Structural Damage Detection by Multi-objective Intelligent Algorithm

Y.W. Wang, Q. Ma & W. Li
Institute of Engineering Mechanics, China Earthquake Administration, China

SUMMARY:
In order to solve the optimization problem of damage detection, a new multi-objective function defined by natural frequencies and accumulative modal assurance criterion (MAC) is proposed, and non-dominated sorting genetic algorithm II (NSGA-II), multi-objective differential evolution optimization (DEMO) and multi-objective particle swarm optimization (CMOPSO) are used for the numerical simulation of damage detection. The results show that the combination of the new multi-objective function and DEMO algorithm has the highest calculation accuracy and efficiency.

Keywords: Structural damage detection, multi-objective function, multi-objective intelligent optimization

1. INTRODUCTION

Damage detection of structures has been developed in the last few decades, is mainly used for structural health monitoring (SHM). Traditional damage detection methods are visual or localized experimental methods such as ultrasonic, acoustic and magnetic methods, x-ray methods, etc. These methods need priori knowledge of the damage distribution and the access to any part of the structure should be feasible (Goch et al., 1999). However, the efficiency of the traditional damage detection methods is reduced because structures become more complicated. In contrast with these traditional, global vibration-based methods would be more suitable for complex and large structures without priori information of the damage location. It is well known that occurrence of damage in a structure changes the characteristics of the structure, such as stiffness, frequencies, shapes and damping factors, and causes some perturbation in its dynamic responses. Global vibration-based methods are based on the detection of damage through changes of these characteristics between the damaged and undamaged state. Although the identification of modal parameters (frequencies, shape and damping factors) are used very popular, modal parameters are difficult to determine the damage position and level of large structures or slight damaged structures. Actually, the damage is the reduction of stiffness, using the changes of stiffness to detect damage is a more direct and sensitive way. Finite element (FE) model updating can be one of the most usual ways to identify the stiffness of structure (Zou et al., 2000). In FE model updating, the mass, stiffness and damping parameters of the numerical model can be defined as a objective function to measure the fit between numerical and measured data, optimization algorithms are used to search these parameters by minimizing the objective function. FE model updating has been usually been developed as single-objective optimization problem, but because of the complexity of damage detection problem in the real world, multi-objective optimization is more suitable to solve the problem than single-objective optimization. Nevertheless, relatively few studies have been reported on FE model updating, and many multi-objective intelligent optimization algorithms appear to be popular choices (Karamanos et al., 2004, Perera et al., 2010, and Perera and Fang, 2010).

In this paper, a FE model updating based on multi-objective intelligent algorithm is carried out for the purpose of damage detection. A new multi-objective function defined by natural frequencies and accumulative modal assurance criterion (MAC) is formulated. Three multi-objective intelligent algorithms, non-dominated sorting genetic algorithm II (NSGA-II), multi-objective differential evolution optimization (DEMO) and multi-objective particle swarm optimization (CMOPSO) , are introduced briefly. In order to verify the new multi-objective function and compare the performance of the three intelligent algorithms, a truss consisting of 31 elements is used for the simulation of damage detection.

2. MULTI-OBJECTIVE FUNCTION FOR DAMAGE DETECTION

In order to solve the damage detection using on FE model updating, the objective function can be defined as various forms of single-objective function with different types of measured data. Certainly, single-objective function may contain some information of structural parameters, but just one aspect, it usually needs other support to make up for the one-sidedness, such as the structure should not be too complex, the measured data should be abundant, the result should not be accurate. Due to this, multi-objective function should be a good choice.

Perera et al. (2010) give a multi-objective function consists of a single-objective function based on measured modal frequencies and a single-objective function based on mode shapes, it can be improved like the following form:

$$\begin{cases} \mathrm{F}_1(\boldsymbol{\theta}) = \dfrac{1}{M}\displaystyle\sum_{i=1}^{M} \dfrac{\left\| w_{meas,i} - w_{nume,i}(\boldsymbol{\theta}) \right\|^2}{\left\| w_{meas,i} \right\|^2} \\ \mathrm{F}_2(\boldsymbol{\theta}) = M - \displaystyle\sum_{i=1}^{M} \mathrm{MAC}_i \end{cases}, \boldsymbol{\theta} \in \{\boldsymbol{\Theta}\} \tag{2.1}$$

where

$$\mathrm{MAC}_i = \frac{\left| \{\boldsymbol{\Phi}_{meas,i}\}^T \{\boldsymbol{\Phi}_{nume,i}(\boldsymbol{\theta})\} \right|^2}{\left(\{\boldsymbol{\Phi}_{meas,i}\}^T \{\boldsymbol{\Phi}_{nume,i}(\boldsymbol{\theta})\} \right) \left(\{\boldsymbol{\Phi}_{nume,i}(\boldsymbol{\theta})\}^T \{\boldsymbol{\Phi}_{meas,i}\} \right)} \tag{2.2}$$

