Int. J. Nonlinear Anal. Appl. In Press, 1–16
ISSN: 2008-6822 (electronic)
http://dx.doi.org/10.22075/ijnaa.2024.34184.5101

Comparison of ASD and LRFD with W sections for the optimization and stress ratio of steel frames using genetic algorithm in SAP2000 and ETABS

Mahdi Mohammadi Farsam[a,*], Masoud Mahmoud Abadi[a], Farzad Lari[b]

[a] *Department of Civil Engineering, Faculty of Engineering, University of Qom, Qom, Iran*

[b] *Department of Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran*

(Communicated by Seyed Hossein Siadati)

Abstract

Any optimum design requires adequate skill and experience. Overall, having a multitude of variables in a design makes manual optimization fairly difficult or even unattainable. Importantly, due to the paucity of resources and the existence of competitive space, one can only implement and accomplish high-throughput plans, thereby making it crucial to profit from optimization methods. In this research, the objective function was the structure's weight, which was supposed to be directly correlated with its cost. Design models were optimized separately, investigated, and compared using genetic algorithm (GA), LRFD, and ASD analyses with W sections for frames. The cross-section of beams and columns were studied as design variables, and the constraints specified in the Iranian National Building Code (Part 10) were considered design constraints. Ultimately, the graphs for GA and stress ratio in each condition of LRFD and ASD for the W sections were obtained and compared, followed by analyzing and comparing the stress ratio in SAP2000.

Keywords: optimization, steel structures, genetic algorithm, LRFD analysis, ASD analysis, Sap2000
2020 MSC: 68W50

1 Introduction

Researchers and engineers attempt to enhance and advance their novel ideas using optimization methods. Here, optimization means evaluating a variety of aspects of an initial idea and then employing the data to improve that idea. Accordingly, optimization algorithms aim to find a satisfactory solution that best complies with the constraints and requirements of the problem. There may be a multitude of solutions for a given problem. Thus, to compare the solutions and choose the optimal answer to that problem, we need to define a function termed the objective function or the cost function, where choosing this function depends on the nature of the concerned problem. Metaheuristic algorithms (MHAs) are algorithms whose design is inspired by nature, physics, and humans. These algorithms are extensively used to solve many optimization problems. MHAs are often used in tandem with other algorithms to attain the optimal solution or to escape local optima. Since MHAs have been widely overlooked by researchers in

*Corresponding author
Email addresses: mohammadimohammadi2024@gmail.com (Mahdi Mohammadi Farsam), m.mahmoudabadi@qom.ac.ir (Masoud Mahmoud Abadi), farzad.lari@gmail.com (Farzad Lari)

Received: February 2024 *Accepted:* May 2024

optimizing steel structures, the role of this algorithm in optimizing these structures needs to be further evaluated in future studies.

Genetic Algorithm (GA) is an optimization heuristic that works based on the principles of natural selection. Engineers and designers have constantly aimed at optimizing structures by reflecting the existing conditions and limitations or the constraint functions. Hence, the designing phase is a decision-making process and is opposite to the structural analysis phase which covers no selection. Though experience is at the center of proper decision-making, optimization techniques offer a systematic framework for making suitable decisions based on logical principles. In a 2010 study, Kaveh et al. were concerned with the optimal design of 2-D steel frames with the improved ant colony optimization algorithm (ACO) [8]. Elsewhere, Kaveh et al. [10] studied the optimal design of 2-D moment steel frames with ACO and GA [10]. Sadik et al. [19] worked with the harmony search algorithm (HSA) to minimize the costs of 3-D steel frames with semi-rigid connections [19].

In a 2011 study, Kripakaran et al. operated with GA to optimize steel frames with two different methods [13]. Togan employed teaching-learning-based optimization (TLBO) algorithms to minimize the weight of 2-D steel frames [22]. Sadik et al. [19] used PSO, GO, and HSA algorithms to optimize 2-D steel frames based on load and resistance factor design (LRFD) [3]. In a 2012 study, Kaveh et al. worked with the charged system search optimization algorithm (CSSOA) to minimize the weight of 2-D and 3-D frames [11].

Kaveh et al. [23] proposed an optimal design of 2-D frames using CSSOA and improved HAS algorithms [12]. Kociecki et al. [14] employed the two-phase GA to optimize 3-D free-form steel space-frame roof structures. These structures were two among all 13 train stations where the members were influenced by torsion and moment and axial loads. Using GA, they reduced the weight of these two structures by 12 and 7%, respectively [14]. Kaveh et al. [9] used CSSOA to optimize 2-D steel frames with semi-rigid connections [9]. Kao et al. [7] first designed several different buildings and then employed the obtained data to model a neural network that can predict the structure's behavior under design loads. Ultimately, they optimized the weight of this approximate model using evolutionary algorithms (EAs) [7]. In a 2014 study, Narimani et al. worked with optimization-based MHAs to minimize the weight of 2-D and 3-D steel frames [15]. Gholizadeh [5] optimized the study buildings using the modified firefly algorithm (MFA) [5]. Phan et al. [18] worked with GA to optimize cold-formed steel portal frames for stressed skin action. They reduced the weight of consumed materials by 53% with the help of GA [18]. Afzali et al. [1] operated optimization algorithms to minimize the weight of 2-D steel frames [1]. In a 2018 review, Ekici et al. explored the use of collective and evolutionary intelligence algorithms in functional computing architecture. After the literature review, they proposed various statistical (e.g., the type of algorithms) and classified approaches in terms of sustainability, cost, performance, and structure. Ultimately, they reported sustainability as a factor that is at the attention center of most studies [4]. Khalafi et al. [6] obtained optimization codes in MATLAB and worked with OpenSees for nonlinear static analyses. They reported that the BAT algorithm (BA) has a much higher convergence speed and yields an accurate optimal solution with a lower optimal weight value [6]. Bahreyni Pour et al. [2] employed GA to minimize the weight of steel moment frames [2]. Sepehari Manesh et al [20] worked with GA to reduce the weight of space-frame structures based on reliability constraints [20]. Sojoodizadeh et al. [21] employed a modified PSO algorithm (MPSO) to solve four truss optimization problems, including a 2-D truss with 14 members, a 2-D truss with 17 members, a 3-D truss with 71 members, and a 3-D truss with 27 members. They found that MPSO outperforms other algorithms in solving optimization problems [16].

