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# A localized identification strategy with neural networks and its application to structural health monitoring

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A localized inverse analysis method with neural networks for health monitoring and parametric identification by the direct use of dynamic responses is proposed for a substructure of a multi-story frame. First a localized emulator neural network is presented for the purpose of identification of the healthy substructure. Dynamic responses of the healthy substructure induced by ground excitation are used to train the localized emulator neural network. The emulator neural network can be used to decide the difference between a damaged substructure and the healthy substructure. An evaluation index of relative root mean square (RRMS) error vector is presented to evaluate the condition of the damaged substructure. And then, a localized parametric evaluation neural network is trained to forecast the stiffness of a damaged substructure. It is shown that the localized parametric identification strategy has the potential of being a practical tool for the health monitoring of civil engineering structures. The proposed strategy is robust for different kinds of ground motion.

*Key Words: neural networks, inverse analysis, identification, damage detection, localized*

## 1. Introduction

Structural identification and health monitoring for infrastructure is a challenging problem that is under vigorous investigation by numerous researchers using a variety of analytical and experimental techniques. Non-destructive evaluation (NDE) methods for the detection of damage in structural systems have been receiving increasing attention in the recent past.

Most structural damage assessments are carried out through visual inspections. Non-destructive damage identification on the basis of observed dynamical signals have been the focus of research studies for many years. A number of localized approaches based on the use of specialized equipment have been proposed to provide detailed information about the specific elements or parts of a structure. These include radiographic, electromagnetic, acoustic emission, X-ray, magnetic, and ultrasonic methods. In general, health monitoring involves the comparison of the changes in structural properties or response, and it can be viewed as a classification problem. The analytical techniques for health monitoring use mathematical models to describe structural behavior and establish mathematical models to approximate the relationship between the specific damage condition and changes in the structural responses. The mathematical-model-based structural identification methods can be categorized into time-domain and frequency-domain approaches[1-4]. Effective classification or interpretation of the changes in structural responses or dynamic properties due to damage is a critical task. Frequency-domain analysis is concerned with spectral estimates and the frequency characteristic of responses. Deterioration and damage results in a reduction of structural parameters for example, the stiffness of structural members. This reduction produces changes in the dynamic properties, such as the natural frequencies and mode shapes. And time-domain analysis involves recursive techniques, maximum likelihood estimates and so on. As described by Zhao et al.[5], although the methods that have been developed are applicable in concept to most structural models, it is not practical to directly apply them to a structural model with a large number of degrees of freedom(DOF) because excessive computation time and computer memory are necessary for convergence, and also it may not be theoretically possible to obtain unique estimates of all parameters. Due to these reasons, a localized identification method for multi-degree-of-freedom (MDOF) structures in the frequency domain was proposed by Zhao et al. [5], and a localized vibration control strategy was presented by Xu et al. [6,7]. And as another kind of method for large-scale structure system, the concept of decentralization for identification and control method was studied by Sandell et al.[8], Magaña et al.[9] and Xu et al.[10]. Wu et al.[11] proposed a decentralized identification strategy for damage detection of a MDOF structure by the use of decentralized parametric evaluation neural network, the stiffness of each substructure can be forecast with high precise. In this study, a substructure of a MDOF structure is taken as an objective, and a localized health monitoring and damage detection strategy is presented.

On the other hand, the ability of artificial neural networks to approximate arbitrary continuous function provides an efficient mechanism for the identification and control problem. Neural networks are suitable for pattern classification and natural information processing tasks. Neural networks are finding application in almost all branches of science and engineering. Modeling dynamic systems by using neural networks has been increasingly recognized as one of the system identification paradigms. The neural network based modeling problem of an unknown linear or non-linear discrete time multivariable dynamic system is to develop a neural network model that is capable of learning and predicting the functional mapping between the inputs and the outputs of the dynamic system. The knowledge acquired by a neural network is stored in its connection weights, which are adaptive and can change in response to outside stimuli. At present, several neural networks with different structures have been proposed to solve identification and control problems. The most widely used neural networks for identification and control problem are the multi-layer neural networks. Numerous engineering applications of neural networks have been reported in the literature of recent years. A great number applications of neural networks for identification and control in civil engineering were reviewed by Xu et al.[6,7,10,11,14], Wu et al.[11], Ghaboussi et al.[12], Chen et al.[13], Nakamura et al.[15], Zhao et al.[16] and Yoshimura et al. [17]. Some researchers have also used neural networks in the identification of the damage in structures.

