APPLICATION OF ARTIFICIAL NEURAL NETWORK AND GENETIC ALGORITHM TO SYSTEM IDENTIFICATION

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ABSTRACT

This paper presents a new identification technique combining the advantages of artificial neural network (ANN) and genetic algorithm (GA). In order to provide a neural network topology that can be merged into the GA identification technique developed by the author, the time history of the ground acceleration and the system parameters of a variety of SDOF systems are used as the input data of neural network, and the time history of the relative acceleration of the corresponding systems as the neural network outputs. After the training of the neural network, the network topology used to evaluate the time history of the relative acceleration of the SDOF systems will be captured. This network topology is then employed to replace the procedure for solving the governing (differential) equation when GA is used to identify the system parameters. Furthermore, this topology is used in the identification of a MDOF system subjected to single input by mode superposition technique.

KEY WORDS

system identification, artificial neural network, genetic algorithm, error index.

INTRODUCTION

Field of system identification has become important discipline due to the increasing need to estimate the behavior of a system with partially known dynamics. Identification is basically a process of developing or improving a mathematical model of a dynamic system through the use of measured experimental data. In addition to updating the structural parameters for better response prediction, system identification techniques made possible to monitor the current state or damage state of the structures. As for structural control problem, the system of interest also needs to be known to some extent. Structural identification can be categorized into classical and non-classical methods. Most of the classical methods are calculus-based search method. They are performed by point-to-point search strategy and normally require gradient or higher-order derivatives of the objective function. There is a possibility to fall into a local minimum rather than the global minimum. Therefore, these methods generally do not function well for structural identification problem involving a large number of unknowns.

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For such problems, the newly developed non-classical methods provide another alternative. Among the methods, the artificial neural network and genetic algorithm are the most common techniques for system identification. Some works of non-classical methods in the context of system identification are review as follows.

Jovanović (1997) proposed a neural network approach for structural dynamic model identification, using the responses recorded in a real frame during earthquakes. A typical three-layer back propagation neural network was used for the purpose of identification and a five-story steel frame was chosen to demonstrate the performance of the neural network. Two earthquakes used for the dynamic model identification were recorded in the frame. They are the Petrovac 1979, component N-S and El Centro 1940, component N-S. The displacement and acceleration time histories were recorded for the sets of earthquakes on each floor. The data set, used for training of the neural network dynamic model, is the first 500 points taken from 1,000 points record of the Petrovac 1979 earthquake and the rest of response histories were used for verification of the trained neural network model. The results showed the great potential of using neural networks in structural dynamic model identification.

Hani and etc. (1999) developed a structural control method using neural network. Experimental verification has been carried out on the earthquake simulator. The test specimen was a 1/4-scale model of a three-story steel frame with the control system of a tendon/pulley system controlled by a single hydraulic actuator. The neural network models used for the system identification were called emulator neural networks. The experimental validation of the mathematical model has been established in the time and frequency domains. The multiple emulator neural networks performance was demonstrated experimentally and shown to be independent of the training data.

Loh and Huang (2001) proposed a neural-network-based method to the modeling and identification of discrete-time nonlinear hysteretic system during strong ground motion. The learning or modeling capability of multilayer neural network was explained from the mathematical point of view. The main idea of the proposed neural approach was explained, and it was shown that multilayer neural network is a general type of NARMAX model and is suitable for the extreme nonlinear input-output mapping problem. Numerical simulation and real structure cases are used to demonstrate the proposed method. The results illustrated that the neural network approach is a reliable and feasible method.

Huang and etc. (2003) used a back-propagation neural network approach with one hidden layer to estimate the dynamic characteristics of a five-storey steel frame, subjected to different intensities of the Kobe earthquake in shaking table tests. The measured acceleration responses of all the floors and the input excitations were used to train the neural network. The modal characteristics of the system were directly evaluated from the weighting matrices of the neural network. The proposed method of estimating the modal parameters was verified by excellent agreement between the present results and those results obtained by a subspace method. The damage of a building can also be diagnosed by detecting changes in its modal parameters and the dynamic responses in earthquakes. The reported non-linear responses to the 60% Kobe earthquake input were found to change significantly in modal shapes and damping values from those for the frame in the 20% Kobe earthquake input.

