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Optimal design of bending steel frame using specialized biogeography-based optimization

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Abstract. Due to resource scarcity, energy crises and environmental pollution, optimization is very important nowadays. For this purpose, various optimization methods have been developed, which are also used in the field of structural design. In this study for the first time, an optimization algorithm based on biogeography with specialized structural objectives was developed and used to minimize the weight and cost of bending steel frames. By adapting the algorithm for use with steel frames, its accuracy and efficiency is increased. In addition, the time to reach the optimal solution was reduced since the search space of the problem has smaller dimensions due to the characteristics of the structure, so that not all variables are evaluated by the objective function; therefore the analysis and design time is reduced. On the other hand, there is a logical balance between the two important features: exploration and exploitation in the optimization process, reducing the computational efforts in the analysis and design of frames. To show the performance and efficiency of this algorithm, four two-dimensional steel frames with three, ten, fifteen and twenty-four stories is presented and the geometric and design constraints is applied according to LRFD-AISC. The developed algorithm selects the optimal W-sections for beams and columns of the frames from the list of 267 W-sections. The optimization codes are written in MATLAB and the SAP2000 software is connected to MATLAB for the analysis and design of steel frames. The results show that this algorithm can develop superior frame designs with low weight compared to other optimization methods and improves computational efficiency in solving structural optimization problems.

Keywords: structural optimization; bending steel frame; biogeography-based optimization (BBO); metaheuristic algorithm; minimum weight

1. Introduction

All economic sectors, including agriculture, industry and the service sector, are inevitably forced to compete due to limited resources. The struggle for limited resources and the attempt to control them have led to the introduction of various approaches to control these resources, commonly referred to as optimization techniques. In recent years, much attention has been paid in the construction industry to reducing construction costs and improving the performance of various structures and increasing their strength. Using minimum resources to build structures with

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maximum strength not only provides economic benefits, but also contributes to reducing environmental pollution, which is currently one of the biggest global problems. Many researchers are drawn attention to work on optimization problems [1-5]. The adoption of novel computational and analytical methods in engineering problems has expanded significantly [6-13]. In any optimization problem, there are several objectives as well as constraints that must be satisfied throughout the process [14, 15]. Optimization problems can be divided into two types based on the solutions generated: classical or deterministic algorithms and non-classical or non-deterministic algorithms, also known as stochastic algorithms [16]. The application of classical or traditional methods in solving optimization problems is often associated with numerous challenges arising from the nature of the problem under consideration. These challenges include discrete problems, the existence of multiple local optimal solutions in a given problem, and problems arising from the search space of the problem, all of which hinder the optimization process and make it difficult to reach an optimal solution. Non-classical or stochastic algorithms, also known as metaheuristic algorithms, have been instrumental in overcoming the limitations of traditional methods. In recent years, the use of these algorithms has become increasingly widespread. In general, these algorithms can be divided into three main groups:

1. Algorithms based on evolution: These algorithms are inspired by the process of evolution in nature, such as the Genetic Algorithm (GA) [17].
2. Population-based algorithms: These algorithms mimic collective and decentralized behaviors that can be observed in nature. They rely on the teamwork and swarm intelligence of individual entities that interact and exchange information to converge to a solution. For example, the Particle Swarm Optimization (PSO) algorithm [18], [19] and the Honey Badger algorithm [20].
3. Physics-based algorithms: These algorithms are inspired by physical laws that govern natural phenomena, such as the Simulated Annealing (SA) algorithm [21], [22].

Various studies have been conducted in the field of structural design and its integration with metaheuristic algorithms. Thu Huynh van and colleagues proposed a novel two-phase heuristic approach for structure design using the particle swarm optimization (PSO) algorithm. In this study, by using the properties of the particle swarm optimization (PSO) algorithm, the search space of the problem was restricted, which not only solved the problem of premature convergence in the optimization process, but also reduced the time required to reach the optimal solution due to the restricted search space [23]. Similarly, Salama and colleagues used metaheuristic algorithms to determine the optimal slope for the roofs of industrial buildings. The results of this study showed that a suitable choice of roof pitch depending on the span and column height can reduce material costs by up to 39.5% [24]. Quoc-Anh Vu and colleagues optimized the weight of steel frames using the Differential Evolution (DE) algorithm. The effectiveness of this improved algorithm was demonstrated by applying it to two structures, one with two stories and one with six stories. Compared to the particle swarm optimization (PSO) algorithm, the DE algorithm required 35% less computational effort and provided better optimal results [25]. Shan and colleagues developed an integrated solution for the optimization of steel frames by combining metaheuristic algorithms and machine learning methods. Metaheuristic algorithms have stochastic properties, which can lead to longer optimization processes and sometimes cause deviations from the optimal solutions. In this study, by integrating machine learning methods, an intelligent approach was developed to initiate and complete the optimization phases, significantly improving the convergence rate of the metaheuristic algorithms. Moreover, the improved performance and efficiency of this approach in terms of reducing the computational cost for large structures was effectively demonstrated [26]. Hasançebi and colleagues applied a bat-inspired algorithm [27] to optimize the weight of steel

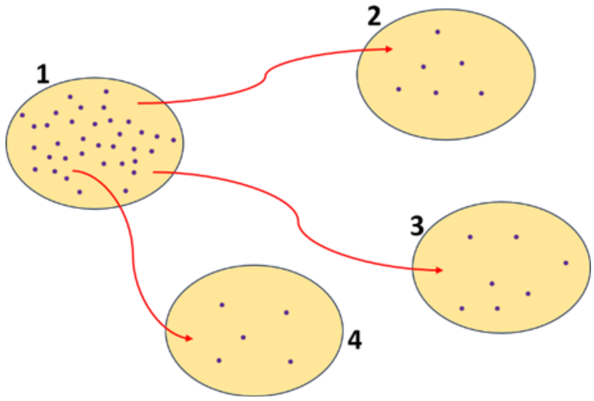

Figure. 1 Migration of species between habitats

frames. The results show that this metaheuristic algorithm provides a lower weight for large steel frames compared to other algorithms, taking into account the resistance and design conditions [28]. In the present study, a modified and specialized BBO algorithm with structural objectives was used.