GA is widely used to optimize moment frames. This algorithm is an EA and works based on intelligent searching. The present study uses GA to find the minimum cost and minimum displacement of the structure and then compares LRFD and ASD methods with W sections for optimization outcomes. The study implies some constraints on LRFD and ASD design methods according to the Iranian National Building Code (Part 10).

Notably, steel structures are optimized with a variety of algorithms, but the present study compares LRFD and ASD methods for their optimization efficiency.

2 Optimizations

2.1 Definition of the objective function

In this research, the objective function was the weight of the structure, which is directly correlated with the structure's cost. Thus, the structure's cost was calculated based on the profile weight parameter.

The design variables intended in this research were the dimensions of the cross-section of the frame's beams and columns. Importantly, this study reflects constraints and items specified in Standard 2800 and the Iranian National Building Code (Part 10), such as stress and displacement. The beams were subjected to the bending moment and the columns were under the synergistic effect of bending moment and axial force. The constraints of the optimization model were the design criteria based on the analytical criteria of LRFD and ASD.

$$\text{Minimize } F = f(\text{cost}) \tag{2.1}$$

$$f(\text{cost}) \propto \text{Weight} \tag{2.2}$$

2.2 Penalty function

The objective function should be defined to allow satisfying all constraints such as the stresses in each of the elements and lateral displacements. It further should cover constraints imposed on the deformation of the structure. For best functioning, the columns of the lower stories should be of larger dimensions than those of the upper stories. Other constraints specified in the building codes need to be further reflected. In case of failure to satisfy these constraints, the objective (cost) functions will be penalized. This method simplifies the objective function and further allows to apply required constraints to increase the structure's cost or displacement, thereby automatically preventing the choice of penalized answers as the optimal solution. A multitude of methods have so far been proposed regarding the penalty function. However, the penalty function in this study is as follows:

$$C_i = \alpha_i V_i \tag{2.3}$$

$$\phi = \sum_{i=1}^{n} C_i \tag{2.4}$$

where (C_i) is the penalty function for each constraint, (α_i) is the penalty factor for each constraint, (V_i) is the amount of penalty for each constraint, and $(\emptyset)$ is the total of penalties applied. The penalty factor is obtained by trial and error and according to the model and takes a unique for each structure.

3 GA

GAs are a group of search and optimization methods inspired by the principles of natural selection and genetics. These algorithms imitate the theory of natural evolution to find optimal solutions to complex problems. This evolutionary algorithm searches among a population of candidate solutions called chromosomes or individuals.

This algorithm randomly generates a number of solutions for the problem where each of these solutions is called a "chromosome" and the set of attempted (generated) solutions are called the "population". After the random population was generated, GA investigates all the chromosomes based on the merit function. Indeed, GA employs a variety of methods such as combination and mutation to select the most qualified individuals to make the next generation made up of better individuals. The combination operator selects some individuals in the population and combines them to integrate their characteristics and allow them to generate better offspring for the next generation. Likewise, the mutation operator selects a number of individuals and then alters some of their characteristics to upgrade the chosen individual to a better (improved) individual.

The number of individuals selected for combination and/or mutation will depend on the type of problem and the size of the population. Similarly, the method of choosing individuals for combination and mutation is a key factor to consider. The sought-after methods for choosing the best individuals are the roulette wheel, tournament selection, and random methods, which can be performed by trial and error according to the type of problem. For the problem concerned here, the roulette wheel outperforms other methods. GAs are usually run as a computer simulator in which the population of candidate solutions (i.e., chromosomes) for an optimization problem results in a better solution for the problem.

According to the regulatory constraints, this study introduces some cross-sections for beams and columns, where GA tries to possibly minimize the cost by choosing the best sections.

4 Regulatory constraints

The Iranian National Building Code (Part 10) has defined some constraints for the resistance of each of the elements, positioning of the elements, and examining the stress in each element.

In this study, the constraints set to the resistance of the columns are investigated based on the synergistic effect of the axial force and flexural moment of the same column. Indeed, when tensile or compressive axial force and the flexural moment in the study column exceed the values specified in the building codes and the stress ratio is greater than one, the column will be penalized. The equations are as follows:

$$\begin{aligned} &\text{A) If } \frac{P_r}{\phi_c P_n} \geq 0.2 \\ &\quad \text{Then, } \frac{P_r}{\phi_c P_n} + \frac{8}{9}\left(\frac{M_{rx}}{\phi_b M_{nx}} + \frac{M_{ry}}{\phi_b M_{ny}}\right) \leq 1.0 \end{aligned} \tag{4.1}$$

$$\begin{aligned} &\text{B) If } \frac{P_r}{\phi_c P_n} \leq 0.2 \\ &\quad \text{Then, } \frac{P_r}{2\phi_c P_n} + \left(\frac{M_{rx}}{\phi_b M_{nx}} + \frac{M_{ry}}{\phi_b M_{ny}}\right) \leq 1.0 \end{aligned} \tag{4.2}$$

where P_r is the compressive strength required, Pn is the nominal compressive strength for the given section, (ϕ_c) is the compressive strength coefficient that takes a value of 0.9, Mrx and Mry are the required flexural strength around strong and weak axes (respectively), Mnx and Mny are the nominal flexural strength around the strong and weak axes (respectively), and (ϕ_b) is flexural strength coefficient taking a value of 0.9

The regulatory constraints set columns are also applied to beams, but the difference is that there are no interaction between axial and flexural forces in the beams and the only determinant factor will be "flexural moment". Here, according to the calculated reduction coefficients of the allowable flexural strength, and when the above condition is not satisfied, the cost function will be penalized to some values.

4.2. In the allowable stress design (ASD) method, the reliability coefficients are applied such that the material's strength is divided into the reliability coefficients and, in calculations, smaller values are assigned to strength.

Further, according to the ASD method, the sections are chosen such that the stress generated under the service loads in any member does not exceed a given allowable stress. This method was first devised according to the theory of elasticity to allow quantifying stress created in the members under the service load.

