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# STATISTICAL VIBRATION BASED DAMAGE IDENTIFICATION USING ARTIFICIAL NEURAL NETWORK

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**Abstract.** Artificial Neural Network (ANN) has been widely applied to detect damages in structures based on structural vibration modal parameters. However, uncertainties that inevitably exist in finite element model and measured vibration data might lead to false or unreliable prediction of structural damage. In this study, a statistical approach is proposed to include the effect of uncertainties in the ANN algorithm for damage prediction. ANN is used to predict the stiffness parameters of structures from measured structural vibration frequencies and mode shapes. Uncertainties in the measured data and finite element model of the structure are considered in the prediction. The statistics of the identified parameters are determined using Rossenblueth's point estimation method and verified by Monte Carlo simulation. The results show that by considering these uncertainties in the ANN model, the damages can be detected with a higher confidence level.

*Keywords*: Artificial neural network; uncertainties; random error

**Abstrak.** Artificial Neural Network (ANN) telah digunakan dengan meluas bagi tujuan mengesan kerosakan dalam struktur menggunakan data-data mod dari gegaran. Walau bagaimanapun, ketidakpastian yang wujud dalam model unsur terhingga dan data dari lapangan yang tidak dapat dielakkan boleh menyebabkan kesilapan dalam meramalkan magnitud dan lokasi kerosakan. Dalam kajian ini kaedah statistik digunakan untuk mengambil kira ketidakpastian ini. ANN digunakan untuk meramalkan parameter-parameter kekukuhan dari frekuensi dan mod bentuk bagi sesebuah struktur. Untuk mengambil kira ketidakpastian dalam ramalan, kaedah statistik digunakan di mana kaedah *Rossenblueth point estimation* diperbandingkan dengan kaedah Monte Carlo diaplikasikan bagi mangambil kira ketidakpastian ini. Keputusan menunjukkan bahawa dengan mengambil kira ketidakpastian dalam membuat ramalan menggunakan ANN, kerosakan boleh diramalkan pada tahap keyakinan yang tinggi.

*Kata kunci*: Artificial neural network; ketidakpastian; kesilapan rawak

## 1.0 INTRODUCTION

Much research efforts have been spent on various structural health monitoring techniques in order to develop a reliable, efficient and economical approach to increase the safety and reduce the maintenance cost of civil structures. Many different techniques have been proposed and investigated ranging from application of electrical

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impedance techniques to structural dynamics approaches. Among these techniques, structural dynamics approaches have been extensively explored by many researchers as they can provide information on unforeseen potential failure mechanisms. Since the earliest work by Cawley and Adams [1], there has been much research utilising modal parameters in damage identification. Many of these studies have concluded that the use of modal parameters allows the existence and location of damage to be identified. This is because dynamic parameters such as natural frequencies, mode shapes and structural damping are functions of various structural parameters, and any degradation of structural properties results in the changes of these parameters

Since last decade, artificial neural network (ANN) have become a popular method for identifying structural damage location and severity due to their capability in providing an efficient tool for pattern recognition. Many researchers in structural dynamics have utilised ANN for damage detection. Modal parameters such as natural frequencies and mode shapes, usually obtained from finite element analysis of the structural model, have been used to train the ANN model for structural damage identification. Most of these researchers concluded that ANN is a promising tool [2–5] and can reliably identify damages in structures. However, in those studies, both the vibration data and finite element model used to train the ANN model and identify the damages are assumed to be error free. In practice, the finite element model of a real structure inevitably contains some errors, and therefore the vibration parameters generated from such a model may not be exact either.

ANN has also been applied to identify the conditions of real structure using data obtained from field vibration tests [6–9]. In those studies, the field measured data were assumed noise free. In reality, measurement noise is unavoidable. Thus, the issue regarding the measurement noise on the reliability of ANN model for structural damage prediction needs to be investigated.

In most ANN applications in damage detection, ANN models are trained using the damage cases generated from analytical finite element (FE) model. The experimental measured modal data for damage structure are introduced to the trained ANN models to obtain the damage location and severity. Most studies assumed that the training data generated from FE model is error free to represent the relationships between the modal parameters and the stiffness parameters. In practice, there are many uncertainties exist, including the inaccuracy of physical parameters, non-ideal boundary condition and structural nonlinear properties which may result in inaccurate FE model and at the same time, the measurement noise is inevitable [10]. Since the efficiency of ANN prediction relies on the accuracy of both components, this might limit the effectiveness of ANN in predicting structural damages [11–13].

