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APPLICATION OF GENETIC ALGORITHM TO STRUCTURAL DYNAMIC PARAMETER IDENTIFICATION

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SUMMARY

The system parameter value or state is obtained or identified by minimizing the accumulated discrepancy or the error index between the recorded response and the identified response. The parameter value evaluated in such a sequence is called an optimal estimate. In consequences, system identification problem can also be considered as an optimization problem. Genetic algorithm (GA) is a search method based on natural selection and genetics and is different from conventional optimization methods in several ways. The GA is a parallel and global search technique that searches multiple points, so it is more likely to obtain a global solution. In this paper, it is intended to propose a new system identification strategy using GA, which is robust to the search space, and can be implemented easily.

The validity and the efficiency of the proposed GA strategy are explored by simulated input/output measurements of both SDOF linear/nonlinear dynamic systems and MDOF linear/nonlinear dynamic systems. The GA provides a stochastic search in the designate ranges of parameters. The system parameters associated with the minimal error index are then exploited after successive evolution of generations. Finally, the comparison is made between the predicted acceleration and the measured one.

INTRODUCTION

Modeling of structures subjected to ground motions is essential in earthquake resistant design. Traditionally, structural dynamic analysis can be categorized as direct analysis problem. Direct analysis for dynamic system is aimed to predict the structural response for given excitation and known structural characteristics. Although various analytical methods are available to predict the dynamic response of a structure, the confidence that can be placed in results obtained with them is severely limited by the uncertainties associated with the simplified modeling processes of structures and of their material and member behaviors. For these reasons, experimental testing remains the most reliable means to evaluate the dynamic behavior of structural systems and to devise structural details to improve their seismic performance. System identification is process of determining parameters of a dynamic system based on

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numerical analysis of measurements of input and the corresponding output and often is categorized as inverse analysis problem. In addition to updating the structural parameters for better response prediction, system identification techniques made possible to monitor the current state of the structures and even the damages based on the changes in the parameters as well.

The modeling and identification of linear and nonlinear dynamic systems through the use of measured experimental data is a problem of considerable importance in engineering. The system parameter value or state is obtained or identified by minimizing the accumulated discrepancy or the error index between the recorded response and the identified response. The parameter value evaluated in such a sequence is called an optimal estimate. In consequences, system identification problem can also be considered as an optimization problem. In the past few decades, many optimization techniques have been employed for system identification problems. These techniques are usually classified under various categories. System identification, which is based on the method of least square fit to identify system parameters, may be classified into two categories: one in a deterministic manner and the other in a statistical manner. These techniques can be used to identify some system parameters of the system [1-2]. Caravani and et al. [3] identified the stiffness and damping coefficient by recursive least square method. The extended Kalman filter is one of the most successful statistical optimization methods for structural identification. Yun and Shinozuka [4] proposed an identification method combining the extended Kalman filter and a weighted global iteration technique to identify the damping coefficient, stiffness and participation factors of an offshore structure. System identification can also be categorized as parametric identification method and nonparametric one. Among the nonparametric identification methods, the artificial neural network [5-6] and genetic algorithm are newly developed techniques for the purposes of identification. A static function mapping can be determined empirically without knowing any fundamental physics of the system by using the neural network technique. However, the dynamic function mapping including dynamic model identification is still a challenging topic in neural network applications. On the other hand, genetic algorithms have been the subjects of considerable interest in recent years, since they appear to be a robust search procedure for solving difficult problems. The essence of genetic algorithm will be discussed in the next section.

GENETIC ALGORITHM

C. Darwin has formulated the fundamental principle of natural selection as the main evolutionary principle long before the discovery of genetic mechanisms. Darwin hypothesized fusion or blending inheritance, supposing that potential qualities mixed together like fluids in the offspring organism. Recently, genetic algorithms have received considerable attention regarding their potential as an optimization technique for complex problems and have been successfully applied in the areas of industrial engineering. GA is a stochastic search technique based on natural selection and genetics, developed by Holland. This algorithm, differing from conventional search techniques, starting with the initial set of random solution called population. Each individual in a population is called a chromosome, representing a solution to the problem at hand. A chromosome is a string of symbols; it is usually, but not necessarily, a binary bit string. The chromosomes evolve through successive iterations, called generations. During each generation, the chromosomes are evaluated, using some measures of fitness. To create next generation, new chromosomes, called offspring, are formed by either (a) merging two chromosomes form current generation using cross over operator or (b) modifying a chromosome by mutation operator. A new generation is formed by (a) selecting, according to fitness values, some of the parents and offspring and (b) rejecting others so as to keep the population size constant. Fitter chromosomes have higher probabilities of being selected. After several generations, the algorithms converge to the best chromosome, which hopefully represents the optimal or suboptimal solution to the problem.

