

Article

Parameter-Free Jaya Algorithm for Steel Frame Optimization Under Natural Frequency Constraints

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Abstract

The optimal design of steel frame structures subjected to natural frequency constraints is a challenging problem due to its highly nonlinear and computationally demanding nature. In this study, Parameter-Free Jaya Algorithm (PFJA) is proposed for the minimum-weight design of planar and spatial steel frame systems under prescribed natural frequency constraints. The standard Jaya Algorithm (JA), which is based on moving toward the best solution and away from the worst solution, is enhanced by eliminating algorithm-specific control parameters and enabling automatic self-adaptation during the optimization process. The performance of the proposed PFJA is evaluated using three planar and two spatial steel frame benchmark problems previously studied in the literature. All structural analyses and optimization procedures are implemented in MATLAB R2020b, and the optimal designs are independently verified using SAP2000 v20, yielding identical natural frequency values. The results demonstrate that PFJA outperforms the standard JA, modified Jaya algorithm (MJA), and several recently developed metaheuristic algorithms in terms of minimum structural weight, convergence speed, and statistical robustness. These findings confirm the superiority and reliability of the proposed PFJA for frequency-constrained structural optimization problems.

Keywords: parameter-free JAYA algorithm; structural optimization; frame structures; natural frequency constraints

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1. Introduction

In recent years, the structural engineering community has witnessed a significant paradigm shift toward automated design, where the primary objective is to minimize material weight while strictly satisfying challenging dynamic performance criteria. Within this domain, numerous metaheuristic algorithms—such as particle swarm optimization (PSO) [1], charged system search (CSS) [2], teaching–learning-based optimization (TLBO) [3], grey wolf optimizer (GWO) [4], improved grey wolf optimizer (IGWO) [5], and their specialized variants—have been successfully applied to the design and optimization of complex frame structures under natural frequency constraints [6]. These algorithms have fundamentally revolutionized structural design by successfully navigating highly nonlinear constraints, sizing variables, and dynamic behavior boundaries. Historically, the application of these metaheuristics to frame structures has evolved from simple member sizing to complex structural system configurations where dynamic constraints prevent resonant states under environmental or mechanical vibrations. However, despite these

advancements, studies comprehensively focusing on high-dimensional planar and spatial steel frame structures that represent the core of modern multi-story buildings remain remarkably scarce in the literature.

In contrast to the limited, yet growing, body of research on frame structures, evolutionary and metaheuristic optimization algorithms have been extensively investigated, benchmarked, and widely utilized for the sizing and layout design of truss structures. Key pioneering and recent studies in this domain include artificial intelligence through simulated evolution [7], adaptation in natural and artificial systems [8], genetic algorithms [9], differential evolution (DE) [10], evolution strategies [11], artificial immune systems [12], artificial bee colony (ABC) [13], dolphin echolocation [14], ant lion optimizer [15], thermal exchange optimization [16], and the cyclical parthenogenesis algorithm [17]. Furthermore, for the size and shape optimization of truss structures under dynamic and frequency constraints, several computational approaches have been successfully implemented, such as the chaotic biogeography algorithm [18], enhanced biogeography-based optimization (Enhanced BBO) [19], two-dimensional colliding-bodies optimization (2D CBO) [20], colliding-bodies optimization with multiple frequency constraints [21], adaptive and improved symbiotic organisms search (SOS) algorithms [22,23], the hybrid CSS-MBLS method [24], and strategies combining migration with differential evolution [25].

Moving beyond these classical approaches, the landscape of structural mechanics within the last few years has rapidly shifted toward advanced, adaptive, and intelligent computational paradigms to resolve the stagnation, local minima entrapment, and high computational costs traditional methods suffer from. Reflecting this trend, in contemporary studies published recently (2025–2026), adaptive metaheuristics have gained significant attention, where algorithm-specific control parameters or search operators are dynamically tuned during the iteration process based on population diversity and continuous feedback from the search space [26]. Concurrently, the computational efficacy of metaheuristics has been increasingly documented for complex steel spatial structures, 3D space frames, and high-dimensional networks. For instance, recent studies have explored multi-objective variations for spatial networks [27,28], circulatory system-based optimization layouts [29,30], and dandelion optimization algorithms considering structural soil-class boundary environments [31]. Furthermore, complex topologies under free vibration have been evaluated using single-step hybrid evolutionary models [32], while high-dimensional dome trusses and space frames have been optimized utilizing advanced bonobo and hybrid slime mold–Jaya algorithms with online distributed computing setups [33–35].

To further alleviate the heavy computational burden associated with repetitive finite element analyses (FEAs) under dynamic and frequency constraints, surrogate-assisted optimization approaches utilizing Kriging, radial basis functions, or response surface methodologies have been widely adopted to approximate structural responses [36,37]. Parallel to these metamodels, machine-learning-driven structural design methods integrating artificial neural networks (ANNs) or deep learning frameworks have emerged to predict critical structural behaviors directly, bypassing heavy gradient calculations and accelerating the evolutionary search process efficiently [38,39]. However, while gradient-based sensitivity analysis, topology optimization with dynamic constraints, and ML-assisted surrogates show capability, they often introduce severe mathematical complexity in gradient derivations, exhibit high sensitivity to initial configurations, or require extensive training datasets and rigorous hyperparameter tuning.

The Jaya Algorithm (JA), proposed by Rao (2016) [40], is a relatively recent metaheuristic optimization method characterized by its simplicity and lack of algorithm-specific parameters. The JA operates based on the principle of approaching the best solution while avoiding the worst solution. Although the JA has demonstrated promising results across diverse engineering applications, such as stability enhancement in automatic voltage reg-

ulator systems [41] and the classification of agricultural diseases using optimized deep neural networks [42], its convergence speed and robustness can still be improved.

This study proposes a parameter-free Jaya algorithm (PFJA) that automatically enhances the search process without introducing additional control parameters. This study is derived from the Ph.D. dissertation of the first author, titled “Optimum design of structural systems with natural frequency constraints using Adaptive Jaya Algorithm” [43], completed at Dicle University in 2021.

Furthermore, this work represents a significant extension of the preliminary research published by Degertekin et al. [44], following two distinct mechanics phases. While the first phase governed the layout–sizing optimization of truss structures under purely axial behaviors [44], the current study represents the independent second phase of this research line, shifting the scientific contribution entirely to planar and spatial steel frame structures under dynamic constraints. Unlike the axial-only mechanics investigated in preliminary works, frame optimization introduces coupled axial–flexural interactions where the natural frequencies are highly sensitive to member bending stiffness (EI) and rotational continuity at rigid joint connections. This physical behavior creates a highly non-convex and higher-dimensional search space. To address this, a specialized self-adaptive constraint-handling scheme is integrated into the PFJA framework to isolate active frequency boundaries (ω_i) without manual parameter tuning. Furthermore, this work bridges the gap between theoretical optimization and structural engineering code verification by cross-validating all optimal design configurations via independent SAP2000 v20 database models [45], ensuring both computational efficiency and physical structural fidelity.

The effectiveness of PFJA is investigated through the optimal design of planar and spatial steel frame structures under natural frequency constraints. The frequency criteria (ω_i) applied as constraints herein are selected in strict accordance with established structural benchmark problems in the literature to ensure a systematic, controlled, and unbiased numerical comparison against alternative metaheuristic techniques.

This study presents five benchmark design examples to assess the numerical performance of PFJA. The test problems are divided into two categories: (i) size optimization of planar frame structures, including a two-story planar frame, a seven-story planar frame, and a ten-story planar frame, and (ii) size optimization of space frames, comprising a single-story spatial frame, and a ten-story spatial frame considered in both continuous and discrete forms.

The rest of this manuscript is structured as follows. Section 2 outlines the mathematical formulation and constraints of the frame optimization problem. Section 3 introduces the proposed parameter-free Jaya algorithm (PFJA) and details its algorithmic implementation for the sizing design of frame structures under dynamic frequency limits. In Section 4, the numerical performance of the proposed methodology is demonstrated through various benchmark design examples, and the comparative optimization results are discussed. Lastly, Section 5 presents the concluding remarks and outlines directions for future research.

2. Optimization Problem of Frame Structures

The main objective of this research is to minimize the total structural weight of steel frame systems while ensuring that the specified natural frequency constraints are strictly satisfied. The sizing optimization problem for a frame structure consisting of n_m members can be mathematically formulated as follows:

$$\text{Determine } \{A\} = [A_1, A_2, \dots, A_{d_1}];$$

$$\text{Minimize } W(\{A\}) = \sum_{i=1}^{n_m} \rho_i A_i L_i \quad (1)$$

Subject to $\omega_k \leq \omega_k^u$

$$\omega_l \geq \omega_l^l$$

$$A_i^{\min} \leq A_i \leq A_i^{\max}, \quad i = 1, 2, \dots, d_1$$

where $W(\{A\})$ represents total structural weight; $\{A\}$ denotes the vectors of design variables corresponding to member cross-sectional areas; A_i is the cross-sectional area of the i -th structural element, limited by lower and upper bounds $A_i^{\min}$ and $A_i^{\max}$; ρ_i and L_i correspond to the material density and length of member i -th; ω_k and ω_k^u denote the k -th natural frequency and its allowable upper limit; and ω_l and ω_l^l represent the l -th natural frequency and its prescribed lower bound.

To enforce natural frequency restrictions, a penalty-based approach is utilized. Accordingly, the augmented objective function is defined as:

$$\varphi(A) = W(A) \times (1 + v)^\varepsilon \quad (2)$$

where ε is the penalty exponential factor, taken as 2 in this paper. The penalty term v accounts for any violation of the frequency constraints and is defined as:

$$v = \sum_{k=1}^{nk} v_{\omega}^k + \sum_{l=1}^{lk} v_{\omega}^l \quad (3)$$

where nk and lk are the numbers of natural frequencies with upper and lower bounds, respectively. The individual penalties v_{ω}^k and v_{ω}^l corresponding to the k -th and l -th natural frequencies are as follows:

$$v_{\omega}^k = \begin{cases} 0 & \text{if } \omega_k \leq \omega_k^u \\ \left| \frac{\omega_k - \omega_k^u}{\omega_k^u} \right| & \text{if } \omega_k > \omega_k^u \end{cases} \quad (4)$$

$$v_{\omega}^l = \begin{cases} 0 & \text{if } \omega_l \geq \omega_l^l \\ \left| \frac{\omega_l - \omega_l^l}{\omega_l^l} \right| & \text{if } \omega_l < \omega_l^l \end{cases}$$

In frame analysis, the characteristics of structural members cannot be fully represented by the cross-sectional area alone. Hence, it is advantageous to relate secondary parameters (i.e., other sectional properties) to primary design variables (cross-sectional areas), thereby ensuring that the optimization problem remains continuous [6]. Based on this approach, the empirical correlations between the cross-sectional area and secondary sectional properties for wide-flange steel sections, adopted from the benchmark formulation in Ref. [6] and based on AISC section data [46], are used as follows:

$$I_z = \begin{cases} 4.6248 A^2, & 0 < A < 44.2 \text{ in}^2 \\ 256A - 2300, & 44.2 < A < 88.3 \text{ in}^2 \end{cases} \quad (5)$$

$$I_y = \begin{cases} 0.1248 A^2, & 0 < A < 61.8 \text{ in}^2 \\ 91.207A - 5225.59, & 61.8 < A < 67.6 \text{ in}^2 \\ 17.618A - 255.29, & 67.6 < A < 88.3 \text{ in}^2 \end{cases} \quad (6)$$

$$J = 0.0072 A^2, \quad 0 < A < 88.3 \text{ in}^2 \quad (1 \text{ in}^2 = 6.4516 \text{ cm}^2) \quad (7)$$

It should be noted that all structural frame models evaluated herein strictly replicate established benchmark problems from the literature to ensure mathematically sound and fair comparative assessments. While the empirical continuous relationships in Equations (5)–(7) are adopted to maintain a smooth and continuous search domain consistent with these reference formulations, they serve as preliminary sizing estimators during the evolutionary search phase. To guarantee that these continuous scaling approximations do not induce critical errors regarding weak-axis bending or complex torsional modes, all final

optimal profile configurations are cross-verified against discrete structural databases. This verification involves comparative evaluations against standard discrete AISC [46] section tables and full-scale 3D finite element validation models executed in SAP2000 v20 [45], ensuring high fidelity in the predicted dynamic characteristics of the frame systems.