The author (Wang & Lin, 2005) applied the real-coded GA to structural identification problems. The GA provides a stochastic search in the designate ranges of parameters. The system parameters associated with the minimal error index were then exploited after successive evolution of generations. The validity and the efficiency of the proposed GA strategy were explored for the cases of both SDOF linear/nonlinear dynamic systems and MDOF linear/nonlinear dynamic systems with simulated input/output measurements. The identified parameters are very close to the true one and the error index is extremely small in each case. As a result, the efficacy of the proposed algorithm was verified.

Many researches have devoted to developing different system identification approaches using neural network. However, most of them cannot capture the change of the system parameters. On the other hand, the identification approach using Genetic algorithm proposed by the author (Wang & Lin, 2005) need to solve differential equations, whenever computing the fitness function is required. To overcome these drawbacks, a new identification technique combining the advantages of both artificial neural network (ANN) and genetic algorithm (GA) is proposed. The time history of the ground acceleration and the system parameters of a variety of SDOF systems are used as the input data of neural network, and the time history of the relative acceleration of the corresponding SDOF systems as the neural network outputs. After training of the neural network, the network topology used to evaluate the time history of the relative acceleration of the SDOF systems will be captured. This network topology is then employed to replace the procedure for solving the governing (differential) equation when GA is implemented to identify the system parameters.

ARTIFICIAL NEURAL NETWORK

Artificial neural networks are data analysis methods and algorithms, which imitate the process of nervous systems of humans and animals. In general terms, an artificial neural network consists of a large number of simple processing units linked by weighted connections. By analogy to human brain, the processing units may be called neurons. Each unit receives inputs from many other units and generates a single output. The output acts as an input to other processing units. Unlike traditional linear algorithms, artificial neural networks use highly distributed representations and transformations that operate in parallel, have distributed control through many highly interconnected neurons, and stored their information in variable strength connections called synapses - just like a human brain. The network is nonlinear in nature and thus is an exceptionally powerful method of analyzing real-world data that allows modeling extremely difficult dependencies. A certain network may be tuned to solve a particular problem, such as the modeling or prediction of the behavior of a complex system, by varying the connection topology and values of the connecting weights between units.

To bring proper results the neural networks require correct data preprocessing, correct architecture selection and correct network training. The most common type of artificial neural network, called the multi-layer feedforward network with the back-propagation training algorithm, consists of three groups, or layers, of units: a layer of "input" nodes is connected to a layer of "hidden" nodes, which is connected to a layer of "output" nodes:

- The activity of the input nodes represents the raw information that is fed into the network.

- The activity of each hidden node is determined by the activities of the input nodes and the weights on the connections between the input and the hidden nodes.
- The behaviour of the output nodes depends on the activity of the hidden nodes and the weights between the hidden and output nodes.

Feedforward ANNs allow signals to travel one way only, from input to output. There is no feedback (loops) i.e. the output of any layer does not affect that same layer. In the standard back-propagation algorithm, the relation between A_j^n, the output in the jth node of the nth layer, and A_i^{n-1}, the outputs of the nodes in the (n-1)th layer, is defined as:

$$A_j^n = f(net_j^n) \tag{1}$$

$$net_j^n = summation \quad output = \sum_i W_{ij} A_i^{n-1} + \theta_j \tag{2}$$

$$f = transfer \quad function = 1 - e^{-x} \big/ 1 + e^{x} \tag{3}$$

where W_{ij} is the connecting weight between nodes in the nth layer and those in the (n-1)th laye; and θ_j is the bias term. The transfer function can be linear or nonlinear. Identification procedure entails a matching between the system outputs and the identified outputs. During training stage, a system error or objective function is defined and used to monitor the performance of the network. In order to achieve the best performance of the network, this function is minimized by adjusting the connecting weights through optimization techniques.

GENETIC ALGORITHM

Genetic algorithm is a stochastic search technique based on natural selection and genetics, developed by Holland (1962). Genetic algorithms model natural processes, such as selection, recombination, mutation, migration, and competition. The algorithms work on populations of individuals instead of single solution. In this way, the search is performed in a parallel manner. At the beginning of the computation, a number of individuals are randomly generated. The objective function is then evaluated for these individuals. If the termination criteria are not met, the creation of a new generation starts. Individuals are selected according to their fitness for the production of offspring. Parents are recombined to produce offspring. All offspring will be muted with a certain probability. The fitness of the offspring are then computed. The offspring are inserted into the population replacing the parents, producing a new generation. This cycle is performed until the optimization criteria are reached. Such a single population GA is powerful and performs well on a wide variety of problems. However, better results can be obtained by introducing multiple subpopulations. Every subpopulation evolves over a few generation isolated (like the single population GA) before one or more individuals are exchanged between subpopulation using the mechanisms of migration and competition. The multipopulation GA models the evolution of a species in a way more similar to nature than single population. Figure 1 shows the structure for such a multipopulation GA.