Before applying the GA to the specific optimization problems, it is essential to define the fitness function according to the characteristic of the problem itself [7]. Through the process of natural selection, including the three mechanisms of selection and reproduction, crossover, and mutation, the optimal solution to the fitness function can be exploited. The detailed procedures involved in genetic algorithm for solving optimization problem are described as follows:

1. Definition of fitness function:
Fitness function $f(\underset{\sim}{x})$ can be deemed as the performance index for genetic algorithm, in which $\underset{\sim}{x}$ is the parameters associated with the performance index or fitness function. Genetic algorithm is employed to obtain the parameters which will maximize or minimize the function, depending on the characteristic of the problem.

2. Choosing the appropriate encoding method:
According to what kind of symbol is used to represent the individual (chromosome), the encoding methods can be classified into binary encoding, real-number encoding and integer encoding. In Holland's work, encoding is carried out using binary string. Binary string encoding for function optimization problems is known to have several drawbacks due to the existence of Hamming cliffs, pairs of encodings such as 011111111 and 100000000 have a large Hamming distance while belonging to points of minimal distance in phenotype space. Real-number encoding is best used for function optimization problems, since the topological structure of the genotype space for real number encoding is identical to that of phenotype space. In order to search the parameters efficiently, the sampling space for each parameter should be defined first.

3. Generating the initial population:
To initial a population, we can simply set some population size of chromosomes and generate them randomly. The size of the population is often relied on the complexity of the problem such as the form of the fitness function and the number of parameters involved.

4. Performing genetic operators:
The genetic algorithm maintains a population of individuals. Each individual represents a potential solution to the problem at hand. Each individual is evaluated to give some measure of fitness. Some individual undergo stochastic transformation by means of genetic operation to form new individuals. There are two type of transformation: mutation, which creates new individuals by making changes in a single individual, and cross over, which creates new individual by combining parts from two individuals. New individuals, called offspring, are then evaluated. A new population is formed by selecting the fitter individual from the parent population and the offspring population. In summary, the next generation can be obtained through the three genetic operators, including selection and reproduction operator, crossover operator, and mutation operator.

5. Checking the termination condition:
If the fitness function is optimized or the value for the function cannot be improved, the process should be terminated; otherwise, the process should be continued for the next generation.

6. Converging to the optimal solution of fitness function:
The fitness function is optimized and the associated parameters are obtained.

FEASIBILITY OF GENETIC ALGORITHM TO IDENTIFICATION OF SDOF LINEAR SYSTEM

System identification is a process of determining parameters of a dynamic system by minimizing the accumulated discrepancy between the recorded response and the identified one. By defining the accumulated discrepancy as the fitness function, the GA can be applied to identify the system parameters. In order to demonstrate the feasibility of the proposed GA identification strategy, simulated input/output measurements of SDOF linear dynamic systems are generated and the GA is then served as the identification strategy to search the optimal parameters.

The behavior of GA is characterized by a balance between exploitation and exploration in the search space. The balance is strongly affected by the strategy parameters such as population size, mutation ratio, and crossover ratio as well by the selection method and crossover method. How to choose a value for each parameter and the appropriate methods are very important to GAs. In this regard, the SDOF linear dynamic system is served for this purpose. Robustness of any identification technique is an important and challenging issue besides accuracies of identified parameters. In this regard, three practical factors are considered. Firstly, the identification strategy should preferably be not too sensitive to the noise of the input and output measurements. Secondly, the strategy should not need good initial guess of the parameters to converge to the global optimal solution. Thirdly, the strategy should not require measurements at all degrees of freedoms. Since the GA strategy start with randomly selected initial population, the first factor is automatically fulfilled. As for the second factor, the contaminated input and output measurements are used to verify the effectiveness of this strategy. Moreover, various sets of output measurement associated with different SDOF linear system are also used to verify the applicability of this strategy.

