INTERNATIONAL JOURNAL OF OPTIMIZATION IN CIVIL ENGINEERING
Int. J. Optim. Civil Eng., 2023; 13(2):177-188

PERFORMANCE-BASED OPTIMIZATION OF STEEL MOMENT FRAMES BY A MODIFIED NEWTON METAHEURISTIC ALGORITHM

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ABSTRACT

The purpose of the current study is to design steel moment resisting frames for optimal weight in the context of performance-based design. The performance-based design optimization of steel moment frames is a highly nonlinear and complex optimization problem having many local optima. Therefore, an efficient algorithm should be used to deal with this class of structural optimization problems. In the present study, a modified Newton metaheuristic algorithm (MNMA) is proposed for the solution of the optimization problem. In fact, MNMA is the improved version of the original Newton metaheuristic algorithm (NMA), which is a multi-stage optimization technique in which an initial population is generated at each stage based on the results of the previous stages. Two illustrative examples of 5-, and 10-story steel moment frames are presented and a number of independent optimization runs are achieved by NMA and MNMA. The numerical results demonstrate the better performance of the proposed MNMA compared to the NMA in solving the performance-based optimization problem of steel moment frames.

Keywords: optimization; performance-based design; seismic total cost; steel moment frame.

Received: 10 October 2022; Accepted: 20 December 2022

1. INTRODUCTION

The most important issue for a structure is its sufficient seismic resistance to ensure availability after an earthquake. For this purpose, the concepts of performance-based design (PBD) [1] has been developed and applied by the seismic design procedures. In the PBD approaches, nonlinear structural analysis methods are used to evaluate the nonlinear inelastic response of structures. However, it is a demanding design procedure requiring a significant amount of computational effort. On the other hand, designing cost-efficient structures with a

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reliable performance subjected to earthquake is the most serious concern of the structural engineers. Therefore, during the last years, performance-based design optimization (PBDO) techniques have been developed and many researches have been conducted in this area [2-9]. To deal with the performance-based design optimization problem of structures, the best candidate is metaheuristic algorithms. Metaheuristics are designated based on stochastic natural phenomena, they do not require gradient computations and therefore their computer implementation is simple [10-12].

In the current study, the Newton metaheuristic algorithm (NMA) [10] is focused. The NMA is a population-based metaheuristic and has been proposed based on the Newton gradient-based method. It has been demonstrated in [10] that the performance of NMA in dealing with the PBDO problem of steel moment frame (SMF) structures is better compared to some recent metaheuristic algorithms. In order to improve the performance of the original NMA and make it a more reliable optimization algorithm, a modified version of this algorithm is proposed in this work. To this purpose, the exterior penalty function method (EPFM) [11] is employed in the framework of a sequential optimization technique. As a result, a small initial population is generated randomly and the position of population is updated in the design space by the NMA using EPFM. As the population size is small, the algorithm quickly converges to a solution. For starting a new optimization process, a new population is generated using the information derived from the results of the previous optimization process. This procedure is continued until a stopping criterion is met.

In order to investigate the efficiency of the proposed MNMA, two design examples including 5-, and 10-story SMFs are illustrated and the performance of NMA and MNMA is compared over a series of independent PBD optimization runs. The numerical results indicate that the proposed MNMA outperforms the original NMA.

2. FORMULATION OF THE PBDO PROBLEM

A seismic performance objective is defined as a given level of performance for a specific seismic hazard level. To define a performance objective, a level of structural performance and its corresponding seismic hazard level should be determined. Here, immediate occupancy (IO), life safety (LS) and collapse prevention (CP) performance levels are considered according to FEMA-356 [1]. Each objective corresponds to a given probability of exceedance in 50 years. A usual assumption is that the IO, LS and CP performance levels correspond respectively to a 20%, 10% and 2% probability of exceedance in 50 year period. In the framework of PBD, the structural response should be evaluated by performing nonlinear structural analysis. In this study, nonlinear static pushover analysis based on the displacement coefficient method [1] is conducted using the OpenSees [12] platform to evaluate the nonlinear structural response during the PBDO process. During the PBDO process and prior to checking the PBD constraints, geometric constraints should be checked at each structural joint to ensure that the dimensions of beams and columns are consistent. In addition, the strength of structural members need to be checked for gravity loads based on AISC 360-16 [13] design code. As the PBD constraints, inter-story drift ratios should be checked in terms of confidence levels at IO and CP levels according to FEMA-350 [14] and plastic rotation constraints should be checked at all levels according to ASCE-41-13 [15].

