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# Optimization of Earthquake Energy Dissipation System by Genetic Algorithm

F. Hejazi*, I. Toloue & M. S. Jaafar

*Department of Civil Engineering, University Putra Malaysia, 43400, Malaysia and Housing Research Center, Faculty of Engineering, University Putra Malaysia, 43400, Malaysia*

&

J. Noorzaei

*Department of Civil Engineering, University Putra Malaysia, 43400, Malaysia*

**Abstract:** *Numerous recent studies have assessed the stability and safety of structures furnished with different types of structural control systems, such as viscous dampers. A challenging issue in this field is the optimization of structural control systems to protect structures against severe earthquake excitation. As the safety of a structure depends on many factors, including the failure of structural members and movement of each structural node in any direction, the optimization technique must consider many parameters simultaneously. However, the available literature on optimizing earthquake energy dissipation systems shows that most researchers have considered optimization processes using just one or a few parameters applicable only to simple SDOF or MDOF systems. This article reports on the development of a multiobjective optimization procedure for structural passive control systems based on genetic algorithm; this research focused on systems that would minimize the effects of earthquake based on realistic structural responses considering plastic hinge occurrence in structural elements and three-directional displacement in all structural nodes. The model was applied to an example of three-dimensional reinforced concrete framed building and its structural seismic responses were investigated. The results showed that the optimized control system effectively reduced the seismic response of structures, thus enhancing building safety during earthquake excitations.*

## 1 INTRODUCTION

Adeli and Saleh (1999) advanced the idea of smart structures where sensors measure the response of a structure during dynamic loading due to strong ground motions and actuators apply internal forces to compensate for the effects of the external forces. Although extensive research has advanced structural control techniques over the last few decades, the optimization of control systems remains a challenging issue due to the complexity of structural seismic responses and the performance of the controllers.

Yang et al. (1992) developed instantaneous optimal control algorithms as an alternative to quadratic optimal control theory for linear, nonlinear, and hysteretic structural systems. This study investigated the effect of weighting matrix of optimization objective function in the stability of the controlled structure, while weighting matrix for controller with velocity and acceleration feedbacks was recommended.

Saleh and Adeli (1994) developed efficient parallel algorithms for optimizing an integrated structural and control system using a combination of vector computations and multitasking approaches to accelerate their performance. They considered nodal displacements, stresses, closed-loop eigenvalues, and corresponding damping factors as optimization constraints. The

*To whom correspondence should be addressed. E-mail: *farzad@fhejazi.com*.


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efficiency of vectorization and parallel optimization processing for improving computational speeds was evaluated by applying the developed algorithm to the optimization of large-sized problems. The results indicated that the algorithms provide stable results consistently for various sizes of problems and are particularly efficient for large problems (Saleh and Adeli, 1996, 1998a; Adeli and Saleh, 1998). Saleh and Adeli (1997) presented robust parallel algorithms for solution of the Riccati equation. Adeli and Saleh (1997) presented active vibration control of smart bridge structures. Saleh and Adeli (1998b) presented optimal control of adaptive building structures subjected to blast loading, a first for blast loading.

Soh and Yang (1998) proposed an optimal layout design using genetic algorithm by minimization of weight in truss bridges. Following this, Yeh (1999) sped up the convergence in the optimization of truss structures.

A significant development in the area of structural control was the introduction of wavelets in vibration control in a seminal work by Adeli and Kim who developed innovative wavelet-based algorithms for robust vibration control of smart structures (Adeli and Kim, 2004; Kim and Adeli, 2004). Next, Kim and Adeli (2005a) developed a new hybrid control system including a semiactive tuned liquid column damper (TLCD) system for vibration control of structures. Subsequently, the developed technique was implemented for optimal structural control of irregular three-dimensional buildings furnished by hybrid damper system and for optimal motion control in high-rise buildings (Kim and Adeli, 2005b). Furthermore, the effectiveness of hybrid viscous fluid damper-TLCDs for wind-induced vibrations of tall buildings was demonstrated by Kim and Adeli (2005d). The effectiveness of the wavelet-based control algorithm for vibration control of cable-stayed bridges was also demonstrated (Kim and Adeli, 2005c).

In recent years, there has been an increasing interest in the application of computational intelligence techniques, that is, neural networks (Lopes and Ribeiro, 2011; Liu and Er, 2012; Lin et al., 2012; Hsu, 2012; Akhand and Murase, 2012), fuzzy logic (Ma et al., 2011; Reuter, 2011; Freitag et al., 2011; Lee and Pinheiro, 2011; Yan and Ma, 2012), and genetic algorithms for development of intelligent systems including smart structures and intelligent transportation systems (Sarma and Adeli, 2001; Adeli and Kim, 2009; Adeli and Jiang, 2009). Neural network-based system identification techniques have been developed by Puscasu and Codres (2011) and neural network-based control algorithms have been developed by Huang et al. (2011), Hemami et al. (2012), and Lin et al. (2012). Theodoridis et al. (2012) presented a dynamic recurrent neurofuzzy identification scheme.

Jiang and Adeli (2008b) presented a neurogenetic algorithm for finding the control forces. The results revealed a significant improvement in the efficiency of the general control methodology. A floating-point genetic algorithm was implemented to find the optimal control force for predicting the response of the structure in the next time step using a dynamic fuzzy wavelet neuroemulator. The result demonstrates that the new model provides accurate prediction of structural displacement responses (Jiang and Adeli, 2008a).

Hejazi et al. (2009) investigated the effects of supplemental viscous damper parameters on the response of reinforced concrete structures through a parametric study and proposed the optimum viscous damper based on the desired performance at various demand levels for the building.

Fisco and Adeli (2011a, b) reviewed the research done on the development of optimal vibration controller for active, semiactive, and hybrid structural control systems. Their study indicated that semiactive and hybrid optimal control systems are more practical for real-life implementation in structures. MR dampers, piezoelectric actuators, and semiactive and hybrid TLCDs have attracted more attention due to their effectiveness, robustness, and minimal operating requirements.

Robust controllers (Rodriguez et al., 2012) have been used in many different applications in recent years, such as building safety (Ko et al., 2012). Furthermore, adaptive and evolutionary optimization techniques such as genetic algorithm have been used for optimizing the performance of control systems.

Singh and Moreschi (2002) used genetic algorithm to optimize the size and location of damper device in structures. They studied different types of dampers including linear viscous dampers, solid viscoelastic dampers, and fluid viscoelastic dampers, as well as considering three performance functions in terms of base shear, overturning moment, and floor acceleration, conducting optimization for each supplemental function.

Dargush and Sant (2005) carried out a similar research by implementing metallic plate dampers, viscous fluid dampers, and viscoelastic solid dampers in a structure with soft story. In the study, deterministic lumped mass was used for modeling steel structure, while memoryless fitness function was used for genetic algorithm.