2. Biogeography-based optimization algorithm

This algorithm, introduced by Dan Simon, originates from science dealing with the geographical distribution of different animal species [29]. The algorithm is inspired by the way species spread across different habitats. By developing a probabilistic model of how species migrate within habitats, a mathematical model was derived that eventually led to the creation of a new optimization model used in this algorithm. As can be seen in Fig. 1, habitat 1 has the highest population. According to this model, animal species migrate from the habitat with the highest population to those with lower populations, as a high population leads to limited food resources. The habitat with the lowest population becomes the main target of migration, while other habitats have a lower priority. Two important concepts, exploration and exploitation, are inherent features of any metaheuristic algorithm. In this study, a balance between these two concepts was established in the improved BBO algorithm. Thus, in habitats with fewer populations, the search capacity is reduced, while the exploitation capacity is increased. Conversely, when a habitat reaches its maximum capacity, search capacity is increased while exploitation is reduced. With these adjustments in the optimization process, the migration of species between habitats became more logical. In addition, by reducing the number of function evaluations, the time required to reach the optimal solution was significantly reduced.

The probability that the population in any habitat at a subsequent moment in time, denoted as $(t + \Delta t)$, will be equal to S, is derived from Eq. (1).

$$p_s(t + \Delta t) = p_s(t)(1 - \lambda_s \Delta t - \mu_s \Delta t) + p_{s-1}\lambda_{s-1}\Delta t + p_{s+1}\mu_s \Delta t \tag{1}$$

In this context, P_s represents the probability of the existence of a population (S) in a habitat. t and Δt denote the current time and the next time step, respectively. λ_s and μ_s indicate the immigration rate and emigration rate of a habitat, respectively.

The steps for executing the biogeography-based optimization algorithm are as follows:
Generation of a set of random habitat locations and their sorting.

- Determine the values of λ_s and μ_s
- Repeat steps 4 to 8 for each habitat location.
- Repeat steps 5 to 8 for each variable at each habitat location.
- Determine the origin of the migration based on the values of μ_s
- Process of migration
- Apply random changes or mutations with a certain probability to the variables
- Evaluate the new solution set
- Return to step 3 if the termination criteria are not met

The fitting process of this algorithm for structural targets is as follows:

After the execution of step 1, the variables of the problem, which are W-rolling steel profiles from the list of 267 available profiles in the AISC, are distributed to different habitats where the search space of the problem is considered. The objective function of the problem, i.e. the weight of the steel frames, is evaluated and on this basis a solution with a lower frame weight is found for each habitat. After this phase, in the next phase, each group of solutions that has a lower rank, i.e. a higher weight for the steel frame, is included in the second cycle with a lower probability than the other solutions. The same logic applies to steel frames where the column sections get smaller and smaller from the bottom floor to the top. This constraint is included as a constraint in the problem definition. Candidate sections that do not meet this constraint are excluded from the optimization cycle, and smaller sections are used for the upper floor. From the perspective of the biogeography-based optimization algorithm, this means that habitats with larger populations have the greatest chance of sending migrants and the least chance of receiving them. In this new definition of the biogeography-based algorithm (BBO), the steel sections are treated as particles in the search space of the problem, facing two possible scenarios. The first scenario is that a particle or a steel section remains in its current position because it satisfies all the constraints applicable to the problem. The second scenario occurs when the current cross-section assigned to a beam or column is replaced by a more optimal cross-section, which is a form of migration. In this case, the current cross-section is replaced by another cross-section and in the subsequent iterations it can find a better position and be used for another element. To summarize, when grouping a steel frame and forming different clusters, each cluster can be considered as a “habitat” from the algorithm’s point of view and the steel sections are analogous to animal species migrating between these habitats. The migration is controlled by defined conditions and constraints and ultimately leads to an optimal design for steel frame. The flowchart of the entire optimization process is shown in Fig. 2.

The standard Biogeography-Based Optimization (BBO) algorithm, while powerful, operates as a general-purpose metaheuristic. To tailor it for the discrete, constrained nature of structural steel design, several key specializations were implemented. These modifications fundamentally align the algorithm’s search logic with the principles of structural engineering, leading to enhanced performance.

The core adaptation lies in redefining the concepts of “habitats” and “migration” within a structural context. In our specialized BBO, each potential design, a specific grouping of W-sections for the frame members, is considered a habitat. The species within these habitats are the individual steel sections assigned to beams and columns. The migration process is no longer a purely probabilistic exchange but is governed by structural feasibility and performance.

Firstly, the initialization of habitats is not entirely random. The algorithm is biased towards

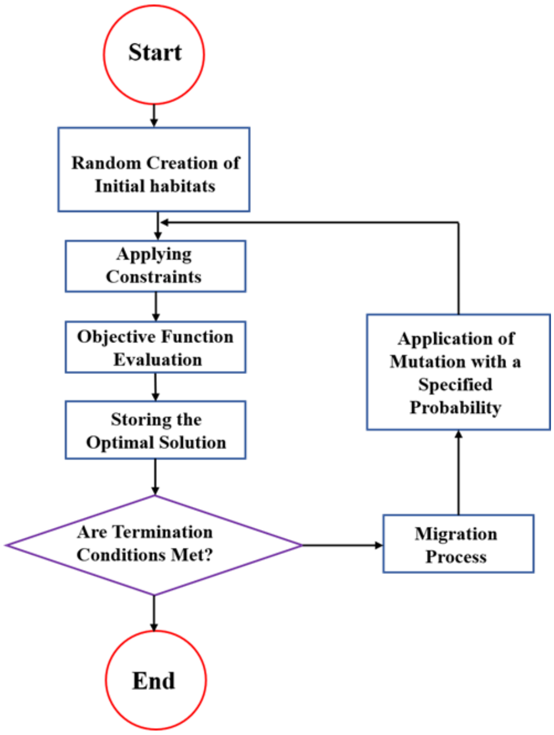

Figure. 2 Flowchart of the optimization process

initial solutions that respect practical construction heuristics, such as assigning larger column sections to lower stories. Secondly, and most critically, the migration operator is constrained. When a section is considered for migration from one member group to another, the algorithm first checks for compliance with geometric constraints (e.g., flange width compatibility for beam-column connections) and the strong-column weak-beam principle. Proposals that violate these constraints are rejected, ensuring that every design evaluated is structurally coherent. This prevents the algorithm from wasting computational resources exploring invalid regions of the search space.