In equation (2.1) and (2.2),$\boldsymbol{\theta}$ is the vector of parameters (e.g. mass, stiffness, elastic modulus), $\mathrm{F}_1(\boldsymbol{\theta})$ is the single-objective function based on modal frequencies, M is the order of measured modal data, $\omega_{meas,i}$ is the measured frequency, $\omega_{nume,i}$ is the calculated frequency from numerical model, $\mathrm{F}_2(\boldsymbol{\theta})$ is the single-objective function based on mode shapes, MAC_i is modal assurance criterion, $\boldsymbol{\Phi}_{i,meas}$ is the measured mode shape, and $\{\boldsymbol{\Theta}\}$ is the search range contains the bounds of each parameter. The optimal result of multi-objective function is different from single-objective function, and it is usually of a set of optimal solutions and called Pareto optimal solutions. A Pareto optimal solution is defined as follows:

Definition 1: Pareto dominance. The vector $\bar{\mathbf{x}} = [\bar{x}_1, \ldots, \bar{x}_k]$ dominates vector $\tilde{\mathbf{x}} = [\tilde{x}_1, \ldots, \tilde{x}_k]$, denoted by $\bar{\mathbf{x}} \prec \tilde{\mathbf{x}}$, $\mathit{iff}\, \forall i \in \{1, \ldots, k\}, \bar{x}_i \le \tilde{x}_i, \exists i \in \{1, \ldots, k\} : \bar{x}_i \le \tilde{x}_i$.

Definition 2: Pareto optimality. $\mathbf{x}^* \in \chi$ is said to be Pareto solution if and only if $\nexists \mathbf{x} \in \chi$ satisfies $\mathrm{Z}(\mathbf{x}) \prec \mathrm{Z}(\mathbf{x}^*)$.

Definition 3: Pareto optimal Set. $\chi^* := \left\{ \mathbf{x}^* \middle| \mathbf{x}^* \in \chi, \nexists \mathbf{x} \in \chi : \mathrm{Z}(\mathbf{x}) \prec \mathrm{Z}(\mathbf{x}^*) \right\}$.

Definition 4: Pareto front. $\bar{\chi}^* := \left\{ \mathbf{x} \middle| \mathbf{x} = \mathrm{Z}(\mathbf{x}), \mathbf{x} \in \chi^* \right\}$

The optimal result of Eq. (2.1) is Pareto optimal front consists of many Pareto optimality solutions, and the final result for damage detection is one Pareto optimality solution which has the minimum the sum of the squares of $\mathrm{F}_1(\boldsymbol{\theta})$ and $\mathrm{F}_2(\boldsymbol{\theta})$.

2.1. NSGA-II

The non-dominated sorting genetic algorithm (NSGA) is proposed by Srinivas and Deb (1995) and has been a popular non-domination based genetic algorithm for multi-objective optimization. NSGA is a very effective algorithm but has been generally criticized for its computational complexity, lack of elitism approach and dependency of sharing parameter. In order to improve NSGA, Samir et al. (2000) proposed NSGA-II which alleviates all the disadvantages of NSGA. NSGA-II uses rapid non-dominated sorting, crowding distance comparison and elitism approach to reduce computational complexity from $O(mN^3)$ to $O(mN^2)$ (where m is the number of objectives and N is the population size), ensure the homogeneous distribution and diversity of Pareto front individuals and keep advantageous individuals. NSGA-II has been applied widely to solve many optimization problems and become a classic.

2.2. DEMO

Differential evolution (DE) algorithm (Storn and Price, 1995) is a heuristic approach that has a great ability to solve complex optimization and converges faster and with more certainty than many other acclaimed global optimization methods. These advantages of DE make it attractive to extend it to solve multi-objective optimization problems. DE for multi-objective optimization (DEMO) proposed by Tea and Bogdan (2005) combines the advantages of DE with the mechanisms of Pareto dominance and crowding distance sorting. In DEMO, the newly created good candidates immediately take part in the creation of the subsequent candidates, this enables fast convergence to the true Pareto front, and while the use of nondominated sorting and crowding distance metric in truncation of the extended population promotes the uniform spread of solution.

