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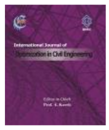

OPTIMAL DESIGN OF TALL STEEL MOMENT FRAMES USING SPECIAL RELATIVITY SEARCH ALGORITHM

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ABSTRACT

The analysis and design of high-rise structures is one of the challenges faced by researchers and engineers due to their nonlinear behavior and large displacements. The moment frame system is one of the resistant lateral load-bearing systems that are used to solve this problem and control the displacements in these structures. However, this type of structural system increases the construction costs of the project. Therefore, it is necessary to develop a new method that can optimize the weight of these structures. In this work, the weight of these significant structures is optimized by using one of the latest metaheuristic algorithms called special relativity search. The special relativity search algorithm is mainly developed for the optimization of continuous unconstrained problems. Therefore, a penalty function is used to prevent violence of the constraints of the problem, which are tension, displacement, and drift. Also, using an innovative technique to transform the discrete problem into a continuous one, the optimal design is carried out. To prove the applicability of the new method, three different problems are optimized, including an eight-story one-span, a fifteen-story three-span bending frame, and a twenty-four-story three-span moment frame. The weight of the structure is the objective function, which should be minimized to the lowest possible value without violating the constraints of the problem. The calculation of stress and displacements of the structure is done based on the regulations of AISC-LRFD requirements. To validate, the results of the proposed algorithm are compared with other advanced metaheuristic methods.

Keywords: Optimal design of steel frames, tall buildings, metaheuristic algorithms, artificial intelligence, special relativity search algorithm.

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1. INTRODUCTION

Structural optimization has been recognized as an important tool in the design process in the past decades. Optimization methods can be grouped by topology, size and shape of optimization. The goal of optimization can be to minimize weight or compliance for a given amount of material and boundary conditions. This method can be used to design engineering structures, but it can also be used to create microstructures. Therefore, a structure is needed to achieve this goal. However, to understand this purpose, the term "best" must be defined. The first characteristic that comes to mind may be that the structure should be as light as possible, that is, it should reach its minimum weight. Another "best" idea can be the discussion of structure strength and resistance, and at the same time, it is possible to consider another idea to make the structure resistant to buckling or instability. It is clear that such maximization or minimization cannot be done without applying any restrictions because a structure that is optimized without constraints will not lead to a suitable solution and result. The parameters that usually limit the problem in the optimization of structures are the tension of members, displacement of nodes or the geometry of the structure.

In this study, the goal is to minimize the weight of the steel moment frame structures, and these types of problems are included in the constrained optimization group. Due to the fact that the objective function is to minimize the weight of the whole structure, the constraints related to tension and displacement should be taken into consideration, because by reducing the weight too much, the stability of the structure is lost and causes irreparable financial and life damage. The design of structures is done in the form of classical methods, gradient-based methods, and metaheuristic methods. The classical method, known as the iterative method, is based on evidence, which can be described as follows. (a) A specific plan is proposed. (b) Performance-based requirements are reviewed. (c) If they are not fulfilled, the tension is too high and a new plan should be proposed. Even if such requirements are met, it may not lead to an optimal design, so a new design may still be required. (d) The proposed new design is returned to step (b). In this way, an iterative process is formed in which, on a mostly intuitive basis, a set of designs is created, the goal of which is to reach an acceptable and convergent final design.

The gradient-based design optimization method is conceptually different from the iterative-intuitive method. In this method, a mathematical optimization problem is formulated, where the requirements arising from the function act as constraints, and the concept of "as good as possible" is given a precise mathematical form. But among the problems of these methods is the computational cost and spending a lot of time to reach the best optimal answer. Instead, metaheuristic methods that have become remarkably popular in the last two decades have been used for these purposes.

The mechanism of metaheuristic methods is completely innovative. Finding a metaheuristic algorithm to provide a suitable solution that has the ability to reach the optimal solution for complex and hard optimization problems. Finding a near-optimal search method based on incomplete or insufficient information is essential in this real world of limited resources, such as computing power and time. In the past three decades, several methods have been presented by researchers, including: Simon [1], presented the optimization algorithm based on biogeography (BBO), which is based on the distribution of vital species

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in different regions. Storn and Price [2], using the mutation process and adding the weight difference of two population vectors to the third vector, produced a new population. Also, Lee and Tom [3], Kennedy and Eberhart [4], who inspired the collective behavior of fish and birds, presented the Particle Swarm Algorithm (PSO). Deriko and his colleagues [5], by observing and being inspired by the collective behavior of ants to find the closest path to food by a chemical called pheromone, proposed the ant colony optimization algorithm (ACO). Caraboga and Kastrek [6] introduced the Artificial Bee Colony (ABC) algorithm by exploiting the relationships between worker bees, guards and queen bees in finding food sources. Chu and his colleagues [7] proposed the Cat Swarm Algorithm (CSO) by using the behavior of cats in searching, tracking and finding prey. Also, Mirjalili and his colleagues [8] also presented a metaheuristic algorithm called Grasshopper Optimization Algorithm (GOA), which is inspired by the behavior of grasshoppers and the influence of their surrounding environment. Also, the methods that follow the laws of physics and chemistry are: Gooderzimehr et al. [9] proposed a new metaheuristic optimization algorithm based on the physics theory of special relativity called Special Relativity Search (SRS). Kaveh and Talatahari [10] presented the Charged System Search algorithm (CSS) based on the laws governing Newtonian mechanics and Coulomb's laws. Hatem Lu [11] introduced the Black Hole (BH) optimization algorithm, which is inspired by the black hole phenomenon in physics, and in this method, the best particle is selected as a black hole, and the stars that are too close to the black hole come close, they will be swallowed by the black hole. Goodarzimehr et al [12] developed special relativity search to solve engineering problems.

Using two or more algorithms in a hybridized process, researchers presented new algorithms that they use to solve problems. The purpose of this action is to identify their strengths and weaknesses as well as establish a balance between exploration and exploitation abilities. Some of these algorithms are: Mahri et al. [13], developed a hybrid algorithm of Genetics Algorithm and Particle Swarm Optimization (GA-PSO) to optimize the size and topology of structures. Talatahri et al. [14] introduced the Teaching Learning Based Optimization and Harmony Search (TLBO-HS) algorithm for the optimization of large-scale structures. Also, Talaatahri et al. [15] used the hybridized algorithm of Symbiotic Organisms Search (SOS) to optimize the size of structures. Topal et al. [16] presented the fundamental frequency optimization of composite quadrilateral plates reinforced with graded carbon nanotubes using an improved hybrid algorithm of particle swarm optimization and genetic algorithm. Gooderzimehr et al. [17] presents a new hybrid algorithm of particle swarm optimization and genetic algorithm for the optimization of spacial trusses with continuous design variables. Dastan et al. [18] presented an optimization algorithm for frame structures with continuous variables. Gooderzimehr et al. [19] optimized statically restrained truss structures using the Banobo algorithm. Dehghani et al. [20] optimized the weight of moment frames by modifying and improving the performance of the Adolescent Identity Search algorithm. Goodarzimehr et al. [21] proposed an improved chaos game optimization algorithm for predicting the optimal frequency of variable stiffness curved composite plate. Goodarzimehr et al [22] investigated the generalized displacement control method and introduced an applicable version for generalized displacement control to perform the nonlinear analysis stage in the optimization of spatial structures. Dastan et al. [23] proposed a new and effective algorithm called hybrid optimization based on teaching-learning and

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charging system search algorithms to solve truss optimization problems. Goodarzimehr et al [24] proposed a weighted chaos game optimization and implemented it to optimize engineering structures with dynamic constraints.