3. Optimization Algorithms

3.1. Jaya Algorithm (JA)

The JA is a population-based metaheuristic that explores the search domain by directing candidate solutions toward the current best while steering them away from the worst. Apart from two standard parameters, population size (ps) and maximum iteration count (it_{max}), the JA does not rely on any algorithm-specific parameters. Initially, the JA randomly generates an initial population of frame design according to the specified population size. The JA is simple to implement and relies on a single updating expression to generate new candidate designs. Let $(A)_{i,l,it}$ represent the value of the it -th design variable for the l -th candidate at iteration it . This value is updated according to the following scheme:

$$(A)_{i,l,it}^{new} = (A)_{i,l,it} + r_{1,i,it}((A)_{i,best,it} - |(A)_{i,l,it}|) - r_{2,i,it}((A)_{i,worst,it} - |(A)_{i,l,it}|) \quad (8)$$

In Equation (8), $(A)_{i,l,it}^{new}$ is the newly generated value for the design variable $(A)_{i,l,it}$; $r_{1,i,it}$ and $r_{2,i,it}$ are two random real numbers drawn from the interval $[0,1]$ for the i -th design variable at the it -th iteration; $(A)_{i,best,it}$ is the value of the i -th design variable for the current best design $(A)_{best,it}$; and $(A)_{i,worst,it}$ is the value of the i -th design variable for the worst design $(A)_{worst,it}$ present in the population. The terms $r_{1,i,it}((A)_{i,best,it} - |(A)_{i,l,it}|)$ and $-r_{2,i,it}((A)_{i,worst,it} - |(A)_{i,l,it}|)$ represent the tendencies of the solution to approach the best design and to move away from the worst design, respectively. The random factors r_1 and r_2 ensure effective exploration of the search space. The use of absolute values $|(A)_{i,l,it}|$ further enhances the exploration capability of the JA [40].

If the newly generated design $(A)^{new}$ outperforms the existing design $(A)^{pre}$ stored in the population, it replaces the previous one; otherwise, $(A)^{pre}$ is retained unchanged. This procedure is repeated for all frame designs in the population, thereby completing one iteration. The process is terminated upon reaching the specified maximum iteration limit.

This strategy has also been successfully applied in other recent studies by the present authors [43,44,47]. It should be highlighted that the modified Jaya algorithm (MJA) proposed in [44,47] incorporates an additional screening mechanism to enhance the computational efficiency of the standard JA. Within this framework, only the structural weight of a newly generated candidate design ($W(A)^{new}$) is initially estimated. A full structural analysis, including penalty function evaluation, is performed selectively. In particular, when the previously accepted design $(A)^{pre}$ is feasible, and the newly generated design yields a higher structural weight irrespective of constraint violations (i.e., $W(A)^{pre} < W(A)^{new}$), the new candidate is considered to lie along a non-descent search direction and is therefore discarded without further evaluation. Otherwise, comprehensive structural analysis and constraint verification are carried out. This selective evaluation strategy effectively reduces unnecessary computational effort and has also been successfully implemented in the authors' recent studies [48,49].

3.2. Parameter-Free Jaya Algorithm (PFJA)

In this paper, several modifications are introduced to the standard JA to improve computational efficiency and convergence performance. Although the conventional JA requires the user to specify the population size (ps) and maximum iteration number (it_{max}), the proposed PFJA replaces these user-defined settings with an initial population rule, an adaptive population-size update, and a convergence-based stopping criterion. The stand-

and JA typically requires multiple trial runs to determine suitable parameter settings, which are often problem-dependent and computationally expensive. To address this issue, PFJA initializes a population of size $(10 \times nd)$, where nd is the total number of design variables. The initial population is generated as follows:

$$A_{i,l}^0 = A_i^{\min} + \text{rand}_{i,l}(A_i^{\max} - A_i^{\min}) \quad i = 1, \dots, d_1; \quad l = 1, \dots, ps \quad (9)$$

Here, $\text{rand}_{i,l}$ is random number sampled from the interval $[0,1]$ to define the i -th sizing variable and the l -th design in the initial population.

In each iteration, the population size is modified according to the following formulation [50]:

$$ps_{\text{next}} = \text{round}(ps_{\text{current}} + \text{rand} \times ps_{\text{current}}) \quad (10)$$

where ps_{current} and ps_{next} are the population sizes in the current and next iterations, respectively, and rand is a random number uniformly distributed in $[-0.5, 0.5]$. Consequently, the population size may increase or decrease during the optimization process, depending on whether rand is positive or negative. According to Equation (10), the new population size ps_{next} can be at most 50% larger than ps_{current} and at least 50% of ps_{current} . This range of variation is intended to maintain sufficient diversity within the population without excessively increasing computational cost.

If $ps_{\text{next}} > ps_{\text{current}}$, the entire current population is carried over to the next generation, and the remaining $(ps_{\text{next}} - ps_{\text{current}})$ positions are populated using the best individuals of the current set. However, the strategy in [50] is modified in this paper to mitigate potential stagnation caused by duplicate solutions. For example, consider a current population of six individuals $\{A, B, C, D, E, F\}$ ranked from best to worst. If the next generation size is nine, the procedure in [50] would yield $\{A, B, C, D, E, F, A, B, C\}$, leading to repeated solutions. To avoid this issue, PFJA randomly selects one design variable for each of the $(ps_{\text{next}} - ps_{\text{current}})$ additional individuals and introduces a random perturbation to either a sizing or layout variable, thereby preserving population diversity.

To enhance the probability of generating improved candidate solutions, PFJA further perturbs the k -th variable ($k = 1, \dots, nd$) of the r -th additional design ($r = ps_{\text{current}} + 1, \dots, ps_{\text{next}}$) to promote a descent direction in the objective function $W(A)$. Let $(A)_r$ and W_r denote the r -th candidate design and its corresponding objective value, respectively. The deviations in the design vector and objective function are defined $\Delta(A)_r = (A)_r - (A)_{\text{opt}}$, respectively, with respect to the current best solution. If $\Delta W_r < 0$, the candidate $(A)_r$ is considered promising and is retained in the population.

Conversely, If $\Delta W_r > 0$, the candidate does not improve the current best solution and is deemed less beneficial for exploitation. In such cases, PFJA applies a mirroring operation, generating a reflected counterpart $(A)_{\text{r,mirr}}$ defined as:

$$(A)_{\text{r,mirr}} = (1 + \eta_{\text{mirr}})(A)_{\text{opt}} - \eta_{\text{mirr}}(A)_r \quad (11)$$

where η_{mirr} denotes a random number uniformly distributed within the interval $(0,1)$. This mirroring mechanism is primarily intended to transform a non-descent search direction, $\Delta(A)_r$, into a descent direction defined by $[(A)_{\text{r,mirr}} - (A)_{\text{opt}}]$. The stochastic coefficient η_{mirr} serves as a scaling factor that controls the step size, thereby pre-venting excessively large reductions in the objective (cost) function that could otherwise drive candidate solutions out of feasible regions into infeasible domains. In addition, the stochastic generation of the mirrored trial solution $(A)_{\text{r,mirr}}$ helps mitigate stagnation, particularly when candidate solutions tend to oscillate around the current best solution without further improvement.

It should be emphasized that Equation (8) inherently defines a descent direction for sizing optimization problems in which the objective function is linear in the design variables, and its gradient remains constant throughout the search space. However, this prop-

erty does not generally extend to layout optimization problems, in which the objective function exhibits nonlinear dependence on nodal coordinates and the associated sensitivities vary across the design domain.

To address this issue, the PFJA evaluates the objective function value of the mirrored solution, denoted as W_r^{mirr} , and incorporates $(A)_r^{\text{mirr}}$ into the subsequent population only if the condition $W_r^{\text{mirr}} < W_{\text{opt}}$ is satisfied. Otherwise, alternative scenarios may arise:

- (i) In the case where $W_r^{\text{mirr}} > W_r > W_{\text{opt}}$, the PFJA discards the mirrored solution $(A)_r^{\text{mirr}}$ and retains the original trial design by defining a temporary solution as $(A)_r^{\text{temp}} \equiv (A)_r$. The corresponding objective function value, W^{temp} , is then evaluated;
- (ii) Conversely, when $W_r > W_r^{\text{mirr}} > W_{\text{opt}}$, the PFJA rejects the original trial design $(A)_r$ and instead adopts the mirrored solution by defining $(A)_r^{\text{temp}} \equiv (A)_r^{\text{mirr}}$, followed by the evaluation of its associated objective function value, W^{temp} .

The temporary solution, $(A)_r^{\text{temp}}$, is subsequently compared with the original design, $(A)_r^{\text{orig}}$, which has been randomly perturbed to prevent duplication within the population. Let W^{orig} denote the objective (cost) function value associated with $(A)_r^{\text{orig}}$. If the condition $W^{\text{temp}} < W^{\text{orig}}$ is satisfied, the temporary design $(A)_r^{\text{temp}}$ is admitted into the new population.

Otherwise, when $W^{\text{temp}} > W^{\text{orig}}$, a different design variable of $(A)_r^{\text{orig}}$ is randomly selected and perturbed to generate a new trial solution, denoted as $(A)_r'$. This newly generated design is then evaluated following the same procedure applied to $(A)_r$.

Numerical experiments performed in this paper indicate that the proposed strategy effectively restricts the occurrence of duplicate candidate solutions to less than 1%.

In summary, when $ps_{\text{next}} > ps_{\text{current}}$, additional $(ps_{\text{next}} - ps_{\text{current}})$ high-quality designs are generated, thereby increasing design freedom and refining its search capability near promising solutions.

When $ps_{\text{next}} < ps_{\text{current}}$, the original approach described in [50] retains only the top ps_{next} individuals from the current population for transfer to the subsequent generation. In contrast, the PFJA further enhances this process by introducing an additional improvement step, whereby one randomly selected design variable of each candidate solution to be transferred is perturbed. The resulting trial solutions are accepted only if they improve on the current best solution or, at a minimum, outperform the corresponding original design after PFJA has randomly perturbed it. Otherwise, such trial solutions are discarded.

When $ps_{\text{next}} = ps_{\text{current}}$, the original strategy in [50] leaves the current population unchanged. As in previous cases, PFJA randomly perturbs designs to improve candidate solutions for the next iteration. Newly generated designs are accepted only if they yield an improvement over the current best solution or, at a minimum, demonstrate superior performance relative to their corresponding counterparts in the existing population.

When $ps_{\text{next}} < nd$, the population size is adjusted to match the number of design variables, such that $ps_{\text{next}} = nd$. In the original method presented in [50], only the top nd individuals from the current population were directly carried over to the next generation. In contrast, the PFJA employs an alternative strategy grounded in sensitivity analysis.

Given that the objective function $W(A)$ is explicitly defined with respect to sizing variables, the exact sensitivity measures $\partial W / \partial A_i$ ($i = 1, \dots, d_1$) can be determined. Accordingly, PFJA evaluates the sensitivities for the best nd candidate solutions and, for each design, randomly perturbs the variable corresponding to the highest sensitivity. A newly generated trial solution is discarded if it fails to improve either the current best solution or the associated perturbed design.

The aforementioned modifications have led to an approximate 20% reduction in the computational cost of PFJA optimization runs compared to the implementation based on the original population-size adaptation scheme proposed in Ref. [50]. This improvement can be attributed to the fact that all population-refinement strategies employed by PFJA

during population-size adjustments are inherently grounded in an elitist framework, with the primary objective of continuously enhancing candidate solutions.

In the conventional JA implementation, the search process is iterated until a predefined maximum number of iterations is reached. However, selecting the parameter it_{max} appropriately generally requires multiple preliminary runs for each design problem. In contrast, PFJA eliminates this limitation by not prescribing a fixed maximum number of iterations.

Instead, the optimization process terminates according to an adaptive criterion. Specifically, PFJA automatically halts the search once the ratio of the standard deviation of the penalized objective function values within the population to their mean value falls below a user-defined convergence threshold.

In essence, this criterion ensures that the algorithm terminates when the population converges to a homogeneous set of candidate solutions representing the same design. That is, the stopping condition is satisfied when the following relationship holds [51]:

$$\frac{STD[\varphi(A,x)^1, \varphi(A,x)^2, \dots, \varphi(A,x)^{ps}]}{\sum_{i=1}^{ps} \varphi(A,x)^i / ps} \leq \epsilon_{conv} \quad (12)$$

In this context, $\varphi(A)^i$ denotes the penalized objective function value corresponding to the i -th design ($i = 1, \dots, ps$) within the population. The convergence tolerance ϵ_{conv} is set to 10^{-15} in this paper, consistent with double-precision floating-point accuracy; therefore, PFJA should be interpreted as eliminating the user-defined population size and maximum iteration number rather than as being completely free of numerical stopping tolerances. This criterion ensures that all candidate solutions in the population are identical to their significant digits.