Hejazi et al. (2009) developed an optimization procedure for active variable stiffness controller using genetic algorithm, while Movaffaghi and Friberg (2006) and Park and Koh (2004) used genetic algorithm along with finite element software to optimize viscoelastic damper positions and sizes.

Many studies have been conducted on the multiobjective optimization of damper distribution and placement in structures using genetic algorithms (Fujita et al., 2010; Silvestri and Trombetti, 2007; Wongprasert and Symans, 2004). In addition, the multiobjective genetic algorithm was also used to identify the conflicting requirements for the design of interstory drift and structural acceleration (Lavan et al., 2008) and to optimize the design of hysteretic dampers for connecting adjacent structures (Yong et al., 2008).

Kargahi and Ekwueme (2009) proposed the use of genetic algorithm techniques for optimizing equivalent damping effects, including viscous dampers and inherent dampers, in existing buildings. Their study considered the nonlinear static response of buildings by performing a pushover analysis. In addition, a sensitivity analysis was also conducted to evaluate the effects of probability ranges of mutation, as well as crossover and population number, on optimization solution by genetic algorithm.

Most studies available in the literature have focused on either a single- or double-discipline optimization algorithm for control devices or structures with a simplified linear model. This study focuses on developing a multiobjective genetic algorithm to optimize viscous damper properties to minimize the seismic response of structure in terms of occurrences of plastic hinges in structural members and three-dimensional displacements at different story levels.

## 2 OPTIMIZATION PARAMETERS

Equation (1) is the main equation of motion for structures equipped with viscous damper systems.

$$M\ddot{u} + (C + C_d)\dot{u} + Ku = F_e \tag{1}$$

where $M$, $C$, and $K$ are the mass, damping, and stiffness of the structure, respectively, and $u$, $\dot{u}$, and $\ddot{u}$ are the displacement, velocity, and acceleration of the structure, respectively. $C_d$ is the damping due to the supplemental viscous dampers (the damping coefficient), and $F_e$ is the earthquake load.

This study considers the viscous damper damping ($C_d$) as design parameter for optimizing the performance of the viscous dampers via genetic algorithm. For this purpose, each viscous damper is simulated as a gene and the damping is treated as a gene feature.

Therefore, the energy dissipation system in a reinforced concrete framed building is simulated as a chromosome. All components of the genetic algorithm, including design variables, objective functions, and design constraints, are developed based on the defined strategy and are explained in the subsequent sections.

### 2.1 Optimization design variables

As mentioned before, the damping coefficient ($C_d$) of the viscous damper is considered as a design variable of the optimization algorithm. During the optimization process, the damping coefficients of supplemental viscous dampers are continuously changed to determine the optimum viscous damper parameters.

So, various viscous damper devices with different ranges of damping coefficient values can be implemented in buildings and used in the genetic algorithm optimization process. The viscous dampers damping are converted to genes and these genes are incorporated into a chromosome. Therefore, each gene of the chromosome is representative of the viscous damper characteristics of each story.

### 2.2 Optimization objective function

Based on the high potential of genetic algorithms for optimizing multiobjective problems, this technique has been widely implemented. Genetic algorithm was used to optimally group the very large number of signals at a nuclear power plant. This reduced the multiobjective problem to a single-objective optimization problem by aggregating two metrics of accuracy and robustness of optimization into a single scalar fitness function (Baraldi et al., 2011). Chabuk et al. (2012) employed the genetic algorithm for optimum design of antenna arrays. Fuggini et al. (2013) also used genetic algorithm for the multistage identification of the parameters that govern the behavior of multiaxial polymer materials and the modeling of composite seismic wallpaper.

In the literature, most available research regarding optimization of structures considers the weight of structures, which represents the major cost of construction as an objective function.

However, in earthquake engineering, the major issue is to assure the safety of a building during seismic excitation. One effective parameter in structural stability is the movement of structures during ground vibration. Therefore, this study considers the effect of energy dissipation system in structural seismic response in terms of displacement as an optimization objective, and the objective function, $f_{obj}$, for the optimization process is defined as a function of all three-dimensional movements of the structure ($\delta_x$, $\delta_y$, $\delta_z$).

Inelastic time history analyses were performed to evaluate the structure's response during earthquake excitation. To assess the critical condition, peak displacements (positive and negative) were used to determine the objective functions.

For simplicity, the peak positive displacement is called maximum displacement and the peak negative displacement is called minimum displacement. This study considers a three-dimensional structural model with multidirectional support excitation. As such, displacements in different directions occur independently and the displacement in each direction independently affects the optimization process. The vertical seismic response of buildings, however, is smaller than displacements in the two horizontal directions. Vertical displacement does not have a significant influence on the optimization procedure.

To consider the effects of displacements in all directions in the optimization process, the following equations are proposed:

$$\Delta_{\mathrm{X}} = \frac{\mathrm{dx}_{\mathrm{Max}} - \mathrm{dx}_{\mathrm{Min}}}{\mathrm{dx}_{\mathrm{Min}}} \tag{2}$$

$$\Delta_{\mathrm{Y}} = \frac{\mathrm{d}_{\mathrm{YMax}} - \mathrm{d}_{\mathrm{YMin}}}{\mathrm{d}_{\mathrm{YMin}}} \tag{3}$$

$$\Delta_{\mathrm{Z}} = \frac{\mathrm{dz}_{\mathrm{Max}} - \mathrm{dz}_{\mathrm{Min}}}{\mathrm{dz}_{\mathrm{Min}}} \tag{4}$$

where $\mathrm{d}_{\mathrm{Max}}$ and $\mathrm{d}_{\mathrm{Min}}$ are the peak minimum and peak maximum of time history displacements in the X, Y, and Z directions. Also, $\Delta_{\mathrm{X}}$, $\Delta_{\mathrm{Y}}$, and $\Delta_{\mathrm{Z}}$ are the net displacement scalars in the X, Y, and Z directions, respectively. These values are determined for each story level, and the proposed objective functions consist of these scalars

$$\mathrm{f}_{obj} = \sum_{n=1}^{\mathrm{StoryNo.}} \Delta_{\mathrm{X}}^2(n) + \Delta_{\mathrm{Y}}^2(n) + \Delta_{\mathrm{Z}}^2(n) \tag{5}$$

Therefore, the genetic algorithm minimized $f_{obj}$ in the optimization process.

### 2.3 Optimization design constraints

The principle of the genetic algorithm is based on unconstrained functions. To apply this method to constrained objectives, a set of objective functions and governing constraints was converted into an equivalent free function (competency function) by adding the penalty function to the objective function.