In this paper, aiming at a substructure of a MDOF structure, a localized health monitoring and parametric identification method with neural networks by the direct use of dynamics responses under earthquake excitations is proposed. The dynamic responses of structures under environmental excitations or small-scale earthquakes are useful and economical information for health monitoring, some information about structural parameters and dynamic properties is stored in it. To identify the substructure by neural networks, the decision and select of variables for input and output is critical, those variable should have clear physical meaning and enough to carry out identification. And for the purpose of practical application, an evaluation index should to be defined and selected properly. The evaluation index must be related with the variation of the structural parameters and be independent to the excitations. The root mean square (RRMS) error has been widely used for evaluation of performance of neural network for identification problem. But it is not suitable evaluation for health monitoring. In this paper, a relative root mean square (RRMS) error vector is introduced as an evaluation index in this study. The reasonableness of this evaluate index is demonstrated by numerical simulation. Results of numerical simulation show that the localized health monitoring strategy with the localized emulator neural network can clearly identify the damage existing with high sensitivity. Moreover, a localized parametric evaluation neural network is constructed and trained to forecast the structural parameter of stiffness based on the RRMS error vector. The robustness of the localized parametric evaluation neural networks is demonstrated. This strategy cannot ascertain which specific component has damaged because the forecast structural parameters are the inter-story stiffness, which consists of a cluster of structural members. But this strategy is suitable for the structural systems where damage results in the changes in stiffness.

## 2. Localized Parametric Identification with Neural Networks Using Dynamic Response

A localized neural network based health monitoring and parametric identification strategy for an illustrative frame structure by the use of structural dynamic responses under small-scale earthquake is proposed.

Usually, a frame structure can be discretized as a MDOF model. It may be further divided into several substructures, which consist of a small number of DOF and are connected with each other through interfaces or boundaries. The substructure in a MDOF frame structure is interconnected with all the remaining upper structures and lower substructures through upper boundary and lower boundary respectively. Zhao et al. [5] testified that the lower boundary can be selected as a reference point and considered as the nominal ground for the substructure. From the vector-matrix equation of motion for a substructure, it is clear that the dynamic response of the substructure can be determined independently from the absolute acceleration of the lower boundary and original conditions of the substructure by numerical simulation step by step.

The full procedure on localized health monitoring and parametric identification with neural networks by the use of dynamic responses shown in Figure 1 can be divided into four steps. Two typical three-layer neural networks trained by back-propagation method are designed for the purpose of health monitoring and parametric evaluation.

In step 1, a localized emulator neural network is constructed and trained to identify the substructure using the dynamic responses of the objective substructure in healthy condition, which can be considered a newly supplied or existing structure. After the localized emulator neural network is trained successfully, the dynamic characteristics of the substructure in healthy condition or current state at the beginning of healthy monitoring can be identified. In other words, the localized emulator neural network is a non-parametric model for the substructure and

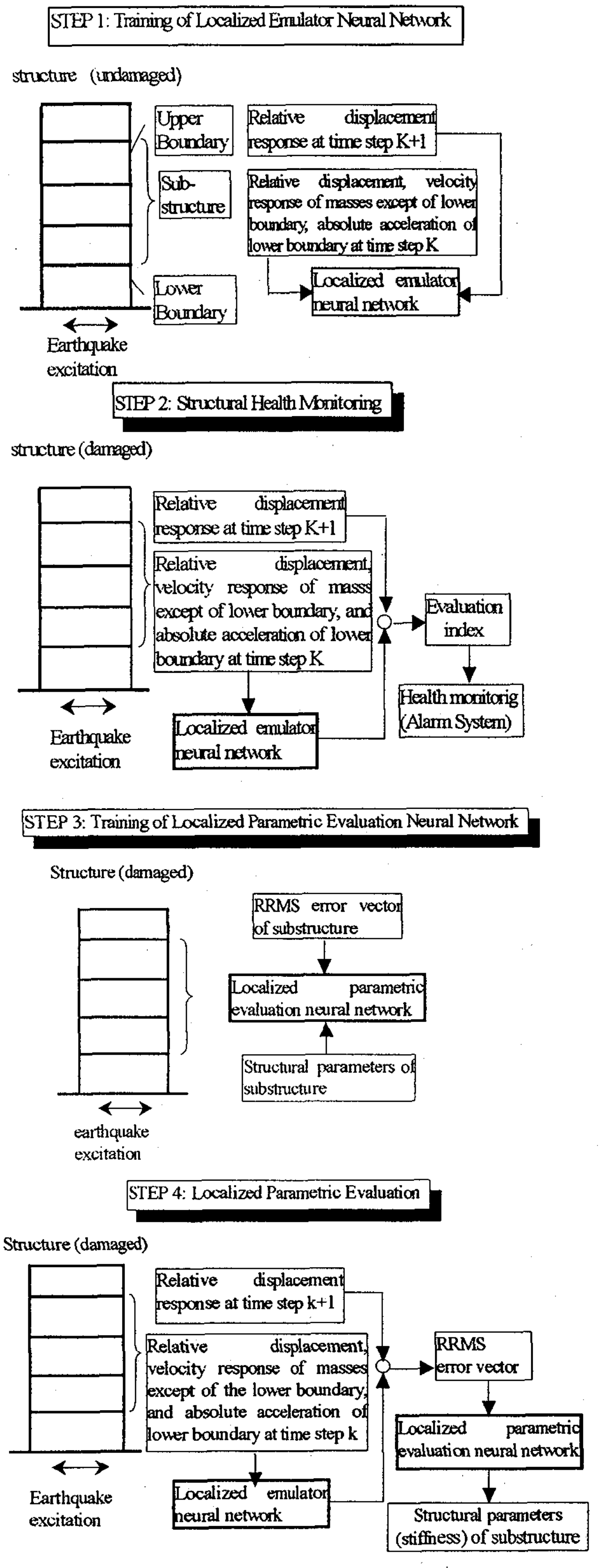



Figure 1. Localized structural health monitoring and parametric evaluation based on neural network with dynamic responses

can be used to forecast the dynamic responses of the structure under earthquake excitations.