It should be emphasized that while a tolerance of 10^{-15} in Equation (12) has no practical physical meaning for actual steel member fabrication sizing, this threshold is utilized strictly as a mathematical indicator of complete population homogeneity. Setting the criterion to the limit of double-precision accuracy guarantees that the optimization process concludes only when all candidate designs in the population have mathematically converged into a singular configuration in the search domain. As demonstrated by the benchmark frame examples in Section 4, this strict tolerance does not lead to an unnecessary waste of computational resources; owing to the highly aggressive convergence characteristics of the PFJA, the algorithm successfully satisfies this homogeneity condition while requiring significantly fewer structural analyses than the fixed budgets used in the competing literature studies.

It should be highlighted that the operational mechanics embedded within the PFJA are designed to eliminate user-dependent parametric tuning, thereby ensuring high reproducibility. The convergence tolerance ($\epsilon_{conv} = 10^{-15}$) acts strictly as a numerical stability threshold linked to computing environments' double-precision boundaries. Variations in this parameter (e.g., setting it to 10^{-10}) do not impact the final optimum structural weight (W) but merely induce minor alterations in total computational time, showcasing the stability of the stopping criterion.

Furthermore, the frequency and magnitude of diversity-enhancing operations are dynamically scaled by Equation (10) and bounded within the physical limits of the primary sizing variables (A_i^{min} and A_i^{max}), whereas secondary properties like the moment of inertia are automatically governed by the empirical formulations [Equations (5)–(7)]. The inherent statistical robustness of this parameter-free layout and sizing scheme is validated by executing 20 independent computational runs for each structural frame problem. The algorithm achieves highly stable convergence with remarkably narrow margins of dispersion, yielding standard deviations as low as 9.99 lb and 19.72 lb for the two-story and seven-story frames, respectively, regardless of the initial random seed.

To eliminate conceptual ambiguity regarding the terminology used herein, a distinction must be drawn between problem-dependent, algorithm-specific tuning parameters and standard dimensional or numerical control settings. While a strictly parameter-free computational procedure does not exist in a literal mathematical sense due to the inherent need for initialization and termination criteria, the proposed PFJA is entirely free from heuristic tuning parameters (such as the mutation rates in genetic algorithms or acceleration weights in particle swarm optimization) that typically require extensive empirical trial runs.

The control settings remaining within the PFJA framework are strictly foundational constants: the initial population multiplier ($10 \times nd$) serves merely as a dimension-proportional baseline to establish initial design space coverage, while the convergence tolerance ($\epsilon_{conv} = 10^{-15}$) represents a rigid machine-epsilon threshold for double-precision stability rather than an empirical tuning variable. Numerical experiments indicate that although successive population sizes (ps_{next}) evolve dynamically based on the previous state via Equation (10), the final structural optimization efficiency and convergence accuracy exhibit high robustness and insensitivity to these foundational boundaries.

The schematic representation of the proposed PFJA is presented in Figure 1. The PFJA procedure for the sizing and layout optimization of frame structures subjected to natural frequency constraints is carried out through the following steps:

- Step 1: PFJA initialization: The initial population is created by randomly generating $10 \times nd$ frame designs according to Equation (9). The penalized objective function ($\varphi(A)$) for each design is evaluated using Equations (1)–(4). The iteration counter is then set to $it = 0$.
- Step 2: Increase the iteration index by setting $it = it + 1$. If $it > 1$, the population size ps is updated using Equation (10), and the population is regenerated by applying elitist selection, mirroring, and/or sensitivity-based strategies (e.g., Equation (8)).
- Step 3: Determine the best and worst designs: The best design $\varphi(A)^{best}$ and the worst design $\varphi(A)^{worst}$ within the current population are determined. The design counter is then set to $id = 0$ ($id = 1, 2, \dots, ps$).
- Step 4: Advance the design index: $id = id + 1$.
- Step 5: Create new designs: Obtain a new design by updating all design variables of the id -th design using Equation (8).
- Step 6: If the preceding design satisfies feasibility conditions and the newly generated design results in a higher structural weight irrespective of penalty terms (i.e., $(A)_{pre}$ is feasible and $W(A)_{pre} < W(A)_{new}$), proceed to Step 8. Otherwise, proceed to Step 7.
- Step 7: Evaluate the penalized objective function of the newly generated design, ($\varphi(A)^{new,id}$), using Equations (1)–(4). If $\varphi(A)^{new,id} < \varphi(A)^{pre,id}$, update the population by substituting the previous id -th design with the new one. Otherwise, if $\varphi(A)^{new,id} > \varphi(A)^{pre,id}$, keep the id -th design unchanged.
- Step 8: If $id = ps$, continue to Step 9; else, return to Step 4 and repeat the procedure.
- Step 9: If Equation (12) is fulfilled, proceed to Step 10; in the opposite case, revert to Step 2 and continue the process.
- Step 10: End of PFJA: The feasible design with the minimum structural weight is recorded as the optimal solution, the results are reported, and the optimization process is concluded.

Defining the initial population size to $10 \times nd$ constitutes a distinctive aspect of the proposed PFJA. A widely observed characteristic of many Jaya-based variants reported in the literature is their low sensitivity to population size in practical applications. For example, Ref. [48] investigated two weight-minimization problems for frame structures with 44 and 81 sizing/layout variables, respectively. In this paper, the population size ranged

from 10 to 1000, yet the convergence performance showed negligible dependence on this broad range. Accordingly, the ratio of population size to the number of design variables varied from $10/81 = 0.1235$ to $1000/81 = 12.35$ for the 81-variable case, and from $10/44 = 0.2272$ to $1000/44 = 22.72$ for the 44-variable case. In PFJA, this ratio is initially set to 10 and may vary during the optimization process according to Equation (10). However, the population size can theoretically continue to increase over successive iterations, the numerical runs in this paper remained within the reported practical range. Therefore, the selected initial population size of $10 \times nd$ effectively spans the range investigated in [48]. As a result, no additional sensitivity analysis of the initial ratio of population size to the number of design variables is necessary for PFJA.

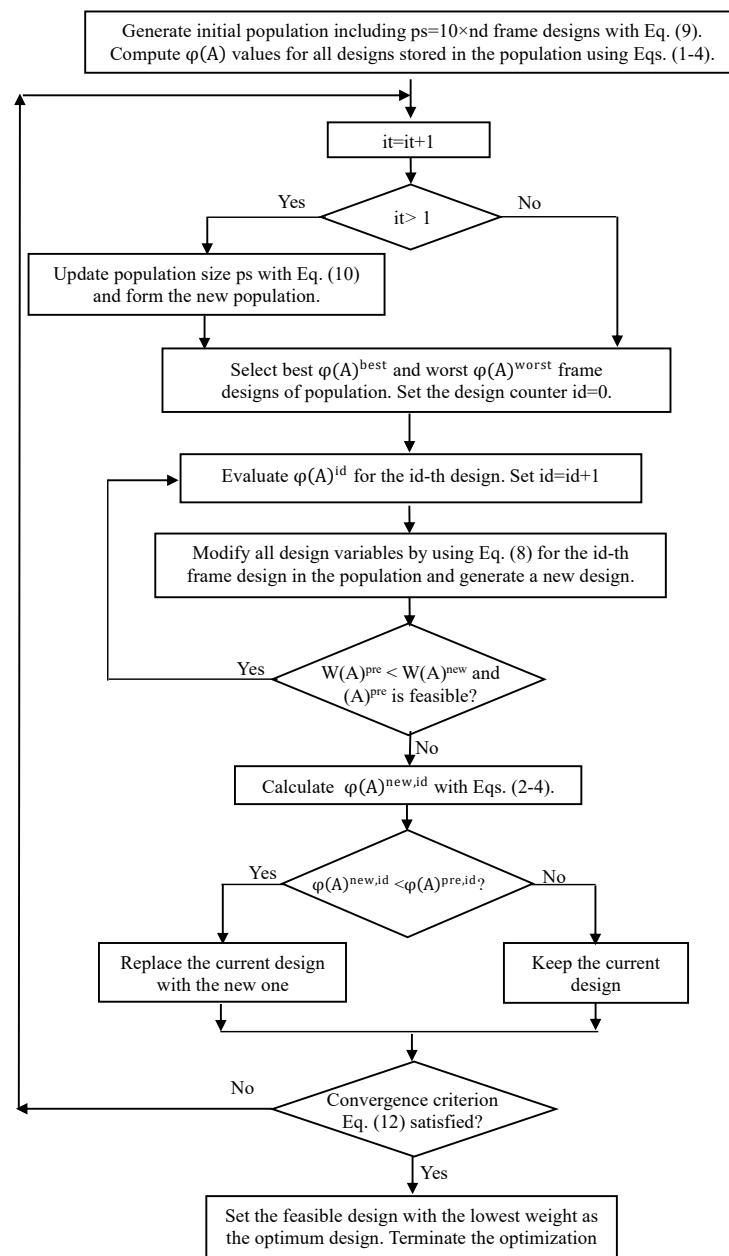


Figure 1. Flowchart of the PFJA for optimization of frame structures with natural frequency constraints.

3.3. Comparative Summary of JA, MJA, and PFJA

To provide a clear and rapid overview of the structural and operational developments introduced in this framework, the core algorithmic differences among the standard Jaya algorithm (JA) [40], the modified Jaya algorithm (MJA), and the proposed parameter-free Jaya algorithm (PFJA) [43,44,47] are systematically summarized in Table 1.

Table 1. Comparative summary of JA, MJA, and PFJA.

Algorithmic Features	Standard Jaya Algorithm (JA)	Modified Jaya Algorithm (MJA)	Parameter-Free Jaya Algorithm (PFJA)
User-Defined Parameters	Population size (ps) and max-imum iteration count (it_{max}).	Population size (ps) and max-imum iteration count (it_{max}).	None. Operates without any user-defined algorithmic tuning parameters.
Initial Population Setup	Randomly generated based on arbitrary or trial-and-error user selection.	Randomly generated based on arbitrary or trial-and-error user selection.	Automatically initialized with a dynamic rule scaled to the design variable count ($10 \times nd$).
Population Size (ps) Handling	Remains constant ($ps_{current} = ps_{next}$) throughout the entire optimization search.	Remains constant throughout the entire optimization search.	Dynamic Adaptation. Population size continuously adjusts, scales, or reduces up to 50% in each iteration.
Solution Diversity & Elitism	Standard update formula applies to all individuals; prone to duplicate solutions.	Employs an extra non-descent screening mechanism to filter out heavier designs early.	Advanced Diversity Control. Integrates mirror operations, perturbation strategies, and sensitivity analysis to suppress duplicate solutions to < 1%.
Structural Evaluation Strategy	Performs a full finite element structural analysis for every newly generated candidate solution.	Selectively performs structural analysis; skips constraint checks if structural weight exceeds the current baseline.	Embeds the selective evaluation framework into an elitist, adaptive population adjustment scheme to minimize unnecessary computational effort.
Termination / Stopping Criterion	Execution halts strictly upon reaching the fixed maximum iteration limit (it_{max}).	Execution halts strictly upon reaching the fixed maximum iteration limit (it_{max}).	Adaptive Convergence Threshold. Automatically terminates once the population converges to a homogeneous set based on standard deviation.

4. Numerical Examples

The computational performance and efficiency of the proposed parameter-free Jaya algorithm (PFJA) were systematically evaluated by solving five benchmark weight-minimization design problems for planar and spatial steel frame structures subject to dynamic natural frequency constraints. To establish a rigorous comparative assessment, the optimization results obtained via PFJA were compared directly with the best-reported outcomes of the modified Jaya algorithm (MJA) [43,44,47], as well as other advanced state-of-the-art metaheuristics documented in the literature [6]. The primary metrics of comparison include the minimum structural weight achieved, the standard deviation of the runs, and the total number of structural analyses (NSAs) required to reach convergence. Furthermore, to mathematically validate the statistical significance of the performance differences between the MJA and the proposed PFJA, a non-parametric Wilcoxon rank-sum test

was systematically executed and evaluated individually for each frame design example based on the computed p -values.