- Furthermore, the mutation operator was specialized to introduce small, structurally meaningful perturbations. Instead of random changes, mutation might swap a section with a structurally similar one from the AISC database (e.g., a W12x65 to a W12x58), facilitating a more refined local search. This approach establishes a more logical balance between exploration (finding new, valid design configurations) and exploitation (refining promising designs). By embedding this structural knowledge directly into the algorithm's operators, the search process becomes more directed and efficient, converging to a high-quality, feasible solution with fewer function evaluations and a reduced risk of premature convergence.

3. Formulation

In the first phase, the frames must be examined and checked with regard to the applied loads and design specifications. Accordingly, the frame elements must fulfill the constraints defined by Eqs. (2, 3) as specified in the AISC 360-16 code [30].

$$\frac{p_u}{\phi_c p_n} < 0.2 \rightarrow \left[\frac{p_u}{2\phi_c p_n} + \left(\frac{M_{ux}}{\phi_b M_{nx}} + \frac{M_{uy}}{\phi_b M_{ny}}\right)\right] - 1 \leq 0 l = 1, \ldots, n_e \tag{2}$$

$$\frac{p_u}{\phi_c p_n} \geq 0.2 \rightarrow \left[\frac{p_u}{\phi_c p_n} + \frac{8}{9}\left(\frac{M_{ux}}{\phi_b M_{nx}} + \frac{M_{uy}}{\phi_b M_{ny}}\right)\right] - 1 \leq 0 l = 1, \ldots, n_e \tag{3}$$

P_u and P_n stand for the required and permissible axial strength of the member. ϕ_c and ϕ_b are the reduction factors for the axial and flexural strength, M_{ux} and M_{uy} denote the required flexural strength, and M_{nx} and M_{ny} are the nominal flexural strengths in the X and Y directions, respectively. In addition, ne stands for the number of frame members. For steel frames, the geometric constraints for the connection of columns to each other and the connection of beams to columns must also be taken into account. These constraints were applied according to Eq. (4, 5) shown in Fig. 3.

$$B_b \leq B_c \tag{4}$$

$$h_{s+1} \leq h_s \tag{5}$$

where $N_{i,j,k}$ is the number of events in the database for which the variable is in state and its parents are in configuration x_j.

The objective function in this study aims to minimize the weight of the steel frames as defined in Eq. (6). In addition, the constraints shown in Eq. (7) are considered.

$$MinimizeW = \sum_{k=1}^{ng} m_k \sum_{i=1}^{nk} L_i \tag{6}$$

$$(\delta_j - \delta_{j-1})/h_j \leq \delta_{ju} j = 1, \ldots, ns \tag{7}$$

In Eq. (6), *ng* represents the total number of groups in the steel frame system, m_k represents the unit weight of the standard steel sections for group *k*, *Li* represents the length of member *i* belonging to group *k*, and *nk* represents the number of members in group *k*. Eq. (7) represents the inter-story drift constraint, where δ_j and δ_{j-1} are the lateral displacements of two adjacent stories in the frames, and δ_{ju} is the allowable lateral displacement. In addition, h_j denotes the story height, and *ns* is the total number of stories in a frame.

4. Design examples

In order to evaluate and demonstrate the performance of the algorithm, four steel frames with 3, 10, 15 and 24 storeys were selected and the optimization process was carried out with them. In the following sections, the geometric specifications, the applied loads and the grouping of the members of the frames are described. The modeling of the frames was performed in the SAP2000 software and the optimization algorithms were implemented in the MATLAB environment.

4.1 Three-Story Frame

The three-story, two-bay frame is shown as the first design example in Fig. 4. This frame

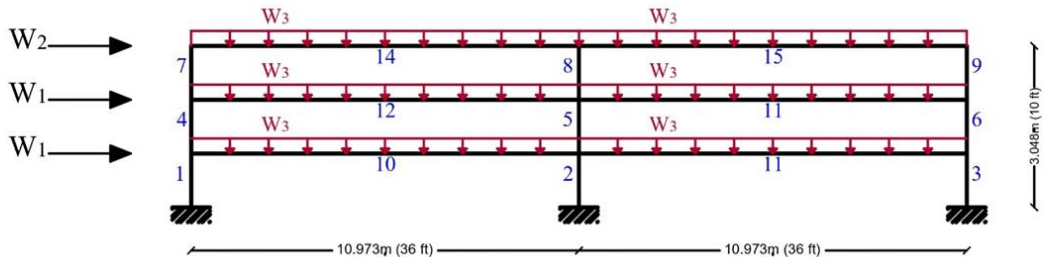

Figure 4. Geometry and loading for the three-story steel moment frame

Table 1. The members associated with the optimal designs for the three-story steel moment frame

Group NO.	GA	PSO	Curent work
1	24X62	21X55	10X77
2	10X60	10X77	10X77
Weight (kg)	8523.908	8532.072	8164.663