Thus, the constraints set for the strength of columns are studied according to the synergistic effect of axial and flexural forces of the same column. In turn, when the tensile or compressive axial force and the flexural moment in the intended column exceed the values set in the building code and the stress ratio is greater than one, the column will be penalized. According to the building codes, these the equations will be as follows:

A) If ($\frac{f_a}{FA} > 0.15$), then,

$$\frac{f_a}{FA} + \frac{C_m \cdot fb}{(1 - \frac{f_a}{F'_{ex}})Fb} \leq 1 \tag{4.3}$$

$$F'_e = \frac{12}{23} \times \frac{\pi^2 E}{\lambda_b^2} \tag{4.4}$$

$$\frac{f_a}{0.6fy} + \frac{fb}{Fb} \leq 1 \tag{4.5}$$

where (λ_b) refers to the slenderness of the free length of the element in the plane of bending.

B) If $\frac{f_a}{FA} \leq 0.15$, then,

$$\frac{f_a}{FA} + \frac{fb}{Fb} \leq 1 \tag{4.6}$$

where (C_m) is a coefficient that its value depends on the condition of the frame and lateral forces.

B-1) In rigid frames (where the ends of the frame have zero rotation), C_m is obtained from equation below:

$$C_m = .6 - .4\frac{M1}{M2} \geq .4 \tag{4.7}$$

where ($\frac{M1}{M2}$) is the ratio of small-to-larger anchor of the free ends of the column and takes a positive value.

Importantly, besides the constraints mentioned above, some other constraints have also been regraded in this research. In turn, the cross-section of columns of the lower stories should definitely be larger than that of the columns of the upper stories. Therefore, if these conditions are not satisfied, or if the cross-section of columns of the lower stories are smaller than that of the columns of the upper stories, the model under consideration will be further penalized beyond the penalty set on the stress ratio. Accordingly, such problems will be automatically omitted from the optimization cycle [11].

5 The study samples

This research investigated two distinct samples to evaluate the performance of the algorithm. For this, two structures were studied. These were two-bay structures, one with three stories and the other with six stories, where the former represents a short-height and the latter represent a medium-height structure. The height of the stories was 3 m and the length of the bays was 4 m. The live and dead loads of the stories were widely applied to the beams of the stories. Similarly, the lateral point loads were applied to the joints of the beams and columns. According to the building codes, the loads were synergistically applied as follows:

$$U = D + 1.2L + 1.2E, \quad U = 0.85D + 1.2E \tag{5.1}$$

Furthermore, uniform dead and live loads were equal to $Dl = 550\ kg/cm^2$ and $Ll = 200\ kg/m^2$, respectively. For the roof, these values were 500 kg/m^2 and 150 kg/m^2, respectively. The compressive strength of steel was equal to $F_y = 2400\ kg/cm^2$.

We can apply various conditions to stop the algorithm, including the "condition of convergence" or "the number of iterations". By examining various "trials and errors" and choosing the best stopping strategy, we selected the condition of "the number of iterations" for this algorithm. To find the best population and number of iterations, we evaluated various populations with different iterations and ultimately picked up a population with 45 members and 250 iterations.

5.1 Study samples

This research investigated two distinct samples to evaluate the performance of the algorithm. For this, two structures were studied. These were two-bay structures, one with three stories and the other with six stories, where the former represents a short-height and the latter represent a medium-height structure. The height of the stories was 3 m and the length of the bays was 4 m.

We applied various conditions to stop the algorithm, including the "condition of convergence" or "the number of iterations". By examining various "trials and errors" and choosing the best stopping strategy, we selected the condition of "the number of iterations" for this algorithm. To find the best population and number of iterations, we evaluated various populations with different iterations and ultimately picked up a population with 45 members and 250 iterations.

In this article, two different samples have been examined to measure the performance of the algorithm. The two investigated models of two-bay structures with three and six floors are considered so that each of the samples are representative of low and medium height structures. The height of the floors is 3 meters and the length of the openings is 4 meters. We further considered 150 and 78 distinct cross-sections for "columns" and "beams", respectively. We further considered 267 distinct cross-sections for "W sections" according to the building codes for both the beam and column.

Sample 1

In this frame, the stories are each 3 m in height and the length of the bays is 4 m. The values of gravity loads have been reported previously, and the values of lateral loads are depicted in Figure 1. There are two types of beams and four types of columns [16].

Information		
$DL = 550\ kg/m$	$LL = 200\ kg/m$	$E = 2E6$
$F = 2400\ kg/cm2$	$LL\ forroof = 250\ kg/m$	
Combination of loads = $1.2D + 1.0E + 1.0L$		
Loads on beams $= 1.2 \times 550 + 200 = 860\frac{kg}{m} = 8.6\ kg/cm$		
Loads on the beams of the roof $= 1.2 \times 500 + 150 = 750\frac{kg}{m} = 7.5\ kg/cm$		

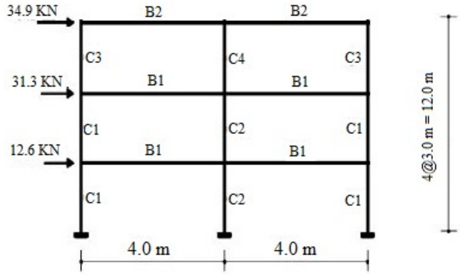

Figure 1: Sample 1

5.1.1 Model 1: Two-bay, three-story structure

In this model, each story is 3 m in height and the length of each bay is 4 m. The seismic load is calculated as follows:

$$H = 9m \ : \ T = 0.08H^{0.75} = 0.08 \times 9^{0.75} = 0.4157 \ s$$

$$A = 0.3 \ , \ I = 1 \ , \ \text{II Type of ground}$$

$$T_0 = 0.1 \ , \ T_S = 0.5 \ , \ S = 1.5 \ , \ S_0 = 1$$

$$B_1 = 2.5 \ , \ N = 1 \ B = B.N = 2.5 \ R_U = 5$$

$$C = \frac{ABI}{R} = \frac{0.3 \times 2.5 \times 1}{5} = 0.15$$

$$W = (0.2 \times 200 + 550) \times 2 \times 8 \times 8 + (0.2 \times 150 + 550) \times 8 \times 8 + (3 \times (3-1)) \times 4 \times 8 \times 250 = 157.44 \ ton$$

$$K = 1 \ , \ V = C.W = 0.15 \times 157.44 = 23.616$$

$$f_i = \frac{w_i.h_i}{\sum w_i.h_i} \ , \ F = f_i \cdot V$$

Table 1: Lateral loads on the structure

Story	Load applied to the story	Load applied to the frame	Load applied to the node
1	3.73	1.26	0.42
2	9.38	3.13	1.64
3	10.46	3.46	1.16

Since the optimization method is a MHA, we cannot consider the answers obtained after the first optimization as the best solutions. Thus, to achieve the best solution, the optimization needs to be repeated in several iterations. In this research, each model was optimized within 11 separate iterations. Figure 2 illustrates the values obtained for the best answer and the average value of answers.