For the first time, Kemp et al. [25] used the Ant Colony Optimization algorithm to optimize the discrete steel frames. Degertkin [26] used Harmony Search (HS) algorithm for optimal design of steel frames. This method is based on the analogy between the process of performing natural music and searching for solutions for optimization problems. Kaveh and Talat Ahri [27] introduced the Imperialist Competitive Algorithm (ICA) for the optimal design of skeletal structures. This method is a multi-agent algorithm where each agent is a country that is either colonial or imperialist. These countries form empires in the search space. Hamid Farrokhi et al [28] proposed a combination of optimization algorithms based on firefly and biogeography for the optimal design of steel frames based on flashing patterns and optimization based on biogeography. Salajegheh et al. [38] developed a novel version of PSO based on first and second order gradients for optimization purposes. Salajegheh et al. [39] hybridized two metaheuristic algorithms based on gradient direction for optimization of structures. Salajegheh et al. [40] advanced Momentum method by PSO for optimization of structures. Goodarzimehr et al. [41] proposed a novel swarm algorithm for optimal design of space structures under the natural frequency constraints. Goodarzimehr et al. [42] developed and investigated a new single objective method for optimization of mathematical and engineering problems. Kaveh et al. [43-56] developed different advanced metaheuristic methods for optimal design of steel frames. To obtain efficient results they developed and investigated different versions of metaheuristic methods such as charged system search, bat algorithm, cuckoo search algorithm, colliding body optimization, and dolphin monitoring operator for optimal design of steel frames with different and unique structural analysis methods. Also, they presented a comprehensive review of the application of metaheuristic methods in structural optimization. Their results indicated that the metaheuristic methods are efficient tools for solving this class of engineering problems.

In this work, the special relativity search algorithm has been developed to optimize the weight of moment frame structures. The special relativity search algorithm is simulated by the inspiration of special relativity physics. One of the most important issues in metaheuristic algorithms is the development of an effective equation for the main step of the algorithm. The main step equation of special relativity search includes several parameters and can effectively measure the displacement vector of particles. In order to evaluate the performance of this algorithm, structural problems have been optimized. To validate and prove the superiority of the proposed algorithm, its results are compared with other advanced metaheuristic methods.

2. SPECIAL RELATIVITY SEARCH ALGORITHM

In this section, the various parameters of the special relativity search algorithm are completely explained. This algorithm is one of the newest metaheuristic algorithms, which was first proposed by Gooderzimehr et al. [9] for the optimization of 83 mathematical functions, including unimodal, multimodal, combined, and composite. After some time, by

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further examining the algorithm and identifying its strengths and weaknesses, they were able to optimize mathematical functions with bounded boundaries, structural and mechanical problems with continuous, discrete and combinatorial variables [12]. The results show that this algorithm has obtained better results than other advanced metaheuristic methods. Also, the low standard deviation and high speed of convergence make its results reliable. But research and efforts are still necessary to reach an effective method that can provide better and more reliable results.

This algorithm has simulated a magnetic space as an feasible search space. The search space is the space where particles can choose the optimal answer from the infinity of optimal answers. The particles in the magnetic field are also considered as the primary population. These particles in each step, by evaluating different points of the search space, improve their position relative to the global optimal response. The interaction between particles in a magnetic field is depicted in Fig. 1 and Fig. 2.

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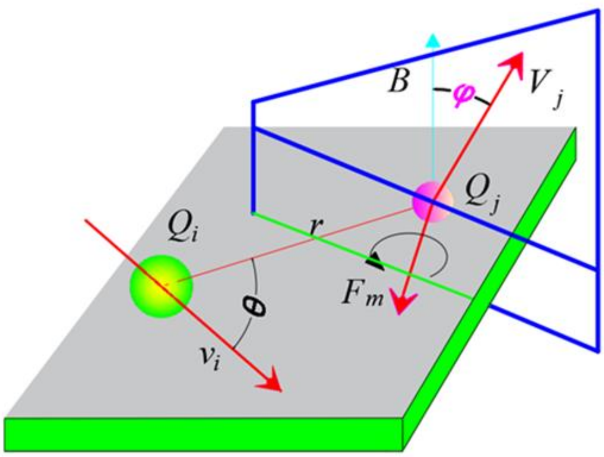

Figure 1. Interaction between particles in a magnetic field

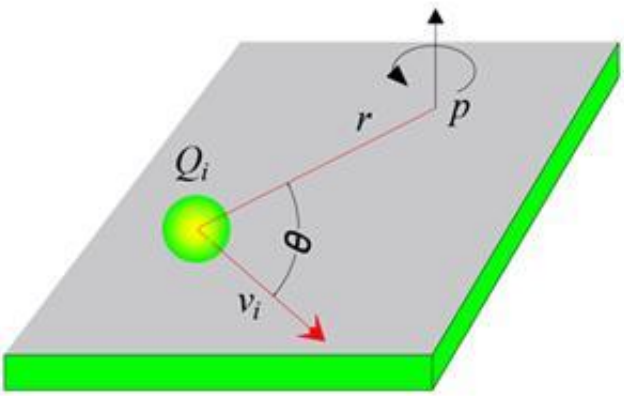

Figure 2. Produced magnetic field by a particle

where the force applied to the Q_j particle is due to the magnetic field created by the Q_j

particle. Also, Q_j creates a magnetic field B_j at the location of Q_i. The direction of B_i is perpendicular to Q_i and the direction of F_i is towards Q_j because B_j is in that direction. If the set at Q_j is accounted by Q_i, the force F_j acting on Q_j is equal in magnitude and opposite in direction to F_i. This is based on Newton's third law, which must be observed. When the particles are in opposite directions, the forces reverse and repel the allied particles. Hence, parallel particles carrying charges in one direction attract and parallel particles carrying charges in the opposite direction repel others. The force between particles has been known as the Lorentz force, which includes two electric and magnetic parts (Eq. (1)).

$$F_j = Q_j[E_i + v_j \times B_i] \tag{1}$$

v_i and v_j is the initial velocity of charged particles i^{th} and j^{th}. Due to the uniformity of the magnetic field, the electric force is ignored and only the magnetic force between the particles is considered. Eq. (1) is rewritten as follows.

$$F_m = Q_j v_j\ B_i \tag{2}$$

As shown in Fig. 3, the magnetic force between the particles causes the particles to move in a circular direction. The way particles move in the magnetic force field is perpendicular to the velocity vector, so in a circular movement, the direction changes but the velocity does not change. The magnetic force is always perpendicular to the velocity vector and does nothing on the particle, therefore the kinetic energy and velocity of the particle remain constant. In such special conditions, the speed of the particles remains constant while the direction of movement is variable. The particle moves in a circular path under the influence of a force in the direction of the center of the circle, which is due to the radial nature of the force. The angle between the velocity vector and the force vector is perpendicular, therefore, a particle with relative mass m and charge Q can be considered to move with velocity v at an angle of 90 degrees to the magnetic field. Since the Lorentz force is perpendicular to the velocity vector, it causes the particle to start rotating in a circular path. Therefore, the Lorentz force is defined as a radial force according to Eq. (3).