1. SDOF linear dynamic system

The motion equation of the single degree of freedom linear system when excited by a uni-directional earthquake ground acceleration is

$$m\ddot{u} + c\dot{u} + ku = -m\ddot{u}_g \tag{1}$$

where m = mass, c = damping coefficient, k =stiffness, and $\ddot{u}_g$ = ground acceleration in one direction. Dividing equation (1) by m gives

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

where ξ = damping ratio and ω = natural frequency. The measured response is the relative acceleration and can be represented as

$$\begin{aligned} y = \ddot{u} &= -\ddot{u}_g - 2\xi\omega\dot{u} - \omega^2 u \\ &= -\ddot{u}_g - A_1\dot{u} - A_3 u \end{aligned} \tag{3}$$

where $A_1 = 2\xi\omega$ and $A_3 = \omega^2$. In order to assess the accuracy of the proposed identification strategy, the error index *E.I.* is defined as the square root of the normalized square error:

$$E.I. = [\frac{\sum_{i=1}^{N}(y-v)^2}{\sum_{i=1}^{N}y^2}]^{\frac{1}{2}} \qquad (4)$$

where N is the number of measurement sequence, y is the measured relative acceleration response of the SDOF system, and v is the estimated or predicted relative acceleration response of the system from the propose GA. Equation (4) also defines the fitness function used in GA. In other word, the proposed GA is applied to estimate the system parameters by which the fitness function or the error index *E.I.* will be minimized. Real-number encoding is used for the proposed GA to avoid the time needed for encoding and decoding. The GA procedure for the identification of the SDOF linear system is shown in table 1.

Table 1 Proposed GA identification strategy of SDOF linear system

Step 1:	Generation of the synthetic input and output measurements of SDOF linear system.
Step 2:	Initiation of population.
Step 3:	Substitute the parameters for each individual generated in step 2 into equation (2) to obtain the displacement response and velocity response.
Step 4:	Substitute the displacement response and velocity response into equation (3) to obtain the acceleration response.
Step 5:	Selection and reproduction according the fitness functions, defined in equation (4), for each individual.
Step 6:	Apply the cross over operator to the individuals of current generation.
Step 7:	Apply the mutation operator to the individuals of current generation.
Step 8:	Selection and reproduction according the fitness functions from the individuals of current generation and those generated in step 6 and step 7.
Step 9:	If the generation number is reached or stopping criterion is satisfied, go to step 10 or else go to step 6.
Step 10:	Stop and the fittest is the solution.

2. Generation of synthetic ground motion

The ground motion $X(t)$ is assumed to be a zero-mean stationary Gaussian process with the one sided spectral density function $S_g(\omega)$. A direct method of obtaining the desired stationary process $X(t)$ is to lump the area under the power density function $S_g(\omega)$ at equal frequency intervals ω and these areas equal one half the square amplitude of a set of discrete harmonics. In this case,

$$X(t) = 2\sum_{i=1}^{N}\sqrt{S_g(i\ \ \omega)\ \ \omega}\cos(i\ \ \omega t - \psi_i) \qquad (5)$$

where ψ_i is a random phase angle having a uniform probability density function over the range $0 < \psi_i < 2\pi$. To obtain an even more representative process for strong ground motion, the nonstationary characteristics of actual accelerograms can be considered. This suggests using a nonstationary process, namely, $\ddot{u}_g$ given by

$$\ddot{u}_g(t) = X(t)\psi(t) \qquad (6)$$

where $\psi(t)$ is a deterministic intensity function defined by

$$\psi(t) = e^{-\alpha t} - e^{-\beta t} \qquad t > 0 \tag{7}$$

where $\alpha = 0.15$, and $\beta = 0.8$. The simulated ground motion is shown in Fig. 1.

