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Structural Damage Detection Using Modal Strain Energy and Hybrid Multiobjective Optimization

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Abstract: *Modal strain energy (MSE) is a sensitive physical property that can be utilized as a damage index in structural health monitoring. Inverse problem solving-based approaches using single-objective optimization algorithms are also a promising damage identification method. However, the research into the integration of these methods is currently limited; only partial success in the detection of structural damage with high errors has been reported. The majority of previous research was focused on detecting damage in simply supported beams or plain structures. In this study, a novel damage detection approach using hybrid multiobjective optimization algorithms based on MSE is proposed to detect damages in various three-dimensional (3-D) steel structures. Minor damages have little effect on the difference of the modal properties of the structure, and thus such damages with multiple locations in a structure are difficult to detect using traditional damage detection methods based on modal properties. Various minor damage scenarios are created for the 3-D structures to investigate the newly proposed multiobjective approach. The proposed hybrid multiobjective genetic algorithm detects the exact locations and extents of the induced minor damages in the structure. Even though it uses incomplete mode shapes, which do not have any measured information at the damaged element, the proposed approach detects damage well. The robustness of the proposed method is investigated by adding 5% Gaussian random white noise as a noise effect to mode shapes, which are used in the calculation of MSE.*

1 INTRODUCTION

With the increasing number of aging infrastructure, monitoring of existing structures as a basis of the assessment of structural safety is becoming critically important. Ensuring structural integrity is one of the main objectives in health monitoring of civil structures. Assessment of structural safety in practice generally depends on the engineering judgment of experts by visual inspections. However, visual inspections may be costly or inefficient, and the safety rating assigned by trained inspectors may be varied (Moore et al., 2001). Thus, damage detection methods using modal properties such as natural frequencies and mode shapes, which can be obtained from sensors placed on the structure, have been widely discussed in order to assess structural integrity. When a finite element model is available, one can compare the measured experimental data, with the predicted data from the model. Calculating model properties such as mass and stiffness from the measurement data on frequencies or mode shapes is an inverse problem, and the solution of which would permit quantification and localization of the damage. Thus, current status of the structures can be estimated by using an inverse problem solving approach based on initial design. In this article, in order to detect minor damage in multiple locations a new damage detection method is proposed using modal strain energy (MSE) as a damage

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index and hybrid multiobjective genetic algorithms (GAs) to solve inverse problems for three-dimensional (3-D) structures.

Modal properties such as natural frequency, mode shape, mode shape curvature, or MSE are useful and easier indices for modal updating than damage indices that can only be calculated from time series, which take longer time than eigenvalue analysis. The MSE has been considered as a damage index because it is more sensitive to damages in structures than pure mode shapes and can provide detailed information with respect to the extent and location of the structural damage. Petro et al. (1997) showed that strain energy-based damage detection was more sensitive than other mode shape-based approaches in the experimental aluminum plate cantilever-type structure. Carrasco et al. (1997) also applied a strain energy-based method to detect multiple damages in a space truss model, but the method detected mostly severe damage cases while some of the less severe cases went undetected. Shi et al. (1998) proposed MSE-based damage detection for a planar structure to localize single and multiple damage scenarios. Shi et al. (2000) also proposed a damage quantification method using differences in the MSE for the simple two-story plain structure. The results were partially successful in quantification of the structural damage in a multiple damage case with errors. Sazonov and Klinkhachorn (2005) carried out analyses to determine the optimal sampling interval in order to minimize the effects of measurement noise and truncation errors on the calculation of the strain energy of mode shapes and to maximize accuracy of damage localization and level. Yan et al. (2010) proposed an efficient algebraic algorithm of element MSE sensitivity to detect damage location and severity. However, the approaches cited have limitations in localizing and identifying the extent of multiple damages sometimes with high errors, predicting damages in actually undamaged structural elements.

GAs have been also used to optimize structural systems and detect structural damage in terms of model updating (Adeli and Cheng, 1993, 1994; Adeli and Kumar, 1995; Sarma and Adeli, 2000, 2001; Kim and Adeli, 2001; Hejazi et al., 2013). Friswell et al. (1998) used a GA to find damages in a simple beam using modal assurance criterion (MAC) of frequencies and mode shapes. Chou and Ghaboussi (2001) used a GA to solve inverse problems to detect the existence, location, and extent of damages in a plane truss structure. The measured and calculated static displacements were used as a damage index. Au et al. (2003) proposed a two-level micro-GA to detect multiple damages in a single-span simply supported beam and a three-span continuous beam. From the study, the multiple damages were well localized but the extent of damages was not detected well. He and Hwang (2006) used displacements of the structures as a damage index using a simulated annealing integrated GA for a simple cantilever beam and a clamped beam. Raich and Liszkai (2007) used implicit redundant representation (IRR) GA to detect damage using a frequency response function (FRF)-based damage index for simple 2-D structures. They compared the performance of the IRR GA to generic simple GAs to detect the structural damage using the same damage index. It is worth noting that IRR GA's performance is superior to other generic GAs. Wang et al. (2012) used correlation-based methods to facilitate damage determination for through-truss bridge structures using multilayer GA. The structure's elements, which were suspected to be damaged, were divided into several groups from the first layer of the GA. The groups were combined to larger groups and the optimization started over at the normalized point of the first layer result. However, this multilayer GA-based approach required some assumptions between first layer and second layer analyses of the GA. This means that if the user chooses an incorrect group location of the damage-suspicious elements, the damages may be assigned to the wrong locations. Meruane and Heylen (2010) used the difference between modes of the damaged and intact structures represented by the MAC for an airplane subjected to three increasing levels of damage and a multiple-cracked reinforced concrete beam. Nobahari and Seyedpoor (2011) used a modified GA (MGA), including two new operators, in which the health operator and simulator operator were used. An efficient correlation-based index (ECBI) in terms of the natural frequencies was used as the damage index. The suggested MGA with ECBI detected multiple damages in a simple cantilever beam but with errors in assessment of the damage levels. Perera et al. (2007) used MAC as damage index and niched Pareto GA proposed by Horn et al. (1994) for a simple experimental beam. Jung et al. (2010) used static measurements as damage index and multiobjective optimization as a search method for a 2-D simple truss structure. Marano et al. (2011) proposed a modified single-objective GA to identify a 2-D structural system subjected to dynamic loads. Fuggini et al. (2013) carried out system identification of retrofitting textile using inverse problem solving based on GAs. Raich and Liszkai (2012) proposed a multiobjective optimization approach that minimizes the number of sensors specified while maximizing the sensitivity of the FRFs collected at each specified sensor location with respect to all possible damaged structural elements. Other damage detection methodologies for infrastructure applications have also been proposed (Qiao et al., 2012; Osornio-Rios et al., 2012; Khelifa and Guessasma, 2013; O'Byrne et al., 2013). In most of these studies cited, single-objective GAs have been applied to detect structural damages, and these approaches were applied to simple cantilever beam or 2-D structures.