Several studies have considered uncertainty effect in application of ANN, and the noise injection learning method proposed by Matsuoka [14] has been a popular approach to reduce the effect of noise in measurement data [11, 12, 15]. However, studies that consider both error in FE model and noises in measurement data are quite limited.

The objective of this work is to apply ANN in damage detection with consideration of uncertainties in FE model and measurement data. A single span steel frame tested in the laboratory [21] is used as an example in the study. The ANN model is trained with vibration data generated from FE model, but smeared with random variations. The trained model is used to predict two damage scenarios that are generated by reducing the stiffness parameter values. Measured vibration data that will be used as input to the ANN model for damage detection are also smeared with random noises. An approach introduced by Papadopoulos and Garcia [16] is used to take into account the uncertainties in FE model and measurement noise.

## 2.0 THEORETICAL BACKGROUND

To include the uncertainty effect in the analysis, the uncertainties in FE model and measurement data are assumed to be normally distributed independent random variables with zero means and specific standard deviations. Thus, the frequencies, mode shapes and stiffness parameters for training and testing are:

$$\lambda_i = \lambda_i^0 \left(1 + X_{\lambda i}\right) \tag{1a}$$

$$\hat{\lambda}_i = \hat{\lambda}_i^0 \left(1 + X_{\lambda i}\right) \tag{1b}$$

$$\phi_i = \phi_i^0 \left(1 + X_{\phi i}\right) \tag{1c}$$

$$\hat{\phi}_i = \hat{\lambda}_i^0 \left(1 + X_{\phi i}\right) \tag{1d}$$

$$\alpha_j = \alpha_j^0 \left(1 + X_{\alpha j}\right) \tag{1e}$$

where $\lambda_i$, $\phi_i$ and $\hat{\lambda}_i, \hat{\phi}_i$ are the *i*th frequencies and mode shapes for training and testing, respectively, and $\alpha_j$ is the stiffness parameter for the *j*th segment. Superscript '0' represents the corresponding mean value and $X_{\lambda i}$, $X_{\phi i}$, $X_{\alpha i}$ are the zero mean random noises in frequencies, mode shapes and stiffness parameters, which are assumed in this study to be the same for both training and testing data.

By using the Rosenbleuth's point estimation method, the mean values and standard deviations of the stiffness parameters for each element are estimated. Thus, four ANN models are developed by considering the mean values and standard deviations ($\sigma$) of the random noises applied to each variable. The training functions and input and output variables for testing are listed in Table 1.

**Table 1** Training functions and testing variables used in point estimation method

| Model | Training function | Testing variable | |
|---|---|---|---|
| | | Input | Output |
| 1 | $\alpha_{j++} = fn(\lambda^0_i + \sigma_{\lambda i}, \phi^0_i + \sigma_{\phi i})$ | $\hat{\lambda}_i^0 + \sigma_{\lambda i}, \hat{\phi}_i^0 + \sigma_{\phi i}$ | $\hat{\alpha}_{++}$ |
| 2 | $\alpha_{j--} = fn(\lambda^0_i - \sigma_{\lambda i}, \phi^0_i - \sigma_{\phi i})$ | $\hat{\lambda}_i^0 - \sigma_{\lambda i}, \hat{\phi}_i^0 - \sigma_{\phi i}$ | $\hat{\alpha}_{--}$ |
| 3 | $\alpha_{j+-} = fn(\lambda^0_i + \sigma_{\lambda i}, \phi^0_i - \sigma_{\phi i})$ | $\hat{\lambda}_i^0 + \sigma_{\lambda i}, \hat{\phi}_i^0 - \sigma_{\phi i}$ | $\hat{\alpha}_{+-}$ |
| 4 | $\alpha_{j-+} = fn(\lambda^0_i - \sigma_{\lambda i}, \phi^0_i + \sigma_{\phi i})$ | $\hat{\lambda}_i^0 - \sigma_{\lambda i}, \hat{\phi}_i^0 + \sigma_{\phi i}$ | $\hat{\alpha}_{-+}$ |

