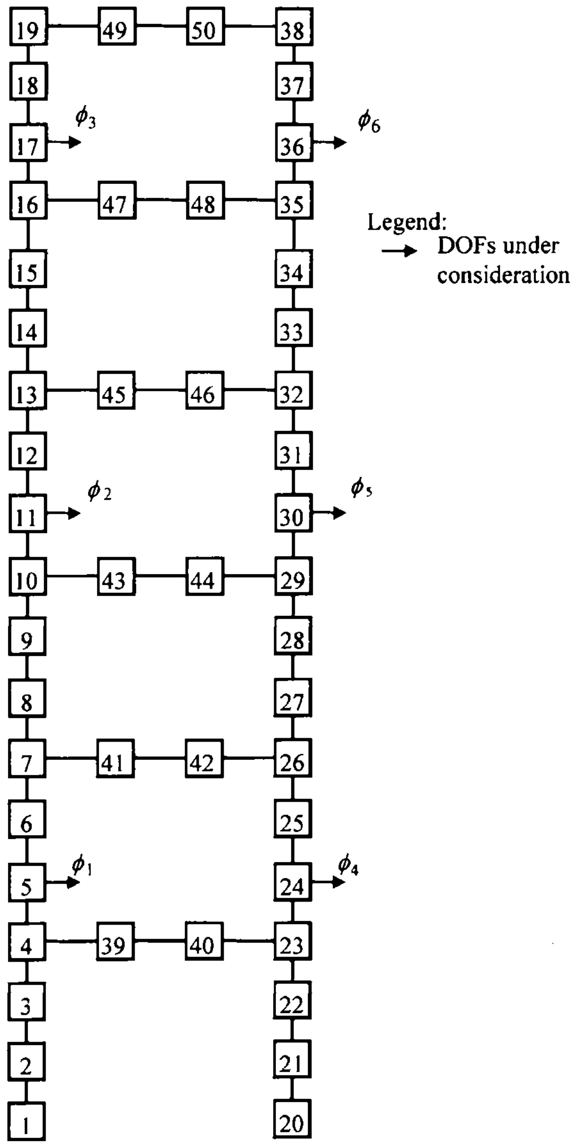

Fig. 1 Modeling of six-storey frame and selected modal components

Measurement uncertainties in estimated modal parameters come from the noise in experimental data and errors introduced by experimental modal analysis. There are commonly two numerical approaches to simulate the measurement error in modal parameters. The first approach consists of generating analytical frequency response functions (FRFs) from the finite element model, applying noise to these FRFs and then using experimental modal analysis technique to generate the noisy modal data (Levin and Lieven, 1998). In the second approach, the exact modal parameters obtained from the analytical model are directly perturbed with noise (Sohn and Law, 1997). For the convenience in numerical simulation, the latter approach is adopted in the present study.

1. Deterministic analysis

The effect of measurement error is first studied in a deterministic manner. The noisy modal data are simply simulated by truncating the exact modal parameters, obtained from the analytical model without or with damage, at a certain number of significant figures. Note that the single-damage at a connection is local in nature and only changes the modal shape of the fundamental mode slightly. To determine differences between the undamaged and damaged truncated modal components, the damage scenarios in damage identification test are simulated by a 50% reduction of rotational stiffness at a specific connection. Referring to Fig. 1, Table 1 shows the modal components of the undamaged frame and the frame damaged to an extent at a specific connection. Due to symmetry, only the damage scenarios on the left side of the frame are considered. The numbers in parentheses indicate the modal component change due to damage. It is seen that in order that such damage-induced change is not concealed, the modal component values must retain three decimal places. Consequently, the noisy modal components are simulated by truncating the true values at the third decimal digit, called accuracy $\delta_m = 0.001$.

For frequency accuracy $\delta_f = 0.1$ and modal component accuracy $\delta_m = 0.001$, all the seven single-damage scenarios are correctly localized. The noisy frequencies with accuracy $\delta_f = 0.1$ are approximately equivalent to the frequencies acquired at a resolution of 0.1 Hz in the experimental modal analysis. When the modal component accuracy is changed to 0.1, however, most of the damage scenarios cannot be correctly localized as the damage information is blurred out.