In step 2, if the structural parameters of the substructure have changed, the real dynamic responses of the substructure will not correspond any more to the output (dynamic responses) forecast by trained localized emulator neural network. The error between the dynamic responses forecast by the localized emulator neural network and it observed from the substructure provide a quantitative measure of the changes of parameters in physical substructure relative to its healthy condition. The proper selection and definition of an evaluation index is a critical work. A suitable evaluation index for health monitoring when dynamic responses under earthquake excitations are used should have the following properties: it should have direct relation with the variation of structural parameters and have relative independence on the earthquake excitations. Even through the Root Mean Square (RMS) error is a widely used index for the evaluation of identification performance of neural networks, as testified in this paper, RMS is depend on the earthquake excitations, it can not be used for health monitoring. So, in this paper, an evaluation index of Relative Root Mean Square(RRMS) error is defined. The performance of the RRMS error is checked by numerical simulations, it is shown that the RRMS error is a suitable index and can be used to show whether damages exist or not in the substructure. In practical application, a threshold level can be set, once the evaluation index exceeds the threshold level, an alarm signal can be made for the users of the structure.

In step 3, in order to evaluate damage (the decrease in structural stiffness) in quantity, a localized parametric evaluation neural network is constructed and trained. Training data sets consisting of structural parameters of substructures with different degree of damages and the corresponding RRMS error vector are used to train the localized parametric evaluation neural network. The localized parametric evaluation neural network identifies the relationship between the RRMS error and structural parameters.

In step 4, by the method described in step 2, the RRMS error can be determined, and then structural parameters can be forecast by inputting RRMS error to the localized parametric evaluation neural network trained in step 3.

## 3. Equation of Motion of Structure Under Earthquake

Without loss of the generality, the performance of the proposed localized identification and parametric evaluation is studied by numerical simulation for a frame structure that is modeled as a mass-spring-dashpot system with $n$ degrees of freedom.

The motion of the structure with $n$ degrees of freedom can be characterized by the following differential equation,

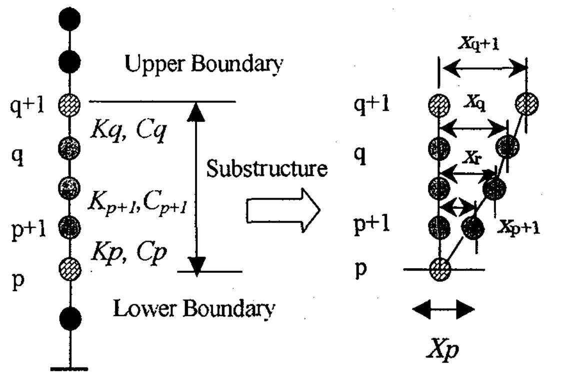



Figure 2. A substructure in a MDOF lumped mass-spring-dashpot system under earthquake excitations

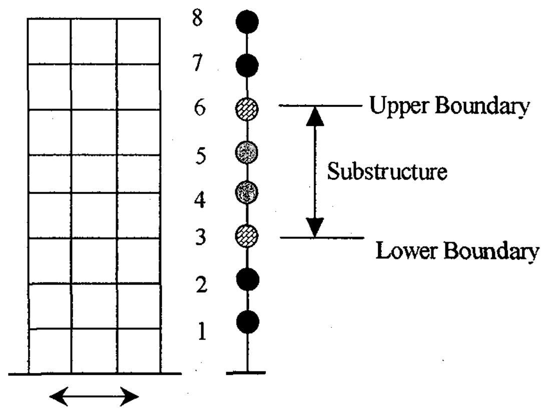



Figure 3. A substructure in an eight stories frame structure

$$[M]\{\ddot{x}\}+[C]\{\dot{x}\}+[K]\{x\}=-[M]\{I\}\ddot{x}_g \quad (1)$$

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, and $\ddot{x}_g$ = the earthquake base acceleration. The equation of the structure is numerically integrated by Newmark- $\beta$ method to obtain the solution of structural dynamic response under earthquake excitations. The integration time step used in the numerical analysis is chosen to be a small fraction (one-twentieth) of the sampling period.

Consider the objective substructure shown in Figure 2, which includes mass $p+1$ to mass $q$ and interconnected with the upper boundary mass $q+1$ and lower boundary mass $p$. The lower boundary mass $p$ is selected as a reference point and considered as the nominal ground for the substructure.