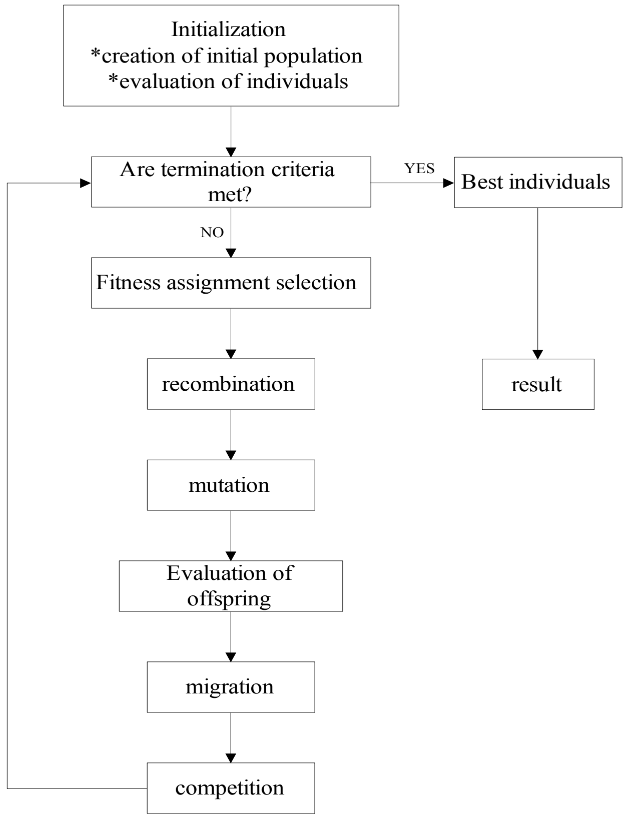

Figure 1. Structure of a multipopulation Genetic Algorithm

NEW IDENTIFICATION TECHNIQUE COMBINING ANN AND GA

NEURAL NETWORK TOPOLOGY OF SDOF SYSTEMS

In this section, we attempt to find the neural network topology for single degree of freedom (SDOF) systems. At first, we try to seek for a network topology that can represent a variety of SDOF systems. The ranges of frequencies (ω) and damping ratios (ξ) considered are 0~20(rad/sec) and 0%~20%, respectively. The motion equation of a SDOF linear system when excited by a uni-directional earthquake ground acceleration is

$$\ddot{u} + 2\xi\omega\dot{u} + \omega^2 u = -\ddot{u}_g \tag{4}$$

where ξ = damping ratio; ω = natural frequency; and $\ddot{u}_g$ = ground acceleration in one direction. The measured response is the relative acceleration and can be represented as

$$y = \ddot{u} = -\ddot{u}_g - 2\xi\omega\dot{u} - \omega^2 u = -\ddot{u}_g - A_1\dot{u} - A_3 u \tag{5}$$

where $A_1 = 2\xi\omega$ and $A_3 = \omega^2$. The network architecture used here is feedforward back-propagation network with two hidden layers illustrated in Figure 2. The input layer is consisted of ground excitation forces at the current state and the past d_1-1 states (or sampling times), and the 2 system parameters, A_1 and A_3, when d_1-1 is considered as the proper number of time delay, while the output layer is consisted of the relative acceleration response at the next state only. The target output for training the network can then be yielded by computing the acceleration response sets according to various combinations of system parameters of the SDOF systems. In this paper, the parameters used to generate the training data are distributed uniformly among the ranges of frequencies (ω) and damping ratios (ξ) aforementioned. To be more specifically, the frequencies are taken as 1,2 ,…,20(rad/sec), while the damping ratios are 1%, 2%,…, 20%. In this regard, there are 400 combinations of the system parameters to yield the sets of training data.

