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Including problem-knowledge based modification into a Differential Evolution Algorithm for optimizing planar moment-resisting steel frames

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ABSTRACT

The Differential Evolution Algorithm (DEA) has been demonstrated to be capable of effectively addressing engineering challenges, although its performance varies considerably when applied to different problems. Customizing the algorithm to the specific characteristics of a given problem has been identified as a valid strategy to enhance its effectiveness and reliability. In this study, a tailored version of the DEA is proposed for the optimization of planar Moment-Resisting Steel Frames (MRSFs) subjected to static loads. A diverse set of heuristics and techniques were incorporated, including advanced strategies for parameter control, initialization, mutation operators, crossover operators, diversity conservation, constraints handling, and dynamic population management. To evaluate the performance of the proposed heuristics and techniques, 7800 DEA configurations were applied to the optimization of seven representative MRSFs. Results indicate that through problem-specific modifications the DEA is highly likely to identify the optimal solutions. By emphasizing both computational efficiency and solution quality, this research provides valuable insights into enhanced applicability of the DEA to structural optimization problems. It is shown that a customized algorithm is a reliable, effective, and robust tool to optimize MRSFs.

1. Introduction

Moment-Resistant Steel Frames (MRSFs) are structural systems used in buildings to resist mostly horizontal loads, especially seismic forces. Due to the large number of MRSF buildings worldwide, optimizing the design of MRSFs is crucial to reduce costs. Typically, the total weight of the structural elements is selected in the literature to define the objective function of the optimization procedure, while technical and constructive constraints must be satisfied. A more comprehensive objective function might include other factors such as connections [1] and construction considerations [2]. In addition, several studies have adopted a multi-objective approach that accounts for the cost of seismic damage over the lifetime of the structure [3]. Regardless of the objective function, the optimization formulation often defines the design variables as the cross sections of commercially available steel members (beams and columns). Technical constraints are based on standard design codes such as American Institute of Steel Construction (ANSI/AISC) 341 [4] and ANSI/AISC 360 [5], with linear or nonlinear analysis used to predict the structural response. In the finite element model, the MRSF analyzed in the literature typically considers fixed base columns, although alternative approaches that account for soil–structure interaction have also been explored [6,7]. Moreover, while connections are often assumed rigid, studies by Liu et al. [8], Truong and Kim [9] have explored the incorporation of real stiffness and connection properties as design variables. Constructive constraints are essential for ensure a feasible structural design, such as the group of elements with similar cross sections. It is also important to recognize the multimodal nature of the search space, which varies in complexity depending on the specific structural response framework under analysis.

The selection of an optimization algorithm is crucial to achieve optimal designs of MRSFs. Over the past two decades, numerous metaheuristic algorithms have been applied to the MRSF Optimization Problem (MRSF-OP). These include Ant Colony Optimization [10], Genetic Algorithms [11], Harmony Search [12], Particle Swarm Optimization [13], Simulated Annealing [14], Eagle Algorithm, Teaching–Learning-Based Optimization [15], Cuckoo Search Algorithm [16], Colling Bodies Optimization [17], Differential Evolution [18], Imperialist Competitive Algorithm [19], Adaptive Dimensional Search Algorithm [20], Tribe-Interior Search Algorithm [21] and Tabu Search [22]. However, the general nature of metaheuristic algorithms does not guarantee optimal solutions in some specific problems. Thus, the subject

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continues to attract significant attention, as evidenced by numerous recent journal articles exploring metaheuristic-based approaches, including worksby Taymus et al. [23], Kaveh and Hamedani [24], Wang et al. [25], Talezadeh and Maheri [26], Carbas and Tunca [27], Gandomi et al. [28], Dastan et al. [29], Hasançebi [30], Kaveh and Rezazadeh Ardebili [31], Korucu and Hasançebi [32], Motamedi et al. [33], Shan et al. [34], Su et al. [35], Al-Bazoon and Arora [36], Zhou et al. [37], Bakhshpoori et al. [38], Kaveh et al. [39], Vu et al. [40], Üstüner and Doğan [41], Carbas [42], Aydogdu et al. [43], Kaveh and Zaerreza [44], Ghasemof et al. [45], Gholizadeh et al. [46], Degertekin and Tutar [47], Kaveh and Hamedani [48], Rastegaran et al. [49], Motamedi et al. [50], Rastegaran et al. [51], Arab et al. [52], Vaez et al. [53] and Turay et al. [54]. Some studies compare the performance of various algorithms in the optimization of MRSFs [53,55–57], using common comparison criteria such as the optimal weight and the number of structural analyzes performed. However, determining the most suitable metaheuristic for MRSF-OP remains a challenge. To accurately assess the efficiency of such methods, it is essential to establish benchmark examples and conduct specific comparisons with state-of-the-art techniques.