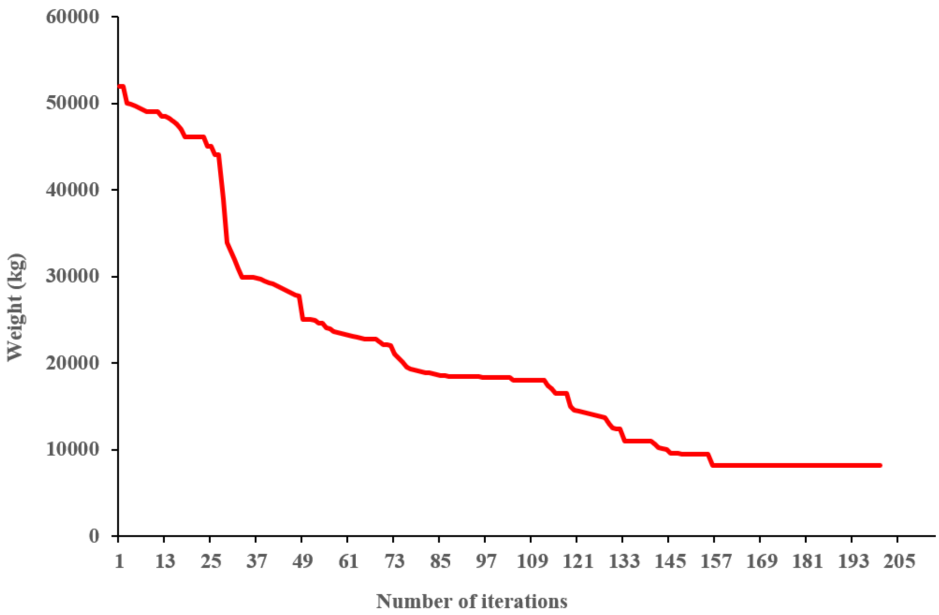

Figure 5. Design history graph for the three-story steel moment frame

consists of fifteen members, which are divided into two categories. The modulus of elasticity for the steel members is E = 29000ksi and the yield stress Fy = 33.4ksi. The loads considered for this frame include W1 = 5k, W2 = 2.5k and W3 = 2.8k/ft (1k = 4.448kN and 1ft = 30.48 cm). The optimal solution for this frame was determined using the BBO algorithm. In addition, the design process was carried out using Genetic Algorithms and Particle Swarm Optimization as shown in Table 1. The convergence process of the algorithm to the optimal solution and the stress ratios of the components are shown in Figs. 5, 6. The minimum stress ratio was 0.44 and the maximum value was 0.97.

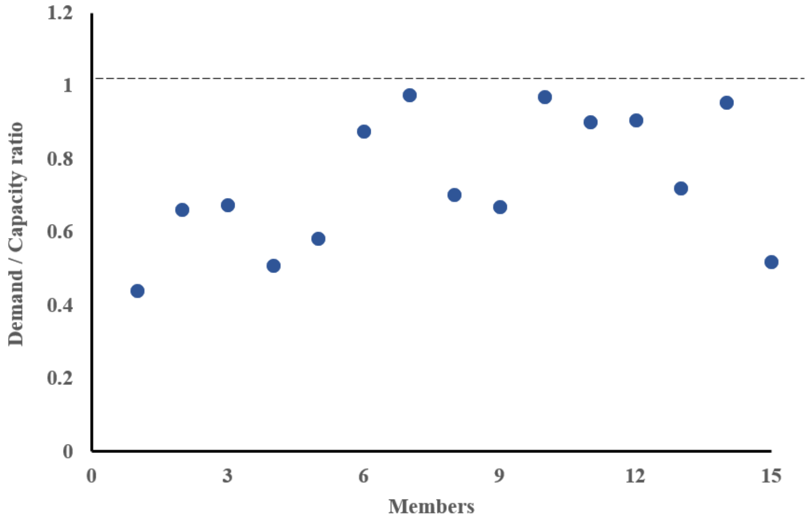

Figure 6. Demand/Capacity ratio for the members of the three-story steel moment frame

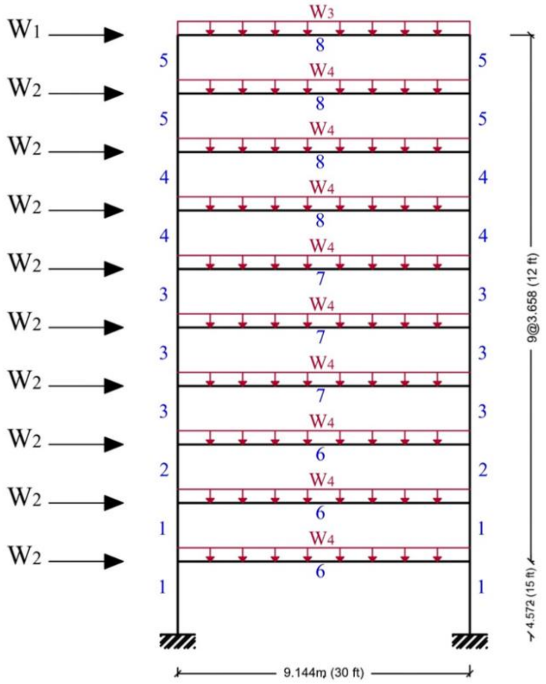

Figure 7. Geometry and loading of the ten-story steel moment frame

4.2 Ten-Story Frame

In the second design example, a single-bay ten-story frame was considered, the geometric specifications of which, including the span and story heights, are shown in Fig. 7. This frame consists of 30 members divided into 9 groups. The modulus of elasticity for the steel members is E

Table 2. Optimal designs for the ten-story steel moment frame

Group no.	GA	PSO	ACO	This study
1	W14X233	W14X99	W14X233	W14X233
2	W14X176	W14X99	W14X176	W14X176
3	W14X159	W14X132	W14X145	W14X145
4	W14X99	W14X159	W14X99	W14X99
5	W12X79	W33X141	W12X65	W12X65
6	W33X118	W30X116	W30X108	W30X108
7	W30X90	W21X68	W30X90	W30X90
8	W27X84	W14X61	W27X84	W27X84
9	W24X55	W40X183	W21X44	W21X44
Weight (kg)	29545.193	29460	28399.418	28037.905

