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A Practical Method for Optimal Rehabilitation of Steel Frame Buildings Using Buckling Restrained Brace Dampers

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ABSTRACT

A novel optimisation method is developed for optimum strengthening design of 2D multi-story steel moment resisting frames using buckling restrained brace (BRB) dampers and externally welded steel plates in compliance with ASCE 41-06. The proposed method is based on the concept of Uniform Distribution of Deformation (UDD), in which structural materials are redistributed from strong to weak parts of a structure until the material capacity is fully exploited. For the first time, an adaptive power function is introduced to improve the computational efficiency and convergence speed of the UDD optimisation method. The results of the proposed optimisation method are compared with metaheuristic optimisation methods using Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO) for a three story and a nine story frame. The demand to capacity ratios of deformation-controlled and force-controlled structural members based on ASCE 41-06 are considered as design constraints in the optimisation process. The results demonstrate the efficiency of the proposed optimisation method in finding the optimum design solution with significantly less computational costs (up to 300 times less number of analyses) compared to both GA and PSO methods. It is shown that, in general, a more suitable distribution of dampers is accompanied by a more uniform distribution of demand to capacity ratios, which confirms the concept of UDD optimisation method.

KEYWORDS: *Optimum Seismic Rehabilitation, BRB Dampers, Genetic Algorithm, Particle Swarm Optimisation, Uniform Distribution of Deformation (UDD) Optimisation, Demand to capacity ratio.*

1. INTRODUCTION

Significant human and financial losses caused by severe earthquakes in the last decade (e.g. Kashmir, 2005; China, 2008; Indonesia, 2009; Haiti, 2010; Turkey, 2011; Nepal, 2015) have highlighted the high seismic vulnerability of the existing building stock especially in developing countries. To improve the seismic performance of structures, either for new building design or strengthening purposes, different types of passive control systems have been introduced such as viscous, viscoelastic, friction and hysteretic dampers. To reduce human and economic losses in future earthquakes using limited available resources, it is crucial to assess the cost and benefit of any strengthening intervention [1]. This highlights the importance of developing efficient methods to obtain more cost effective design solutions. In one of the early attempts in this direction, Gurgoze and Muller [2] developed an energy-based method to identify the best position of viscous dampers in a linear multi-story shear model. Maximum displacement demand has been also used by several researchers (e.g. Zhang and Soong [3], Shukla and Datta [4] and Tsuji and Nakamura [5]) to find the best design of viscous dampers, where a greater damping coefficient is usually obtained for the stories with higher relative inter-story drift ratios.

As the new generation of optimisation methods, metaheuristic algorithms have been also used for optimum strengthening/rehabilitation design of different types of structural systems. While earlier studies mainly applied Genetic Algorithm (e.g. [6-13]), other methods such as Artificial Bee Colony Algorithm [14], Backtracking Search Optimisation Algorithm [15], and Hybrid methods [16] were also adopted. In general, metaheuristic algorithms are suitable to obtain the best global optimum solution for non-linear systems. However, their convergence speed is relatively low and they are computationally expensive especially for more complicated problems. Therefore, these methods are not suitable for practical optimisation of non-linear passive control systems under dynamic earthquake excitations.

Gradient-based algorithms are also applied to find the best design solutions for different passive control systems. Takewaki [17] developed a procedure to find the best placement of viscous dampers to reduce a transfer function related to the maximum inter-story drifts. It was shown that to improve the seismic performance of the system, viscous dampers should be concentrated mainly in the stories with higher transfer function amplitude. In a follow up study, Takewaki et al. [18] used the steepest direction search method to obtain the best distribution of viscous dampers. In general, it has been shown that gradient-based algorithms can lead to optimum results in less number of iterations compared to the metaheuristic optimisation algorithms (e. g. [19-24]). However, they have some drawbacks such as convergence to local optimal solutions, difficult implementation, high computational effort needed to calculate derivatives of the objective functions at each load step and susceptibility to numerical noise [25, 26]. More recently, Nabid et al. [27, 28] developed a practical method for more efficient design of friction-based wall dampers and showed that the energy dissipation capacity of the dampers can be significantly increased by using a more appropriate distribution of friction forces. Altieri et al. [29] also used a linear approximation method (COBYLA) for reliability-bases optimal design of nonlinear viscous dampers for enhancing the seismic performance of steel moment resisting frames. They minimised the sum of the damper forces to reduce the damper cost, while the probability of structural failure was controlled under a stochastic earthquake input.

In severe earthquakes, generally the deformation demand in some parts of the structures does not reach the maximum allowable level [30], which means the material capacity is not fully exploited. Therefore, it can be assumed that a status of uniform deformation demand is a direct consequence of the optimum use of material. The concept of Uniform Distribution of Deformation (UDD) can be easily adopted to find the optimum seismic design of different types of structural systems. In this method, to achieve the best design solution, inefficient material is gradually shifted from strong parts to weak parts of a structure until a state of uniform deformation or damage prevails. UDD algorithms have been used in different studies to find the optimum seismic design of shear buildings [31-35], concentrically braced frames [36], eccentrically braced frames [37, 38], reinforced concrete frames [39], and truss-like structures [26]. In the present study, for the first time, a Modified Uniform Distribution of Deformation (MUDD) algorithm is introduced for optimum strengthening design of multi-story steel moment resisting frames with buckling restrained brace (BRB) dampers by using adaptive convergence factors. While earlier studies on optimum strengthening mainly considered global responses such as inter-story drift or acceleration of stories as the performance measure, in this study the demand to capacity ratio (DCR) of the members is considered as the key performance criterion as per ASCE41-06 [40]. To show the efficiency of the proposed method, the results of the MUDD algorithm for optimum strengthening design of three-story and nine-story 2D steel moment resisting frames are compared with Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO) metaheuristic optimisation methods.

2 OPTIMISATION PARAMETERS

2.1 Design Parameters

The cross section of the adopted buckling restrained brace (BRB) damper is depicted in Fig. 1. The steel tube and the encasing mortar can prevent the buckling of BRB by confining the steel core. Since only the steel core carries the axial forces, the un-bonding material between the mortar and the steel core can cause relative displacements between these sections (see Fig. 1). The width of the steel core is considered a constant value of 150 mm, while the thickness of the core is one of the design variables varying between 4 mm and 100 mm. For practical purposes, in each story the thicknesses of all BRB dampers are considered to be similar. It should be noted that the optimum design method proposed in this study is general and can be easily applied on other shapes of BRB dampers such as square or circular hollow tubes.

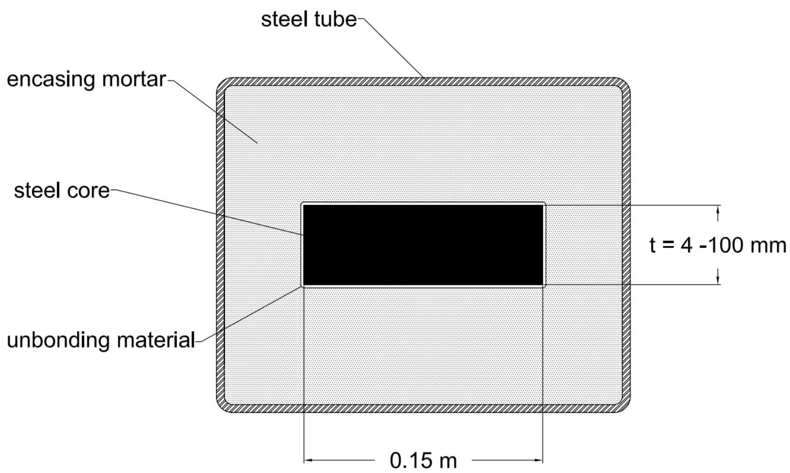


Fig.1. Employed BRB cross-section

To increase the capacity of the structural members, additional plates are also welded to the beam and column elements when required. Fig. 2 shows the configuration of the welded plates in beam and column sections. The thickness of the welded plates considered in this study are 0 (no plate), 8, 10, 12, 14, 16, 18, 20, 22 or 24 mm.