$$F_j = ma = \frac{mv^2}{r} = Q_j\ v_j\ B_i \tag{3}$$

By applying inverse Lorentz transformations and two important phenomena of length contraction and time dilation, the main step of the algorithm is defined using Eq. (4).

$$X_{ij}(t+1) = \beta^2 X_j(t) + V_j(t)\sqrt{1-\beta^2} + X_j(t)\sqrt{1-\beta^2} \tag{4}$$

After determining the new position and speed of the particles, we need to make sure that it is in the feasible space. Therefore, the optimal answer must be between the upper and lower bounds. Particle speed is a random value that must be updated in each iteration. In the next step, the value of the objective function is determined and to avoid convergence to the

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local optimal point, it is necessary to update the local and global optimal vectors. For more information about this algorithm, refer to *Refs.* [9] and [12]. Trajectory path of a particle with mass m is shown by Fig. 3.

In most cases, metaheuristic algorithms are inherently incapable of solving constrained problems, because these methods are primarily designed to solve unconstrained problems. In this study, where the main focus is on solving bounded problems, it is necessary to use an effective strategy to solve these types of problems. To solve the constraint problem, the function presented in Eq. (5) is applied. For more information about this function, refer to *Ref.* [37].

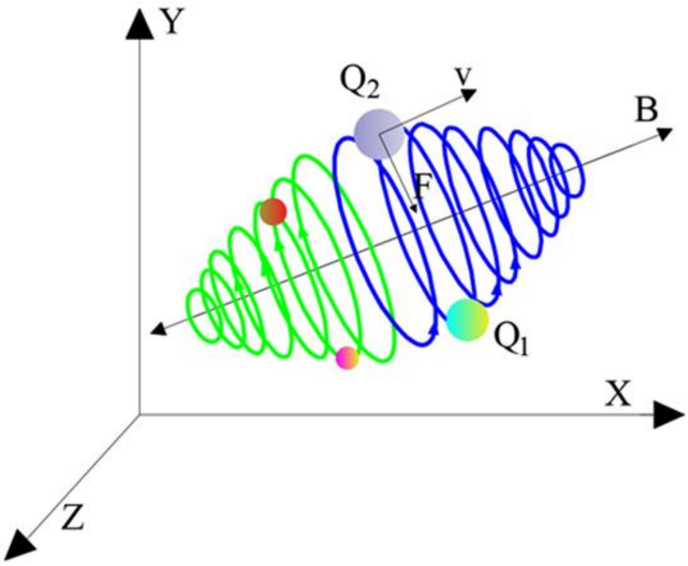

Figure 3. Trajectory path of a particle with mass m in a magnetic field

$$F(X) = f(X) + \beta \sum_{k=1}^{n_g} \max(0, g_k(X)) + \mu \sum_{k=1}^{n_h} \max(0, h_k(X)), \quad k = 1, 2, ..., n_{g,h} \tag{5}$$

where, *f(x)* is the objective function. g_k and h_k the bound functions are unequal and equal, respectively. β and μ there are penalty factors.

3. DEFINITION AND FORMULATION OF STEEL MOMENT FRAMES PROBLEM

The problems that are investigated in this work include the optimal design of skeletal structures such as standard frame of one span-8 stories, three spans-15 stories and 24 stories three spans. These problems have been chosen to show the reliability and applicability of the presented method. The frame optimization problem is formulated as follows.

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$$\begin{aligned} &\text{Minimize} \quad f(X) \\ &\text{Subject to} \quad g_i(X) \le 0 \qquad i = 1,2,\ldots,m \\ &\qquad X = \{x_1, x_2, \ldots, x_j, \ldots, x_n\} \in R^d \end{aligned} \tag{6}$$

where *g(X)* is the constraints of the problem and *m* represents the number of constraints. In structure optimization problems, the main objective is usually to minimize the weight of the structure under design constraints. The design variables are selected as the cross-sectional area of the elements. The cross section of the element is selected from a discrete set. Therefore, the optimization problem can be formulated as follows:

$$\begin{aligned} &\text{Minimize} \quad f(\mathrm{X}) = W(\boldsymbol{A}_i) = \sum_{i=1}^{Ne} \rho_i A_i L_i \\ &\text{Subject to} \quad g_{Dj} = \frac{\Delta_j(A_i)}{\Delta_u} - 1 \le 0, \qquad j = 1,2,\ldots,N_n \\ &g_{Si} = \begin{cases} \left(\dfrac{P_u}{\phi P_n}\right) + \dfrac{8}{9}\left(\dfrac{M_{ux}}{\phi_b M_{nx}} + \dfrac{M_{ux}}{\phi_b M_{nx}}\right) - 1 & \text{for } \dfrac{P_u}{\phi P_n} \ge 0.2 \\ \left(\dfrac{P_u}{2\phi P_n}\right) + \left(\dfrac{M_{ux}}{\phi_b M_{nx}} + \dfrac{M_{ux}}{\phi_b M_{nx}}\right) - 1 & \text{for } \dfrac{P_u}{\phi P_n} < 0.2 \end{cases} \\ &\boldsymbol{A}_i \in \boldsymbol{A}_e = \{A_{e1}, A_{e2}, \ldots, A_{ep}\} \end{aligned} \tag{7}$$

where W shows the weight of structures. A_i, ρ_i and L_i represent the cross-sectional area, material density and length of the i-th member, respectively. Δ_j and Δ_u are the displacement of floor j^{th} and the allowed displacement (which is equal to one three hundredth of the height of the floor), respectively. N_e indicates the number of members and N_n indicates the number of floors of the structure. In addition, A_e is a list of available discrete cross-sections.

The penalty method replaces a constrained optimization problem with a set of unconstrained optimization problems. These problems are created by adding a condition to the objective function, which includes a penalty parameter and a degree of constraint violation. As an example, the use of penalty parameters was used in 1999 with the Rayleigh-Ritz method in modeling rigid boundaries [31]. In this research, the penalized weight is calculated based on the penalty function as follows:

$$\gamma(x) = W(x)[1+\mu]^{\varepsilon} \tag{8}$$

where ε represents the power of the penalty function and μ is the constraint violation function, which is:

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$$\mu = \sum_{j}^{N_n} g_{D\,j} + \sum_{i}^{N_e} g_{S\,i} \tag{9}$$

which g_{Dj} and g_{Si} are the violation of the displacement and drift restrictions of the floors and the violation of the stress constraints, which have been used in accordance with the requirements of the LRFD approach. The value of the penalty function g_{Si} is equal, which is formulated as follows (Eq. (10)).

$$g_{S\,i} = \begin{cases} 0 & if \quad g_{S\,i} \le 0 \\ g_{S\,i} & if \quad g_{S\,i} > 0 \end{cases} \tag{10}$$

3.1. One span-8 stories moment frame

The member groups are formed in such a way that consecutive two-story columns (starting from the base) form a column group and consecutive three-story beams (starting from the foundation) form a separate beam group. except for the roof beam, which is just a separate group of beams. There are a total of 8 independent size design variables in the grouping. The geometry of this structure is shown in Fig. 4. The design variables related to the beam element groups were selected from the W267 sections. The frame material has yield stress F_y = *36 Ksi* and modulus of elasticity *E = 200 Gpa*. The unbraced length for each beam is considered to be one fifth of the length of the span. Columns are assumed to be unbraced along their length. The optimal design of the frame is based on the requirements of AISC-LRFD with regard to displacement and resistance limits.