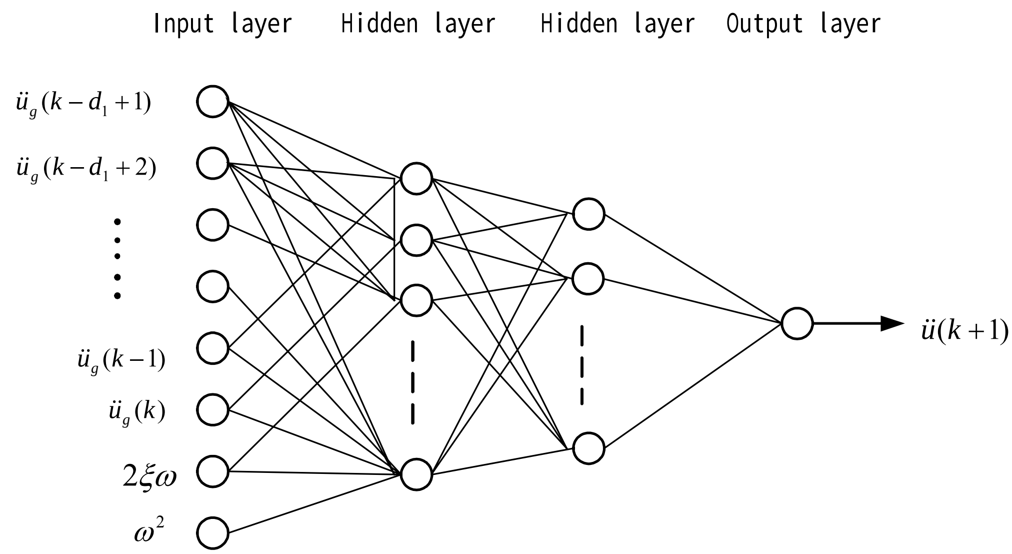

Figure 2 Time delay feedforward neural network model

Before applying the neural network to the training data sets, the objective function associate with the network output error is defined as

$$E = \frac{\sum_i (y_i - a_i)^2}{N} \tag{6}$$

where N is the number of measurement sequence; y_i is the measured relative acceleration response of the SDOF system; and a_i is the identified relative acceleration response of the system. Based on the diagram sketched in Figure 2, the objective function given in Eq. (6) is minimized by propagating the output error back through the network. Unfortunately, the value of the objective function can not be reduced to a reasonable level, when the network is trained using the 400 sets of whole time history data of structural dynamic responses. This indicates that the intention to use one network topology to represent the dynamic characteristic of SDOF systems is failed. Alternatively, the training data is divided into 16 groups, with each group of data constituted by 25 sets of data as shown in Table 1. Each group of data sets is trained to yield the network parameters, such as the connecting weights and bias terms. In other words, a set of 16 network topologies are used to represent the dynamic characteristics of the SDOF systems. To demonstrate the effect of network training, the identified response of the SDOF system with parameters of $\xi = 6\%, \omega = 19 rad/\sec$ can be estimated through the corresponding network topology and be shown in Figure 3, where the error index (E.I.) and the normalized error of peak value defined below, are 4.63% and 7.04%.

$$E.I. = \frac{\sum_i (y_i - a_i)^2}{\sum_i {y_i}^2} \tag{7}$$

$$e = \frac{|y_{\max} - a_{\max}|}{y_{\max}} \tag{8}$$

Table 1 Combination of system parameters of data used for training network

ξ \ ω	1,2,...,5	6,7,...,10	11,12,...,15	16,17,...,20
1%,2%,...,5%	Group 1	Group 2	Group 3	Group 4
6%,7%,...,10%	Group 5	Group 6	Group 7	Group 8
11%,12%,...,15%	Group 9	Group 10	Group 11	Group 12
16%,17%,...,20%	Group 13	Group 14	Group 15	Group 16

