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Invited Paper

Constraint control method of optimization and its application to design of steel frames

S.F. Mansouri[a] and M.R. Maheri[b,*]

a. *Department of Civil Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran.*
b. *Department of Civil Engineering, Shiraz University, Shiraz, Iran.*

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Abstract. Different optimization methods are available for optimum design of structures including classical optimization techniques and metaheuristic optimization algorithms. However, engineers do not generally use optimization techniques to design a structure. They attempt to decrease the structural weight and increase its performance and efficiency, empirically, by changing the variables and controlling the constraints. Based on this professional engineering design philosophy, in this paper, a simple algorithm, termed the Constraint Control Method (CCM), is developed and presented whereby optimum design is achieved gradually by controlling the problem constraints. Starting with oversized sections, the design was gradually improved by changing sections based on a 'control function' and controlling the constraints to be below the target values. As the constraints moved towards their targets, the design moved towards an optimum. The general functionality of the proposed algorithm was first demonstrated by solving several linear and nonlinear mathematical problems, which had exact answers. The performance of the algorithm was then evaluated through comparing design optimization results of three 2D steel frame benchmark problems with those of other metaheuristic optimization solutions. The proposed method led to the minimum structural weight while performing a considerably small number of structural analyses compared to other optimization methods.

1. Introduction

Due to the limitations of space, time, and raw materials, optimization problems are generally solved subject to different constraints. The optimal response of a system is obtained if these limitations are maximally used and the variable which brings all constraints to their maximum acceptable values will be the optimized response. The aim of designing structures is to use minimum cost and maximum performance. For achieving this goal, different optimization techniques have been developed and the performance and applicability of these optimization methods have been compared.

Before the advent of digital calculation, most answers to the structural analysis problems would be reached through analytical equations composed of infinite series. Similarly, classical optimization techniques, such as Linear Programming (LP), Non-Linear Programming (NLP) and Dynamic Programming (DP) were developed. In many cases, due to the complexity of relations or lack of availability, application of these mathematical programming methods to real systems was not possible. Also, it was soon observed that, as a result of low speed and reduced efficiency, these

*. *Corresponding author. Tel.: +98 71 36133019*
E-mail addresses: fazlolah.mansouri@gmail.com (S.F. Mansouri); maheri@shirazu.ac.ir (M.R. Maheri)

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methods were not suitable for solving problems with discrete variables.

Earlier works by Razani [1] and Gallagher and Zienkiewicz [2] on alternative optimal design methods of structures utilized the fully-stressed members concept. They found that when the stresses in the members reached their full (or allowable) values, the structure was optimally designed. Later, Patnaik and Hopkins [3] modified the fully-stressed design technique to obtain optimal design of frames and trusses. Haftka and Starnes [4] investigated the application of internal penalty method for optimization of structures using the quadratic equation. Baugh et al. [5] and Brill et al. [6] aimed at reducing the distance between target (objective) function and selected values by orienting the latter towards the former. Kripakaran et al. [7] used an alternative method, combined with the genetic algorithm, to carry out the optimal design of steel moment resisting frames. Their method started with selecting the smallest profiles for all member groups and by gradually increasing the profile sizes, the member stresses and structural displacements would be brought to the maximum allowable values. Subsequently, by reducing the distance between the target point and the optimum value, the design of the structure was optimized.

More recent heuristic optimization methods include the one conducted by Flager et al. [8]. They presented a method based on Optimal Criteria (OC), which rendered the optimal designing in a step by step and gradual manner and applied it to member sizing optimization. Azad and Hasançebi [9] extended and reformulated the Guided Stochastic Search (GSS) method to optimally design steel frame structures based on AISC-LRFD code of practice. Also, Mahallati Rayeni et al. [10] developed an Improved Multi-Objective Evolutionary Algorithm (IMOEA) to design planar steel frames. In this method, constraints were used as a new objective function in a multi-objective optimization process.

In order to increase the optimization speed and efficiency, many different metaheuristic optimization techniques have been developed. Most metaheuristic algorithms have been inspired by nature. They require a population of answers during the search and need memory for storing data. Some of the most common algorithms in this category include Genetic Algorithm (GA) [11], Ant Colony Optimization (ACO) [12], Particle Swarm Optimization (PSO) [13], Harmony Search (HS) [14], Imperialist Competitive Algorithm (ICA) [15], Honey-Bee Mating Optimization (HBMO) [16], teaching and learning-based optimization algorithms [17], etc. However, other metaheuristic algorithms, such as Tabu Search (TS) [18] and Simulated Annealing (SA) methods [19], work on only one answer; they are not inspired by nature and do not require memory for recording data. The major problem with the above algorithms is their inherent inability to distinguish between the local optima and the global optima. In recent years, a number of techniques have been developed to improve their performance in searching for global optima [20-28]. However, many of these techniques lead to increased analysis time and effort. Comprehensive reviews of new developments in metaheuristic optimization approaches for engineering problems were given by Saka [29], Lamberti and Pappalettere [30], and Saka and Doğan [31].

Due to the above shortcomings, optimization techniques are rarely used by engineers for design purposes. Engineers usually arrive at an optimum design empirically by changing the problem variables and controlling the constraints. In this paper, an alternative optimization algorithm is presented based on the conventional method adopted by the engineers, which deals with only one answer, does not require memory for storing data, and is not inspired by nature. Moreover, although the algorithm is simple, it is a suitable and efficient method for optimum design of discrete structural systems such as sway frames. Through controlling the constraints, the need for relationship between the target function and constraints is eliminated by the maximum use of limitations. Starting from a point and keeping the best response will gradually orient the solution to the optimal point. The proposed method is termed 'Constraint Control Method (CCM).' It is based on numerical search and starts with a conservative design, which generally satisfies the problem constraints. Then, through small steps, the solution is gradually improved by changing the variables and controlling the problem constraints. As the problem constraints approach their limit states, the solution approaches its optimum state. The proposed method achieves the optimal response with far fewer analyses than required by the innovative and metaheuristic methods. In order to illustrate the performance of the proposed CCM method, first, some linear and nonlinear continuous mathematical optimization problems, which have exact answers, are solved. The proposed method is then applied to the more practical discrete problems of optimum design of side-sway steel frames.

2. The proposed Constraint Control Method (CCM)

Optimization problems are generally solved subject to certain constraints. The optimum answer to a system takes place when these constraints are used to the maximum and the variables which maximize the value of all constraints are the optimized answer. In the proposed method, by considering the ratio of any constraint value to its limit value, the constraints are transformed into coefficients ranging from 0 to 1.

They are, therefore, dimensionless so that they could be compared with each other and the constraint value is significant; that is, when the value of the constraint is zero, the answer is far from the optimum answer and the constraint value of one is the maximum value which a constraint could reach.

Based on the aforementioned considerations, the optimized answer is located on a constraint boundary ($g_i = 1$) under the condition that other constraints ($g_1, ..., g_{nc}$) are also equal to 1 [32]. Figure 1 shows the state of g_i constraints of a two-variable (X_1, X_2) problem with 3 constraints (g_k, g_m, g_n). According to the mathematical planning principles [25], it can be shown that the optimal response lies in one of the intersections of the constraints boundaries (in Figure 1, intersection A, B or C).

In the proposed method, first, a certain point of the system in which the constraints have low values is chosen. Then, through changing the variables (X_i), controlling constraints (g_i), and changing the function value (Z), all the constraints are gradually directed towards having values approaching unity at which point the target function (F) is optimized. In other words, in minimization, the starting point is to select large values for the variables and gradually decreasing the variables, whereas, in maximization, small variables are first selected and by gradually increasing the variables, we reach optimum solution. in both cases, the starting constraints have low values, eventually reaching close to unity.

In each step, all variables are changed by a small increment (ITR). Then, the variable which has the highest decrease in the objective function $(Z(X))$ and the lowest increase in constraints (g_i) among all is selected. In order to determine this, a parameter '*check*' is defined. This parameter, given in Eq. (1), determines which variable in each stage is selected:

$$check\,(i) = \min\left\{\frac{\Delta Z_i}{\Delta g_1}, \frac{\Delta Z_i}{\Delta g_2}, \ldots, \frac{\Delta \mathrm{Z_i}}{\Delta \mathrm{g_{n_c}}}\right\} = \min\left\{\frac{Z_0 - Z}{g_1 - g_0}, \frac{Z_0 - Z}{g_2 - g_0}, \ldots, \frac{Z_0 - Z}{g_{n_c} - g_0}\right\}, \tag{1}$$

$$control = \max\,(check)$$

$$Z\,(X) = F^r \text{ where}$$

$$\begin{cases} r = 1 & \text{for minimization} \\ r = -1 & \text{for maximization} \end{cases} \tag{2}$$

where, F is the target function of the problem and $Z(X)$ is the objective function (Eq. (2)). Also, Z_0 and g_0 are respectively the target function and constraints accepted in the previous step. Eq. (1) is illustrated graphically in Figure 2, in which by changing a variable (X), both $Z(X)$ and g_i change and the lowest gradient is selected as parameter *check* for that variable. Then, the maximum of the *checks* of different variables is selected as the best answer in that step. The control parameter in each step is equal to the maximum *check* value of the previous step. The response in any step is considered to be the best if the *check* value is greater than the control value in that step.