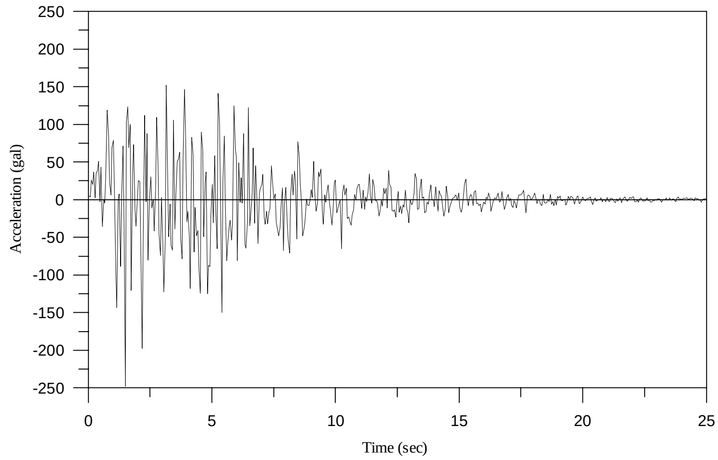

Fig. 1 The simulated ground motion

3. Selection of GA associated methods and parameters

When applying the GA, the searching result and computation time can be affected by the size of population, probability of crossover, and probability of mutation in addition to by the methods of selection and cross over. In order to realize these effects, the parameters of the SDOF system are searched using different combinations of GA associated methods and parameters. More specifically, the size of population is set to be 20, 50, 80, or 100, the probability of cross over be 0.4, 0.6, 0.8, or 1.0, and the probability of mutation be 0.1, 0.05, 0.01, 0.005, or 0.001. As for the method of selection, roulette wheel selection, stochastic universal sampling, tournament selection or truncation selection can be chosen, and for that of cross over, discrete recombination, average recombination or line recombination can be chosen. In the meantime, the system parameters A_1 and A_3 used for testing are set to be 0.9 and 80. From the testing results of SDOF linear system, the size of population, the probability of cross over, and the probability of mutation are chosen to be 1000, 0.1 and 0.01, respectively, while the selection method and cross over method are chosen to the truncation selection method and average recombination method, respectively.

4. Identification of SDOF linear systems with different dynamic characteristics

In order to verify the applicability of the proposed GA strategy to system identification, it is applied to the SDOF linear systems with different dynamic characteristics or system parameters. Basically, there are two types of buildings to be identified, one type of them is the reinforced concrete (RC) building with damping ratio of 5%, and the other one of them is the steel building with damping ratio of 2%. The RC buildings to be identified are 2-story, 5-story and 12-story, and the steel buildings are 22-story and 50-story. In addition to the system with parameters $A_1 = 0.9$ and $A_3 = 80$, system parameters A_1 and A_3 of the above five buildings are computed according to the specification in "Seismic Design Code for Buildings" [8] of Taiwan and the results are tabulated in table 2. Substituting any set of the parameters A_1 and A_3 in table 1 into equation (3), the related system measured response is then obtained. The designate ranges of parameters for GA are set as those in table 3. Then, the GA strategy is performed to identify the system parameters. True parameters versus identified ones in each case are also shown in table 2. As expected, the identified values are highly accurate no matter how the system parameters of SDOF linear system vary. From the error indices in table 3, the same conclusion can be made, too. Fig.2 illustrates the comparison of the true acceleration measurement with the predicted one for the first case. There is a good agreement between the predicted response and the measured one. Therefore, the applicability and accuracy of the proposed GA strategy are then verified.

Table 2 Parameters of SDOF systems

	ξ	ω	$2\xi\omega$	ω^2
Artificial system	0.05	8.944	0.9000	80.000
2-story RC building	0.05	19.365	1.9635	385.530
5-story RC building	0.05	10.102	1.0102	102.050
12-story RC building	0.05	5.289	0.5289	27.934
22-story steel building	0.02	2.769	0.1108	7.668
50-story steel building	0.02	1.500	0.0600	2.250

Table 3 True parameters versus identified ones of SDOF linear systems

	search range		true parameters		identified parameters		error index
	$2\xi\omega$	ω^2	$2\xi\omega$	ω^2	$2\xi\omega$	ω^2	E.I.
Artificial system	[0,10]	[30,90]	0.9000	80.000	0.9000	80.000	0.00001380%
2-story RC building	[0,10]	[350,450]	1.9635	383.530	1.9635	383.530	0.00017489%
5-story RC building	[0,10]	[30,120]	1.0102	102.050	1.0102	102.050	0.00004421%
12-story RC building	[0,10]	[0,50]	0.5289	27.934	0.5289	27.934	0.00067565%
22-story steel building	[0,1]	[0,20]	0.1108	7.668	0.1108	7.668	0.00007273%
50-story steel building	[0,0.5]	[0,10]	0.0600	2.250	0.0600	2.250	0.00003889%