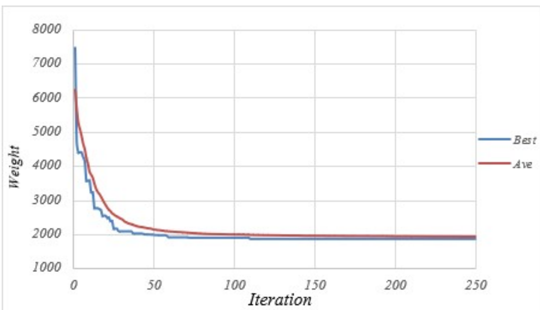

Figure 2: The optimization process for sample 1 based on the method of ultimate strength (W sections)

Regarding ultimate strength, the weight of a 3-story structure is reduced from 7491.80 kg to 1868.40 kg at best, and its average weight is reduced from 6250.9 kg to 1930.2 kg [17].

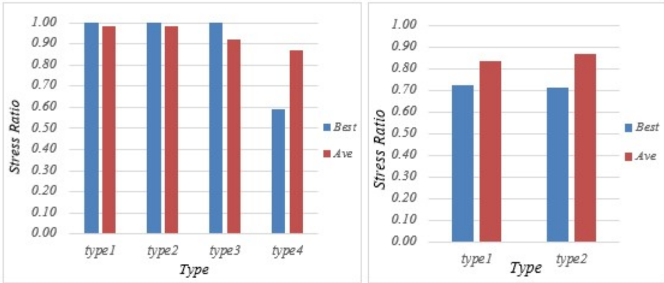

Figure 3: The ratio of stresses generated in beams and columns for sample 1 at ultimate strength (I section)

Table 2: Specifications of the beams (3-story) – ultimate strength

Type	W section	Stress ratio
1	W14×22	0.72
2	W12×14	0.72

Table 3: Specifications of the columns (3-story) – ultimate strength

Type	W section	Stress ratio
1	W16×26	1.00
2	W18×50	1.00
3	W12×16	1.00
4	W16×26	0.59
Best Weight		1868.40 kg
Worst Weight		7491.80 kg
Ave Best Weight		1930.21 kg
Displacement		1.61 cm

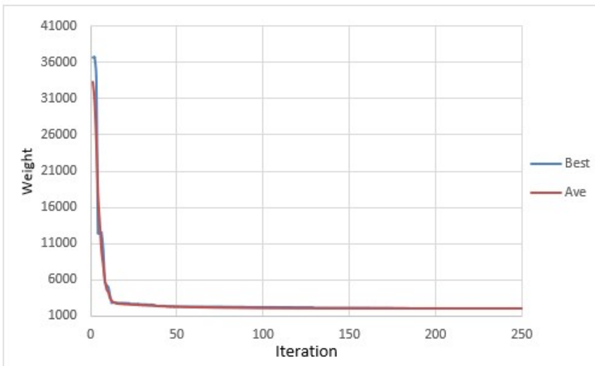

Figure 4: Optimization of the first model with the method of ultimate strength (W section)

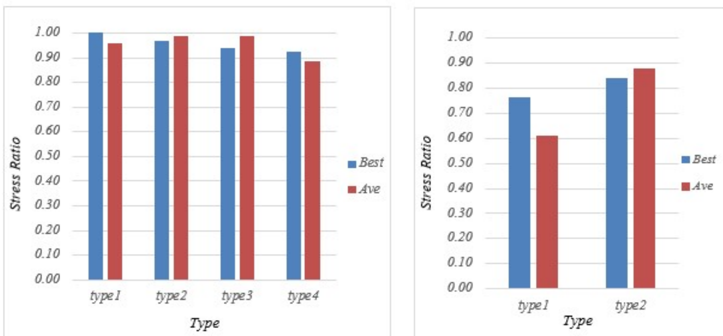

Figure 5: The ratio of stresses generated for the first model under allowable stress (W section)

Table 4: Specifications of the beams (3-story) – allowable stress

Type	W section	Stress ratio
1	W12×19	0.76
2	W8×10	0.84

Table 5: Specifications of the columns (3-story) – allowable stress

Type	W section	Stress ratio
1	W8×31	1.00
2	W10×60	0.97
3	W8×24	0.94
4	W8×24	0.92
Best Weight		1983.90 kg
Worst Weight		36763.00 kg
Ave Best Weight		2047.95 kg
Displacement		3.13 cm

Regarding allowable stress, the weight of a 3-story structure is reduced from 36763 kg to 1983.90 kg at best, and its average weight is reduced from 33313.20 kg to 2047.95 kg.

Figure 6 compares the weight of W sections for ASD and LRFD.

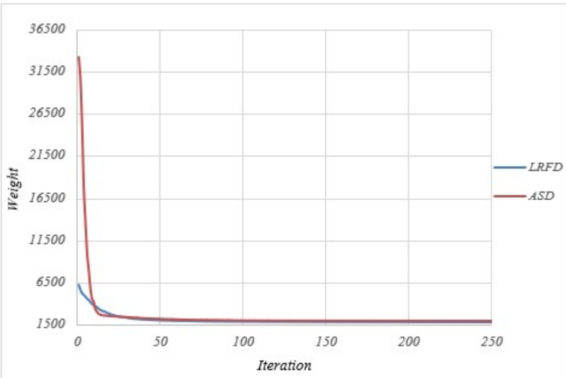

Figure 6: Comparison of the process of optimization for the first model under ASD and LRFD