The above-mentioned literature review shows that the single-objective GAs have been applied primarily to 2-D structures in determining damages, and there is limited research with respect to 3-D structures (Jiang and Adeli, 2005, 2007). Moreover, to date, there has been little research regarding multiobjective formulations to explore structural damages for 3-D civil structures. In particular, there is little study of GA-based multiobjective optimal formulations for minimizing errors of damage indices between actual damaged structures and damage simulated structures. In this article, in order to remove the defects of the single-objective GA-based approaches, multiobjective GAs are proposed to detect multiple damages in various 3-D structures. Thus, this article is focused on comparison between single- and multiobjective optimization approaches without considering non-GA-based approaches. To demonstrate the effectiveness of the proposed approach, multiobjective optimization problems are formulated in terms of two objective functions. The two objective functions are formulated by considering different mode shapes to calculate MSE. Minor damages do not significantly affect changes in the governing structural mode shapes, and thus such damage with multiple locations in a structure are difficult to detect using traditional damage detection methods based on modal properties. The efficacy of the proposed multiobjective optimization-based damage detection method for detecting minor damages is evaluated using simulations of three different 3-D steel frame structures with various minor damage scenarios. Furthermore, effects of incomplete mode shapes missing any measured information on the damaged structural element are investigated in the calculation of MSE.

2 STRAIN ENERGY-BASED DAMAGE INDEX

It has been shown that the strain energy-based damage index is more sensitive to damages than the modal property-based damage index (Shi et al., 1998; Sazonov and Klinkhachorn, 2005; Wang et al., 2012). Thus, here we formulate an MSE term as a damage index to detect damages in three different 3-D steel frame structures using advanced multiobjective GAs to solve the inverse problem. The elemental MSE is defined as the product of the elemental stiffness matrix and the second power of the mode shape component. For the ith mode and the jth element, the MSE before and after occurrence of damage is given as

$$MSE_{ij}^{s} = \Phi_i^{sT}\mathbf{K}_j\Phi_i^{s} \tag{1}$$

$$MSE_{ij}^{d} = \Phi_i^{dT}\mathbf{K}_j\Phi_i^{d} \tag{2}$$

where MSE_{ij}^{s} and MSE_{ij}^{d} are damage-simulated and damage-induced MSE of the jth element for the ith mode shape, respectively, and Φ_i^{s} and Φ_i^{d} are ith mode shapes of the damage-simulated and damage-induced structures, respectively. To approximate MSE_{ij}^{d}, the undamaged elemental stiffness matrix $\mathbf{K}_j$, in which global coordinates are used for each elemental stiffness matrix, is used instead of the damaged one, because the damaged elements are not known. The difference of the modal strain energy (MSEC) of the ith mode for the jth element is obtained from the mode shapes as

$$MSEC_{ij} = \Phi_i^{dT}\mathbf{K}_j\Phi_i^{d} - \Phi_i^{sT}\mathbf{K}_j\Phi_i^{s} \tag{3}$$

where i and j denote the mode number and element number, respectively. Thus, the total energy difference of the MSE between the damage-induced structure and damage-simulated structure is expressed as

$$\text{Total difference of MSE} = \sum_{i=1}^{ms}\sum_{j=1}^{el}\left|\Phi_i^{dT}\mathbf{K}_j\Phi_i^{d} - \Phi_i^{sT}\mathbf{K}_j\Phi_i^{s}\right| \tag{4}$$

where ms and el denote the total number of mode shapes and the total number of elements of a structure considered, respectively. Structural damages can be represented as a reduction in the structural stiffness (Barroso and Rodriguez, 2004; Van Houten et al., 1999). The reduction of stiffness may not represent all types of damages in civil structures and hence the use of this approach may be considered as a limitation of this work. Nevertheless, the method would be applicable to possible linear types of damage such as reduction of stiffness due to bolt loosening, corrosion, and cracking due to cyclic loadings. In any case, for computational purposes it is appropriate to express degradation as a reduction of stiffness for the present work. Consequently, in order to simulate damages at any element of the structure, the Young's modulus of each element is reduced from the original value using the following formulation:

$$E_j^{s} = (1-\alpha_j)E_j^{o} \tag{5}$$

where E_j^{o} is the Young's modulus of elasticity of the intact structural element, E_j^{s} is the Young's modulus of elasticity of jth damage-simulated element, and $\alpha_j$is a percentage of the reduction of the Young's modulus at the jth element of the structure. Thus, reduction of the Young's modulus in the entire structure is expressed as

