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Localized and decentralized identification for large-scale structures

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Mathematical-model-based structural identification algorithms for the damage detection and performance evaluation of civil engineering structures have been widely proposed and their performance for small and simple structural models has been studied in the past two decades. Actual civil engineering structures, however, usually have a great number of degrees of freedom (DOFs). It is unpractical to directly apply these conventional methods for the identification of large-scale structures, because excessive computation time and computer memory are necessary for the search of optimal solutions in inverse analysis, which is often computationally inefficient and even numerically unstable. Moreover, for the identification of large-scale structures, it is difficult to obtain unique estimates of all structural parameters by the optimization search processes involved in the conventional identification algorithms requiring the use of secant, tangent, or higher-order derivatives of the objective function. The ability of artificial neural networks to approximate arbitrary continuous function provides an efficient soft computing strategy for structural parametric identification. Based on the concept of localized and decentralized information architecture, novel decentralized and localized identification strategies for large-scale structure system by the direct use of structural vibration response measurements with neural networks are proposed in this paper. These methodologies does not require the extraction of structural frequencies and mode shapes from the measurements and have the potential of being a practical tool for on-line near-real time and damage detection and performance evaluation of large-scale engineering structures.

1. Introduction

The increasingly intensive research activities on structural identifications are related to the fact that the number of damaged or deteriorated infrastructures grows rapidly in many developed countries. Moreover, the damage detection for the vulnerability and post-hazard safety evaluation of infrastructures that serve as lifelines or that are crucial for recovery following a seismic event, accidents or man-made terrorism remain a pressing need. Material deterioration and damage usually result in changes in structural parameters, for example, the stiffness of a structural member or a substructure. These changes lead to the modification of the structural dynamic properties, such as natural frequencies and mode shapes. With the recent development in computer technology for data acquisition, signal processing and analysis, the structural parameters identification can be carried out from the measured responses under certain excitation, such as earthquake, wind, traffic loads or environmental excitations based on a monitoring system. Most of the identification strategies use mathematical models to describe structural behavior and establish the relationship between a specific damage scenario and its corresponding changes in structural response or eigenvalues and eigenvectors. These mathematical model-based identification technologies can be categorized into time-domain approaches and frequency-domain approaches [3, 6, 23]. Some comprehensive literature reviews on system identification methods in civil engineering can be found in [1, 10].

Although having successfully been applied into simple engineering structures, many of the current identification methods requiring the use of secant, tangent, or higher-order derivatives of the objective function inherently involve a complicated optimization process for parameters identification. Thus, they are often computationally inefficient and even numerically unstable for actual infrastructures that have a significant number of degrees of freedom (DOFs). Moreover, response measurement for a whole engineering structure is difficult and the accuracy of parameters estimation is rarely reliable. There is a critical need for additional research in order to develop much more robust, adaptive and effective identification algorithms for large-scale or complex structures. Yun *et al.* proposed a substructural identification method for the estimation of local damage in complex structural systems using an auto-regressive and moving average with stochastic input (ARMAX) model [22].

An alternate solution to structural identification can be derived with the use of neural networks. Indeed, modelling a linear or nonlinear structural system with neural networks has been increasingly recognized as one of the system identification paradigms [4, 5, 7, 8, 24]. Among various neural networks with different topology structures, multi-layer neural networks are most commonly used in structural identification and control. Although several neural network based strategies are available for qualitative evaluation of damage that may have taken place in a structure, it was not until recently that a quantitative way of detecting damage has been proposed with neural networks. Yun *et al.* presented a method for estimating the stiffness parameters of a complex structural system by using a back-propagation neural network with natural frequencies and mode shapes as inputs [21]. Xu *et al.* and Wu *et al.* proposed a series of neural networks based identification strategies with the direct use of free, forced or earthquake induced vibration measurement and no eigenvalues and mode shapes need to be extracted from the responses [17, 19, 20].

In this paper, a general soft structural identification methodology by the direst use of dynamic measurements with neural networks is described firstly. For large-scale structures, localized and decentralized methodologies are proposed and their rationality, sensitivity, accuracy, and adaptability are discussed with numerical simulations. Results show that neural networks based decentralized and localized identification strategies are applicable for structural model updating or damage detection of large-scale infrastructures whether the exact model of the healthy infrastructure is known or not and should play an important role in the parametric identification for infrastructure and the development of smart material systems and structures.

2. General soft structural identification methodology using dynamic measurements with neural networks

2.1. Base-excitation-induced vibration measurement

Structural dynamic response measurements under base excitations such as small-scale earthquakes or environmental ambient excitation are useful and economical information for parametric identification, damage detection and model updating, especially in Japan where small-scale earthquakes occur very frequently. Xu *et al.* proposed a structural parameters assessment approach using base-excitation-induced vibration measurement with neural networks [20]. Two neural networks are constructed to facilitate the process of damage identifications. The rationality of the proposed methodology is explained and the theory basis for the construction of emulator neural network (ENN) and parametric evaluation neural network (PENN) are described according to the discrete time solution of the structural state space equation. An evaluation index called root mean square of prediction difference vector (RMSPDV) is presented to evaluate the condition of different associated structures. Based on the trained ENN, which is a non-parametric model of the object structure in healthy state, and the PENN that describes the relation between structural parameters and the components of the corresponding RMSPDVs, the inter-storey stiffness of the object damaged structure is identified.

The accuracy, sensibility and efficacy of the proposed strategy for different ground excitations are also examined using a multi-storey shear building structure with numerical simulations.

2.2. Forced vibration measurement

The neural network based strategy for the direct structural parameters identification from forced vibration response measurements was proposed by Xu *et al.* [17]. Both structural stiffness and damping coefficients can be identified while the mass matrix is assumed to be known. This strategy is a common method for structural parameter identification and it is unnecessary to know the exact parameters of the object structure in its undamaged or original state. The performance and computational efficacy of the proposed strategy was demonstrated with a 5-story shear type of frame with simulated displacement and velocity time histories that mimic the measured dynamic responses in practice. The effect of measurement noise on the accuracy of the identified parameters has been investigated. A noise injection method was also proposed to improve the accuracy of identification results.

2.3. Vibration-induced strain measurement

Most existing parameter identification procedures involve the use of the applied excitations and/or the measured acceleration, displacement and/or velocity responses. In recent years, advanced new sensors such as distributed optical fibers and piezoelectric sensors are being developed to continuously monitor the structural strain distribution [9]. The rapid development of these strain sensing techniques necessitates the development of a new structural identification methodology based on strain measurements. Wu *et al.* and Xu *et al.* also proposed structural identification strategies of bending beam structure and planer truss structure using simulated and measured macro-strain response from long-gauge fiber Bragg grating (FBG) sensors by a three-step neural network strategy [14, 16].

The above proposed neural networks based identification methodologies are very attractive alternatives for near real-time identification and damage detection because only earthquake-induced, forced and free vibration response or excitation measurements are needed and no time-consuming eigenvalue and mode shape extraction is necessary. The theoretical concept makes the proposed methodologies common and also applicable whether the exact values of the parameters of the object structure in healthy state is known or not. Moreover, no direct optimization search is necessary during the identification procedures. The proposed methodologies can give the parametric identification results in near real-time only using several seconds of response measurements. This characteristic is very attractive and meaningful for the on-line near real-time identification, especially for the post-earthquake or post-event damage detection and evaluation for infrastructures.