The PBOD problem of SMFs can be formulated as follows:

$$\text{Find: } X = \{X_1 \quad X_2 \quad \cdots \quad X_{ne}\} \tag{1}$$

$$\text{To Minimize: } f(X) = \sum_{i=1}^{ne} \rho_i L_i A_i \tag{2}$$

$$\text{Sobjec to: } g_j(X) \le 0 \,,\, j = 1, \dots, nc \tag{3}$$

where X is a vector of design variables; X_1 to X_{ne} are design variables; ne is the number of elements; f is the objective function (weight of the structure); ρ_i, L_i, and A_i are weight density, length and cross-sectional area of the ith element, respectively; g_j is the jth design constraint; and nc is the number of design constraints.

In this study, the constraints of the PBDO problem are handled using the EPFM [11] in which the pseudo unconstrained objective function is expressed as follows

$$\Phi(X) = f(X)\left(1 + r_p \sum_{i=1}^{nc} \left(max\{0, g_j(X)\}\right)^2\right) \tag{4}$$

where Φ is the pseudo unconstrained objective function; and r_p is the penalty parameter.

3. NEWTON METAHEURISTIC ALGORITHM

Newton metaheuristic algorithm (NMA) [10] is a population based optimization algorithm designed on the basis of Newton’s gradient-based iteration. In this algorithm, a population of n particles is generated on a random basis in the design space of the optimization problem. The NMA requires the numerical approximations of the derivatives of the objective function to update the position of the population in the design space. Thus, in each iteration, the objective values of all individuals are evaluated and the population is sorted in ascending order of the objective function values. For a discrete optimization problem the position of ith search agent in iteration t is updated as follows

$$X_i^{t+1} = X_i^t + \Delta X_i^t \tag{5}$$

$$\Delta X_i^t = round\left(\left(\frac{t}{t_{max}}\right).R_1^t.\Gamma.\left(X_{i-1}^t - X_{i+1}^t\right) + \left(1 - \frac{t}{t_{max}}\right).R_2^t.\left(X_B - X_i^t\right)\right) \tag{6}$$

$$\Gamma = \frac{\kappa^2 \Phi\left(X_{i+1}^t\right) + (1 - 2\kappa)\Phi\left(X_i^t\right) - (1 - \kappa)^2 \Phi\left(X_{i-1}^t\right)}{2\kappa\Phi\left(X_{i+1}^t\right) - 2\Phi\left(X_i^t\right) + 2(1 - \kappa)\Phi\left(X_{i-1}^t\right)} \tag{7}$$

$$\kappa = \frac{\|X_i^t - X_{i-1}^t\|}{\|X_{i+1}^t - X_{i-1}^t\|} \tag{8}$$

where R_1^t and R_2^t are vectors containing uniformly distributed random numbers between 0 and 1; t_{max} is the maximum number of iterations; and X_B is the best design found so far.

The flowchart of the NMA is shown in Fig. 1.

