Validation of an Identification Methodology for a Model Frame Structure on Shaking Table Using Laser Displacement Sensing

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ABSTRACT: For the purpose of health monitoring, post-earthquake condition evaluation and safety appraisal of existing infrastructures, many structural parameter identification methodologies based on eigenvalue and/or mode shape extraction from structural vibration measurement have been proposed. In this study, a general structural parameter identification strategy based on neural networks is proposed and the theoretical base for the construction of a neural network emulator(NNE) and a parametric evaluation neural network(PENN) is explained. A two-story model frame structure on a shaking table is employed as an illustrative structure to validate the performance of the proposed approach for structural stiffness identification and damage detection using vibration displacement response measurement from laser displacement sensors. Results show that the NNE can forecast the displacement of the reference structure with high accuracy, and PENN can describe the mapping between an evaluation index and structural stiffness parameter. Compared with results that from traditional identification method based on frequencies extraction, the performance of the proposed methodology is validated. The proposed algorithm is a general and applicable way in practice for near real-time identification, damage detection and structural model updating.
KEYWORDS: parameter identification, damage detection, neural network, time series, laser displacement sensor

1. INTRODUCTION

In the past hundred years, there have been frequent natural disasters, such as mud-rock flows, seismic sea waves, earthquakes, windstorms and the stretching of new deserts. The disasters have killed millions upon millions of people, destroyed countless homes, and wiped out numerous pieces of fertile land. China frequently suffers the ravages of natural disasters, such as earthquakes, floods, droughts, windstorms and hailstorms, which have adversely affected people's lives. The magnitude 8.0 quake flattened houses, schools and offices of the southwestern province of Sichuan on May, 2008 and more than 1,000 aftershocks have been recorded. So it is especially important to evaluate the performance of the post-earthquake structures. In recent years, parameter identification has become an increasingly important research topic for health monitoring, post-earthquake performance assessment and safety evaluation of infrastructures.

In the last two decades, some eigenvalue-based structural parameters identification algorithms have been proposed (Chang *et al.*, 2001, Doebling *et al.*, 1998, Lee *et al.*, 1991, Wu *et al.*, 2003). However, it is well known that eigenvalues and/or mode shapes extracted from dynamic measurements from traditional sensors may be too noise-corrupted to identify low to intermediate level of local damage. On the other hand, structural lower frequencies extracted from field measurement are usually insensitive to local damage initiation or development or parameter variation.

With the ability to approximate arbitrary continuous function and its parallel computation character, artificial neural networks (ANN) provide an efficient soft computing strategy for inverse analysis(Worden *et al.*,1997, Nakamura *et al.*,1998). In the work by Xu et al., vibration-induced displacement measurements were employed to identify beam and truss structures(Xu *et al.*, 2004, 2005, 2007). For lager-scale and complex structures, Wu et al. proposed a decentralized identification methodology using dynamic response measurements with neural networks and validated with numerical simulation(Wu *et al.*, 2002). Moreover, with the development of sensing technology, it is realizable to measure vibration displacement response of structure using sensing device, like laser displacement sensors etc.

In this study, a neural network based structural parameter identification method for multi-degree-of freedom (MDOF) structure on shaking table without any mode shapes and frequency extraction has been proposed and validated using vibration-induced displacement measurements from laser displacement sensors. The theoretical base of the proposed method for structural parameter identification is explained based on the discrete solution of dynamic response of the structure. The accuracy, sensibility and efficacy of the proposed methodology are examined. Results show that the proposed methodology can identify the inter-story stiffness of the frame structure within acceptable accuracy.

2. PARAMETERIC IDENTIFICATION METHODOLOGY

2.1 Theoretical base

The motion of a linear structure system with *n* degrees of freedom (DOF) under base excitation can be characterized by the following equation,

$$M\ddot{x} + C\dot{x} + Kx = f \tag{2.1}$$

In case of earthquake excitation, the external force f can be represented as the following equation,

$$f = -MI\ddot{x}_g \tag{2.2}$$

where the matrices M, C and $K \in R^{n \times n}$, are the structure mass, damping, and stiffness matrices, respectively; $\ddot{x}$, $\dot{x}$ and $x \in R^n$, are the acceleration, velocity, and displacement vectors, respectively; $I \in R^n$ is a unitary vector, $\ddot{x}_g$ represents the excitation acceleration.