To enhance the performance of a metaheuristic algorithm for solving engineering problems, its structure must be modified to improve exploration and exploitation based on the characteristics of the problem. The algorithm must adapt to the nature of the search space, which is often multimodal in MRSF-OP. Consequently, many modifications to various algorithms tailored to the specific characteristics of MRSF-OP have been presented in the literature. Initial modifications consist of defining the design variables and to organize the database of cross-sections. Hasancebi [30] suggested considering cross-sectional orientation and database definition to enhance the spatial configuration of MRSFs. Turay et al. [54] investigated the impact of group members and the size of the discrete cross-section pool. Similarly, it is possible to propose specific processes for the random generation of the initial population. For instance, Baradaran and Madhkhan [58] proposed to divide the generation of the initial population into two phases. It is also possible to modify the mathematical operators that guide the search process. Talezadeh and Maheri [26] suggested dynamically adjusting the limits of the search space to confine the optima within a smaller space. Korucu and Hasancebi [32] proposed a guided evolution strategy to improve convergence by directing the search process based on prior design constraints, known as guided mutation, which supplements stochastic mutation to accelerate convergence. Rastegaran et al. [51] introduced an oriented genetic algorithm that takes advantages of design constraint violation values. Azad [59] introduced a monitored convergence curve to track the convergence of the algorithm in each run relative to previous runs. Fernández-Cabán and Masters [60] proposed a hybrid approach that begins with exploration and then moves to the exploitation of the search space. As can be seen, there are several alternatives to make a metaheuristic suitable for the MRSF-OP.

The Differential Evolution Algorithm (DEA) emerged two decades ago as a numerical tool to solve continuous problems in engineering. Its applications are widespread, including structural optimization [61], structural damage detection [62], cement mill operation [63], construction project scheduling [64], bridge maintenance plans [65], speed limit control [66], rainfall-runoff models [67], reservoir operation [68] and slope stability [69]. This range of applications in various areas of civil engineering demonstrates the versatility of DEA. For the MRSF-OP, the DEA has shown promise with modifications tailored to its specific requirements. Le et al. [18] enhanced DEA with two key improvements in the mutation and selection phases. They introduced a Modified Roulette Wheel Selection method to select individuals for mutant vector generation and incorporated an elitist operator for the next generation. Likewise, Babaei and Mollayi [70] proposed a hybrid mutation method, termed $C\&R$ that further improved the performance of the DEA. Safari et al. [71] compared 11 different variants of the DEA, focusing on the mutation process. The variants that used the best individual as the base vectors outperformed those that used a random base vector. Vu et al. [40] introduced a novel DEA variant featuring a new mutation technique that uses the two p-best individuals. Gandomi et al. [28] demonstrated that the DEA exhibits a higher convergence rate for the MRSF-OP compared to a Particle Swarm Optimization (PSO) algorithm. These results underscore the ability of the DEA to address the MRSF-OP. Notably, the performance of the DEA relies heavily on parameter definition, and fixed parameters used in the cited examples highlight opportunities for enhancement through parameter control techniques.

Many modified DEA are tailored for specific structural problems, limiting their applicability to structures with varying dimensions. This study addresses this limitation by identifying robust strategies that remain effective across a broader range of cases. Additionally, prior research often lacks a structured evaluation framework, making it difficult to assess the overall effectiveness of different DE modifications. To overcome this, a six-filter assessment is introduced to ensure that solutions are feasible, efficient, and reliable. Furthermore, most studies rely on predefined or heuristically selected evolutionary strategies, without a systematic approach to determine the most effective combination of operators. In contrast, this research provides a structured methodology to identify optimal configurations of mutation, crossover, and constraint-handling techniques, enhancing the adaptability and performance of DE in structural optimization.

