Non-Probabilistic Artificial Neural Network to Consider Noisy Data in Vibration-Based-Damage Detection

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ABSTRACT: The effectiveness of Artificial Neural Networks (ANNs) when applied to pattern recognition in vibration-based damage detection has been demonstrated in many studies because they are capable of providing accurate results and the reliable identification of structural damage based on modal data. However, the use of ANNs has been questioned in terms of its reliability in the face of uncertainties in measurement and modeling data. Attempts to incorporate a probabilistic method into an ANN by treating the uncertainties as normally distributed random variables has delivered promising solutions to this problem. However, the probabilistic method is less reliable in practice because it is not possible to obtain a probabilistic distribution of the uncertainties. In this study, a non-probabilistic ANN is proposed to address the problem of uncertainty in vibration damage detection using ANNs. The input data for the network consist of natural frequencies and mode shapes, and the output is the Young's modulus (*E* values), which acts as an elemental stiffness parameter (ESP). Through the interval analysis method, the noise in measured frequencies and mode shapes are considered to be coupled rather than statistically distributed. A numerical model is utilized to demonstrate the efficacy of the method in improving the accuracy of the ANN in the presence of noise. This study demonstrated that the proposed method is able to more efficiently address uncertainties using an ANN.

1 INTRODUCTION

Many approaches based on vibration parameters have been proven to be effective in addressing problems in detecting damage in basic and complex structures. One of the best explored computational approaches to vibration-based damage detection is ANNs. The ANN technique has proven effective in damage detection due to its capability to model the nonlinear relationship between the vibration parameters and the damage location and severity (Barai and Pandey 1995; Lee et al. 2005; Masri et al. 1996; Pawar et al. 2006; Wu et al. 1992; Zang and Imregun 2001).

The issues of uncertainty become more significant as civil engineering structures become more complex. There are two unavoidable uncertainties in the application of ANNs in damage detection: modeling error and measurement noise. Modeling error refers to the existence of uncertainties in the FE model due to the inaccuracy of physical parameters, non-ideal boundary conditions, finite element discretization and nonlinear structural properties that may result in the FEM not representing the exact behavior of the modeled structures. Because the ANN model is trained using data generated from an FEM, the trained ANN model is unable to represent the exact relationship between the input parameters (vibration data) and the damage information. On the other hand, an error in measurement data that are normally used in the testing phase may also lead to false damage identification. Bakhary et al. (2007) and Bakhary et al. (2010) demonstrated the effect of uncertainties in training and testing data on the performance of ANNs, and they suggested the use of a probabilistic ANN method to consider the existence of uncertainties in the FE model and measurement data. The study demonstrated that the probabilistic method is capable of facilitating accurate damage detection based on noisy data.

Despite its efficiency in handling noisy data, the probabilistic method suffers from several disadvantages such as its treatment of uncertain values as normally distributed random variables with a given variance that then produce statistical structural damage results. However, in practice, it is not possible to obtain the probability density function due to the complexity of the sources of uncertainty (Shu et al. 2013; Tadesse et al. 2012). Furthermore, insufficient data in experimental studies also reduce the capability of obtaining a probability density function. Moreover, the probabilistic method also requires multiple sets of data for the probabilistic analysis. These data sets are normally generated through an established FEM or ANN model based on a specific standard deviation. This process involves an iterative process of simulation that is very time consuming.

This study investigates applicability of the non-probabilistic method using ANNs to consider uncertainties in damage detection. For this purpose, an ANN is trained using frequencies and mode shapes as inputs and elemental stiffness parameters (ESPs) as the output variables. The uncertainties are considered by calculating the lower and upper bounds of the input parameters based on interval mathematics to produce the lower and upper bounds of the output parameters (ESP). Therefore, two different types of ANNs are presented and used to determine the upper and lower bounds of the noisy input data. SRFs and PoDE are later used to define the reduction in the ESP values and the existence of damage. To provide a better indicator of damage existence, the DMI is adopted. The applicability of the proposed method is demonstrated through a numerical model of a steel portal frame. The results show that the proposed method is able to efficiently provide the location and severity of damage.

2 METHODOLOGY

2.1 Artificial Neural Network

In this study, a multilayer perceptron Levenberg-Marquardt back-propagation algorithm with 20 hidden neurons is used as the ANN model, and tangent sigmoid transfer functions are employed for all layers, as shown in Figure 1. The input parameters are the natural frequencies (λ) and mode shapes (ϕ), and the outputs are the ESPs (α). In the training phase, a series of damage cases are randomly generated using a finite element model (FE). The damage cases are idealized by reducing the ESPs of selected elements. Several damage cases are generated to test the efficiency of the trained ANN model.