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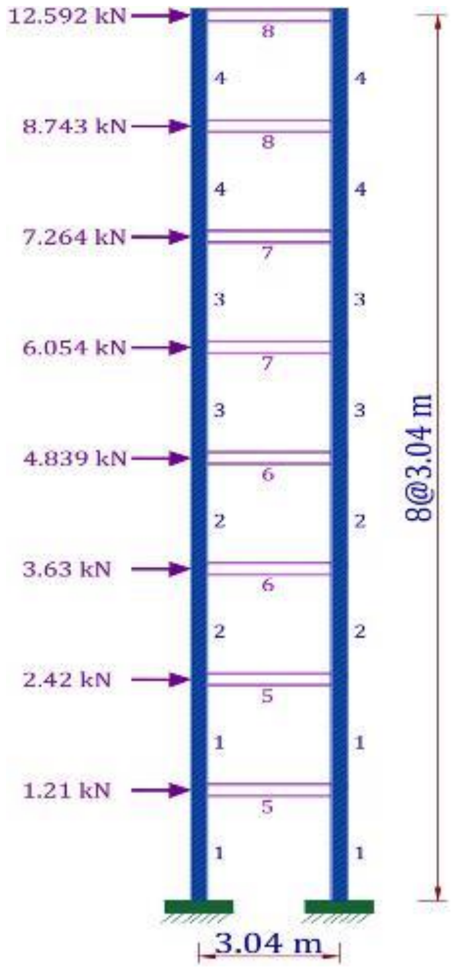

Figure 4. Topology of 8 stories moment frame

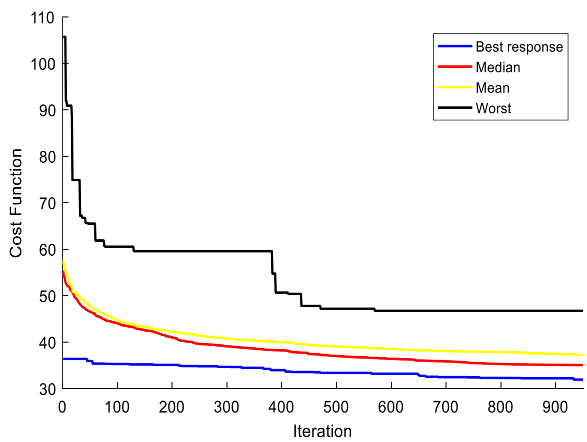

Figure 5. Convergence history of 8 stories moment frame

The results of the SRS algorithm and other metaheuristic methods that have optimized

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the weight of this structure in the past years are presented in Table 1 for validation. The best optimal response obtained by SRS, ACO, GA, PSOPC and PSOPC+ACO is equal to 31.89, 31.68, 32.83, 34.21, and 32.29, respectively. As observed, SRS and ACO have obtained the best optimal answers. In order to more accurately evaluate the results of the SRS algorithm, a statistical analysis has also been carried out, which is presented in Table 1. This statistical analysis is based on the Best answer, Median, Average, Worst optimal answer and Standard Deviation. One of the important features of metaheuristic algorithms, which has made research on these methods continue, is that the algorithm obtains stable results. The stability of the results of an algorithm depends on the value reported by the standard deviation. The value of standard deviation (SD) of SRS algorithm is equal to 0.0976. This shows that the results of the proposed method are reliable. This is despite the fact that other metaheuristic methods have not reported values related to standard deviation and other statistical parameters. Also, to graphically display the process of convergence of the optimal responses obtained from the statistical analysis of these results, it is drawn in Fig. 5.

Table 1. performance comparison for 8 stories moment frame

Element group (Eg)	GA [29]	ACO [30]	PSOPC [31]	PSOPC+ACO [31]	SRS
Eg (1)	W18×46	W21×50	W18×35	W18×35	W14×43
Eg (2)	W16×31	W16×26	W14×26	W16×31	W14×43
Eg (3)	W16×26	W16×26	W16×26	W14×22	W8×18
Eg (4)	W12×16	W12×14	W14×26	W12×16	W16×31
Eg (5)	W18×35	W16×26	W24×62	W21×48	W10×33
Eg (6)	W18×35	W18×40	W18×35	W18×40	W14×22
Eg (7)	W18×35	W18×35	W16×31	W16×31	W6×20
Eg (8)	W14×26	W14×22	W12×30	W16×36	W10×26
Best weight (kip)	32.83	31.68	34.21	32.29	31.89
Median (kip)	N/A	N/A	N/A	N/A	32.02
Average weight (kip)	N/A	N/A	N/A	N/A	32.39
Worst response (kip)	N/A	N/A	N/A	N/A	34.98
SD (kip)	N/A	N/A	N/A	N/A	0.0976

3.2. Three span-15 stories moment frame

The 15-story 3-span frame structure consists of 64 joints and 105 members. Columns are grouped into ten distinct element groups, while all beams form only one group. Column groups are formed in such a way that the outer columns of three consecutive floors (starting from the foundation) form a separate column group and the internal columns form another separate column group. Therefore, it has 11 distinct design variables. The geometry of this structure is shown in Fig. 6. All design objects (groups of members) are selected from the W267 sections. The modulus of elasticity of steel is $E = 29,000\ Ksi$ and the yield stress of

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steel is F_y = $36\ Ksi$. The unbraced length for each beam is considered as one-fifth of the span length. Columns are assumed not to be combinable along their length. The length factors of members and performance settings are similar to the 8-story 1-span frame structure.