In this study, a broad set of configurations of the DEA are explored for the structural optimization of MRSFs. Such configurations are obtained by testing several alternatives for the algorithmic components of the DEA. These components refer to the population initialization phase, the generation of new solutions by the mutation and crossover operators, the strategy for handling constraints, the parameter adaptation, the definition of mechanisms to preserve diversity, and procedures to reduce the computational cost by dynamically adjusting the population size. The performance of each DEA configuration is assessed using seven planar MRSF models with different numbers of stories and bays, enabling a comprehensive evaluation under diverse design conditions. The main contributions of this work are summarized as follows:

- Comprehensive performance evaluation of DEA variants through a multi-filter framework:
  A total of 7800 DEA configurations were tested. Their performance was assessed through a sequential filtering process based on six quality criteria. These criteria included: (1) structural feasibility, (2) proximity to the optimal solution, (3) consistency across repeated runs, (4) statistical dominance, (5) computational efficiency, and (6) convergence behavior. Through this framework, a systematic evaluation of the influence of different configurations on performance is obtained.
- Identification of recommended DEA configurations based on structural complexity:
  Due to the variability in structural complexity, the effectiveness of specific DEA configurations for different problem dimensionalities such as low-, mid-, or high-rise frames was studied. By analyzing algorithm configurations across a diverse set of MRSF cases, tailored strategies were identified to improve the adaptability and effectiveness of the algorithm in practical design scenarios.
- Analysis of the structural meaning of optimized solutions:
  The analysis of results was extended beyond numerical evaluation by examining the engineering relevance of the optimized frames. Cross-section selections, element groupings, and resulting frame layouts were reviewed to verify their consistency with structural logic and design principles. Through these assessments, the connection between algorithmic results and practical structural performance was reinforced.

Finally, a clear and structured overview of the MRSF-OP and the DEA is provided to make them clear to readers that are newcomers to the field of structural optimization and metaheuristics. In Section 2,

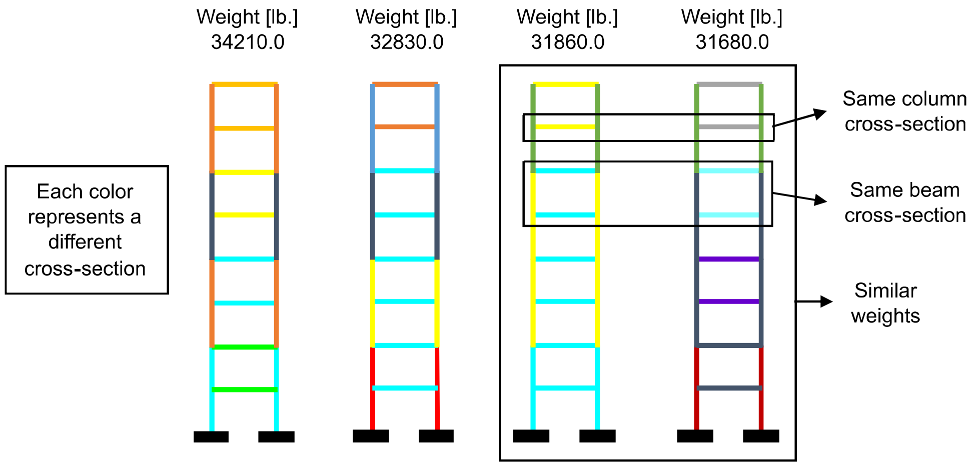

Fig. 1. Impact of cross-section variations on structural weight in steel frames.

the formulation of design variables, constraints, and the objective function is presented, and the role of each algorithmic operator is described. This section serves as a useful reference for both researchers and practitioners interested in applying DEA to structural engineering problems.