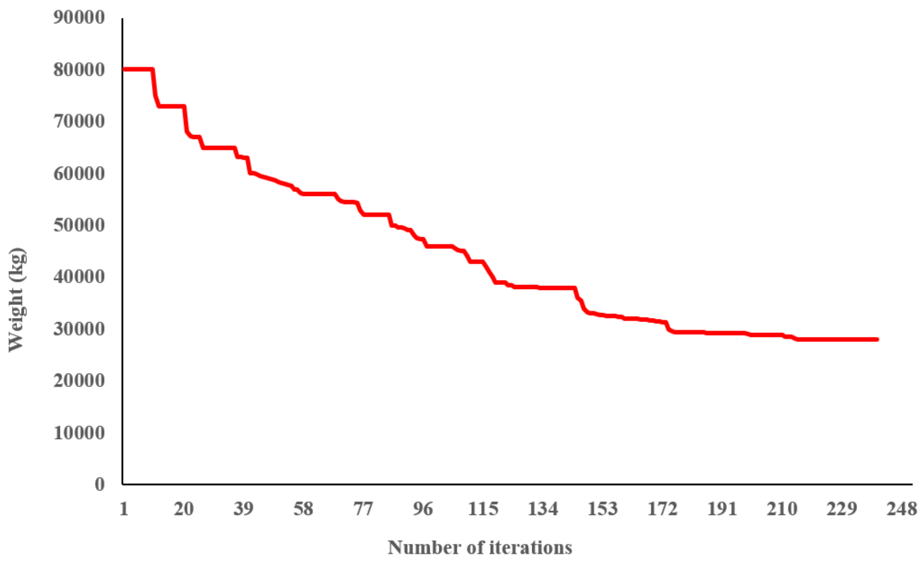

Figure. 8 Design history graph for the ten-story steel moment frame

= 29000ksi and the yield stress is F_y = 33.4ksi. The loads considered for this frame include W1 = 5k, W2 = 10k, W3 = 3k/ft and W4 = 6k/ft (1k = 4.448kN and 1ft = 30.48 cm). To achieve the optimal solution and the lowest possible weight for this frame, four algorithms were used: Genetic Algorithm, Particle Swarm Optimization, Ant Colony Optimization [31] and the biogeographic optimization algorithm developed in this study. The results of these four algorithms are shown in Table 2. The biogeography-based optimization algorithm provided the optimal solution with a weight of 28037.905 kg in 220 iterations, and the convergence process is shown in Fig. 8. The minimum stress ratio for the members was 0.41 and the maximum value was 0.97. The complete stress ratio data for all members of this frame are shown in Fig. 9.

4.3 Fifteen-Story Frame

To demonstrate the high efficiency and performance of the algorithm developed in this study,

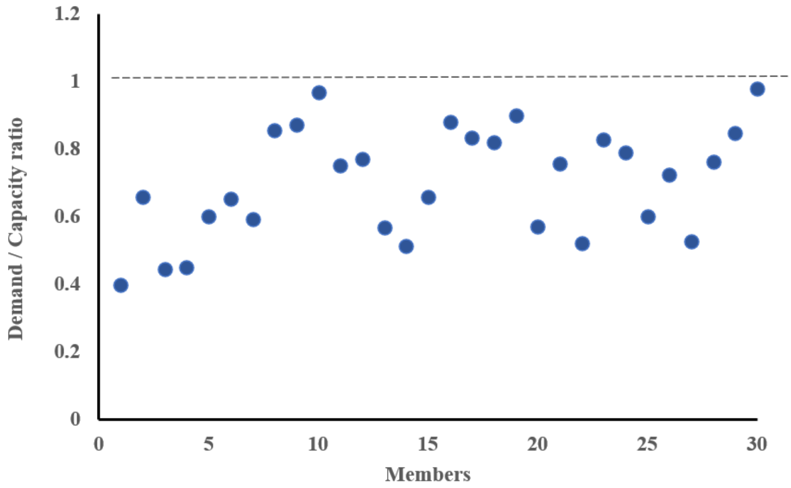

Figure 9. Demand/Capacity ratio for the members of the three-story steel moment frame