Different forms of penalty functions for the optimum design of structures have been suggested in the literature.

Adeli and Hung (1995) proposed a new algorithm for training multilayer feed-forward neural networks by integrating a genetic algorithm with an adaptive conjugate gradient-neural network learning algorithm for image recognition and structural design. To obtain the unconstrained optimization problem for the genetic algorithm, the average squared system error of the corresponding neural network was defined as objective function.

Adeli and Kumar (1995) developed concurrent genetic algorithms for optimizing large-space structures on parallel machines/supercomputers and in a distributed computing environment of personal computers or workstations connected via computer networks, such as LANs (Adeli and Kumar, 1999).

Kim and Adeli (2001) developed a floating-point parameter genetic algorithm as an alternative to the popular binary genetic algorithm and used it for cost optimization of composite floors, which is a mixed integer-discrete structural optimization problem. Adeli and Sarma (2006) developed fuzzy augmented Lagrangian genetic algorithm for life-cycle cost optimization of steel structures.

Park et al. (2006) developed a distributed hybrid genetic algorithm to reduce the computation time taken by a master or slave computer for optimizing space truss structure. The constraints, which were functions of stress, maximum displacement, and interstory drift, were added to the objective function, which was the designed weight of the structure, using the exterior penalty function to transform into an unconstrained minimization problem.

This research considered the yielding of beams, columns, and damper sections, along with the total number of plastic hinge events occurring during loading and unloading of structural members during earthquake excitation as optimization constraints. Thus, the penalty function is defined as

$$P = f_{obj} \times \sum_{i=1}^{nc} R_{Pi} \times PH_i \tag{6}$$

where $P$ is the penalty function and $PH_i$ represents the design constraints, which are the number of sections yielding and the total number of plastic hinges occurring in structural members.

In this equation, $R_{Pi}$ represents the adjusting coefficient for constraints, and a large value is defined for $R_{Pi}$, to avoid the occurrence of plastic hinges. Therefore, during the optimization process, the genetic algorithm will try to avoid yielding and plastic hinge occurrences in structural members as an optimization constraint and will minimize structural movements in three directions for all stories as the main objective of the optimization.

To impose a limit on displacement (permissible drift), the penalty function should involve the displacement limitation. For this purpose, the following penalty function is proposed:

$$P = f_{obj} \times \left( \sum_{i=1}^{nc} R_{Pi} \times PH_i + R_{Pd} \sum_{i=1}^{nd} \mathbb{Z}^+ \left( \frac{dmax_i}{\overline{dp_i}} \right) \right) \tag{7}$$

where $R_{Pd}$ is the adjusting coefficient for the displacement restraints, $nd$ is the number of nodes, $\mathbb{Z}^+$ is a positive integer function, $dmax_i$ is the maximum displacement in the X, Y, and Z directions during the earthquake, and $\overline{dp_i}$ is the permissible displacement or drift in the corresponding direction, which is defined based on provision codes (U.B.C., 1997; FEMA-356, 2000; FEMA-273, 1997; ATC 40, 1996).

This penalty function restrains the genetic algorithm in terms of the plastic hinge occurrences and the ineligible displacements simultaneously. The supplemental function is obtained by adding the penalty function to the objective function as follows:

$$\Phi = f_{obj} + p \tag{8}$$

where $\Phi$ is the competency function or the equivalent free function.

### 2.4 Crossover and mutation operators

The most important factors for the success of the genetic algorithm in the optimization procedure are the crossover and mutation operations. To make possible the exchange of some genes between two chromosomes to improve the fitness of the next generation, the crossover operation is carried out in two steps:

1. *Random crossover*: In this case, some genes randomly change between two selected chromosomes.
2. *Multipoint crossover*: In a single or multipoint crossover, genes are exchanged among one, two, or many randomly selected locations of two chromosomes.

The crossover operation is applied only to some selected generation of chromosomes because, if applied to all chromosomes, it may lead to the elimination of some chromosomes with high fitness rates.

In any population, genes from some part of a chromosome may get eliminated during reproduction and crossover operations. Recovering these eliminated genes is impossible through the reproduction and crossover operations. To address this problem, some genes of some chromosome are exchanged randomly within a chromosome through a mutation operation. Therefore, some genes of a chromosome are selected randomly and changed.

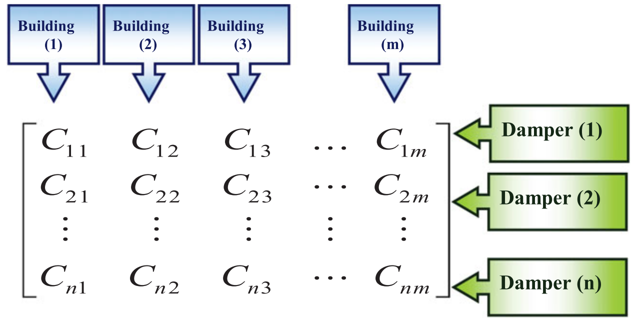



**Fig. 1.** Different damping coefficients for each structure.

## 3 OPTIMIZATION PROCEDURE USING A GENETIC ALGORITHM

As already mentioned, this work has attempted to minimize both horizontal and vertical displacements at all stories of a structure.

Therefore, the optimization process must consider minimizing many parameters simultaneously. For this purpose, this research proposes a new computational procedure for optimizing an earthquake energy dissipation system using the genetic algorithm.

A brief description of the computational process and the steps adopted in this study is outlined below:

*Step I*: Generate the initial random population of chromosomes representing various arrangements of viscous damper properties in structure.

So, for each structure, assume different damping coefficients randomly and convert all selected damping coefficients into matrix notation, as shown in Figure 1.

*Step II*: Decode the random population from integer numbers to the binary series.

*Step III*: Analyze the sets of buildings with different ranges of viscous dampers and calculate the corresponding displacements for each set at different story levels using the finite element program code.

During the time history response, the peak values for each story displacement in the vertical and two horizontal directions are determined.

Also, the sections yielding and occurrences of plastic hinges in structure are detected, along with displacements and results are stored.

*Step IV*: Determine the objective function for each individual structure using Equation (5).

*Step V*: Apply the design constraints for each individual in the population and determine the penalty function by Equation (6) or (7).

*Step VI*: Compute the competency function ($\Phi$) using Equation (8).

*Step VII*: Rank the individual population according to their competency functions.

*Step VIII*: Check for the convergence criteria or determine whether the population fitness level is satisfied.

Convergence occurs and the algorithm terminates when either the maximum number of generations have been produced or a satisfactory fitness level has been reached for the population.

*Step IX*: If the convergence criterion is not satisfied, apply crossover and mutation operators to the population and repeat Steps II to IX.