The vector-matrix equation for the substructure under earthquake excitations can be written as

$$[M_s]\{\ddot{x}_s\}+[C_s]\{\dot{x}_s\}+[K_s]\{x_s\}=f_s(t) \quad (2)$$

where

$$[M_s]=\begin{bmatrix} m_{p+1} & 0 & 0 & 0 & 0 \\ 0 & \cdots & 0 & 0 & 0 \\ 0 & 0 & m_r & 0 & 0 \\ 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & 0 & m_q \end{bmatrix} \quad (3a)$$

$$[K_s]=\begin{bmatrix} k_p+k_{p+1} & -k_{p+1} & 0 & 0 & 0 \\ -k_{p+1} & k_{p+1}+k_{p+2} & -k_{p+2} & 0 & 0 \\ 0 & \cdots & \cdots & & 0 \\ 0 & 0 & -k_{q-2} & k_{q-2}+k_{q-1} & -k_{q-1} \\ 0 & 0 & 0 & -k_{q-1} & k_{q-1}+k_q \end{bmatrix} \quad (3b)$$

$$\{x_s\}=\begin{Bmatrix} x_{p+1} \\ \vdots \\ x_r \\ \vdots \\ x_q \end{Bmatrix} \quad (3c)$$

$$f_s(t)=\begin{Bmatrix} -m_{p+1}\ddot{x}_p \\ \vdots \\ -m_r\ddot{x}_p \\ \vdots \\ -m_q\ddot{x}_p+c_{q+1}\dot{x}_{q+1}+k_{q+1}x_{q+1} \end{Bmatrix} \quad (3d)$$

$[C_s]$ is the same form as $[K_s]$ except using $c_r$ for $k_r$, and $x_r$, $r=(p+1,\cdots,q)$ is the relative displacement of each mass with respect to lower boundary of mass $p$ and $\ddot{x}_p$ is the absolute acceleration of mass $p$. $m_r, c_r, k_r$ represent mass, damping and stiffness coefficient for mass $r$, $r=(p+1,\cdots,q)$.

From the motion equation (2) of the substructure, it is clear that the substructure can be considered as an independent part and the dynamic response of the substructure can be determined by the time series of dynamic response of the lower and upper boundaries step by step completely. The dynamic responses of the substructure at time step K+1 can be determined according to the dynamic responses of the substructure and boundary acceleration at time step K. This is the theoretical basement for establishing the architecture of the emulator neural networks for localized identification.

In this study, an eight stories frame structure with known parameters shown in Figure 3 is assumed for the illustrative model in healthy condition and discretized as a 8 DOF of mass-spring-dashpot model. The model parameters are assumed known as the following, mass $m_i = 185kg$ , stiffness $k_i = 5.0*10^5 N/m$ and damping coefficient $c_i = 2.0*10^3 N.s/m$ for each mass ($i$=1,⋯,8). The first four natural frequencies of the frame structure are 1.53 Hz, 4.53 Hz, 7.38 Hz and 9.97 Hz.

It is widely reported that some buildings were destroyed in the middle stories in the Hyogo-ken Nanbu Earthquake (17 January, 1995). The middle part is usually a critical part for a shear building under earthquake excitations. So in this study, the middle part of the structure, which includes mass 4 to mass 5 and interconnected with the upper boundary mass 6 and lower boundary mass 3, is considered as objective substructure.

## 4. Simulation on Localized Identification Using Dynamic Responses with Emulator Neural Network

### 4.1 Localized Emulator Neural Network for Substructure

System identification for damage detection and health monitoring is to model a structural system mathematically and to adjust the parameters of the analytical model to minimize the difference between the analytically predicted and empirically measured response. System identification is an inverse problem, which requires comprehensive search process. On the other hand, the inverse problem can be solved by using the neural network approach without any comprehensive search methods, such as extended Kalman filter, recursive least squares, and modal perturbation.

A three-layer neural network called as localized emulator neural network is constructed and trained to identify the dynamics of the substructure in a nonparametric manner. For the purpose of health monitoring, accelerometers are considered to place at each story of the substructure. The measured acceleration data can be converted into velocity and displacement by integration with respect to time. And then the relative displacement and velocity of the masses of the substructure with respect to the lower boundary can be determined.

Even through it is important to choose a proper network size for identification, to determine the best network size for a given system is not straightforward. Usually, the size of a neural network can be decided through a trial-and-error proc ess. The input and output variables should be selected logically with the consideration of physical meaning. As des-

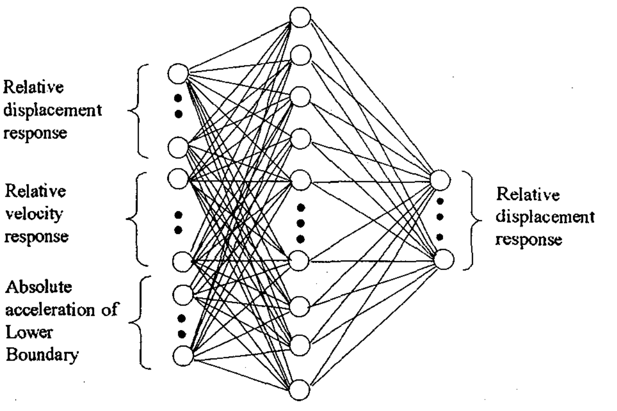



Figure 4. Localized emulator neural network

cribed above, according to the equation of motion of substructure, the dynamic response of the substructure can be determined by numerical integration step by step. The dynamic responses of the substructure at time step K+1 can be determined according to the dynamic responses of the substructure and boundary acceleration at time step K. A loc alized emulator neural network is constructed to identify the dynamic characteristic of the substructure in the form of forecasting the dynamic response at time step K+1 from the dynamic responses and boundary conditions at the time step K.