The expectation (mean values, $\mu_\alpha$) and standard deviations ($\sigma_\alpha$) of $\alpha$ are calculated as below:

$$E(\alpha) = \frac{1}{4}\left(\hat{\alpha}_{++} + \hat{\alpha}_{--} + \hat{\alpha}_{+-} + \hat{\alpha}_{-+}\right) \tag{2}$$

$$\sigma_\alpha = \left[E\left(\alpha^2\right) - \left[E(\alpha)\right]^2\right]^{\frac{1}{2}} \tag{3}$$

where $E(\alpha^2)$ is calculated using Eq. (2) with $\alpha^2$ terms substituted for the $\alpha$ terms.

The probability of damage existence (PDE) can be estimated from statistical distributions of the stiffness parameters of the undamaged and damaged models. For example, if the stiffness parameter ($\alpha_j$) of the undamaged segment $j$ is normally distributed with mean $E(\alpha_j)$ and standard deviation $\sigma(\alpha_j)$, the probability density function can be obtained as illustrated in Figure 1.

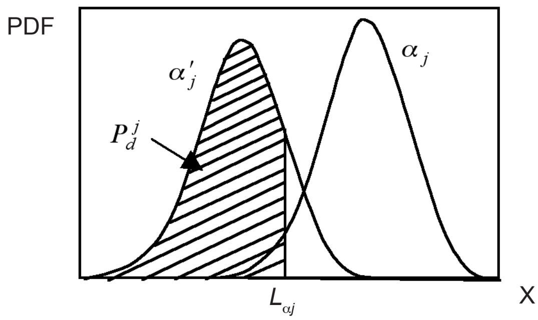


**Figure 1** Probability density functions for $\alpha_j$ and $\alpha_j'$ and probability of damage existence, $P_d^j$

where $L_{\alpha j}$ is the lower bound of the healthy parameter. In this study, the confidence level is set to 95%, thus the lower bound $L_{\alpha j} = E(\alpha_j) - 1.645\sigma(\alpha_j)$, which indicates that there is a probability of 95% that the healthy stiffness parameter falls in the range of $[E(\alpha_j) - 1.645\sigma(\alpha_j), \infty]$ Similarly, for the stiffness parameter of segment *j* in the damaged state $(\alpha'_j)$, the distribution is again assumed as normal with mean $E(\alpha'_j)$ and standard deviation $\sigma(\alpha'_j)$, and the corresponding probability density function is also plotted in Figure 1. The PDE is defined as that of $\alpha'_j$ not within the 95% confidence healthy interval. Thus the PDE of segment *j* is

$$\begin{aligned} P_d^j &= 1 - prob(L_{\alpha j} \le x_{\alpha'} \le \infty) \\ &= prob(-\infty \le x_{\alpha'} \le L_{\alpha j}) \end{aligned} \tag{4}$$

PDE is a value between 0 and 1, and if the PDE of a segment is close to 1, then it is most likely the element is damaged. If the PDE is close to 0, damage existing in the element is very unlikely.

## 3.0 NUMERICAL EXAMPLE

A single span steel portal frame as shown in Figure 2 was used as an example. The model was fabricated and tested in the laboratory. The cross section of beam is 40.50 × 6.0 mm$^2$, and columns are 50.50 × 6.0 mm$^2$. Rigid connections were applied between beam and columns and supports were welded to a steel plate with fixed boundary condition. The frame was divided to 6 sections as shown in Figure 2. Each section consists of 5 elements. The material properties used are:

$$E = 2.1 \times 10^{11}\ N/m^2,\ \rho = 7.67 \times 10^3,\ \nu = 0.2$$

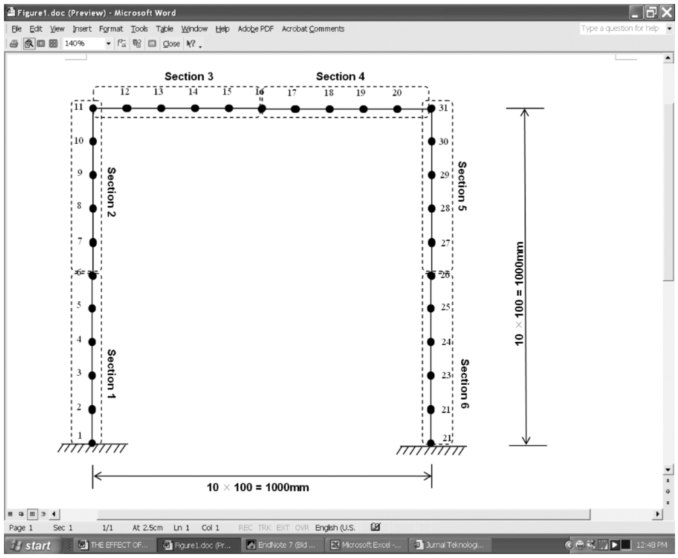


**Figure 2** Finite element model of the frame

Modal analysis was conducted using FE model to generate input and output data to train ANN models. Two damage scenarios have been generated to assess the ANN prediction performance. Scenario 1 consists of damage in two sections of the frame (section 1 & 4), and, Scenario 2 consists of damage in four sections (section 1, 3, 5 & 6). The detail of the damages provided in Table 2. The frequencies and mode shapes of the first three modes are shown in Table 3 and Figure 2. The modal parameters produced by FE model are considered as noise-free data.

**Table 2** E values for scenario 1 and scenario 2

| Segment | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| **Scenario 1** | 0.4 × E | 1.0 × E | 1.0 × E | 0.2 × E | 1.0 × E | 1.0 × E |
| **Scenario 2** | 0.4 × E | 1.0 × E | 0.3 × E | 1.0 × E | 0.4 × E | 0.3 × E |

**Table 3** Frequencies of frame for undamaged, scenario1 and scenario 2 for the first three modes

| | Undamaged | Scenario 1 | Scenario 2 |
|---|---|---|---|
| **Mode 1** | 4.628 | 3.9373 | 3.530 |
| **Mode 2** | 16.112 | 12.567 | 11.269 |
| **Mode 3** | 20.649 | 16.491 | 14.891 |

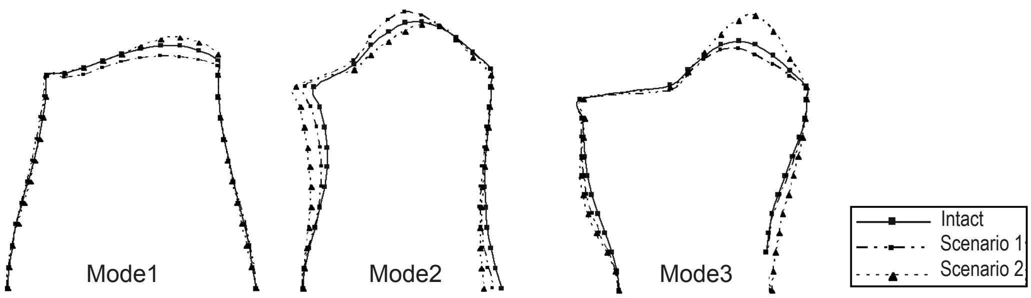


**Figure 3** Mode shapes for undamaged, scenario1 and scenario for first 3 modes

## 4.0 ARTIFICIAL NEURAL NETWORK MODEL

An ANN model was developed to achieve a model that can relate modal parameters with stiffness parameters of the frame. This model was trained using data from original FE model. A multilayer perceptron with Levenberg-Marquardt backpropagation algorithm was utilised to train the model. There were 1200 data used in training. The training data were selected using Latin hypercube sampling [17]. To deal with overfitting problem, early-stopping method [18] has been used, therefore the data were divided to three parts with the ratio of 2:1:1. A trial and error method based on Kalmorogov's and Lippmann approach [19] was utilised to attain the best ANN topology. To avoid the '*curse of dimensionality*' as discussed by Bishop [20], only nine mode shape points and frequencies for the first three modes were used as the input parameters. The output parameters are Young's modulus (E values) of every sections. The numbers of neurons in the input and output layers are the same as the number of input and output variables respectively.