2. Methods

2.1. Formulation of the optimization problem

The formulation of the MRSF-OP defines four key components of the mathematical model: (i) design variables, (ii) design parameters, (iii) objective function, and (iv) constraints. The design variables for the MRSF-OP are the cross-sections of structural elements, such as beams and columns. To simplify construction, frame elements with similar properties can be grouped to share the same cross-section. Fig. 1 illustrates the same frame with various cross-section options, each denoted by a distinct color. This example includes eight design variables: one for each column across every two stories and four for the beams, also grouped by two-story segments. This strategy significantly reduces the number of variables, as demonstrated by Kaveh et al. [72]. In their study, a 24-story frame with 168 elements was optimized using only 20 design variables, reducing the search space from 267^{168} to 267^{20} combinations, where 267 is the number of available cross-sections. The geometric configuration of the frame and its material properties were kept constant throughout the optimization process. In particular, the structural response of the MRSFs, including forces and displacements, was evaluated using a linear elastic finite element analysis.

The objective function (see Eq. (1)) minimizes the weight of the frame, where A_i, L_i, and γ_i denote the cross-sectional area, length, and specific weight of the element i, respectively. The selection of cross-sections as design variables is crucial for MRSF optimization, as they directly influence structural strength and stability. Since steel sections are standardized in commercial catalogs (e.g., ANSI/AISC 360), the problem becomes discrete and practical for real-world applications. In some structures, restricting the range of feasible beam sections compared to columns reduces the search space, enhances optimization efficiency, and ensures structural feasibility. Additionally, this approach improves comparability and consistency with previous studies.

Fig. 1 illustrates the weight of four structures with different cross-section configurations. In practice, various cross-section distributions can result in similar weights, as seen in the structures highlighted within the black box. However, higher-cost solutions can lead to heavier alternatives.

$$Minimize : W = \sum_{i=1}^{n}(A_i L_i \gamma_i) \tag{1}$$

The technical constraints in structural design, as defined by the ANSI/AISC 360 Code [73], are applied at both the element and the structural levels. These include: (i) maximum roof displacement (Δ_T), (ii) maximum inter-story drift (ISD), and (iii) strength capacity, which is evaluated based on internal forces (IF). Eqs. (2) and (3) specify the global constraints within the optimization approach.

$$g_1 : \frac{\Delta_T}{H} - R \leq 0 \tag{2}$$

$$g_2 : \frac{d_i}{h_i} - R_i \leq 0 \tag{3}$$

where Δ_T is the roof displacement, H denotes the total height of the structure, and R is the allowable roof displacement (expressed as $1/300$). Furthermore, d_i corresponds to the ISD of the ith story, h_i indicates the height of the ith story, and R_i specifies the allowable ISD of the ith story (expressed as $h_i/300$).

Eqs. (4a) and (4b) specify the constraints that govern frame resistance at the level of individual elements:

$$g_3 : \frac{P_u}{2\phi_c \overline{P_n}} + \left(\frac{M_{u_x}}{\phi_b \overline{M_{n_x}}}\right) - 1 \leq 0 \rightarrow \frac{P_u}{\phi_c \overline{P_n}} < 0.2 \tag{4a}$$

$$g_4 : \frac{P_u}{\phi_c \overline{P_n}} + \frac{8}{9}\left(\frac{M_{u_x}}{\phi_b \overline{M_{n_x}}}\right) - 1 \leq 0 \rightarrow \frac{P_u}{\phi_c \overline{P_n}} \geq 0.2 \tag{4b}$$

where P_u represents the applied axial strength, M_{u_x} denotes the applied flexural strength, $\overline{P_n}$ is the nominal axial strength and $\overline{M_{n_x}}$ is the nominal flexural strength. The parameters ϕ_c and ϕ_b represent resistance reduction factors. Appendix A provides the equations employed in this study to support the design procedure of an MRSF.

Fig. 2 illustrates the effects of deformation in a three-story frame at the structural and element levels. The left diagram shows the axial and flexural requirements at the element level. Meanwhile, the right diagram illustrates the concept of overlimit, which occurs when the ISD or Δ_T exceed their maximum allowable values. The graphical scale at the bottom of the figure depicts the penalty index, which remains low within acceptable limits but increases when those limits are exceeded. This information is used to evaluate the quality of the structural design. More complex factors, such as warping effects [74], natural frequencies [57], or the stiffness of the connection [8], can be incorporated as technical constraints.