In addition to g_i constraints, in most problems, another set of specific constraints (g_s) may also be needed so that a specific range of variables (a, b) could be defined, according to Eq. (3):

$$a \le X_i \le b \Rightarrow 0 \le g_s\,(i) = \frac{X_i - a}{b - a} \le 1. \tag{3}$$

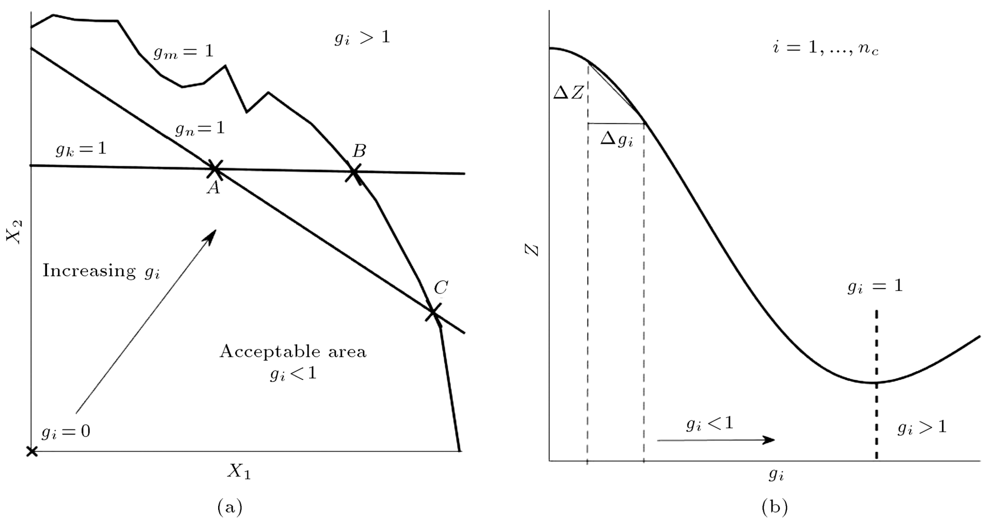

Figure 1. (a) Optimal points for a two-variable (X_1, X_2) problem with three constraints. (b) Changes in the objective function and constraints for one unit of change in the variable.

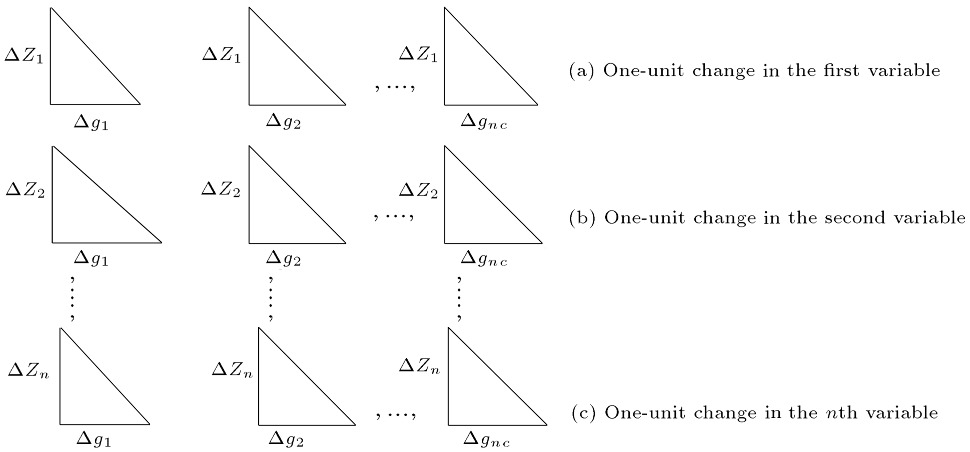

Figure 2. Schematic representation of evaluating $check(i)$ (Eq. (1)).

If g_i and g_s constraints become higher than 1 or lower than 0, the target function is penalized according to Eq. (4):

$$Z = \begin{cases} Z(X) & \text{if } 0 \leq g_i, g_s \leq 1 \\ Z(X).\left(1 + {g_i}^2\right) & \text{if } g_i > 1 \text{ or } g_i < 0 \end{cases} \tag{4}$$

The general procedure for the proposed Constraint Control Method (CCM) is as follows:

1. Determine the target function (F); the number of variables, n; the problem constraints, g_i; and specific constraints, g_s. Define the value of ITR for gradual change of the variables and set the value of r ($r = 1$ for minimization and $r = -1$ for maximization);
2. As the start, assign values to different variables, X_i, such that g_i constraints are small, then, calculate g_i and g_s;
3. Evaluate F and calculate $Z(X)$ and Z from Eqs. (2) and (4);
4. Set X_{OPT}, Z_0, and g_0 equal to X, Z, and g, respectively, and set the analysis number, $NA = 1$;
5. Set variable counter $j = 0$;
6. $j = j + 1$, set X equal to X_{OPT};
7. Evaluate $X(j) = X(j) - r * ITR$ and calculate g_i, g_s, F, $Z(X)$, and Z; then, $NA = NA + 1$;
8. Calculate *check(i)* from Eq. (1);
9. If *check(i)* > *control*, set X_{OPT}, Z_0, and g_0 equal to X, Z, and g_i, respectively, and repeat stage 7; otherwise, go to the next step;
10. If $j < n$, repeat stage 6; otherwise, calculate control from Eq. (1);
11. If *control* ≥ 0, repeat stage 5; otherwise, terminate the algorithm.

A flowchart, summarizing the proposed algorithm, is also shown in Figure 3.

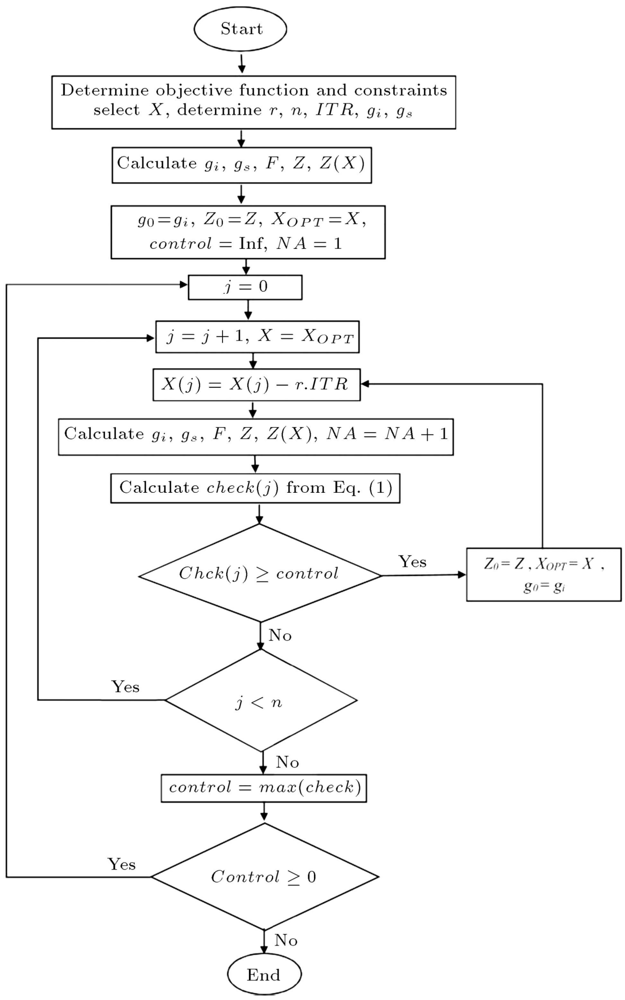

Figure 3. Flowchart of the proposed CCM algorithm.

3. Application of the CCM to mathematical optimization problems

In this section, several mathematical optimization problems, which have clear and exact answers, are solved using the proposed CCM algorithm so that the functionality and accuracy of this method are explored.