The architecture of the localized emulator neural network is shown in Figure 4. The input layer includes relative displacements, velocities response of mass No. 4 to mass No.6, and the absolute acceleration of the lower boundary (mass No.3) at time step K. The number of neurons in hidden layer is set to be two times of it in input layer. The neuron in output layer represents the forecast displacements of mass No. 4 to mass No.5 at the next time step K+1. So the input, hidden and output layer includes 7, 14 and 2 neurons, respectively.

The training process for the localized emulator neural network is to establish the appropriate connection weights between neurons of each layer by a form of supervised learning with the help of training data sets, which are composed of a number of patterns of inputs and desired outputs of the substructure. The training data sets are constructed from the time series of dynamic responses by numerical integration analysis results.

Based on the error back-propagation algorithm, the localized emulator neural network is off-line trained first. The error function is calculated from the difference between the outputs of the localized emulator neural network and the displacements of each story of the substructure. At the beginning of training the localized emulator neural network, the weights are initialized with small random values. The localized emulator neural network can be trained to achieve a desired accuracy for modeling the dynamic behavior of the substructure.

In this paper, three earthquake excitations (load cases) are studied. And the three earthquake excitations are scaled with velocity amplitude of 0.30m/s.

(1) Case 1: 8 seconds of Taft earthquake (July 21,1952, Kern County);

(2) Case 2: 8 seconds of El Centro earthquake (May 18,1940, Imperial Valley);

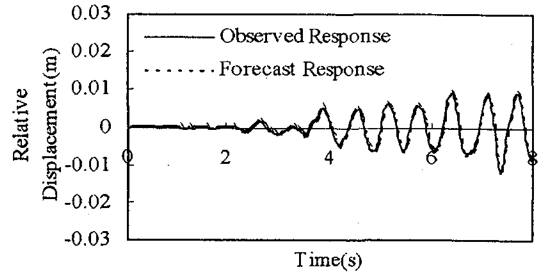
(3) Case 3: 8 seconds of Kobe earthquake (January 17, 1995, Hyogo-ken).

The training data sets for the purpose of training localized emulator neural network are constructed from the numerical integration analysis results in load case 1. The numerical integration analysis is carried out with integration time step of 0.002 second. Earthquake excitations are linearly interpolated with time step of 0.002 second for numerical integration. The training data sets are performed with the data taken at the intervals of the sampling period of 0.04 second. The training data sets, used for training the neural networks are the 200 patterns of input and output data taken from 8 seconds of dynamic response records of the substructure. Generally, the multiplayer neural network requires the normalization of the input and output data, because it is difficult to train the neural network without the normalization. In this study, a linear normalization pre-conditioning for the training data sets is carried out[15].

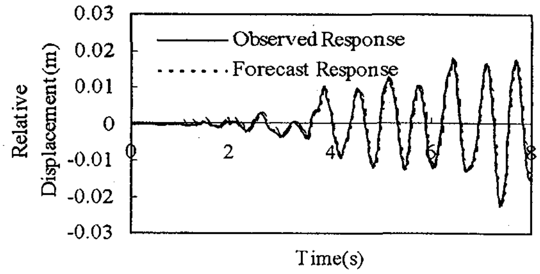
The whole off-line training process takes 10000 cycles. By means of the error back-propagation learning rule, the training data sets performed above are used to train the localized neural network in order to model the structural dynamics of the substructure. Figure 5 gives the result of comparison between the displacements determined from the numerical integration analysis (called as observed responses) and those forecast by the trained localized emulator neural network of mass No. 4, 5, respectively, in load case 1. It can be seen that localized identification can be carried out with high accuracy.