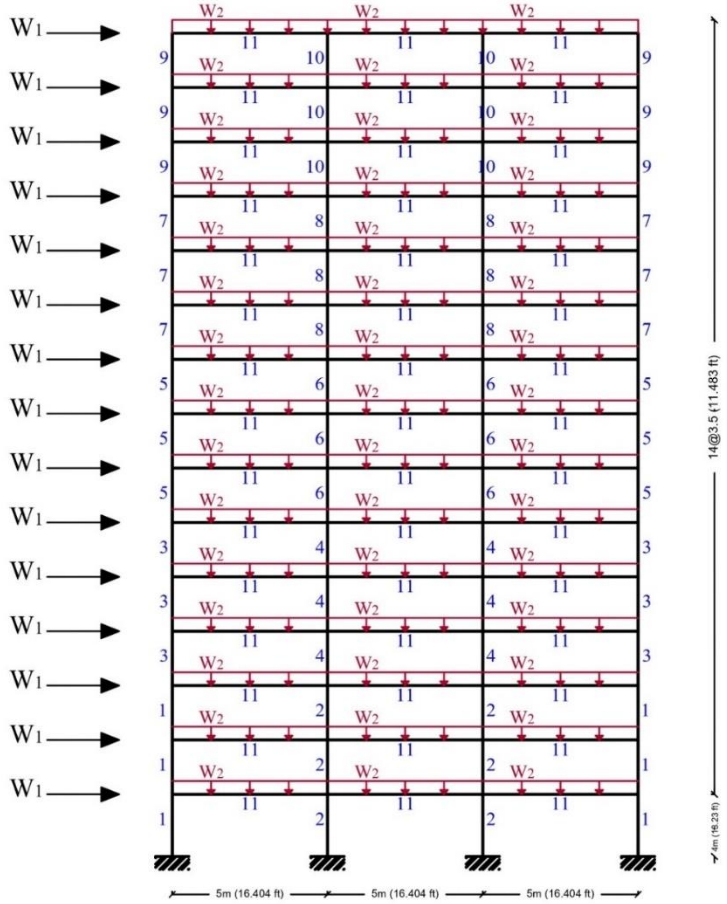

Figure 10. Geometry and loading of the fifteen-story steel moment frame

Table 3. Optimal designs for the fifteen-story steel moment frame

Group no.	PSO	GA	TLBO	This study
1	W33X118	W24X104	W12X96	W14X90
2	W33X263	W40X167	W27X161	W33X169
3	W24X76	W27X84	W27X84	W16X77
4	W36X256	W27X114	W24X104	W24X104
5	W21X73	W21X8	W10X68	W10X60
6	W18X86	W30X90	W30X90	W18X86
7	W18X65	W8X48	W8X48	W10X45
8	W21X68	W21X68	W24X68	W14X68
9	W18X60	W14X34	W8X28	W8X24
10	W18X65	W8X35	W10X39	W16X40
11	W21X44	W21X50	W21X50	W21X44
Weight (kg)	50647.255	42542.552	43202.308	38983.743

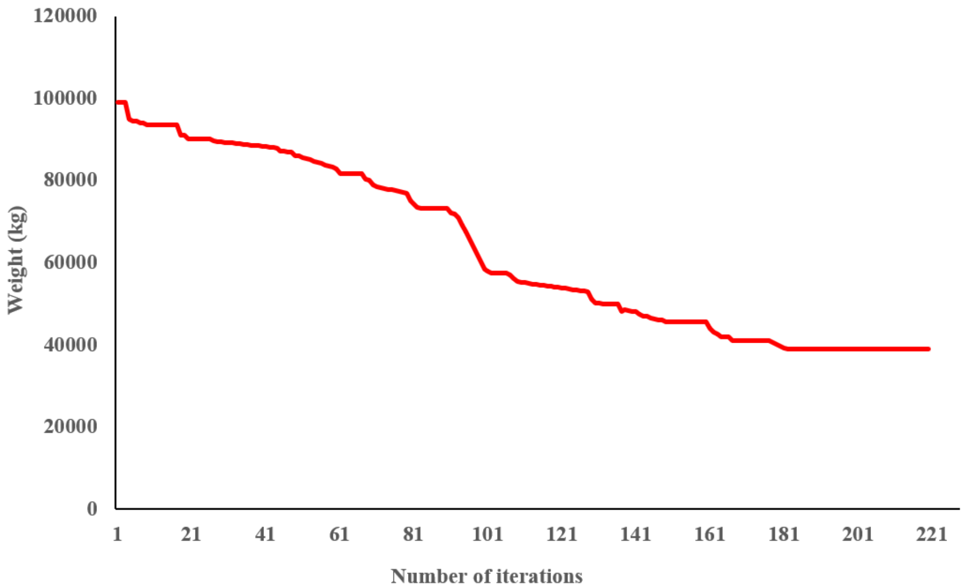

Figure. 11 Design history diagram for the fifteen-story rigid steel frame

in the third example, the design of a fifteen-story, three-bay frame was analyzed using Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Teaching-Learning-Based Optimization (TLBO) [32], [33] and Biogeography-based Algorithm (BBO). The geometric specifications of this frame, which consists of 105 members divided into eleven groups, are shown in Fig. 10. The modulus of elasticity for the steel members is E = 29000ksi and the yield stress is Fy = 33.4ksi. The loads considered for this frame include W1 = 30kN and W2 = 50kN/m (1k = 4.448kN and 1ft = 30.48 cm). Among the above algorithms, the BBO algorithm showed the best convergence rate and achieved a weight of 38,983.743 kg in 183 iterations. The complete design results for the members of this frame using each algorithm are shown in Table 3. The history of convergence

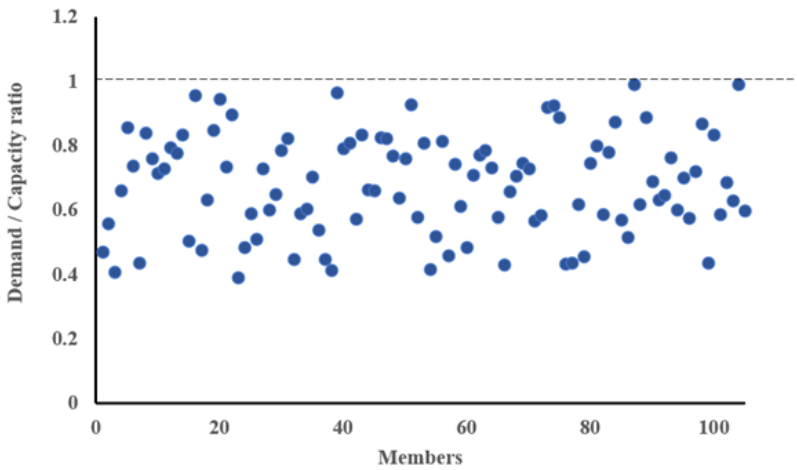

Figure 12. Demand/capacity ratio for the members of the fifteen-story steel moment frame

Table 4. Optimal designs for the twenty-four story steel moment frame

Group no.	HS	IACO	HBMO	This study
1	30X90	30X99	10X22	10X22
2	10X22	16X26	27X539	27X539
3	18X40	18X35	8X21	8X21
4	12X16	14X22	33X221	33X221
5	14X176	14X145	14X145	14X145
6	14X176	14X132	14X145	14X132
7	14X132	14X120	14X68	14X120
8	14X109	14X109	14X22	14X74
9	14X82	14X48	14X48	14X68
10	14X74	14X48	14X68	14X38
11	14X34	14X34	14X132	14X30
12	14X22	14X30	14X342	14X22
13	14X145	14X159	14X159	14X99
14	14X132	14X120	14X109	14X99
15	14X109	14X109	14X99	14X90
16	14X82	14X99	14X48	14X90
17	14X61	14X82	14X43	14X68
18	14X48	14X53	14X53	14X61
19	14X30	14X38	14X176	14X38
20	14X22	14X26	14X211	14X22
Weight (kg)	97458.857	98640.011	97453.414	91386.948

according to the BBO algorithm is shown in Fig. 11. In the final and optimal solution of the algorithm, the minimum stress ratio for the members was 0.37 and the maximum value was 0.99. The complete results of the stress ratios for all members of the frame are shown in Fig. 12.