2.3. CMOPSO

Particle swarm optimization (PSO) is an evolution computation technique developed by Kennedy and Eberhart (1995), inspired by social behavior of bird flocking or fish schooling. PSO is simple in concept and easily implemented, it has been successfully used to solve many single-objective optimization problems and shown to have high performance and flexibility. The advantages of PSO have made it to be extended for multi-objective optimization, and such extended PSO is referred as multi-objective particle swarm optimization (MOPSO). Many of MOPSO methods have been proposed in the literature, and the MOPSO developed by Coello and Lechuga (2002) is one of the earliest MOPSO and considered as a milestone. This MOPSO is marked as CMOPSO to differentiate MOPSO. CMOPSO uses Pareto dominance to determine the flight direction of a particle and maintains previously found nondominated vectors in a global repository that is later used by other particles to guide their own flight.

3. NUMERICAL EXAMPLE

A numerical example is a truss-type structure, which contains 31 truss elements, 17 nodes and 30 nodal DOFs as shown in Fig.1. Values of the material and geometric properties are as follows: the elastic modulus E=2.06E+11 Pa; the cross-sectional area A= 0.01m^2; the mass density ρ=7.85E+03 kg/m^3; the length of each bay l=1.00m. The measured data is three lowest vibration modes calculated by using finite element method. The reduction of elastic modulus is used to represent the damage, the reduction ratio of elastic modulus represents the damage level, and the element number represents the damage position. Assuming the elements 2, 4, 6, 11, 22 and 28 are damaged with reduction ration 0.1, 0.2, 0.3, 0.4, 0.5 and 0.6.

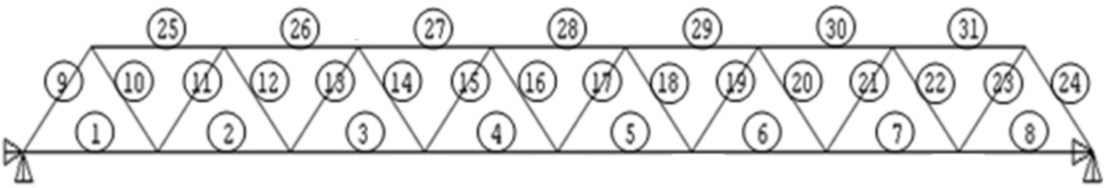

Figure 1. 31 elements truss structure for damage detection simulation

The numerical example is used to check the performance of the NSGAII, DEMO and CMOPSO with multi-objective function Eq. (2.1). Each algorithm is executed 5 times and chooses the best result, and the control parameter settings are shown in Table 3.1.

Table 3.1. Control parameter settings of each intelligent algorithm

Algorithm	Control parameters
NSGAII	*NP*=50; *Pc*=0.7; *Pm*=0.08; searching range=[0,1]
DEMO	*NP*=50; *F*=0.5; *Cr*=0.9; searching range =[0,1]
CMOPSO	*NP*=50; *w*=0.8; *c1*= *c2* =2; *Ncube*=200; searching(velocity) range =[0,1]

In Table 3.1, the control parameter settings, NSGAII referring GA (YU Youming et al., 2006): *NP* is population (total number of individuals) size and is usually set to 1.5 times of the size of the parameters vector, *Pc* is crossover factor and is usually set to [0.4,0.9], and *Pm* is mutation factor and is suggested to set [0.0001,3]; DEMO (Rönkkönen et al., 2005): *NP* should be set from 2 times to 40 times dimension of parameters, *F* is mutation factor should be [0.4,0.95], and *Cr* is crossover factor [0.9,1]; CMOPSO referring PSO: *NP* is usually set from 20 to 80, *w* is the inertia weight should be set 0.8 (Eberhart and Shi 2000), *c1* and *c2* are the acceleration coefficients and *c1* = *c2* =2 suggested by Cralisle and Dozier (2001), and *Ncube* is the number of hypercubes should be set 30-50.

Fig. 2, Fig. 3, and Fig. 4 show the results obtained by NSGAII, DEMO and CMOPSO respectively, from these figures, it can be seen that the Pareto front obtained by DEMO has the smallest values of both F1 and F2 of Eq. (2.1) and the reduction factor of the modulus elastic of each element identified by DEMO perfectly match the assuming damage. The Pareto front and the reduction factor obtained by NSGAII and CMOPSO have too large errors to detect the damage of the structure.