## 4.2 Discussion on Adaptability of Emulator Neural Networks

In order to carry out health monitoring by the use of dynamic responses under earthquake excitation, it is necessary to discuss the adaptability of the localized emulator neural network trained above for other kinds of earthquake excitations, because a structure is seldom excited by two same earthquake. As other examples, we investigate the performance of the trained emulator neural network when the structure is subjected to different kinds of earthquakes. Usually, the root mean square (RMS) error is a widely used evaluation index to evaluate the performance of neural networks for identification. The RMS error of forecast displacements in each load case is demonstrated in Table 1. The RMS errors can reach a very little value. It is shown that localized identification can be carried out precisely by proposed method. This indicates that the trained localized emulator neural network has been

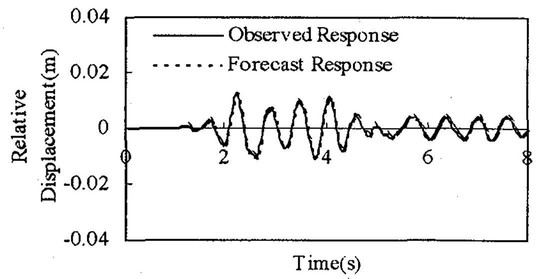



(a) Mass 4

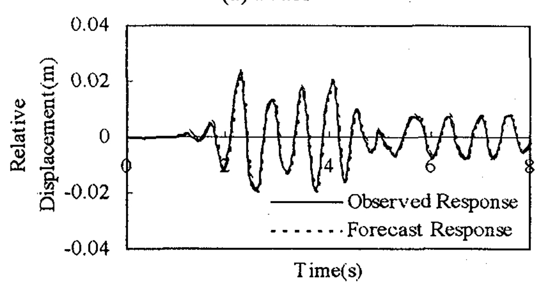



(b) Mass 5

Figure 5. Compression of displacements in case 1



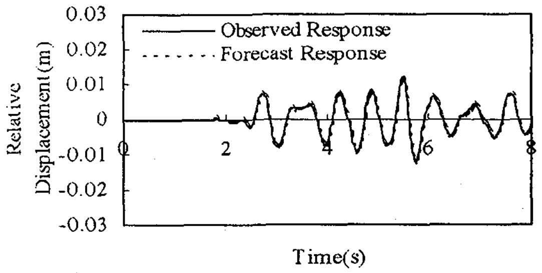

(a) Mass 4



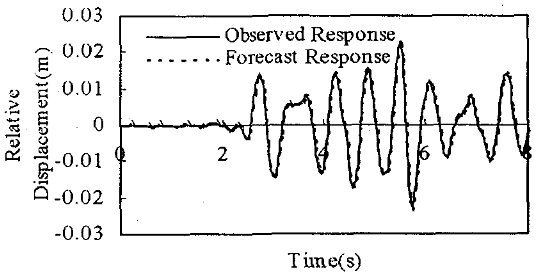

(b) Mass 5

Figure 6. Compression of displacements in case 2

able to forecast the displacements of the substructure well under different seismic excitations with higher accuracy. And the decision and select of variables for input and output of the localized emulator neural network is suitable and enough to carry out identification for the corresponding substructure.




(a) Mass 4




(b) Mass 5

Figure 7. Compression of displacements in case 3

TABLE 1 RMS ERROR

| | RMS Error ($*10^{-6}$ m) | |
|---|---|---|
| | Mass No. 4 | Mass No. 5 |
| Case 1 | 4 | 7 |
| Case 2 | 6 | 12 |
| Case 3 | 3 | 5 |

## 4.3 Health Monitoring with Emulator Neural Networks

As described above, the deviation between the output from a damaged substructure and the output from the trained localized emulator neural network provides a quantitative measure of the changes in stiffness in the physical system relative to the healthy condition.

In order to make this methodology practical, it is necessary to choose an evaluation index, which is independent on the earthquake excitations, because it is scarce for a structure to be excited by two same earthquakes during the life cycle. For the purpose of health monitoring, an evaluation index that is independent on the characteristics of excitations should to be defined. As shown in Table 1, the RMS error of displacement response of each mass is dependent on the earthquake excitations. So the RMS error is not a suitable index for evaluating the degree of structural damage of structure, because it changes with the excitations.

Because of the difference of response spectrum of different earthquake excitations, the amplitudes of dynamic responses are different. The RMS error is a kind of absolute error, it should be related to the amplitude of responses, an error which is defined in relative form maybe independent on the earthquake excitations and suitable for health monitoring. In this paper, a relative root mean square (RRMS) error vector is defined as an evaluation index for health monitoring. The RRMS error vector *{e}* can be defined as follow,

$$e = \{e_1 \quad \dots \quad e_n\} \tag{4}$$

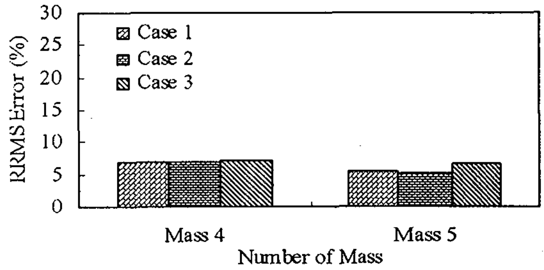
$$e_i = \frac{\sqrt{\frac{1}{M-1}\sum_{m=1}^{M}(a_{mi} - b_{mi})^2}}{\sqrt{\frac{1}{M}\sum_{m=1}^{M}(b_{mi})^2}}, \quad (i = 1, \cdots n) \tag{5}$$

where $M$ = the number of sampling data, $a_{mi}$ = the output of localized emulator neural network corresponding to the DOF of $i$ at sampling step $m$, $b_{mi}$ = the displacement corresponding to the DOF of $i$ decided through the dynamic responses analysis under earthquake excitations at sampling step $m$. And $n$ is the number of the neurons in the output layer of the localized emulator neural network.