The reliability of the trained ANN model was then assessed by using modal parameters of the two damage scenarios. Figure 4 shows the predicted E values in comparison with the actual values. Damage severities are quantified using an elemental Stiffness Reduction Factor (SRF), defined by Equation (5). The higher the SRF, the more severe is the damage.

$$\text{SRF} = 1 - \frac{E'}{E} \tag{5}$$

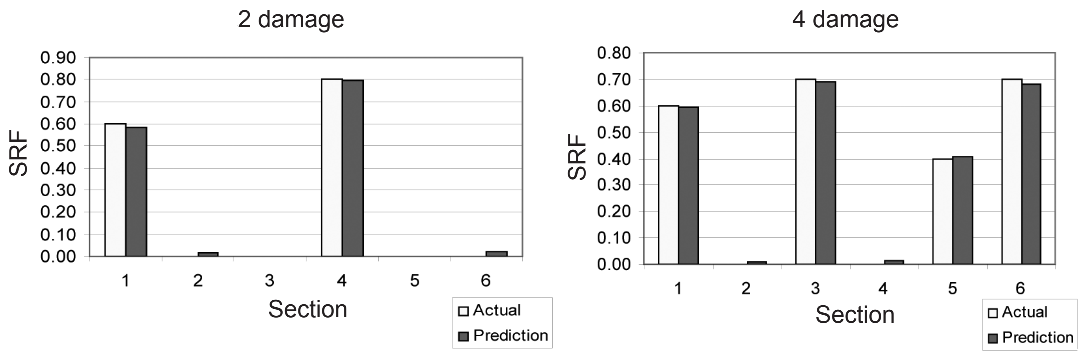


**Figure 4** Prediction of ANN for scenario 1 and scenario 2 compared to the actual value using noise-free input data

The results show that the ANN model is able to predict the damage successfully if introduced by noise-free input data. To obtain the effect of noise, artificial error was introduced to the damage data, whereby 2% and 15% random errors in terms of coefficient of variations (C.O.V) were applied to frequencies and mode shapes respectively. Figure 5 shows the ANN prediction using input data with error for both damage scenarios.

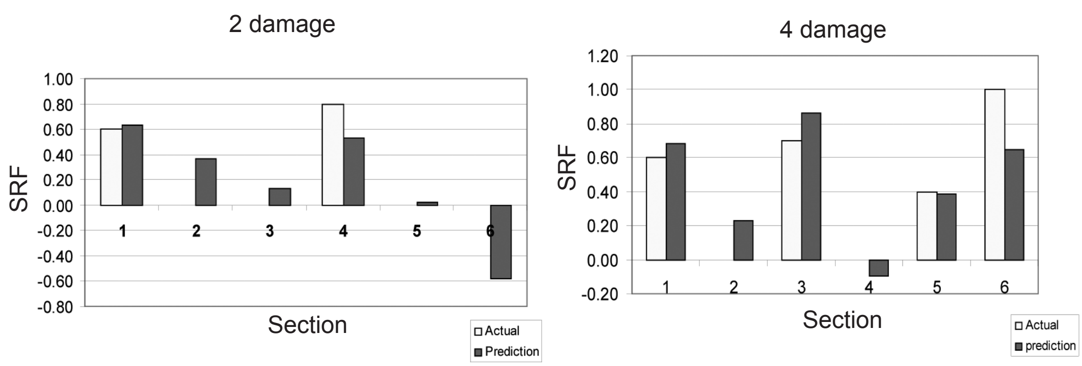


**Figure 5** Prediction of ANN for scenario 1 and scenario 2 compared to the actual value using input data with error

The Figure shows that for scenario 1, the false damage identification occurs at segment 2 and 3, while the stiffness of segment 6 is overpredicted. The same situation occurred in scenario 2, where ANN falsely identified damage at segment 2, overestimated damage at segment 1 and 3, but underestimated at segment 6. This indicates that the common ANN model trained with simulated vibration parameters from finite element model cannot give reliable structural damage prediction if the testing data contain noise.

## 5.0 STATISTICAL APPROACH

As mentioned above, the measured data and the initial FE model inevitably contain errors, which lead to unreliable or even false prediction. To consider these uncertainties, the error in FE model and input data are assumed consisting of normal distribution random variable with zero means and specific variance [21]. This implies that if the system is measured many times independently, 95% of the measurement will fall within the mean values with plus or minus two standard deviations. By using the same training and input data with error (testing), a normally distributed random variable is added to training and testing data.