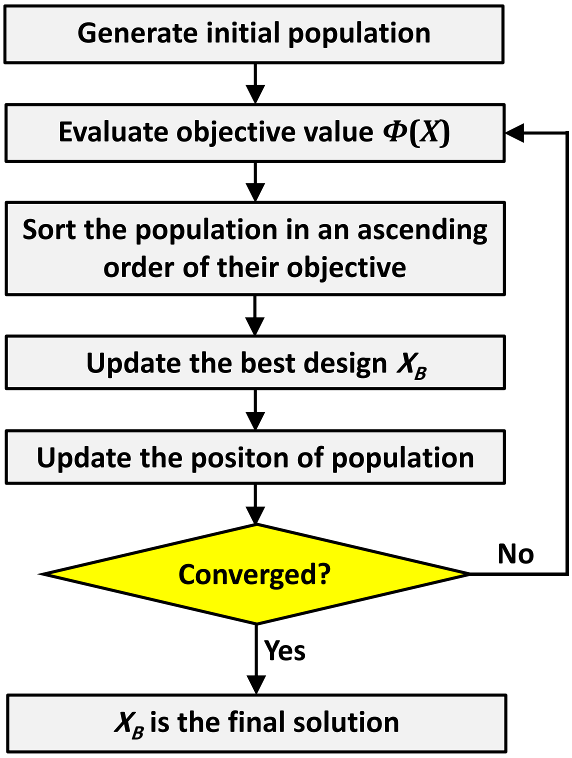

Figure 1. Flowchart of NMA

4. MODIFIED NEWTON METAHEURISTIC ALGORITHM

In complex optimization problems (such as PBDO problem of SMFs) to increase the probability of finding global optimum, a modified Newton metaheuristic algorithm (MNMA) is proposed in the present study. To this purpose, an algorithm based on sequential implementation of NMA is proposed. In other words, in the framework of MNMA, the NMA is implemented sequentially using the EPFM for handling the design constraint. In the first stage of MNMA, an initial population consisting of *n* individuals is randomly generated in the design space, and the NMA is employed to perform an optimization process considering a small value for the penalty parameter r_p. Since the value of r_p is small, the algorithm will converge to an infeasible solution. In the next stage, a new population is generated in the neighborhood of the best solution found in the previous stage X_B. As a result, X_B is directly introduced into the new population and the rest of the population is randomly generated using the following equation:

$$X_i = F_N(X_B, \sigma X_B) \tag{9}$$

where F_N is a random normal distribution with the mean X_B and the standard deviation σX_B.
The penalty parameter r_p is updated for the new stage by a magnification factor γ as:

$$r_p \rightarrow \gamma r_p \tag{10}$$

The most influential parameters on the convergence rate of the MNMA are σ and γ. The best values of these parameters are 0.1 and 10, respectively determined by sensitivity analysis. The optimization process is continued until one of the stopping conditions is satisfied. The flowchart of MNMA is shown in Fig. 2.