Constraints divide the search space into feasible and infeasible solutions. Fig. 3 (left) shows a three-story frame with two variables: one for column cross-sections and the other for beam cross-sections. A-36 steel was used, defined by a yield strength of $Fy = 36000\left(\frac{lb}{in^2}\right)$, and a modulus of elasticity of $E = 29 \times 10^6 \left(\frac{lb}{in^2}\right)$. The search space, shown in the center of the figure, uses green dots to represent feasible

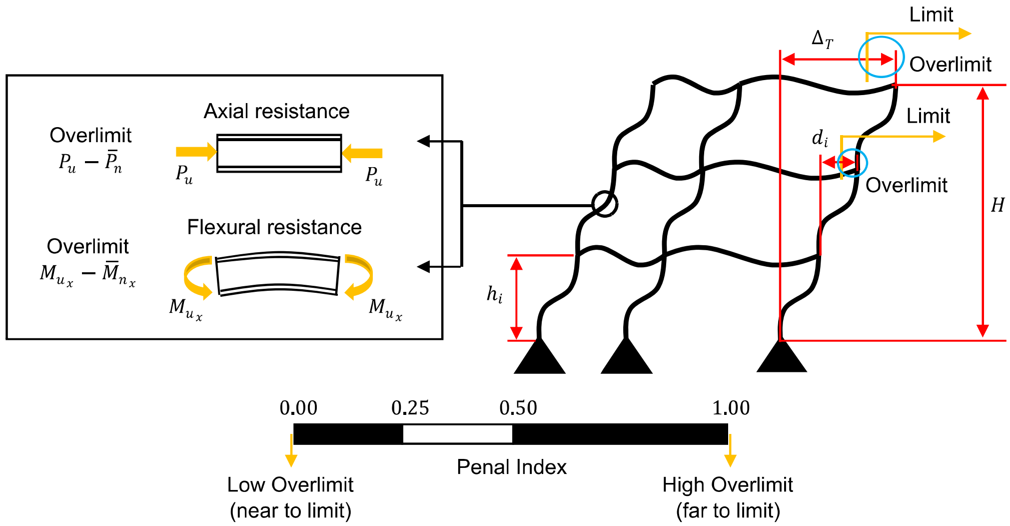

Fig. 2. Graphical representation of axial and flexural strength and ISD limits in a deformed steel structure.

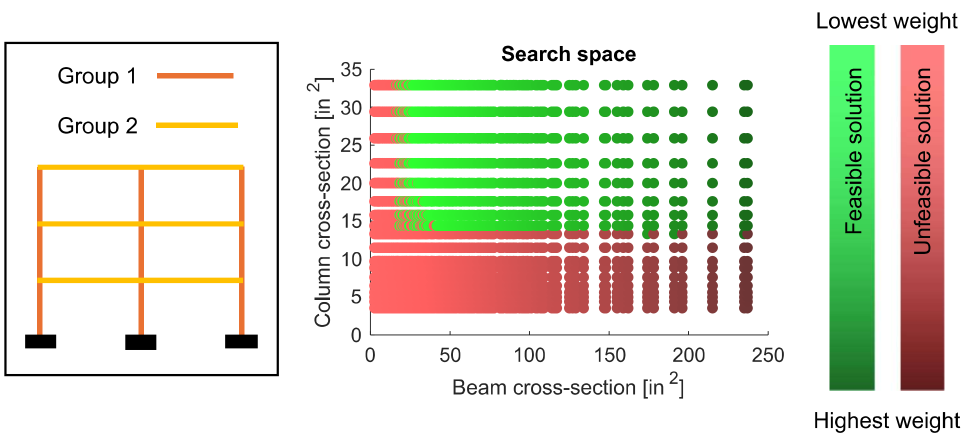

Fig. 3. Visualization of feasible and infeasible solutions in a discretized search space.

solutions and red dots to denote infeasible ones. Lighter color intensities correspond to lower weights, suggesting that small cross-sectional areas in both columns and beams often fail to satisfy constraints related to element strength or maximum allowable displacement. In contrast, darker colors represent higher structural weights. Although these solutions may satisfy the constraints, they are likely far from optimal. A distinct region in the search space, marked by an intense green color, indicates the probable location of the optimal solution. To address infeasibility, constraints are typically incorporated through a penalty approach, which ensures that infeasible solutions are progressively eliminated in subsequent generations.