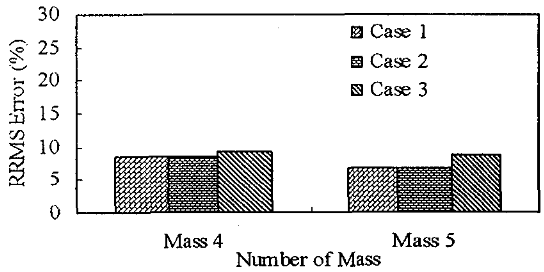
Here, some results about RRMS error vector are described. Let the stiffness of the substructure decrease to 90%, 80%, 70%, 60% of the original values respectively, the components of RRMS error vector corresponding to the relative displacement of mass 4 and 5 in the three cases are shown in Figure 8.

From Figure 8, it is clearly that the RRMS error in different cases does not change greatly. The results of RRMS error in Case 1 and Case 2 are very close, even through there are some difference between the results in Case 3 and its in Case 1 and Case 2. And the relationship between the RRMS error and the degree of damage in stiffness of each substructure exists. The RRMS error is a suitable and useful index for health monitoring. In a practical application, a threshold level may be set, if the RRMS error exceeds the threshold level, the method can directly notify the residents of the building that damage occurs. This automatic notification capability is quite useful for real-time health monitoring.

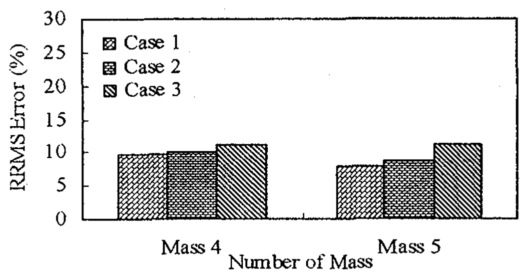
Figure 9 gives the relationship between the modulus of the RRMS error vector and the degree of stiffness decrease. It is shown that the RRMS error increases with the degree of damage. And it indicates that the evaluation index can be used for health monitoring with high sensitivity. For example, when the stiffness is degraded by 10% in Case 1, the emulator neural network gives a RRMS error, which has 21% of modulus increase compared to the RRMS error of the healthy structure. And a 20% of stiffness in stiffness results in a 43% modulus increase in RRMS error modulus.



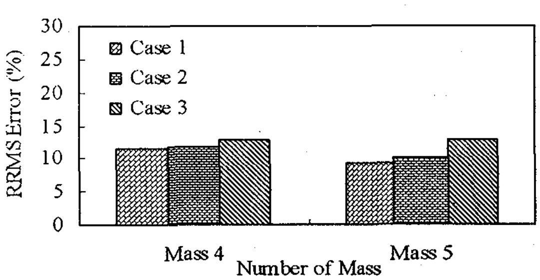

(a) Healthy Substructure



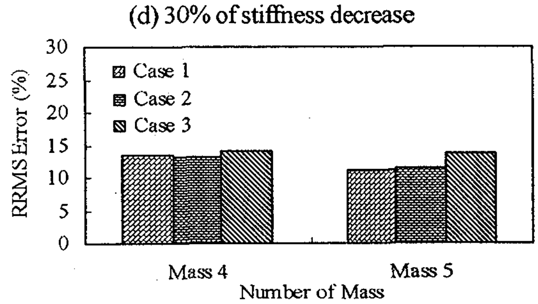

(b) 10% of stiffness decrease




(c) 20% of stiffness decrease




(d) 30% of stiffness decrease




(e) 40% of stiffness decrease

Figure 8. RRMS error of different kinds of damaged substructures

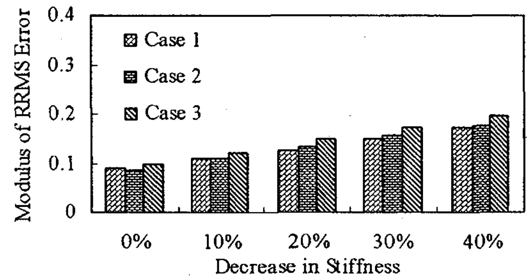



Figure 9. Modulus of RRMS error vector

## 5. Simulations on Localized Parametric Evaluation with Neural networks

Up to now, neural networks have been widely used for non-parametric identification for linear or non-linear dynamic system for the purpose of health monitoring or control. And neural network is proved as a useful tool. In the study of Nakamura et al.[13)], because of its non-parametric nature, the approach under discussion can not ascertain the degree of the stiffness decrease in qua ntity. In this paper, a localized parametric identification method by neural networks is developed. As described above, for the purpose of real-time health monitoring, a non-parametric identification method has presented. And the RRMS error vector is related with the degree of damage (the decrease in stiffness). If another neural network which describes the relationship between the RRMS error vector and the stiffness of substructure, can be established and trained, the stiffness of the substructure can be evaluated according to the RRMS error vector. This procedure is corresponding to the step 3 and 4 in Figure 1.