In this study, it was assumed that the noise levels of frequencies, and mode shapes were 2% and 15% respectively. This indicates that the standard deviation of noises for frequencies and mode shapes are 2% and 15% respectively. Using point estimation method as mentioned previously, mean values of undamaged states were obtained by developing 8 ANN models. Each of them provides the output of different F value; therefore the mean and standard deviation can be calculated. The result was then verified by Monte Carlo simulation.

In Monte Carlo simulation, the random noise was added to the training and testing data in each cycle. The training and testing process was repeated until the means and standard deviations of E values converge. The results show that the E values have normal type of characteristic. This was verified by Kolmorogov-Smirnov goodness-of-fit test (K-S test). In the simulation stopped at 192$^{nd}$ iteration. The K-S test results are shown in Table 4. Figure 6 shows the mean values and C.O.V of E values for both methods.

**Table 4** K-S test result

| Section | K-S test | |
|---|---|---|
| | **KS value** | **Critical value** |
| 1 | 0.067 | 0.097 |
| 2 | 0.078 | 0.097 |
| 3 | 0.051 | 0.097 |
| 4 | 0.089 | 0.097 |
| 5 | 0.039 | 0.097 |
| 6 | 0.041 | 0.097 |

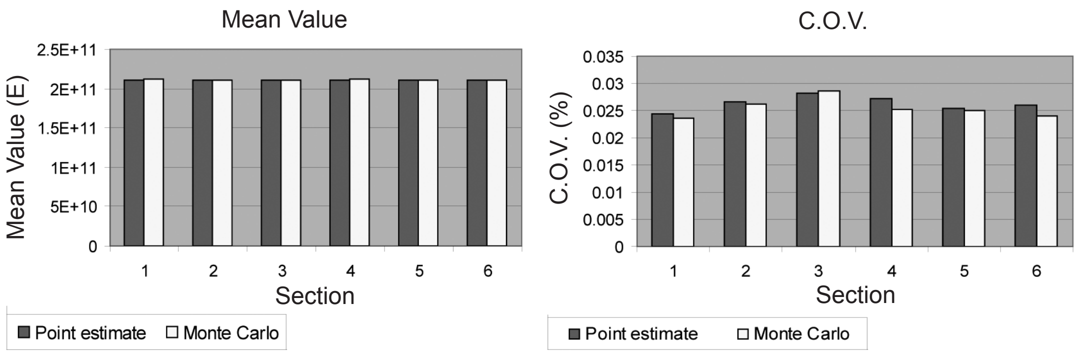


**Figure 6** Mean values and coefficients of variation (C.O.V) of E values in undamaged state

It is observed that both methods provide the similar results, indicating the point estimation method is reliable. After the distribution of undamaged and damage states are obtained, the probability of damage existence (PDE) can be estimated for every section. The PDE for both scenarios are listed in Table 5.

**Table 5** Probability of damage existence (PDE) for every section of scenario 1 and scenario 2

| | Section 1 | Section 2 | Section 3 | Section 4 | Section 5 | Section 6 |
|---|---|---|---|---|---|---|
| **Scenario 1** | ***0.850*** | 0.385 | 0.003 | ***1.000*** | 0.000 | 0.000 |
| **Scenario 2** | ***1.000*** | 0.0342 | ***0.998*** | 0.333 | ***1.000*** | ***1.000*** |

It can be seen that the damages for both damage scenarios are correctly identified. The PDEs of section 1 & 2 of scenario 1 and section 1,3,5,& 6 of scenario 2 are high indicating that it is very likely that damages exist in these sections. This demonstrates that the statistical approach can provide confidence estimation of the damage occurrence by taking into consideration all the uncertainties.

## 6.0 CONCLUSION

A statistical approach has been used together with ANN model to consider uncertainties in this study. A point estimation method has been used to obtain the statistics of stiffness parameters of the undamaged and damaged structure. By assuming that the FE model and input data contain normal distribution noise, the PDE of damage sections can be estimated, thus the damaged section can be identified correctly. The following conclusions have been made based on the results obtained.