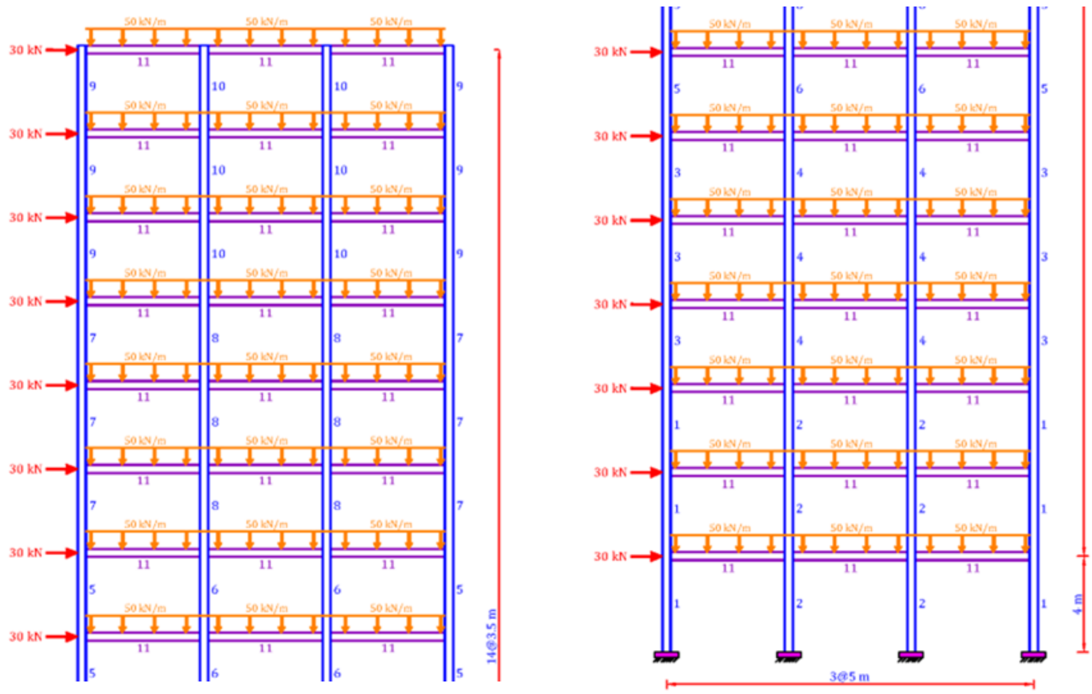

Figure 6. Topology of 15 stories moment frame

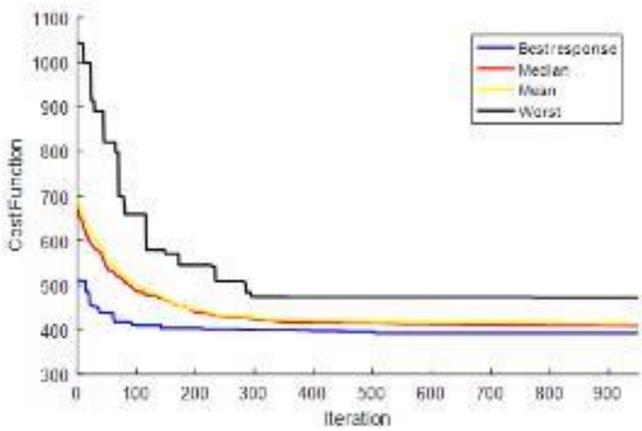

Figure 7. Convergence history of 15 stories frame

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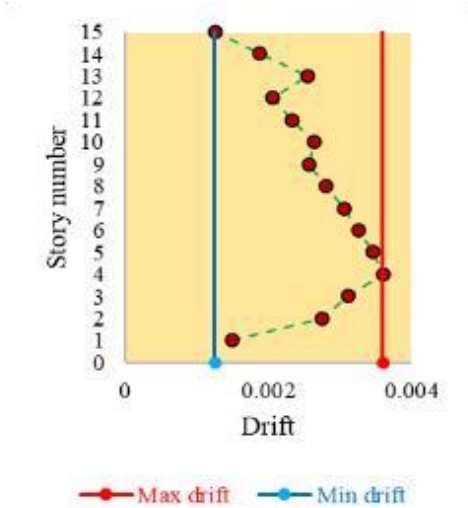

Figure 8. Drift diagram of 15 stories moment frame

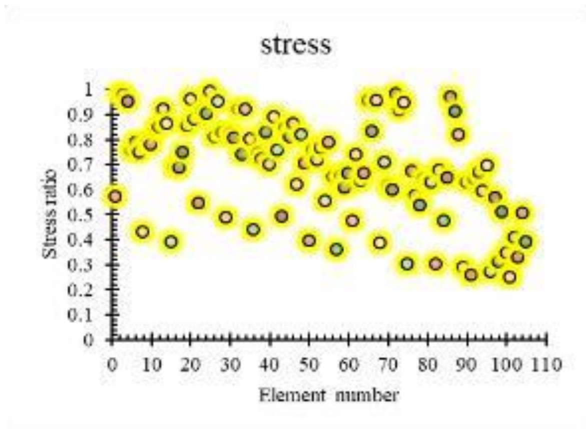

Figure 9. Member's stresses of 15 stories moment frame

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Table 2: performance comparison for 15 stories moment frame

Element group (Eg)	BB-BC [32]	ICA[27]	EWOA [33]	CSS[35]	SRS
Eg (1)	W24×117	W24×117	W14×99	W21×147	W12×106
Eg (2)	W21×132	W21×147	W27×161	W18×143	W26×146
Eg (3)	W12×95	W27×84	W27×84	W12×87	W12×79
Eg (4)	W18×119	W27×114	W24×104	W30×108	W24×103
Eg (5)	W21×93	W14×74	W21×68	W18×76	W14×82
Eg (6)	W18×97	W18×86	W18×86	W24×103	W18×86
Eg (7)	W18×76	W12×96	W21×48	W21×68	W21×73
Eg (8)	W18×65	W24×68	W14×68	W14×61	W18×65
Eg (9)	W18×60	W10×39	W8×31	W18×35	W10×19
Eg (10)	W10×39	W12×40	W10×45	W10×33	W16×36
Eg (11)	W21×48	W21×44	W21×44	W21×44	W21×44
Best weight (KN)	434.54	417.45	392	412.6	391.5788
Median (KN)	N/A	N/A	N/A	N/A	394.5969
Average weight (KN)	N/A	N/A	403.99	N/A	395.3113
Worst response (KN)	N/A	N/A	N/A	N/A	399.5649
SD (KN)	N/A	N/A	N/A	N/A	2.5566

The optimal answers obtained for SRS, BB-BC, ICA, EWOA and CSS, which are 391.5788, 434.54, 417.45, 392, 412.6, respectively, are presented in Table 2. SRS has obtained the most optimal answer in this problem and has performed better than other methods. EWOA has also performed well and is ranked second. The statistical results calculated for SRS indicate that this algorithm extracts reliable answers. The value of SD in solving this problem is equal to 2.5566, which is higher than the SD obtained for the previous problem. The reason for this is the increase in the height of the floors. In addition, in the 15-story frame problem, in addition to displacement and stress constraints, drift constraint is also considered in order to control the displacement of the floors in the height of the building. The SRS convergence diagram is drawn in Fig. 7. As you can see, SRS has converged to acceptable optimal responses after 100 iterations. The diagram of drift and stress created in the structural elements for the best optimal response is drawn in Fig. 8 and Fig. 9, respectively.