$$\alpha = \left(\alpha_1\ \alpha_2\ \ldots\ \alpha_{el}\right) \tag{6}$$

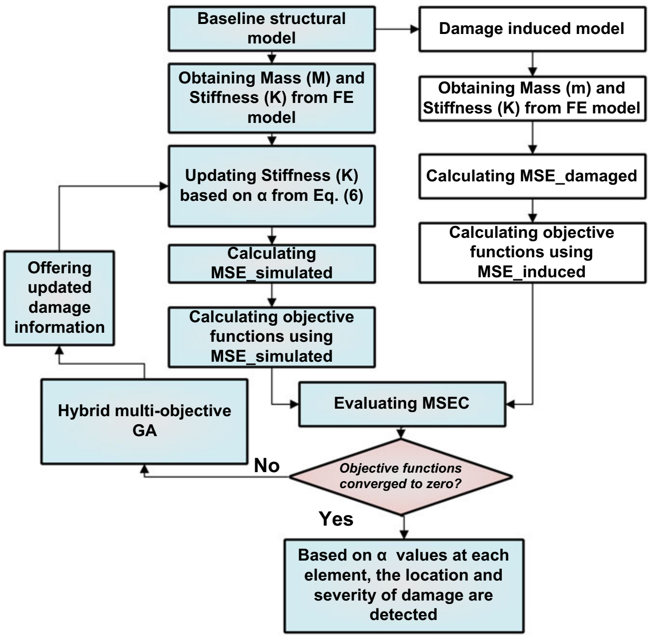


Fig. 1. Overall procedure for damage detection using multiobjective NS2-IRR GA.

Thus, any extent and location of structural damage can be generated based on these randomly simulated α by using a multiobjective GA.

3 DAMAGE DETECTION BY INVERSE PROBLEM SOLVING

To detect structural damages, an inverse solving concept is adopted using GAs based on the extensive literature reviews summarized in the "Introduction" section. The overall procedure for the damage detection using the proposed multiobjective GA is expressed as a flowchart as shown in Figure 1. A baseline structural model is developed by using finite element method (FEM) as a first step. This developed FEM model is assumed to represent the intact structure accurately. A damage-induced structural model is also developed by reducing Young's modulus of some structural members. Mass and stiffness matrices of both the damage-induced and the damage-simulated models are obtained. From the obtained matrices, mode shapes of the damage-induced and the damage-simulated structures from GAs are calculated. MSE is calculated using the calculated mode shapes. In this article, the objective functions are defined as the discrepancy between the MSE of the induced damages and the simulated damages using GAs. If the discrepancy of the two MSE is zero, then the simulated damages are stipulated to be the same as the induced damages. The simulated damage scenarios are the predicted damages of the structure. Thus, in order to minimize the objective functions, the stiffness matrix of the damage-simulated structure is dynamically changed based on fitness of the objective functions using the hybrid multiobjective GAs. The optimization process is stopped when the objective functions converge to zero value, otherwise it is continued to the next generation until the objective functions converge to zero values or some required criteria are met, such as the predefined maximum number of generations.

3.1 Hybrid multiobjective GAs

One of the disadvantages of the single-objective GA as a traditional approach for detecting structural damages based on modal updating is that it does not perform well using multiple damage indices (Cha and Buyukozturk, 2014). For example, when mode shapes or natural frequencies are used as the damage indices, multiple mode shapes or natural frequencies, which are required to use for damage detection, are stacked in one objective function with different weighting factors for each mode shape or natural frequency. However, when we try to minimize the objective function, it is not easy to choose reasonable weighting factors for each mode shape or natural frequency because we do not know which mode shape or natural frequency is important for a specific damage detection problem. Therefore, it is not guaranteed that the objective function having smaller values always offer better solutions. However, from comparative numerical studies, multiobjective approach showed significantly better performance than traditional single-objective approach in detecting multiple minor damages in a steel structure (Cha and Buyukozturk, 2014). Thus, to eliminate the shortcomings of the single-objective approach, a hybrid multiobjective approach is proposed to consider multiple modal properties in detail and to find multiple minor structural damages by integrating the best features of the IRR GAs as an encoding policy and nondominated sorting GA-II (NSGA-2) (Deb et al., 2002) as a selection method. This hybrid multiobjective NS2-IRR GA was previously proposed to find optimal layouts of the control devices and sensors for a 3-D high-rise building (Cha et al., 2012, 2013a, b).

The IRR GA, first proposed by Raich and Ghaboussi (2000), is used as an encoding policy. The advantages of the IRR GA come from utilizing three different genetic factors: a gene locator (GL), redundant segments, and longer than required string length. The GL indicates the starting point of a gene instance containing encoded variables (i.e., α in Equation (6)). The redundant segments, which contain currently nonencoded segments, can become part of the encoded gene instances in later

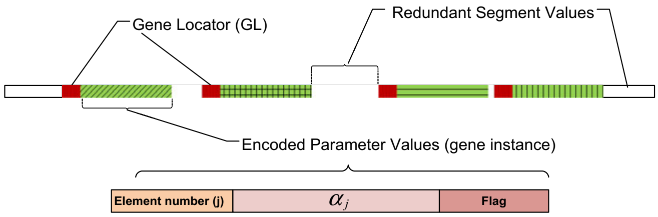


Fig. 2. Encoded simulated damages using IRR GA.