5.1.2 Sample 2

Similar to sample 1, the stories are each 3 m in height and the length of the bays is 4 m. In this sample, there are three types of beams and six types of columns. The gravity loads include both dead and live loads, similar to sample 1. Figure 7 shows the values of lateral loads and the types of beams and columns. This figure further shows the separate values of stress applied to beams and columns. The allowable displacement in calculated from equation below:

$$\begin{cases} \Delta m = 0.7R\Delta w \\ \Delta m < 0.025h \end{cases} \quad \rightarrow \ \Delta w < \frac{0.025 \times 1800}{0.7 \times 5} = 12.8 \ cm$$

5.1.3 Model 2: Two-bay, six-story structure

The seismic load is calculated as follows:

$$H = 18m \ : \ T = 0.08H^{0.75} = 0.08 \times 18^{0.75} = 0.699 \ s$$

$$A = 0.3 \ , \ I = 1 \ , \ \text{II type of ground}$$

$$T_0 = 0.1 \ , \ T_S = 0.5 \ , \ S = 1.5, S_0 = 1$$

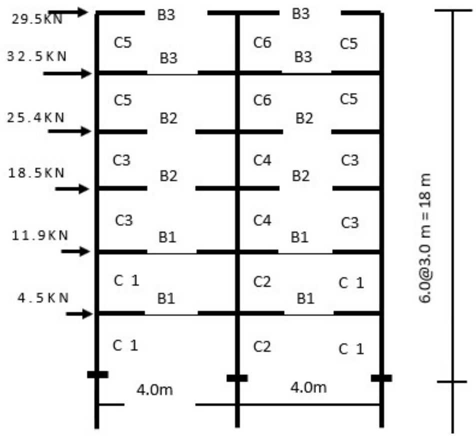

Figure 7: Sample 2

$$B_1 = (S+1)\left(\frac{T_S}{T}\right) = 1.788,\ N = 1B = B.N = 1.788\ R_U = 5$$

$$C = \frac{ABI}{R} = \frac{0.3 \times 1.788 \times 1}{5} = 0.107$$

$$W = (0.2 \times 200 + 550) \times 5 \times 8 \times 8 + (0.2 \times 150 + 500) \times 8 \times 8 + (3 \times (6-1)) \times 4 \times 8 \times 250 = 342.72\ ton$$

$$K = 0.5T + 0.75 = 1.099\ ,\ V = C.W = 0.107 \times 342.72 = 36.67$$

$$f_i = \frac{w_i.h_i}{\sum w_i.h_i}\ ,\ F = f_i.V$$

Table 6: Lateral loads on the structure

Story	Load applied to the story	Load applied to the frame	Load applied to the node
1	1.34	0.45	0.15
2	3.56	1.19	0.4
3	5.56	1.19	0.4
4	7.62	2.54	0.85
5	9.74	3.25	1.08
6	8.85	2.95	0.98

Since the optimization method is a MHA, we cannot consider the answers obtained after the first optimization as the best solutions. Thus, to achieve the best solution, the optimization needs to be repeated in several iterations. In this research, each model was optimized within 11 separate iterations. Figure 2 illustrates the values obtained for the best answer and the average value of answers.

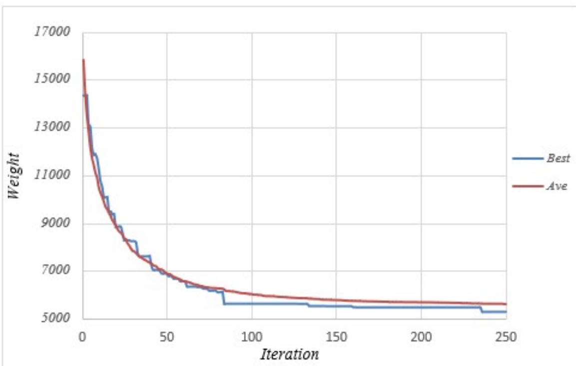

Figure 8: The optimization process for sample 2 based on the method of ultimate strength (W sections)

Regarding ultimate strength, the weight of a 6-story structure is reduced from 14344 kg to 5286 kg at best, and its average weight is reduced from 15867 kg to 5648 kg.

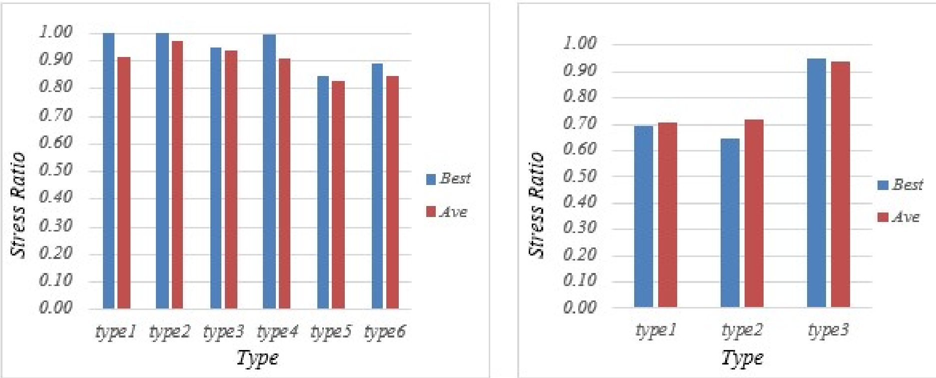

Figure 9: The ratio of stresses generated in beams and columns for sample 1 at ultimate strength (I section)

Table 7: Specifications of the beams (6-story) – ultimate strength

Type	W section	Stress ratio
1	W14X22	0.69
2	W14X22	0.65
3	W14X22	0.95

Table 8: Specifications of the columns (6-story) – ultimate strength

Type	W section	Stress ratio
1	W10X49	1.00
2	W10X77	1.00
3	W8X40	0.95
4	W10X54	1.00
5	W8X40	0.85
6	W10X54	0.89
Best Weight		5286 kg
Worst Weight		14344 kg
Ave Best Weight		5648 kg
Displacement		8.37 cm

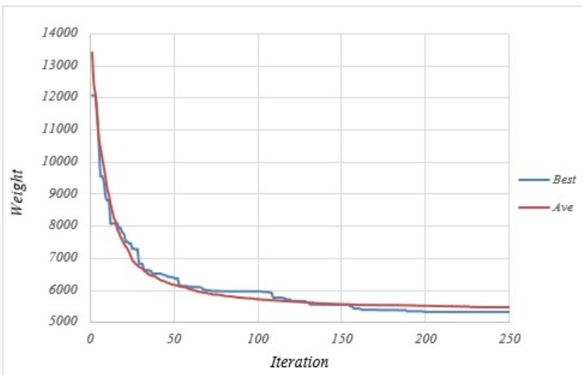

Figure 10: Optimization of the first model with the method of ultimate strength (W section)

Regarding allowable stress, the weight of a 6-story structure is reduced from 12089 kg to 5335 kg at best, and its average weight is reduced from 13409 kg to 5483 kg. Figure 12 compares the weight of W sections for ASD and LRFD.