3. Localized soft identification algorithm using time histories with neural networks

Comprehensive literature reviews on system identification methods in civil engineering are available. Although having successfully been applied into simple engineering structures with few DOFs and few unknown structural parameters, many of the current identification methods inherently involve a complicated optimization process for the parameters identification. Thus, they are often computationally inefficient and even numerically unstable for actual infrastructures that have a significant number of DOFs. Moreover, response measurement for a whole engineering structure is difficult and the accuracy of parameters estimation is rarely reliable. If the object structure is divided to several substructures, measurement and identification may be performed more efficiently. Form such a point of view, several substructural identification algorithms have been proposed in recent

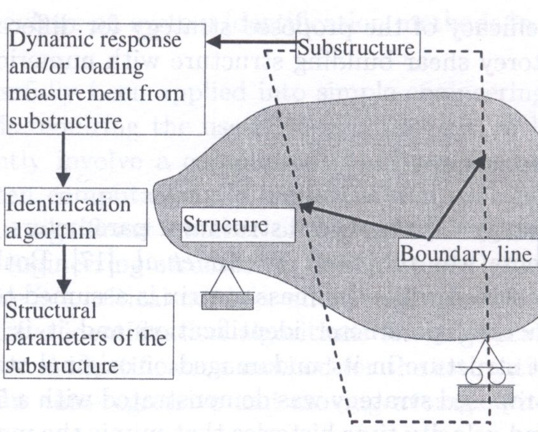


Fig. 1. Concept of localized identification

years [21, 22]. The basic concept of localized identification is shown in Fig. 1, where only a localized area (substructure) rather than the entire structure is identified. For localized identification, sensors are usually located within a small portion of the entire structure (substructure). Dynamic response measurement in a localized area is somewhat simpler than it for the whole structure. The neural networks-based localized identification algorithms are described and verified as follows [15].

3.1. Equation of motion for a substructure

The motion of a structure with n DOFs under dynamic excitation can be characterized by the following equation,

$$M\ddot{x}+C\dot{x}+Kx=Lu \tag{1}$$

where M, C and K – the mass, damping, and stiffness matrices of the structure, $\ddot{x}$, $\dot{x}$ and x – the acceleration, velocity, and displacement vectors, u – the excitation vector, and L is the input coefficient matrices. Considering the substructure shown in Fig. 2, Eq. (1) can be rewritten in a partitioned matrix format as

$$\begin{bmatrix} M_{mm} & M_{mi} & 0 \\ M_{im} & M_{ii} & M_{ir} \\ 0 & M_{ri} & M_{rr} \end{bmatrix}\begin{Bmatrix} \ddot{x}_m \\ \ddot{x}_i \\ \ddot{x}_r \end{Bmatrix}+\begin{bmatrix} C_{mm} & C_{mi} & 0 \\ C_{im} & C_{ii} & C_{ir} \\ 0 & C_{ri} & C_{rr} \end{bmatrix}\begin{Bmatrix} \dot{x}_m \\ \dot{x}_i \\ \dot{x}_r \end{Bmatrix}$$
$$+\begin{bmatrix} K_{mm} & K_{mi} & 0 \\ K_{im} & K_{ii} & K_{ir} \\ 0 & K_{ri} & K_{rr} \end{bmatrix}\begin{Bmatrix} x_m \\ x_i \\ x_r \end{Bmatrix}=\begin{bmatrix} L_{mm} & L_{mi} & 0 \\ L_{im} & L_{ii} & L_{ir} \\ 0 & L_{ri} & L_{rr} \end{bmatrix}\begin{Bmatrix} u_m \\ u_i \\ u_r \end{Bmatrix} \tag{2}$$

where m, i, r denote the master, interfacial and remaining DOFs. Therefore, the motion equation of the substructure can be derived as

$$M_{mm}\ddot{x}_m+C_{mm}\dot{x}_m+K_{mm}x=L_{mm}u_m+L_{mi}u_i-[M_{mi}\ddot{x}_i+C_{mi}\dot{x}_i+K_{mi}x_i]\,. \tag{3}$$

If the structure can be reasonably modeled as a lumped-mass-spring-dashpot system, the $M_{mi}=0$. Then Eq. (3) can be obtained as

$$M_{mm}\ddot{x}_m+C_{mm}\dot{x}_m+K_{mm}x_m=f_{mi} \tag{4}$$

where

$$f_{mi}=L_{mm}u_m+L_{mi}u_i-[C_{mi}\dot{x}_i+K_{mi}x_i] \tag{5}$$

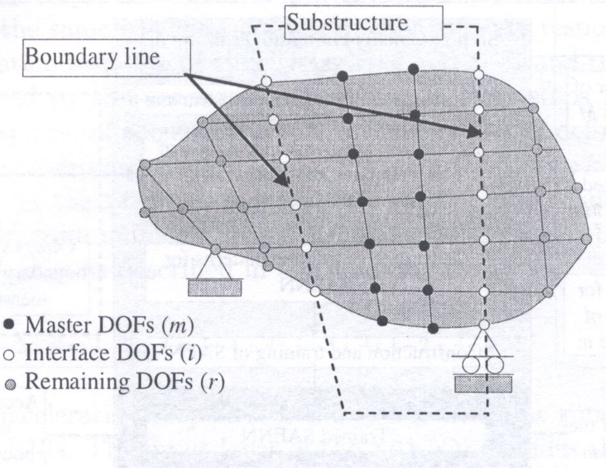


Fig. 2. Substructure and degrees of freedom

Equations (4) and (5) indicate that the substructure can be treated as an independent part and the corresponding structure dynamic response is uniquely determined by the actual excitation to the substructure and the boundary, and the velocity and the displacement responses at the interfacial DOFs.

3.2. Localized soft parametric identification strategy using acceleration measurements

To facilitate the localized identification process using neural networks, a reference substructure and a number of associated substructures that have the same overall dimension and topology as the object substructure are created, and an substructural acceleration-based emulator neural network (SAENN) and a substructural parameter evaluation neural network (SPENN) are established and trained to identify the physical parameters of the object substructure. The basic three-step procedure for localized identification of the substructure is shown in Fig. 3 and described in detail in the following context.

(1) Rationality and construction of SAENN for the reference substructure

In Step 1, the SAENN is constructed and trained using the responses of the reference substructure under the measured boundary and inner excitations and boundary responses. The SAENN is treated as a non-parametric model of the reference substructure that acts as a baseline of the parametric identification for the object substructure. To make sure the SAENN is meaningful, the mapping or function from the input to output should uniquely exist.

Equation (5) can be rewritten in state space as the following first-order vector differential equation,

$$\dot{Z}_m = AZ_m + Bf_{mi} \tag{6}$$

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

$$Z_m = \begin{Bmatrix} \dot{x}_m \\ x_m \end{Bmatrix}, \tag{7}$$

$$A = \begin{bmatrix} -M_{mm}^{-1}C_{mm} & -M_{mm}^{-1}K_{mm} \\ I & 0 \end{bmatrix}, \tag{8}$$