Table 1 Modal components of undamaged and damaged frame at selected DOFs

Damage case	Modal components at the selected six DOFs					
	ϕ_1	ϕ_2	ϕ_3	ϕ_4	ϕ_5	ϕ_6
Undamaged	0.232	0.656	0.944	0.232	0.656	0.944
D1	0.244	0.660	0.938	0.245	0.660	0.938
	(0.012)	(0.004)	(-0.006)	(0.013)	(0.004)	(-0.006)
D4	0.245	0.662	0.937	0.243	0.662	0.937
	(0.013)	(0.006)	(-0.007)	(0.011)	(0.006)	(-0.007)
D7	0.228	0.663	0.940	0.229	0.663	0.940
	(-0.004)	(0.007)	(-0.004)	(-0.003)	(0.007)	(-0.004)
D10	0.225	0.658	0.947	0.224	0.656	0.947
	(-0.007)	(0.002)	(0.003)	(-0.008)	(0.000)	(0.003)
D13	0.226	0.647	0.952	0.227	0.648	0.952
	(-0.006)	(-0.009)	(0.008)	(-0.005)	(-0.008)	(0.008)
D16	0.230	0.651	0.951	0.230	0.651	0.950
	(-0.002)	(-0.005)	(0.007)	(-0.002)	(-0.005)	(0.006)
D19	0.231	0.655	0.945	0.231	0.655	0.946
	(-0.001)	(-0.001)	(0.001)	(-0.001)	(-0.001)	(0.002)

Note: Data in parentheses are differences between damaged and undamaged states modal components.

Table 2 shows the performance of the damage extent identification ANN, with modal component accuracy $\delta_m = 0.001$ and frequency accuracy $\delta_f = 0.1$, 0.01 and 0.001 respectively. The influence of measurement error due to different frequency resolutions in the experimental modal analysis can be observed from this test. When the frequency accuracy is 0.1, the ANN fails to identify the damage extent in two damage scenarios which occur at the node 16 (D16) and at the node 19 (D19) respectively. For the damage case D16, the poor resolution of 0.1 Hz makes the "measured" frequencies of four modes (1st, 5th, 6th, 8th) unchanged from the undamaged to damaged state. For the damage case D19, unobservable frequency change also occurs at two modes, and the maximum variation of the selected modal components due to the damage is only 0.002. These may explain why so bad identification results arise in D16 and D19. When the frequency accuracy is 0.01, all the damage scenarios are satisfactorily identified. The accuracy of damage extent identification cannot be further improved if the frequency accuracy is 0.001. In conclusion, the networks can identify damage only when measurement error does not obscure the change in modal parameters caused by the damage. This implies that the influence of measurement error on damage identification is relative.

Table 2 Performance of damage extent identification ANN with measurement error

Frequency accuracy	Identified damage amount (%)						
	D1	D4	D7	D10	D13	D16	D19
$\delta_f = 0.1$	33.9	66.5	39.6	46.4	66.1	0.2	0.0
$\delta_f = 0.01$	49.3	47.8	26.0	58.8	73.2	39.3	36.3
$\delta_f = 0.001$	45.4	48.5	27.2	59.6	74.0	39.5	36.4

Note: True damage extent is 50%, modal component accuracy $\delta_m = 0.001$.

2. Probabilistic simulation

Measurement error is then introduced in a probabilistic manner. In recognizing that the resolution-induced error is irrelevant to the magnitude of natural frequencies, the noise modal parameter, Y_r, is produced in the following form

$$Y_r = Y + \varepsilon R \tag{1}$$

where Y is the true value of the modal parameter; R is a sequence of normally distributed random variables with zero mean and unit variance; ε represents the error level. Each sequence consists of 500 random variables.