For a frame with the number of stories equal to N_S, the variables vector (I) can be expressed according to Equation (1):

$$I = [t_1, t_2, \dots, t_i, \dots, t_{N_s}, T_1, T_2, \dots, T_j, \dots, T_{N_e}] \quad (1)$$

where, t_i is the thickness of the steel core for the dampers in i th story, N_e represents the number of frame elements and T_j is the thickness of the externally welded steel plates for j th element. Considering that the width of the steel core in the BRB elements used in this study is assumed to be 0.15 m (see Fig. 1), the cross-sectional area of the BRB core can be directly calculated based on the thickness of the steel core (t_i) using the following equation.

$$A_i = 0.15 \times t_i \quad (2)$$

where, A_i is the cross-sectional area of the BRB core for the dampers in i th story in m^2.

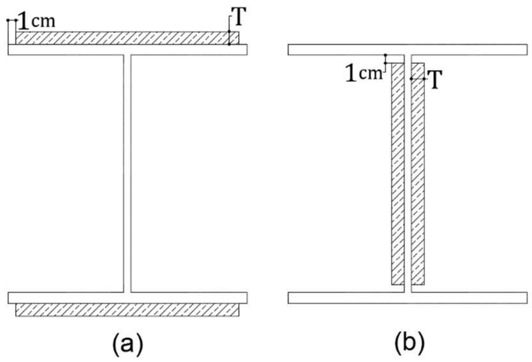


Fig.2. Details of externally welded steel plates to frame elements: a) beams b) columns

2.2 Design Constraints

In this paper the demand to capacity ratio (DCR) limits of the structural members in compliance with ASCE41-06 [40] is considered as the design constraints. According to this standard, the chord rotation is the primary criterion to calculate the DCR of the deformation-controlled elements. Therefore, for the DCR of the beam elements (which are always considered to be deformation-controlled due to their flexural action) can be defined by Equation (3):

$$DCR_{beam} = \frac{\theta_{beam}}{\theta_{y,beam} + \theta_{p,beam}} \quad (3)$$

where θ_{beam} is the total chord rotation of the beam, $\theta_{y,beam}$ is the yield rotation of the beam and $\theta_{p,beam}$ is the permissible plastic rotation of the beam determined in accordance with ASCE41-06 [40].

According to ASCE41-06 [40], the columns with the axial load, *P*, less than 50% of the lower-bound axial column strength, P_{CL}, are deformation-controlled, while the columns with higher axial loads (i.e. $P > 0.5P_{CL}$) shall be considered as force-controlled. Therefore, in this study the following equation is used to calculate the DCR of the force-controlled and deformation-controlled columns:

$$DCR_{column} = \begin{cases} \dfrac{\theta_{column}}{\theta_{y,column} + \theta_{p,column}} & \dfrac{P}{P_{CL}} < 0.5 \\ \\ \dfrac{P}{P_{CL}} + \dfrac{M_x}{M_{CL,x}} + \dfrac{M_y}{M_{CL,y}} & \dfrac{P}{P_{CL}} \geq 0.5 \end{cases} \quad (4)$$

where θ_{column} is the total chord rotation of the column, $\theta_{y,column}$ is the yield rotation of the column, and $\theta_{p,column}$ is the permissible plastic rotation of the column determined in accordance with ASCE41-06 [40]. M_x and M_y denote the bending moment in the column about x-axis and y-axis, respectively. Similarly, $M_{CL,x}$ and $M_{CL,y}$ show the lower-bound flexural strength of the column about the principal axes.

In this study, a Nonlinear Static Procedure (NSP) is used to evaluate the design constraints in the above equations. The frames are subjected to gradually increasing lateral load with a load pattern based on the first mode until the target displacement calculated in accordance with ASCE41-06 [40] is achieved for seismic hazard levels of BSE-1 and BSE-2 as shown in Fig. 3.

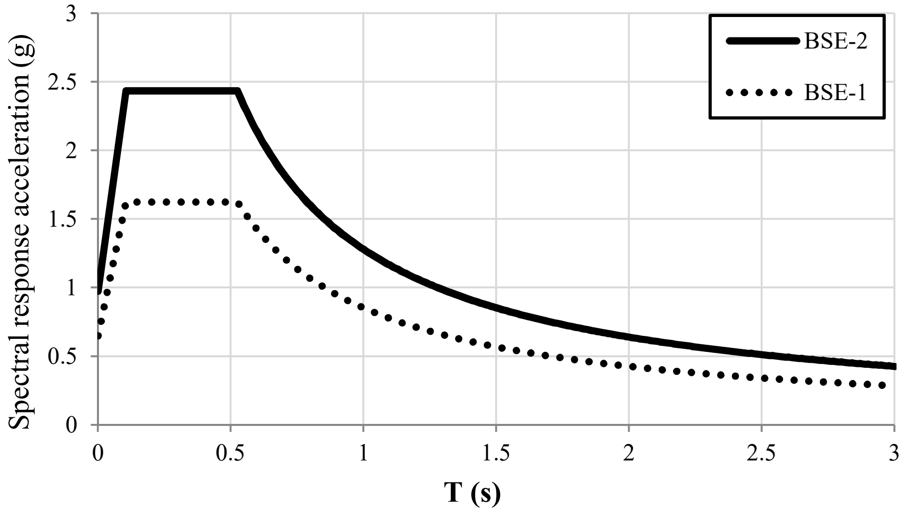


Fig.3. Design response acceleration spectrums for seismic hazard levels BSE-1 and BSE-2

2.3 Objective Function

In general, the main cost for seismic strengthening of steel structures with BRB dampers is determined by the cost of steel material used in the dampers and externally welded plates as well as the associated construction and installation costs. In this study, for simplicity, the total amount of the required material is considered as the objective function (F) of the optimisation process using the following equation:

$$F = f_{BRB} \times \alpha_{Penalty-1} \times \alpha_{Penalty-2} \times 100 \quad (5)$$

where

$$f_{BRB} = 1 + \frac{A_{tot} - N_{BRB} \times A_{min}}{N_{BRB} \times (A_{max} - A_{min})} \quad (6)$$

$$\alpha_{Penalty-1} = 1 + V_{Plate} \quad (7)$$

$$\alpha_{Penalty-2} = (1 + \sum_{i=1}^{N_E} g_i)^2 \quad (8)$$

and

$$g_i = \begin{cases} DCR_i - 1 & DCR_i > 1 \\ 0 & DCR_i \le 1 \end{cases} \quad (9)$$

where A_{tot} represents the sum of all BRB dampers' cross-sectional area; N_{BRB} is the total number of BRB dampers; $A_{\min}$ and $A_{\max}$ are the minimum and maximum cross-sectional area of a single damper, respectively; V_{Plate} is the total volume (or weight) of additional externally welded plates to the total volume (or weight) of the structural elements; and DCR_i is the demand to capacity ratio of i[th] element. To calculate $A_{\min}$ and $A_{\max}$ (based on Equation 2), $t_{\min}$ and $t_{\max}$ are assumed to be 4 mm and 100 mm, respectively.

In the proposed objective function, f_{BRB}, is the total area of the BRB dampers that is scaled based on the minimum and maximum possible area of dampers that can be practically used in the structure. This parameter varies from 1 to 2, for the case with minimum and maximum possible area of BRB dampers, respectively. $\alpha_{Penalty-1}$ is a penalty factor corresponding to the use of externally welded plates due to their relatively higher construction and installation costs. $\alpha_{Penalty-2}$ is a penalty factor that is used to ensure the optimum design solution satisfies the predefined performance target.

3 MUDD ALGORITHM

In this study, a Modified Uniform Distribution of Deformation (MUDD) algorithm is introduced to find the best thicknesses of the BRB dampers at different story levels that can satisfy the prescribed performance targets using minimum amount of structural material. In the proposed method, first the smallest thickness ($t_{\min}$) is assigned to all BRB dampers. The maximum demand to capacity ratio (DCR) of all beam and column elements at each floor is then calculated to identify the most critical stories. For example, the DCR of the second story in the frame shown in Fig. 4 is equal to the largest DCR of the specified members.

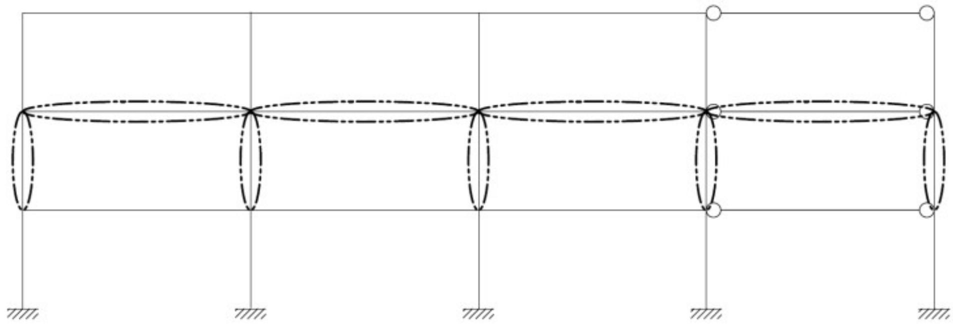


Fig.4. Relevant members to the second story.