Example 1. Determine the minimum value of Z (linear problem)

$$\begin{cases} \text{Min } Z = x_1 + x_2 \\ \text{subject to} \\ 2.x_1 + 4.x_2 \geq 18 \Rightarrow g_1 = \frac{18}{2.x_1+4.x_2} \leq 1.0 \\ 4.x_1 + 3.x_2 \geq 26 \Rightarrow g_2 = \frac{26}{4.x_1+3.x_2} \leq 1.0 \\ x_i \geq 0 \Rightarrow g_{si} = \frac{1}{1+x_i} \leq 1.0 \end{cases}$$

The exact solution to the above problem is $x_1 = 5$, $x_2 = 2$. To show the robustness of the algorithm, three different runs are conducted, starting at different points, O_1, O_2, and O_3, and selecting a different ITR value for each run (1, 0.5, and 0.1 for O_1, O_2, and O_3 runs, respectively). In Table 1, values of the constraints and the target function for the intersection points (points A, B, C, D, and E in Figure 4) and the 3 stating points are listed. It is evident in Figure 4 that all three runs converge to the minimum value (point E). This indicates that the CCM solution accuracy and convergence are not sensitive to the starting point, nor, in this particular example, to the value of ITR, as all three runs have converged to the exact solution. However, in general, the lower the value of ITR, the more accurate the solution will be. Table 2 presents the computational process of CCM in reaching the optimum answer for the run with the starting point O_1 and $ITR = 1$.

Example 2. Determine the maximum value of Z (linear problem)

$$\begin{cases} \text{Max } Z = 40.x_1 + 50.x_2 \\ \text{subject to} \\ 4.x_1 + 3.x_2 \leq 120 \Rightarrow g_1 = \frac{4.x_1+3.x_2}{120} \leq 1.0 \\ x_1 + 2.x_2 \leq 40 \Rightarrow g_2 = \frac{x_1+2.x_2}{40} \leq 1.0 \end{cases}$$

The problem constraints and the convergence history of the CCM algorithm in reaching the optimal answer for this problem are plotted in Figure 5. One run is conducted starting from point O (0, 0) (see Figure 5). The exact solution to this problem is $x_1 = 24$, $x_2 = 8$ (Point E in Figure 5). The computational process of CCM in reaching the optimum answer is presented in Table 3. The optimum value obtained through CCM matches the exact optimal value.

Table 1. Values of constraints and target function for different points of the linear (Example 1).

Point(s)	g_1	g_2	Z
O_1, O_2, O_3	Small	Small	Large
A	1	< 1.0	9
B	> 1.0	1	Unjustified
C	1	> 1.0	Unjustified
D	< 1.0	1	8.667
E	1	1	7

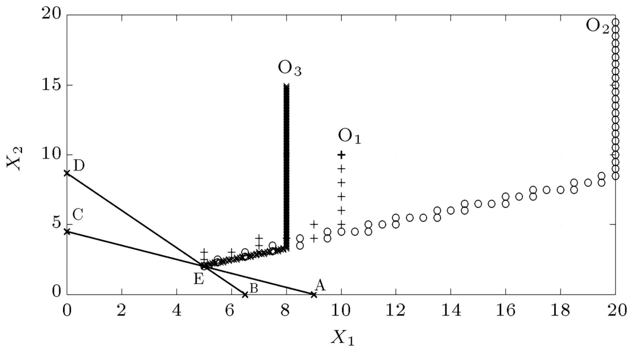

Figure 4. The constraints and convergence histories of the three runs for the linear (Example 1).

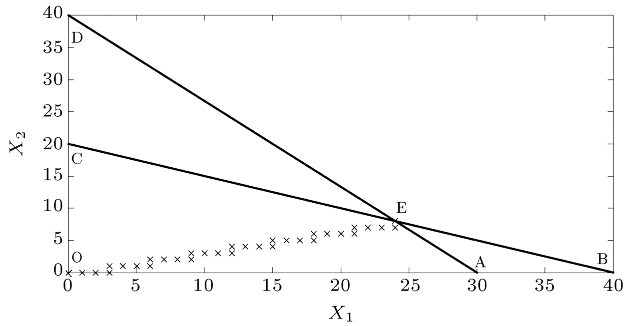

Figure 5. The constraints and convergence history of the CCM run for the linear (Example 2).

Table 2. The computational process of CCM algorithm for the linear (Example 1).

Step	x_1	x_2	g_1	g_2	Z	*Check*	*Control*
1	10	10	0.3	0.371	20	–	Inf
2	10	9	0.321	0.388	19	60.13	60.13
3	10	8	0.346	0.406	18	54.97	54.97
4	10	7	0.375	0.426	17	50.05	50.05
5	10	6	0.409	0.448	16	45.36	45.36
6	10	5	0.45	0.473	15	40.9	40.9
7	9	5	0.474	0.51	14	26.97	26.97
8	9	4	0.529	0.542	13	31.38	26.97
9	8	4	0.563	0.591	12	20.31	20.31
10	7	4	0.6	0.65	11	16.92	16.92
11	7	3	0.692	0.703	10	18.97	16.92
12	6	3	0.75	0.788	9	11.74	11.74
13	5	3	0.818	0.897	8	9.202	9.202
14	5	2	1	1	7	5.5	5.5

Table 3. The computational process of CCM algorithm for the linear (Example 2).

Step	x_1	x_2	g_1	g_2	Z	*Check*	*Control*
1	0	0	0	0	0	–	Inf
2	1	0	0.033333	0.025	40	Inf	Inf
3	2	0	0.066667	0.05	80	0.375	0.375
4	3	0	0.1	0.075	120	0.125	0.125
5	3	1	0.125	0.125	170	0.098039	0.098039
6	4	1	0.15833	0.15	210	0.033613	0.033613
7	5	1	0.19167	0.175	250	0.022857	0.022857
8	6	1	0.225	0.2	290	0.016552	0.016552
9	6	2	0.25	0.25	340	0.020284	0.016552
10	7	2	0.28333	0.275	380	0.009288	0.009288
11	8	2	0.31667	0.3	420	0.007519	0.007519
12	9	2	0.35	0.325	460	0.006211	0.006211
13	9	3	0.375	0.375	510	0.008525	0.006211
14	10	3	0.40833	0.4	550	0.004278	0.004278
15	11	3	0.44167	0.425	590	0.003698	0.003698
16	12	3	0.475	0.45	630	0.003228	0.003228
17	12	4	0.5	0.5	680	0.004669	0.003228
18	13	4	0.53333	0.525	720	0.002451	0.002451
19	14	4	0.56667	0.55	760	0.002193	0.002193
20	15	4	0.6	0.575	800	0.001974	0.001974
21	15	5	0.625	0.625	850	0.002941	0.001974
22	16	5	0.65833	0.65	890	0.001586	0.001586
23	17	5	0.69167	0.675	930	0.00145	0.00145
24	18	5	0.725	0.7	970	0.00133	0.00133
25	18	6	0.75	0.75	1020	0.002021	0.00133
26	19	6	0.78333	0.775	1060	0.00111	0.00111
27	20	6	0.81667	0.8	1100	0.001029	0.001029
28	21	6	0.85	0.825	1140	0.000957	0.000957
29	21	7	0.875	0.875	1190	0.001474	0.000957
30	22	7	0.90833	0.9	1230	0.00082	0.00082
31	23	7	0.94167	0.925	1270	0.000768	0.000768
32	24	7	0.975	0.95	1310	0.000721	0.000721
33	24	8	1	1	1360	0.001123	0.000721

Example 3. Determine the maximum value of Z (nonlinear problem)

$$\begin{cases} \text{Max } Z = x_1.x_2 \\ \text{subject to} \\ {x_1}^2 + x_2 \leq 3 \Rightarrow g_1 = \frac{{x_1}^2+x_2}{3} \leq 1.0 \\ x_i \geq 0 \Rightarrow g_s = \frac{1}{1+x_i} \leq 1.0 \end{cases}$$

The third example is maximization of a nonlinear problem, selected to show applicability of the proposed algorithm to solving nonlinear problems. The exact solution to this problem is: $x_1 = 1$, $x_2 = 2$ (Point E in Figure 6). As shown in Figure 6, two different runs are conducted, starting at different points, O_1 and O_2, and selecting a different ITR value for each run. Figure 6 indicates that both runs converge to the minimum value (point E). This shows again that the convergence of CCM solution is not sensitive to the starting point. Nevertheless, selecting a lower value for ITR results in a more accurate solution. However, the lower the selected value of ITR, the higher the computational effort. Table 4 presents the computational process of

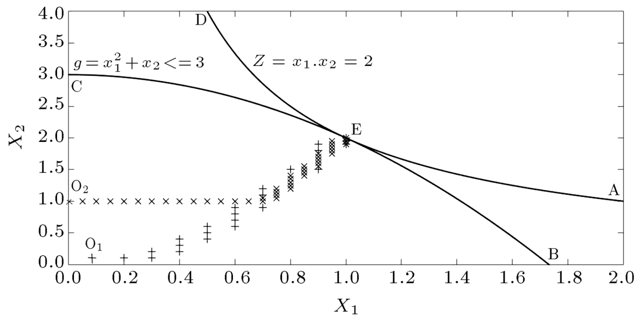

Figure 6. The constraints and convergence histories of the two runs for the nonlinear (Example 3).