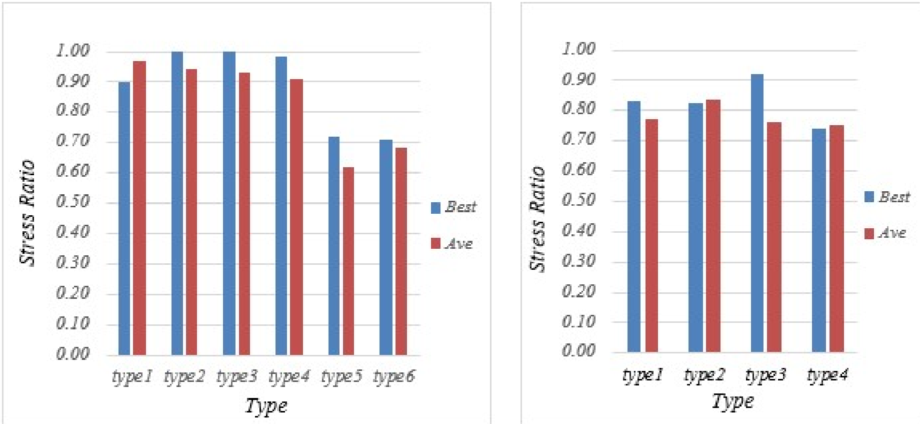

Figure 11: The ratio of stresses generated for the first model under allowable stress (W section)

Table 9: Specifications of the beams (6-story) – allowable stress

Type	W section	Stress ratio
1	W14X22	1.00
2	W14X26	0.96
3	W12X14	1.00

Table 10: Specifications of the columns (3-story) – allowable stress

Type	W section	Stress ratio
1	W18X50	1.00
2	W30X90	1.00
3	W16X40	0.89
4	W16X45	0.96
5	W14X38	0.53
6	W21X50	0.71
Best Weight		5335 kg
Worst Weight		12089 kg
Ave Best Weight		5483 kg
Displacement		4.37cm

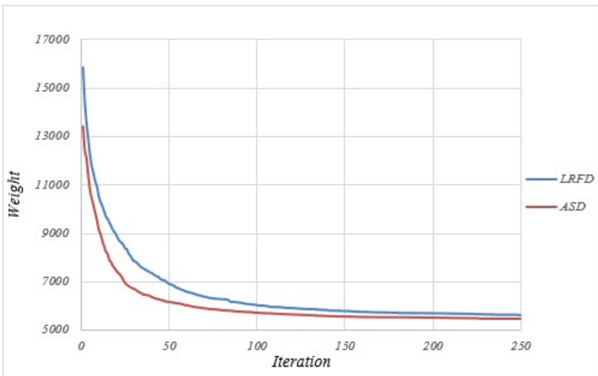

Figure 12: Comparison of the process of optimization for the first model under ASD and LRFD

5.1.4 Comparison of GA with PSO algorithms

This research compared the results obtained from the GA algorithm for a 15-story structure in this study with those results obtained from the PSO algorithm for the same structure reported by Kaveh and co-workers. Similar to the structure in the study by Kaveh et al., the model studied in this research was a 15-story 3-bay structure with W sections. This model was analyzed within 30 iterations and the results are given in the following sections. Figure 13 shows the 15-story 3-bay structure in the study by Kaveh et al.

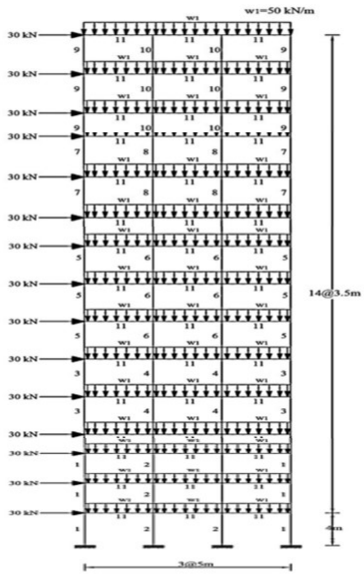

Figure 13: A 15-story model with W sections

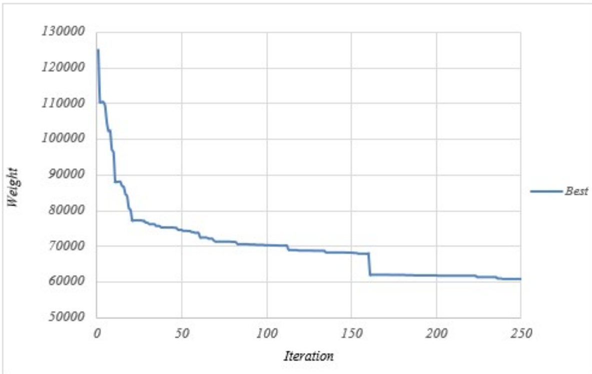

Figure 14: Showing optimization process with genetic algorithm

This study compares the performance of GA with PSO for a 15-story 3-bay model. As can be seen, the structure's weight has been reduced from 125230 kg to 60790 kg at best, and its average weight has been reduced from 144094 to 64094 kg.