- The point estimation method is an efficient method to be used together with ANN model to calculate the mean and standard deviation of stiffness parameters with consideration of uncertainties.
- A probabilistic approach with ANN model is capable of identifying the damaged members with high confidence.

## REFERENCES

[1] Cawley, P. and R. D. Adams. 1979. The Location of Defects in Structures from Measurements of Natural Frequencies. *Journal of Strain Analysis*. 14(2): 49–57.

[2] Tsou, P. and M. H. H. Shen. 1994. Structural Damage Detection and Identification using Neural Networks. *AIAA Journal.* 32(1): 176–183.

[3] Barai, S. V. and A. K. Pandey. 1995. Vibration Signature Analysis using Artificial Neural Network. *Journal of Computing in Civil Engineering*. 9(4): 259–265.

[4] Chen, H. M. *et al*. 1995. Neural Networks for Structural Control. *Journal of Computing in Civil Engineering.* 9(2): 168–176.

[5] Pandey, P. C. and S. V. Barai. 1995. Multilayer Perceptron in Damage Detection of Bridge Structures. *Computers & Structures*. 54(4): 597–608.

[6] Farrar, C. R., S. W. Doeblíng, and D. A. Nix. 2001. Vibration-based Structural Damage Identification. *Philosophical Transactions: Mathematical, Physical & Engineering Sciences*. 359: 131–149.

[7] Ren, W. and G. D. Reock. 2002. Structural Damage Identification using Modal Data 1: Simulation Verification. *Journal of Structural Engineering*. 128(1): 96–104.

[8] Xia, P. and J. M. W. Brownjohn. 2004. Bridge Structural Condition Assessment using Systematically Validated Finite-element Model. *Journal of Bridge Engineering*. 9(5): 418–423.

[9] Zapico, J. L. *et al*. 2003. Finite Element Model Updating of a Small Scale Bridge. *Journal of Sound and Vibration.* 268(5): 993–1012.

[10] Xia, Y. and H. Hao. 2003. Statistical Damage Identification of Structures with Frequency Changes. *Journal of Sound and Vibration*. 263(4): 853–870.

[11] Yeung, W. T. and J. W. Smith. 2005. Damage Detection in Bridges using Neural Networks for Pattern Recognition of Vibration Signatures. *Engineering Structures.* 27(5): 685–698.

[12] Sahin, M. and R. A. Shenoi. 2003. Quantification and Localisation of Damage in Beam-like Sructures by Using Artificial Neural Networks with Experimental Validation. *Engineering Structures.* 25(14): 1785–1802.

[13] Yun, C. B., J. H. Yi, and J. D. KIim. 2001. Health Monitoring Method for Bridges under Ordinary Traffic Loadings. *Journal of Sound and Vibration.* 257(2): 247–264.

[14] Matsouka, K. 1992. Noise Injection into Inputs in Back-propagation Learning. *IEEE Transaction of System, Man and Cybernatics.* 22(3): 436–440.

[15] Yun, C. B. and E. Y. Bahng. 2000. Substructural Identification using Neural Networks. *Computers & Structures*. 77(1): 41–52.

[16] Papadopoulos, L. and E. Garcia, E. 1998. Structural Damage Identification: A Probabilistic Approach. *AIAA Journal.* 39(11): 2137–2145.

[17] Helton, J. C. and F. J. Davis. 2003. Latin Hypercube Sampling and The Propagation of Uncertainty in Analyses of Complex System. *Reliability Engineering and System Safety.* 81: 23–69.

[18] Prechelt, L. 1999. Early Stopping - but when? In G.B. Orr and O.R. Muller, Editors. *Neural Networks : Tricks of The Trade.* Berlin, Germany: Springer-Verlag Telos.

[19] Maren, A. J., D. Jones, and S. Franklin. 1990. Configuring and Optimizing the Back-propagation Network. In A. Maren, C. Harston, and R. Pap., Editors. *Handbook of Neural Computing Applications.* San Diego, CA: Academic Press.

[20] Bishop, C. M. 1995. *Neural Network forPattern Recognition*. Oxford: Oxford University Press.

[21] Xia, Y. *et al*. 2002. Damage Identification of Structures with Uncertain Frequency and Mode Shape Data. *Earthquake Engineering and Structural Dynamics.* 31(5): 1053–1066.