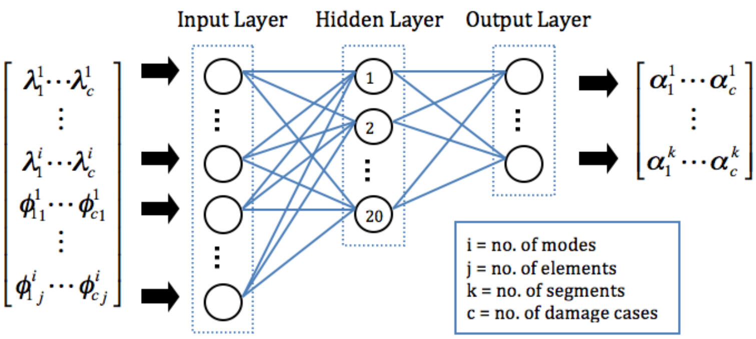


Figure 1. Multilayer perceptron ANN architecture

The stiffness reduction ratio (SRF), as shown in Equation 1, represents the changes in the stiffness parameter for each segment.

$$SRF = 1 - \frac{\alpha_d}{\alpha_u}\pi r^2 \tag{1}$$

where:

d = ESP value in damaged state

u = ESP value in undamaged state

Because the ANN model requires training to establish the relationship between the input and output parameters, an initial baseline FE model is needed to generate a set of training data. Once the ANN model is trained, the testing data is then fed to the trained model to predict the damage locations and severities. If the training and testing data are free from uncertainties, the ANN model is very efficient in predicting the output; however, in reality, both the FE model and the testing data will inevitably contain noise due to uncertainties in the measurements and modeling, which will lead to inaccurate outputs.

In this study, modeling errors and measurement errors are considered using non-probabilistic interval analysis. Through this method, the uncertainties are considered by calculating the lower and upper bounds of the input parameters as well as the ANN outputs (ESPs) with lower and upper bounds. Once the lower and upper bounds of the ESPs are obtained, the possibility of damage existence (PoDE) determination can be followed by the calculation of the damage measure index (DMI), which is used to indicate the damage severity.

Based on this method, only two ANN models are needed to predict the upper and lower bounds of the ESP values. Compared to the conventional statistical ANN method (Bakhary et al. 2007), the proposed non-probabilistic method provides an advantage in terms of its requirement of fewer ANN models. In the conventional statistical ANN method, which is based on a point estimate method (Rosenblueth 1975), four ANN models are required to calculate the statistical behavior of the *E* values, whereas in this method, only two ANN models are involved. The small number of required ANN models leads to lower prediction error. In the statistical ANN model, the prediction error normally increases the standard deviation of the probability density function (PDF) used to calculate the probability of damage existence (PDE). This higher standard deviation may result in lower probability values when detecting damage in structures.

To consider both uncertainties, the basic concept of interval mathematics is adopted by providing the upper and lower bounds of input parameters that will produce the upper and lower bounds of the output parameters. Due to the nature of the ANN model used to establish the relationship between the input and output via a black box procedure, the basic equation of interval analysis proposed by Polyak and Nazin (2005) can be directly applied to the input parameters (frequencies and mode shapes) to produce the intervals of the output parameters (ESP values). The intervals of the ESPs, natural frequencies and mode shapes for the undamaged and damaged states can be formulated as follows:

$$\lfloor \underline{a} \rfloor \approx [\underline{\lambda}; \underline{\theta}] = \text{ESP value lower bound} \tag{2}$$

$$[\overline{a}] \approx [\overline{\lambda}; \overline{\theta}] = \text{ESP value upper bound} \tag{3}$$