Subsequently, the thickness of the BRB dampers at the stories with DCR values higher and lower than the allowable performance limit is increased and decreased, respectively, by using an iterative method. To have good convergence, the following equation is suggested to modify the thickness of the BRB dampers at each step:

$$t_{i+1,n} = t_{i,n} \times \beta_{i+1,n}^{\frac{DCR_{i,n} - DCR_{target,n}}{\left|DCR_{target,n}\right| + \left|DCR_{i,n} - DCR_{target,n}\right|}} \quad (10)$$

where $t_{i,n}$ is the thickness of BRB damper used at n[th] story in i[th] iteration; $DCR_{i,n}$ is the DCR of n[th] story in i[th] iteration; $DCR_{target,n}$ is the target DCR of n[th] story, and $\beta_{i+1,n}$ is the adjustment coefficient for n[th] story in (i+1)[th] iteration. Parameter β can directly control the convergence speed of the optimisation process. Fig. 5 shows that using higher β values results in more significant changes in the thickness of dampers at each step. Therefore, this factor plays an important role in the convergence of the proposed optimisation process. In this study, a constant β value of 1.2 is utilized to provide a balance between accuracy and convergence speed.

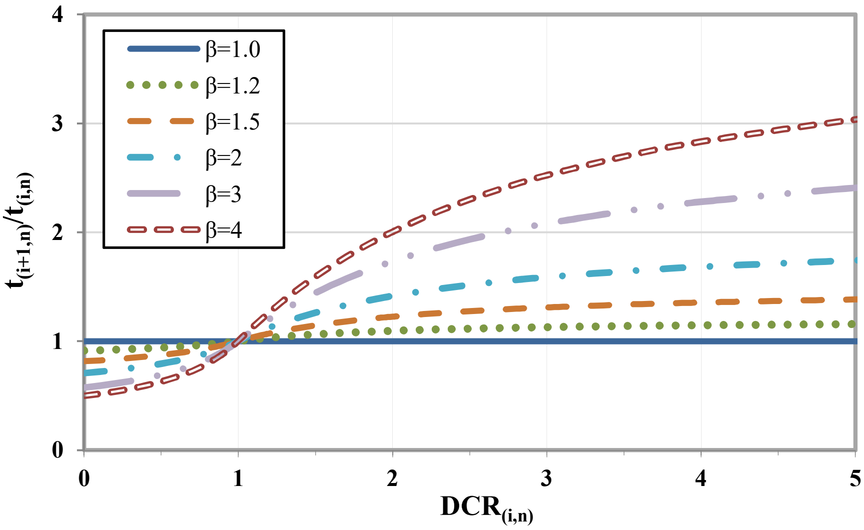


Fig.5. Influence of β on the variation of the thickness of dampers at each step

While according to ASCE41-06 [40], all columns with P/PCL <0.5 are considered to be deformation-controlled, the allowable plastic rotation capacity is considerably higher for the columns with P/PCL<0.2. It means that increasing the axial load may reduce the deformation capacity of the column elements. While an increase in the thickness of the dampers can reduce the lateral displacements and rotation demands of the structural elements, the additional stiffness will increase the axial loads in the BRB dampers and their adjacent columns. This can thereby reduce the deformation capacity of these members and hence increase their DCR. To address this issue, if the axial load in a column with the largest DCR in a story changes the ASCE41-06 acceptance criteria, the DCR of the column is reduced by using externally welded plates as discussed in previous section (see Fig. 2). Using MUDD algorithm, the following procedure is suggested for optimum strengthening design of multi-story steel structures:

1. Analysing the vulnerable structure under the design earthquake to calculate the DCR of all structural elements using the Nonlinear Static Procedure (NSP) based on ASCE41-06 [40]. At this stage a minimum thickness is assigned to all BRB dampers.
2. Modifying the thickness of the BRB dampers at each story according to Equation (10).
3. Adding externally welded plates to the required elements according to ASCE41-06 acceptance criteria.
4. Analysing the structure under the design earthquake according to the changes occurred in Steps 2 and 3.
5. If at least one of the conditions defined in Equations (11) and (12) is satisfied, the optimisation procedure will be terminated. Otherwise, the optimisation procedure will be repeated from Step 2.

$$\left|DCR_{i,n} - DCR_{target,n}\right| \le 0.005 \tag{11}$$

,

$$t_{i+1,n} = t_{\min}\ ,\ DCR_{i,n} \le DCR_{target,n} \tag{12}$$

The first condition is to check if the DCR at all stories is close enough to the target value. It should be noted that in some cases (e.g. if the thickness of the BRB dampers is minimum) the DCR at some stories may be lower than the target value. In this case, the latter condition is considered to end the optimisation process. In this study, the target DCR for all stories was considered to be 0.995 (i.e. $DCR_{target,n} = 0.995$). It should be noted that in the proposed optimisation method, the externally welded steel plates are only used when the maximum size of BRB dampers cannot satisfy the ASCE41-06 [40] design requirements. This ensures that the minimum amount of steel plates is utilised in the final design solution, due to the additional construction costs required to weld the external plates.

4 GENETIC AND PARTICLE SWARM OPTIMISATION ALGORITHMS

Genetic Algorithms (GA) [41] and Particle Swarm Optimisation (PSO) [42] are two popular stochastic search methods that have been widely used to obtain the global optimum solution of complex nonlinear problems. In the first step, these methods generate a population of candidate solutions. Subsequently, according to the objective function and the adopted method, they produce better solutions over successive generations whereby the fittest individuals survive and reproduce. In general, GA methods have three primary operators including Selection, Crossover and Mutation. A penalty resulting from violating a design constraint in GA results in a reduced opportunity for parent properties to be passed on to the next generation. On the other hand, PSO is a population-based algorithm, which is inspired by the swarming behaviour of biological populations such as flocks of birds or schools of fish. Unlike GA, solutions are optimised by updating generations without any evolution operators such as crossover or mutation.

In this study, the GA and PSO metaheuristic algorithms were used to assess the adequacy of the proposed MUDD algorithm. The Optimisation Toolbox in Matlab [43] was used to perform GA optimisation, while the methodology developed by Perez and Behdinan [44] was adopted for PSO. For GA optimisation, the Roulette, Heuristic and Uniform functions in Matlab [43] were utilised for Selection, Crossover and Mutation operators, respectively. The Roulette selection function chooses the parents by assuming that the area of the section corresponding to an individual is proportional to its expectation. The algorithm is then uses a random number to select one of the sections with a probability equal to its area. The Heuristic cross over function returns a child a small distance away from the better parent (i.e. better fitness value) in the direction away from the parent with the worse fitness value. The Uniform mutation function creates a random initial population with a uniform distribution. The most important setting parameters to control the convergence of PSO algorithm are cognitive parameter, social parameter and Inertia Weight. Using inappropriate parameters can result in destabilization of the optimisation process or lead to premature convergence. In this study, the cognitive and social parameters were set to be equal to 2 as recommended by Perez and Behdinan [44]. The Inertia Weight was also changed between 1.2 to 0.9 with each iteration using the dynamic decrease function proposed by Fourie and Groenwold [45].

5 MODELLING AND ASSUMPTIONS

A three-story and a nine-story moment resisting steel frame are designed as case study examples to investigate the efficiency of the proposed optimisation method in this study. In this study, the analyses were conducted on 2D frame models. The geometry, loading condition and material characteristics of the frames are similar to the FEMA-SAC buildings located in Los Angeles [46]. Figs. 6 and 7 show the frame layout, location of BRB dampers, and beam and column section sizes of the three-story and the nine-story frames, respectively. The utilized lateral load resisting system in these buildings consists of four independent moment resisting frames in perpendicular directions separated by hinge connections. According to ASCE41-06 [40], the seismic performance of these frames was evaluated under the following load combination:

$$1.1DL + 1.1LL \pm E \tag{13}$$

where DL, LL and E represent the design “Dead Loads”, “Live Loads” and “Earthquake Loads”, respectively. Opensees software [47] was used for nonlinear static analyses of the frames under seismic loads. To model BRBs damper, the Corot Truss element in Opensees [47] was used. The steel core was modelled using fiber elements with the Yield stress of 36 ksi (24.83 kN/cm^2). The P-delta effects were considered in the pushover analyses by taking into account all leaning columns as suggested by Foutch and Yun [48].