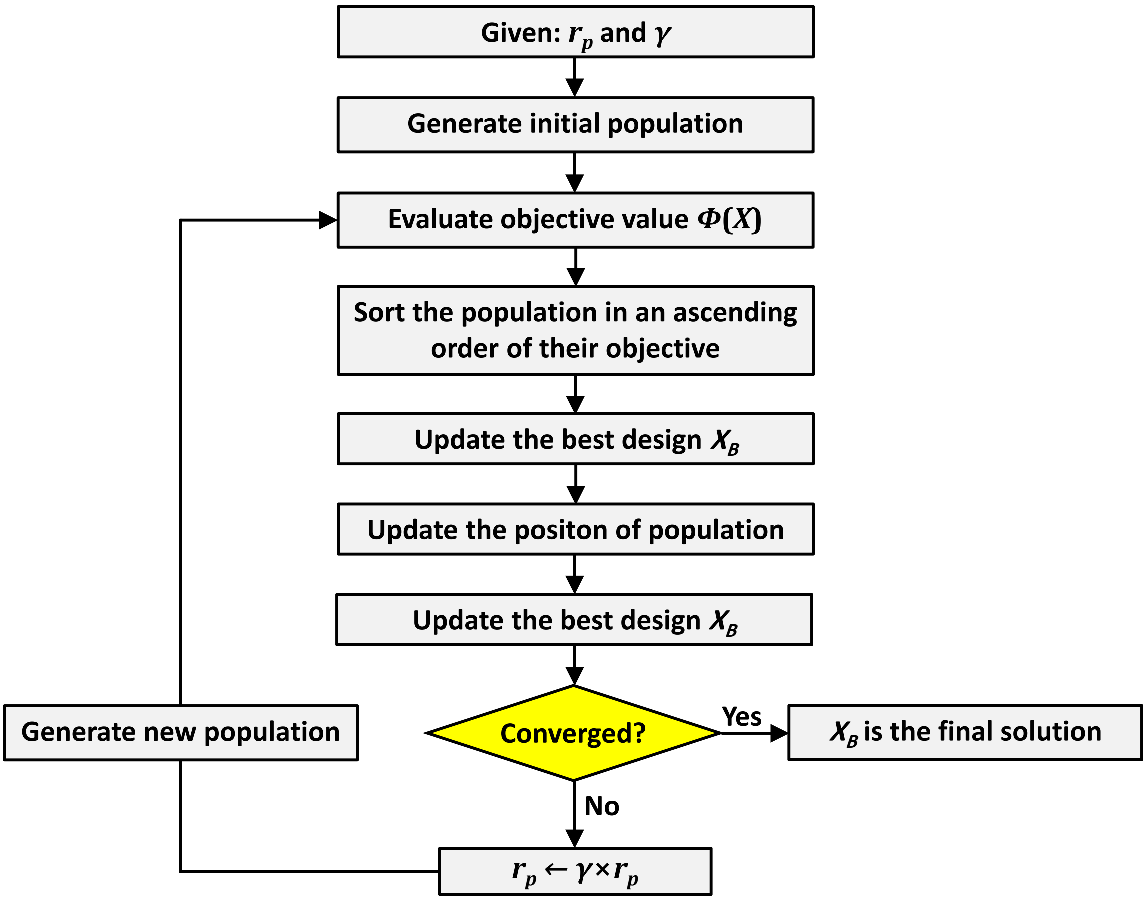

Figure 2. Flowchart of MNMA

5. NUMERICAL EXAMPLES

Two illustrative design examples of SMFs are presented. The dead and live loads of 2500 and 1000 kg/m are applied to the all beams, respectively. The modulus of elasticity and yield stress of materials are 210 GPa and 235 MPa, respectively. The constitutive law is bilinear with pure strain hardening slope of 1% of the elastic modulus. The sections of beams and columns are selected from the W-shaped sections listed in Table 1.

In the framework of MNMA, the population size and number of stages is chosen such that the total number of structural analysis required by both NMA and MNMA is the same.

Table 1: Available W-shaped sections

Columns				Beams			
No.	Profile	No.	Profile	No.	Profile	No.	Profile
1	W14×48	13	W14×257	1	W12×19	13	W21×50
2	W14×53	14	W14×283	2	W12×22	14	W21×57
3	W14×68	15	W14×311	3	W12×35	15	W24×55
4	W14×74	16	W14×342	4	W12×50	16	W21×68
5	W14×82	17	W14×370	5	W18×35	17	W24×62
6	W14×132	18	W14×398	6	W16×45	18	W24×76
7	W14×145	19	W14×426	7	W18×40	19	W24×84
8	W14×159	20	W14×455	8	W16×50	20	W27×94
9	W14×176	21	W14×500	9	W18×46	21	W27×102
10	W14×193	22	W14×550	10	W16×57	22	W27×114
11	W14×211	23	W14×605	11	W18×50	23	W30×108
12	W14×233	24	W14×665	12	W21×44	24	W30×116

Acceleration response spectra of the hazard levels are based on Iranian seismic design code [16] for soil type III in a very high seismicity region as shown in Fig. 3. hazard levels corresponding to 50%, 10% and 2% probability of exceedance in 50 years, are denoted by 50./50, 10./50 and 2./50, respectively.