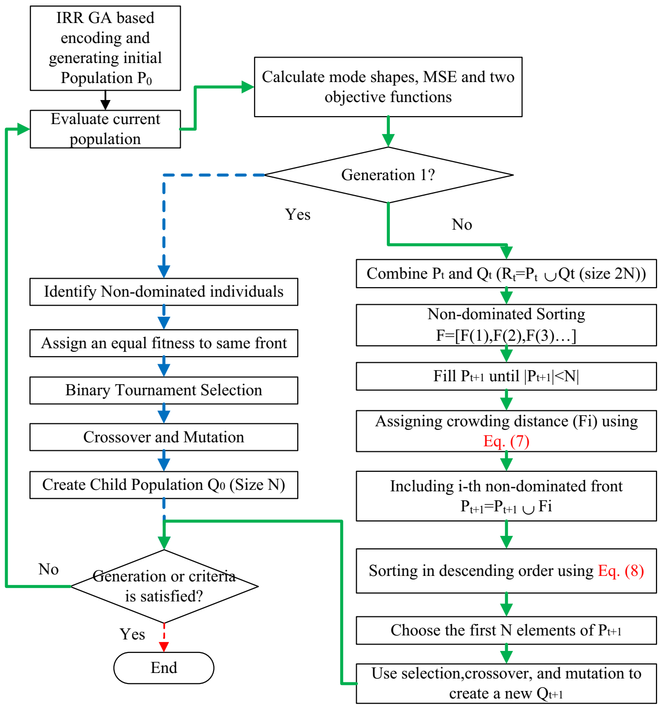


Fig. 3. Flowchart of the NS2-IRR GA to search damage extents and locations.

generations. For the damage index optimization problem, each IRR gene instance encodes the reduction of the Young's modulus on a specific structural element as binary numbers, as shown in Figure 2. In addition, a flag is encoded to help determine which encoded gene instance information to use if more than one segment's encoded information decodes to the same structural element. The IRR encoding allows the percentage reduction of the Young's modulus to dynamically change by the actions of crossover and mutation among individuals in the same population and in future generations during the search process.

The NSGA-II is used as a selection method to keep competitive candidate solutions and transfer those to next generation of the genetic iterations. The detailed procedure of the selection method for the multiobjective NS2-IRR GA is expressed in Figure 3. For the first step, the mode shapes of the damaged structure are calculated and the MSEs (i.e., Equations (1) and (2)) are calculated using those mode shapes. The multiobjective NS2-IRR GA generates IRR-based binary strings as an initial random population, P_0. In the case of initial generation, fitness values of the individuals are calculated and assigned to each individual without considering the individual's crowding factors, in which same rank will be assigned same dummy fitness value. The ranks of each individual are assigned by a nondominated sorting procedure. From the second generation of the multiobjective NS2-IRR GA, a combined population ($R_t = P_t \cup Q_t$) is formed with size $2N$, where N is the predefined size of the parent and child populations. This combined population R_t is sorted according to nondomination. The P_{t+1} is filled with nondominated fronts with a smaller size than the predefined parent population size N. Crowding distances are assigned for the best remedy front $F(i)$, which is ith rank from the nondominated sorting procedure, and then P_{t+1} and $F(i)$ are combined together.

The NS2-IRR GA uses crowding distances to calculate a fitness value of each individual to consider density of solutions and then to prevent converging to local optimal solutions. The crowding distance, which estimates the density of individuals surrounding a particular individual in the phenotype nondominated Pareto front, is calculated as an average distance of the two individuals on either side of this point along each of the objectives based on the following equation:

$$I\left[j\right]_{distance} = I\left[j\right]_{distance} + \left(I\left[j+1\right].m - I\left[j-1\right].m\right) \quad (7)$$

where m is the number of objectives and $I\left[j\right].m$ is the mth objective function value of the jth individual in the set I, respectively. The P_{t+1} is also sorted according to the crowded comparison operator. Thereafter, only N number of individuals will be selected as P_{t+1}. The crowded comparison operator is as shown in the following equation:

$$\begin{aligned} &j \geq_n k \text{ if } (j_{rank} < k_{rank}) \text{ or } ((j_{rank} = k_{rank}) \\ &\text{and } (j_{\text{distance}} > k_{\text{distance}})) \end{aligned} \quad (8)$$

where j_{rank} and k_{rank} are nondominated rank of the j and kth individuals, respectively, and j_{distance} and k_{distance} are local crowding distance of the jth and kth individuals, respectively. The binary tournament selection, crossover, and mutation operators are carried out to create a new child population Q_{t+1}, from the P_{t+1}. These steps are continued until satisfying the defined criteria or generation.

3.2 Formulation of the multiobjective functions

The hybrid multiobjective NS2-IRR GA is adopted in this article to detect structural damages for the three different modular structures. The differences in the MSE between the damage-induced structure and the damage-simulated structure by GA process can be expressed as objective functions of the hybrid multiobjective NS2-IRR GA. The proposed GA minimizes the total differences of the MSE as shown in Equation (4). To calculate Equation (4), incomplete mode shapes are used by removing rotational components, which are difficult to measure. Therefore, the objective functions as a manner of multiobjective optimization are newly formulated based on the total differences of the MSE as follows:

$$\min(Objective1, Objective2) \tag{9}$$

where $Objective1$ and $Objective2$ are

$$Objective1 = \sum_{i=1}^{ms/2} \sum_{j=1}^{el} \left| \Phi_i^{dT} \mathbf{K}_j \Phi_i^d - \Phi_i^{sT} \mathbf{K}_j \Phi_i^s \right| \tag{10}$$

$$Objective2 = \sum_{i=ms/2+1}^{ms} \sum_{j=1}^{el} \left| \Phi_i^{dT} \mathbf{K}_j \Phi_i^d - \Phi_i^{sT} \mathbf{K}_j \Phi_i^s \right| \tag{11}$$

where *ms* is the selected number of incomplete mode shapes.

4 MODULAR STEEL STRUCTURE

To evaluate the proposed damage detection method, models of a 3-D modular steel frame structure have been developed and analyzed.