CCM in reaching the optimum answer for the run with starting point O_1.

Comparing the CCM solutions of the above 3 mathematical problems with their exact solutions, the efficiency and robustness of the proposed optimization algorithm in solving continuous linear and nonlinear problems are favorably assessed. The algorithm also provides accurate answers with a high speed for discrete problems. In the following, the application of this method to design optimization of moment resisting steel frames, as discrete problems, is presented.

4. Constraint Control Method (CCM) for structural optimization

In optimum design of steel structures, the objective function is to minimize the weight of the structure $W(x)$ based on Eq. (5) subject to $g_k(x)$ constrains given in Eq. (6). The problem variables, X, here are groupings of beams and columns.

$$\text{Minimize}: W(x)=\sum_{i=1}^{n_g}\rho_i A_i \sum_{j=1}^{n_m} L_j, \tag{5}$$

$$\text{Subject to}: g_k(x)\leq 0, \quad k=1,2,\ldots,n_c \tag{6}$$

$$X=\left\{x_1,\ldots x_i,...,x_{n_g}\right\}^T,$$

Table 4. The computational process of CCM algorithm for the nonlinear (Example 3).

Step	x_1	x_2	g_1	$f(x)$	Z	*Check*	*Control*
1	0.1	0.1	0.037	0.01	100	–	Inf
2	0.2	0.1	0.047	0.02	50	5000	5000
3	0.3	0.1	0.063	0.03	33.33	1000	1000
4	0.3	0.2	0.097	0.06	16.67	500	500
5	0.4	0.2	0.12	0.08	12.5	178.6	178.6
6	0.4	0.3	0.153	0.12	8.333	125	125
7	0.4	0.4	0.187	0.16	6.25	62.5	62.5
8	0.5	0.4	0.217	0.2	5	41.67	41.67
9	0.5	0.5	0.25	0.25	4	30	30
10	0.5	0.6	0.283	0.3	3.333	20	20
11	0.6	0.6	0.32	0.36	2.778	15.15	15.15
12	0.6	0.7	0.353	0.42	2.381	11.91	11.91
13	0.6	0.8	0.387	0.48	2.083	8.929	8.929
14	0.6	0.9	0.42	0.54	1.852	6.944	6.944
15	0.7	0.9	0.463	0.63	1.587	6.105	6.105
16	0.7	1	0.497	0.7	1.429	4.762	4.762
17	0.7	1.1	0.53	0.77	1.299	3.896	3.896
18	0.7	1.2	0.563	0.84	1.19	3.247	3.247
19	0.8	1.2	0.613	0.96	1.042	2.976	2.976
20	0.8	1.3	0.647	1.04	0.962	2.404	2.404
21	0.8	1.4	0.68	1.12	0.893	2.06	2.06
22	0.8	1.5	0.713	1.2	0.833	1.786	1.786
23	0.9	1.5	0.77	1.35	0.741	1.634	1.634
24	0.9	1.6	0.803	1.44	0.694	1.389	1.389
25	0.9	1.7	0.837	1.53	0.654	1.226	1.226
26	0.9	1.8	0.87	1.62	0.617	1.089	1.089
27	0.9	1.9	0.903	1.71	0.585	0.975	0.975
28	1	1.9	0.967	1.9	0.526	0.923	0.923
29	1	2	1	2	0.5	0.789	0.789

where, X is the design vector, x_i are design groups, n_g is the total number of design groups, n_m is the total number of members in each design group, ρ_i is the member specific weight, A_i is the member cross-sectional area, L_j is the member length, and n_c is the number of constraints. In addition, given that it is a minimization problem, $r = 1$ and ITR is one unit reduction in the size of steel profile from the available table of construction profiles.

The weight of each design is penalized (W_{ST}) according to Eq. (7):

$$W_{ST} = W(x) * \left(1 + \sum_{1}^{n_c} \left(\max\{0, g_k\}^2\right)\right). \qquad (7)$$

In this study, design groups are selected from W-shape steel sections of AISC table and sorted based on weight per unit length (G) such that the first section is the heaviest and the last section is the lightest.

The general procedure of CCM in solving this type of discrete problem is to start from the heaviest design associated with the smallest constraint ratios (violating constraints the least), and step by step finding a design with the smallest increases in the constraint ratios and the largest reduction in structural weight compared to the design in the previous step. To achieve this, as it was stated in Section 2, the algorithm is based on two parameters, '*check*' and '*control*'. In each step, j, and for every design group, i, $check(i)$ is defined according to Eq. (8):

$$check(i) = \min\left\{\frac{\left(W_{OPT} - W_{ST(j)}\right)}{\left(MCR(1) - MCRL(1)\right)}, \ldots, \frac{\left(W_{OPT} - W_{ST(j)}\right)}{\left(MCR_{(k)} - MCRL_{(k)}\right)}, \ldots, \frac{\left(W_{OPT} - W_{ST(j)}\right)}{\left(MCR(n_c) - MCRL(n_c)\right)}\right\}, \qquad (8)$$

where, $W_{ST(j)}$ is the penalized structural weight in step j, W_{OPT} is the structural weight of the best solution up to step $j-1$, $MCR_{(k)}$ is the maximum constraint ratio within each design group for constraint k, and $MCRL_{(k)}$ is the maximum constraint ratio within each design group associated with the best solution up to step $j-1$. The Constraint Ratio (CR) is defined as the ratio of any constraint value to the maximum allowable value for that constraint. The *control* parameter is used to control the *check* parameter to ensure that a design with the smallest increase in the constraint ratios and the largest reduction in weight is selected. It is defined as the max *check* parameter for all design groups. i.e.,

$$control = \max(check).$$

Since at the start of the algorithm, parameter $check(i)$ cannot be evaluated, *control* parameter is initially set to a large value.

Different steps in the proposed CCM are as follows:

1. A large number is assigned as the initial value to the *control* parameter ($control = \text{Inf}$).
2. The largest design variables (the largest W-shape section permitted for a design group) are assigned to members in all groups. This design is termed X.
3. The structure is then analyzed, constraint ratios are evaluated, and for every constraint k, and the maximum values of constraint ratios, $MCR_{(k)}$, are extracted and stored as vector MCR in Eq. (9). Then, the initial values of $MCRL$, W_{OPT}, and X_{OPT} are set respectively to MCR, W_{ST}, and X.
$$MCR = \left\{MCR_{(1)}, \ldots, MCR_{(k)}, \ldots, MCR_{(n_c)}\right\}. \qquad (9)$$
4. At this stage, to find a new X, one design group from n_g groups of X_{OPT} is randomly selected and to the members of that group, a new smaller section from the allowed list of W-shape sections is assigned. This is repeated for all design groups. At any round, the selected design groups in the previous rounds are not selected again. For each design group, stages 5 and 6 are repeated; then, the solution moves to stage 7.
5. At this stage, the structure is analyzed and new W_{ST} and MCR are calculated using Eqs. (3) and (6), respectively. The $check(i)$ parameter is also calculated using Eq. (4).
6. If $check(i) \geq control$, then $X_{OPT} = X$ and $W_{OPT} = W_{ST}$; and stages 4 to 6 are repeated. If $check(i) < control$, $MCRL$ is set to MCR.
7. At this stage, the control value is calculated according to Eq. (5). Then, the solution goes back to stage 4 and it continues until $control = 0$. The last X_{OPT} and W_{OPT} are the optimum design and its associated structural weight, respectively.

As it can be noted, this method directs the solution towards the final answer by controlling constraints or by decreasing the structural weight through small increases in stress and drift towards their limits. Figure 7 presents the flowchart of the algorithm in details. In the following, 3 benchmark sway frame problems are optimized by the proposed method and the results are compared with those of other solutions available in the literature.