Therefore, the interval bounds for each parameter can be derived as

$$\lambda_c^I = \left[\underline{\lambda_C^I}, \overline{\lambda_c^I}\right] = \{\lambda_{c1}^I, \lambda_{c2}^I, \cdots, \lambda_{ci}^I\}^T, \lambda_{ci}^I = \left[\underline{\lambda_{ci}^I}, \overline{\lambda_{ci}^I}\right] \tag{4}$$

$$\phi_c^I = \left[\underline{\phi_C^I}, \overline{\phi_c^I}\right] = \left\{(\phi_{c1}^I)^T, (\phi_{c2}^I)^T, \cdots, (\phi_{cj}^I)^T\right\}^T, \phi_{cij}^I = \left[\underline{\phi_{cij}^I}, \overline{\phi_{cij}^I}\right] \tag{5}$$

$$\alpha_c^I = \left[\underline{\alpha_C^I}, \overline{\alpha_c^I}\right] = \{\alpha_{c1}^I, \alpha_{c2}^I, \cdots, \alpha_{ck}^I\}^T, \alpha_{ck}^I = \left[\underline{\alpha_{ck}^I}, \overline{\alpha_{ck}^I}\right] \tag{6}$$

where

c = number of damage cases, i = number of modes, j = number of elements of structures and k = number of segments of structures

and the middle values of the input and output are denoted as

$$x^c = m(x) = \frac{(\underline{x} + \overline{x})}{2} \quad (7)$$

where x indicates the exact values of the input parameters (frequencies and mode shapes) and output parameters (ESPs). The upper and lower bars denote the upper and lower bounds of x, respectively.

Thus, the training and testing functions of the ANN are established based on equations (2-7). The uncertainties are coupled with λ and ϕ in terms of the interval bounds. These natural frequencies (λ) and mode shapes (ϕ) are used as input parameters, while the ESPs (α) are used as outputs. Thus, two ANN models, which include the lower bound and upper bound analyses, are provided, as shown in Table 1.

Table 1.Training and testing input and output variables

Model	**Training Input**	**Testing Input**	**Output**
ANN1	$\underline{\lambda_{ci}^{Ir}} = \lambda_{ci}^{Ir} - \lambda_{ci}^{Ir}(\omega_\lambda)$ $\underline{\phi_{cij}^{Ir}} = \phi_{cij}^{Ir} - \phi_{cij}^{Ir}(\omega_\phi)$	$\underline{\lambda_{ci}^{Ie}} = \lambda_{ci}^{Ie} - \lambda_{ci}^{Ie}(\omega_\lambda)$ $\underline{\phi_{cij}^{Ie}} = \phi_{cij}^{Ie} - \phi_{cij}^{Ie}(\omega_\phi)$	$\underline{\alpha_{ck}}$
ANN2	$\overline{\lambda_{ci}^{Ir}} = \lambda_{ci}^{Ir} + \lambda_{ci}^{Ir}(\omega_\lambda)$ $\overline{\phi_{cij}^{Ir}} = \phi_{cij}^{Ir} + \phi_{cij}^{Ir}(\omega_\phi)$	$\overline{\lambda_{ci}^{Ie}} = \lambda_{ci}^{Ie} + \lambda_{ci}^{Ie}(\omega_\lambda)$ $\overline{\phi_{cij}^{Ie}} = \phi_{cij}^{Ie} + \phi_{cij}^{Ie}(\omega_\phi)$	$\overline{\alpha_{ck}}$

where the superscripts *Ir* and *Ie* represent the interval variables of training and testing, respectively. The variable ω indicates the uncertainty level for the input data by which the values of the uncertainties differ for the natural frequencies and mode shapes. The boundaries (lower and upper bounds) of the input parameters are applied through the + and – values of the uncertainties in two different ANN models: ANN1 and ANN2. $\underline{\alpha}$ and $\overline{\alpha}$ are the outputs of the ANN models and represent the lower and upper bounds of the predicted ESPs of damage case *c*. Once the lower and upper bounds of the stiffness parameters are obtained, the PoDE can be calculated.

2.2 *Possibility of Damage Existence (PoDE)and Damage Measure Index (DMI)*

The PoDE is calculated by comparing the vectors of the ESPs in the damaged and undamaged states. The vectors are the interval bounds (lower and upper bounds) of the ESPs, which are the outputs of ANN1 and ANN2 (refer to Table 1), respectively. The expressions are as follows:

$$\alpha_u^I = \{\alpha_{u1}^I, \alpha_{u2}^I, \cdots, \alpha_{uk}^I\}^T \quad (8)$$

$$\alpha_d^I = \{\alpha_{d1}^I, \alpha_{d2}^I, \cdots, \alpha_{dk}^I\}^T \quad (9)$$

where α_u^I denotes the interval bound for the undamaged ESP ($[\overline{a_{uk}}, \underline{a_{uk}}]$) and α_d^I denotes the interval bound for the damaged ESP ($[\overline{a_{dk}}, \underline{a_{dk}}]$).