To execute the iterative optimization loop with maximum computational efficiency, the dynamic finite element analyses (FEAs) were performed using in-house 2D and 3D frame analysis codes programmed by the authors within the MATLAB R2020b environment. During the active optimization search, external structural software packages and application programming interfaces (APIs) were excluded to eliminate the heavy computational overhead associated with repetitive input–output file transfers and software calling delays. However, once the proposed PFJA converged to the final optimum cross-sectional design vector, the commercial finite element package SAP2000 v20 [45] was employed as an independent cross-verification tool. The final optimized profile configurations were explicitly modeled in SAP2000 v20 [45] to verify the accuracy of the structural weight, mode shapes, and the satisfaction of the natural frequency constraints (ω_i).

To evaluate the algorithmic robustness and eliminate the impact of stochastic variation, 20 independent optimization runs were executed for each benchmark problem. Each independent run was initiated with a distinct, randomly generated initial population according to Equation (9). The comparative results are comprehensively reported in terms of the best, worst, and mean structural weights, along with the standard deviation (SD) of the objective function values over the independent runs. Furthermore, the number of structural analyses (NSAs) and the percentage of constraint violation (CV) for the best-obtained design are documented. All optimization procedures and structural analyses were implemented on a personal computer equipped with an Intel Core i7-9750H CPU @ 2.60 GHz processor and 16.0 GB of RAM operating under a 64-bit Windows 10 platform. The material properties, cross-sectional area bounds, and specified natural frequency constraints for all evaluated benchmark frames are summarized in Table 2 [6].

Table 2. Material properties, area limits, and frequency constraints of benchmark steel frames.

Test Cases	Modulus of Elasticity E (lb/in ²) *	Material Density ρ (lb/in ³)	Poisson Ratio	Cross-Sectional Area Limits (in ²)	Natural Frequency Constraints (Hz)
Planar two-story frame	3×10^7	0.28	0.3	$3 < A < 88.28$	$\omega_1 \geq 5, \omega_2 \geq 18, \omega_3 \geq 35$
Planar seven-story frame	3×10^7	0.28	0.3	$7.9187 \leq A \leq 88.28$	$\omega_1 = 1.6234$
Planar ten-story frame	3×10^7	0.28	0.3	$3 < A < 88.28$	$\omega_1 \geq 2, \omega_2 \geq 7, \omega_3 \geq 15$
Spatial one-story frame	3×10^7	0.28	0.3	$0.1 \leq A \leq 88.3$	$\omega_1 \geq 5, \omega_2 \geq 9, \omega_3 \geq 15$
Spatial ten-story frame (Continuous variable)	3×10^7	0.28	0.3	$0.1 \leq A \leq 88.3$	$\omega_1 \geq 0.5, \omega_2 \geq 0.8, \omega_3 \geq 1.2$
Spatial ten-story frame (Discrete variable)	3×10^7	0.28	0.3	$0.1 \leq A \leq 88.3$	$\omega_1 \geq 0.5, \omega_2 \geq 0.8, \omega_3 \geq 1.2$

* 1 in = 2.54 cm; 1 lb = 4.448×10^{-3} kN.

4.1. The Planar Two-Story Frame

The first steel frame design example is the planar two-story frame structure shown in Figure 2. The structure has six design variables, as shown in Figure 2 and listed in Table 3. A uniformly distributed load of 10 lb/in (1 lb/in = 0.17513 kN/m) has been added to all beams of the frame system. The structure was previously optimized by Zakian (2019) [6] using different methods (PSO, CSS, TLBO, GWO, and IGWO). Table 3 compares the results obtained from PFJA, MJA, and other methods. Table 4 presents the first three natural frequencies corresponding to the design results in Table 3.

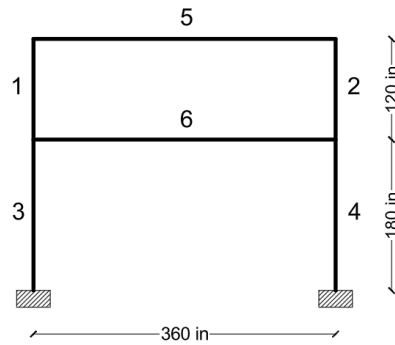


Figure 2. Schematic of the planar two-story frame structure [6].

Table 3. Comparison of optimization results for the planar two-story frame problem.

Design Variables (in ²) *	PSO [6]	CSS [6]	TLBO [6]	GWO [6]	IGWO [6]	MJA	PFJA
1	10.4830	3.7755	10.4979	3.8064	10.7295	3.0000	3.0000
2	3.7418	10.4271	3.7411	10.5934	3.7342	10.5818	10.6221
3	29.7480	3.0065	29.7384	3.0000	29.5943	3.8320	3.8315
4	3.0000	29.7753	3.0000	29.7558	3.0002	30.2273	30.1994
5	3.0000	3.0017	3.0000	3.0225	3.0011	3.0000	3.0000
6	3.0000	3.0034	3.0000	3.0000	3.0000	3.0000	3.0000
Best weight (lb) **	2733.2520	2734.7324	2733.2460	2741.7958	2733.6560	2777.7406	2777.6554
Mean weight (lb)**	2795.2559	2778.2240	2733.5099	2795.5196	2736.7087	2787.9090	2787.73820
SD (lb) **	126.1530	145.6291	0.3566	27.1642	4.9400	11.1924	9.99500
CV (%)	7.7976	7.6703	7.7985	7.7267	7.7828	0.00000	0.00000
NSA	2000	2000	2000	2000	2000	2070	1960

* 1 in² = 6.4516 cm²; ** 1 lb = 0.4536 kg.

Table 4. Natural frequencies of the optimized planar two-story frame designs.

Frequency Number (Hz)	PSO [6]	CSS [6]	TLBO [6]	GWO [6]	IGWO [6]	MJA	PFJA
1	5.0000	5.0002	5.0000	5.0122	4.9999	5.0001	5.0000
1 *	4.9488	4.9491	4.9488	4.9606	4.9482	5.0002	5.0000
2	18.7548	18.7198	18.7648	18.8507	18.9200	18.5433	18.5698
2 *	18.3309	18.2960	18.3409	18.4281	18.4973	18.5434	18.5698
3	35.0011	35.0113	35.0001	35.1406	35.0068	35.0028	35.0009
3 *	32.2709	32.3154	32.2705	32.2957	32.2760	35.0030	35.0010

* The values of the first three natural frequencies were extracted from SAP2000 v20 [45].

In Table 3, it was found that all the methods used by Zakian (2019) [6]—namely PSO, CSS, TLBO, GWO, and IGWO—violated the natural frequency constraints at rates ranging from 7.6703% to 7.7985%. In contrast, PFJA achieved the best design that satisfied the frequency constraints, with a structural weight of 2777.6554 lb. Thus, among the compared designs, PFJA provides the lightest feasible solution satisfying all prescribed natural frequency constraints. Furthermore, Table 3 shows that PFJA required 1960 structural analyses, whereas the other methods required 2000 structural analyses.

The optimum design obtained with PFJA was modeled in SAP2000 v20, and the results for the first three modes are presented in Figure 3a–c. As shown in Figure 3, the mode values obtained from SAP2000 v20 and PFJA are identical.

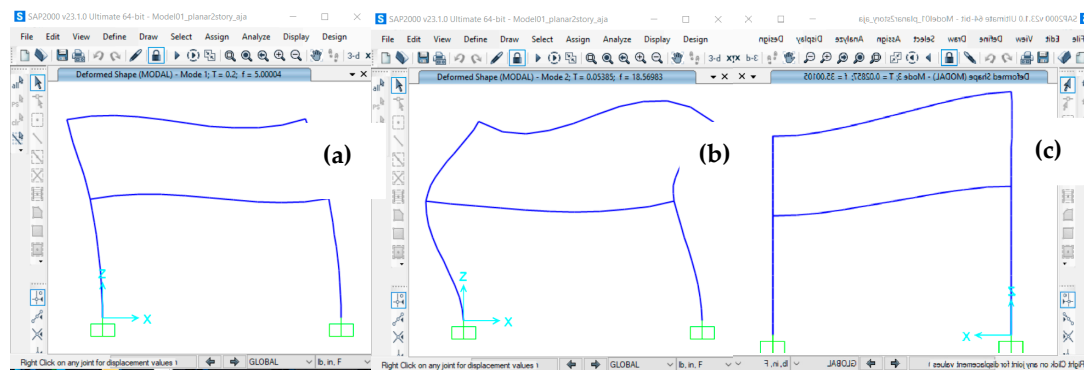


Figure 3. The first 3 modes of two-story planar steel frame structure modeled with SAP2000 v20. (a) First mode. (b) Second mode. (c) Third mode.

The convergence curves for PFJA and MJA, compared with those of the other methods, are shown in Figure 4. The presented convergence curves demonstrate that PFJA and MJA are faster than the other methods from the outset and possess strong convergence capability.

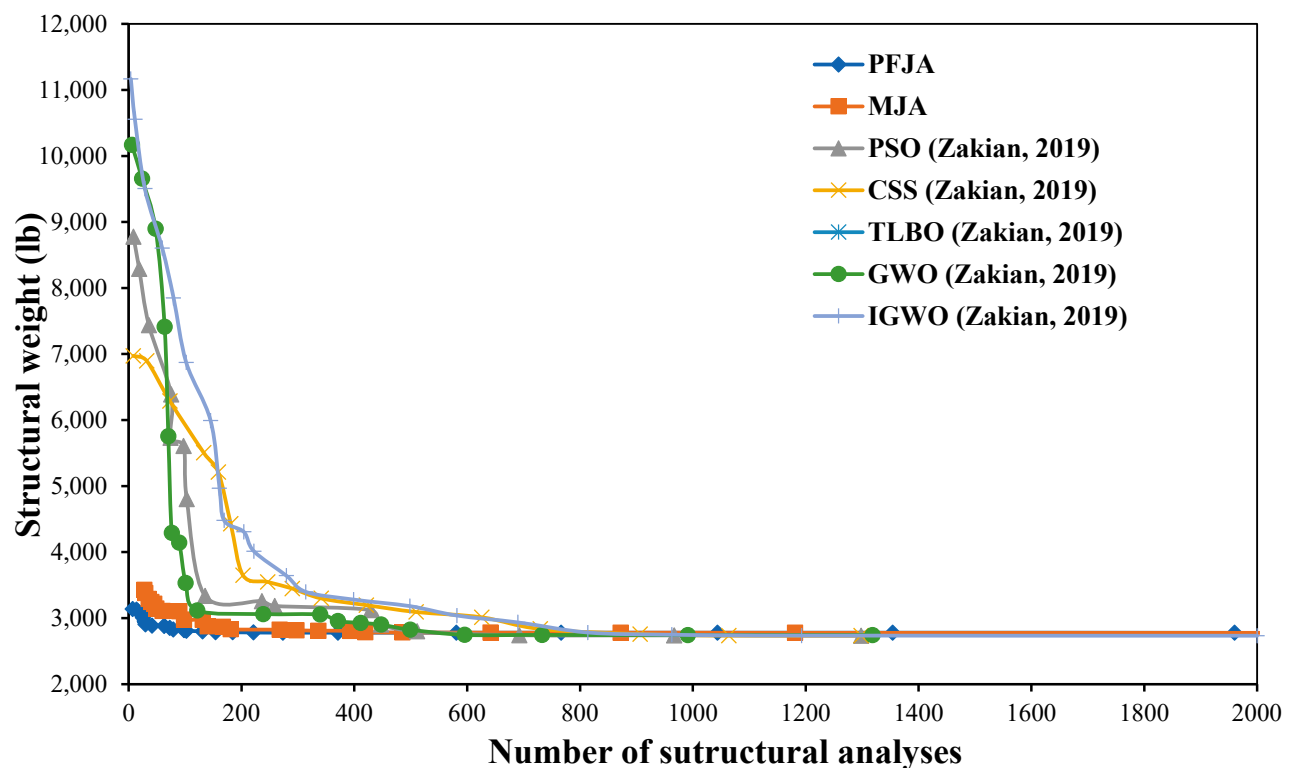


Figure 4. Comparison of the convergence curves recorded for the two-story planar problem (1 lb = 0.4536 kg).