These iterations are carried out until either the convergence criterion is satisfied or the number of generations exceeds the predefined limit value. In this case, the optimum damping coefficients corresponding to each viscous damper are identified and the optimization procedure is completed.

The developed genetic algorithm optimization procedure is illustrated in the flowchart shown in Figure 2.

The special computer program code, based on presented computational steps, was written for the optimization of earthquake energy dissipation system in reinforced concrete framed buildings. Also, the special finite element program code for the inelastic analysis of a reinforced concrete framed building equipped with earthquake energy dissipation system was developed (NARCBEEEDS, 2012) and implemented in optimization procedure.

So, as shown in Figure 2 during the optimization process, the structural simulation program has been used as a structural analyzer. Genetic algorithm sends viscous damper characteristic to the structural simulation program. Then, analysis outputs in terms of nodal displacements and structural members yielding are used by genetic algorithm for calculating the objective functions using Equation (5) and check the optimization constrain by Equation (6) respectively.

As two constraints were considered (the number of sections yielding and total number of plastic hinge occurrences), therefore, Equation (5) can be rewritten as

$$P = f_{obj} \times (R_{P1} \times PH_1 + R_{P2} \times PH_2) \quad (9)$$

where $PH_1$ represents the number of damaged beam, column, and damper elements and $PH_2$ is the total number of hinge occurrences during an earthquake excitation in the structure. $R_{P1}$ *and* $R_{P2}$ are corresponding adjusting coefficients for the mentioned constraints.

The developed optimization process for earthquake energy dissipation systems is a comprehensive computational algorithm; any supplemental objective function or design constraint can be added to the algorithm.

Also, it is adjustable with any code of practice and applicable for the design of structure using performance-based design method by defining the desired demand as a design constraint.

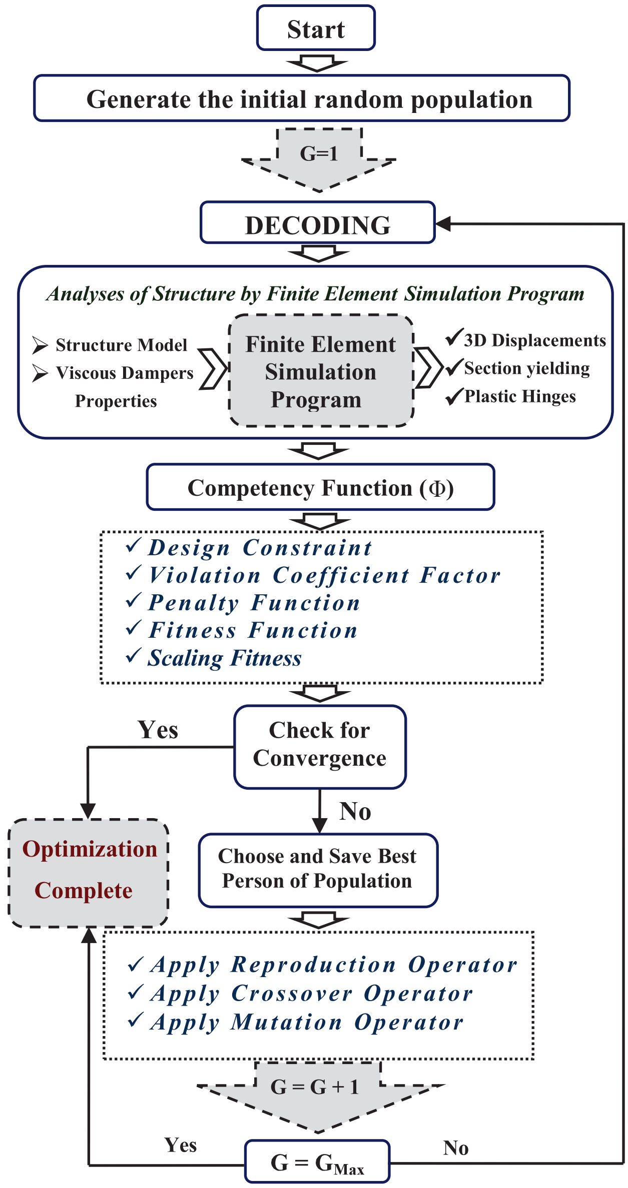
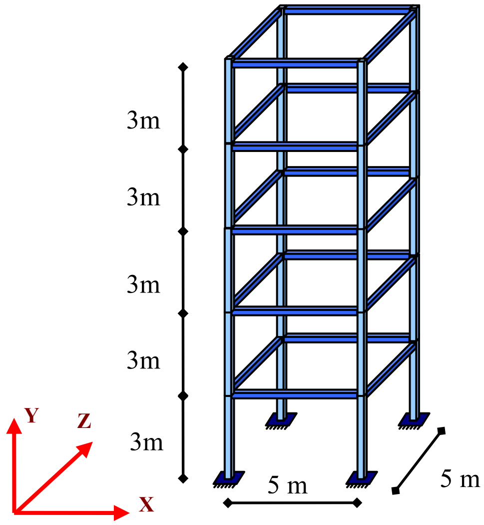


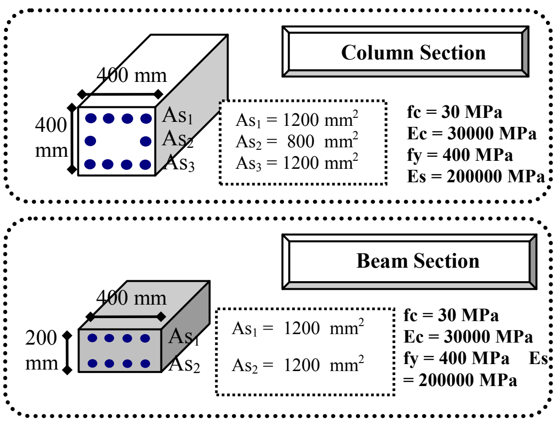

**Fig. 2.** Flowchart of the genetic algorithm.

## 4 APPLICATION TO FIVE-STORY REINFORCED CONCRETE FRAME BUILDING

The developed optimization algorithm was applied to a three-dimensional model of a five-story reinforced