5. Design examples

The CCM developed in this work is tested in three 2D side-sway steel frame optimization problems. Op-

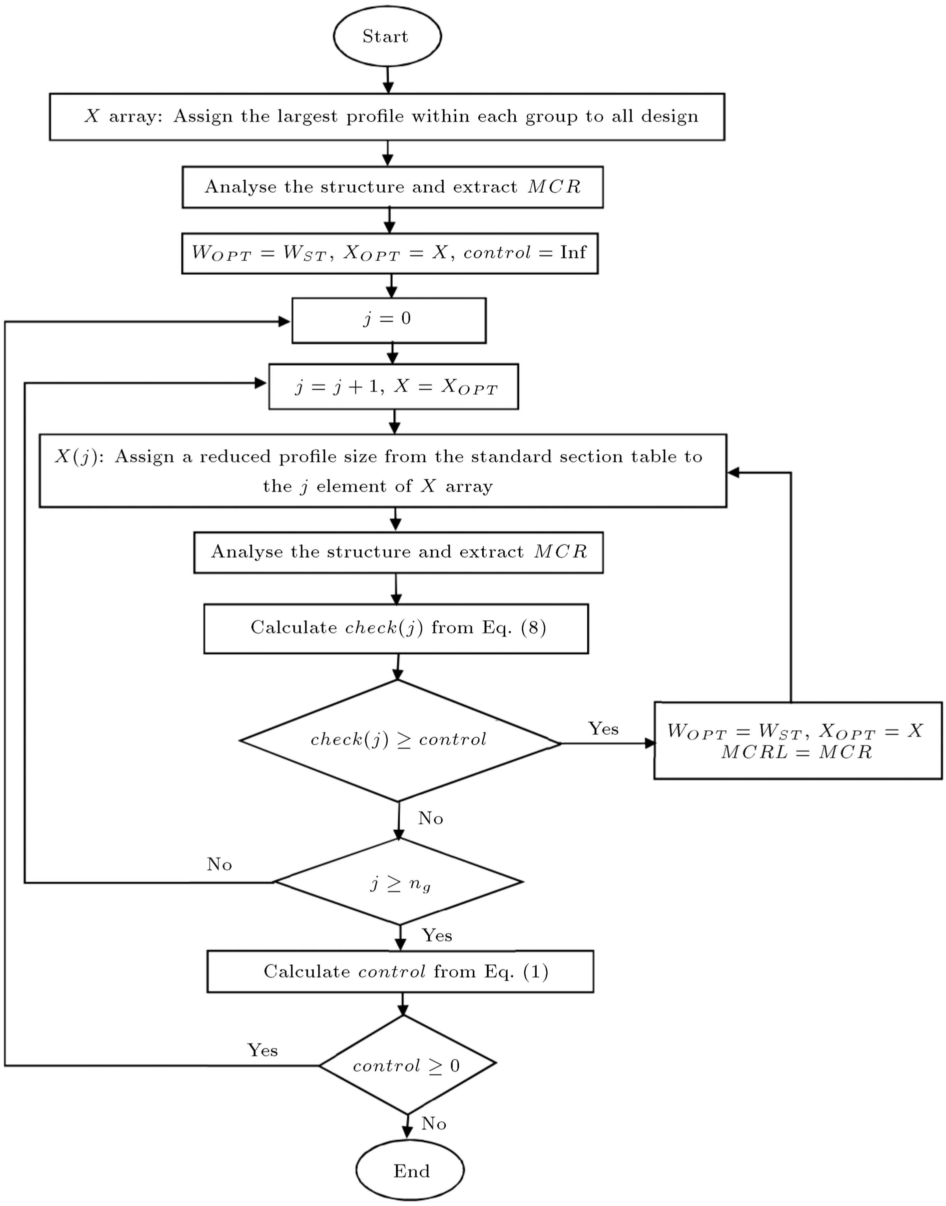

Figure 7. Flowchart of the proposed CCM algorithm for optimum design of steel frames.

$$\begin{cases} g_1(x) = \left(\frac{P_u}{\emptyset . P_n}\right)_i + \frac{8}{9}\left(\frac{M_{ux}}{\emptyset_b M_{nx}} + \frac{M_{uy}}{\emptyset_b M_{ny}}\right) - 1 \leq 0 & \text{If } \left(\frac{P_u}{\emptyset . P_n}\right)_i \geq 0.2 \\ g_1(x) = \left(\frac{P_u}{\emptyset . P_n}\right)_i + \left(\frac{M_{ux}}{\emptyset_b M_{nx}} + \frac{M_{uy}}{\emptyset_b M_{ny}}\right) - 1 \leq 0 & \text{if } \left(\frac{P_u}{\emptyset . P_n}\right)_i < 0.2 \end{cases} \tag{10}$$

for $i = 1, 2, ..., n_m$

Box I

timized designs are compared with those reported in the literature using metaheuristic algorithms. In line with the assumptions made by others in solving these problems, the shear deformations are ignored. Design of the frames is subject to stress and relative story drift constraints. The stress constraint ratio for members undergoing axial force and bending moment is specified according to Eq. (10), as shown in Box I, based on the AISC-LRFD specifications [33].

In Eq. (10), P_u is the required axial force and P_n is the nominal axial capacity. Also, M_{nx} and M_{ny} are nominal bending capacities, and M_{uy} and M_{ux}

are factored bending moments in x and y directions, respectively; ϕ_b is bending strength reduction factor and ϕ is axial strength reduction factor.

Inter-story drift constraint ratio is specified according to Eq. (11):

$$g_2(x) = \frac{\Delta_i}{\Delta_i^u} - 1 \leq 0, \quad \text{where}, \quad i = 1, ..., n_s, \tag{11}$$

where, Δ_i and Δ_i^u are respectively the inter-story drift and allowable inter-story drift of story i and n_s is the total number of stories.

5.1. Two-bay, three-story planar frame

The first benchmark problem (see Figure 8) is a two-bay, three-story frame optimized by Pezeshk et al. [34] under a single-load case in accordance with the American Institute of Steel Construction specification [33] using GA. This frame was subsequently designed subject to the same specification by Camp et al. [35] using an ACO algorithm; by Değertekin [36] using HS method; by Toğan [17] using Teaching-Learning Based Optimization (TLBO) algorithm; by Safari and Maheri [20,37] using Modified Multi-Deme GA (MMDGA); and by Maheri and Narimani [23] using an Enhanced Harmony Search (EHS) algorithm. In this design problem, construction conditions lead to a uniformity between beams and columns sections. Hence, there are two section groups as listed in Table 5. Beams section is selected from all W-sections lists of AISC standard table and columns section is limited to W10-section table. Steel special weight is considered to be $c = 7850 \frac{\text{kg}}{\text{m}^3}$ $(0.284 \frac{\text{Ib}}{\text{in}^3})$, Young's modulus is considered to be $E = 200$ GPa (29000 ksi), yield stress is $F_y = 248$ MPa (36 ksi), and beams unbraced length coefficient is 0.167.

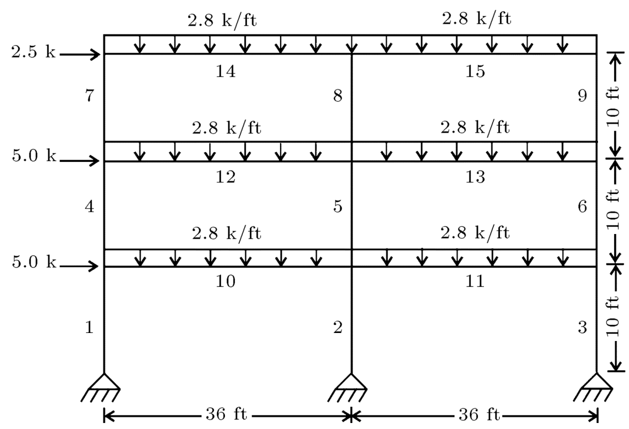

Figure 8. Geometry and loading details of the two-bay, three-story frame.

Table 5. Design groups for the two-bay, three-story frame.

Group	Members
1	1, 2, 3, 4, 5, 6, 7, 8, 9
2	10, 11, 12, 13, 14, 15

The best design achieved by the proposed CCM weighs 18.792 kips, obtained after only 55 runs. This design is compared with the designs reported in the literature using other algorithms in Table 6. It can be seen that only TLBO and EHS produce lighter designs (respectively by 5.3% and 4.2%). However, the proposed CCM reaches the optimum design much faster than all the other algorithms. The number of analyses required by CCM for reaching its best design is only a fraction of the number of analyses carried out in the other algorithms to achieve their best designs, this fraction being 3.1% compared to GA and 1.8%, 3%, 31.4%, and 25% compared respectively to ACO, HS, MMDGA, and EHS algorithms.