The Wilcoxon rank-sum test results for the planar two-story frame are illustrated in the p -value heatmap shown in Figure 5. The calculated p -value between the MJA and PFJA is 0.989. Since this value is substantially higher than the threshold of 0.05, the performance difference between the two algorithms is statistically insignificant. In this low-dimensional and structurally simpler design space, both algorithms successfully converge to similar global optimum regions with equivalent robustness, indicating that the baseline algorithm already operates at maximum efficiency for smaller problems.

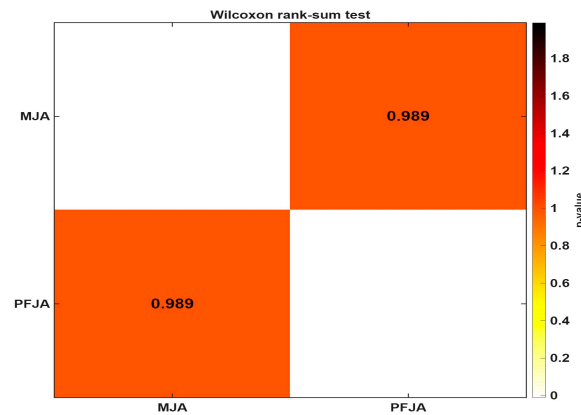


Figure 5. *p*-Values from the Wilcoxon rank-sum test for planar two-story frame optimization.

4.2. The Planar Seven-Story Frame

The second steel frame design problem in this paper is the planar seven-story frame shown in Figure 6. The structure has 21 design variables shown in Figure 6 and provided in Table 5. A uniformly distributed load of 10 lb/in has been added to all beams of the frame system. This planar frame structure was previously optimized by Zakian (2019) [6] using PSO, CSS, TLBO, GWO, and IGWO. Table 5 compares the results obtained from PFJA, MJA, and other methods. Table 6 presents the first three natural frequencies corresponding to the design results in Table 5.

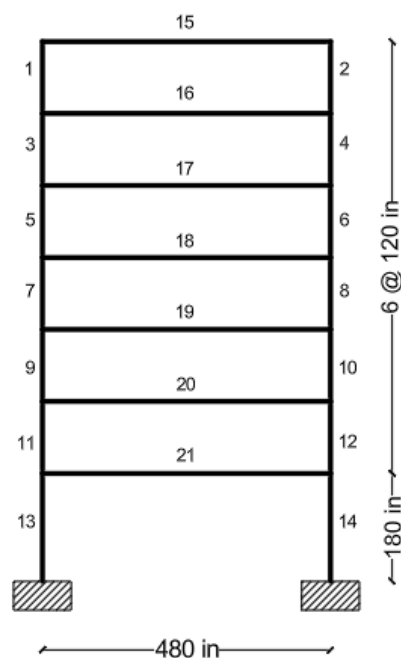


Figure 6. Schematic of the planar seven-story frame structure [6].

Table 5 shows that the methods used by Zakian (2019) [6] (PSO, CSS, TLBO, GWO, IGWO) violated the frequency limits, with varying rates ranging from 0.073% to 0.224%. In contrast, PFJA achieved the best design that satisfied the frequency limits, with a structural weight of 16,114.418 lb. Furthermore, Table 5 shows that PFJA required 3600 structural analyses, whereas the other methods required between 2000 and 4000.

Table 5. Comparison of optimization results for the planar seven-story frame problem.

Design Variables (in ²) *	PSO [6]	CSS [6]	TLBO [6]	GWO [6]	IGWO [6]	MJA	PFJA
1	7.919	7.970	7.919	7.919	7.920	7.919	7.919
2	7.919	7.954	7.920	7.919	7.919	7.919	7.919
3	7.919	7.951	7.920	7.919	8.099	7.919	7.919
4	7.919	7.940	7.919	7.919	7.937	7.919	7.919
5	7.919	8.159	7.921	7.919	7.977	7.919	7.923
6	15.969	8.030	7.919	8.802	8.733	7.919	7.919
7	7.919	8.014	9.494	7.919	9.716	7.924	7.919
8	11.134	9.196	7.920	14.193	8.061	9.486	9.478
9	26.711	11.869	7.919	7.919	8.456	11.429	11.326
10	7.919	8.026	11.166	7.999	10.099	7.939	7.966
11	44.194	8.009	13.746	14.397	14.256	7.919	7.919
12	7.919	13.415	7.919	10.512	7.923	14.071	14.074
13	71.522	7.992	40.479	8.983	41.524	7.919	7.919
14	7.919	41.860	7.919	46.167	7.919	41.238	41.121
15	7.919	7.922	7.919	7.919	7.920	7.919	7.919
16	7.919	7.926	7.920	7.919	7.919	7.919	7.919
17	16.399	8.677	9.515	7.919	9.251	9.540	9.588
18	7.919	13.187	13.002	14.785	12.849	12.896	12.845
19	7.919	14.160	14.337	12.640	14.860	14.437	14.395
20	7.919	14.860	14.651	16.087	13.937	14.266	14.376
21	7.919	8.049	7.919	7.919	7.919	7.919	7.919
Best weight (lb)**	18,015.072	16,142.397	16,105.118	16,625.483	16,123.887	16,114.502	16,114.418
Mean weight (lb) **	21,748.073	16,193.186	16,141.284	16,845.6255	16,148.840	16,133.946	16,136.586
SD (lb) **	3144.883	45.698	55.752	151.195	20.660	22.076	19.727
CV (%)	0.086	0.073	0.075	0.224	0.075	0.000	0.000
NSA	4000	2000	2200	4000	4000	3800	3600

* 1 in² = 6.4516 cm² ** 1 lb = 0.4536 kg.**Table 6.** Natural frequencies of the optimized planar seven-story frame.

Frequency Number	PSO [6]	CSS [6]	TLBO [6]	GWO [6]	IGWO [6]	MJA	PFJA
(Hz)							
1	1.6234	1.6234	1.6234	1.6282	1.6234	1.6234	1.6234
1 *	1.6220	1.6222	1.6222	1.6270	1.6222	1.6234	1.6234
2	4.9392	4.2478	4.2602	4.2784	4.2616	4.2671	4.2705
2 *	4.9304	4.2450	4.2569	4.2765	4.2585	4.2671	4.2705
3	8.6486	8.1862	8.1026	8.4829	8.2172	8.1309	8.1189
3 *	8.6599	8.1884	8.1044	8.4795	8.2191	8.1309	8.1189

* The values of the first three natural frequencies were extracted from SAP2000 v20 [45].

The optimum design obtained with PFJA was modeled in SAP2000 v20, and the results for the first three modes are presented in Figure 7a–c. As shown in Figure 7, the mode values obtained from SAP2000 v20 and PFJA are identical.

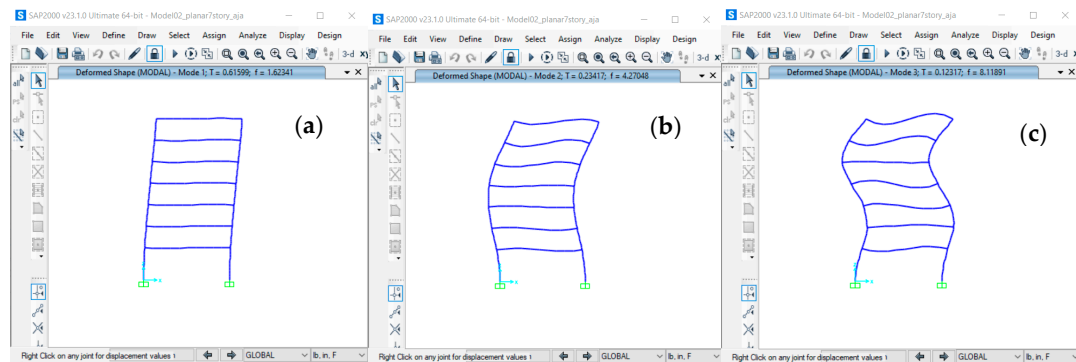


Figure 7. The first 3 modes of seven-story planar steel frame structure modeled with SAP2000 v20. (a) First mode. (b) Second mode. (c) Third mode.

The convergence curves for PFJA and MJA, compared with those of the other methods, are shown in Figure 8. As shown, PFJA converges faster than the other methods.

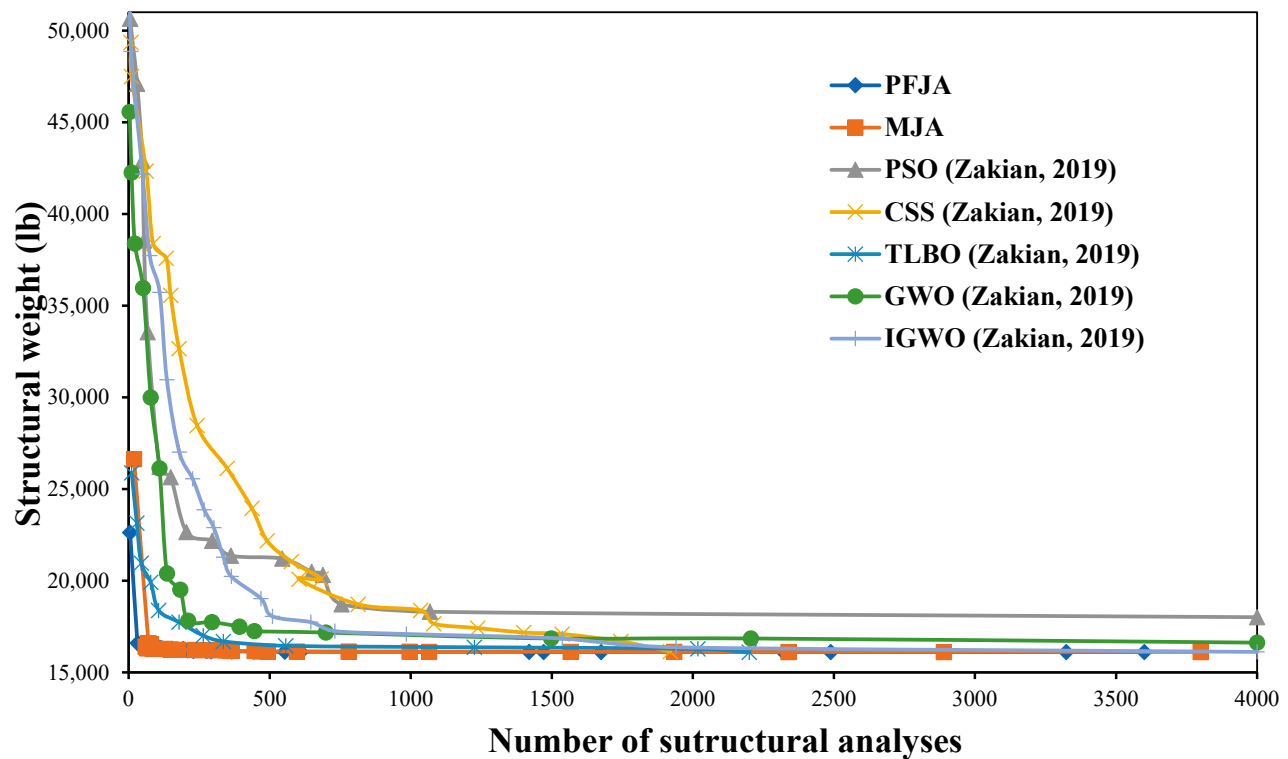


Figure 8. Comparison of the convergence curves recorded for the seven-story planar problem (lb = 0.4536 kg).

Figure 9 presents the statistical significance test heatmap for the planar seven-story frame, yielding a p -value of 0.473. Although the complexity of the frame is higher than the two-story model, the calculated p -value remains above 0.05. This demonstrates that both the MJA and PFJA maintain statistically equivalent convergence capabilities. The baseline stability is preserved under moderately increased dimensions, and both algorithms prove to be highly robust in navigating this search space.

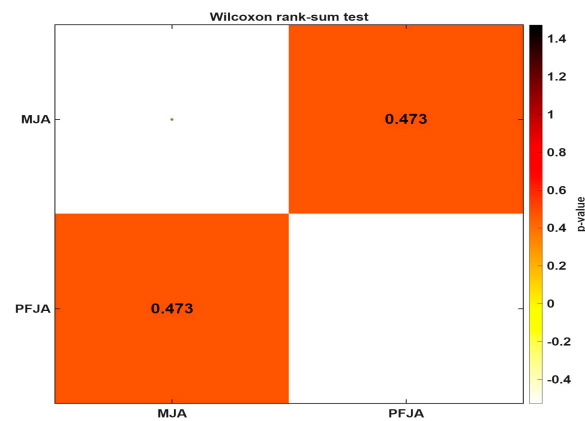


Figure 9. p -Values from the Wilcoxon rank-sum test for planar seven-story frame optimization.