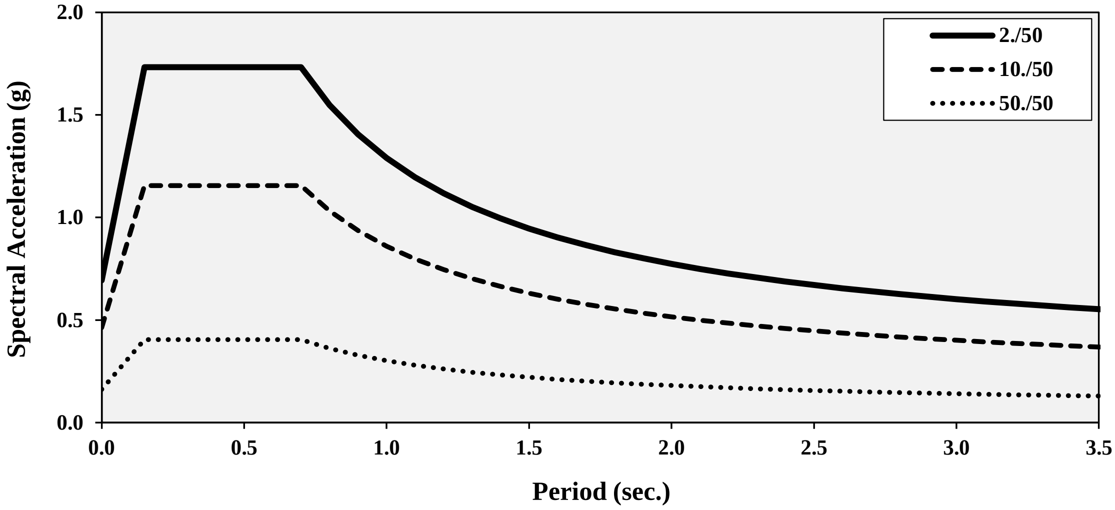

Figure 3. Acceleration response spectra

5.1 Five-story SMF

The 5-story SMF is shown in Fig. 4. There are 11 design variables in the PBD optimization problem of this example. In this example, 30 independent PBD optimization runs are performed using NMA and MNMA. For the NMA, the population size and the maximum number of iterations are 60 and 100, respectively. For the MNMA, the population size, the maximum number iterations and the number of stages are 30, 50, and 4, respectively. This means that both NMA and MNMA techniques require 6000 structural analyses. The results obtained by both algorithms in all runs are given in Table 2. In addition, the optimal weights obtained by NMA and MNMA are shown in Fig 5.

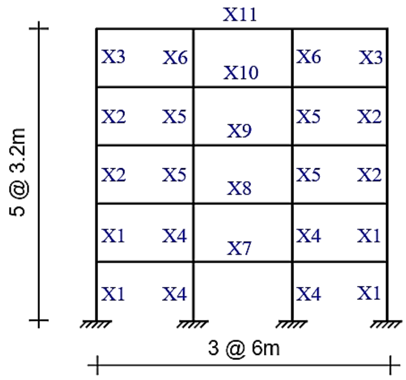

Figure 4. 5-story steel SMF

Table 2: Optimization results for 5-story SMF

Design variables	NMA		MNMA	
	Best	Worst	Best	Worst
X1	W14×53	W14×68	W14×48	W14×53
X2	W14×48	W14×53	W14×48	W14×48
X3	W14×48	W14×53	W14×48	W14×48
X4	W14×68	W14×68	W14×68	W14×74
X5	W14×68	W14×68	W14×68	W14×68
X6	W14×48	W14×48	W14×48	W14×48
X7	W18×35	W18×35	W18×35	W18×35
X8	W18×35	W12×35	W18×35	W18×35
X9	W12×35	W12×35	W18×35	W12×35
X10	W12×22	W12×22	W12×22	W12×22
X11	W12×22	W12×22	W12×22	W12×22
Weight (kg)	9430.72	9861.81	9333.48	9547.41
Average Weight (kg)	9544.21		9435.40	
Standard Deviation (kg)	155.73		61.58	

The weight of the optimum design found by the MNMA (9333.48 kg) is better than the NMA (9430.72 kg). Also, the average of optimal weight found by MNMA (9435.40 kg) is better than the NMA (9544.21 kg). The standard deviation of the optimal weights obtained by MNMA is considerably better than the NMA. In addition, the distribution of the optimal weights over 30 independent optimization runs provided in Fig. 5 indicate that in this example, the performance of the MNMA is better than that of the NMA.