In Figure 9, the convergence curve of CCM solution to this problem is compared with that obtained by the EHS solution, as one of the best and fastest metaheuristic solutions available. It can be noted that CCM shows a relatively uniform and considerably fast trend towards the optimum design compared to the EHS algorithm. To graphically observe the state of stresses in the members, the stress ratios for all members of the frame are shown in Figure 10. It could be observed that all the stress ratios are lower than 1.

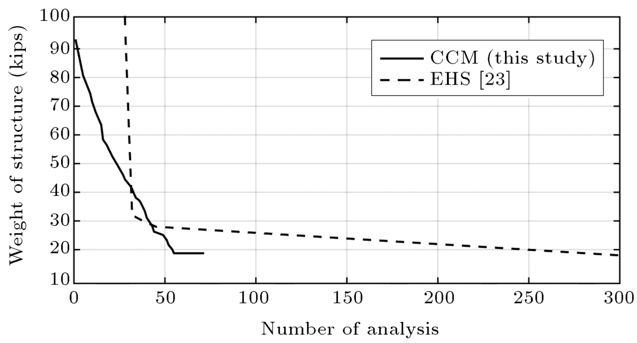

Figure 9. Weight versus number of analyses for the two-bay, three-story frame problem.

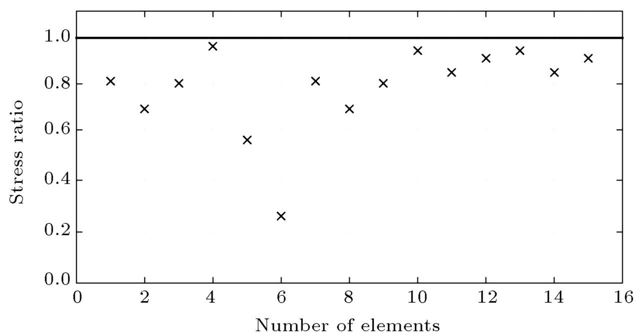

Figure 10. The stress ratio for elements of the two-bay, three-story frame problem.

Table 6. Comparison of optimum designs for the two-bay, three-story frame.

Group no.	GA [34]	ACO [35]	HS [36]	TLBO [17]	MMDGA [20]	EHS [23]	CCM (this study)
Beam	W24×62	W24×62	W21×62	W24×62	W24×62	W21× 55	W24×62
Column	W10×60	W10×60	W10×54	W10×49	W10×60	W10×68	W10×60
Weight (lb)	**18,792**	**18,792**	**18,292**	**17,789**	**18,792**	**18,000**	**18,792**
No. of analyses	**1800**	**3000**	**853**	–	**175**	**220**	**55**

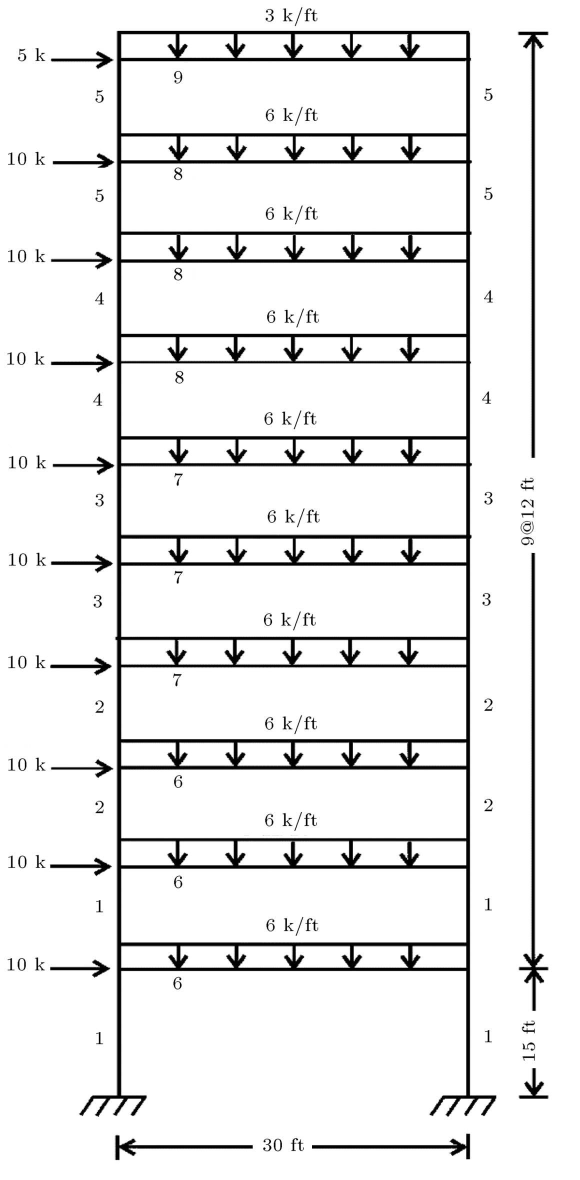

Figure 11. Geometry and loading details of the one-bay, ten-story frame.

5.2. One-bay, ten-story frame

The second benchmark problem is a 2D, one-span, ten-story frame consisting of 30 members as shown in Figure 11. This frame was first optimized by Pezeshk et al. [34] using simple GA. It has subsequently been optimized by Kaveh & Talatahari [38] using the Improved ACO (IACO) algorithm; by Toğan [17] using TLBO algorithm; by Camp et al. [35] using ACO algorithm; by Değertakin [36] using HS algorithm; by Doğan & Saka [39] using PSO method; by Safari & Maheri [20] using MMDGA; and by Maheri and Narimani [23] using EHS algorithm. The AISC-LRFD specification [33] has been used for optimum design of this frame with displacement constraint satisfying inter-story drift<story height/300. Young's modulus of $E = 29,000$ ksi and yield stress of $f_y = 36$ ksi are used. The members of this frame are divided into 9 design groups as listed in Table 7. Four beam element groups are chosen from 267 W-shapes and 5 column groups selected from only W14 and W12 sections (66 W-shapes). The effective length factors of members are calculated as $K_x \geq 1$ [40], whereas the out-of-plane length factor K_y is assigned 1. For each beam member, the out-of-plane effective length factor is specified to be $K_y = 0.2$.

Table 7. Design groups for the one-bay, ten-story frame.

Group	Members
1	1, 2, 4, 5
2	7, 8, 10, 11
3	13, 14, 16, 17
4	19, 20, 22, 23
5	25, 26, 28, 29
6	3, 6, 9
7	12, 15, 18
8	21, 24, 27
9	30

The proposed CCM solution produces a best design weighing 61.041 kips after 424 runs. This design is compared with designs reported for other algorithms in Table 8. It can be observed that the CCM produces the lightest design except for the EHS algorithm. CCM design is only 2.5% heavier than that of EHS algorithm, but it is lighter than GA by 6.7%, ACO by 2.6%, HS by 1.35%, IACO by 1.28%, PSO by 6.4%, TLBO by 1.26%, and MMDGA by 0.5%. Furthermore, the proposed CCM algorithm again reaches the optimum

Table 8. Comparison of optimum designs for the one-bay, ten-story frame.

Group no.	GA [34]	ACO [35]	HS [36]	IACO [38]	PSO [39]	TLBO [17]	MMDGA [20]	EHS [23]	CCM (this study)
1	W14×233	W14×233	W14×211	W14×233	W33×141	W14×233	W12×230	W14×159	W14×211
2	W14×176	W14×176	W14×176	W14×176	W14×159	W14×176	W14×159	W14×730	W14×145
3	W14×159	W14×145	W14×145	W14×145	W14×132	W14×145	W14×120	W14×61	W14×120
4	W14×99	W14×99	W14×90	W14×90	W14×99	W14×99	W14×90	W12×87	W14×90
5	W12×79	W12×65	W14×61	W12×65	W14×99	W12×65	W12×58	W14×283	W12×58
6	W33×118	W30×108	W33×118	W33×118	W30×116	W30×108	W33×118	W24×68	W36×135
7	W30×90	W30×90	W30×90	W30×90	W21×68	W30×90	W30×108	W14×99	W30×108
8	W27×84	W27×84	W24×76	W24×76	W14×61	W27×84	W24×76	W21×111	W24×76
9	W24×55	W21×44	W18×46	W14×30	W40×183	W21×44	W16×40	W33×201	W18×40
Weight (lb)	**65,136**	**62,610**	**61,864**	**61,820**	**64,948**	**61,813**	**61,345**	**59,514**	**61,041**
Number of analyses	**3000**	**8300**	**2690**	–	**7500**	–	**1800**	**1412**	**424**

design much faster than all the other algorithms. The 424 analyses conducted in CCM are only 14% of the number of analyses in GA, 5.7% of the number of analyses in PSO, 5% of the number of analyses in ACO, 11.5% of the number of analyses in HS, 23.6% of the number of analyses in MMDGA, and 30% of the number of analyses in EHS method.