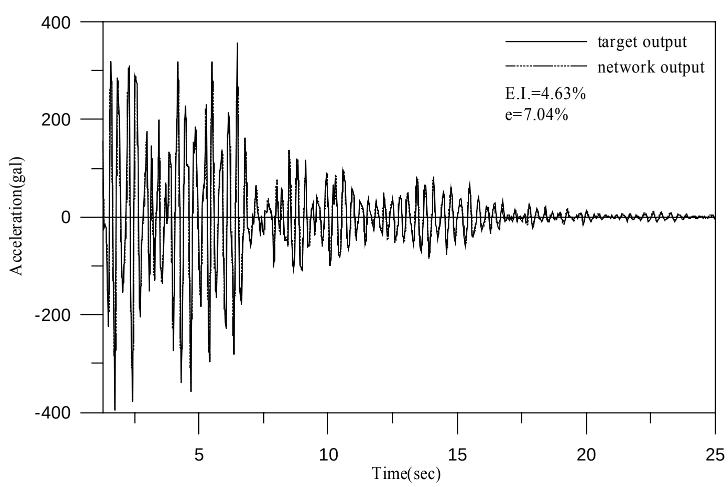

Figure 3 Comparison of the measured response with the identified one of the SDOF system using ANN ($\xi = 6\%, \omega = 19 rad/\sec$)

NEW IDENTIFICATION TECHNIQUE COMBINING ANN AND GA FOR SDOF SYSTEM

Many researches have engaged in developing their own neural network models for system identification. However, most of the models developed cannot be used to estimate the response when the system parameters and ground excitation are supplied. In the previous section, a set of 16 neural network topologies for various groups of SDOF systems were developed to fulfill the requirement of estimating the response of SDOF systems. They can then be employed to replace the procedure for solving the governing (differential) equation when computing the fitness function is required during the process of performing the GA identification. Thus, a new identification technique combining ANN and GA is proposed, mainly based on the procedure of GA developed by the author (Wang & Lin, 2005) with the neural network topologies replacing the system dynamic characteristics. To demonstrate the effect of the new identification technique, it is applied to the output response of a system with parameters of $\xi = 9\%, \omega = 8rad/\sec$, subject to a specific ground motion. The parameters identified is $\xi = 9.1\%$ and $\omega = 8rad/\sec$. The time history of the identified response is sketched in Figure 4.

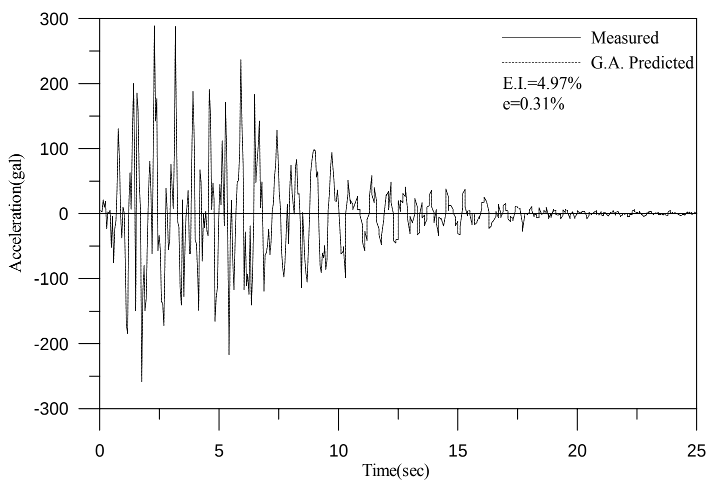

Figure 4 Comparison of the measured response with the identified one of the SDOF system using the new identification technique combining ANN And GA ($\xi = 9\%, \omega = 8rad/\sec$)

APPLICATION TO STRUCTURAL MODAL PARAMETERS OF MDOF SYSTEM

The equation of motion for a linear MDOF system with classical damping can be converted to a set of independent modal equation as:

$$\ddot{y}_m + 2\xi_m \omega_m \dot{y}_m + \omega_m^2 y_m = -P_m \ddot{u}_g \tag{9}$$

where y_m is the normal coordinate in mode m; ξ_m = modal damping ratio; ω_m = modal natural frequency; and P_m = modal participation factor. Pre-multiplying ϕ_{sm}, the mode shape in mode m at the sth DOF, equation (9) can be rewritten as follows:

$$\ddot{u}_{sm} + 2\xi_m \omega_m \dot{u}_{sm} + \omega_m^2 u_{sm} = -P_{sm} \ddot{u}_g \tag{10}$$

where u_{sm} is the modal displacement in mode m at the sth DOF, and P_{sm} the effective participation factor in mode m at the sth DOF associated with the ground motion $\ddot{u}_g$