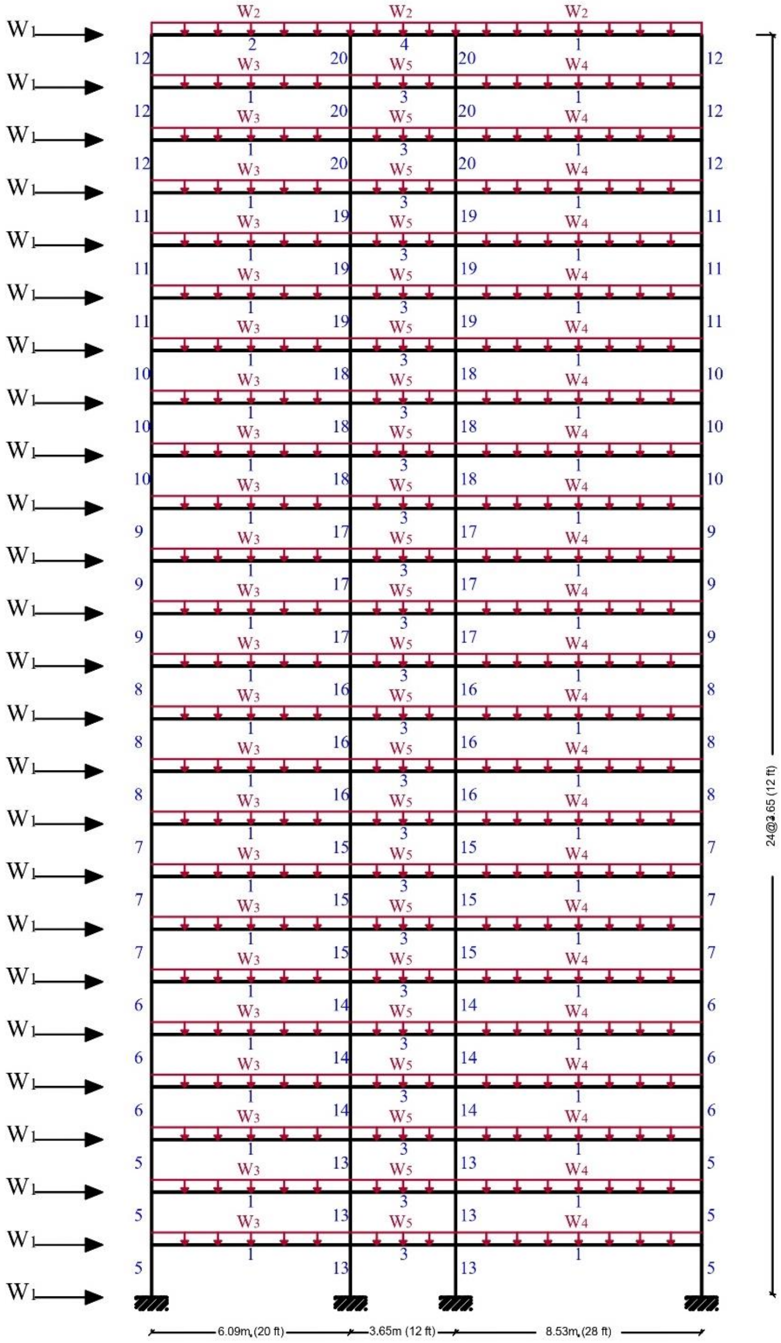

Figure. 13 Geometry and loading of the twenty-four-story steel moment frame

4.4 Twenty-four-Story Frame

The 24-story steel frame with three spans is shown in Fig. 13, which contains information such