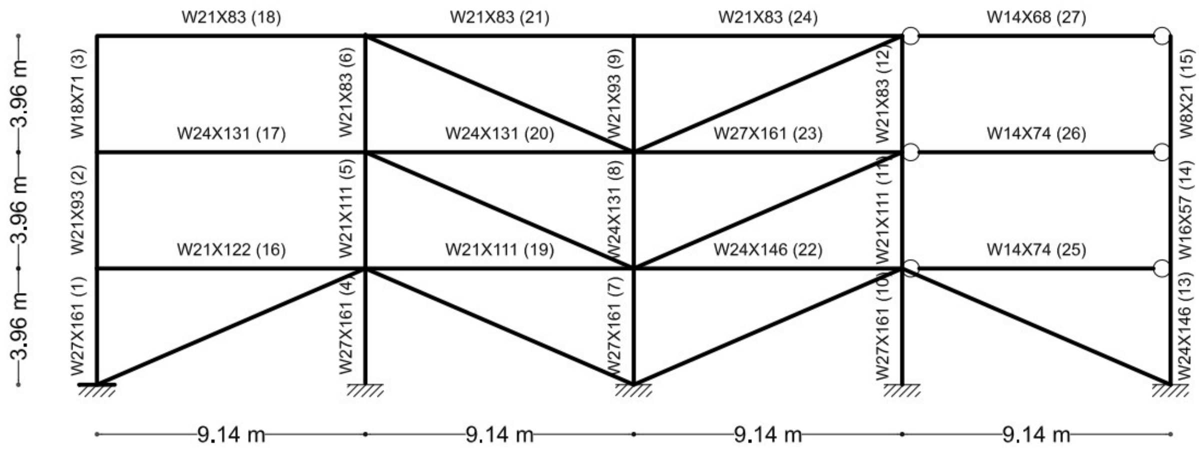


Fig.6. The frame layout, location of dampers, and beam and column section sizes, three-story frame

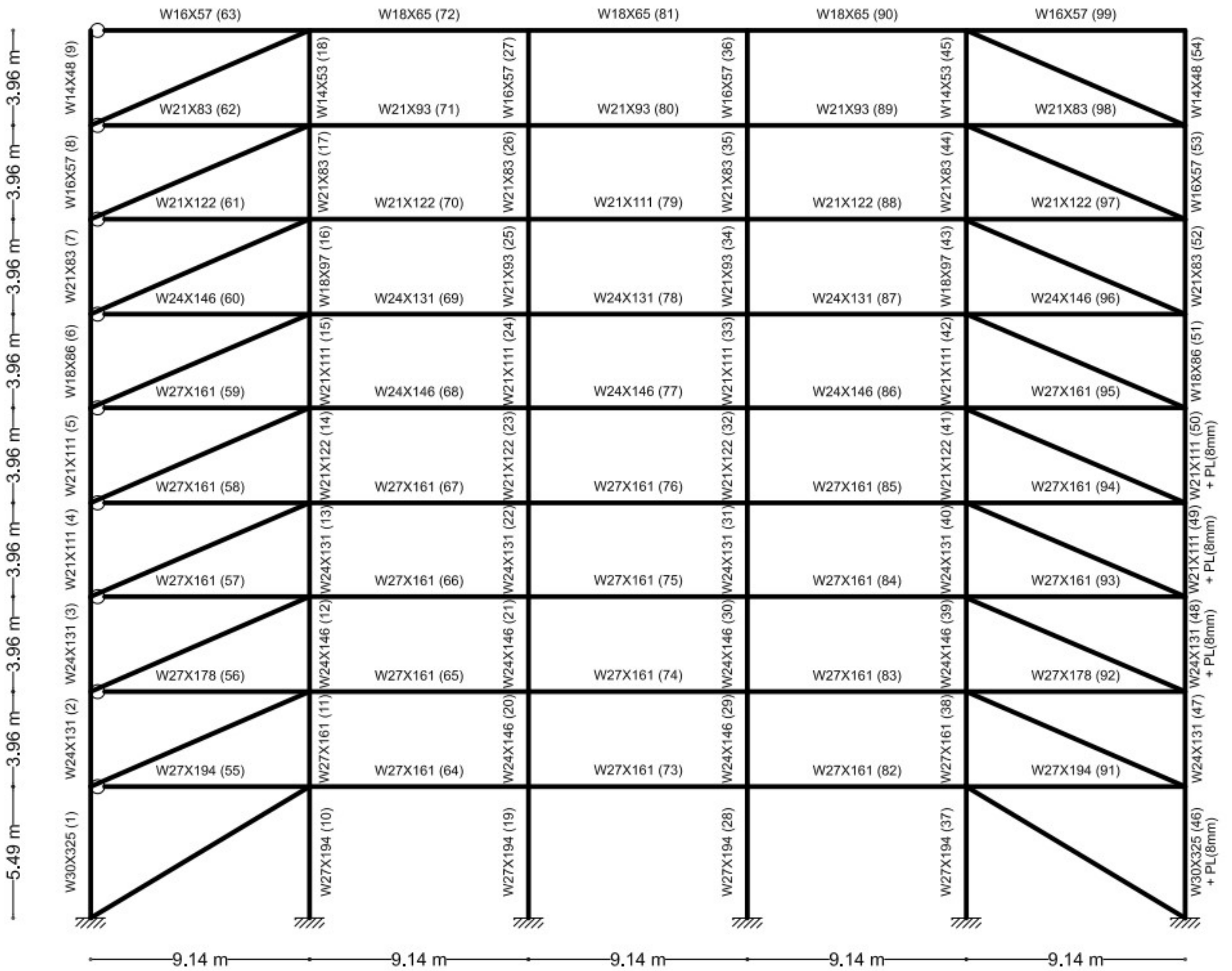


Fig.7. The frame layout, location of dampers, and beam and column section sizes, nine-story frame

6 RESULTS AND DISCUSSIONS

6.1 Three-story frame

The performance (or strengthening) target for the three-story frame was to achieve Immediate Occupancy (IO) for the seismic hazard level of BSE-1 [40]. As shown in Fig. 6, the selected frame has 15 column and 12 beam elements and 8 BRB dampers. The design variables in this case where the thickness of the steel core for the dampers at each story and the is the thickness of the externally welded steel plates for the beam and column members (i.e. 30 design variables in total). Fig. 8 shows the variation of the objective function, F, during the optimisation process using MUDD algorithm. While the selected objective function was not directly used in the MUDD optimisation algorithm, its descending trend clearly shows the efficiency of the proposed method to reduce the required structural weight by using the concept of uniform distribution of deformation demands. It is shown in Fig. 8 that the convergence was practically achieved after only 70 steps. The local increments in the objective function in Fig. 8 are mainly associated to the changes in the permissible plastic rotation of columns due to the variation of the axial loads during the optimisation process. As mentioned before, according to ASCE41-06 [40], the permissible plastic rotation of the deformation-controlled columns, $\theta_{p,column}$, is different for the columns with $P/P_{CL}>0.2$ and $P/P_{CL}<0.2$.