Equation (2.1) can be rewritten in state space as the following first-order vector differential equation,

$$\dot{Z} = AZ + Bf \tag{2.3}$$

where the state vector Z and the system matrix A and B are defined as

$$Z = \begin{Bmatrix} x \\ \dot{x} \end{Bmatrix}, A = \begin{bmatrix} 0 & I \\ -M^{-1}K & -M^{-1}C \end{bmatrix}, B = \begin{bmatrix} 0 \\ M^{-1} \end{bmatrix} \tag{2.4-2.6}$$

the discrete time solution of the state equation can be written as,

$$Z_k = e^{AT} Z_{k-1} + f_{k-1} \int_0^T e^{A\tau} B d\tau \quad , \quad (k = 1, \cdots, K) \tag{2.7}$$

where Z_k and Z_{k-1} are the state variables at time step *k* and *k-1*, respectively, *T* is time interval. From (2.7), it can be seen that the state variable at time step *k* is fully determined by the state variable at time step *k-1* and excitation acceleration at time step *k-1*. Moreover, the velocity response at time step *k-1* is determined by displacement response the at time step *k-1* and *k-2*, so, it is clear that the displacement response at time step *k* is fully determined by them at time steps *k-2* and *k-1*, and the excitation acceleration at time step *k-1*.

2.2 Identification procedure

The full procedure for parametric identification by the direct use of displacement response with two neural networks can be carried out in three steps as described in Figure 1.

First of all, a finite element model of the object structure to be identified is considered. The purpose of the identification is to identify the parameters of the finite element model in form of materials Young's modulus or element stiffness or damping coefficients.