(a) Five-story RC model




(b) Beam and column sections details

**Fig. 3.** Five-story reinforced concrete (RC) model illustrating beam and column sections and material properties.

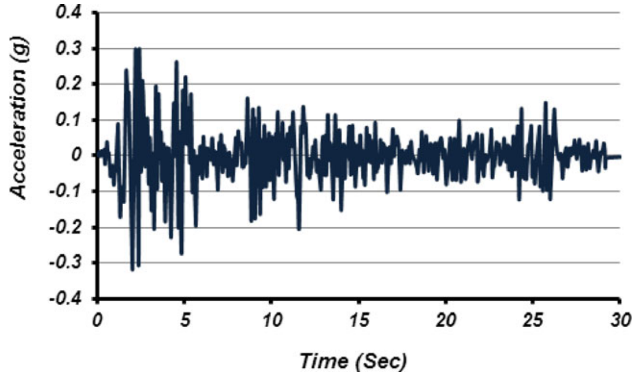



**Fig. 4.** Earthquake record of the north–south component of the El Centro earthquake (USA, 1940).

**Table 1**
Available viscous damper damping coefficients

| *Damping coefficient parameters* | *Damping coefficient values (kN.sec/m)* |
|---|---|
| $C_{d1}$ | 0 |
| $C_{d2}$ | 100 |
| $C_{d3}$ | 200 |
| $C_{d4}$ | 300 |
| $C_{d5}$ | 400 |
| $C_{d6}$ | 500 |
| $C_{d7}$ | 600 |
| $C_{d8}$ | 700 |

concrete structure, shown in Figure 3. The same figure illustrates the beam, column section, and material properties.

The considered model provides just an example of a reinforced concrete frame and it is used to evaluate the developed optimization algorithm.

All sections of beams, columns, viscous damper elements, and material properties were defined; structural modeling was performed by finite element simulation program.

The structure was subjected to the multisport excitations in three directions exhibited by the El Centro earthquake (USA, 1940) record, shown in Figure 4. To consider the worst conditions of excitation, the same record was used for all directions.

So, as Figure 4 shows, in the third step of the optimization process, the finite element software is used to analyze the structural model with various viscous damper properties (damper damping), as determined by the optimization algorithm in each generation.

The damping coefficients considered were in the range of $C_d = 0$ to 700 kN.sec/m, as tabulated in Table 1.

After performing the time history plasticity analysis of the structure for the considered earthquake record, the seismic response of structures was assessed in terms of number of failures and damage to structural members, including damper devices and structural displacements and used to determine the competency function.

Thus, during the optimization process, various damping coefficients were selected from Table 1.

The structure was equipped with two dampers on both sides of each story (a total of 20 viscous dampers in the entire structure). The same damper parameter is assumed on both sides of each story, so five different viscous dampers were selected in the structural model (one damper selection for each story), as shown in Figure 5.

As five genes existed for each structure, five design variables were defined for the optimization algorithm.

Hence, the five-story model was considered, and the optimization objectives evaluated displacements in

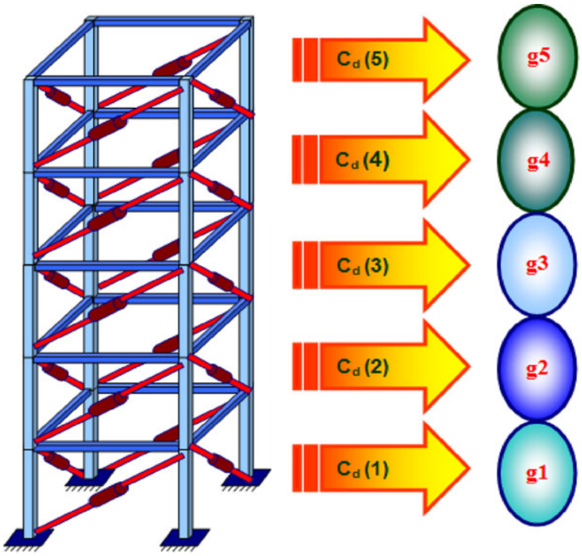
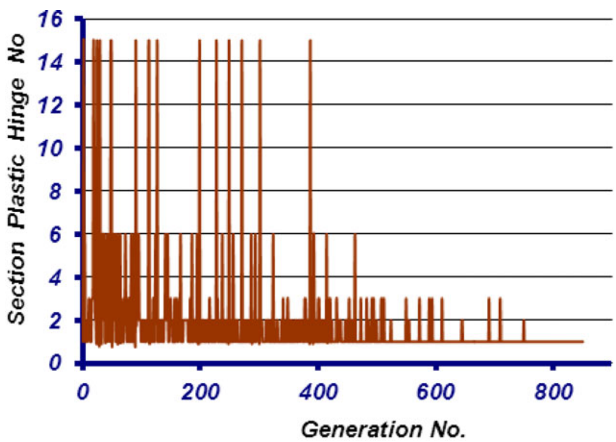
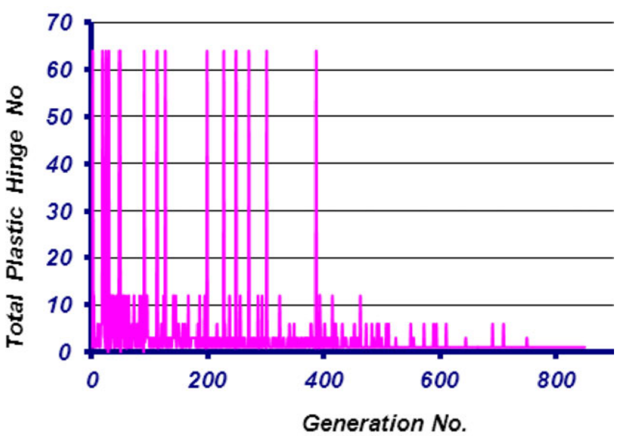



**Fig. 5.** Convert the viscous dampers to genes.




(a) Yielding in beam and columns sections




(b) Total number of plastic hinges

**Fig. 6.** Sections yielding and plastic hinges occurrence in structural member.

three dimensions ($\Delta_X$, $\Delta_Y$, $\Delta_Z$) at all stories, thus, the objective function (Equation (5)) comprised 15 variations displacements in the X, Y, and Z directions at all five story levels.

Some references suggested the number of the initial population as 30, 50, and 70 (Mishra et al., 2004; Jiang and Adeli, 2008b).

In this work, based on the design parameters of the model example and after some trial and error process, the initial number of population was considered as 50. Therefore, 50 chromosomes comprising various genes formed the initial generation by random selection of genes from Table 1. After preparation of the initial population, the chromosomes were decoded and the optimization process was started.

The optimization of the viscous damper parameters for the considered structure model subjected to earthquake excitation was completed after producing 17 generations.

The time history nonlinear analyses of the structure subjected to the El Centro earthquake were performed 850 times (50 times for each generation).

The load step for the nonlinear analyses was considered as 0.002 second; therefore, the time history nonlinear analyses were performed through 15,590 load steps.

The allowable number of iterations to reach the nonlinear convergence was limited to 100 loops, and the convergence tolerance was fixed at 0.001 for the seismic nonlinear analyses.

The optimization computation time was approximately 5,010 minutes, which is equivalent to 83.3 hours with a desktop computer with a 2 GHz Intel Core with two CPUs and 2 GB of RAM.

