STRUCTURAL PARAMETERS IDENTIFICATION BASED ON DIFFERENTIAL EVOLUTION AND PARTICLE SWARM OPTIMIZATION

Wang Yanwei*
MEE08167

Supervisor : Xue Songtao**
Tang Hesheng***

ABSTRACT

Civil structures always suffer many kinds of damage caused by long use, strong wind, earthquakes, and so on, therefore it is very important to detect the damage of structures in advance. The basic theory of damage is that the changes of the dynamic parameters, such as stiffnesses, of structures are caused by damage. So the structural parameters identification becomes a key method of damage detection. Based on the research of previous researchers, this thesis uses Differential Evolution (DE) and Particle Swarm Optimization (PSO) to identify the structural parameters. The two methods belong to optimization method and minimize the mean square error function of the accelerations of numerical model and the identified system to identify parameters. In order to confirm the efficiency and validity of them, a simulation with several cases is performed. The results show that both DE and PSO can identify structural parameters very well in simulation.

Keywords: Structural parameters identification, Differential evolution, Particle swarm optimization.

1. INTRODUCTION

Structural parameters identification is a method that obtains the dynamics parameters of a structure based on physical measurements and mathematical analysis. It is an active field of research in the civil engineering, driven by the need of structure health monitoring (SHM). Since P. Cawley and R.D. Adams (1979) used natural frequency to detect damage, the technologies of structural parameters identification based on vibration measurements have a tremendous development. These technologies are currently becoming increasingly common. Hoshiya M. and Saito E. (1984) used the Extended Kalman Filter to identify the structural stiffnesses. Sato T. and Qi K. (1988) used $H\infty$ filter to identify the structural stiffnesses. Particle filtering was also successful to identify stiffnesses by Li S et al (2004) and Tang H et al (2005). Differential Evolution (DE) and Particle Swarm Optimization (PSO) appeared in 1990s, as novel optimization algorithms, they have greater advantage than traditional algorithms, and which developed rapidly and were successfully applied in many fields. H. Tang (2007, 2008) used the both algorithms to identify masses, stiffnesses and damping ratios and concluded that the two methods converged fast and had high accuracy. To confirm the performances of the two methods, this thesis attempts to use DE and PSO to identify the stiffnesses and damping ratios of Multi-Degree-Of-Freedom (MDOF) system with several cases.

2. BASIC THEORY OF IDENTIFICATION

* Institute of Engineering Mechanics (IEM), China Earthquake Administration (CEA).
** Department of Architecture, School of Science and Engineering, Kinki University, Japan.
***Research Institute of Structural Engineering & Disaster Reduction, Tongji University, China

Because most of the buildings belong to MDOF system, MDOF system should be used to discuss. The dynamic function of MDOF is equation (1).

$$M\ddot{x} + C\dot{x} + Kx = -M\ddot{u}_g \tag{1}$$

Where *M* is the mass matrix, *K* is the stiffness matrix, *C* is the damping matrix, *x* is the displacement vector, and $\ddot{u}_g$ is the acceleration of earthquake.

It can be said that the responses of MDOF system can be determined by *M*, *K* and the damping ratio ζ, so the identification work of *K* and ζ becomes to find a MDOF system whose outputs are the same as the identified system's under the same M and inputs. Therefore, we can define the mean square error function as equation (2).

$$F(\theta) = \frac{1}{N}\sum_{k=1}^{N}\left\|\ddot{x}(k) - \hat{\ddot{x}}(k)\right\|^2 \tag{2}$$

Where $\theta = [k_1, k_2, \dots, k_d, \zeta_1, \zeta_2]$ (*d* is degree of freedom) is the solution vector, $\ddot{x}(k)$ is the acceleration of numerical model calculated by Newmark integration method(β=1/4), and $\hat{\ddot{x}}(k)$ is measured from the unknown system. When $F(\theta)$ is the minimum, the values of θ are the stiffnesses and damping ratios of the identified system.

Then the parameters identification becomes the problem of finding the minimum of $F(\theta)$, so it is a problem of optimization. θ is the solution vector and $F(\theta)$ is used as the fitness function, DE and PSO both can do the search work directly.