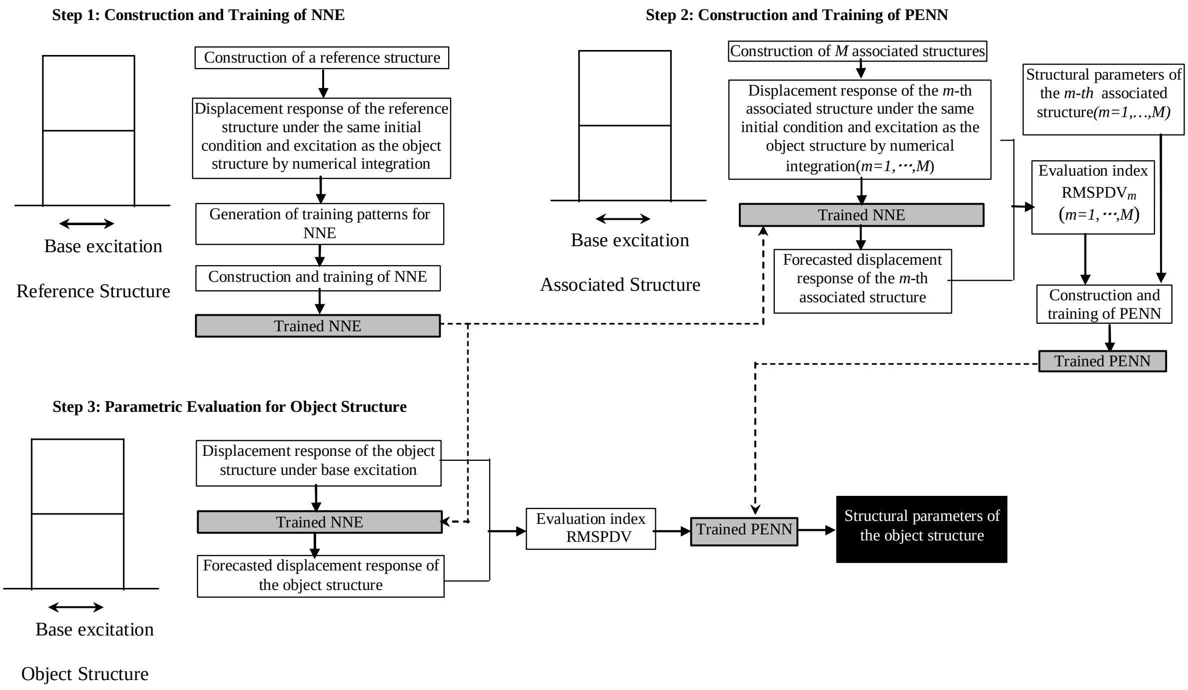


Figure 1 Displacement-based parametric identification strategy with neural networks

In step 1, a reference structure which under the same initial conditions, excitations and has the same finite element model with the object structure is assumed. The parameters of the reference structure are assumed according to the design experience of the object structure. Using the displacement response of the reference structure that from numerical integration, a neural network emulator(NNE) can be constructed and trained to forecast the displacement response step by step for the reference structure as described in the following equation,

$$x_k^f = \mathrm{NNE}(x_{k-2}, x_{k-1}, \ddot{x}_{g,k-1}),\ (k = 3, N) \tag{2.8}$$

where *N* is the sample number of the structure dynamic response time series.

In step 2, changing the parameters of the reference structure, *M* associated structures that have the same finite element model with the object structure are considered. The dynamic displacement responses of the *m*-th associated structure under the same initial conditions and excitations can be determined by numerical integration. If the trained NNE is used to forecast the displacement response of the *m*-th associated structure, then the forecasted value at time step *k* can be given:

$$x_{m,k}^f = \mathrm{NNE}(x_{m,k-2}, x_{m,k-1}, \ddot{x}_{g,k-1}) \quad (m = 1, M\ , k = 3, N) \tag{2.9}$$

In this study, assume the stiffness parameters of each associated structured are differ from the reference structure, so the dynamic displacement response determined by numerical simulation will not correspond any more to the output of NNE. Corresponding to the *j*-th degree, the difference vector can be evaluated by

$$e_{m,k}^{(j)} = x_{m,k}^{(j)f} - x_{m,k}^{(j)}, \quad (j=1,n) \tag{2.10}$$

Define an evaluation index called the root mean square of the prediction difference vector (RMSPDV). For the *j*-th degree, *m*-th associated structure, it can be written as

$$RMSPDV_m^{(j)} = \sqrt{\frac{1}{N-2}\sum_{k=3}^{N}(e_{m,k}^{(j)})^2}, \quad (m=1,M \ , j=1,n) \tag{2.11}$$

On the other hand, it should be a function of structural matrices as described in Equation (2.12),

$$RMSPDV_m = f(M_m, K_m, C_m) \tag{2.12}$$

Therefore, a parametric evaluation neural network (PENN) is constructed and trained to describe the mapping between the evaluation index and structural parameters as described in the following equation,

$$(M_m, K_m, C_m) = \mathrm{PENN}(RMSPDV_m) \tag{2.13}$$

In step 3, after finishing the training of PENN, the object structural parameters can be identified by inputting RMSPDV of the object structure to PENN with the help of NNE constructed and trained in step 1.

3. IDENTIFICATION FOR A MODEL FRAME STRUCTURE AND EXPERIMENTAL VALIDATION

3.1Description of the shaking table test

A shaking table test for a two-storey steel frame structure which is selected as the object structure shown in Figure 2 was conducted to validate the proposed methodology. The inter-storey height of the frame structure is 490mm. The structure can be modeled as a two DOF mass-spring-dashpot system as shown in Figure 3. The mass of the first and the second floor are 1.16kg and 1.38kg, respectively.