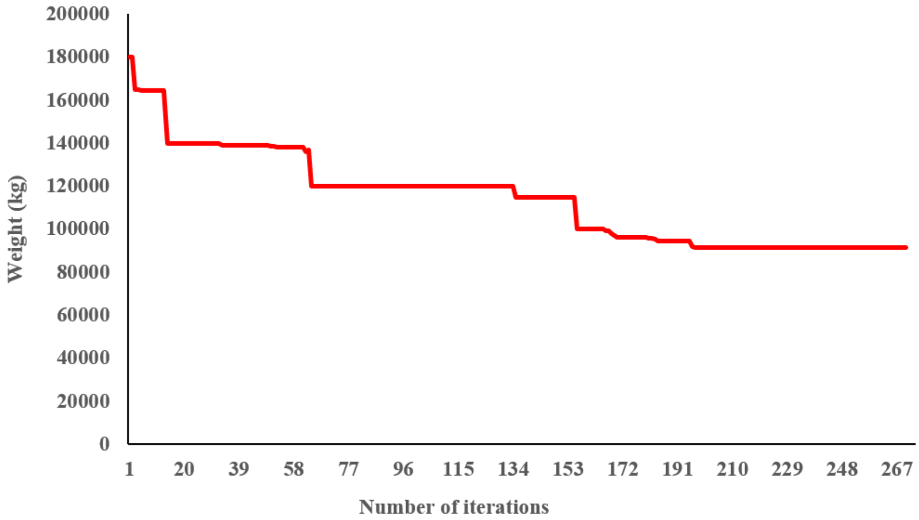

Figure 14. Design history diagram for the twenty-four-story steel moment frame

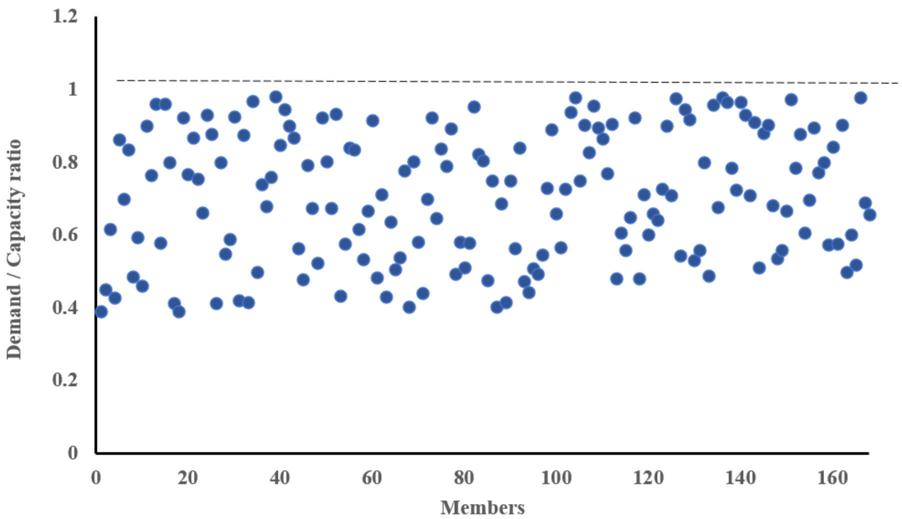

Figure 15. Demand/capacity ratio for the members of the twenty-four-story steel moment

as spans, story heights, member groups and applied loads. The Harmony Search algorithm [34], the modified Ant Colony algorithm, the Bee Mating algorithm [35] and the developed biogeography-based optimization algorithm were used to optimize this frame under the applied boundary conditions. The modulus of elasticity for the steel members is E = 29000ksi and the yield stress is Fy = 33.4ksi. The loads considered for this frame include W1 = 5761 lb, W2 = 300 lb/ft, and W3 = 436 lb/ft, and W4 = 408 lb/ft, and W5 = 474 lb/ft (1k = 4.448kN and 1ft = 30.48 cm). The final analysis and design results for the frame can be found in Table 4. The biogeography-based optimization algorithm discussed in this study outperformed the other algorithms with a weight of 91386.948 kg after 201 iterations. The convergence process for the final design of this framework is shown in Fig. 14. However, further studies should also be conducted with other metaheuristic algorithms. For this frame, the minimum stress ratio for the members was 0.36 and the maximum ratio was 0.98. The complete stress ratios for all members of the frame are shown in Fig. 15.

To ensure a fair and equitable comparison between the specialized Biogeography-Based Optimization (BBO) algorithm and other metaheuristic methods, all algorithms were implemented with careful attention to their parameter settings and were allocated identical computational budgets. The goal was to isolate the effect of the algorithmic logic and specialization, rather than differences in tuning or resource allocation. A comprehensive tuning process was first conducted on each algorithm using a subset of the design examples to determine a robust set of parameters. Furthermore, to standardize the stopping criterion across all methods, a fixed computational budget was defined in terms of the maximum number of structural analyses (e.g. function evaluations 50,000). This approach is considered more reliable than setting a fixed number of iterations, as it directly accounts for the computational cost of evaluating each candidate design. The key parameter (optimally tuned parameters) are Crossover and Mutation for GA, Inertia weight and c1 to c2 for PSO and Habitat modification and mutation probability for proposed specialized BBO. It is noteworthy to mention that TLBO is parameter-free. To ensure a fair and reproducible comparison, all algorithms in this study were executed under a standardized computational budget. The termination criterion for each optimization run was defined as a maximum number of structural analyses (function evaluations), which was kept consistent for all algorithms applied to a given frame. Furthermore, key parameters (such as population size, crossover, and mutation rates) for the comparative algorithms were selected based on established values from the structural optimization literature and preliminary tuning exercises. This setup guarantees that the observed performance differences are a result of the algorithmic logic and not disparities in computational effort or parameter tuning.

5. Conclusions

This study successfully developed and applied a specialized Biogeography-Based Optimization (BBO) algorithm for the minimum-weight design of steel moment frames. The core achievement of this research is the effective integration of structural engineering knowledge into the metaheuristic framework, transforming it from a general-purpose optimizer into a specialized design tool. The algorithm’s performance was rigorously validated through four design examples of varying complexity, ranging from a 3-story to a 24-story frame. The results support several key conclusions:

• Enhanced Performance and Efficiency: The specialized BBO algorithm consistently produced lighter or comparable steel frame designs compared to other established metaheuristics such as GA, PSO, and ACO. More importantly, it achieved these superior results with improved computational efficiency, often requiring fewer iterations to converge. This improvement is directly attributable to the reduction of the problem’s search space, as the algorithm was designed to avoid structurally invalid or impractical design choices from the outset.

• The Critical Role of Structural Specialization: The algorithm’s success is rooted in its domain-specific modifications. By encoding constraints and engineering heuristics directly into the migration and mutation processes, the search is guided toward feasible regions. This strategic guidance prevents computational effort from being wasted on evaluating nonsensical designs, a common pitfall when applying standard metaheuristics to structural problems.

• Robust Search Dynamics: The specialized BBO maintains a healthy balance between exploring new design configurations and exploiting known good solutions. The constrained migration strategy ensures diversity in the population, helping the algorithm escape local optima and increasing the likelihood of finding the global optimum or a near-optimal solution.

• Practical Value: The significant reduction in frame weight directly translates to lower material costs and a reduced environmental footprint, making the algorithm a valuable tool for sustainable structural design.

For future work, this research opens several promising directions. The logical next step is to extend the current single-objective formulation to a multi-objective optimization framework, simultaneously minimizing weight, cost, and embodied carbon. Furthermore, to enhance practical relevance for seismic regions, integrating dynamic analysis under earthquake loading would be a critical advancement. Finally, incorporating machine learning surrogates could further accelerate the analysis process, making the optimization of even larger and more complex structures computationally tractable. The specialized BBO algorithm presented here provides a robust foundation for future explorations in intelligent structural design.

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