3.3. Three span-24 stories moment frame

The 24-story, 3-span steel frame structure, shown in Fig. 10, including 168 members (96 columns and 72 beams) is studied here as a final design example. This structure is one of the most popular examples in the field of optimizing the structures with descrete variables. All

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structural elements are classified into 20 distinct element groups (16 column groups and 4 beam groups). 16 groups are selected from 14 W sections, while 4 beam groups are selected from all 267 W sections. The modulus of elasticity of the materials used is equal to $E = 29732\ ksi$ and the yield stress is $F_y = 33.4\ ksi$. The operation length coefficients are calculated as $k_x \geq 0$ for the oscillation allowed frame and the out-of-plane operation length is determined as $k_y = 1.0$. All the columns and beams are considered to be incapacitated in their length. In this example, the resistance and displacement levels are obtained in accordance with the requirements of the AISC-LRFD code

Table 3: performance comparison for 24 stories moment frame

Element group	ACO [30]	HS [26]	ES-DE [36]	FA-BBO [28]	SRS
Eg (1)	W30×90	W14×176	W30×90	W30×90	W8×13
Eg (2)	W8×18	W14×145	W21×55	W12×14	W12×16
Eg (3)	W24×55	W14×176	W24×48	W21×48	W12×14
Eg (4)	W8×21	W14×132	W10×45	W6×9	W14×30
Eg (5)	W14×145	W14×132	W14×145	W14×145	W14×26
Eg (6)	W14×132	W14×109	W14×109	W14×120	W14×22
Eg (7)	W14×132	W14×109	W14×99	W14×120	W14×30
Eg (8)	W14×132	W14×82	W14×145	W14×74	W14×26
Eg (9)	W14×68	W14×82	W14×109	W14×68	W14×22
Eg (10)	W14×53	W14×61	W14×48	W14×53	W14×30
Eg (11)	W14×43	W14×74	W14×38	W14×38	W14×26
Eg (12)	W14×43	W14×48	W14×30	W14×22	W14×43
Eg (13)	W14×145	W14×34	W14×99	W14×109	W14×43
Eg (14)	W14×145	W14×30	W14×132	W14×109	W14×22
Eg (15)	W14×120	W14×22	W14×109	W14×109	W14×34
Eg (16)	W14×90	W14×22	W14×68	W14×90	W14×26
Eg (17)	W14×90	W30×90	W14×68	W14×74	W14×22
Eg (18)	W14×61	W10×22	W14×68	W14×68	W14×22
Eg (19)	W14×30	W18×40	W14×61	W14×30	W14×34
Eg (20)	W14×26	W12×16	W14×22	W14×22	W14×22
Best weight (kip)	220.47	214.86	212.39	202.90	200.0548
Median (kip)	N/A	N/A	N/A	N/A	204.9118
Average weight (kip)	229.56	222.62	N/A	N/A	209.6410
Worst response (kip)	N/A	N/A	N/A	N/A	214.9812
SD (kip)	4.56	N/A	N/A	N/A	4.5564

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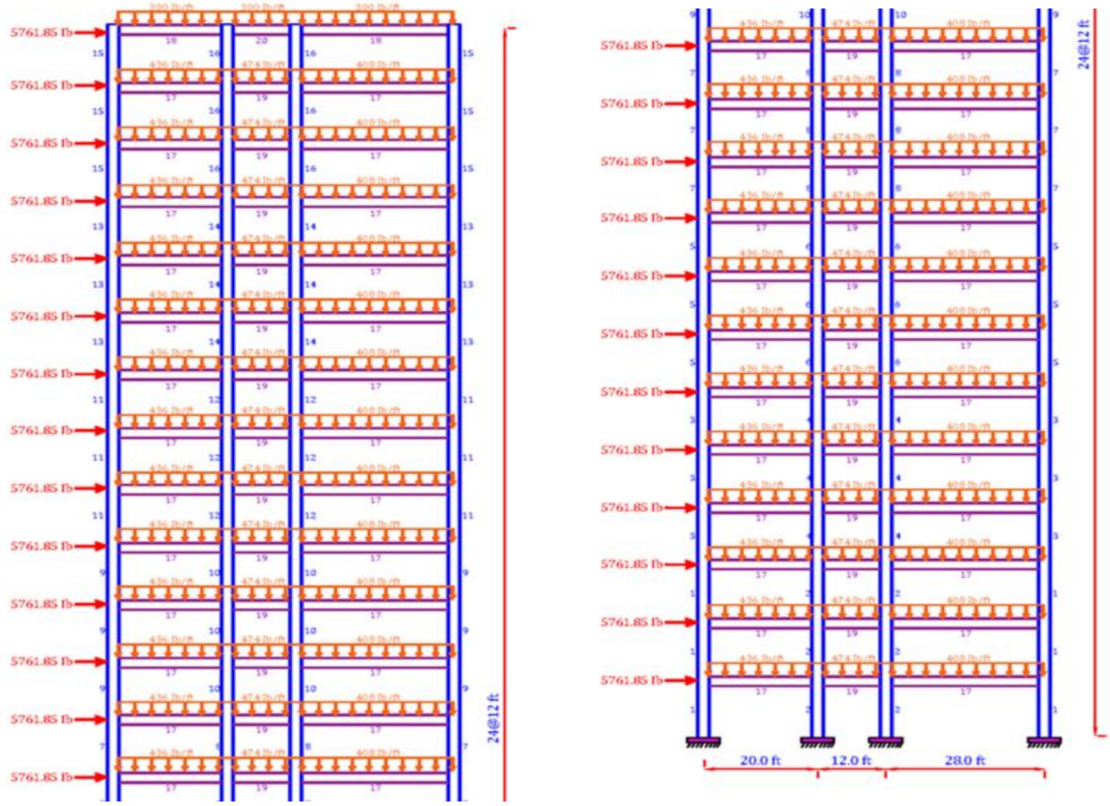

Figure 10. Topology of 24 stories moment frame

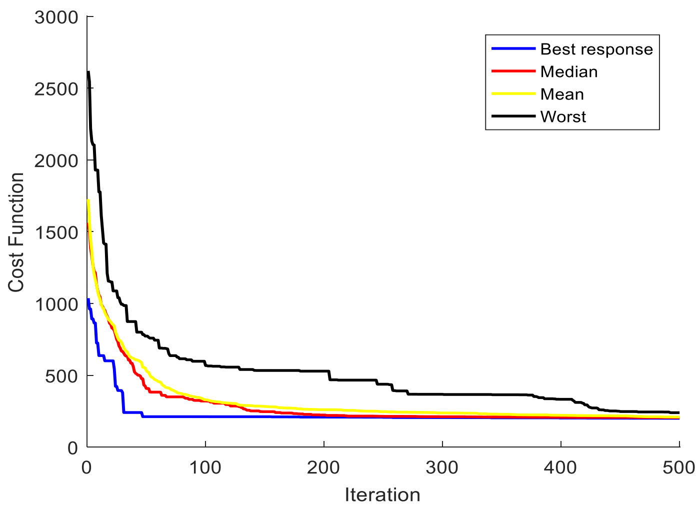

Figure 11. Convergence history of 24 stories frame

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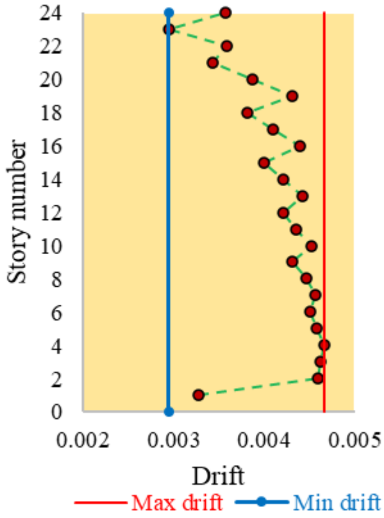