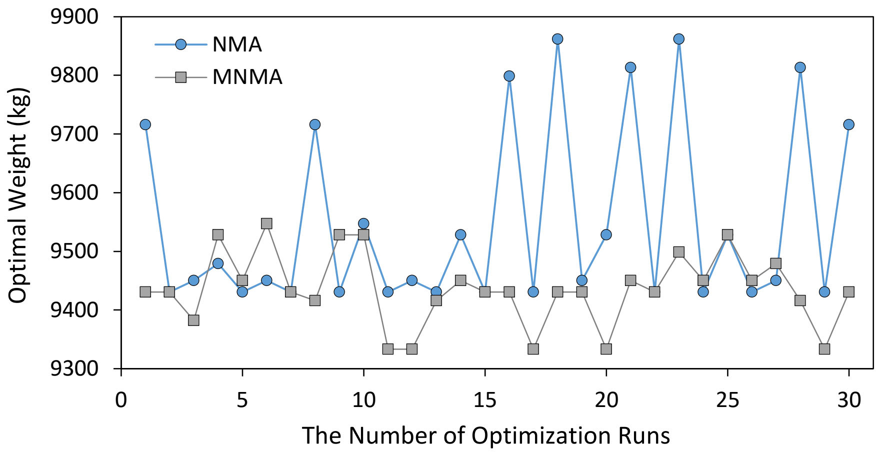

Figure 5. Optimal weights obtained by NMA and MNMA for 5-story SMF

It is worth to mention that for all the optimally designed 5-story SMFs, the inter-story drift constraint at IO performance level dominates the designs. Fig. 6 shows the inter-story drift profile for the best optimal designs obtained by NMA and MNMA at IO and CP performance levels.

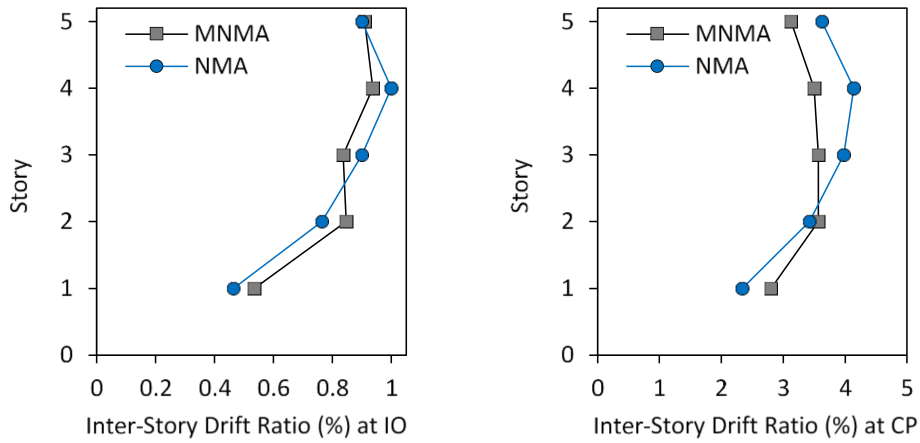

Figure 6. Inter-story drifts of the best designs found by NMA and MNMA for 5-story SMF

5.2 Ten-story SMF

The 10-story SMF is the second example of the current study, as shown in Fig. 7. There are 25 design variables in this PBD optimization problem. As well as the first example, in this example also, NMA and MNMA are used to achieve 30 independent PBD optimization runs. For the NMA, the population size and the maximum number of iterations are chosen to be 100 and 150, respectively. For the MNMA, the population size, the maximum number iterations and the number of stages are 50, 75, and 4, respectively. This means that both NMA and MNMA techniques require 15000 structural analyses. The results obtained by NMA and MNMA in all runs are reported in Table 3. In addition, the optimal weights obtained by these algorithms are shown in Fig 8.