4.3. The Planar Ten-Story Frame

The third steel frame design problem in this paper is a ten-story planar frame given in Figure 10. The structure has 70 design variables shown in Figure 10 and given in Table 7. A uniformly distributed load of 10 lb/in is added to all beams of the frame system. The planar frame structure was previously optimized by Zakian (2019) [6] using PSO, CSS, TLBO, GWO, and IGWO methods. Table 7 compares the results obtained from PFJA, MJA, and other methods. Table 8 shows the first three natural frequency values of the design results in Table 7.

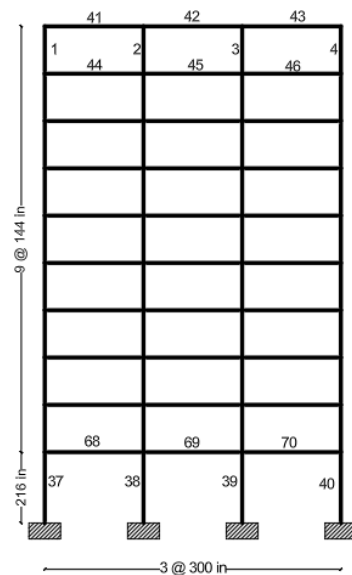


Figure 10. Schematic of the planar ten-story frame structure [6].

Table 7 shows that all methods used by Zakian (2019) [6] (PSO, CSS, TLBO, GWO, IGWO) violated the natural frequency limits, with percentage deviations ranging from 1.9321% to 21.7121%. In contrast, PFJA achieved the best design that satisfied the frequency limits, with a structural weight of 119,250.9251 lb (1 lb = 0.4536 kg). Furthermore, Table 7 shows that PFJA required 6900 structural analyses, whereas the other methods required 8000.

Table 7. Comparison of optimization results for the planar ten-story frame problem.

Design Variables (in ²)*	PSO [6]	CSS [6]	TLBO [6]	GWO [6]	IGWO [6]	MJA	PFJA
1	29.5197 36 33.6549	1 9.0595 36 37.4742	1 3.0015 36 22.1005	1 3.0000 36 14.8100	1 4.6338 36 41.9878	1 3.3129 36 16.7501	1 3.0082 36 25.8040
2	56.0686 37 62.3277	2 44.9220 37 42.6536	2 42.8000 37 45.5537	2 76.7831 37 88.2800	2 45.9518 37 59.9886	2 41.8869 37 49.1688	2 37.0039 37 47.1140
3	51.0850 38 53.8149	3 29.8205 38 45.6266	3 36.1444 38 80.1003	3 88.2800 38 74.1726	3 57.3066 38 49.3658	3 43.2773 38 84.2163	3 42.6459 38 60.4385
4	30.3950 39 54.6463	4 10.2679 39 82.4349	4 3.0323 39 50.4617	4 3.1957 39 88.2800	4 8.6656 39 74.2058	4 3.0000 39 50.9946	4 3.0027 39 52.1542
5	37.4872 40 57.4868	5 30.3284 40 62.4833	5 47.5447 40 44.5336	5 36.4190 40 74.3477	5 7.0983 40 54.4365	5 44.9053 40 44.2629	5 43.5854 40 57.3217
6	24.6963 41 3.0000	6 39.1328 41 3.5698	6 25.1435 41 3.0044	6 41.6098 41 5.4863	6 35.8760 41 5.4696	6 27.8314 41 3.0067	6 36.8292 41 3.0020
7	44.4298 42 3.0000	7 62.0522 42 33.2252	7 44.1524 42 29.0885	7 48.4907 42 3.6124	7 46.7428 42 3.1025	7 26.0135 42 39.6594	7 25.3845 42 32.9056
8	25.5762 43 3.0000	8 39.0820 43 5.4702	8 39.7907 43 3.0000	8 10.1905 43 4.4459	8 44.3974 43 3.0778	8 43.5606 43 3.0021	8 42.5670 43 3.0761
9	51.6692 44 33.3543	9 21.2109 44 37.4164	9 16.1085 44 38.1968	9 34.4618 44 63.0352	9 4.3259 44 3.4710	9 29.0917 44 44.1722	9 27.8891 44 43.9596
10	26.0943 45 47.4641	10 47.7581 45 42.9331	10 39.7181 45 39.4737	10 77.7641 45 82.7444	10 41.3986 45 68.9757	10 41.3880 45 3.0006	10 44.1616 45 26.1155
11	46.1273 46 41.0117	11 43.5721 46 43.6959	11 43.8141 46 39.9570	11 82.8627 46 3.0000	11 45.9778 46 47.1158	11 43.8907 46 45.0015	11 43.3562 46 44.3488
12	39.0085 47 38.9506	12 50.1162 47 40.0182	12 34.8891 47 44.1926	12 4.9180 47 31.9705	12 41.7316 47 9.1771	12 26.2513 47 50.3804	12 19.6232 47 51.3927
13	42.2062 48 48.4108	13 15.5862 48 6.1057	13 17.3102 48 3.0024	13 45.7692 48 56.0556	13 5.6217 48 48.0278	13 29.8628 48 3.0000	13 32.5899 48 3.0000
14	45.3889 49 44.2000	14 34.1207 49 69.4682	14 38.1008 49 47.9975	14 18.7481 49 8.5576	14 43.8835 49 53.0359	14 41.9788 49 50.2901	14 38.0153 49 44.6129
15	21.3996 50 23.1173	15 41.3569 50 16.1663	15 35.7644 50 3.0004	15 80.1337 50 34.9689	15 40.5803 50 6.1905	15 41.6095 50 3.0096	15 43.6470 50 3.0149
16	55.8747 51 25.2248	16 34.0594 51 52.8570	16 28.6058 51 43.9622	16 3.6303 51 6.0126	16 43.2366 51 3.9220	16 28.6243 51 48.0994	16 22.3983 51 49.9213
17	54.6989 52 3.0000	17 35.8065 52 4.1114	17 20.2536 52 38.5748	17 26.0943 52 16.5495	17 5.9044 52 46.7173	17 30.1451 52 3.1087	17 32.5500 52 3.0007
18	44.3630 53 3.0000	18 34.4436 53 3.4906	18 43.5231 53 3.0006	18 88.2800 53 44.3998	18 41.5151 53 9.9630	18 43.4577 53 3.0005	18 44.6185 53 3.0000
19	69.2845 54 45.0476	19 42.0667 54 10.7157	19 39.7598 54 44.1550	19 36.5706 54 3.2490	19 44.1385 54 3.0993	19 43.3245 54 47.5516	19 42.4504 54 45.2440
20	36.3042 55 33.2372	20 41.1269 55 42.6278	20 35.2746 55 3.0000	20 3.6994 55 7.2914	20 42.6853 55 44.1764	20 29.6134 55 3.0183	20 26.4988 55 3.0336
21	51.4064 56 51.3823	21 29.8335 56 20.0221	21 35.9488 56 44.1095	21 22.8482 56 50.2551	21 7.4434 56 7.8372	21 45.7577 56 48.4865	21 43.0138 56 45.3739
22	59.0334 57 34.0133	22 42.4877 57 48.5791	22 43.6314 57 5.9869	22 56.4145 57 88.2800	22 43.4209 57 50.2297	22 33.4780 57 3.0687	22 33.4740 57 3.0000
23	52.5156 58 3.0000	23 53.2635 58 21.4132	23 42.0223 58 44.0728	23 72.4224 58 3.0000	23 55.4360 58 44.1736	23 32.6013 58 45.6906	23 33.5453 58 45.1681
24	88.2800 59 52.5090	24 35.1364 59 38.1539	24 38.9425 59 38.5628	24 8.0787 59 12.4085	24 39.9090 59 3.2029	24 43.8519 59 45.3846	24 43.8805 59 46.6098
25	27.8664 60 29.8101	25 26.1959 60 15.6696	25 18.1414 60 43.2648	25 33.8972 60 68.8886	25 3.0193 60 45.1477	25 22.6359 60 3.0420	25 26.8387 60 3.0004
26	60.8462 61 37.8282	26 44.6208 61 50.2004	26 38.7693 61 44.4428	26 62.3369 61 5.0984	26 21.8692 61 44.8072	26 46.1230 61 47.0565	26 41.7481 61 44.1848
27	49.4879 62 35.9664	27 33.7693 62 7.9297	27 43.7478 62 3.1884	27 52.1827 62 50.7306	27 45.1819 62 3.0598	27 43.9085 62 3.0070	27 43.8663 62 3.0011
28	35.6458 63 3.0000	28 49.6919 63 43.6860	28 25.4297 63 43.5943	28 4.8242 63 10.9981	28 44.3409 63 7.8814	28 20.5754 63 44.1680	28 19.8762 63 43.8899
29	35.2384 64 3.0000	29 8.3112 64 3.6401	29 21.5336 64 3.0000	29 27.3140 64 3.0000	29 3.0256 64 42.1576	29 22.4167 64 3.0000	29 27.6589 64 3.0004
30	50.7653 65 3.0000	30 45.7488 65 5.8682	30 21.4388 65 16.0365	30 28.0415 65 3.0000	30 30.4577 65 3.4860	30 35.5686 65 3.0341	30 29.8719 65 3.0000
31	26.9287 66 3.0000	31 24.8783 66 9.8094	31 43.4149 66 3.0055	31 31.4979 66 47.0715	31 23.9756 66 3.2132	31 42.9410 66 3.0000	31 43.4160 66 3.0000
32	25.1350 67 4.3747	32 42.9816 67 3.4524	32 24.1805 67 3.0118	32 4.4834 67 3.0000	32 43.6214 67 18.5162	32 16.8153 67 3.1519	32 24.3275 67 3.0261
33	25.7039 68 39.4951	33 12.2387 68 4.1140	33 26.9063 68 26.1270	33 22.1488 68 40.7262	33 8.8847 68 44.1659	33 17.6170 68 43.0204	33 25.0112 68 44.0735
34	30.9292 69 3.0000	34 47.3799 69 43.2039	34 24.6183 69 44.1568	34 49.5387 69 62.1344	34 34.4806 69 5.5788	34 35.9868 69 44.2218	34 28.7345 69 3.5073
35	47.1990 70 69.5588	35 26.4803 70 45.6091	35 42.6831 70 3.0597	35 49.5348 70 5.0830	35 20.9954 70 48.3381	35 41.2733 70 3.0495	35 35.7768 70 44.1695
Best weight (lb)**	140,127.5309	130,115.2747	122,576.8819	143,448.7343	120,635.7922	119,560.7260	119,250.9251
Mean weight (lb)**	158,293.3047	133,489.9963	126,179.5055	153,209.0455	125,677.0802	121,062.8870	120,160.9070
SD (lb)**	7,532.3112	2,027.1734	2,014.1626	4,204.8825	2,980.1319	776.9077	506.4807
CV (%)	1.9321	2.3386	1.7731	14.8820	21.7121	0.0000	0.0000
NSA	8000	8000	8000	8000	8000	7200	6900

* 1 in² = 6.4516 cm²; ** 1 lb = 0.4536 kg.

Table 8. Natural frequencies of the planar ten-story frame designs.

Frequency Number (Hz)	PSO [6]	CSS [6]	TLBO [6]	GWO [6]	IGWO [6]	MJA	PFJA
1	2.0000	2.0060	2.0013	2.2755	2.0408	2.0192	2.0017
1 *	1.9975	2.0041	1.9993	2.2728	2.0385	2.0192	2.0017
2	7.0000	7.0095	7.0004	7.0971	7.0000	7.0001	7.0003
2 *	6.9614	6.9684	6.9483	7.0410	6.9320	7.0001	7.0003
3	15.0000	15.0006	14.9984	15.1538	15.0000	15.0003	15.0002
3 *	14.7102	14.6492	14.7340	12.7677	11.7432	15.0004	15.0002

* The values of the first three natural frequencies were extracted from SAP2000 v20 [45].

The optimum design obtained with PFJA and the results for the first three modes modeled in SAP2000 v20 are presented in Figure 11a–c. As shown in Figure 11, the mode values obtained from PFJA match those from SAP2000 v20.