Figure 12. Drift diagram of 24 stories moment frame

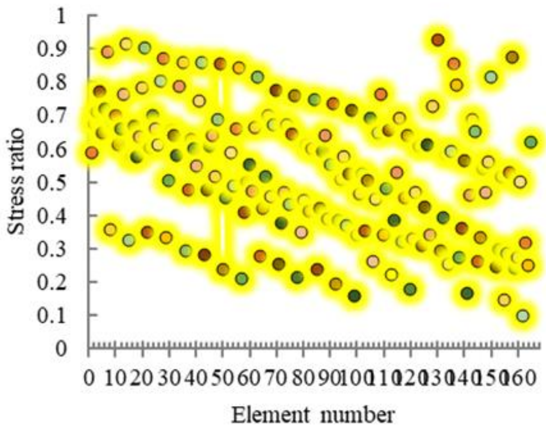

Figure 13. Member's stresses of 24 stories frame

The results of the optimal design of the three-span 24-story structure for the methods SRS, ACO, HS, ES-DE and FA-BBO are presented in Table 3. These results are 200.0548, 220.47, 214.84, 212.39, and 202.90, respectively. The best answer in solving this problem belongs to SRS. This structure has 24 floors and its total height is 86.4 meters. Using the moment frame system to control the displacement and drift of this structure increases the construction cost. Therefore, reducing the cost of building materials can be significantly economical. The results of statistical analysis are presented in Table 3. This is while other methods have reported only the optimal weight. The SRS convergence diagram is drawn in Fig. 11. The drift changes in the height of the structure are plotted in Fig. 12. Also, the stress of the structural elements for the best optimal response is drawn in Fig. 13.

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4. CONCLUSION

In order to optimize the weight of high-order moment frame structures, SRS algorithm was used. This algorithm is one of the newest metaheuristic methods developed for optimization purposes. The main idea of this algorithm is to simulate the movement of particles in a magnetic field. Then, for the first time, the physics of special relativity has been used to formulate the equations. This algorithm has recently shown good performance in solving optimization problems of complex mathematical functions. However, good results were not obtained in solving structural engineering problems, including high-rise moment frames. Therefore, to solve this problem by making changes and using the penalty function, it was adapted to the problem. To evaluate the effectiveness and performance of SRS algorithm in solving structural problems, three steel frame problems including 8-story one-span, 15-story three-span and 24-story three-span frames were designed and optimized. The optimal design results obtained from this algorithm showed that this method can be used as a powerful algorithm in the optimal design of steel frames. According to the allowed values of drift and stress of the members, it is possible to understand the ability of the proposed algorithm in optimization, because the drift values are close to the maximum allowed value and the stress ratio of most of the members has values close to one. By comparing the results of the proposed algorithm with some previous methods presented by other researchers, the results showed that the SRS algorithm has a high capability in optimizing the weight of steel frames. The standard deviation (Std) obtained from 50 independent executions of the program showed that the proposed algorithm has high stability with a lower SD value compared to other compared algorithms. This new meta-heuristic algorithm can be easily used in other complex mathematical and optimization problems.

REFERENCES

1. Simon D. Biogeography-based optimization. *IEEE Trans Evol Comput*, 2008; **12**: 702–13.
2. Storn R, Price K. Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces. *J Glob Optim*, 1997; **11**: 341–59.
3. Li Z, Tam V. A novel meta-heuristic optimization algorithm inspired by the spread of viruses. *ArXiv Prepr ArXiv*, 2020, 200606282.
4. Eberhart R, Kennedy J. Particle swarm optimization. *Proc IEEE Int Conf neural networks*, 1995; **4**: 1942–48.
5. Dorigo M, Birattari M, Stutzle T. Ant colony optimization. *IEEE Comput Intell Mag*, 2006; **1**: 28–39.
6. Karaboga D, Basturk B. A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm. *J Glob Optim*, 2007; **39**: 459–71.
7. Chu SC, Tsai PW, Pan JS. Cat swarm optimization. *Pacific Rim Int Conf Artif Intell*, Springer 2007; 854–8.
8. Mirjalili SZ, Mirjalili S, Saremi S, Faris H, Aljarah I. Grasshopper optimization algorithm for multi-objective optimization problems. *Appl Intell*, 2018; **48**: 805–20.
9. Goodarzimehr V, Shojaee S, Hamzehei-Javaran S, Talatahari S. Special relativity

[DOI: 10.22068/ijoce.2024.14.1.575]

search: A novel metaheuristic method based on special relativity physics. *Knowl Based Syst*, 2022; **257**: 109484.

10. Kaveh A, Talatahari S. A novel heuristic optimization method: charged system search. *Acta Mech*, 2010; **213**, 267–89.
11. Hatamlou A. Black hole: A new heuristic optimization approach for data clustering. *Inf Sci (Ny)*, 2013; 222: 175–84.
12. Goodarzimehr V, Talatahari S, Shojaee S, Hamzehei-Javaran S., Special relativity search for applied mechanics and engineering. *Comput Methods Appl Mech Eng*, 2023; **403**: 115734.
13. Maheri MR, Askarian M, Shojaee S. Size and topology optimization of trusses using hybrid genetic-particle swarm algorithms. *Iran J Sci Technol Trans Civ Eng*, 2016; **40**: 179–93.
14. Talatahari S, Goodarzimehr V, Taghizadieh N. Hybrid teaching-learning-based optimization and harmony search for optimum design of space trusses. *J Optim Ind Eng*, 2020; **13**(1): 177-194.
15. Talatahari S, Goodarzimehr V, Shojaee S. Symbiotic organisim search and harmony search algorithms for discrete optimization of structures. *Int J Optim Civil Eng*, 2021; **11**: 177–194.
16. Topal, U, Goodarzimehr V, Bardhan A, Vo-Duy T, Shojaee S. Maximization of the fundamental frequency of the FG-CNTRC quadrilateral plates using a new hybrid PSOG algorithm. *Compos Struct*, 2022; **295**: 115823.
17. Goodarzimehr V, Omidinasab F, Taghizadieh N. Optimum design of space structures using hybrid particle swarm optimization and genetic algorithm. *World J Eng*, 2022; **20**(3), 591-608.
18. Dastan M, Goodarzimehr V, Shojaee S, Hamzehei Javaran S, Talatahari S. Optimal Design of Planar Steel Frames Using the Hybrid Teaching–Learning and Charged System Search Algorithm. *Iran J Sci Technol Trans Civ Eng*, 2023; **47**: 3357–73.
19. Goodarzimehr V, Topal U, Kumar Das A, Vo-Duy T. Bonobo optimizer algorithm for optimum design of truss structures with static constraints. *Structures*, 2023; **50**: 400-417.
20. Dehghani A, Goodarzimehr V, Shojaee S, Hamzehei Javaran S. Modified adolescent identity search algorithm for optimization of steel skeletal frame structures. *Scientia Iranica*, 2023.
21. Goodarzimehr V, Topal U, Vo-Duy T, Shojaee S. Improved chaos game optimization algorithm for optimal frequency prediction of variable stiffness curvilinear composite plate. *J Reinf Plast Compos*, 2022; **42**(19-20), 1054-66.
22. Goodarzimehr V, Shojaee S, Talatahari S, Hamzehei-Javaran S. Generalized displacement control analysis and optimal design of geometrically nonlinear space structures. *Int J Comput Meth*, 2022; **20**(7), 2143018.
23. Dastan M, Shojaee S, Hamzehei-Javaran S, Goodarzimehr V. Hybrid teaching–learning-based optimization for solving engineering and mathematical problems. *J Braz Soc Mech Sci Eng*, 2022; **44**: 431.
24. Goodarzimehr V, Talatahari S, Shojaee S, Hamzehei-Javaran S, Sareh P. Structural design with dynamic constraints using weighted chaos game optimization. *J Comput*