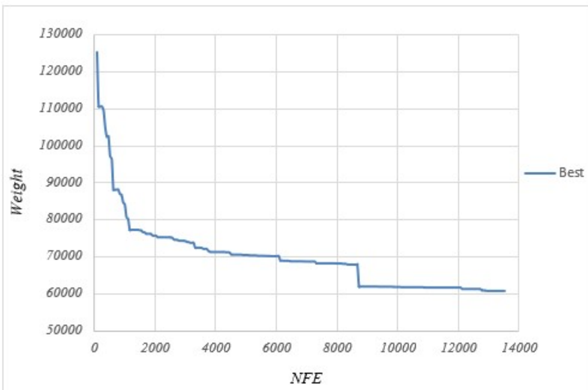

Figure 15: Optimization with GA

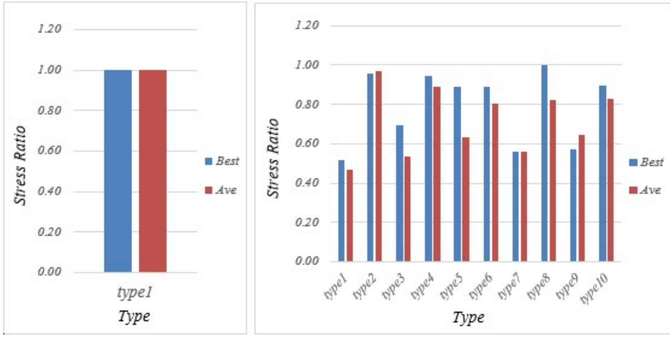

Figure 16: The ratio of stresses generated in beams and columns in GA

Table 11: Specifications of the beams (12-story) – ultimate strength

Type	**W section**	**Stress ratio**
1	W24×84	**1.00**

Table 12: Specifications of the columns (12-story) – ultimate strength

Type	**W section**	**Stress ratio**
1	W30×90	0.52
2	W12×279	0.96
3	W18×50	0.70
4	W30×211	0.95
5	W21×50	0.89
6	W18×158	0.89
7	W8×48	0.56
8	W10×77	1.00
9	W8×31	0.57
10	W16×50	0.89
Best Weight		60790 kg
Worst Weight		125230 kg
Ave Best Weight		64094 kg
Displacement		16.13 cm

Table 13: Optimal design comparison for the 3-bay 15-story planar frame

	GA	**PSO**
1	W16×50	W33X118
2	W30×90	W33X263
3	W12×279	W24X76
4	W18×50	W36X256
5	W30×211	W21X73
6	W21×50	W18X86
7	W18×158	W18X65
8	W8×48	W21X68
9	W10×77	W18X60
10	W8×31	W18X65
11	W24×8	W21X44
Weight(kg)	**60790**	**49668**

Comparison of stress in a 3-story structure in SAP2000

6 Conclusion

In this research, it was confirmed from the results that, as an advantage, GA is less dependent on the initial population. Collectively, the results obtained from optimization can be summarized as follows:

1) Regarding the values of stress in the beams and columns, it can be found that LRFD uses all the capacity of the section and it is the final goal of this algorithm.

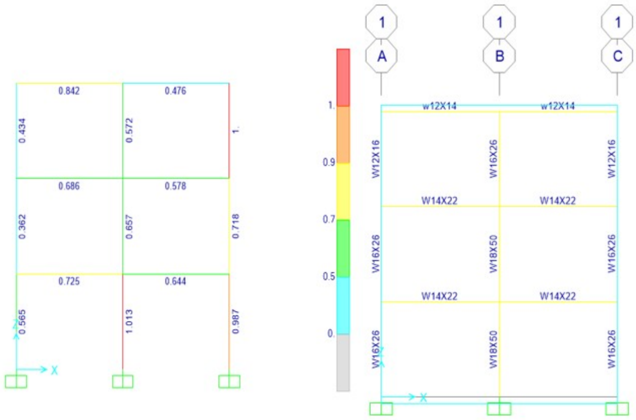

Figure 17: The stress ratio in a 3-story structure using the Sap-(W section) LRFD method

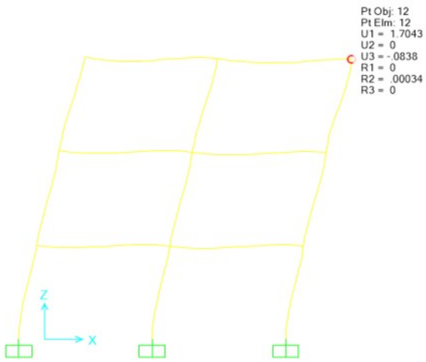

Figure 18: Displacement of a 3-story structure using the Sap-(W section) LRFD method

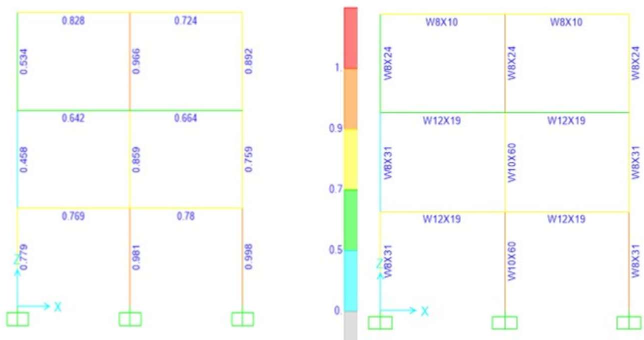

Figure 19: Stress ratio in a 3-story structure using the Sap (W-section) ASD method

2) Regarding the graphs depicting the performance of algorithms, it can be concluded that GA has not stopped at the local optima and has achieved the overall optima.

3) When comparing optimization using W section by LRFD and ASD methods, LRFD can trivially outperform ASD for both 3-story and 6-story structures and achieve lighter structure.

4) When comparing a 15-story 3-bay model using the PSO algorithm reported by Kaveh et al., it is observed that PSO offer a structure that is 10000 kg lighter than that offered by GA, implying PSO's superiority in achieving structure optimization.