4.1 Modular steel structure models

To create various structure types simple column and frame (beam) structural elements are designed. Detailed material properties are given in Table 1. The column section is 0.00635 m by 0.0508 m with a length of 0.6096 m; the frame section is 0.00635 m by 0.0508 m with a length of 0.6096 m in each bay.

Using these elements, four-story prototype is modeled, and irregular and asymmetric configurations are introduced by adding and removing one or more bays to the four-story prototype structure. To investigate various damage scenarios, three different numerical models for these structures have been developed using the FEM with 12×12 stiffness matrices and consistent mass matrix. Each node has six degrees-of-freedom (DoFs) comprising three translational DoFs and their three rotational DoFs. Thus, the prototype structure has 144 DoFs, irregular and asymmetric structures have 156 DoFs and 144 DoFs, respectively.

Table 2 presents the first eight natural frequencies calculated using SAP2000, which is a commercial structural analysis tool, and numerical coding using MATLAB for the designed structures. The calculated first eight natural frequencies show good agreement with each other.

5 APPLICATIONS TO VARIOUS STRUCTURE TYPES AND DAMAGE SCENARIOS

As a basis for damage detection studies, three different structures are considered with three different multiple damage scenarios, as shown in Table 3. The damage scenarios in each structure are visualized in Figure 4. All damages are expressed as thick dashed red lines in each structure. To investigate the robustness of the proposed damage detection methodology, damage locations are well scattered in the entire structures.

For the four-story irregular structure, the multiobjective NS2-IRR GA is applied with a population size of 5,000, tournament selection size of 2, crossover rate of 0.9, and mutation rate of 0.01. To calculate the two objectives of the hybrid multiobjective NS2-IRR GA, first eight mode shapes are used with only global translational X and Y components of the mode shapes. For the *Objective*1 (i.e., Equation (9)), 1st, 3rd, 5th, and 7th mode shapes are used, and for the *Objective*2 (i.e., Equation (10)), 2nd, 4th, 6th, and 8th mode shapes are used. Here, the mode shapes are divided into two objectives to distribute MSE evenly. However, any combination of the mode shapes in each objective function is possible. All displacement DoFs are assumed to be observable. Even though the mode shape information may not be completely available, MSE can still be computed from the available incomplete mode shapes with decreased accuracy.

Figure 5 shows the near initial population and near optimized population in the 687th generation. The near optimized individuals are well converged to zero in both objectives. Then, the α (from Equation (6)) of the individual, which has minimum summation values of both objectives, is checked as predicted damages. Even though 1% and 2% errors in structural elements 1, 10, and 33 are found and noise of 1% is found as shown in Figure 6, the overall induced damages are well detected. To remove these minor errors and noise, the optimization problem domain is reduced to a maximum 10% possible damage based on current predicted damage information. With this reduced optimization domain and reduced population size of 1,000, the population quickly converges to zero in both objectives, and one of the

Table 1
Member material properties

Structural element	*Young's modulus* (N/m^2)	*Density* (kg/m^3)	*Volume* (cm^3)	*Mass* (kg)
Beam for 2-bay	1.96E11	7,880.00	1,327.00	10.35
Column	1.96E11	7,880.00	217.57	1.70

Table 2
Natural frequencies of structures

	Four-story (prototype)		*Irregular*		*Asymmetric*	
Mode/Freq. (Hz)	*SAP2000*	*MATLAB*	*SAP2000*	*MATLAB*	*SAP2000*	*MATLAB*
1	2.202	2.209	2.692	2.706	2.926	3.047
2	4.219	4.530	5.717	5.948	6.944	7.435
3	5.558	5.608	6.769	6.911	8.208	8.374
4	6.915	7.085	7.897	8.477	9.590	9.793
5	12.078	12.873	11.911	12.754	15.853	17.038
6	16.422	18.061	15.543	17.286	29.263	33.454
7	16.636	18.587	18.074	20.295	40.818	44.716
8	27.038	27.802	26.681	27.635	43.792	45.327

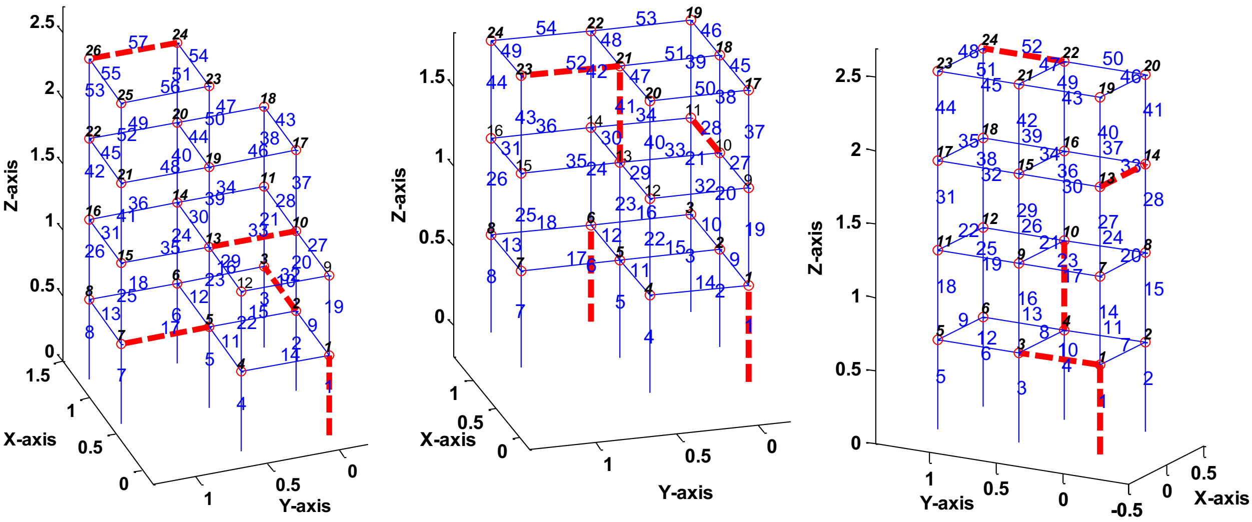
Table 3
Damage scenarios

Damage scenario	*Element number and % of damage induced*				
Damage scenario 1 for four-story irregular structure	1 (5%)	10 (5%)	17 (5%)	33 (5%)	57 (5%)
Damage scenario 2 for three-story asymmetric structure	1 (5%)	6 (5%)	28 (5%)	41 (5%)	52 (5%)
Damage scenario 3 for four-story prototype structure (noise)	1 (20%)	10 (30%)	17 (20%)	33 (30%)	52 (30%)