Figure 2 illustrates the intersection of the intervals of the damaged and undamaged ESPs on the same axis, where the shaded region indicates the PoDE. The middle value (x^c) disparity between the two states will increase as the damage increases. The PoDE ranges between 0 to 100%, with 100% indicating a high possibility of damage and 0% indicating that no damage occurred at that specific element. Thus, the quantitative measure of the PoDE can be introduced as below:

$$PoDE = \frac{A_{damage}}{A_{total}} \times 100\% \quad (10)$$

Thus, damage measure index (DMI) is calculated as below:

$$DMI = SRF \times PoDE \quad (11)$$

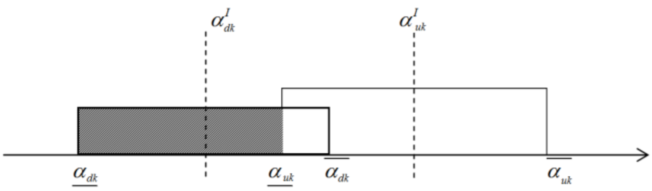


Figure 2. Scheme for PDE

3 NUMERICAL EXAMPLE

A numerical model of the single-span steel portal frame used in Bakhary et al. (2007) is selected for verification and the results are compared. Figure 3 shows the model of the frame. The numerical model is constructed using 30 beam elements, with 10 elements in each member. Rigid connections are applied between the beam and the columns, and the supports are assumed to be fixed. The material properties are E= 2.1 x 10^{11} N/m^3, ρ= 7.67 x 10^3 kg/m^3, and ν= 0.2. The cross section of the beam is 40.5 x 6.0 mm^2, and that of the column is 50.5 x 6.0 mm^2. For damage detection purposes, the frame is divided into 6 segments, as shown in the figure.

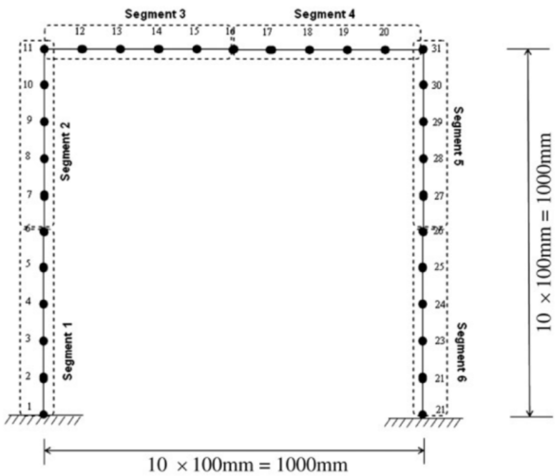


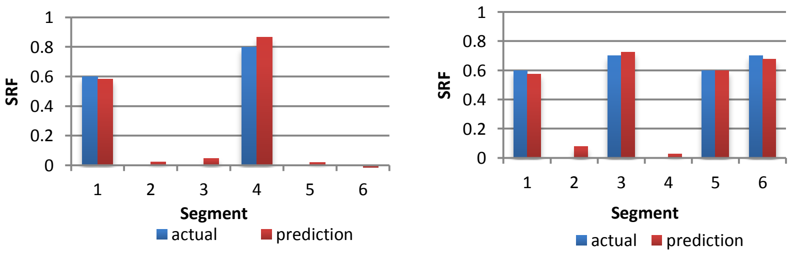
Figure 3. Finite element model of the frame

The numerical model of the frame is used as a baseline model to generate the training data. In this example, 2000 damage cases are generated as the training data. The early stopping method is applied to avoid the overfitting phenomenon. Thus, the data is divided into 60% training and 40% validation data. The first three modes of the frequencies and mode shapes are used as the input parameters, and the output parameters are the ESP values of each segment. Two damage scenarios are simulated to assess the ANN prediction performance. Table 2 shows the ESPs for both damage scenarios.