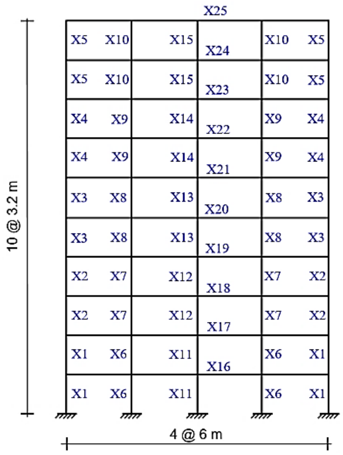

Figure 7. 10-story steel SMF

Table 3: Optimization results for 10-story SMF

Design variables	NMA		MNMA	
	Best	Worst	Best	Worst
X1	W14×82	W14×132	W14×82	W14×132
X2	W14×68	W14×82	W14×82	W14×82
X3	W14×53	W14×82	W14×53	W14×74
X4	W14×48	W14×68	W14×48	W14×53
X5	W14×48	W14×48	W14×48	W14×48
X6	W14×132	W14×132	W14×132	W14×132
X7	W14×132	W14×132	W14×82	W14×132
X8	W14×74	W14×82	W14×82	W14×82
X9	W14×68	W14×82	W14×74	W14×74
X10	W14×53	W14×48	W14×48	W14×48
X11	W14×132	W14×132	W14×132	W14×132
X12	W14×132	W14×132	W14×132	W14×132
X13	W14×74	W14×82	W14×82	W14×82
X14	W14×68	W14×82	W14×68	W14×74
X15	W14×53	W14×53	W14×53	W14×48
X16	W21×44	W18×50	W21×44	W21×44
X17	W21×44	W18×50	W21×44	W21×44
X18	W21×44	W18×46	W18×40	W18×40
X19	W18×40	W16×50	W18×40	W18×40
X20	W18×35	W18×40	W18×40	W18×40
X21	W18×35	W18×35	W18×35	W18×40
X22	W18×35	W18×35	W18×35	W18×35
X23	W18×35	W18×35	W18×35	W18×35
X24	W12×22	W12×35	W12×22	W12×22
X25	W12×22	W12×35	W12×22	W12×22
Weight (kg)	31576.59	36530.08	31146.31	33756.36
Average Weight (kg)	32690.70		31631.58	
Standard Deviation (kg)	922.01		455.73	

The results reveal that the best weight obtained by the MNMA (31146.31 kg) is better than the best weight of NMA (31576.59 kg). Also, the average of optimal weight found by MNMA (31631.58 kg) is better than the NMA (32690.70 kg). It can be observed that the standard deviation of the optimal weights obtained by MNMA is considerably better in comparison to the NMA. The obtained results indicate that, the performance of the MNMA is better than that of the NMA.