individuals converges to zero values of both objectives at the 167th generation of the GA as shown in Figure 7. The α (from Equation (6)) of the individuals, which are fully converged to zero values for both objectives, is plotted as shown in Figure 8. The hybrid multiobjective NS2-IRR GA, with the same GA properties as those of the full optimization domain problem, detects all induced multiple damages using incomplete mode shapes.

In the case of the asymmetric structure, vertical components of the first eight mode shapes are included to calculate the two objective functions, because the induced damage scenarios in Table 3 do not detect well without considering vertical components of the mode shapes. From the second trial of the hybrid multiobjective NS2-IRR GA, one of the individuals is fully converged to zero values of both objective functions, as shown in Figure 9. The α of this individual is plotted in Figure 10.

It is worth mentioning that the suggested multiobjective NS2-IRR GA has good computational performance in solving these highly complex nonlinear optimization problems, which have trade-off among objectives. Thus, multiobjective GAs have been developed to search a well-distributed optimal Pareto curve for problems that have trade-off among objectives (Cha et al., 2012, 2013a, b). However, in this article, the two objectives do not have any trade-off characteristics because even though one of the objective values is decreased, the other objective value is not increased due to reduction of the first objective value. However, multiobjective GAs used in this study show good performance in solving multiobjective optimization problems, which do not have any trade-off characteristics among objectives. The multiobjective NS2-IRR GA uses a crowding distance schema (i.e., Equation (7)), crowded operation selection method (i.e., Equation (8)) in assigning fitness values, and tournament selection step to keep well-fit individuals for the next generation of the GA. These advanced fitness assigning methods and selection schema with advanced encoding policy may prevent individuals of the population in the multiobjective NS2-IRR GA from premature convergence to local



(a) 4-story irregular (b) 3-story asymmetric (c) 4-story prototype

Fig. 4. Three different structures and induced damage locations.

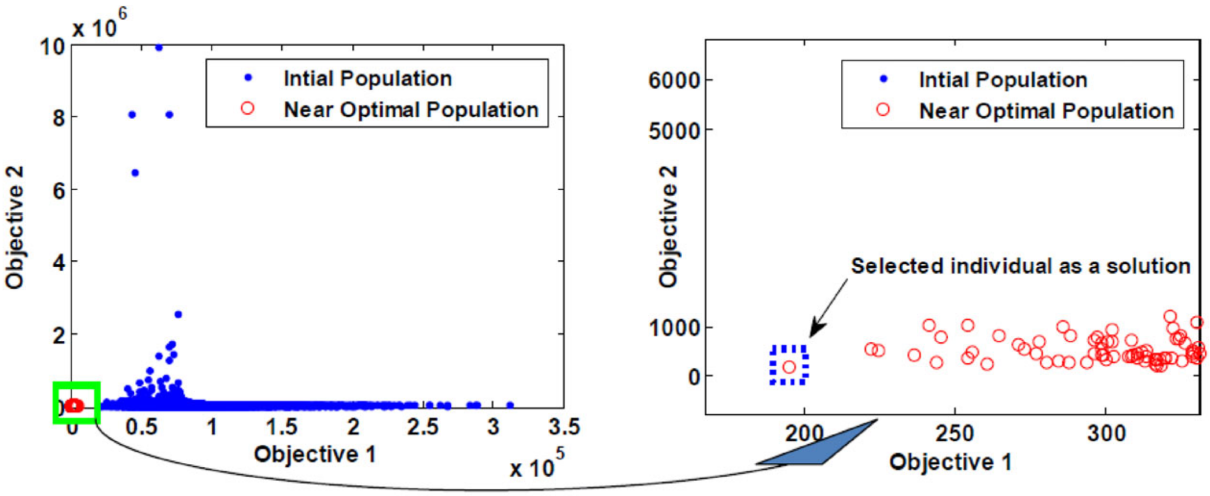


Fig. 5. Nearly converged population of multiobjective NS2-IRR GA in irregular structure.

optimal solutions by keeping various individuals that have competitive design variables of the optimization (i.e., $\alpha_1, \alpha_2, \ldots, \alpha_{el}$ from Equation (6)).

Note that in this article, the proposed methodology uses eight or more number of mode shapes to detect damages. To apply this methodology to real systems, measuring mode shape is a key important task. Ten or more number of mode shapes of a 15-story reinforced concrete shear core building, Heritage Court Building (HCB) in Vancouver, Canada, have been measured using limited number of acceleration sensors from ambient responses of the building (Ventura et al., 2001; Brincker and Andersen, 2000). Using a nonparametric frequency domain decomposition of the spectral density function matrix (Brincker et al., 2001), the measured mode shapes between numerical model and experimental results showed good agreement with almost identical mode shapes within smaller than 5% errors. Even though there is a limitation in measuring higher mode shapes, the methodology proposed in this article may use only first several mode shapes to calculate MSE for damage detection. Therefore the accuracy of the damage detection using the developed algorithm depends on the number of available mode shapes.