$$B = \begin{bmatrix} M_{mm}^{-1} \\ 0 \end{bmatrix}. \tag{9}$$

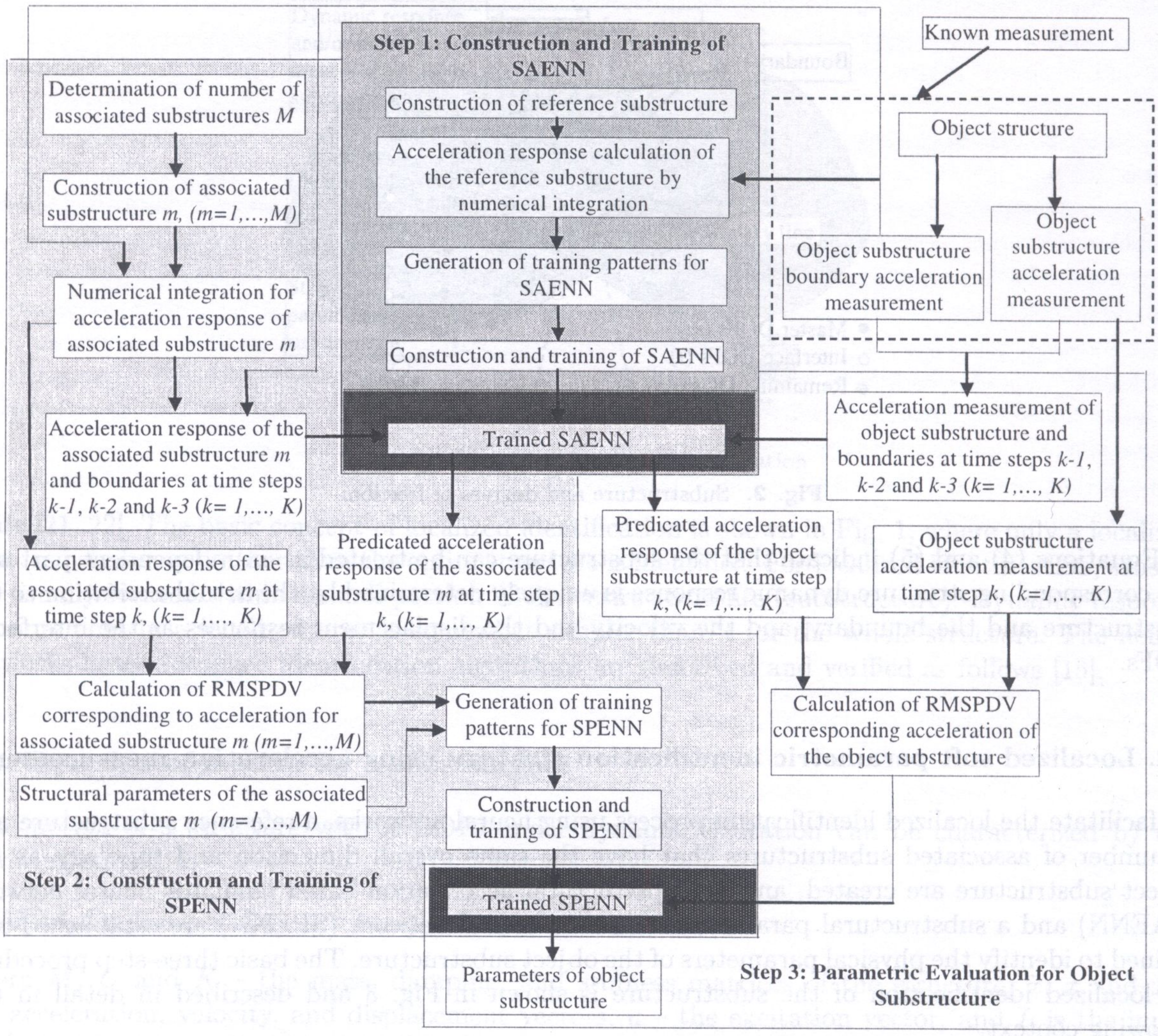


Fig. 3. General localized soft structural parametric identification strategy based on neural networks using acceleration measurement

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

$$Z_{m,k} = e^{AT} Z_{m,k-1} + f_{mi,k-1} \int_0^T e^{A\tau} B \,\mathrm{d}\tau \qquad (k = 1, \ldots, K), \tag{10}$$

where $Z_{m,k}$ and $Z_{m,k-1}$ are the state variables of the substructure at time instants, kT and $(k-1)T$ with T being time interval, respectively. Equation (10) shows that the response of the substructure $Z_{m,k}$ is uniquely and fully determined by the state vector $Z_{m,k-1}$ and $f_{mi,k-1}$. So, if the state vector $Z_{m,k}$ is treated as the output of the SAENN, and state vector $Z_{s,k-1}$ and $f_{s,k-1}$ are selected as its inputs, the mapping between the inputs and outputs uniquely exists.

Using the vibration time series of the reference substructure under excitations and the measured boundary conditions form numerical integration, the SAENN can be trained until the difference between the state vector $Z_{m,k}$ at time step k and its output reach a very small value. The trained SAENN can be used to forecast the structural state vector step by step as described in the following equation,

$$Z^f_{m,k} = SAENN(Z_{m,k-1}, f_{m,k-1}) \qquad (k = 1, \ldots, K), \tag{11}$$

where $Z^f_{s,k}$ is the forecast state vector at time step k by the trained SAENN.

Because the acceleration response at time step k is completely determined by the velocity and displacement response at the same time step. Moreover, the velocity response at time step $k-1$ is determined by the acceleration response at time steps $k-2$ and $k-1$ and the displacement response at time $k-1$ is determined by the acceleration response at time steps $k-3$, $k-2$ and $k-1$. Therefore, acceleration response of the substructure at time step k is definitely determined by the acceleration responses of the substructure and the interfaces at time steps $k-3$, $k-2$ and $k-1$. Using the acceleration responses of the reference substructure with known structural parameters under certain interface excitations from numerical integration, the SAENN can be trained to forecast the acceleration vector step by step as described in the following equation,

$$\ddot{x}^f_{m,k} = SAENN_a\left(\ddot{x}_{m,k-3}\,,\, \ddot{x}_{m,k-2}\,,\, \ddot{x}_{m,k-1}\,,\, \ddot{x}_{i,k-3}\,,\, \ddot{x}_{i,k-2}\,,\, \ddot{x}_{i,k-1}\right) \qquad (k = 3, \ldots, K), \tag{12}$$

where $\ddot{x}^f_k$ is the forecast acceleration response of the substructure at time step k. Figure 4 shows the architecture of the SAENN. The input layer of the SAENN includes the acceleration responses of the substructure and them at the interfaces at time steps $k-3$, $k-2$ and $k-1$, and the output layer includes acceleration response of the substructure at time step k. For a substructure involving S DOFs with interfaces that have R DOFs, the number of neurons in input and output layers are $3 \times (S + R)$ and S, respectively.