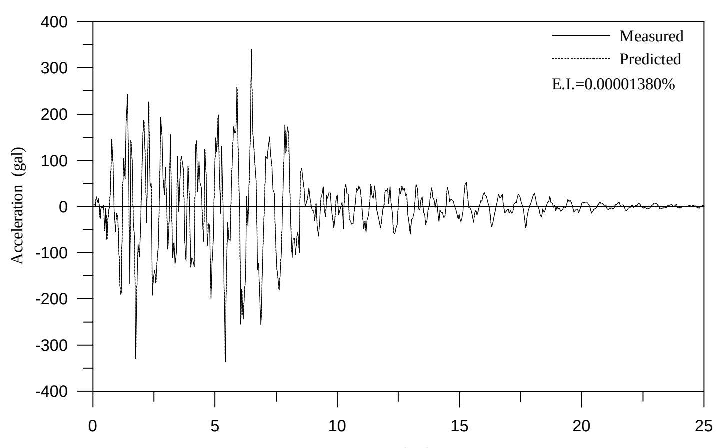

Fig. 2 Comparison of the measured response with the identified one of the SDOF system

5. Identification of SDOF linear systems with noise contamination

For realistic simulation, the time histories of the applied excitation as well as the acceleration of the mass were noise contaminated. This was accomplished by adding to each data vector a corresponding noise vector whose rms level was equal to a certain percentage of the rms of the uncontaminated data vector. The components of all the noise are uncorrelated, with a zero-mean and a Gaussian distribution. Five levels of noise contamination were investigated: 6%, 12%, 18%, 24%, and 30%. The system used here is the one with parameters $A_1 = 0.9$ and $A_3 = 80$. The same GA strategy is applied to identify the system parameters using contaminated input and output. Table 4 shows the designate range of parameters, true parameter versus identified ones, and the error index at each specified level of noise contamination. Since the error index computed for each case is consistent with the noise level and the identified parameters are close to the true ones, the strategy is demonstrated to be able to identify the system parameters even though the signals are contaminated. Fig. 3 illustrates the comparison of true acceleration measurement with the predicted ones for the case of noise contamination of 6%. In summary, it can be concluded that the proposed GA strategy is not sensitive to the noise involved in the input and output measurements. Furthermore, the application of this strategy to the measurements of real systems is quite promising and enchanting.

Table 4 True parameters versus identified ones of the SDOF linear system with noise Contamination ($A_1 = 0.9$, $A_3 = 80$)

S/N	designate ranges of parameters		true parameters		identified parameters		error index
	$2\xi\omega$	ω^2	$2\xi\omega$	ω^2	$2\xi\omega$	ω^2	E.I.
6%	[0,10]	[30,90]	0.9	80	0.87419	79.884	6.300%
12%	[0,10]	[30,90]	0.9	80	0.85111	79.764	12.430%
18%	[0,10]	[30,90]	0.9	80	0.83073	79.641	18.470%
24%	[0,10]	[30,90]	0.9	80	0.81303	79.516	24.310%
30%	[0,10]	[30,90]	0.9	80	0.79811	79.391	29.900%

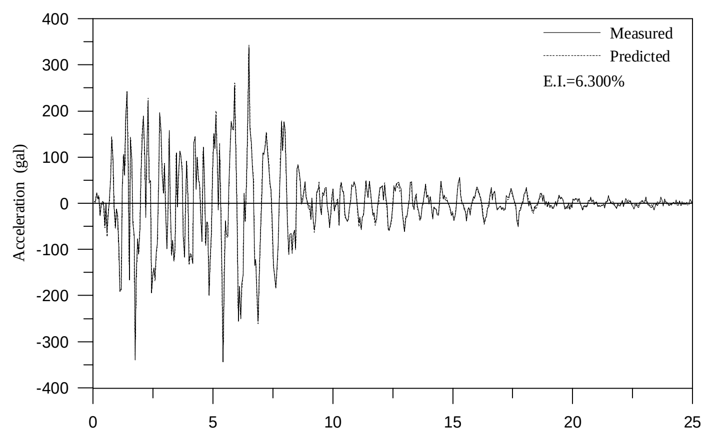

Fig. 3 Comparison of the measured response with the identified one of the SDOF system with 6% noise

STRUCTURAL DYNAMIC PARAMETER IDENTIFICATION OF SIMULATED SYSTEMS

After the applicability of the GA strategy is validated, the same strategy is expanded to apply to the simulated SDOF nonlinear system as well as the simulated MDOF linear and nonlinear systems.