The convergence curve for the CCM solution to this problem is compared with that for the EHS solution in Figure 12. It can be seen that CCM has a faster trend towards optimum design than EHS algorithm. To observe the state of problem constraints such as story drift and member stresses during solution, the story ratio, as the ratio of the story drift to its allowable value, and the stress ratio, as the ratio of stress to allowable stress, are plotted in Figure 13 and Figure 14, respectively. These figures show that both constraints are well controlled, as all ratios fall below unity.

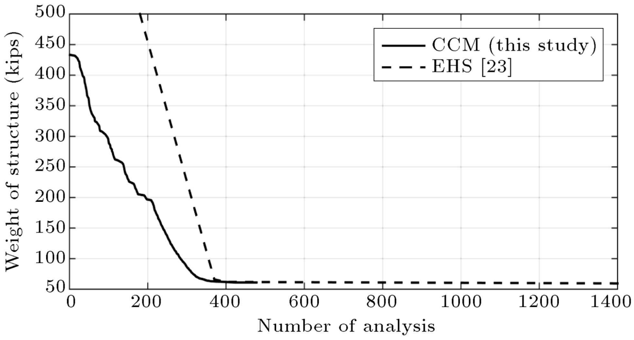

Figure 12. Weight versus number of analyses for the one-bay, ten-story frame problem.

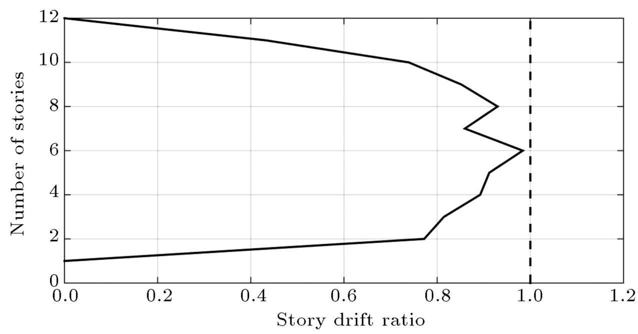

Figure 13. Relative drift in different stories for the one-bay, ten-story frame problem.

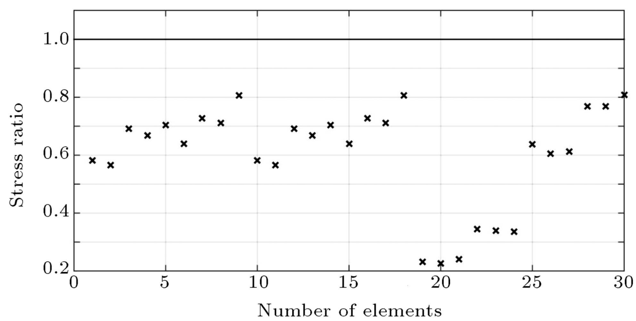

Figure 14. The stress ratio for all elements in the one-bay, ten-story frame problem.

5.3. Three-bay, twenty-four-story frame

The third benchmark problem is a three-bay, twenty-four-story steel frame shown in Figure 15. The frame was first designed by Camp et al. [35] using the ACO algorithm. It was later optimized by Değertekin [36] using HS; by Kaveh and Talatahari [38] using

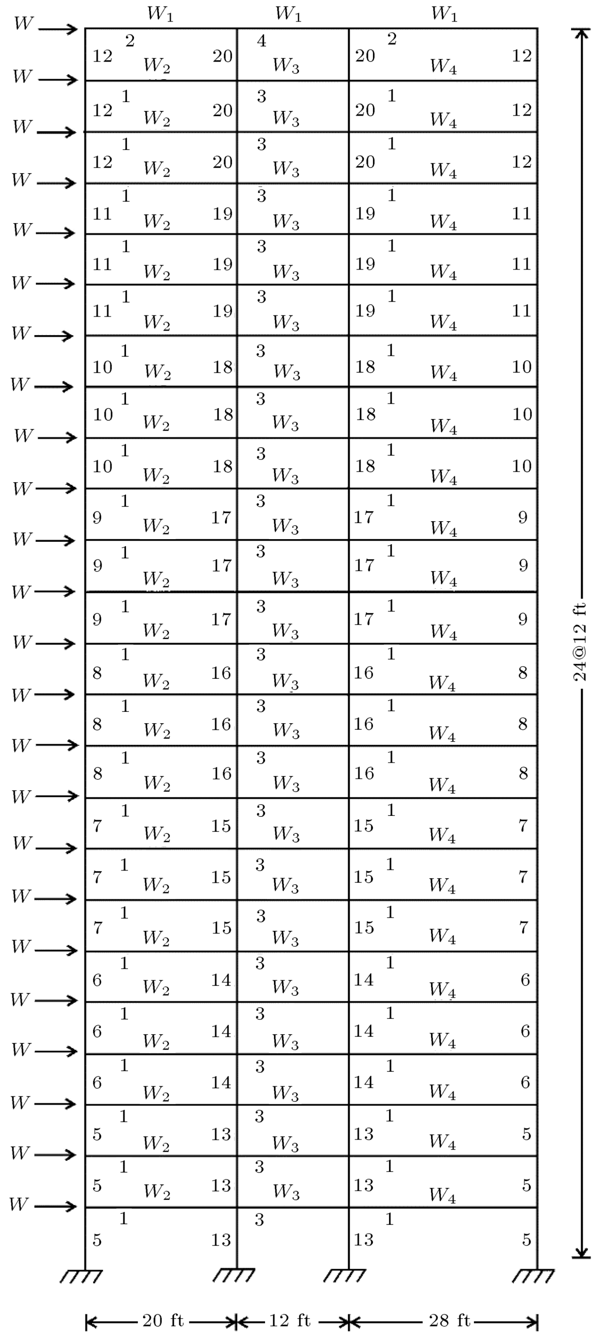

Figure 15. Geometry and loading details of the three-bay, twenty-four-story frame.

Improved ACO (IACO); by Kaveh and Talatahari [15] using the Imperialist Competitive Algorithm (ICA); by Toğan [17] using TLBO algorithm; by Safari et al. [20] using MMDGA algorithm; and by Maheri and Narimani [23] using Enhanced Harmony Search (EHS) algorithm. The loads are $W = 5,761.85$ lb, $W_1 = 300$ lb/ft, $W_2 = 436$ lb/ft, $W_3 = 474$ lb/ft, and $W_4 = 408$ lb/ft (1 lb = 4.448 N).

The frame has been designed using American Institute of Steel Construction specifications [33] under the inter-story drift displacement constraint (inter-story drift < story height/300).

The material properties are assigned as: modulus of elasticity $E = 29,732$ ksi and yield stress $f_y = 33.4$ ksi. The effective length factors of the members are calculated at $K_x \geq 1.0$ from the approximate equation proposed by Dumonteil [40]. The out-of-plane effective length factor is $K_y = 1.0$. All members are unbraced along their lengths. The members of this frame are divided into 20 design groups, listed in Table 9. Each of the 4 beam element groups are chosen from all of the 267 W-sections, whereas 16 column member groups are selected from only W14 sections.

The optimum design obtained using the proposed CCM solution weighs 198.85 kips, obtained after 1119 analyses. This design is compared with other optimum designs reported in the literature for this test problem in Table 10. This table shows that, similar to the previous test problems, the CCM produces the lightest design, except for the EHS algorithm, being only 2.2% heavier; but it obtains lighter designs than ACO by 10.87%, HS by 8.05%, IACO by 1.28%, ICA by 6.98%, TLBO by 2.09%, and MMDGA by 1.54%. Also, the proposed CCM algorithm reaches the optimum design much faster than all the other algorithms. The 1119 analyses conducted in CCM are only 7.2% of the number of analyses in ACO, 32% of the number of analyses in IACO, 14.9% of the number of analyses in ICA, 9.3% of the number of analyses in TLBO, 7.6% of the number of analyses in HS, 23.6% of the number of analyses in MMDGA, and 88.9% of the number of analyses in EHS solutions.