## 5 RESULTS AND DISCUSSION

The seismic response of the structure was evaluated with respect to sections yielding and plastic hinge development in the structural members and displacements at different story levels during earthquake in the optimization process.

### 5.1 Sections yielding and plastic hinges in structural members

The number of beam, column, and damper sections, which yielded under earthquake excitation in the optimization process, is shown in Figure 6a. It is obvious from this plot that the number of yielded sections was reduced from 15 in the first generation to 2 at 450 generations (the middle of the optimization process) and to 1 in the final optimum case. This corresponds to a 93.3% reduction in number of yielded sections.

**Table 2**
Peak displacements in the X (horizontal) direction during the optimization process for all stories

| *Item* | *Story no.* | *Optimization process (0–850 generations)* First | Mid | End | *Reduction due to optimization* (mm) | % |
|---|---|---|---|---|---|---|
| Peak maximum displacement (mm) | 1 | 3.76 | 1.06 | 0.88 | 2.88 | 76.6 |
| | 2 | 19.71 | 2.73 | 2.13 | 17.58 | 89.2 |
| | 3 | 33.89 | 2.96 | 2.2 | 31.69 | 93.5 |
| | 4 | 42.44 | 2.93 | 2.14 | 40.3 | 95.0 |
| | 5 | 49.74 | 3.08 | 2.19 | 47.55 | 95.6 |
| Peak minimum displacement (mm) | 1 | – 4.08 | – .085 | – 0.7 | – 3.38 | 82.8 |
| | 2 | – 21.22 | – 2.45 | – 1.85 | – 19.37 | 91.3 |
| | 3 | – 33.33 | – 2.51 | – 1.74 | – 31.59 | 94.8 |
| | 4 | – 44.35 | – 2.26 | – 1.58 | – 42.77 | 96.4 |
| | 5 | – 42.35 | – 2.26 | – 1.58 | – 40.77 | 96.3 |
| Peak movement amplitude (mm) | 1 | 7.84 | 1.145 | 1.58 | 6.26 | 79.8 |
| | 2 | 40.93 | 5.18 | 3.98 | 36.95 | 90.3 |
| | 3 | 67.22 | 5.47 | 3.94 | 63.28 | 94.1 |
| | 4 | 86.79 | 5.19 | 3.72 | 83.07 | 95.7 |
| | 5 | 92.09 | 5.34 | 3.77 | 88.32 | 95.9 |

**Table 3**
Peak displacements in the Z (horizontal) direction during the optimization process for all stories

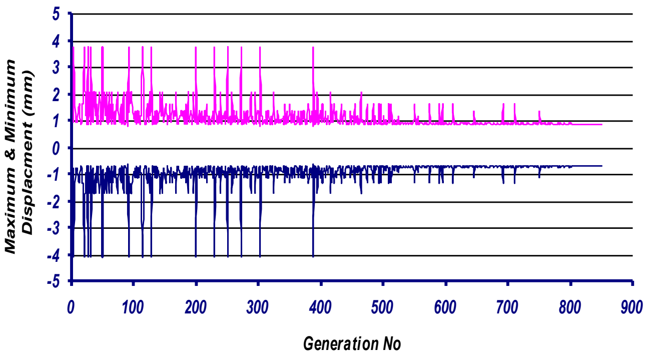
| *Item* | *Story no.* | *Optimization process (0–850 generations)* First | Mid | End | *Reduction due to optimization* (mm) | % |
|---|---|---|---|---|---|---|
| Peak maximum displacement (mm) | 1 | 2.77 | 1.09 | 0.91 | 1.86 | 67.1 |
| | 2 | 21.18 | 2.85 | 2.19 | 18.99 | 89.7 |
| | 3 | 33.99 | 2.89 | 2.13 | 31.86 | 93.7 |
| | 4 | 40.52 | 2.89 | 2.12 | 38.4 | 94.8 |
| | 5 | 46.46 | 3.08 | 2.2 | 44.26 | 95.3 |
| Peak minimum displacement (mm) | 1 | – 3.44 | – 0.81 | – 0.68 | – 2.76 | 80.2 |
| | 2 | – 22.73 | – 2.56 | – 1.91 | – 20.82 | 91.6 |
| | 3 | – 35.74 | – 2.4 | – 1.66 | – 34.08 | 95.4 |
| | 4 | – 46.07 | – 2.26 | – 1.62 | – 44.45 | 96.5 |
| | 5 | – 46.92 | – 2.29 | – 1.71 | – 45.21 | 96.4 |
| Peak movement amplitude (mm) | 1 | 6.21 | 1.9 | 1.59 | 4.62 | 74.4 |
| | 2 | 43.91 | 5.41 | 4.1 | 39.81 | 90.7 |
| | 3 | 69.73 | 5.29 | 3.79 | 65.94 | 94.6 |
| | 4 | 86.59 | 5.15 | 3.74 | 82.85 | 95.7 |
| | 5 | 93.38 | 5.37 | 3.91 | 89.47 | 95.8 |

The overall number of plastic hinges occurring during loading and unloading of structural members due to earthquake vibration, in the genetic algorithm optimization process, is shown in Figure 6b.

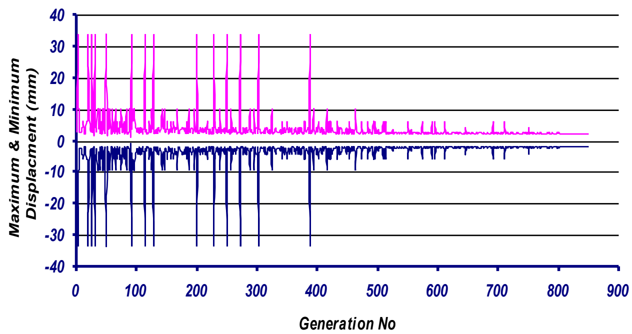
## 5.2 Displacement

The genetic algorithm attempts to arrange the viscous dampers in such a way as to minimize the total plastic hinge occurrence in buildings. The total number of plastic hinges developed in the structure decreased from 64 in the first generation to 3 at 450 generations (the middle of the optimization process) and to 1 for the optimum result. This corresponds to a 98.4% reduction in total number of plastic hinges.

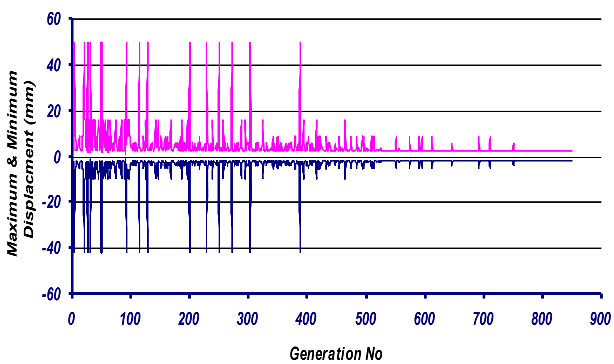
The three-dimensional displacements of structures in story levels were the optimization objective of this study. So, the displacement result is showing the variation of optimization objective function.