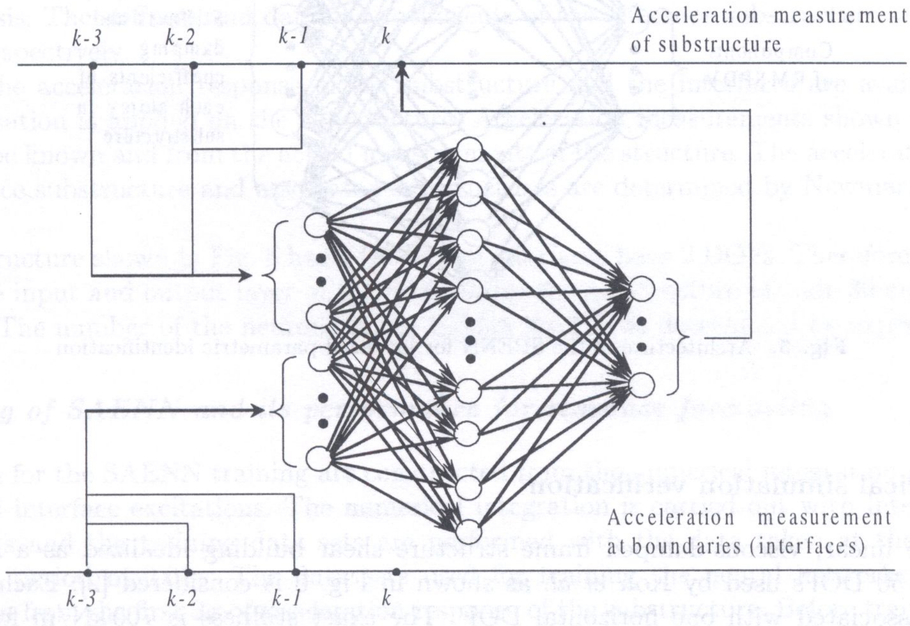


Fig. 4. Architecture of SAENN

(2) Rationality and construction of SPENN for localized identification

In Step 2, consider N associated substructures that have different structural parameters from the reference substructure in Step 1. On one hand, the responses of an associated substructure n at time step k under the same boundary condition and excitations as used in Step 1 for the reference substructure can be calculated with the numerical integration method. On the other hand, the responses can be predicted from the SENN trained for the reference substructure. Since the parameters of the associated substructure differ from those of the reference substructure, it is expected that the predicted responses are different from those computed by numerical integration. The difference provides a quantitative measure of the physical parameters of the substructure relative to the reference substructure. The corresponding RMSPDV is employed to identify the structural parameters of the object substructure. It is obvious that the RMSPDV depends on the mass, stiffness and damping matrices of the associated substructure n. Because the mass usually does not change with the occurrence of damage, it can be considered as a known constant. Therefore, the RMSPDV is then completely determined by the stiffness and damping parameters of the substructure.

If the above relation is known, the structural parameters can be determined according to the RMSPDV. For this purpose, the SPENN is constructed and trained to describe the inverse function

$$(K_{m,n}\,,\, C_{m,n}) = SPENN(e_n). \tag{13}$$

Generally speaking, the inputs to the SPENN include the components of the RMSPDV. The outputs are the stiffness parameters and damping coefficients of the corresponding substructure. The architecture of the SPENN is shown in Fig. 5.

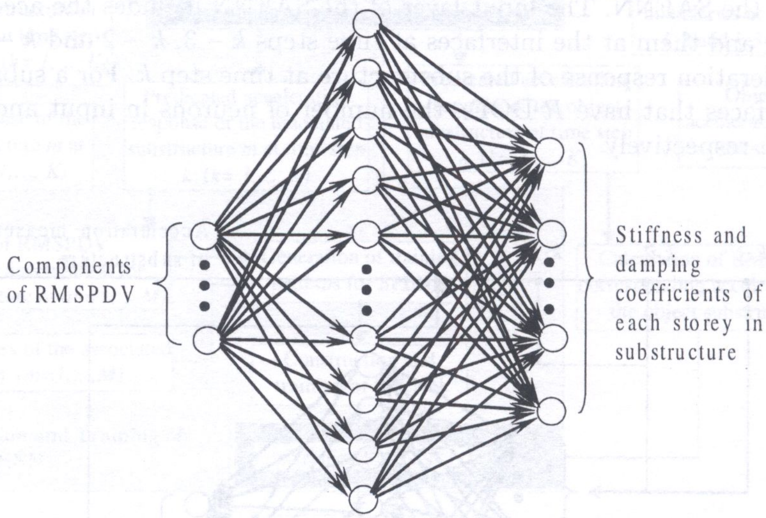


Fig. 5. Architecture of the SPENN for localized parametric identification

3.3. Numerical simulation verification

A large-scale linear, viscous-damped frame structure shear building idealized as a lumped mass system with 50 DOFs used by Koh *et al.* as shown in Fig. 6 is considered [2]. Each story of the building is associated with one horizontal DOF. The exact stiffness is 700 kN/m for each story, while the mass is 600kg for the first story and 300 kg for others. Damping coefficients for each story is assumed to be 500 N·s/m for each story. A substructure including mass 32 to mass 39 and interconnected with the upper boundary mass 40 and lower boundary mass 31 is considered as the object substructure.

(1) Construction of SAENN for nonparametric localized identification of reference substructure

In practice, an existing substructure in its current condition is referred to as an object substructure. If archived information is available, a substructural model based on as-built drawings of the existing substructure that describe its undamaged or healthy condition can be selected as the reference substructure. But the reference substructure is not necessarily determined according to the as-built drawings. In case the original drawings and archives of the object substructure are not available, a finite element model determined from the initial estimation on the material parameters can be

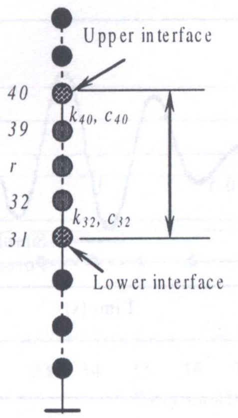


Fig. 6. A substructure in a structural system with 50 DOFs

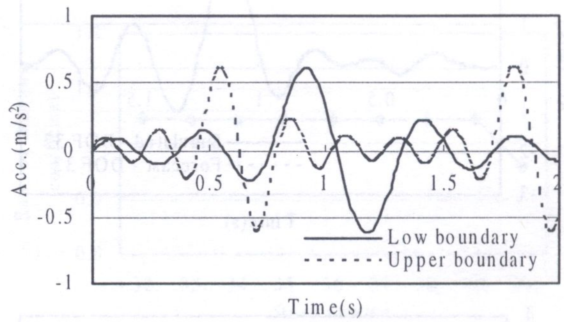


Fig. 7. Acceleration measurements on interfaces

considered as a reference substructure. Essentially, the reference substructure here functions as a baseline for identification. The reference substructure acts as the search starting point, which is based on the initial estimate of structure parameters, for the optimization problems of any traditional inverse analysis. The stiffness and damping coefficients of the reference substructure are 777 kN/m, 450 N·s/m, respectively.

Suppose the acceleration response of the substructure and the interfaces are available and no external excitation is applied on the substructure. Acceleration measurements shown in Fig. 7 are supposed to be known and from the actual measurements of the structure. The acceleration response of the reference substructure and associated substructures are determined by Newmark integration method.

The substructure shown in Fig. 6 has 8 DOFs and interfaces have 2 DOFs. Therefore, for the substructure, the input and output layer of the SAENN for the substructure include 30 and 8 neurons, respectively. The number of the neurons in the hidden layer is 30 determined by experience.

(2) Training of SAENN and its performance for response forecasting

The data sets for the SAENN training are constructed from the numerical integration results under the measured interface excitations. The numerical integration is carried out with integration time step of 0.002 s and the training data sets are performed with the data taken at the intervals of the sampling period of 0.01 s. The data sets used for training the neural networks are the 197 patterns taken from the first 2 s of acceleration response of the substructure. Before training, a linear normalization pre-conditioning for the training data sets is carried out before the training with the error back-propagation algorithm and the weights are initialized with small random values at the beginning of training the SAENN.

Figure 8 gives the comparison between the acceleration responses determined from the numerical integration and those forecast by the trained SAENN. It can be seen that the forecast acceleration responses meet with the numerical integration results very well.