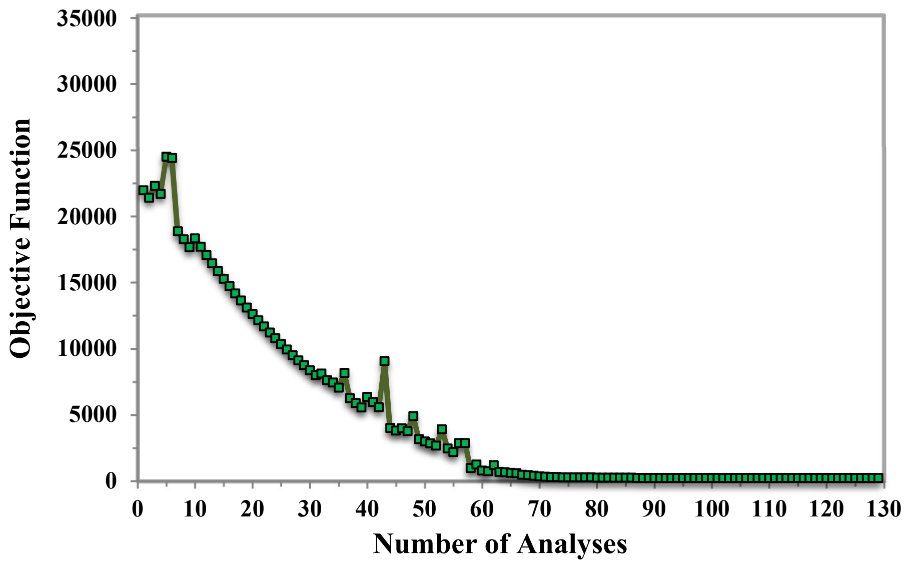


Fig.8. Variation of the objective function for optimal strengthening of the three-story frame using MUDD algorithm

Fig. 9 shows the variation of the DCR of all stories during the optimisation process using MUDD algorithm. As discussed before, the increase in the DCR of the first and second story in the fifth iteration is due to the changes in the $\theta_{p,column}$ of a few deformation-controlled columns. Fig. 10 illustrates the variation of the externally welded plates' volume during the optimisation process. It can be seen that by increasing the DCR of the stories in the fifth iteration, MUDD algorithm added some externally welded plates to the weak columns in order to compensate the changes in their permissible plastic rotation. Consequently, it is shown in Figs. 8 and 9 that this modification resulted in a decrease in the DCR of the first and the second story as well as the objective function in the sixth iteration.

For comparison purposes, the above optimisation problem was solved again by using GA and PSO methods. The analyses were started with a population size of 100 individuals and the optimisation was run three times using each method. The best solution (i.e. with the minimum value of objective function) was then compared with the results of MUDD algorithm. The repeated optimisations are represented by GA-1, GA-2, GA-3 and PSO-1, PSO-2, PSO-3 for GA and PSO methods, respectively. The GA and PSO algorithms were terminated at an assigned maximum number of iterations equal to 350 (i.e. 35000 number of analyses). For better comparisons, Fig. 11 shows the variation of the objective functions at different iterations.

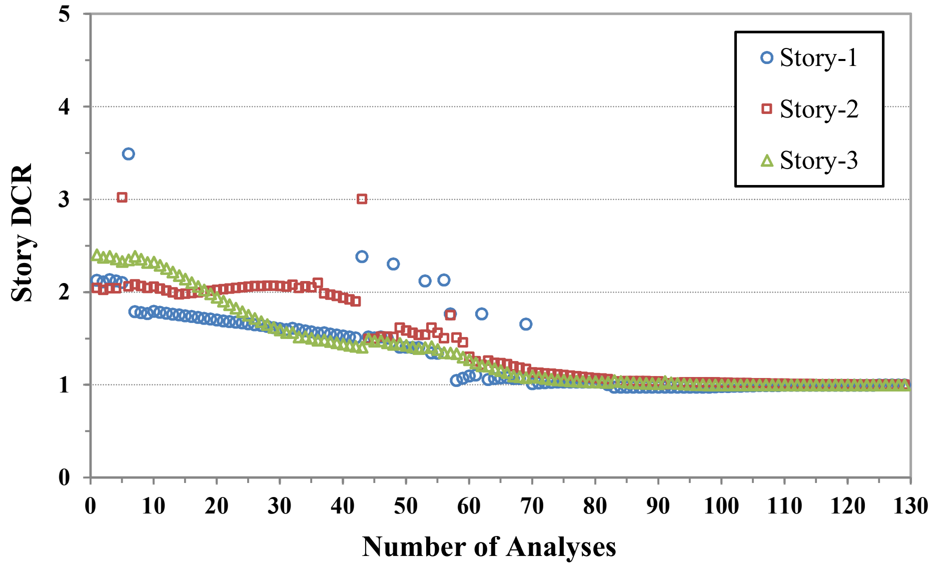


Fig.9. Variation of DCR of stories using MUDD algorithm

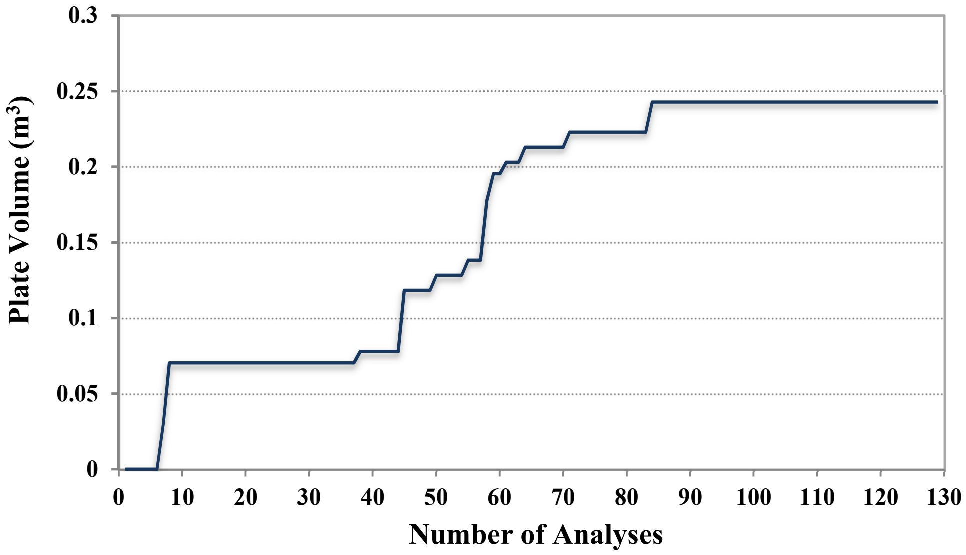
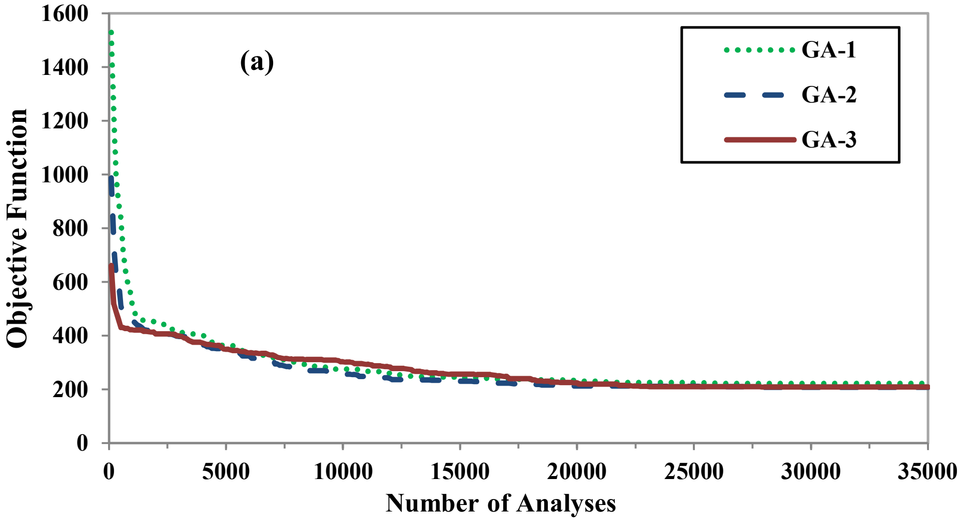


Fig.10. Variation of externally welded plates' volume using MUDD algorithm

To compare the number of iterations required to reach the optimum design solution using different algorithms, the objective function one percent above the final answer was considered as the bench mark. Based on the results in Figs. 9 and 11, to achieve the optimum answer, MUDD, GA and PSO methods require around 90, 27200 and 24000 iterations, respectively. This highlights the efficiency of the proposed MUDD method to converge to the optimum solution in significantly less number of iterations (or analyses) compared to both GA and PSO methods. Also it can be noted that the in general PSO algorithm converged to the optimum answer faster than GA.