Table 3 Measurement error cases

Error level	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
ε of frequency	0.001	0.01	0.001	0.01	0.01	0.1	0.1
ε of modal component	0.0001	0.0001	0.0005	0.0005	0.001	0.0005	0.001

A total of seven error cases with different combinations of ε in frequency and modal component are taken into consideration as listed in Table 3. It should be noted that if ε and δ have the same value, the measurement error generated from the normally distributed random sequence is more serious than that generated by truncating the modal parameters. It was mentioned before that the degree of the effects of measurement error depends on damage extent. Fig. 2 illustrates the probabilities of damage location identifiability versus damage extent, where the damage location identification criterion is defined as:

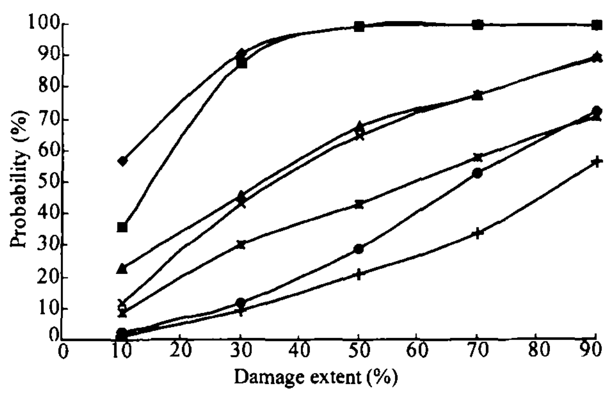

Fig. 2 Probability of damage location identifiability versus damage extent

error case 1 error case 2 error case 3
error case 4 error case 5 error case 6
error case 7

Damage location is judged as correctly identified if $O_d \geq 0.9$ and $O_u < 0.1$, where O_d and O_u are the elements of the output vector of the damage localization network, and d and u correspond to the locations with and without damage.

Table 4 shows the probabilities of damage extent identifiability when the true damage extent is 50% at a specific connection, in which the damage extent identification criteria are defined as:

Criterion A: Damage extent is regarded as well identified if the estimated damage amount is from 40% to 60%, with maximum deviation of 10%;

Criterion B: Damage extent is regarded as satisfactorily identified if the estimated damage amount is from 30% to 70%, with maximum deviation of 20%;

Criterion C: Damage extent is regarded as acceptably identified if the estimated damage amount is from 20% to 80%, with maximum deviation of 30%.

It is seen that for all the seven error cases, the probabilities of damage identifiability increase with increase of damage extent. This phenomenon is particularly obvious when the error is relatively large. This verifies again that the influence of measurement error on damage identifiability depends on damage extent. Small extent damage can be identified only when the measurement error is not serious. By comparing the error cases 1 and 2, the increase of frequency noise level from 0.001 to 0.01 only affects the probabilities of damage location identifiability when the damage extent is less than 30%. When the damage extent exceeds 30%, both cases yield identifiability probabilities greater than 90%. However, the difference of the frequency noise level significantly affects the probabilities of damage extent identifiability. When the damage extent is 90%, which corresponds to locally destroying the rigid joint at a specific connection and making it nearly into a hinge joint, the probabilities of damage location identifiability are greater than 50% even in the error case 7. As measurement error directly affects the test (identification) process rather than the training process of ANN, the ability to accurately identify damage extent is seriously deteriorated by large measurement error.

Table 4 Probability of damage extent identifiability with measurement error (%)

Criterion	Error case 1	Error case 2	Error case 3	Error case 4	Error case 5	Error case 6	Error case 7
A_E	81.14	58.86	34.94	29.40	16.97	9.31	4.89
B_E	95.54	84.26	56.23	49.46	30.83	15.11	9.77
C_E	98.66	91.91	72.71	66.00	42.80	24.03	15.54

Note: True damage extent is 50%.

3. Combined effect of both modeling and measurement errors

The numerical simulation test is finally performed by considering both modeling and measurement errors. Following the probabilistic approach, the modeling error is simulated in terms of "$X_r = X(1+\varepsilon R)$" (Wang et al., 1998) with the error level ε being 0.1 to 0.25. On the other hand, the measurement error is simulated in the deterministic manner by truncating the modal parameters. As shown in Table 5, six modal accuracy cases in terms of different combinations of frequency accuracy δ_f and modal component a accuracy δ_m are adopted as the measurement error.