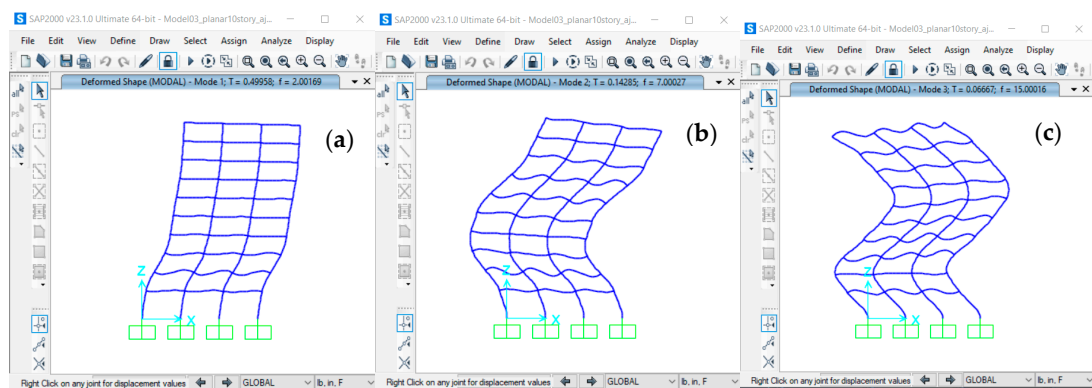


Figure 11. The first 3 modes of ten-story planar steel frame structure modeled with SAP2000 v20. (a) First mode. (b) Second mode. (c) Third mode.

The convergence curves for PFJA and MJA, compared with other methods, are shown in Figure 12. Comparing these curves, it can be seen that PFJA and MJA converge to the optimum design faster than other methods.

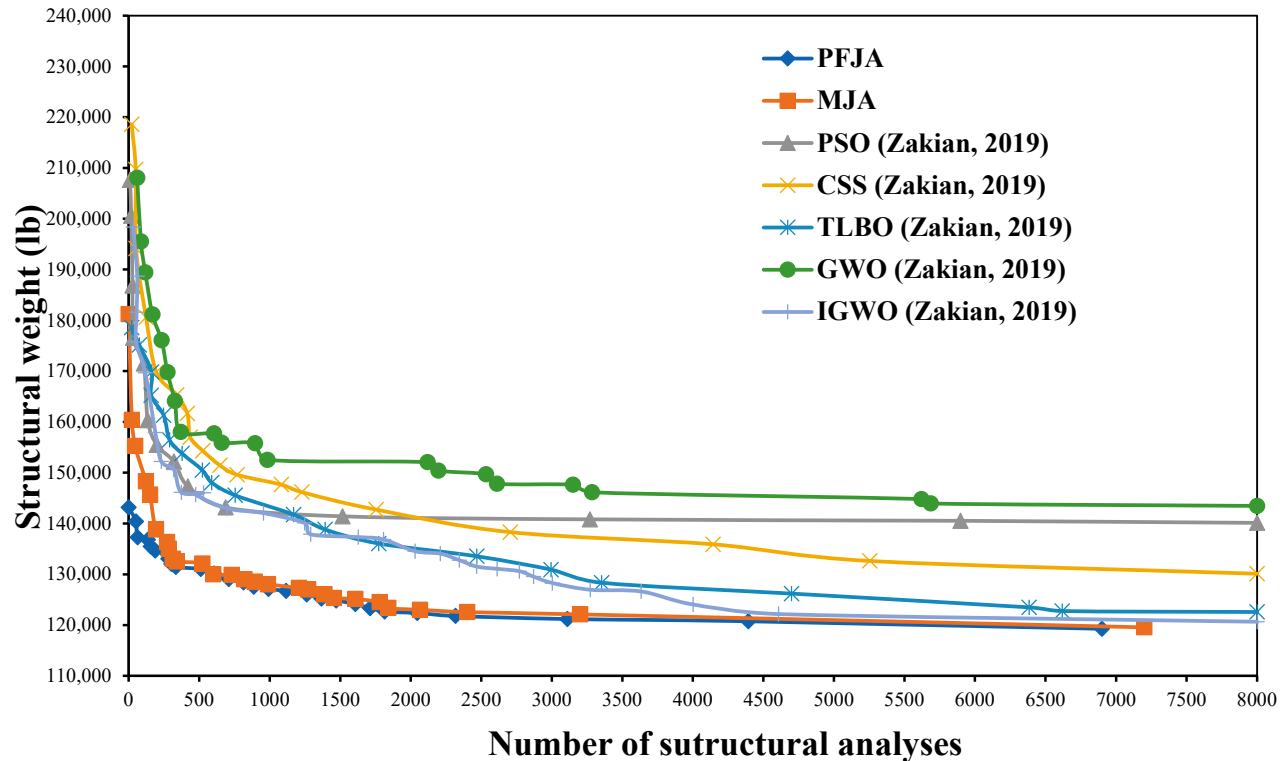


Figure 12. Comparison of the convergence curves recorded for the ten-story planar problem.

The statistical comparison for the planar ten-story frame is depicted in Figure 13. For this design problem, the Wilcoxon rank-sum test yields p -value of 0.015. Since $p < 0.05$, the performance difference is statistically significant. As the structural height and the number of design variables scale up, the parameter-free adaptive search mechanism of PFJA successfully enhances the exploration–exploitation balance, leading to a statistically proven superiority over MJA.

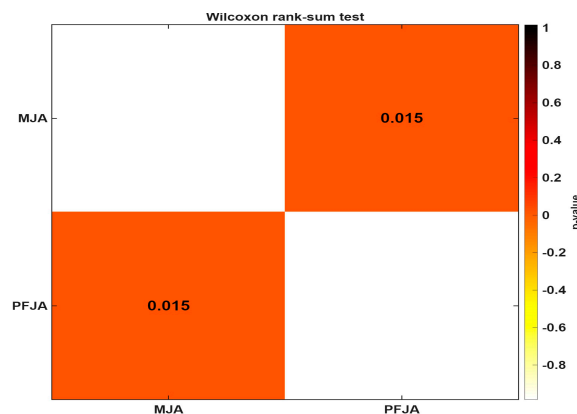


Figure 13. p -values from the Wilcoxon rank-sum test for planar ten-story frame optimization.

4.4. The Spatial One-Story Frame

The fourth steel frame design problem in this paper is the spatial one-story frame shown in Figure 14. The structure has eight design variables, as shown in Figure 14 and listed in Table 9. A uniformly distributed load of 3 lb/in is added to all beams of the frame system. The space frame structure was previously optimized by Zakian (2019) [6] using PSO, CSS, TLBO, GWO, and IGWO methods. Table 9 compares the results obtained from

PFJA, MJA, and other methods. Table 10 presents the first three natural frequency values from the design results in Table 9.

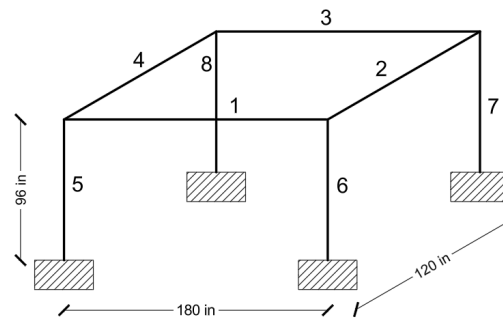


Figure 14. Schematic of the spatial one-story frame structure [6].

Table 9 shows that the CSS, GWO, and IGWO methods used by Zakian (2019) [6] violated the natural frequency limits, with variations ranging from 12.33% to 19.33%. In contrast, PFJA achieved the best design that satisfied the frequency limits, with a structural weight of 1008.8406 lb. Furthermore, Table 9 shows that PFJA required 1530 structural analyses, compared to 2000 by the other methods.

Table 9. Comparison of optimization results for the spatial one-story frame problem.

Design Variables (in ²)*	PSO [6]	CSS [6]	TLBO [6]	GWO [6]	IGWO [6]	MJA	PFJA
1	0.1000	2.7182	0.3592	2.8164	2.3433	0.2992	0.2216
2	0.1000	2.2241	0.2105	1.9026	2.4823	3.9858	2.2688
3	0.5562	2.1025	0.1461	2.3821	2.4674	0.1338	0.2820
4	0.2573	2.2819	0.2577	2.6751	2.1192	2.6856	4.5922
5	16.4721	1.7919	30.8533	1.8398	17.9522	0.1049	0.3426
6	0.6942	19.6538	1.1417	21.4221	2.0558	18.8305	9.2553
7	30.7735	1.9471	16.3904	2.5412	15.0437	0.3917	0.3970
8	1.2797	13.6300	0.8244	13.1767	1.8691	9.7921	18.0159
Best weight (lb)**	1368.0990	1389.5362	1363.9561	1463.5965	1389.4987	1028.7048	1008.8406
Mean weight (lb)**	1526.4091	1486.2002	1412.4037	1515.4149	1455.0272	1122.9778	1049.7988
SD (lb)**	144.1973	60.5297	43.4286	26.2333	53.7335	40.6125	31.3452
CV (%)	0.0000	13.9028	0.0000	12.3303	19.3331	0.0000	0.0000
NSA	2000	2000	2000	2000	2000	1600	1530

* 1 in² = 6.4516 cm²; ** 1 lb = 0.4536 kg.

Table 10. Natural frequencies of the one-story frame designs.

Frequency Number (Hz)	PSO [6]	CSS [6]	TLBO [6]	GWO [6]	IGWO [6]	MJA	PFJA
1	5.0016	5.0006	5.0190	5.1761	5.0001	5.4572	5.0816
1 *	5.4747	6.3362	5.4300	6.4654	6.8913	5.4572	5.0816
2	9.0278	9.0004	9.0070	9.3870	9.0006	9.1361	9.1587
2 *	9.0857	7.7488	9.2999	7.8903	7.2600	9.1361	9.1587
3	15.2678	15.2127	15.0794	15.4378	15.3228	15.4640	16.2633
3 *	17.5761	26.4427	20.3347	26.1521	28.6935	15.4640	16.2633

* The values of the first three natural frequencies were extracted from SAP2000 v20 [45].

The optimum design obtained with PFJA and the results for the first three modes modeled in SAP2000 v20 are presented in Figure 15a–c. As shown in Figure 15, the mode values obtained from PFJA match those from SAP2000 v20.

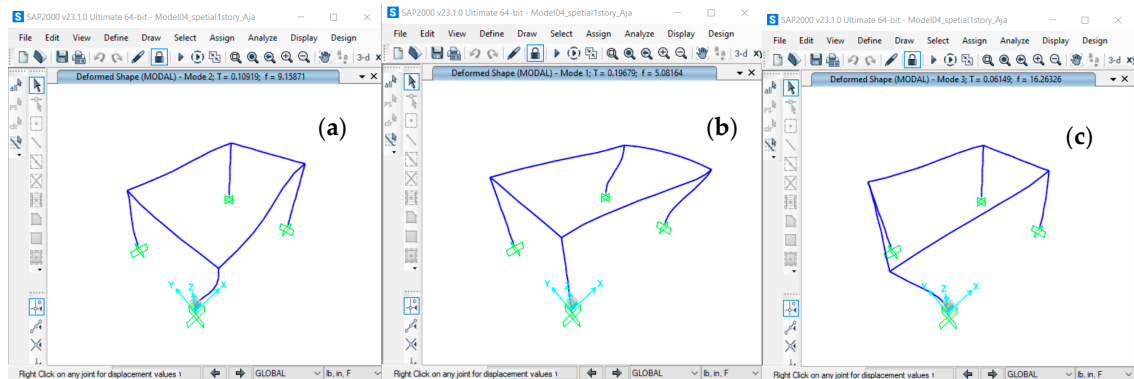


Figure 15. The first 3 modes of a spatial one-story steel frame structure modeled with SAP2000 v20. (a) First mode. (b) Second mode. (c) Third mode.

The convergence curves for PFJA and MJA, compared with other methods, are shown in Figure 16. Comparing these curves, it can be seen that PFJA and MJA converge to the optimum design faster than other methods.