The penalization factor typically depends on the number of unsatisfied constraints. Eq. (5) presents a common static penalization expression, where higher values correspond to poor solutions and lower values to better ones.

$$W_{penal} = W\left(1 + \alpha \frac{N_{ST}}{N_T}\right)^{\beta} \tag{5}$$

here, α and β are user-defined parameters, N_{ST} represents the number of unsatisfied constraints, and N_T denotes the total number of constraints. The effect of this strategy is depicted in Fig. 4, which uses the same color and intensity nomenclature was used in Fig. 3. The left side presents the search space for the previous optimization problem, where feasible, low-weight solutions are expected. The right side emphasizes the importance of a constraint management strategy. Two alternatives are illustrated: in the upper graph, the lowest-weight solutions are identified as optimal without applying a penalty function filter, which includes infeasible solutions. In contrast, in the bottom graph, feasible solutions are identified as optimal with the aid of a penalty function filter.

2.2. The differential evolution algorithm

DEA is a widely used optimization technique to address complex problems. Candidate solutions are iteratively refined through evolutionary operators, including mutation, crossover, and selection. The algorithm is recognized for its simplicity, robustness, and efficiency in the exploration of the search space. Among its various applications, the DEA is particularly effective in structural optimization problems, such as minimization of the weight of MRSF structures. In this context, the design variables represent the cross-sections of beams and columns, selected from a commercial database. The initial step defines the computational representation of these design variables. For this purpose, a vector with integer values is used, where each position represents the cross-section of a specific group of elements. Fig. 5 illustrates a 3-bay, 4-story steel frame with seven element groups, each defined by a distinct color. A vector-based computational representation is employed to assign properties to the elements. The position in the vector corresponds to the element ID number, while the magnitude represents the assignment of the group, as shown at the top of the figure. The element ID number can be customized according to the user preferences. Since this problem is discrete and the DEA was originally

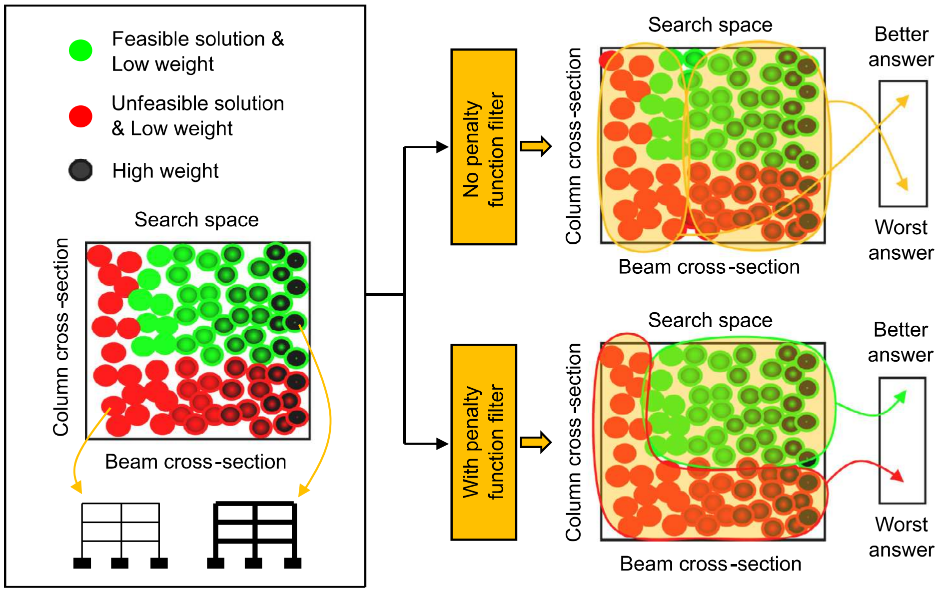

Fig. 4. Use of the penalty function in the classification of best and worst solutions.