Table 2. ESPs of damage scenarios 1 and 2

Segment	1	2	3	4	5	6
Scenario 1	0.4 x E	1.0 x E	1.0 x E	0.2 x E	1.0 x E	1.0 x E
Scenario 2	0.4 x E	1.0 x E	0.3 x E	1.0 x E	0.4 x E	0.3 x E

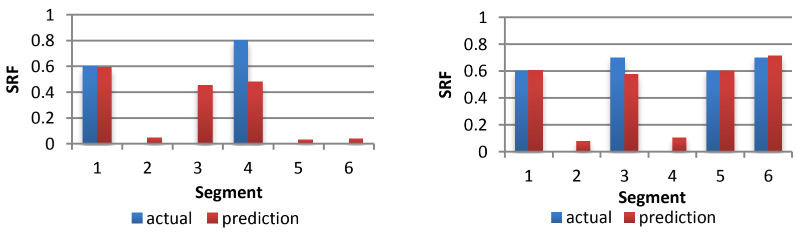
To assess the applicability of the proposed method, damage detection is first performed using a deterministic ANN model that is trained using error-free data generated from the FE model. This ANN model is tested using two sets of testing data. The first set is assumed to be measurement error free, whereas the second set is contaminated with measurement errors of 2 and 15% in the frequencies and mode shapes, respectively. Figures 4 and 5 show the ANN outputs for the two scenarios. The results in Figure 4 demonstrate that the ANN is able to provide satisfactory results in identifying damage in both scenarios when tested with noise-free testing data. However, when tested with noisy data, the prediction outputs are no longer accurate.



(a) Scenario 1

(b) Scenario 2

Figure 4. ANN predictions compared to the actual values using noise-free input data



(a) Scenario 1

(a) Scenario 2

Figure 5. ANN predictions compared to the actual values using noise-free input data

Based on the proposed approach, the uncertainties in the FE model and the measurement data are considered. Two models of ANNs are constructed to predict the lower and upper bounds of the ESPs. Errors of 2 and 5% are applied to the training and testing data based on the ANN function in Table 1. The non-probabilistic ANN models are trained using the same damage cases as the deterministic model, and the same testing data are applied. The PoDEs and DMIs are shown in Table 3. In scenario 1, higher PoDE values are obtained at segments 1 and 4 compared to the undamaged segments. The DMI value of segment 4 is also higher than that of segment 1; both of these segments are the true damage locations with different severity conditions. The same situation is observed for scenario 2, where higher PoDE values observed at segments 1, 3, 5 and 6 and the DMI values are also higher at the segments with higher severity. These results demonstrate that the proposed method provides an improvement over the conventional statistical method by providing a more meaningful damage severity indicator compared to the statistical ANN method, which only indicates the damage severity in terms of probabilities.

Table 3. PoDEs and DMIs for the six segments of the frame.

Segment no.	**Scenario 1**		**Scenario 2**	
	PoDE (%)	**DMI (%)**	**PoDE (%)**	**DMI (%)**
1	100.00	60.32	100.00	60.86
2	0.00	0.00	0.00	0.00
3	0.00	0.00	100.00	68.68
4	100.00	80.91	0.00	0.00
5	0.00	0.00	100.00	57.22
6	0.00	0.00	100.00	67.42

To further prove the capability of the proposed method, Table 4 compares the PoDE values obtained by the proposed method with the PDEs values for the same damage cases calculated using a statistical method developed by Bakhary et al. (2007). From the table, the PoDE is shown to be a more accurate damage indicator, generating smaller errors in both scenarios. For example, for scenario 1, in segment 2, which is undamaged, the proposed method shows a 0% PoDE value compared to a 38.5% PDE value. The same situation occurred in scenario 2, where undamaged segment 4 shows 0% damage, and the statistical method indicates a 13.5% probability of damage. It is also observed that for both scenarios, the proposed method provides higher PoDE values at the damaged segments compared to the PDE value. The main reason is that because, as mentioned earlier, the proposed non-probabilistic method used fewer ANN models than the statistical method, it generated smaller prediction errors.

Table 4. PoDEs and PDEs for the six segments of the frame.

Segment no.	**Scenario 1**		**Scenario 2**	
	PoDE (%)	**PDE (Bakhary et. al (2007) (%)**	**PoDE (%)**	**PDE Bakhary et. al (2007) (%)**
1	100.00	96.00	100.00	99.70
2	0.00	38.50	0.00	1.00
3	0.00	3.00	100.00	100.00
4	100.00	99.80	0.00	13.50
5	0.00	0.00	100.00	99.70
6	0.00	0.00	100.00	99.90

4 CONCLUSION

In this paper, a non-probabilistic ANN model is proposed to consider the existence of measurement noise and modeling error in damage detection. An interval analysis is adopted for use with the ANN to consider the uncertainties using the interval bounds of the uncertainties in the input parameters of the ANN. The efficacy of this method is demonstrated throughout the study using numerical example. To prove the accuracy of the proposed method, SRF and PoDE are used to identify the location and reduction in the ESP values. The results show that the proposed method enables a reliable damage detection method with noisy data.

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