3. SIMULATION

3.1 The numerical mode

A 5 stories mass lumped model (5 DOF system) is chosen as the numerical mode, as shown in the Figure 1. The masses and stiffnesses of the 5 DOF system are list in Table 1, the first mode damping ratio ζ_1 is 0.02 and the second mode ratio ζ_2 is 0.04.

Table 1. Masses and stiffnesses of the 5 DOF system

Story (i)	k_i (N/m)	m_i (kg)
1	60	30
2	55	25
3	50	20
4	45	15
5	40	10

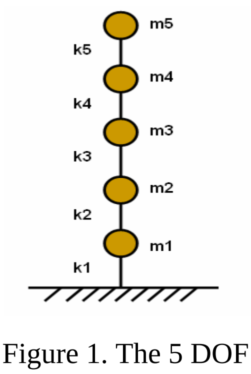


Figure 1. The 5 DOF system.

An earthquake record, El-centro, is the input of the 5 DOF system, whose sampling rate is 50Hz and duration is about 53 seconds. The Newmark integration method(β =1/4) is used to calculate the system's outputs which consist of the acceleration of each story. The interval of the response calculation is 0.02 second.

In order to check the abilities of identification of DE and PSO, three cases are used in the simulation:

Case 1, the outputs don't have noise;
Case 2, the outputs polluted by different levels of noise;
Case 3, the stiffness of each story is changed at 11th second during the vibration.

In case 2, suppose that the noise is White Gaussian Noise (WGN) and different levels of noise are added into the output. The level of noise is defined as equation (3).

$$L = \frac{\sigma_w}{\sigma_r} \times 100\% \qquad (3)$$

Where L is the level of noise, σ_w is the standard deviation of WGN and σ_r is the standard deviation of acceleration record. There are five levels: 5%, 10%, 15%, 20%, 25%, and 30%.

Table 2. All Stiffness change at 11th second.

Stroy	k (N/m) before 11th sec	k (N/m)after 11th sec
1st	60	45
2nd	55	48
3rd	50	46
4th	45	40
5th	40	35

In case 3, the masses and damping ratios of the 5 DOF system keep constant during vibration, but all the stiffnesses are changed at 11 th second. Because the reducing of stiffnesses is caused by damage, we can reduce the stiffnesses to simulate damage. At at 11th second, the damage of each story happens, as shown in the Table 2.

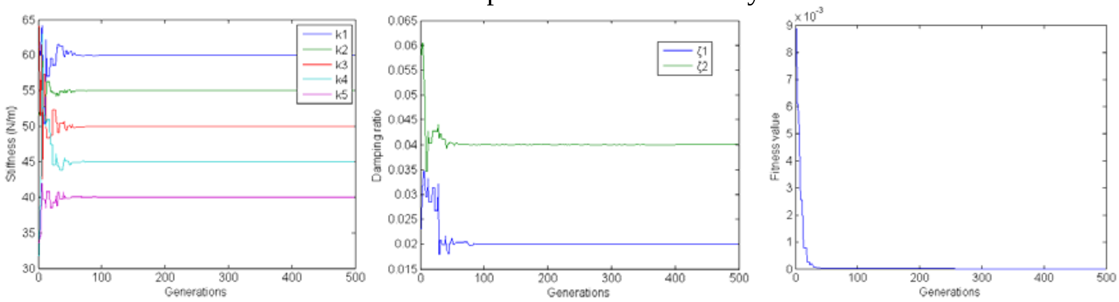
Now suppose that the stiffnesses and damping ratios of the 5 DOF system are unknown in three cases, the identification work of these parameters is just based on the masses, the input and outputs, the error of each parameter identified by DE and PSO is defined as equation (4).

$$error = \left| \frac{(real\ value) - (identified\ value)}{real\ value} \right| \times 100\% \qquad (4)$$

3.2 Identification via DE

To use DE to identify the above 5 DOF model, some initial work must be done firstly. The settings of the control parameters are: the size of population *NP*=50, the maximum number of generations *G*=500, the weighting factor *F*=0.8, the crossover probability *C*r=0.9, and the search range b_L=0.5*$[k_1, k_2, k_3, k_4, k_5, \zeta_1, \zeta_2]$ and b_U =2*$[k_1, k_2, k_3, k_4, k_5, \zeta_1, \zeta_2]$.