1. Simulated SDOF nonlinear dynamic system with bilinear hysteresis

Consider a SDOF system whose restoring force is governed by a bilinear hysteresis model. The equation of motion is given by

$$\ddot{u} + A_1\dot{u} + h(u, \dot{u}, A_2, A_3, A_4, t) = -\ddot{u}_g \tag{8}$$

where h is the nonlinear restoring force considered as a bilinear hysteresis model shown in Fig. 4. The constants A_2, A_3, and A_4 in the bilinear hysteresis model may be defined as yield strength, initial stiffness, and post yield stiffness, respectively. The measured response is represented as

$$y = \ddot{u} = -\ddot{u}_g - A_1\dot{u} - h(u, \dot{u}, A_2, A_3, A_4, t) \tag{9}$$

The values of A_1, A_2, A_3, and A_4 are set as those in table 5. The same GA strategy is applied to this case, and then the identified parameters and the associated error index are shown in table 5. The error index, which is 0.01521%, is extremely small as expected. Fig. 5 illustrates the true acceleration measurement versus the predicted ones. Again, the predicted response coincides with the measured one and thus the strategy is proved to be quite efficient in this case, too.

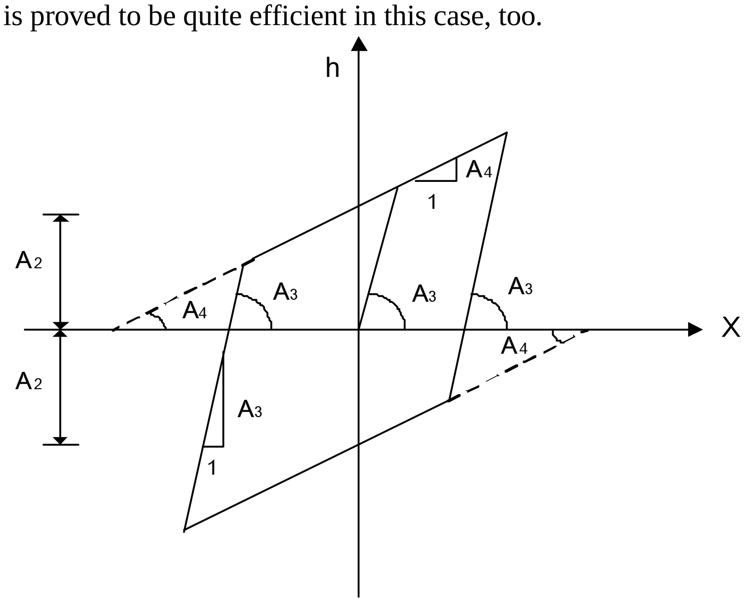

Fig. 4 Bilinear hysteresis model

Table 5 True parameters versus identified parameters of the SDOF nonlinear system

	A_1	A_2	A_3	A_4
designate range	[0,10]	[20,80]	[60,120]	[20,50]
true parameters	0.9	64	80	24
identified parameters	0.89993	63.943	80.002	24.042
error index	0.01521%			
No. of generations	585			