(3) Construction and training of SPENN for parametric identification of substructure

For the substructure shown in Fig. 6, the numbers of neurons in input and output layers of SPENN are 8 and 18, respectively. The input layer includes the 8 components of RMSPDV and the output layer represents the stiffness and damping coefficients from 32 to 40 of the substructure. The hidden layer has 50 neurons. For the purpose of training of the SPENN, a number of associated substructures with different structural parameters within the interested space are assumed, and

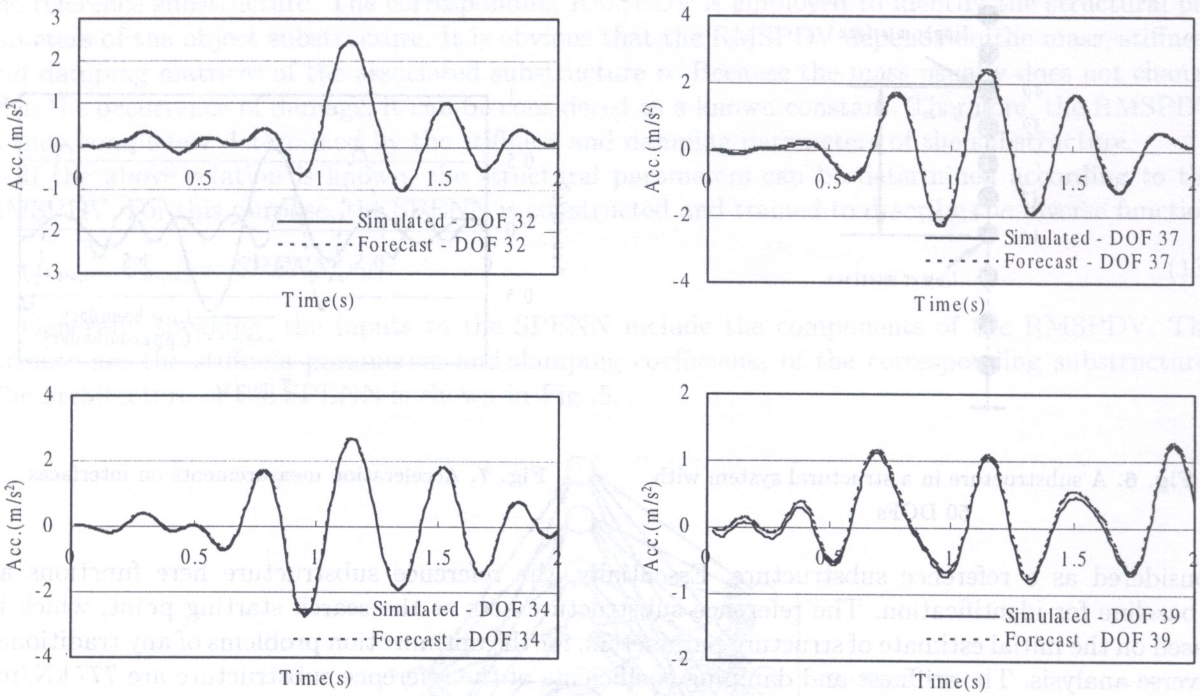


Fig. 8. Comparison between the acceleration responses determined from the numerical integration (called observed responses) and those forecast by the trained SAENN

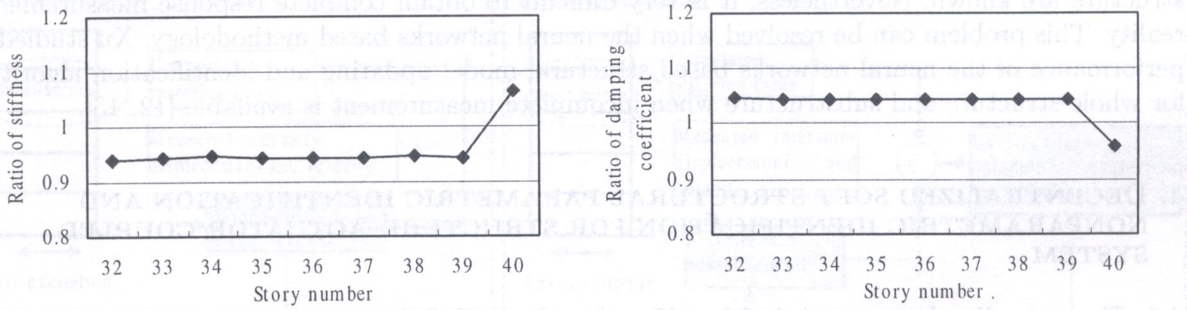
the RMSPDVs are calculated with the help of the trained SAENN. The stiffness of some assumed damaged substructures and the corresponding RMSPDVs are used to train the SPENN.

Suppose the difference of the stiffness parameters and damping coefficients between the object substructure and the reference are within ±30% of the values of the reference substructure. Totally, 512 associated substructures are constructed with randomly selected structural parameters within the interested field. Therefore, 512 associated substructures are constructed and 512 pairs of training data are determined.

(4) Substructural stiffness and damping coefficients identification with SPENN

After the SPENN has been successfully trained, it will be applied in Step 3 into the object substructure to forecast the structural parameters with RMSPDV determined from the trained SAENN and the acceleration measurements of the object substructure. Figure 9 shows the ratio of the identified stiffness and damping coefficients of the 9 stories in the substructure to their exact values. It is clear that the inter-story stiffness and damping coefficients of the substructure can be forecasted with acceptable accuracy. The maximum relative errors between the forecasted stiffness and the true value of the selected damage scenarios are about 5%.

The SPENN above is trained with 512 training patterns. Here, the performance of the proposed methodology when a relatively smaller number of training patterns are employed is discussed. Suppose only half of the randomly constructed associated structures (256 training patterns) are randomly selected to train another SPENN, and the newly trained SPENN is employed to identify another substructure. The results are shown in Table 1. Figure 10 shows the corresponding ratios of stiffness and damping coefficients. The average of the ratios coefficients are 0.996 and 1.007. It is clear that the SPENN trained with a smaller number of training patterns can also identify structural parameters with an acceptable accuracy. Results of numerical simulation show that the localized identification strategy can forecast parameters of a substructure based on the RMSPDV.

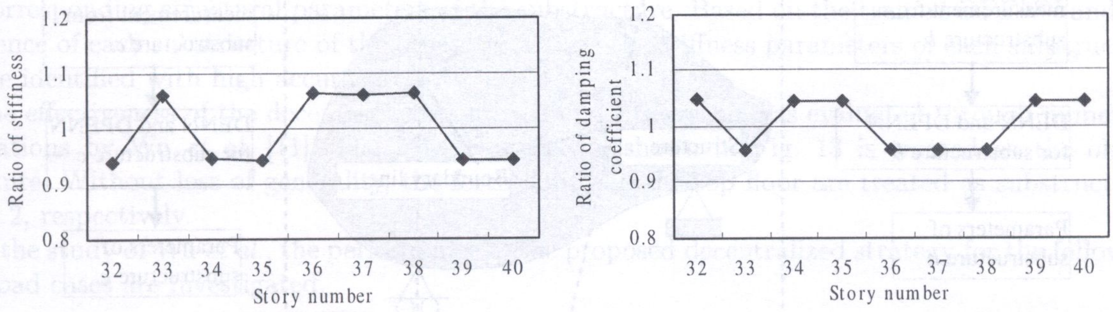


(a) Stiffness identification results (b) Damping coefficients identification results

Fig. 9. Substructural parametric identification results

Table 1. Example of identification results using SPENN trained with 256 patterns

DOF number		32	33	34	35	36	37	38	39	40
Stiffness (kN/m)	Identified	651.2	653.6	655.1	654.4	654.5	654.4	654.7	654.1	654.5
	Exact	693.0	616.0	693.0	693.0	616.0	616.0	616.0	693.0	693.0
Damping coefficients (kN·s/m)	Identified	519.3	518.0	517.4	517.5	517.5	517.6	517.6	517.6	517.6
	Exact	495.0	540.0	495.0	495.0	540.0	540.0	540.0	495.0	495.0



(a) Stiffness identification results (b) Damping coefficients identification results

Fig. 10. Ratio of stiffness and damping coefficients for another object substructure using SPENN trained with 256 patterns

3.4. Localized identification using incomplete response measurement

The above localized identification procedure assumes that the responses for all DOFs of the substructure are known. Nevertheless, it is very difficult to obtain complete response measurement in reality. This problem can be resolved when the neural networks based methodology. Xu studied the performance of the neural networks based structural model updating and identification algorithms for whole structure and substructure when incomplete measurement is available [12, 13].