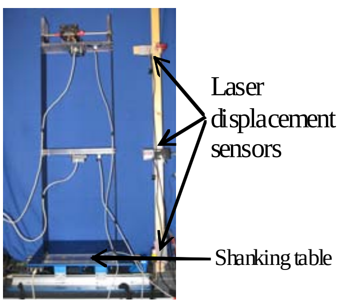


Figure 2 Shaking table test

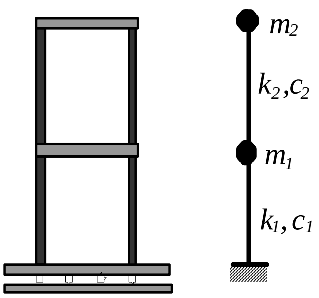


Figure 3 Computational model

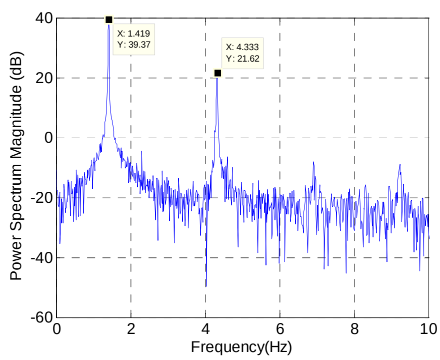


Figure 4 Power Spectrum of the object structure

The shaking table is excited by sine wave with a frequency of 2.5Hz. The displacement measurements of the base, first and second floor are synchronously acquired by three Keyence LB-70(W) laser displacement sensors with sampling rate of 1,000Hz.

The model structure was also carried on sweep excitation test and free-vibration decay test. Two natural frequencies of the structure are 1.419Hz and 4.333Hz acquired from sweep excitation test as shown in Figure 4, The damping ratio of both control frequencies of the structure is 0.4% which presents a light damping.

3.2 Architecture and training of NNE

Based on the preliminary estimation of the object structure to be identified, a reference structure is constructed, whose inter-storey stiffness parameters for the first and second floor are assumed to be 300N/m and 300N/m, respectively. The displacement response of the first and second floor under the measured base excitation is determined by Newmark-β integration method. The integration time step is 0.001s. Take 3 seconds of displacement response from time 6.0s to 9.0s as the training data sets, a typical three-layer neural network is constructed and trained for displacement forecasting of the reference structure as shown in Figure 5. The number of neurons in the input and output layers of the NNE is set to be 5 and 2, respectively. While for the hidden layer, it is 6 determined by trial-and-error. The whole off-line training process takes 3,000 epochs.

Table 1 Prediction error of NNE

DOF	RMSPDV Absolute error/mm	RMSPDV Relative error/%
1	5.382×10^{-4}	2.166×10^{-3}
2	3.879×10^{-4}	1.821×10^{-3}

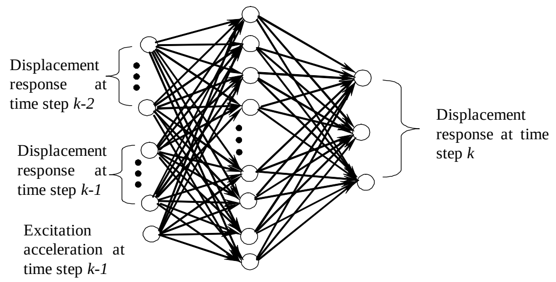
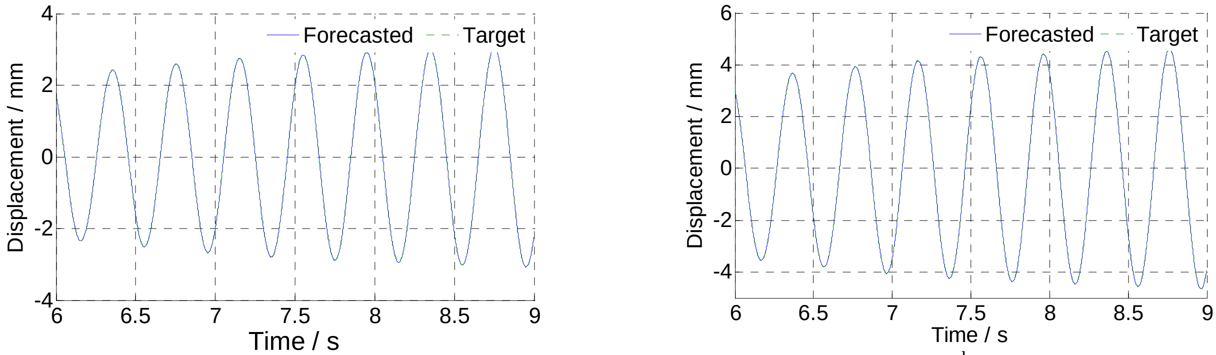