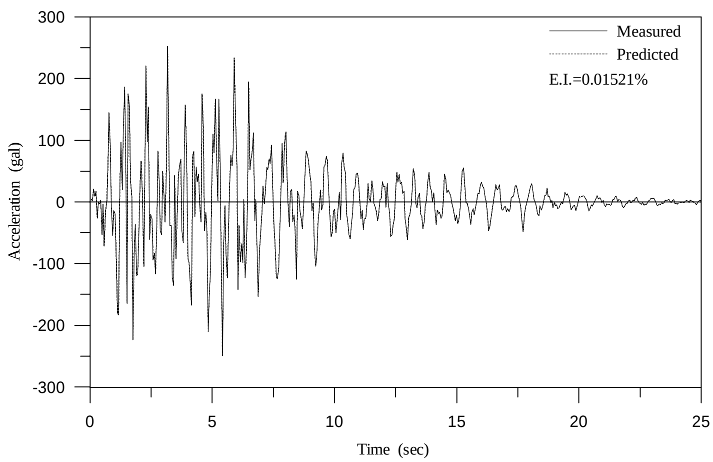

Fig. 5 Comparison of the measured response with the identified one of the SDOF nonlinear system

2. Simulated MDOF linear dynamic system

Consider a three-story shear building, illustrated in Fig. 6, subjected to ground motion $\ddot{u}_g$. The equation of motion can be written as

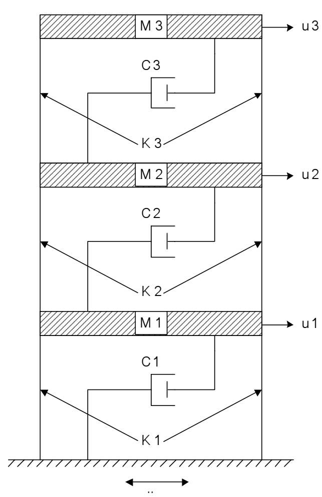

Fig. 6 3-story shear building

$$\{\ddot{u}\}+[C]\{\dot{u}\}+[K]\{u\}=-\begin{Bmatrix}1\\1\\1\end{Bmatrix}\ddot{u}_g \tag{10}$$

where $\{u\}$, $\{\dot{u}\}$, and $\{\ddot{u}\}$ is the relative displacement vector, relative velocity vector, and relative acceleration vector, $[C]$ is the damping matrix and $[K]$ is the stiffness matrix. The damping matrix of this structure is

$$[C]=\begin{pmatrix}\frac{c_1+c_2}{m_1} & -\frac{c_2}{m_1} & 0\\ -\frac{c_2}{m_2} & \frac{c_2+c_3}{m_2} & -\frac{c_3}{m_2}\\ 0 & -\frac{c_3}{m_3} & \frac{c_3}{m_3}\end{pmatrix} \tag{11}$$

and the stiffness matrix is

$$[K]=\begin{pmatrix}\frac{k_1+k_2}{m_1} & -\frac{k_2}{m_1} & 0\\ -\frac{k_2}{m_2} & \frac{k_2+k_3}{m_2} & -\frac{k_3}{m_2}\\ 0 & -\frac{k_3}{m_3} & \frac{k_3}{m_3}\end{pmatrix} \tag{12}$$

where m_i, c_i, and k_i are the mass, damping coefficient, and stiffness of the ith floor. If the accelerograms are installed in each floor of the building, the acceleration measurement vector is represented as

$$\{y\}=-\begin{Bmatrix}1\\1\\1\end{Bmatrix}\ddot{u}_g-[C]\{\dot{u}\}-[K]\{u\} \tag{13}$$

In order to account for the errors of all the measurement simultaneously, the error index is redefined as

$$E.I. = \left[\frac{\sum_{i=1}^{N}(y_1 - v_1)^2 + \sum_{i=1}^{N}(y_2 - v_2)^2 + \sum_{i=1}^{N}(y_3 - v_3)^2}{\sum_{i=1}^{N} y_1^{\ 2} + \sum_{i=1}^{N} y_2^{\ 2} + \sum_{i=1}^{N} y_3^{\ 2}} \right] \tag{14}$$

where y_i and v_i are the measured acceleration response and the predicted one of the ith floor. The GA identification procedures are similar to the flowchart shown in table 1. The values of system parameters are summarized in table 6. The identified parameters and the associated error index are shown in table 6. The error index, which is 0.00110%, is extremely small and this implies that the predicted response and the measured one are almost overlapped.