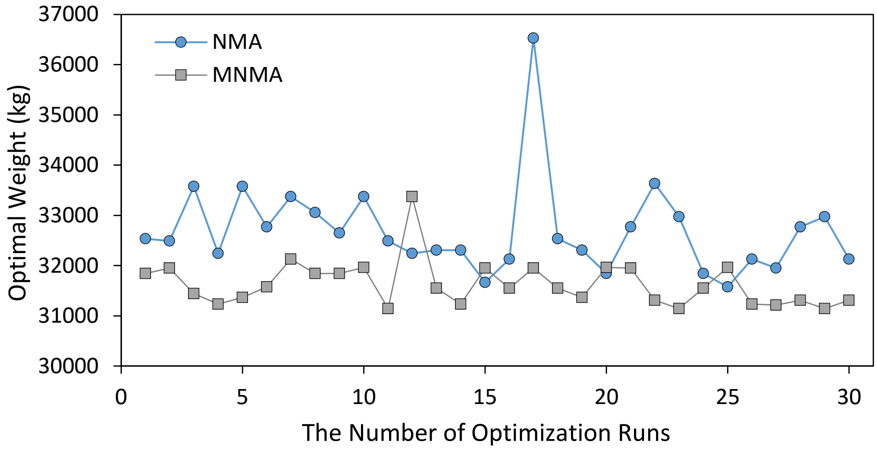

Figure 8. Optimal weights obtained by NMA and MNMA for 10-story SMF

For all the optimal 10-story SMFs, the active constraint of the PBDO process is the inter-story drift constraint at IO performance level. The inter-story drift profile for the best optimal designs obtained by NMA and MNMA at IO and CP levels are shown in Fig. 9.

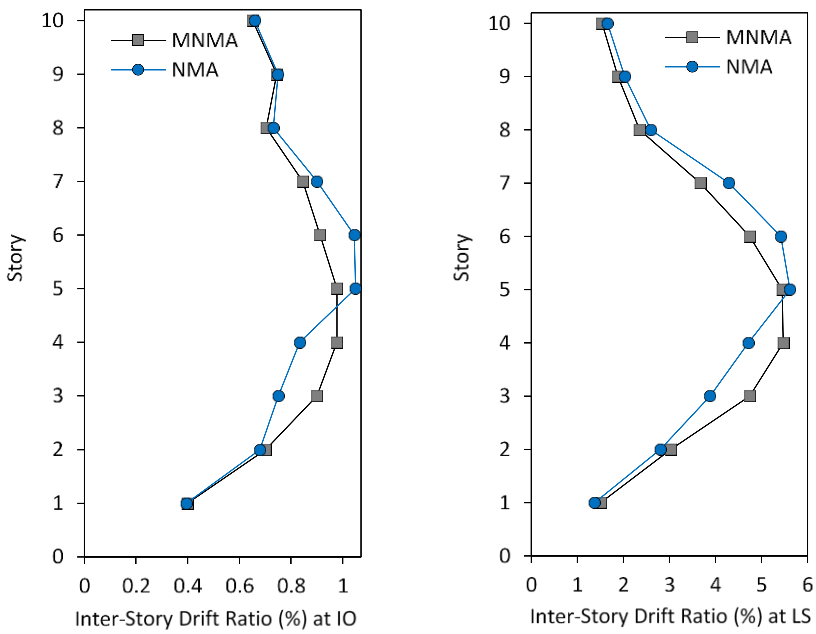

Figure 9. Inter-story drifts of the best designs found by NMA and MNMA for 10-story SMF

6. CONCLUSIONS

This study is devoted to addressing one of the most challenging structural optimization problems namely, performance-based design optimization of steel moment frames. Obviously, a powerful algorithm should be used to deal with this class of highly nonlinear structural optimization problems. For this purpose, a modified Newton metaheuristic algorithm (MNMA) is proposed in this research based on a sequential implementation strategy of a Newton metaheuristic algorithm (NMA). The original NMA has be developed based on the Newton's gradient-based method in a population-based strategy. To enhance the convergence of the original NMA and to reduce the probability of getting trapped in local optima in the design space of the performance-based design optimization problem of steel moment frames, MNMA is proposed in this work. In this case, the exterior penalty function method (EPFM) is used in the framework of a sequential optimization strategy.

In order to illustrate the efficiency of the proposed MNMA, two examples of 5-, and 10-story SMFs are presented. The nonlinear static pushover analysis is performed to evaluate the seismic response of the structures during the optimization process. A total number of 30 independent optimization runs is carried out using NMA and MNMA techniques.

The numerical results reveal that the proposed MNMA technique is better than the original NMA in terms of the best weight, the average weight and standard deviation of the optimal weights. Therefore, it can be concluded that the proposed MNMA optimization technique outperforms the original NMA and it is a powerful algorithm for solving performance-based design optimization problem of steel moment frames.

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