Figure 5 NNE

Figure 6 gives the comparison between the displacement responses determined by the Newmark-β method and those predicted by the trained NNE. The root mean square (RMS) of the difference between the two curves and the relative RMS error are given in Table 1. It can be seen that the maximum relative RMS error can reach a very small value and the trained NNE is able to forecast the displacement response for the reference structure with high accuracy.



(a) 1st floor (b) 2nd floor

Figure 6 Comparisons between the displacement responses of the reference structure determined by Newmark-β method and those forecasted by the trained NNE

3.3 Architecture and training of PENN

Because the mass of a structure can be known easily and it usually does not change with the occurrence of damage, it is usually considered as a known constant. Besides, the damping ratio of the model is very small and can be treated as known. Therefore, in this study, it is reasonable that the evaluation index completely depends on stiffness parameters. Equation (2.11) can be rewritten in the following form,

$$(k_1, \cdots, k_n, \cdots, k_N)_m = \mathrm{PENN}(RMSPDV_m) \tag{3.1}$$

where k_n is the inter-storey stiffness of the n-th storey of m-th associated structure.

To generate training patterns, a number of associated structures with different structural properties are considered. Let the inter-story stiffness of the first and second floor to be 210N/m, 225N/m, 240N/m, 255N/m, 270N/m, 285N/m, 300N/m, 315N/m, 330N/m, 345N/m, 360N/m, 375N/m, 390N/m. Therefore, totally 169 structures are constructed and 121 among them are selected as associated structures randomly.

The displacement response of each associated structure under the measured base excitation is determined by Newmark- β integration method. Using the displacement response of each associated structure from 6.0s to 9.0s as input to above trained NNE, totally 121 RMSPDVs can be obtained and employed as training patterns for the PENN.

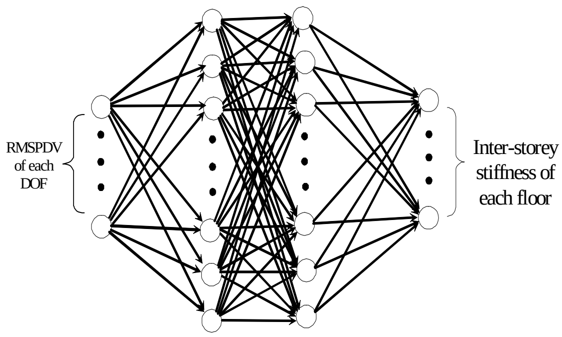


Figure 7 PENN

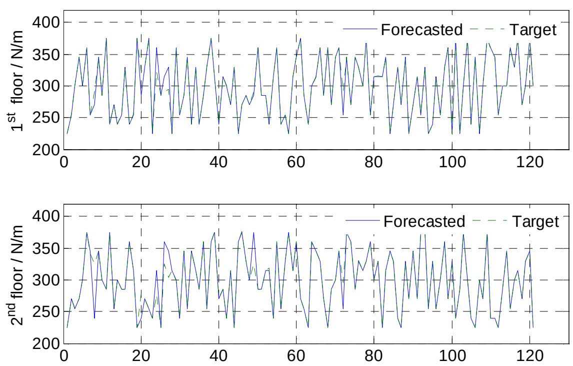


Figure 8 Comparisons between the target stiffness and the output of the trained PENN

Figure 7 shows the architecture of the PENN. It is constructed of four layers. The number of neurons in the input and output layers is set to be 5 and 2, respectively, and 8 for the two hidden layers by trial-and-error. The entire off-line training process for the PENN takes 5,000 epochs. Figure 8 gives the comparisons between the target stiffness and the output of the trained PENN and Table 2 gives the relative RMS error corresponding to each inter-story. Results show that the trained PENN has enough precision.