As described above, the parametric identification is an inverse problem. When neural network is used to solve the inverse problem, the training data, which can be obtained as the solution of the direct problem, is necessary. Some structures with different degree of damage are assumed, and the RRMS error can be calculated by the method described in Chapter 2. In this paper, the structural damage is assumed to result in stiffness decrease. The stiffness of some assumed damaged substructures and the corresponding RRMS error vector data in Case 1 are used to train the localized parametric evaluation neural network with error back-propagation algorithms. Let stiffness of each story of the substructure equals to 1.0, 0.9, and 0.8 times of the original value respectively, and the corresponding RRMS error vector can be calculated by the method described in step 2 in Figure 1. So 27 pairs of training data are decided.

A localized parametric evaluation neural network is established. The input to the localized parametric evaluation neural network includes the RRMS error vector of the substructure. In order to improve the performance of the localized parametric evaluation neural network, the hig

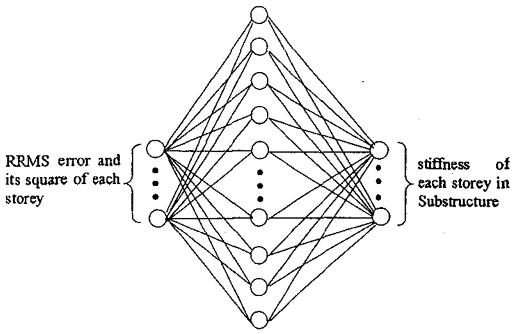



Figure 10. Localized parametric evaluation neural network

TABLE 2 PARAMETER EVALUATION RESULTS

| | | | Stiffness ($10^6$ N/m) | | |
|---|---|---|---|---|---|
| Damaged Structure No. 1 | Ture Value | | 0.500 | 0.500 | 0.450 |
| | Forecast Value | Case 1 | 0.504 | 0.491 | 0.455 |
| | | Case 2 | 0.501 | 0.486 | 0.456 |
| | | Case 3 | 0.490 | 0.466 | 0.462 |
| Damaged Structure No. 2 | Ture Value | | 0.450 | 0.450 | 0.450 |
| | Forecast Value | Case 1 | 0.463 | 0.458 | 0.468 |
| | | Case 2 | 0.464 | 0.460 | 0.468 |
| | | Case 3 | 0.445 | 0.425 | 0.478 |
| Damaged Structure No. 3 | Ture Value | | 0.400 | 0.450 | 0.500 |
| | Forecast Value | Case 1 | 0.390 | 0.445 | 0.483 |
| | | Case 2 | 0.393 | 0.451 | 0.483 |
| | | Case 3 | 0.373 | 0.431 | 0.493 |

h-order terms of the square of the RRMS error are also used as the input patterns. And the output is the forecast stiffness of the substructure. The architecture of the localized parametric evaluation neural network is shown in Figure 10. In this study, for the substructure, the number of neurons in input, hidden and output layer is 4, 8 and 3 respectively.

The localized parametric evaluation neural network is trained with those training data. Then the localized parametric neural network can be used to recognize the unknown structural parameters (stiffness) from the RRMS error vector. Thus, the inverse analysis can be avoided through the training process of the neural network.

Without loss of generality, three damaged structures with different degree of stiffness decrease are studied here. According to the RRMS error vector, the stiffness of the damaged substructure can be forecast through the trained parametric evaluation neural network. The results are shown in Table 2. From Table 2, it is clear that the inter-story stiffness of each floor in the substructure can be forecasted accurately in Case 1, 2 and 3 respectively. The maximum error between the forecasted stiffness and the true value is not great than 5%.

It is demonstrated that localized parametric evaluation neural network can forecast the stiffness of the 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.

## 6. Conclusions

In this paper, a localized inverse analyses process for health monitoring and parametric evaluation with the direct use of dynamic responses by neural network was proposed. First, for the purpose of health monitoring, corresponding to a substructure, a localized emulator neural network was constructed.

Numerical simulations shown that the architecture of the localized emulator neural network corresponding to the substructure is feasible, and the select of input and output variables is reasonable and the selected variables are enough to carry out localized identification. For the purpose of health monitoring, a suitable and practical evaluation index was defined, and the adaptability of the evaluation index was testified. And then a localized parametric identification diagram is conducted by combining the localized emulator neural network and the localized parametric evaluation neural network. The performance of the proposed strategy is evaluated through numerical simulations for substructures with different degree of damage. The stiffness of the damaged substructure can be identified through the localized parametric neural network with good precise.

It is shown that the localized inverse analyses with neural network by direct use of dynamic responses with neural networks have the potential of being a practical tool for health monitoring and parametric evaluation of civil engineering structures, especially for large-scale structures with great number of DOF. It is possible to apply this approach to whole structure identification if the required response records are available.

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