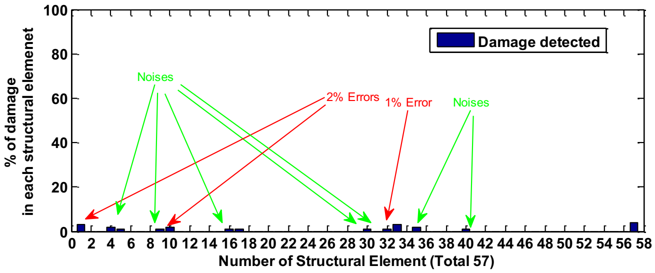


Fig. 6. Damage detected in entire four-story irregular structure from full domain.

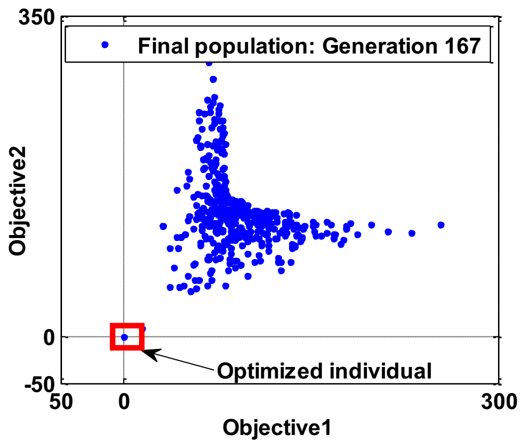


Fig. 7. Fully converged population of multiobjective NS2-IRR GA in entire irregular structure.

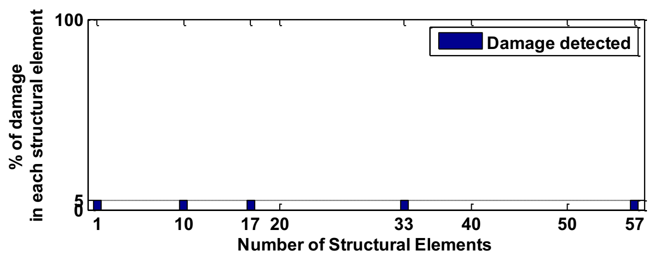


Fig. 8. Damage detected in entire four-story irregular structure from reduced domain.

5.1 Effects of incomplete mode shapes

In this article, complete mode shapes, which have information on all measured nodes in the structure, are used to calculate the MSE. However in reality, due to limitation of available funds or materials and malfunction of sensors, complete mode shapes may not be available for structural damage detection from real measurements. Thus, in this section, effects of incomplete mode shapes that do not have any information on the damaged structural element are investigated using the four-story prototype structure. Damages are assigned to element 1 (5%) and 10 (5%) as shown in Figure 11. In the figure, node 1 with missing mode shape information is designated by a green box. The mode shape information of node 1 connecting elements 1, 7, 10, and 14 is assumed not available.

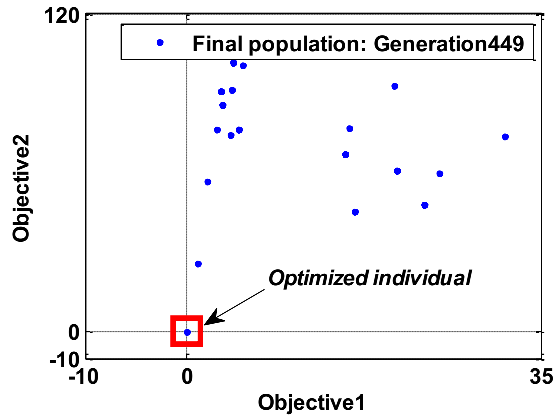


Fig. 9. Fully converged population of multiobjective NS2-IRR GA in entire asymmetric structure.

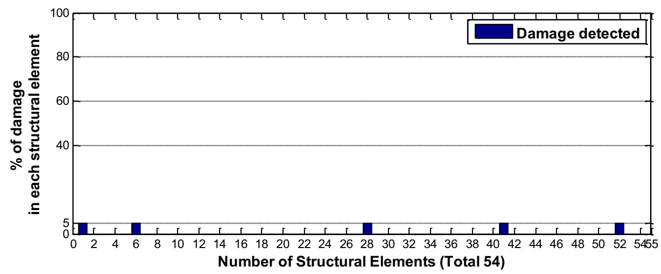


Fig. 10. Damage detected in entire asymmetric structure from reduced domain.

Using the first two complete mode shapes with only global X and Y translational components, all the induced damage is detected with correct locations and extents of the damage. The multiobjective NS2-IRR GA used a total of 65,000 trials to detect all induced structural damages. However, using the same mode shapes that do not have information at node 1, the proposed approach used a total 72,000 trials. It means that the proposed approach can detect damages well with incomplete mode shapes, which do not have information on the damaged structural element with some additional trials compared to using complete mode shapes. The reason for this may be that the measured mode shapes are changed throughout the entire structure due to local damage. Thus, even though the proposed approach does not have any mode shape information around the damaged element, it can detect damages well.

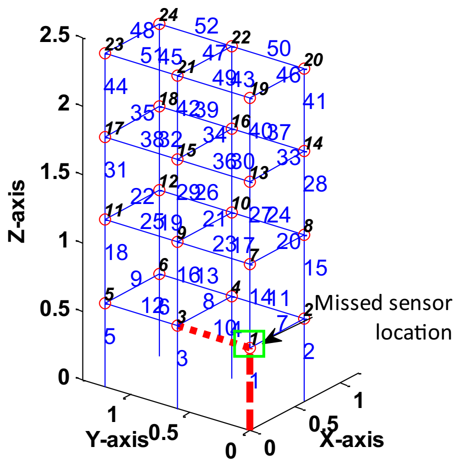


Fig. 11. Structure without mode shape information at damaged structural element node 1.