Table 2 Relative RMS error of PENN

DOF	RMSPDV relative error/%
1	4.24
2	3.89

Table 3 Comparisons of the inter-storey stiffness

	Identified by PENN(N/m)	Eigenvalues based (N/m)	Relative error(%)
1st floor	254.5	245.8	3.54
2nd floor	369.7	383.7	3.65

3.4 Identification for the object structure

Using 3 seconds of the displacement measurement of the object structure from 6.0s to 9.0s as input to the trained NNE, the corresponding RMSPDV are calculated. Then, inputting the RMSPDV to the trained PENN, stiffness parameters of the object structure are identified. Table 3 shows the identified inter-storey stiffness of the model frame structure and comparisons with results from eigenvalue-based method. It demonstrates that identification can be carried out with enough acceptable accuracy.

4. DAMAGE IDENTIFICATION

In the frame model studied here, each end of each column is connected to the beam with 3 screws. The number 1, 2, 3, 4 in the right hand of Figure 9 denote the beam-column joint number. Local damage is introduced by loosening some screws of the beam-column joints near to the first floor (mark 2 and 3), as shown in Figure 9. Similar shaking table test is carried out for the damage frame structure and the displacement measurements of the table, first and second floor are synchronously acquired by laser displacement sensors.

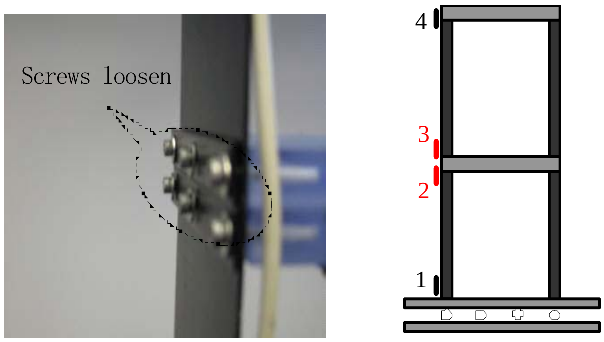


Figure 9 Damaged structure

With the above mentioned identification methodology, the stiffness parameters of the damaged structure are identified using 3 seconds of the displacement measurement of damaged structure from 6.0s to 9.0s.

Table 4 shows comparisons of the inter-storey stiffness of the damaged structure between identified and eigenvalues based method. Results show that with the help of two neuron networks, the inter-story stiffness of the model structure can be identified with acceptable accuracy. Compared with the stiffness of the original structure as shown in Table 3, the two inter-story stiffness of the damage structure are reduced obviously by the loosening of the connection screws.

Table 4 Comparisons of the inter-storey stiffness

	Identified by PENN(N/m)	Eigenvalues based (N/m)	Relative error(%)
1st floor	143.2	137.5	4.15
2nd floor	237.5	228.9	3.76

5 CONCLUSIONS

In this paper, a direct parametric identification methodology using displacement measurements with neural networks is proposed. The rationality and the implementation of the methodology are explained and the theory basis for the construction of NNE and PENN are described. The performance of the proposed strategy is evaluated using displacement measurements from laser displacement sensors for a model frame structure on a shaking table. Structural inter-storey stiffness identification results show that the proposed methodology can identify the inter-storey stiffness of the frame structure within an acceptable accuracy when displacement response time series are employed. The strategy does not require the extraction of structural dynamic characteristics such as frequencies and mode shapes from measurement and can be an applicable method in practice for near real-time structure model updating and post-earthquake damage detection.

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