Table 5 Modal accuracy cases

(1)	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
δ_f	0.01	0.001	0.01	0.01	0.1	0.1
δ_m	0.00001	0.0001	0.0001	0.001	0.0001	0.001

Table 6 Probability of damage extent identifiability with both modeling and measurement errors (%)

Criterion	Accuracy					
	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
A	75.00	73.97	72.17	36.09	19.06	16.20
B	92.83	94.26	92.34	62.40	43.60	33.26
C	97.40	98.77	97.23	77.89	55.86	47.89

Note: True damage extent is 50%, Modeling error level $\varepsilon = 0.1$.

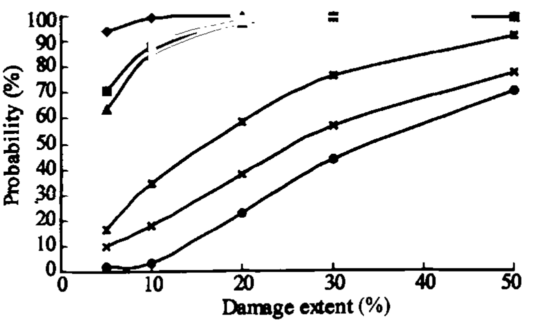

Fig.3 Probability of damage location identifiability versus damage extent
—◆— accuracy case 1 —■— accuracy case 2 —▲— accuracy case 3
—×— accuracy case 4 —*— accuracy case 5 —●— accuracy case 6

Fig.3 shows the probabilities of damage location identifiability versus damage extent, corresponding to the modeling error $\varepsilon = 0.1$ and six measurement error levels (modal accuracy cases). The damage location identification criteria are the same as before. The curves are similar to those obtained only with measurement error. This means that measurement error is dominant in affecting the damage identification. Modeling error has only a slight influence. It is observed that for the modal accuracy cases 1, 2 and 3, the damage locations are nearly completely identifiable when the damage extent exceeds 20%. The accuracy cases 2 ($\delta_f = 0.001$) and 3 ($\delta_f = 0.01$)

give rise to almost identical probabilities. When the damage extent exceeds 50%, the probabilities of damage location identifiability are greater than 70% for all the six accuracy cases. Table 14 shows the probabilities of damage extent identifiability when the true damage extent is 50% at a specific connection. The random modeling error level ε is 0.1 and the damage extent identification criteria are same as those in studying measurement error. It is seen that the damage extent identification results from the modal accuracy cases 1, 2 and 3 are fairly accurate and are very close to each other. This means that change of δ_f from 0.01 to 0.001 and change of δ_m from 0.0001 to 0.00001 do not improve the identification accuracy any more. On the other hand, change of δ_f from 0.01 to 0.1 (cases 5 and 6) results in a sharp decrease of the identification accuracy. In this example, therefore, $\delta_f = 0.01$ and $\delta_m = 0.0001$ is the best option for measurement error control and $\delta_f = 0.01$ and $\delta_m = 0.001$ is the second-optimum option.

EXPERIMENTAL VERIFICATION

Results of an experiment on a two-storey steel frame carried out by Lam (1994) are used to verify the damage identification capacity of ANN with modeling and measurement errors. The elevation of the tested frame is shown in Fig.4. Fig.5 shows the corresponding finite element model consisting of 18 equal length two-dimensional beam elements with semi-rigid joints. Six damage scenarios were simulated in the experiments and are summarized in Table 7. Except for the damage scenario D4b, all the damage scenarios were simulated by removing both the top and seat angles connecting a specific joint. For D4b, only the top angle was removed in order to simulate damage with smaller extent. A detailed description of the physical and geometric properties of the frame and on the experimental modal analysis under undamaged and damaged states is given in Lam (1994).