Figs. 12 and 13 show the sum of BRBs thicknesses at different stories as well as the thicknesses of the required externally welded plates (to control the DCR of the structural elements) using MUDD, PSO and GA. The element numbers are given in Fig. 6. Overall, the results indicate that the selected methods provided very similar design solutions with the additional plates mainly assigned to the elements 4, 5, 6, 9, 10, 11 and 12. It demonstrates the efficiency of the methodology used to obtain the required externally welded plates in MUDD algorithm that can significantly simplify the complex optimisation process.



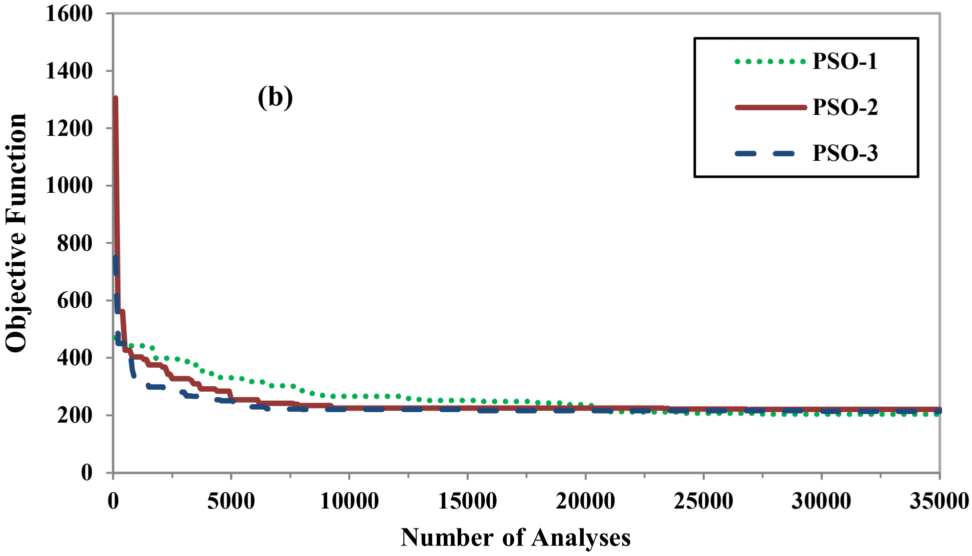


Fig.11. Variation of the objective function for optimal strengthening of the three-story frame using: a) GA; b) PSO

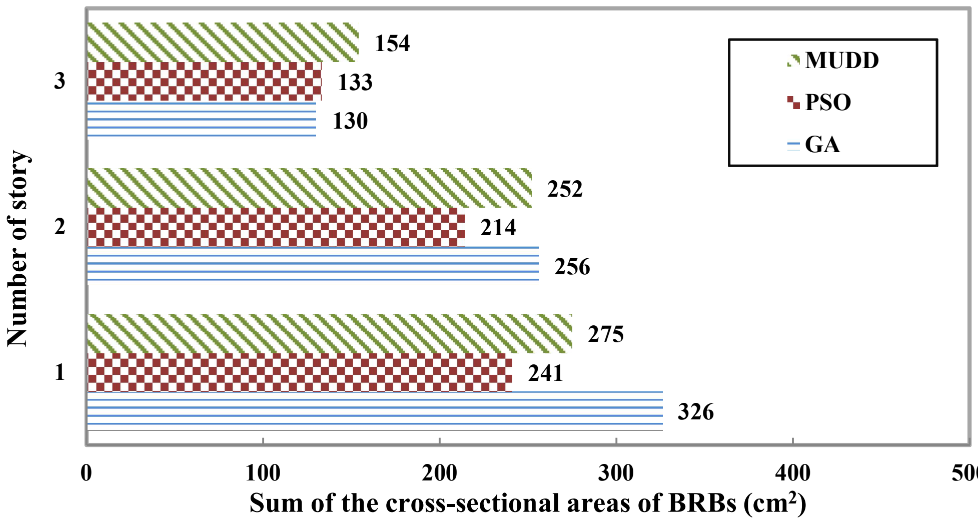


Fig.12. Optimum distribution of BRBs cross-sectional areas using MUDD, PSO and GA, three-story frame

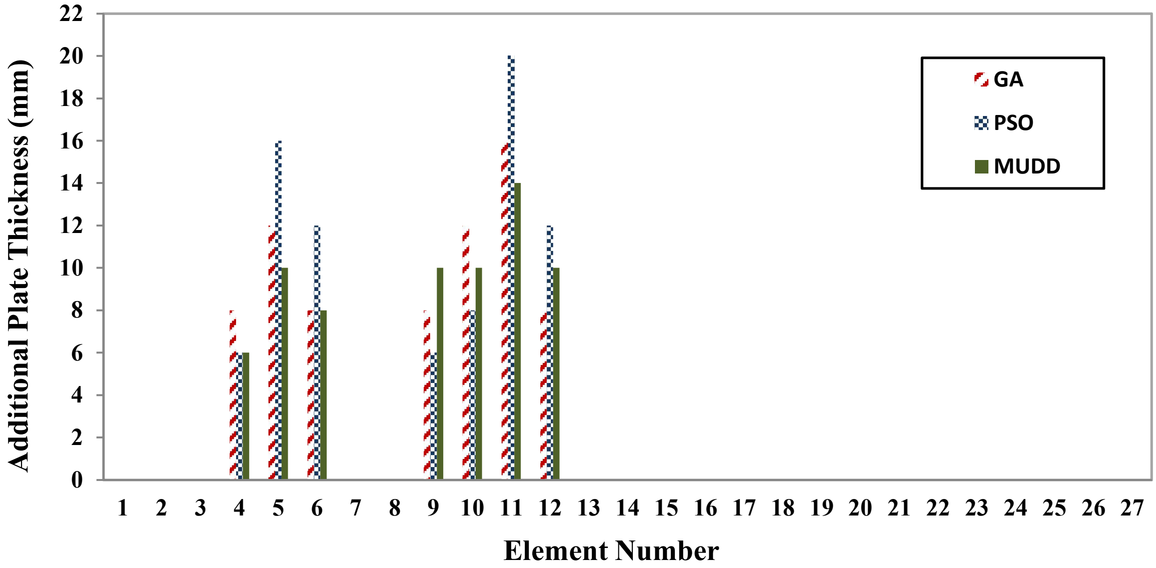


Fig.13. Thickness of the additional externally welded plates required for optimum strengthening of structural elements, three-story frame

For a better comparison, the final optimisation results obtained by different optimisation algorithms are listed in Table 1. It is shown that GA, PSO and MUDD methods led to the design solutions with the objective functions of 209.1, 207.5 and 208.3, respectively. The objective function of the MUDD algorithm was slightly better than GA and only 0.5% higher than that of the PSO method. This indicates that the MUDD algorithm was capable to converge to the optimum design solution with significantly lower computational efforts (i.e. up to 300 times less number of analyses) compared to both GA and PSO methods.

Table 1 Comparison of the optimum design solutions using GA, PSO and MUDD optimisation methods, three-story frame.

Optimisation method	Sum of BRB plate cross-sectional areas (cm^2)	Volume of added plates (cm^3)	Number of analyses	Objective function
GA	712	268×10^3	27200	209.1
PSO	588	317×10^3	24000	207.5
MUDD	681	243×10^3	90	208.3

Fig. 14 compares the distribution of DCRs of the stories for the three-story bare frame (before strengthening) with the frames optimised using different methods. While the initial structure did not satisfy the target performance-based design requirements, all three optimisation methods led to acceptable design solutions (i.e. DCRs <1). It is shown that GA, PSO and MUDD methods all led to the design solutions with uniform distribution of DCRs, where the maximum demand to capacity ratios of all stories reached the target value (i.e. DCR=0.995). This can verify the adequacy of the using the concept of uniform distribution of demands in obtaining the best design solutions using minimum structural weight.