4. Decentralized soft structural parametric identification and nonparametric identification for structure–actuator coupled system

4.1. Decentralized parametric identification for MDOF structures

All of the modern state space methods rest on the common presupposition of centrality. All of the information about the system, and the calculations based upon this information are centralized. When considering large-scale systems the presupposition of centrality fails to hold due either to the lack of centralized information or the lack of centralized computing. The basic description of the neural networks based decentralized soft identification algorithm is shown in Fig. 11. The whole structure to be identified is discretized as a discrete system and further divided into several substructures, which consist of a smaller number of DOFs and are connected with each other through interfaces and boundaries. In practice, substructures can be selected according to visual inspection and taken as independent objects which will be identified by decentralized neural networks in parallel manner.

To facilitate the decentralized identification process, corresponding to each object substructure, a reference substructure and a number of associated substructures are created, and an decentralized emulator neural network (DENN) and a decentralized parameter evaluation neural network (DPENN) are established and trained to identify the physical parameters of the object substructure. For an object structure including n substructures, n set of DENN and DPENN are necessary to realize the decentralized identification. Figure 12 shows the basic process of the decentralized parametric identification for a MDOF shear building structure using the interstory displacement and velocity measurement under base excitation. The decentralized parametric identification or damage detection procedure is employed by three steps [11]. The information for the decentralized identification for each object substructure is the interstory displacement and velocity measurements

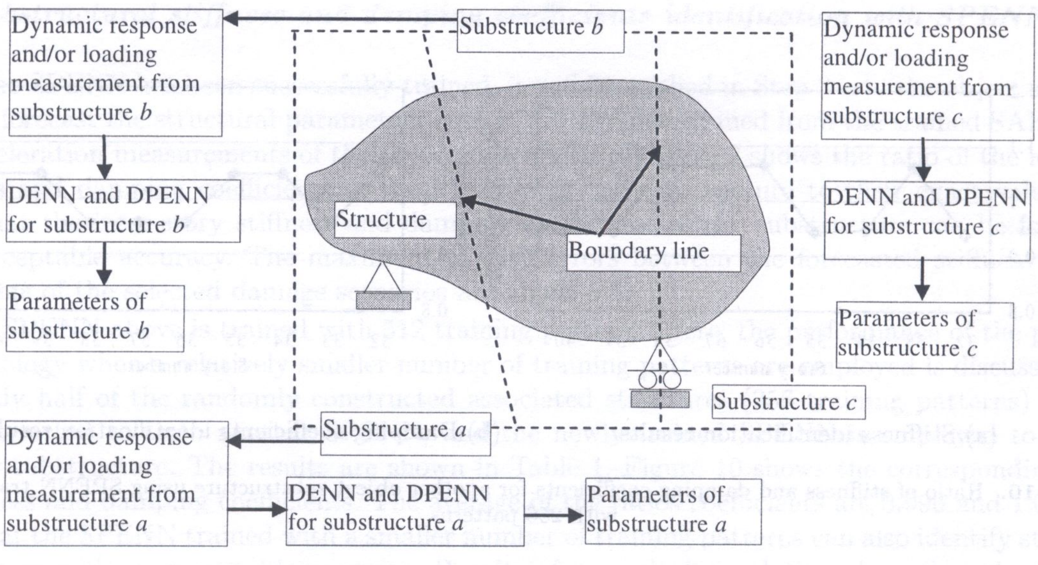


Fig. 11. Decentralized soft identification with neural networks

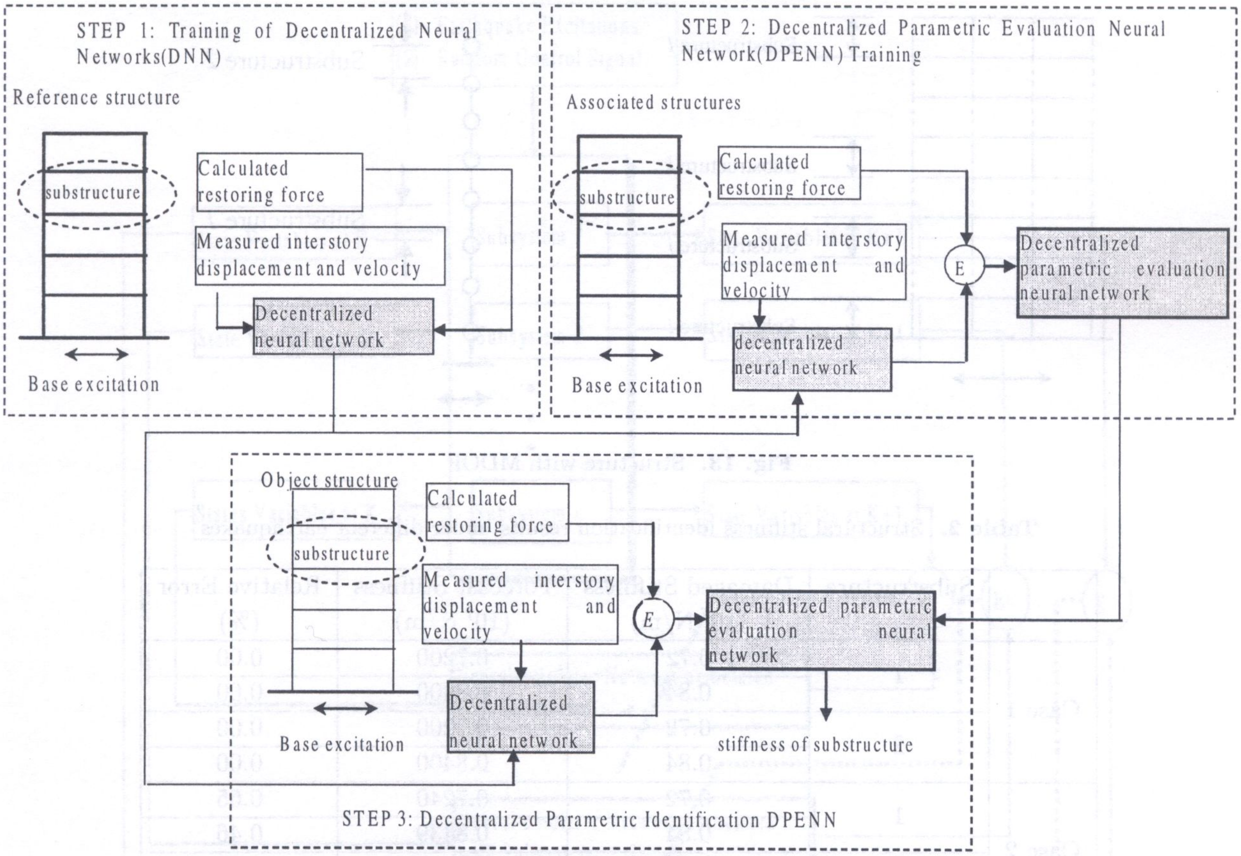


Fig. 12. Decentralized soft identification for a MDOF structure

and the base excitation acceleration. Assuming the mass distribution of the MDOF structure is known, the restoring force can be determined. In step 1, the displacement and velocity measurements for each substructure of a healthy object or a reference substructure and the corresponding restoring force are used to train the DENN to identify the corresponding substructure in a non-parametric manner. In step 2, a number of associated substructures are constructed. By using the trained DENN, the difference of the inter-story restoring force between the associated substructures and the corresponding substructures can be determined. Corresponding to each substructure, a DPENN is constructed and trained with the training data sets composed of the difference and the corresponding structural parameters of the substructure. Based on the trained DPENN and the difference of each substructure of the object structure, the stiffness parameters of each substructure can be identified with high accuracy.