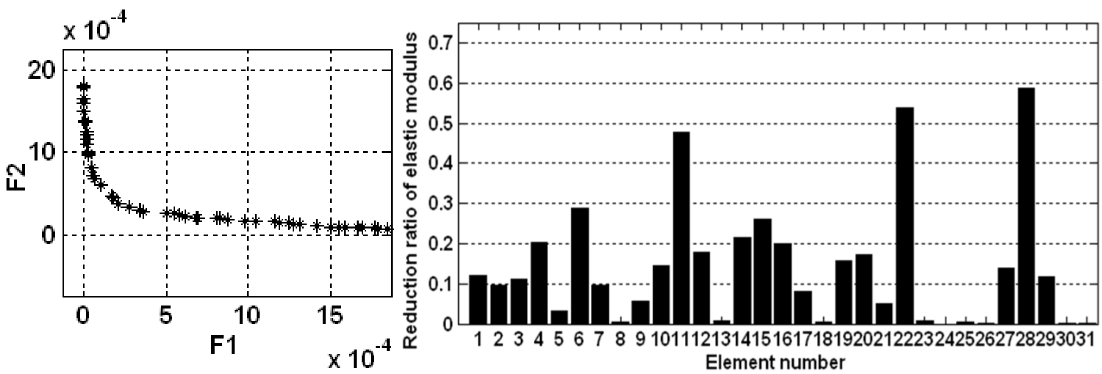

Figure 2. Pareto front and reduction ratio obtained by NSGAII

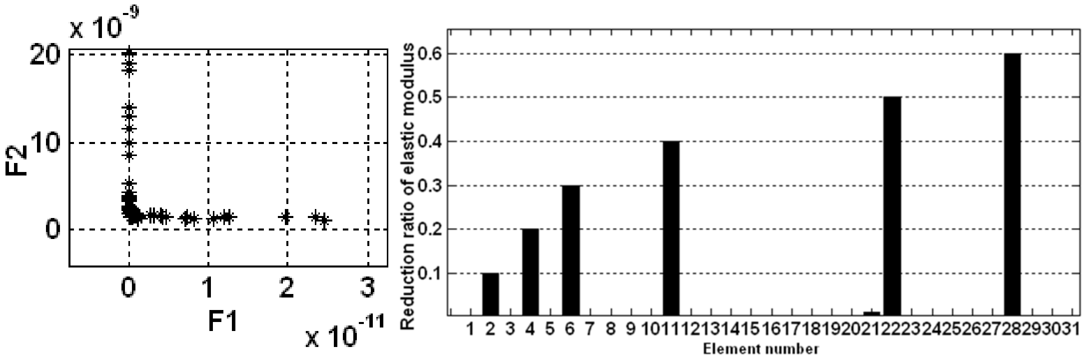

Figure 3. Pareto front and reduction ratio obtained by DEMO

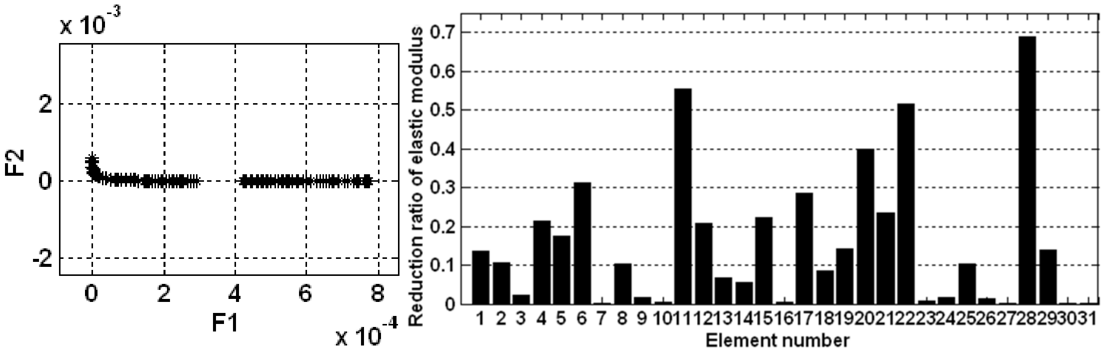

Figure 4. Pareto front and reduction ratio obtained by CMOPSO

4. CONCLUSION

In order to solve the optimization problem of damage detection based on finite element (FE) model updating, a new multi-objective function defined by natural frequencies and accumulative modal assurance criterion (MAC) is proposed, and non-dominated sorting genetic algorithm II (NSGA-II), multi-objective differential evolution optimization (DEMO), and multi-objective particle swarm optimization (CMOPSO) are introduced briefly. A numerical simulation of truss structure shows that by optimizing the new multi-objective function DEMO identified the assuming damage position and level accurately, and NSGA-II and CMOPSO failed. The numerical results demonstrate that using the proposed multi-objective function and DEMO to detect structural damage is effectual.

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