5) When comparing the stress ratio and displacement of the 3-story structure by LRFD and ASD methods in Sap2000, it can be seen that OpenSees provides results that are comparable to those obtained in Sap2000, indicating the

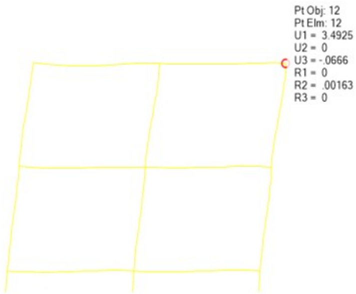

Figure 20: Displacement of a 3-story structure using the Sap-(W sections) ASD method

Figure 21: Stress ratio in a 3-story structure using the Etabs- (W section) ASD

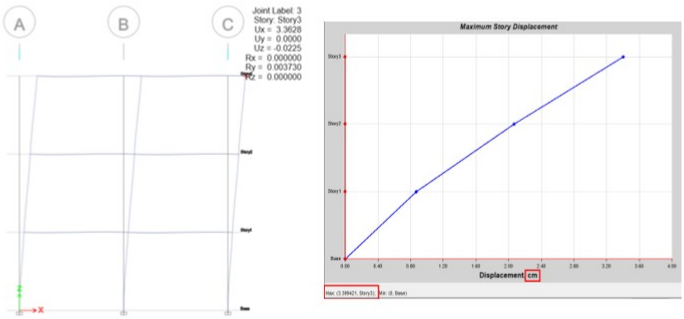

Figure 22: Displacement of a 3-story structure using the Etabs-(W section) ASD method

analytical potency of OpenSees in obtaining stress ratio and displacement values.

6) When comparing the stress ratio and displacement for a 3-story structure by ASD, it can be seen that the corresponding values obtained in Sap2000 and are close to those obtained in Etabs, implying the good performance of both software.

References

[1] S.H. Afzali, A. Darabi, and M. Niazkar, *Steel frame optimal design using MHBMO algorithm*, Steel Struct. **16** (2016), no. 2, 455–465.

[2] M. Bahreynipour Sirjani and A. Robati, *Weight optimization of steel moment frame based on genetic algorithm*, 3^{rd} Int. Conf. Civil Engin. Archit. Urban Design, Tabriz, 2018.

[3] E. Dogan and M.P. Saka, *Optimum design of unbraced steel frames to LRFD–AISC using particle swarm optimization*, Adv. Engin. Software **46** (2012), no. 1, 27–34.

[4] B. Ekici, C. Cubukcuoglu, M. Turrin, and I.S. Sariyildiz, *Performative computational architecture using swarm and evolutionary optimisation: A review*, Build. Envir. **147** (2018), no. 9, 356–371.

[5] S. Gholizadeh, *Performance-based optimum seismic design of steel structures by a modified firefly algorithm and a new neural network*, Adv. Engin. Software **81** (2015), no. 10, 50–65.

[6] S. Khalafi and S.A. Hoseyni, *Performance optimization of steel moment frame structure using meta-heuristic optimization algorithms*, 2^{nd} Nat. Conf. Appl. Res. Civil Engin. (structural engineering and construction management), Tehran, 2017.

[7] C.S. Kao and I. Yeh, *Optimal design of reinforced concrete plane frames using artificial neural networks*, Comput. Concrete **14** (2014), no. 4, 445–462.

[8] A. Kaveh, B. Farahmand Azar, A. Hadidi, F. Rezazadeh Sorochi, and S. Talatahari, *Performance-based seismic design of steel frames using ant colony optimization*, J. Construct. Steel Res. **66** (2010), no. 4, 566–574.

[9] A. Kaveh and A. Nasrollahi, *Performance-based seismic design of steel frames utilizing charged system search optimization*, Appl. Soft Comput. **22** (2014), no. 6, 213–221.

[10] A. Kaveh and S. Talatahari, *An improved ant colony optimization for the design of planar steel frames*, Engin. Struct. **32** (2010), no. 3, 864–873.

[11] A. Kaveh and S. Talatahari, *Charged system search for optimal design of frame structures*, Appl. Soft Comput. **12** (2012), no. 1, 382–393.

[12] A. Kaveh and P. Zakian, *Optimal design of steel frames under seismic loading using two meta-heuristic algorithms*, J. Construct. Steel Res. **82** (2013), no. 3, 111–130.

[13] P. Kripakaran, B. Hall, and A. Gupta, *A genetic algorithm for design of moment-resisting steel frames*, Struct. Multidisc. Optim. **44** (2011), no. 2, 559–574.

[14] M. Kociecki and H. Adeli, *Two-phase genetic algorithm for topology optimization of free-form steel space-frame roof structures with complex curvatures*, Engin. Appl. Artific. Intell. **32** (2014), no. 4, 218–227.

[15] M.R. Maheri and M.M. Narimani, *An enhanced harmony search algorithm for optimum design of side sway steel frames*, Comput. Struct. **136** (2014), no. 8, 78–89.

[16] M. Mohammadi Farsam, M.R. Adel Parvar, and M. Mahmoodabadi, *Optimization of steel frames with genetic algorithm and LRFD analysis*, Int. Conf. Civil Engin. Archit. Urban Plann. Contemp. Iran, Tehran, 2017.

[17] M. Mohammadi Farsam and M. Mahmoodabadi, *Comparison of optimization of steel frames by ASD method with I and W sections using genetic algorithm*, 11th Nat. Conf. 4th Int. Conf. Struct. Steel 2nd Nat. Conf. Light Steel Frames (LSF), Tehran, 2024.

[18] D.T. Phan, J.B. Lim, T.T. Tanyimboh, A. Wrzesien, W. Sha, and R. Lawson, *Optimal design of cold-formed steel portal frames for stressedskin action using genetic algorithm*, Engin. Struct. **3** (2015), no. 2, 36–49.

[19] O. Sadik, M. Degertekin, and S. Hayalioglu, *Harmony search algorithm for minimum cost design of steel frames with semi-rigid connections and column bases*, Ind. Appl. **42** (2010), no. 5, 755–768.

[20] M. Sepehari Manesh, B. Ahmadi Nadoushan, and H.A. Rahimi Bandarabadi, *Optimization of space-frame structures using genetic algorithm based on reliability theory*, 12^{th} Nat. Cong. Civil Engin., Tabriz, 2020.

[21] R. Sojoodizadeh and S. Gholizadeh, *Elite particle method in discrete optimization of structures*, Civil Envir. Engin. **52** (2023), no. 3.

[22] V. Togan, *Design of planar steel frames using Teaching: Learning based optimization*, Engin. Struct. **34** (2012), no. 4, 225–232.

[23] G. Yanglin, X. Yusong, and X. Lei, *Optimal capacity design of eccentrically braced steel frameworks using nonlinear response history analysis*, Engin. Struct. **48** (2013), no. 4, 28–36.