The effectiveness of the decentralized parametric identification was evaluated through numerical simulations by Wu *et al.* [11]. The MDOF structure shown in Fig. 13 is treated as the object structure. Without loss of generality, the forth floor and the top floor are treated as substructures 1 and 2, respectively.

In the study of Wu *et al.*, the performance of the proposed decentralized strategy for the following four load cases are investigated.

Case 1: 12 seconds of El Centro earthquake (May 18,1940, Imperial Valley) of 30% of the amplitude,

Case 2: 12 seconds of Taft earthquake (July 21,1952, Kern Country) with 100% of the amplitude,

Case 3: 12 seconds of Taft earthquake with 50% of the amplitude, and

Case 4: 12 seconds of Kobe earthquake (January 17, 1995, Hyogo-ken Nanbu) with 20% of the amplitude.

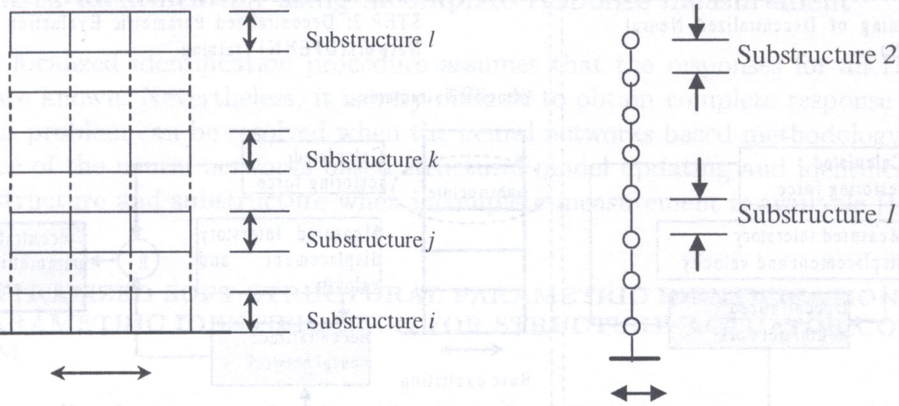


Fig. 13. Structure with MDOF

Table 2. Structural stiffness identification results under different earthquakes

	Substructure	Damaged Stiffness (10^7 N/m)	Forecast Stiffness (10^7 N/m)	Relative Error (%)
Case 1	1	0.72	0.7200	0.00
		0.84	0.8400	0.00
	2	0.72	0.7200	0.00
		0.84	0.8400	0.00
Case 2	1	0.72	0.7240	0.65
		0.84	0.8439	0.46
	2	0.72	0.7203	0.04
		0.84	0.8444	0.52
Case 3	1	0.72	0.7227	0.38
		0.84	0.8457	0.68
	2	0.72	0.7194	−0.83
		0.84	0.8432	0.38
Case 4	1	0.72	0.7381	2.50
		0.84	0.8602	2.40
	2	0.72	0.7296	1.33
		0.84	0.8536	1.62

The decentralized parametric identification results in the above four cases are shown in Table 2. It is demonstrated that decentralized parametric evaluation neural network can forecast the stiffness of the corresponding substructure with high accuracy. Moreover, the identification results are not depended on the earthquake excitations. This kind of characteristics is very useful for practical application.

4.2. Decentralized nonparametric identification for structure–actuator coupled system [18]

The structural identification and dynamic control of large-scale structures are considered to be difficult due to the structural complexity and system uncertainties. Active Mass Driver (AMD) has been used as an efficient control actuator based on conventional control methods and control design. Based on the concept of decentralized information architecture for large-scale systems and artificial neural networks, a decentralized non-parametric identification method for earthquake response control design of large-scale structures was proposed. The concept of decentralized identification by neural

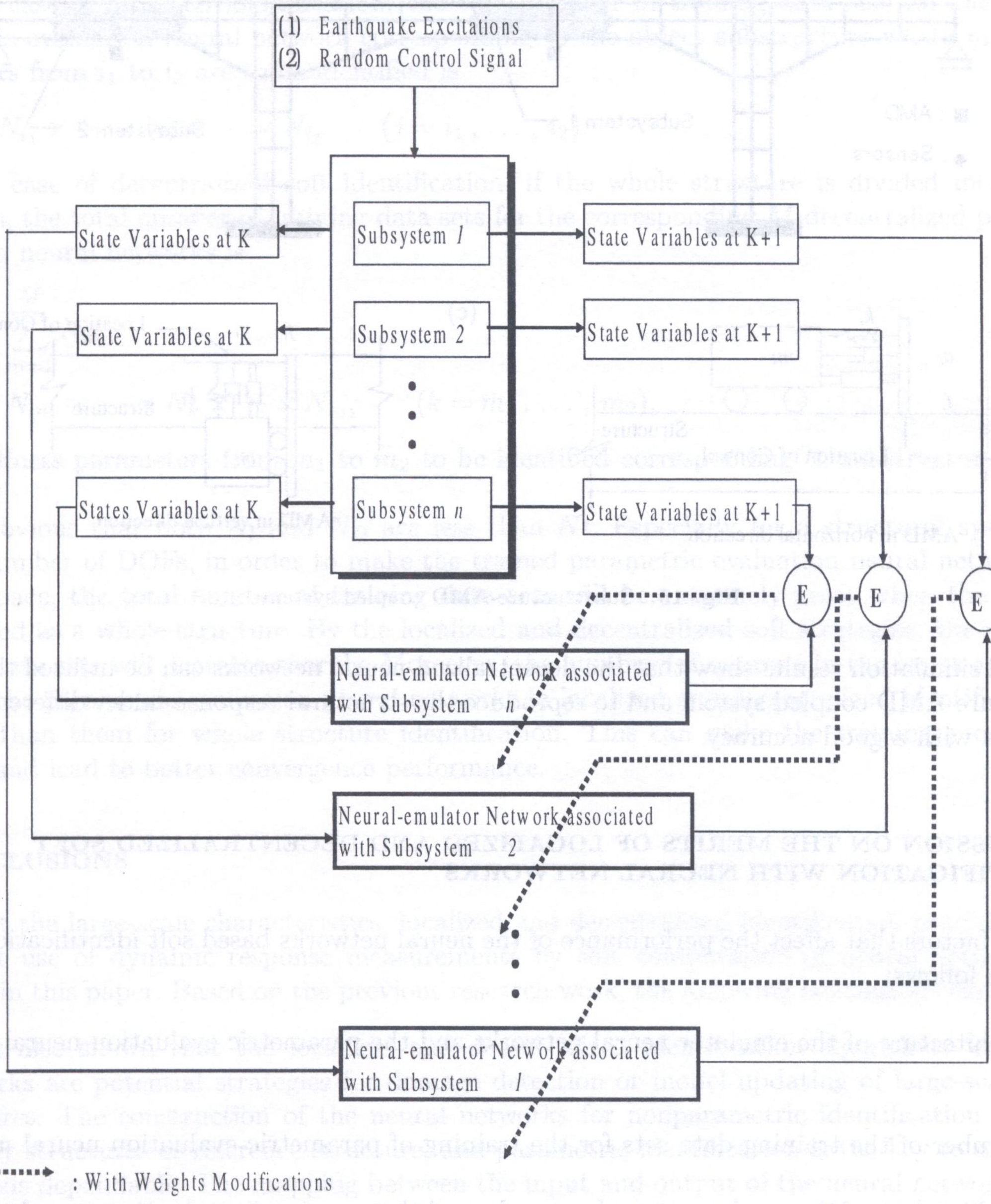


Fig. 14. Nonparametric identification for dynamic system with neural networks

networks is shown in Fig. 14. The structural system is dived into several subsystems, and there are several neural-emulators used to identify the corresponding subsystems. Because accelerometers can readily provide reliable and inexpensive measurement of absolute structural acceleration at strategic points on a structure, the decentralized nonparametric identification strategy based on acceleration was presented.