In case 1, Figure 2 shows the procedure of parameter identification of DE, from which we can see that the solution vector converges very fast and the fitness value almost equals 0 after its stabilization. It means that DE identified the parameters without any error.



(a) The stiffnesses (b) The damping ratios (c) The fitness function

Figure 2. The procedure of DE in case 1.

In case 2, we just give the errors (eq. (4)) of the results in Table 3. The stiffnesses can be correctly identified by DE even the outputs are polluted by 30% noise, but damping ratios have large errors as the increasing of noise level.

Table 3. The error of each parameter identified by DE under different noise levels

DE							
Noise	k1 error(%)	k2 error(%)	k3 error(%)	k4 error(%)	k5 error(%)	ζ 1 error(%)	ζ 2 error(%)
10%	0.3405	0.404	0.001	1.132	0.4965	10	2.5
15%	1.134333	1.150364	0.002496	0.488889	0.472	20	6.75
20%	1.412667	1.510364	0.023166	0.144444	0.32	5.5	0.5
25%	3.258833	2.706909	0.029128	0.669556	2.755	48	2.5
30%	3.395	0.663818	0.027372	0.594444	1.45475	39.5	1

In case 3, because the stiffnesses changed during the vibration and we didn't know when the change happened, the identification work of DE was repeated every 5 seconds. During the procedure of identification, the accelerations of every potential solution vector were calculated by the Newmark integration method(β=1/4), so DE needed the displacements and velocities of each 5 seconds to initialize the Newmark method. From Table 4, we can see that DE can identify correctly the stiffnesses even the stiffnesses change or damage happens during the vibration, but the damping ratios can't be identified correctly.

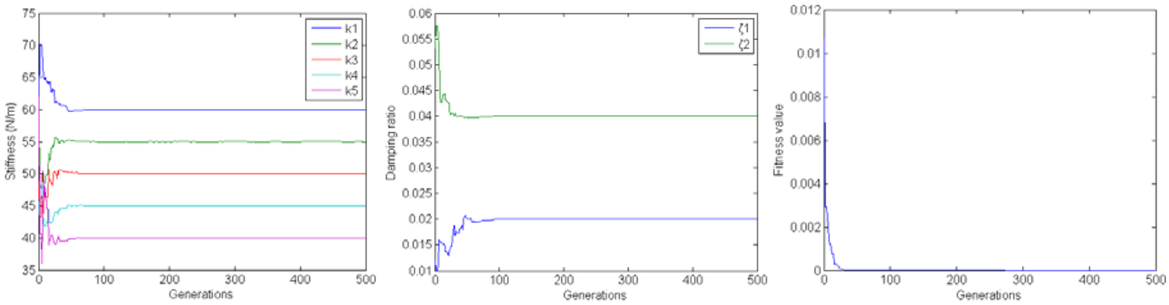
Table 4. The stiffnesses and damping ratios idenfified by DE in case 3.

Time(sec)	k_1	k_2	k_3	k_4	k_5	ζ_1	ζ_2
0-5	59.9939	54.922	50.187	45.637	40.4877	0.0215	0.0411
5-10	59.6737	54.7686	50.0317	44.9618	39.9694	0.0266	0.0419
10-15	47.64	52.9184	47.8865	40.7562	36.663	0.02	0.0436
15-20	44.5535	48.0386	45.8191	40.1513	35.0253	0.0312	0.0425
20-25	46.8932	47.1476	45.5701	39.5993	34.9329	0.0176	0.0425
25-30	44.5813	47.4439	45.8807	39.7995	34.8804	0.0257	0.0415
30-35	44.8205	47.6999	46.3446	40.022	35.0047	0.0205	0.04
35-40	44.9988	48.142	46.0594	40.1193	35.0967	0.0225	0.0402
40-45	44.8462	48.118	46.0672	39.9862	34.9729	0.0219	0.0402
45-53	45.1769	48.3868	45.8995	39.8307	34.9893	0.0176	0.0398

3.3 Identification via PSO

The identification procedure of PSO is similar to that of DE, and some initial work must be done firstly. The settings of the control parameters are: the size of swarm N=50, the maximum number of iterations G=500, the inertia weight ω=0.8, acceleration coefficients c_1=c_2=2, the search range (x_{max} -x_{min}) is $\left(2*[k_1,k_2,k_3,k_4,k_5,\zeta_1,\zeta_2],0.5*[k_1,k_2,k_3,k_4,k_5,\zeta_1,\zeta_2]\right)$ and the max velocity is v_{max}=0.4*(x_{max} -x_{min}).