Table 6 True parameters versus identified parameters of the MDOF linear system

	C_1	C_2	C_3	K_1	K_2	K_3
designate range	[0,5]	[0,5]	[0,5]	[120,200]	[100,180]	[90,160]
true parameters	2	1.5	1.5	140	120	110
identified parameters	1.9999	1.5	1.5001	140	120	110
error index	0.00110%					
No. of generations	345					

3. Simulated MDOF nonlinear dynamic system with bilinear hysteresis

Consider a 3DOF system with bilinear hysteresis model to characterize the behavior of restoring force. The equation of motion of the system subjected to ground motion may be written as

$$\{\ddot{u}\} + [C]\{\dot{u}\} + \{F\} = -\begin{Bmatrix} 1 \\ 1 \\ 1 \end{Bmatrix} \ddot{u}_g \tag{15}$$

where the damping matrix $[C]$ is already defned in equation (11), and the restoring force matrix $\{F\}$ is

$$[F] = \begin{Bmatrix} \frac{k_1}{m_1} h_1(u_1) & -\frac{k_2}{m_1} h_2(u_2 - u_1) \\ \frac{k_2}{m_2} h_2(u_2 - u_1) & -\frac{k_3}{m_2} h_3(u_3 - u_2) \\ \frac{k_3}{m_3} h_3(u_3 - u_2) & 0 \end{Bmatrix} \tag{16}$$

h_i is the bilinear hysteresis restoring force in unit stiffness k_i. The constants a_{2i}, a_{3i}, and a_{4i} in h_i may be defined as yield strength, initial stiffness, and post yield stiffness of the ith floor, respectively. Define

α and β as the ratios of post yield stiffness and yield strength to initial stiffness, namely, $\alpha_i = {a_{4i}}/{a_{3i}}$, and $\beta_i = {a_{2i}}/{a_{3i}}$. The measurement equation is written as

$$\{y\} = -\begin{Bmatrix} 1 \\ 1 \\ 1 \end{Bmatrix} \ddot{u}_g - [C]\{\dot{u}\} - \{F\} \tag{17}$$

The parameters of damping coefficients c_i and initial stiffness k_i of the i-th floor are the same as those in the MDOF linear system case. Values of α_i and β_i are assumed to be 0.6 and 0.3 for each floor. Fig. 7 shows the true acceleration measurement versus the predicted ones of the top floor. The error index 0.01438% in this case. Again, the predicted response coincides with the measured one and the strategy is proved to be quite efficient in this case, too.

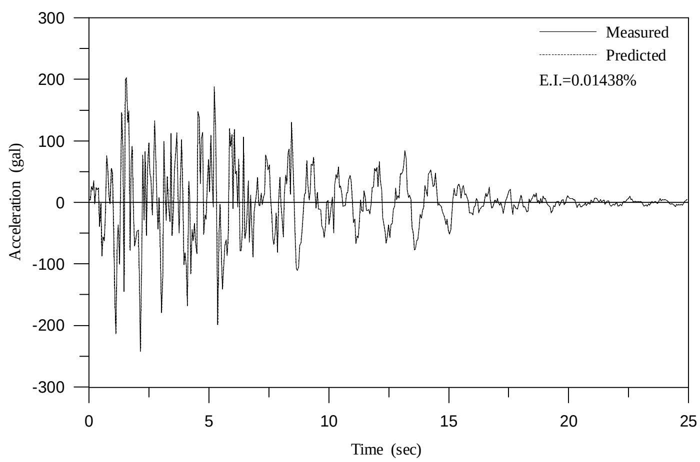

Fig. 7 Comparison of the measured response with the identified one of the MDOF nonlinear system

CONCLUSIONS

Calculus-based methods usually assume a smooth search space, and most of them use the gradient-following technique. A GA is different from conventional optimization methods in several ways. The GA is a parallel and global search technique that searches multiple points, so it is more likely to obtain a global solution. Due to the way the GA explores the region of interest it avoids getting stuck at a particular local minimum and locates the global minimum. Structural identification is a very challenging task form the computational point of view. An efficient GA identification strategy has been proposed and applied to the simulated input/output measurements of SDOF linear and nonlinear dynamic systems as well as MDOF linear and nonlinear dynamic systems. 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 propose strategy to structural dynamic parameter identification is proved. Moreover, the strategy is also shown to be not sensitive to the noise contamination. This assures the feasibility of future application to the measurements of real systems.

In summary, the proposed GA identification provides 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. The identification accuracy is assured when the noise is present. Therefore, the proposed GA strategy is demonstrated to fulfill the requirement of good identification method.

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