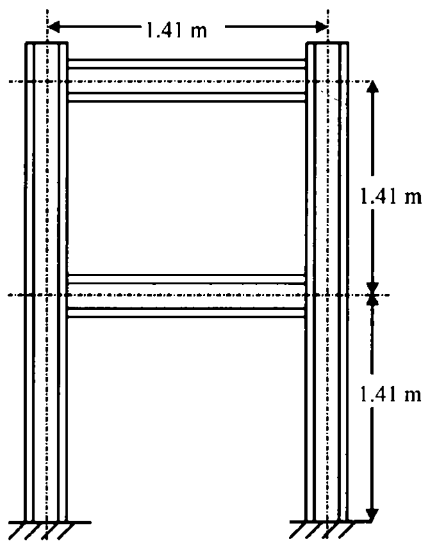

Fig.4 Elevation of tested frame

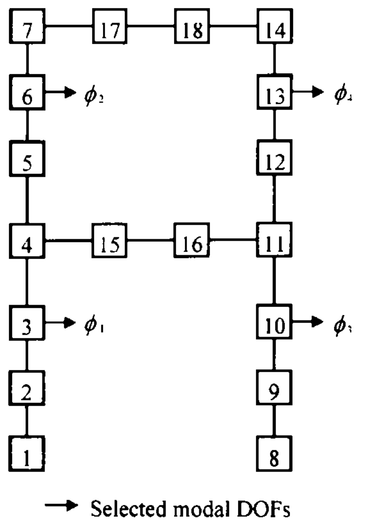

Fig.5 Modeling of tested frame

Table 7 Damage scenarios in tested frame

No.	Damage scenario	Damage description
1	D4a	Severe damage at node 4
2	D4b	Moderate damage at node 4
3	D7	Damage at node 7
4	D4&11	Damage at nodes 4 and 11
5	D7&11	Damage at nodes 7 and 11
6	D4,7&11	Damage at nodes 4, 7 and 11

The measured natural frequencies were acquired with a resolution of 0.01 Hz. For the intact frame, the maximum relative error between the measured and computed natural frequencies of the first six modes is 8.2%, and the maximum relative error between the measured and computed modal components of the first mode at the selected four DOFs is 1.3%. The maximum relative deviation of natural frequencies in the damage scenario D4b is 8.4% and the corresponding maximum relative deviation of modal components is 10.9%. This indicates that the finite element model of the tested frame is not well established. The frequency deviation due to the modeling error appears confused with that caused by the damage.

The computed modal parameters of the frame model in undamaged and damaged states are used to train ANN. These simulation data used in training are corrupted by modeling error. The networks are trained using four modal components at nodes 3, 6, 10 and 13. For identifying damage location, one damage extent, i.e. 50% reduction in the rotational stiffness is applied to each connection respectively to train ANN. For identifying damage amount, six levels of the damage extent, respectively 10%, 20%, 30%, 40%, 50% and 90% reduction in the rotational stiffness are used to train ANN.

The trained networks are then used for damage identification. The measured modal parameters of the frame before and after damage are used in this process. The output layer of the networks has four nodes. The elements in the output set are the signatures of damage incurred at nodes 4, 7, 11 and 14 respectively. The ANN performance for damage location identification is shown in Table 8. It is seen that all the six damage scenarios are localized correctly. Table 8 also shows the performance of damage extent identification for the damage scenarios D4a and D4b. The identification results indicate that the damage extent of the event D4a is more serious than that of the event D4b. In conclusion, it is feasible to detect structural damage by using the ANN under certain modeling and measurement errors.

Table 8 Damage Identification Results of Tested Frame

Damage scenario	Location identification results		Damage extent identification results
	Target set	Output set	
D4a	1, 0, 0, 0	1.000, 0.000, 0.001, 0.000	90.57%
D4b	1, 0, 0, 0	1.000, 0.000, 0.004, 0.000	77.55%
D7	0, 1, 0, 0	0.000, 1.000, 0.017, 0.000	------
D4&11	1, 0, 1, 0	1.000, 0.004, 1.000, 0.000	------
D7&11	0, 1, 1, 0	0.000, 0.933, 1.000, 0.002	------
D4,7&11	1, 1, 1, 0	0.999, 0.984, 1.000, 0.000	------

SUMMARY

Through deterministic and probabilistic numerical simulation tests for damage identification with measurement error on a six-storey frame, it can be found that there exists a critical level of measurement error beyond which the probability of correct identification is sharply decreased. ANN can identify damage only when measurement error does not obscure the change in modal parameters caused by the damage. Large extent damage can be identified in spite of serious measurement error, while small extent damage can be identified only when the damage is not serious. It can be concluded that the influence of measurement error on damage identification is relative and depends on damage extent. The experimental verification on a two-storey steel frame shows that ANN with proper input vectors can be used to identify the damage in the presence of modeling and measurement errors.

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