(a) Story 1

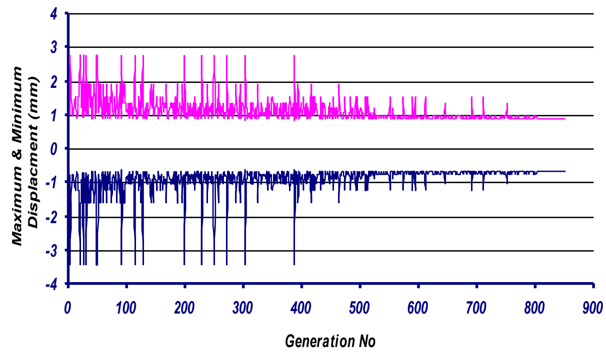



(b) Story 3

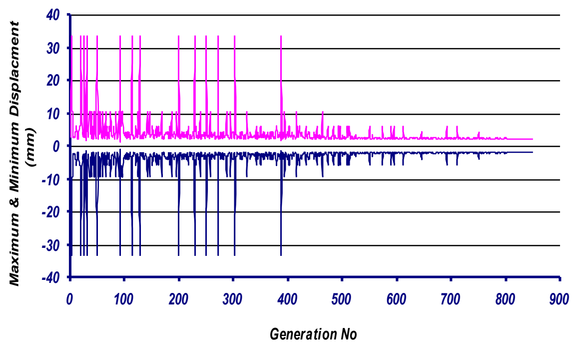



(c) Story 5

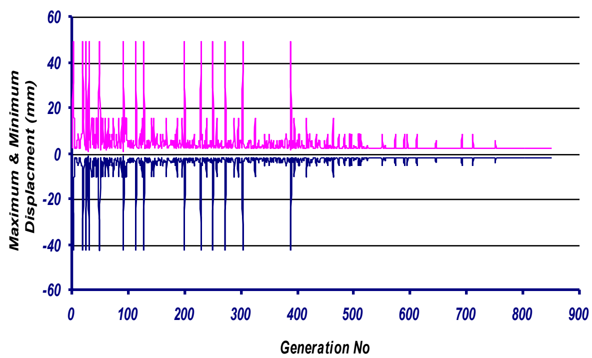
**Fig. 7.** Maximum and minimum displacements in the X direction during the optimization process.




(a) Story 1




(b) Story 3




(c) Story 5

**Fig. 8.** Maximum and minimum displacements in the Z direction during the optimization process.

The peak minimum and peak maximum displacements in the X (horizontal) direction during the optimization process at different story levels are tabulated in Table 2 and shown in Figure 7.

It is noteworthy that for purposes of illustration, only the peak movement of the stories during the earthquake excitation is considered.

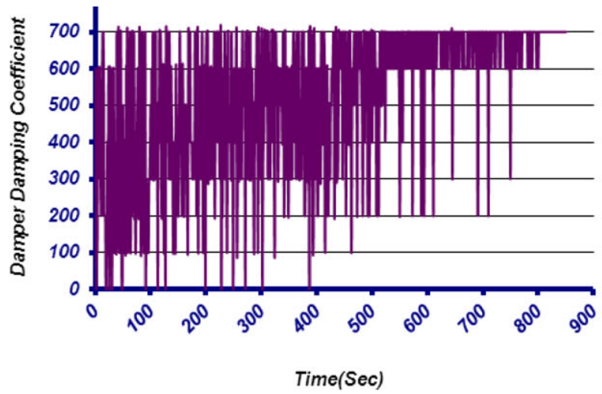
The results show that the algorithm successfully minimized the seismic movements in all stories. The reductions in the peak minimum and peak maximum displacements in the X direction were found to be in the range of 75.6% to 95.6% and 82.8% to 96.3%, respectively.

The results for the peak displacement in the Z (horizontal) direction during the optimization process and the generation numbers are tabulated in Table 3 and plotted in Figure 8.

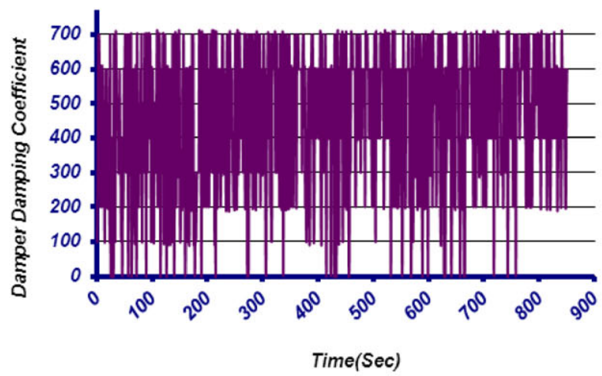
It can be observed from the table that the reduction in the peak minimum and peak maximum displacements due to optimization were in the range of 80.2% to 96.4% and 67% to 95%, respectively.

### 5.3 Damping variation

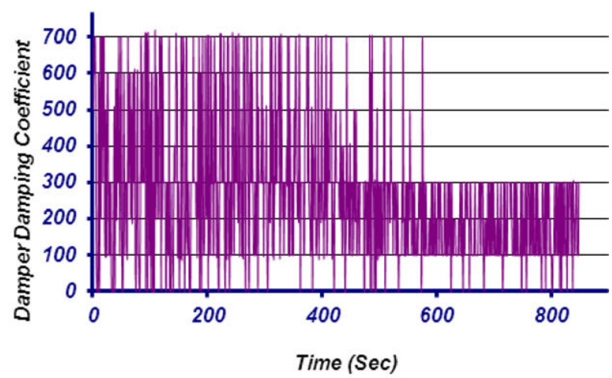
Figure 9 shows the viscous damper damping variation for stories 1, 3, and 5 during optimization process by genetic algorithm.