In case 1, the results of PSO are almost the same as DE's, from Figure 3 shows the procedure of parameter identification of PSO, from which we can see that the solution vector converges very fast and the fitness value almost equals 0 after its stabilization. It means that PSO identified the parameters without any error.



(a) The stiffnesses (b) The damping ratios (c) The fitness function

Figure 3. The procedure of PSO in case 1.

In case 2, the errors (eq. (4)) of each identified parameter in different noise level are listed in Table 5, from which we find that the damping ratios can not be identified correctly as noise level increasing, but PSO has a good ability to identify stiffnesses even the output polluted by 30% noise.

Table 5. The error of each parameter identified by PSO under different noise levels

PSO							
Noise	k1 error(%)	k2 error(%)	k3 error(%)	k4 error(%)	k5 error(%)	ζ 1 error(%)	ζ 2 error(%)
10%	0.757667	0.850909	0.022612	0.712	0.01875	4.5	0.5
15%	1.0955	1.264364	0.034262	1.038222	0.0095	7.5	1
20%	2.609	2.184182	0.02341	0.530444	2.19475	38	2
25%	1.9975	1.049455	0.024906	4.591333	1.77	50	5.25
30%	1.948667	2.452	0.070764	1.883333	0.0745	16	1.75

In case 3, PSO gave a result of every parameter in each 5 seconds, and the displacements and velocities of each 5 seconds were both used as initial values of Newmark integration method(β =1/4). From Table 6, we can see that PSO can identify correctly the stiffnesses when the stiffnesses change or damage happens, but the damping ratios can't be identified correctly.

Table 6. The stiffnesses and damping ratios idenfified by PSO in case 3.

Time(sec)	k_1	k_2	k_3	k_4	k_5	ζ_1	ζ_2
0-5	59.9939	54.922	50.187	45.637	40.4877	0.0215	0.0411
5-10	59.6737	54.7686	50.0317	44.9618	39.9694	0.0266	0.0419
10-15	47.64	52.9184	47.8865	40.7562	36.663	0.02	0.0436
15-20	44.5535	48.0386	45.8191	40.1513	35.0253	0.0312	0.0425
20-25	46.8932	47.1476	45.5701	39.5993	34.9329	0.0176	0.0425
25-30	44.5813	47.4439	45.8807	39.7995	34.8804	0.0257	0.0415
30-35	44.8205	47.6999	46.3446	40.022	35.0047	0.0205	0.04
35-40	44.9988	48.142	46.0594	40.1193	35.0967	0.0225	0.0402
40-45	44.8462	48.118	46.0672	39.9862	34.9729	0.0219	0.0402
45-53	45.1769	48.3868	45.8995	39.8307	34.9893	0.0176	0.0398

4. CONCLUSIONS

In this thesis, the basic theories of structural parameters identification of MDOF system were introduced firstly, and then DE and PSO were used to identify the siffnesses and damping ratios of a 5 DOF system. From the simulant results, some conclusions are summarized in the followings:

1) DE and PSO almost have the same performance of the structural parameters identification, such as accuracy and convergence speed.
2) Both DE and PSO can identify the stiffnesses and damping ratios correctly when the outputs have no noise and the parameters are constant at all times;
3) When the outputs are polluted by noise, DE and PSO both can identify the stiffnesses with high accuracy, but both of them can not identify damping ratios. It means that DE and PSO have the anti-noise abilities for stiffnesses;
4) When the stiffeness changes during vibration, the stiffnesses can be identified by DE and PSO with very small errors, but the damping ratios can not be identified by them. It means that DE and PSO have the abilities of damage detection;

5. RECOMMENDATION

We believe that this thesis contains useful contributions to the structural parameters identification. Although DE and PSO can identify the parameters of MDOF system in simulation, it is difficult to say they can be used to identify a real build successfully. Therefore the future research is certainly needed to use real buildings to confirm the performances of the two methods.

AKNOWLEDGEMENT

I would like to deeply appreciate my adviser Prof. Toshihide Kashima for his guidance, support and encouragement.

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