The convergence curve for the proposed CCM solution to this problem is compared with that for EHS solution in Figure 16. It is noted that, although the CCM solution is initially slower than EHS solution, it picks up later and shows a faster trend towards optimum design. To observe the state of story drift and member stress constraints during solution, the story ratio, as the ratio of the story drift to its allowable value, and the stress ratio, as the ratio of member stress to allowable stress, are plotted in Figures 17

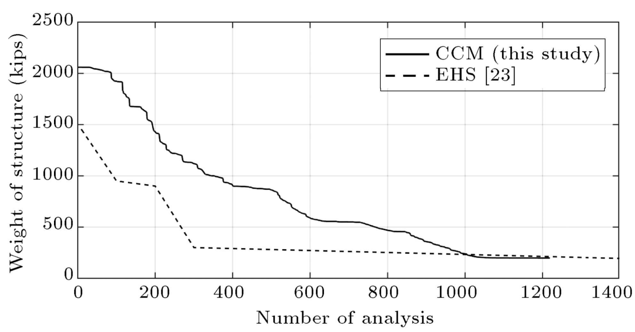

Figure 16. Weight versus number of analyses for the three-bay, twenty-four-story frame problem.

Table 9. Design groups for the three-bay, twenty-four-story frame.

Group	Members
1	5, 7, 12, 14, 19, 21, 26, 28, 33, 35, 40, 42, 47, 49, 54, 56, 61, 63, 68, 70, 75, 77, 82, 84, 89, 91, 96, 98, 103, 105, 110, 112, 117, 119, 124, 126, 131, 133, 138, 140, 145, 147, 152, 154, 159, 161
2	166, 168
3	6, 13, 20, 27, 34, 41, 48, 55, 62, 69, 76, 83, 90, 97, 104, 111, 118, 125, 132 , 139, 146, 153, 160
4	167
5	1, 4, 8, 11, 15, 18
6	22, 25, 29, 32, 36, 39
7	43, 46, 50, 53, 57, 60
8	64, 67, 71, 74, 78, 81
9	85, 88, 92, 95, 99, 102
10	106, 109, 113, 116, 120, 123
11	127, 130, 134, 137, 141, 144
12	148, 151, 155, 158, 162, 165
13	2, 3, 9, 10, 16, 17
14	23, 24, 30, 31, 37, 38
15	44, 45, 51, 52, 58, 59
16	65, 66, 72, 73, 79, 80
17	86, 87, 93, 94, 100, 101
18	107, 108, 114, 115, 121, 122
19	128, 129, 135, 136, 142, 143
20	149, 150, 156, 157, 163, 164

Table 10. Comparison of optimum designs for the three-bay, twenty-four-story frame.

Group no.	ACO [35]	HS [36]	IACO [38]	TLBO [17]	ICA [15]	MMDGA [20]	EHS [23]	CCM (this study)
1	W30×90	W30×90	W30×99	W30×90	W30×90	W30×90	W10×19	W30×90
2	W8×18	W10×22	W16×26	W8×18	W21×50	W8×15	W12×190	W14×22
3	W24×55	W18×40	W18×35	W24×62	W24×55	W24×55	W6×8.5	W24×55
4	W8×21	W12×16	W14×22	W6×9	W8×28	W10×15	W24×370	W6×9
5	W14×145	W14×176	W14×145	W14×132	W14×109	W14×159	W14×132	W14×145
6	W14×132	W14×176	W14×132	W14×120	W14×159	W14×132	W14×30	W14×109
7	W14×132	W14×132	W14×120	W14×99	W14×120	W14×90	W14×99	W14×90
8	W14×132	W14×109	W14×109	W14×82	W14×90	W14×90	W14×53	W14×68
9	W14×68	W14×82	W14×48	W14×74	W14×74	W14×61	W14×74	W14×53
10	W14×53	W14×74	W14×48	W14×53	W14×68	W14×48	W14×26	W14×34
11	W14×43	W14×34	W14×34	W14×34	W14×30	W14×48	W14×68	W14×22
12	W14×43	W14×22	W14×30	W14×22	W14×38	W14×22	W14×193	W14×22
13	W14×145	W14×145	W14×159	W14×109	W14×159	W14×109	W14×145	W14×90
14	W14×145	W14×132	W14×120	W14×99	W14×132	W14×99	W14×26	W14×109
15	W14×120	W14×109	W14×109	W14×99	W14×99	W14×99	W14×26	W14×99
16	W14×90	W14×82	W14×99	W14×90	W14×82	W14×74	W14×43	W14×99
17	W14×90	W14×61	W14×82	W14×68	W14×68	W14×68	W14×26	W14×82
18	W14×61	W14×48	W14×53	W14×53	W14×48	W14×53	W14×120	W14×68
19	W14×30	W14×30	W14×38	W14×34	W14×34	W14×26	W14×426	W14×48
20	W14×26	W14×22	W14×26	W14×22	W14×22	W14×22	W14×68	W14×22
Weight (lb)	**220,465**	**214,860**	**217,464**	**203,008**	**212,725**	**201,907**	**194,400**	**198,850**
Number of analyses	**15500**	**9924**	**-**	**-**	**7500**	**4750**	**1259**	**1119**

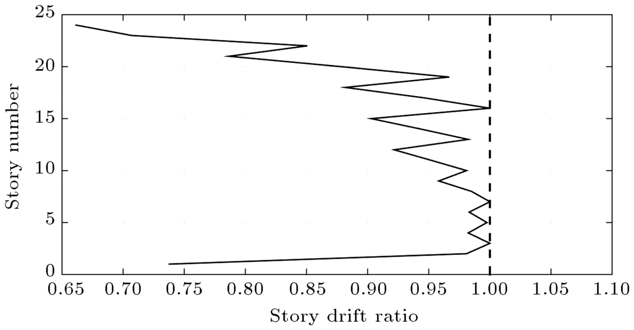

Figure 17. Drift ratio in different stories for the three-bay, twenty-four-story frame problem.

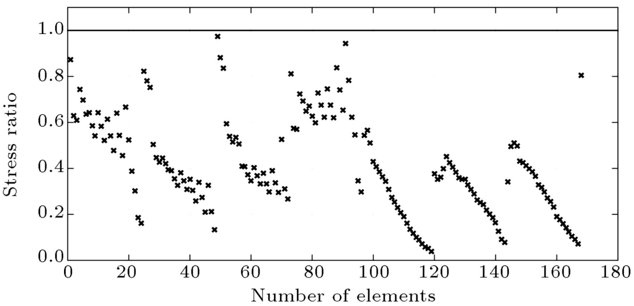

Figure 18. The element stress ratio in the three-bay, twenty-four-story frame problem.

and 18, respectively. These figures show that, also for this problem, both constraints are well controlled, as all ratios fall below unity.

6. Conclusions

Based on conventional engineering design philosophy, whereby optimum design is achieved gradually by controlling the problem constraints, a simple algorithm, termed the Constraint Control Method (CCM), was developed and presented. The functionality of the proposed algorithm was first demonstrated by solving several linear and nonlinear mathematical problems, which had precise answers. The performance of the proposed method was then evaluated through comparing design optimization results of three 2D steel frame benchmark problems with the results from other metaheuristic optimization solutions. The comparison led to the following conclusions:

1. This method is appropriate for solving linear and nonlinear mathematical systems. It can also be used for both continuous and complex discrete systems;
2. The advantage of the proposed method, besides its simple logic and ease of implementation, is that it does not require mathematical equations and the optimized values and proper targets could be reached through the output of computer software and the CCM;
3. In the linear and nonlinear mathematical problems, the convergence of CCM solution is not sensitive to the starting point. However, selecting a lower value for *ITR* results in a more accurate solution;
4. In all benchmark steel frame problems, the proposed CCM leads to a design lighter than almost all the reported metaheuristic optimization solutions, being only marginally heavier than the EHS solution;
5. The main advantage of the simple CCM over other algorithms is in its solution speed, requiring much smaller number of structural analyses than all the metaheuristic algorithms in reaching the optimum solution.

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Biographies

Seyyed Fazlolah Mansouri was born in 1980 in Shiraz, Iran. After graduation from the Department of Civil Engineering at University of Shahid Bahonar Kerman in 2001, he received MSc degree in 2003 from Iran University of Science and Technology. He is now a PhD candidate in Civil Engineering Department of the Science and Research Branch of Islamic Azad University, Tehran, Iran. He is interested in heuristic and metaheuristic optimization research.

Mahmoud Reza Maheri is a Professor of Civil and Structural Engineering at Shiraz University, Iran. He obtained his PhD in Earthquake Engineering from Bristol University, UK, in 1987. He conducted post-doctoral research work in University College, London, before returning to Iran to teach at Shiraz University in 1991. He is currently a member of the Central Council of Iran National Building Codes of Practice and the Head of Committee on Code for Masonry Buildings. He is also a core member of the Center of Excellence for Computational Mechanics. Professor Maheri's research interests include seismic retrofitting of structures, masonry buildings, optimization methods, and structure-fluid dynamic interaction.