[DOI: 10.22068/ijoce.2024.14.1.575]

Des Eng, 2022: **9**(6): 2271–2296.
25. Camp C V, Bichon BJ, Stovall SP. Design of steel frames using ant colony optimization. *J Struct Eng*, 2005; **131**:369–79.
26. Degertekin SO. Optimum design of steel frames using harmony search algorithm. *Struct Multidiscip Optim*, 2008; **36**: 393–401.
27. Kaveh A, Talatahari S. Optimum design of skeletal structures using imperialist competitive algorithm. *Comput Struct*, 2010; **88**: 1220–9.
28. Ghatte HF. A hybrid of firefly and biogeography-based optimization algorithms for optimal design of steel frames. *Arab J Sci Eng*, 2021; **46**: 4703–4717.
29. Camp C, Pezeshk S, Cao G. Optimized design of two-dimensional structures using a genetic algorithm. *J Struct Eng*; 1998; **124**: 551–9.
30. Kaveh A, Shojaee S. Optimal design of skeletal structures using ant colony optimization. *Int J Numer Methods Eng*, 2007; **70**: 563–81.
31. Kaveh A, Talatahari S. A discrete particle swarm ant colony optimization for design of steel frames. *Asian J Civ Eng*, 2007; **9**(6): 563-575.
32. Kaveh A, Talatahari S. A discrete big bang-big crunchalgorithm for optimaldesign of skeletal structures. *Asian J Civ Eng*, 2010;**11**(1): 103-122.
33. Kaveh A. *Applications of metaheuristic optimization algorithms in civil engineering*. Springer, 2016.
34. Kaveh A, Kamalinejad M, Hamedani KB. Enhanced versions of the shuffled shepherd optimization algorithm for the optimal design of skeletal structures. *Structures*, 2021; **29**: 1463–95.
35. Kaveh A, Talatahari S. Charged system search for optimal design of frame structures. *Appl Soft Comput*, 2012; **12**: 382–93.
36. Talatahari S, Gandomi AH, Yang X-S, Deb S. Optimum design of frame structures using the eagle strategy with differential evolution. *Eng Struct*, 2015; **91**: 16-25.
37. Michalewicz Z. A survey of constraint handling techniques in evolutionary computation methods, *in: Proceedings of the 4th Annual Conference on Evolutionary Programming*, MIT Press, Cambridge, MA, 1995;135–155.
38. Salajegheh F, Salajegheh E, PSOG: Enhanced particle swarm optimization by a unit vector of first and second order gradient directions. *Swarm Evol Comput*, 2019; **46**: 28-51.
39. Salajegheh F, Salajegheh E, and Shojaee, S, An enhanced approach for optimizing mathematical and structural problems by combining PSO, GSA and gradient directions. *Soft Computing*, 2022; **26**(21): 11891-11913.
40. Salajegheh F, Kamalodini M. and Salajegheh, E, Momentum method powered by swarm approaches for topology optimization. *Appl Soft Comput*, 2020; **90**, 106174.
41. Goodarzimehr V, Talatahari S, Shojaee S, Gandomi A. H. Computer-aided dynamic structural optimization using an advanced swarm algorithm, *Eng Struct*, 2024; **300**: 117174.
42. Goodarzimehr V, Fanaie N, Mirjalili S. *Computer-Aided Structural and Mathematical Optimization Using an Advanced Metaheuristic Algorithm*. Available at SSRN: https://ssrn.com/abstract=4643749 or http://dx.doi.org/10.2139/ssrn.4643749
43. Kaveh A, Nasrollahi A. Performance-based seismic design of steel frames utilizing

[DOI: 10.22068/ijoce.2024.14.1.575]

charged system search optimization. *Appl Soft Comput*, 2014; **22**: 213-21.
44. Kaveh A, Zakian P. Enhanced bat algorithm for optimal design of skeletal structures, *Asian J Civ Eng*, 2014;**15**(2): 179-212.
45. Kaveh A, Laknejadi K, Alinejad B. Performance based multi-objective optimization of large steel structures, *Acta Mechanica*, 2012; **2**: 223355-69.
46. Kaveh A, Kalateh-Ahani M, Fahimi-Farzam M. Life-cycle cost optimization of steel moment-frame structures: performance-based seismic design approach, Earthquakes and *Structures*, 2014; **3**(7): 271-294.
47. Kaveh A, Zakian P. Optimal design of steel frames under seismic loading using two meta-heuristic algorithms, *J Constr Steel Res*, 2013; 82111-130.
48. Kaveh A, Bakhshpoori T. Optimum design of steel frames using Cuckoo Search algorithm with Lévy flights, *Struct Des Tall Spec Build*, 2013; **13**: 221023–1036.
49. Kaveh A, Zakian P. Seismic Design Optimisation of RC Moment Frames and Dual Shear Wall-Frame Structures via CSS Algorithm, *Asian J Civ Eng*, 2014; **15**: 435-465.
50. Kaveh A, Bolandgerami A., Optimal design of large scale space steel frames using cascade enhanced colliding body optimization, Stuctural Multidisciplinary Optimization, 2017; 55237–256.
51. Kaveh A, Hoseini Vaez SR, Hosseini P. Modified dolphin monitoring operator for weight optimization of frame structures. *Period Polytech Civ Eng*, 2017; **61**(4): 770–779.
52. Kaveh A, Ilchi Ghazaan M, Optimum seismic design of 3D irregular steel frames recently developed modern meta-heuristic algorithms, *Comput Civil Eng*, 2018; **32**(3) 04018015: (1-9).
53. Zakian P, Kaveh A. Seismic design optimization of engineering structures: a comprehensive review, *Acta Mechanica*, 2023; **234**: 1305–1330.
54. Kaveh A, Fahimi-Farzam M, Kalateh-Ahani M. Optimum Design of Steel Frame Structures Considering Economic Cost and Damage Index, Smart Struct Syst, 2015; **1**(16): 1-26.
55. Kaveh A, Kalateh-Ahani M, Fahimi-Farzam M. Damage-based optimization of large-scale steel structures, Earthq Struct, 2014; **6**(7): 1119-39.
56. Kaveh A, Fahimi-Farzam M, and Kalateh-Ahani M. Performance-based multi-objective optimal design of steel frame structures: nonlinear dynamic procedure, *Scientia Iranica*, 2015; **2**(22): 373-87.

[DOI: 10.22068/ijoce.2024.14.1.575]