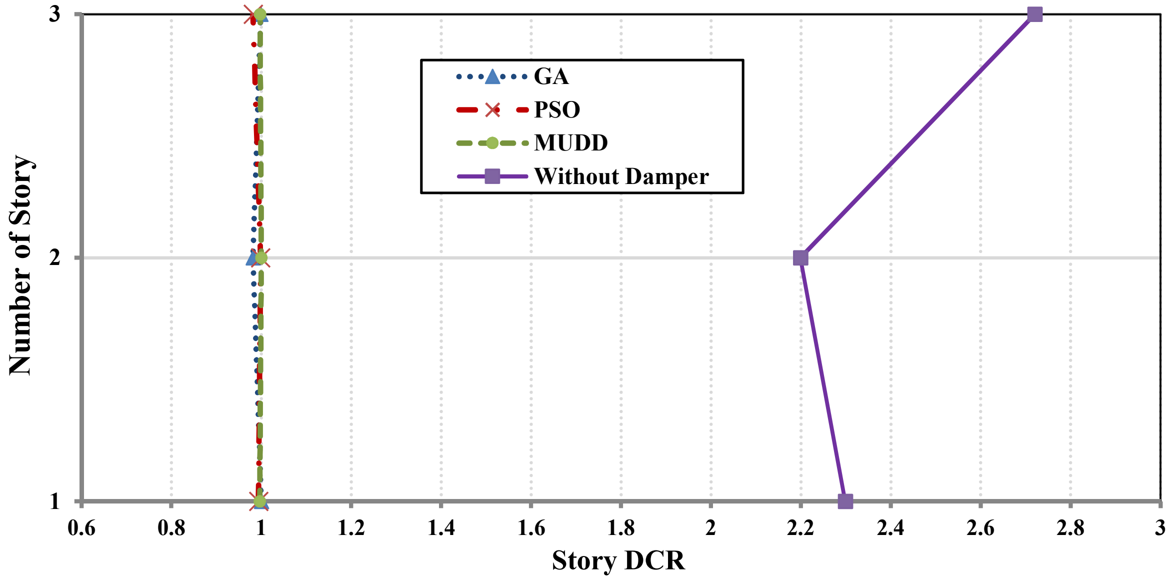


Fig.14. Distribution of DCRs of the stories for the three-story bare frame and the frames retrofitted using different optimisation methods

6.2 Nine-story frame

In this section, the nine-story moment resisting steel frame shown in Fig. 7 is retrofitted to satisfy the performance level of Life Safety (LS) under ASCE 41-06 BSE-2 seismic hazard level. The selected frame has 54 column and 45 beam elements and 20 BRB dampers. Fig. 15 shows the variation of the objective function with the number of iterations using the MUDD optimisation algorithm. The results indicate that the MUDD algorithm reached a design solution with the objective function of 123.6 after 73 iterations. MUDD algorithm assigned externally welded plates with the thickness of 8 mm to the elements 46, 48, 49, and 50 (element numbers are given in Fig. 7). Considering the target objective function one percent above the final answer, it can be concluded that the convergence was practically achieved after only 72 steps. It should be noted that by considering the thicknesses of the externally welded plates as design variables for optimum strengthening of the nine-story frame, the search space would be up to 10^{99} times larger than the case where only the distribution of BRB dampers is considered. This makes it impractical to use computationally expensive optimisation methods such as GA and PSO. For this reason, the nine-story frame was designed in such a way that the BRB elements can satisfy the ASCE 41-06 design requirements without using externally welded plates. Therefore, the design variables in this case where the thickness of the steel core for the BRB dampers at each story.

For GA and PSO, the population size was set to be 60 and each algorithm was repeated three times, using different random initial populations, to obtain the best design solution with minimum BRB weight. The predefined iteration number for Genetic Algorithm and PSO method was considered to be 12000 (i.e. in total over 2 million analyses for each method). The repeated optimisations are represented by GA-1, GA-2, GA-3 and PSO-1, PSO-2, PSO-3 for GA and PSO methods, respectively.

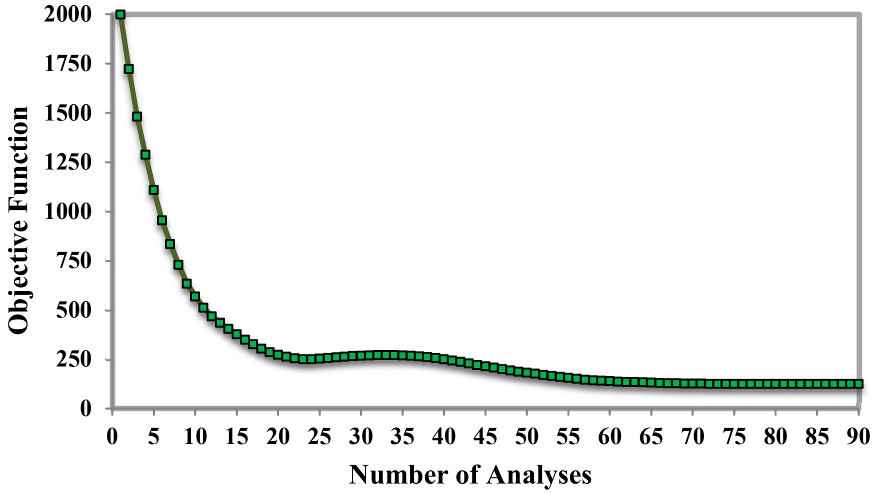


Fig.15. Variation of the objective function for optimal strengthening design of the nine-story frame using MUDD algorithm.

Fig. 16 compares the objective function of GA and PSO methods for optimum design of the nine-story frame in different iterations. It is shown that, GA and PSO methods reached the optimum design solution after almost 8700 and 4200 iterations, respectively. While the results demonstrate the faster convergence of PSO compared to GA, both methods are too computationally expensive to be practical when compared with MUDD method.

Fig. 17 shows the height-wise distribution of the total BRB required thicknesses (proportional to the total BRB weight) for the nine-story frame optimised using MUDD, PSO and GA methods. The details of the final optimisation results are also provided in Table 2. The results indicate that MUDD algorithm led to the lowest objective function, which is 2% and 17% lower than that of GA and PSO methods, respectively. Furthermore, it is shown in Table 2 that the total BRB required thicknesses (or weight) for the GA and PSO design solutions are around 22% and 167% higher than the MUDD algorithm. This confirms again the capability of the proposed MUDD method to converge to the optimum global design solution (even better than GA and PSO) in only a few iterations.

The height-wise distribution of DCR in the nine-story bare frame (before strengthening) and the optimum retrofitted design solutions using GA, PSO and MUDD methods are compared in Fig. 18. While the initial structure exceeded the maximum allowable demand to capacity ratios at the bottom six stories, all three optimisation methods led to acceptable design solutions (i.e. DCR<1). It can be noted that the optimised structures also exhibited a more uniform distribution of demand to capacity ratios compared to the initial frame. It is worth mentioning that BRBs at the top three stories of GA, PSO and MUDD optimum solutions have the minimum acceptable thickness (see Equation (12)), and therefore, it was not possible to reduce the DCRs of these stories to achieve a more uniform distribution.