$$P_{sm} = \frac{\phi_{sm}\{\phi_m\}^T[M]\{l\}}{\{\phi_m\}^T[M]\{\phi_m\}} \tag{11}$$

where $[M]$ is the mass matrix, $\{\phi_m\}$ the mode shape in mode m, and $\{l\}$ the ground influence coefficient matrix with elements 0 and 1. If only one accelerograph installed at the sth DOF, the measurement equation can be represented as

$$y = \ddot{u}_s = \sum_{m=1}^{N} \ddot{u}_{sm} = -\sum_{m=1}^{N} P_{sm}\ddot{u}_g - 2\xi_m\omega_m\dot{u}_{sm} - \omega_m{}^2 u_{sm} \tag{12}$$

where $\ddot{u}_s$ is the relative acceleration at the sth DOF, and N the total number of modes. From Eq. (12), it can be concluded that the modal parameters, $2\xi_m\omega_m$, $\omega_m{}^2$, and P_{sm} are the parameters to be identified for a MDOF system. The similar techniques in the previous section can be applied here for the identification of a MDOF system except that the system response is obtained by the superposition of modal responses, which can also be calculated by the proper network topologies provided in the previous section.

A 2-story shear building with accelerograph mounted at the top floor is presented to demonstrate the efficacy of the proposed modal parameter identification technique associated with the ANN and GA. The system properties of the model structure are M1 = M2= 1kip-s2/in, K1 = 187.69kip/in, and K2 = 77.44kip/in. Rayleigh dampings of 6% and 10% are assumed for the first and the second modes. The complete modal parameters are identified using the top floor accelerogram. Fig. 5 shows the comparison of true acceleration measurement with the predicted one. There is a good agreement between the predicted response and the measured one. From the error index in Figure 5, the same conclusion can be reached. Therefore, the efficacy and the accuracy of the proposed identification strategy are verified.

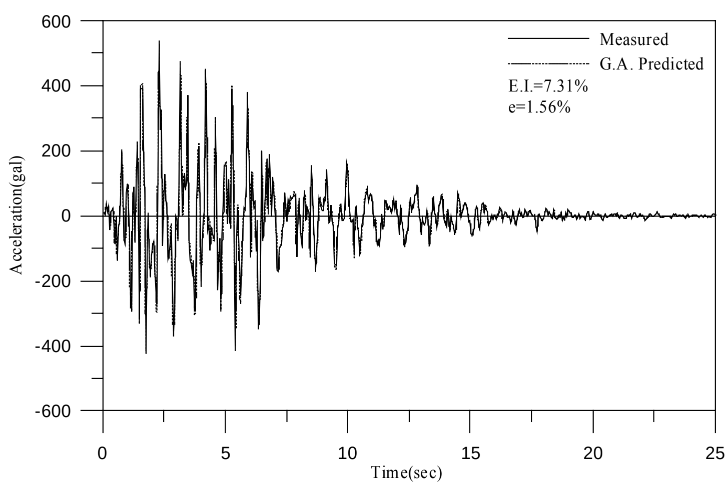

Figure 5 Comparison of the measured response with the identified one of a MDOF system using the new identification technique combining ANN And GA

CONCLUSIONS

Artificial neural networks, with their remarkable ability to gain information from complicated or imprecise data, can be used to derive model and extract parameters that are too complex to be noticed by either humans or other computer techniques. On the hand, genetic algorithms provide a very attractive computation method as its implementation is relatively straightforward. Unlike many classical methods, there is no need to compute the derivatives with respect to the parameters. No initial guess is required. Furthermore, the fitness function can be defined in terms of the measurement quantities directly. In this regard, application of ANN and GA is very promising. Based on study of numerical examples in this paper, the following conclusion can be made:

- A set of new neural network topologies is presented to predict the system response when the system parameters and ground motion are provided for a SDOF system.
- The set of neural network topologies developed in this paper is provided to replace the procedure for solving the governing (differential) equation when GA is used to identify the system parameters. As a result, an efficient identification technique combining GA and ANN is developed and applied to the simulated input/output measurements of SDOF linear dynamic systems as well as MDOF linear The identified parameters are very close to the true one and the error index is extremely small in each case. Also, the predicted responses and the measured ones are almost overlapped in all the cases. Consequently, the applicability of the proposed strategy to structural dynamic parameter identification is proved.

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