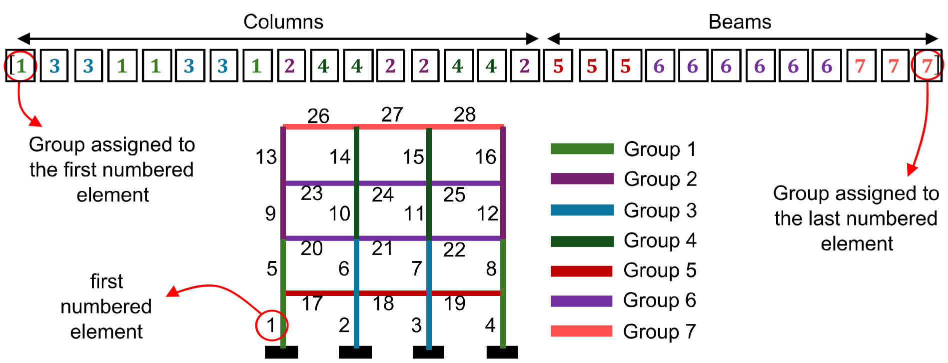

Fig. 5. Computational representation of 3 bays - 4 stories steel frame.

designed for continuous variables, rounding is required during operations to eliminate decimal values. Furthermore, sorting the database according to specific criteria, such as area, inertia, or weight, ensures accurate correspondence with values that represent positions in the DEA.

A distinctive feature of the DEA is its ability to progressively improve a set of potential solutions, called the population. Notably, the population size is directly linked to the number of design variables. However, there is no consensus on the optimal degree of this dependence for a given problem. All solutions within the population are modified through evolutionary operators to generate new solutions that are expected to demonstrate improvements over their predecessors. This iterative process continues until a predefined stopping criterion is met.

Fig. 6 presents a flowchart of the optimization process of a planar MRSF using DEA. The process begins with the generation of an initial population, referred to as the target population, typically created through a random process. These initial solutions lack structural significance as they are generated without problem-specific knowledge. This is evident in the target structure, where an intermediate story appears weaker than the others in terms of lateral stiffness, potentially compromising its capacity to adequately support seismic loads. As a result, constraints such as the limits of internal forces (IF) are frequently not satisfied.

In the subsequent stage of the DEA, each solution is evaluated using the fitness function and its compliance with the constraints, followed by the generation of a mutated population. Mutation is performed using a mutated operator, which consists of a base vector and a perturbation. The base vector guides the exploration of the search space, while the perturbation is derived from a combination of randomly scaled solutions, controlled by a mutation factor (F). Eq. (6) presents a standard mutation operator employed in the DEA.

$$v_{i,j}^{G} = x_{r1} + F(x_{r2} - x_{r3}) \tag{6}$$

here, $v_{i,j}$ is defined for $\forall i \in \{1, 2, \dots, PS\}$ and $\forall j \in \{1, 2, \dots, D\}$, where PS and D denote the population size and the dimension of the problem, respectively. x_r represents a solution in the target population, while the subscripts $r1$, $r2$ and $r3$ denote distinct random solutions. At this stage, new candidate solutions that may outperform those in the previous population can be generated. Subsequently, the target and mutated populations are compared using a CR coefficient to generate the trial population. Eq. (7) outlines the selection process.

$$u_{i,j}^{G} = \begin{cases} v_{i,j}^{G}, & \text{if } rand(0,1) \le CR \text{ or } j = j_{rand}, \\ x_{i,j}^{G}, & \text{otherwise} \end{cases} \tag{7}$$

here $v_{i,j}$ represents a solution within the mutant population. In the trial structure, characteristics of the mutant structure are incorporated into the target structure, potentially producing a structure superior to the original target structure. The fitness function is then evaluated. The selection process consist of comparing solutions i from both the target