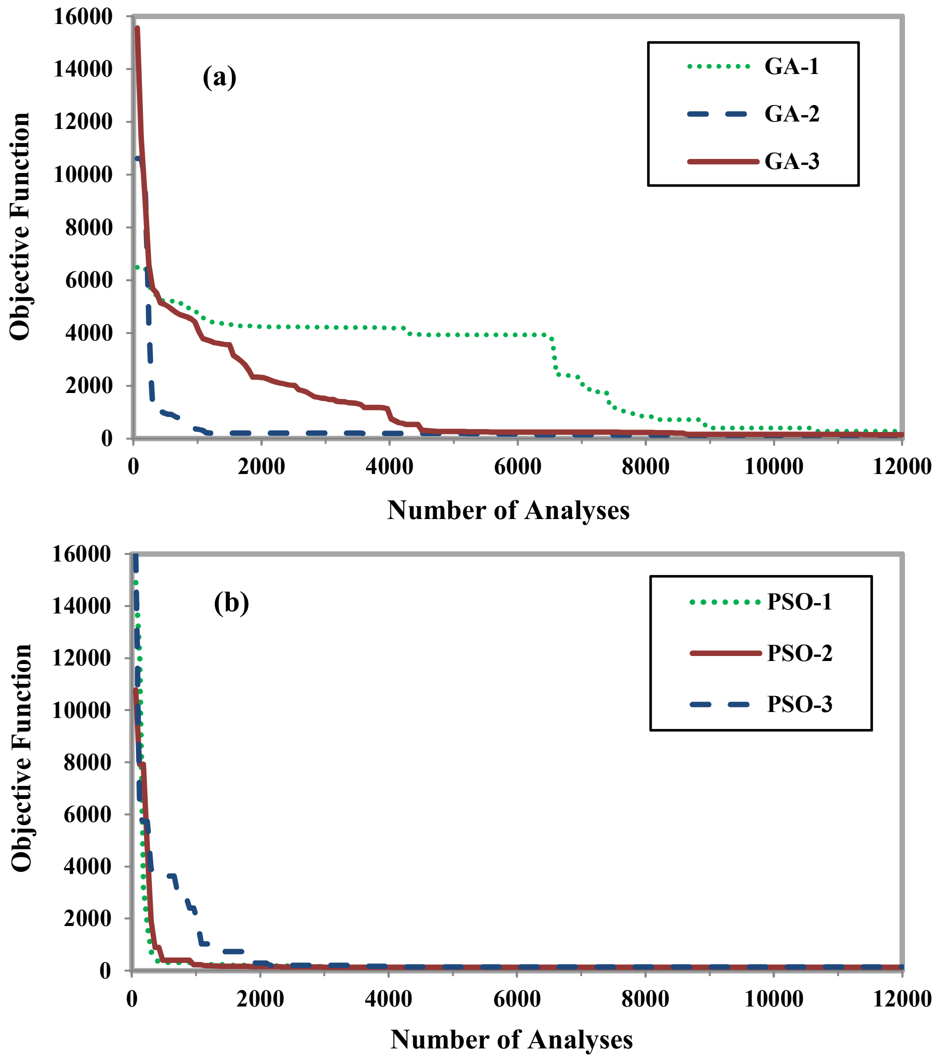


Fig.16. Variation of the objective function for optimum strengthening design of the nine-story frame using: a) GA; b) PSO Algorithm

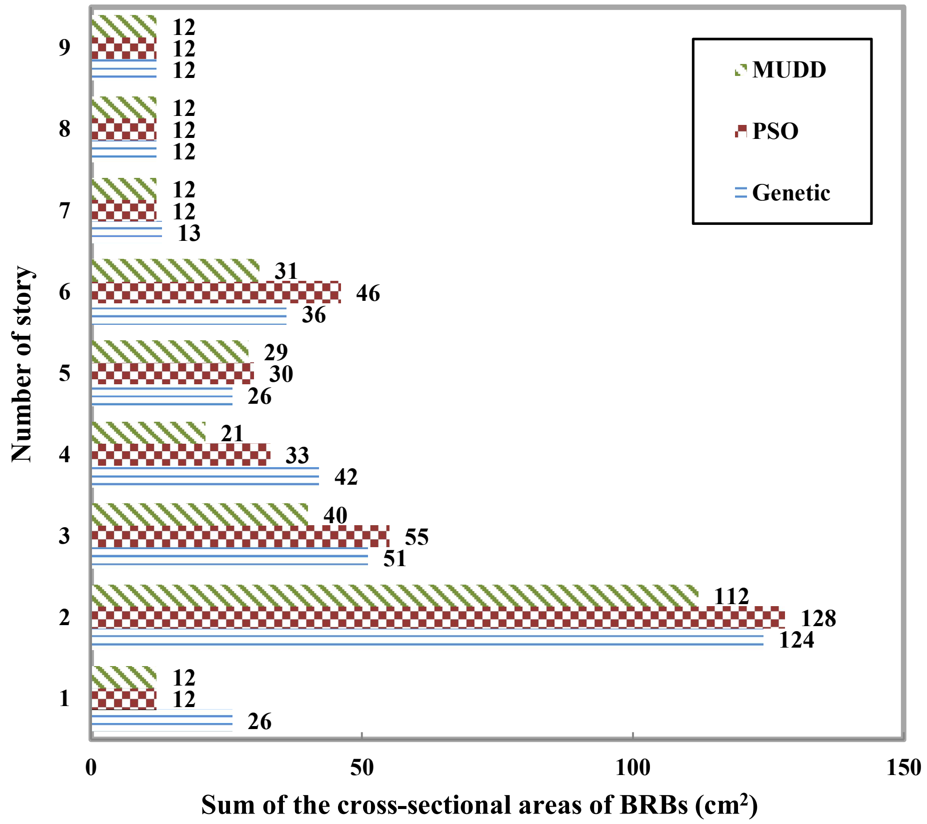


Fig.17. Optimum distribution of BRB required thicknesses using MUDD, PSO and GA methods, nine-story frame

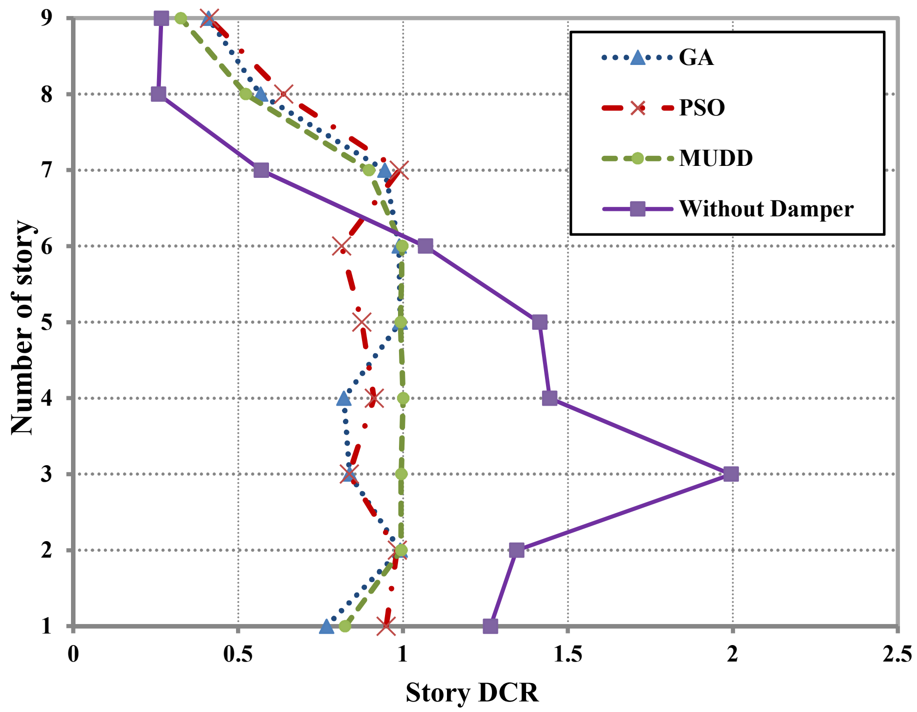


Fig.18. Distribution of DCRs of the stories for the bare frame and the frames retrofitted using GA, PSO and MUDD optimisation methods, nine-story frame

Table 2 Comparison of the optimum design solutions using MUDD, PSO and GA methods, nine-story frame.

Optimisation method	Sum of BRB plate cross-sectional areas (cm^2)	Volume of added plates (cm^3)	Number of analyses	Objective function
GA	342	---	8700	126.4
PSO	340	---	4200	126.2
MUDD	281	---	72	123.6

7 CONCLUSIONS

A novel performance-based optimisation method (MUDD) was introduced, based on the concept of uniform distribution of deformation demands, for strengthening design of multi-story steel moment frames using buckling restrained brace (BRB) dampers and externally welded steel plates. The proposed method was applied for optimum strengthening design of a three and a nine-story frame to satisfy Immediate Occupancy (IO) and Life Safety (LS) performance targets under BSE-1 and BSE-2 seismic hazard levels, respectively. The results were then compared with metaheuristic optimisation methods using Genetic Algorithms (GA) and Particle Swarm Optimisation (PSO). While the initial structures before strengthening did not satisfy the target design requirements, all three optimisation methods led to acceptable design solutions. The results indicated that the proposed MUDD method is capable of converging to the optimum global design solutions with the objective functions very close to those of GA and PSO methods, while it is significantly less computationally expensive. For example, it was shown that for the three-story frame GA and PSO methods require over 27000 and 24000 number of analyses to converge to the optimum solution, respectively, while by using MUDD the optimum design solution is achieved only after 90 iterations. A similar trend was also observed for the nine-story frame. The descending trend of the objective function (total structural weight required for strengthening) during the MUDD optimisation process highlighted the efficiency of using the concept of uniform distribution of deformation demands to simplify the optimisation process. This conclusion was further confirmed by the observation that the methods with lower objective functions (i.e. less required structural weight) in general exhibit a more uniform distribution of demand to capacity ratios (DCRs). Therefore, the computationally efficient optimisation methodology proposed in this study should prove useful in performance-based strengthening design of multi-story steel structures.

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