(a) Story 1




(b) Story 3

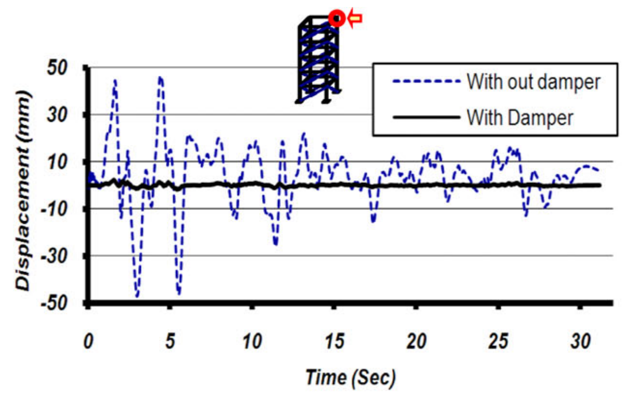



(c) Story 5

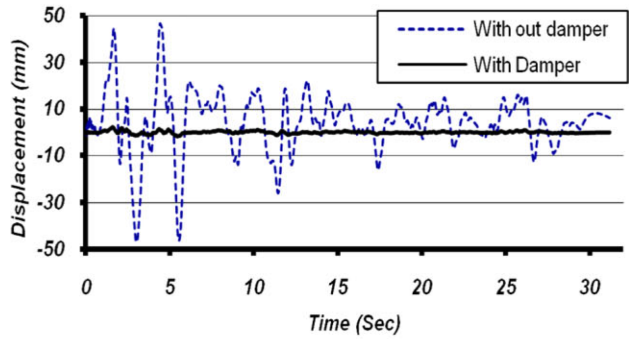
**Fig. 9.** Variations in viscous damper damping during the optimization process (kN.sec/m).

**Table 4**
Optimum viscous damper damping coefficients

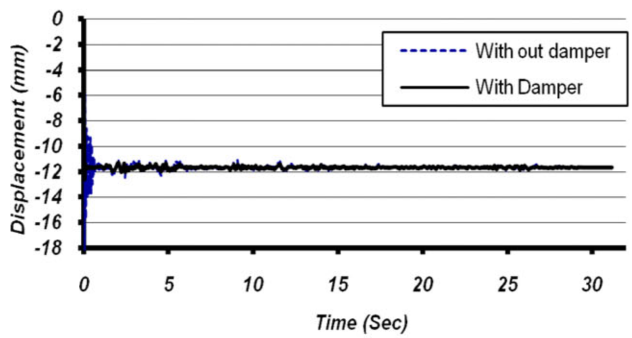
| *Story no.* | *Optimum damper damping coefficient (kN.sec/m)* |
|---|---|
| 1 | 700 |
| 2 | 400 |
| 3 | 100 |
| 4 | 100 |
| 5 | 200 |




(a) Horizontal displacement in the X direction




(b) Horizontal displacement in the Z direction




(c) Vertical displacement in the Y direction

**Fig. 10.** Time history displacement of top node of structure with optimum dampers.

**Table 5**
Summary of the analysis results

| *Seismic response* | *Section plastic hinges* | *Total plastic hinges* | *Story no. 1* | *2* | *3* | *4* | *5* | *Average reduction* |
|---|---|---|---|---|---|---|---|---|
| Plastic hinge reduction (%) | 93.3 | 98.4 | – | – | – | – | – | 95.9 |
| Peak horizontal displacement amplitude reduction in the X direction (%) | – | – | 79.8 | 90.3 | 94.1 | 95.7 | 95.9 | 91.2 |
| Peak horizontal displacement amplitude reduction in the Z direction (%) | – | – | 74.4 | 90.7 | 94.6 | 95.7 | 95.8 | 90.2 |
| Peak vertical displacement amplitude reduction in the Y direction (%) | – | – | 31.7 | 89.2 | 93.5 | 95.0 | 38.0 | 69.5 |
| Peak rotation reduction in the X direction (%) | – | – | 74.9 | 63.2 | 65.1 | 70.1 | 60.0 | 66.7 |
| Peak rotation reduction in the Z direction (%) | – | – | 83.9 | 76.8 | 84.5 | 90.0 | 83.3 | 83.7 |
| Peak rotation reduction in the Y direction (%) | – | – | 56.5 | 62.2 | 67.2 | 72.7 | 62.2 | 64.2 |
| Average reduction % | | | 66.9 | 78.7 | 83.2 | 86.5 | 72.5 | 80.2 |

The optimum viscous dampers that can minimize the response of considered model of reinforced concrete framed structure under severe earthquake multisupport excitation at the completion of the optimization procedure (after 850 generations) are identified and tabulated in Table 4.

### 5.4 Time history displacements with optimum dampers

The time history displacements of the top node, with and without optimum dampers, are plotted in Figure 10.

The locations of the considered node in the structure are also shown in the figure. The plots show that the optimum viscous dampers effectively reduced the horizontal vibrations of structure in the X and Z directions during the earthquake with 95.9% and 95.8% reductions in the X and Z directions, respectively.

### 5.5 Discussion

The results for the optimization of viscous dampers system in the five-story reinforced concrete structure, using the genetic algorithm are summarized in Table 5.

The results indicated that the average reduction in the sections yielding and total plastic hinge occurrence in the structure utilized with optimum viscous damper during earthquake excitation is 95.9%. Therefore, using the determined optimum damper systems in considered structural model would be able to diminish 95% of structural damage due to earthquake vibration.

Also, the average peak horizontal displacement amplitude reductions for all stories in the X and Z directions are 91.2% and 90.25%, which shows efficiency of optimum damper device in reduction vibration of structure subjected to severe ground motion.

The overall reduction in seismic response of structure in terms of plastic hinge formation in structural members, the displacements, and the rotations of all floors in the building is calculated to be approximately 80.2%. This result reveals that the developed genetic algorithm successfully optimizes the earthquake energy dissipation system and can mitigate the effects of earthquakes on structures. So, this technique can significantly increase the building's stability and safety during earthquakes.

Although the optimization procedure for the considered model successfully completed after 17 generations after only 83 hours of computation time, using the response surface methodology, which is a collection of mathematical and statistical techniques, may lead to obtaining the best generations more quickly, and reducing the optimization procedure and computation time. Implementing this technique remains for further research efforts (Simpson et al., 1998).

## 6 CONCLUSIONS

This study developed a multiobjective optimization computation procedure based on genetic algorithm to enhance the performance of earthquake energy dissipation systems and to minimize the seismic response of structures in terms of damage to structural members and simultaneous displacements of all story levels through 6 degrees of freedom. The characteristics of damper devices were considered as design parameters and optimization objective was defined based on three-dimensional movement of structural nodes with avoidance of beam and column failures as design constraint. The developed optimization process is comprehensive computational algorithm and it allows the addition of any supplemental objective function or design constraint to algorithm.

The developed computational algorithm was applied to a model of a five-story reinforced concrete framed structure under a multidirectional earthquake load, and the results of the optimization were evaluated. Analysis showed that, overall, the use of the optimized damper devices reduced the structural seismic response by approximately 80.2%. This result indicates that the genetic algorithm developed in this study successfully optimized the earthquake energy dissipation system and can significantly increase building safety in the event of severe earthquake.

## ACKNOWLEDGMENTS

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