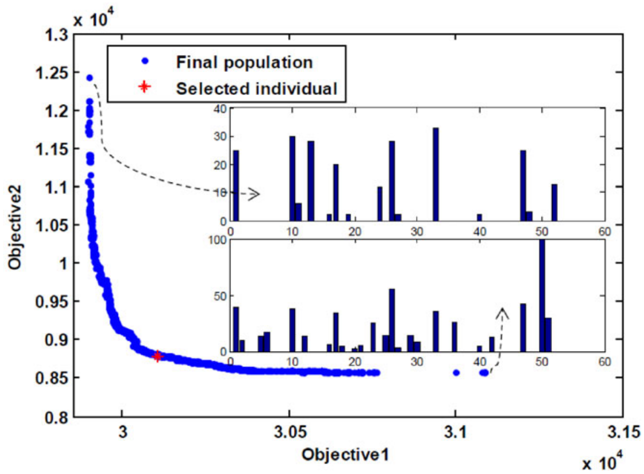


Fig. 12. Near-optimal Pareto curve of the multiobjective NS2-IRR GA for mode shapes with noise.

5.2 Noise effects on detection of damage

The robustness of model and measurement uncertainties is one of the important issues in model updating-based damage detection or system identification studies (Mottershead and Friswell, 1993; Beck and Katafygiotis, 1998; Moaveni et al., 2009). To investigate the robustness of the proposed damage detection methodology in terms of measurement uncertainties, the first eight modes of the actual damaged structure are used in the damage identification. The mode shapes are contaminated with 5% Gaussian random white noises to study the noise effect of measurements. The contaminated mode shapes are represented as

$$\hat{\Phi}_{ij}^{d} = \Phi_{ij}^{d}[1 + \gamma \,\mathrm{randn}\,|\Phi_{i}^{d}|_{\max}] \qquad (12)$$

where $\hat{\Phi}_{ij}^{d}$ is contaminated jth component of the ith mode shapes, γ is noise level in decimal format, randn is the random Gaussian number generator function in MATLAB, and $|\Phi_{i}^{d}|_{\max}$ is the maximum values of the ith absolute mode shape.

The damages are assigned to elements 1 (20%), 10 (30%), 17 (20%), 33 (30%), and 52 (30%) for the four-story prototype structure as shown in Table 3. To adequately consider the problem domain of a damage scenario with noise added, the population size of the GA is defined as 5,000. Using the 5% Gaussian white noise-contaminated mode shapes, the MSE and the two objectives are calculated.

From the multiobjective NS2-IRR GA, near-optimal Pareto curves are obtained as shown in Figure 12. The damages detected from individuals that have minimum values using only *Objective1* and using only *Objective2*, respectively, are plotted in Figure 12 as subgraphs. From this figure, it should be noted that both objectives should be fully optimized. Thus, the individual that has the minimum summation of the two objectives is chosen as a final solution for the damage detection. The solution is plotted in Figure 13 with an induced

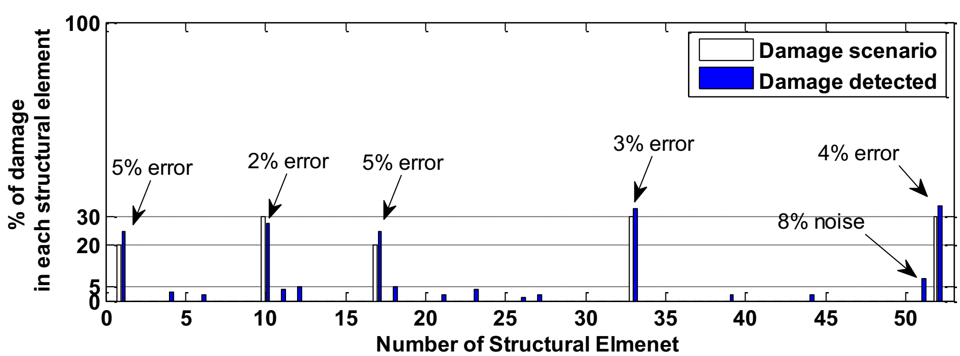


Fig. 13. Damage detected in prototype structure with 5% white noises.

damage scenario. All of the damages are detected even though there are noises and some errors. Furthermore, although there are noises that are bigger than 5%, the overall performance of the damage detection using the 5% noise-contaminated mode shapes is reasonable and competitive.

6 CONCLUSION

Hybrid multiobjective GAs are proposed as a damage detection method to solve inverse problems to minimize difference in the MSE in each structural element. To investigate the performance of the proposed method, three different 3D modular steel structures are designed and numerically modeled using FEMs. The newly proposed damage detection method using hybrid multiobjective NS2-IRR GA shows significantly good performance in detecting multiple minor damages, which have little effect on the modal properties of the structure. The multiobjective optimization method used in detecting structural damages was originally developed to find an optimal Pareto curve having a well-distributed solution set to satisfy multiple objectives having trade-off characteristics among objectives. Although the multiobjective GAs used in this article are applied to damage detection problems that do not have trade-off characteristics, they still demonstrated good performance in solving multiobjective problems. The newly proposed approach uses limited mode shapes containing only global translational components to remove difficulties in measuring rotational components of the mode shapes. The hybrid multiobjective optimization method detects the locations and extents of multiple minor damages in three different 3-D steel structures without errors or noise. Even though the proposed approach uses incomplete mode shapes, which do not have any mode shape information on the damaged structural element, it can still detect damage well. Furthermore, using mode shapes contaminated with 5% Gaussian white noise, the suggested approach detects all damage with an error smaller than 5%. Future research would involve experimental validation with real measurements from sensors. Mode shapes would be extracted using any method such as frequency domain decomposition and stochastic subspace identification.

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