In order to demonstrate the performance of the decentralized identification strategy based on neural networks for a large-scale or complex structure under earthquakes, a plane structure model of a continuous concrete bridge coupled with two AMDs shown in Fig. 15 is adopted. The positions of sensors and actuators are illustrated in Fig. 15(a), and the gray parts are termed as two substructures (decentralized subsystems). One AMD system associated with each subsystem is located in the corresponding substructure. In decentralized control area 1, the AMD is coupled with the vibration in vertical direction, while decentralized control area 2, the motion of AMD is coupled with the vibration in horizontal direction. Two decentralized emulator neural networks are constructed and trained to identify the substructure-AMD coupled system in a non-parametric format.

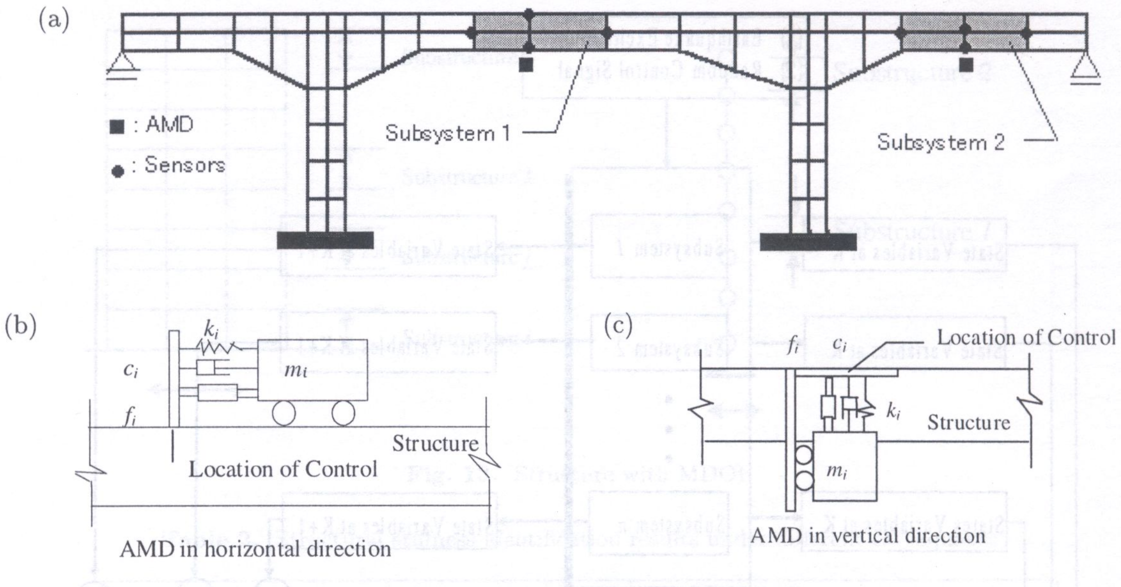


Fig. 15. Substructure-AMD coupled system

Numerical simulation results show that the decentralized neural networks can be utilized to identify the structure-AMD coupled system and to reproduce the structural response under different seismic excitations with a good accuracy.

5. DISCUSSION ON THE MERITS OF LOCALIZED AND DECENTRALIZED SOFT IDENTIFICATION WITH NEURAL NETWORKS

The main factors that affect the performance of the neural networks based soft identification strategies are as follows:

1. the architecture of the emulator neural networks and the parametric evaluation neural network; and

2. the number of the training data sets for the training of parametric evaluation neural network.

The architecture of the emulator neural networks and the parametric evaluation neural network is dependent on what kind of dynamic responses are employed. By identifying substructure of a whole structure, the numbers of neurons in the input and output layer of both the emulator neural network and the parametric evaluation neural network are decreased, then the time consumed for training will be shorter and the convergence performance should be better.

The training data sets preparation for the parametric evaluation neural network is time-consuming especially for large-scale structures. For a structure with the m stiffness parameters to be identified, if it is identified as a whole structure, the total number of training data sets for the parametric evaluation neural network can be described in the following equation,

$$N_t = N_1 \times N_2 \times \cdots \times N_i \times \cdots \times N_{m-1} \times N_m \qquad (i = 1, \ldots, m), \tag{14}$$

where N_i is the number of the discrete values within its interested range (i.e., with a resolution of $1/N_i$) of the i-th stiffness parameters in the associated structures. For instance, if there are ten unknown parameters to be identified and each unknown is divided into 100 discrete values within its search range (i.e., with a resolution of 1%), there will be a total of 10^{20} possible training data sets – an astronomical figure to work with even for the currently available powerful advanced computers.

In the case of localized identification, the total number of training data sets for the localized parametric evaluation neural network corresponding to the object substructure where m_s stiffness parameters from i_1 to i_2 are to be identified is

$$N_L = N_{i_1} \times \cdots \times N_j \times \cdots \times N_{i_2} \qquad (j = i_1\,, \ldots\,, i_2). \tag{15}$$

In the case of decentralized soft identification, if the whole structure is divided into M substructures, the total number of training data sets for the corresponding M decentralized parametric evaluation neural networks is

$$N_D = \sum_{m=1}^{M} N_m\,, \tag{16}$$

$$N_m = N_{m_1} \times \cdots \times N_k \times \cdots \times N_{m_2} \qquad (k = m_1\,, \ldots\,, m_2), \tag{17}$$

where stiffness parameters from m_1 to m_2 to be identified corresponding to substructure m ($m = 1, \ldots, M$).

It is obvious that both N_l and N_D are less than Nt. Especially for a structural system with a great number of DOFs, in order to make the trained parametric evaluation neural network cover enough space, the total number of training data sets will be extremely great when the structure is identified as a whole structure. By the localized and decentralized soft strategies, the number of training data sets will decrease sharply. Moreover, the numbers of neurons in the input and output layers of the parametric evaluation neural networks in localized and decentralized identification are also less than them for whole structure identification. This can make the training process more effective and lead to better convergence performance.

6. Conclusions

Aiming at the large-scale characteristics, localized and decentralized identification procedures with the direct use of dynamic response measurements by soft computation of neural networks were reviewed in this paper. Based on the previous research work, the following conclusions can be made:

1. It was also shown that the localized and decentralized identification algorithms with neural networks are potential strategies for damage detection or model updating of large-scale infrastructures. The construction of the neural networks for nonparametric identification for either healthy structures or reference structure, and parametric identification is the key to make these methods dependable. The mapping between the input and output of the neural networks should have clear physical meaning and be enough to carry out identification and unique even though the architecture to describe a certain function is not unique. The non-uniqueness of the architecture of neural networks makes the localized and decentralized identification strategies soft.

2. Localized and decentralized identification strategies based on neural networks have great potential for the on-line or post-event damage detection, performance and safety evaluation of large-scale infrastructures.

With the development of advanced sensing technologies, more and more structural responses can be derived easily. The artificial intelligence should play a more and more important role in the identification problem for infrastructure with massive information and promote the development of smart material systems and structures.

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