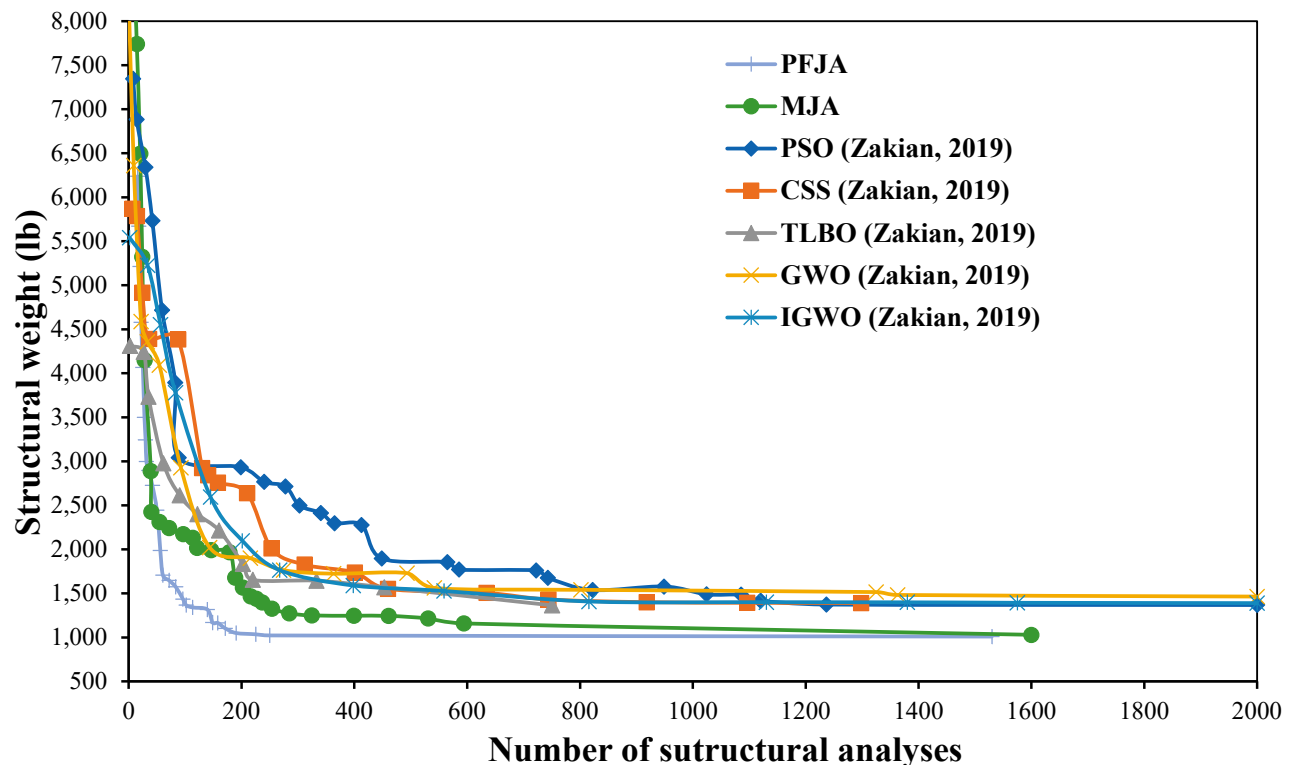


Figure 16. Comparison of the convergence curves recorded for the spatial one-story frame problem.

The heatmap for the spatial one-story frame is displayed in Figure 17. The test reveals an extremely small p -value of 7.083715×10^{-9} $p < 0.01$. This highly significant statistical difference demonstrates the immense advantage of the proposed PFJA in spatial configurations. The introduction of torsional effects and increased degrees of freedom drastically compli-

cates the design space. Under these highly nonlinear conditions, PFJA demonstrates an outstanding and decisive superiority over the baseline MJA.

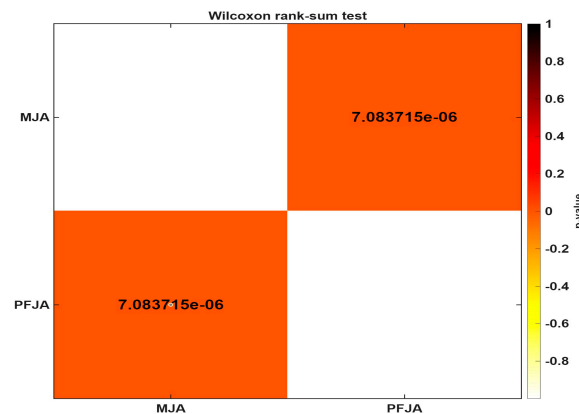
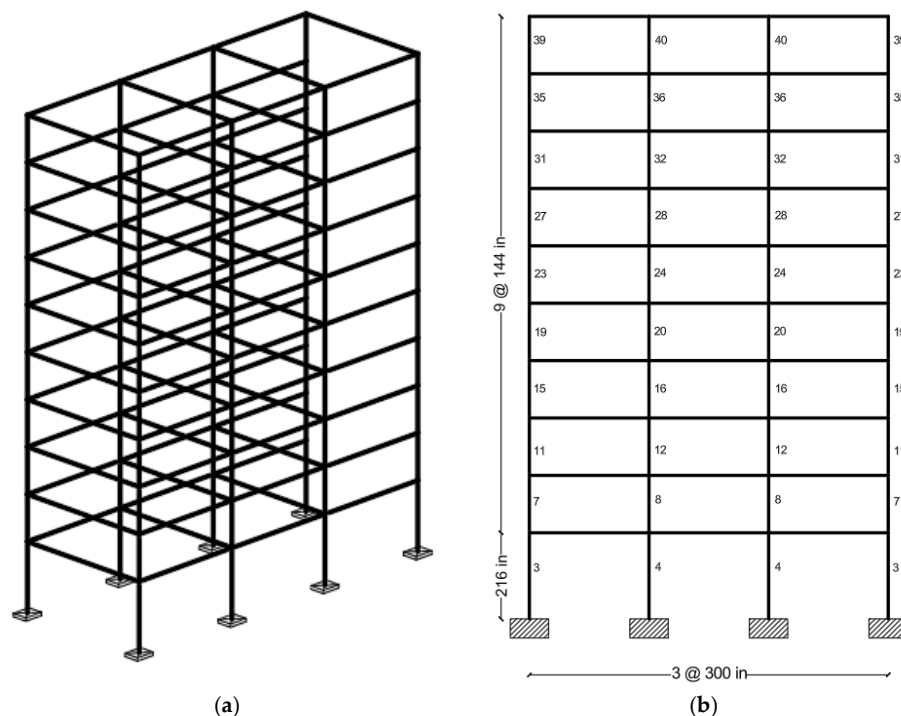


Figure 17. *p*-values from the Wilcoxon rank-sum test for spatial one-story frame optimization.

4.5. The Spatial Ten-Story Frame

4.5.1. The Spatial Ten-Story Frame Continuous Variable

The fifth steel frame design problem in this study is the 180-element space frame given in Figure 18. The structure has 40 design variables shown in Figure 18 and given in Table 11. A uniformly distributed load of 1 lb/in is added to all beams of the frame system. The space frame structure was previously optimized by Zakian (2019) [6] using PSO, CSS, TLBO, GWO, and IGWO methods. Table 11 compares the results obtained from PFJA, MJA, and other methods. Table 12 shows the first three natural frequency values of the design results in Table 11.



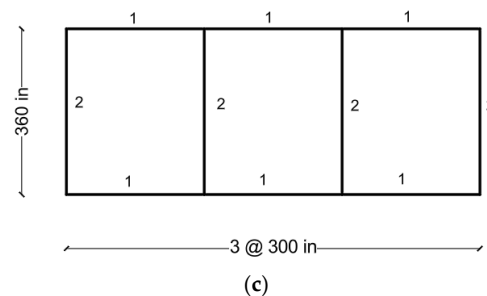


Figure 18. Schematic of the spatial ten-story frame structure in (a) 3D view, (b) plan view with typical numbering for the first floor, and (c) side view [6].

Table 11 shows that all methods used by Zakian (2019) [6] violated the natural frequency limit, with percentages ranging from 19.75% to 52.97%. In contrast, PFJA achieved the best design that satisfied the frequency-limiting factors, with a structural weight of 218,239.4068 lb (1 lb = 0.4536 kg). Furthermore, Table 11 shows that PFJA required 1800 structural analyses, compared to 8000 by the other methods.

Table 11. Comparison of optimization results for the spatial ten-story frame problem (continuous variable).

Design Variables (in ²) *	PSO [6]	CSS [6]	TLBO [6]	GWO [6]	IGWO [6]	MJA	PFJA
1	0.1000	0.1888	0.3262	0.1000	3.2273	10.0370	5.5862
2	0.1000	0.4645	0.1073	1.5761	2.0254	16.2850	17.3080
3	88.3000	86.4269	87.1440	84.3460	88.3000	54.2500	83.6480
4	88.3000	66.9769	65.2097	88.3000	67.5826	19.3470	10.7830
5	4.4972	10.7977	67.4120	0.1000	17.7627	18.5730	6.1309
6	88.3000	1.0795	0.1119	0.1000	1.2183	8.6974	11.8620
7	88.3000	75.3116	73.4420	52.2624	74.9111	56.2750	69.4340
8	88.3000	63.2388	29.1774	69.3575	27.7966	22.5400	7.0990
9	88.3000	68.5115	0.6878	69.7214	29.7388	0.5338	3.9490
10	0.1000	7.9026	0.1003	10.7183	5.4843	18.0020	13.1190
11	88.3000	72.3510	67.5503	52.8890	45.5068	34.5720	45.2910
12	12.3347	34.0518	45.7861	74.9032	26.2909	6.3066	20.7510
13	0.2699	0.6803	0.2141	0.8454	28.6634	24.6920	3.6140
14	0.1000	74.8927	0.1038	88.3000	73.4011	13.1740	1.5477
15	88.3000	8.9077	42.3125	13.3676	26.3181	53.8820	38.6470
16	88.3000	87.5720	6.0861	85.6000	39.4443	10.8790	38.4690
17	0.1000	11.8660	40.7009	3.3492	19.7496	7.1717	14.4830
18	88.3000	3.7241	68.9520	6.0605	3.0184	15.5570	40.1130
19	33.0377	50.1077	52.4054	22.1542	33.3194	43.4570	82.8820
20	39.6756	37.9478	20.5977	42.9277	20.0858	9.6657	12.2770
21	0.1000	26.5062	0.2531	26.2148	18.8967	13.1070	7.9448
22	0.1000	68.3921	67.5809	2.1890	68.7819	17.0230	7.1121
23	44.0158	14.3849	9.9608	8.3817	17.9295	15.6410	39.5300
24	17.0245	10.4721	67.4447	59.7403	20.0762	16.7340	24.3680
25	41.0508	1.9517	15.4225	19.9607	11.8798	7.2416	1.9692
26	19.5328	0.8346	0.1272	72.3724	2.6131	9.7753	18.6960
27	28.6516	39.6721	25.6752	15.3653	29.9612	22.7560	44.5780
28	37.2729	26.7773	20.2590	18.1867	24.7756	10.6420	26.7530
29	0.1000	11.5216	0.1000	14.5910	12.4219	16.2610	20.6140

30	0.1000	4.1805	0.1241	0.1100	4.8299	28.4830	18.0480
31	17.4556	20.0367	18.9098	6.7082	16.7096	13.0680	13.5640
32	67.9411	6.9156	15.3729	43.3249	15.5048	46.0850	88.2670
33	0.1000	0.5439	8.5047	11.2396	0.6683	27.9400	0.5757
34	0.1000	1.4262	5.4781	0.1008	0.8185	18.3310	5.4924
35	5.8423	8.8287	9.3272	28.4679	9.5107	25.5210	13.6910
36	88.3000	15.1104	8.0229	17.1479	17.2761	31.6580	11.6330
37	0.1000	2.3169	0.1018	0.1904	2.4683	0.1000	0.1000
38	0.1000	2.4345	0.1004	0.1000	2.8170	1.8187	3.0444
39	2.0461	3.0810	2.2411	12.2518	3.0461	52.6190	16.6580
40	14.5773	4.6380	11.5688	6.8047	4.0334	10.4060	73.7530
Best weight (lb)**	327,019.5018	265,201.2994	246,681.0175	290,325.1730	250,541.2056	218,315.5868	218,239.4068
Mean weight (lb)**	387,450.8623	301,818.9141	273,429.6439	326,456.5541	263,001.2203	234,500.3699	230,811.8295
SD (lb)**	34,638.1317	18,544.1334	16,752.0160	19,895.9107	10,288.2032	8224.5513	7702.1065
CV (%)	52.4343	25.0933	43.6953	52.9724	19.7473	0.0000	0.0000
NSA	8000	8000	8000	8000	8000	1950	1800

* 1 in² = 6.4516 cm²; ** 1lb = 0.4536kg.

Table 12. Natural frequencies of the ten-story frame designs (continuous variable).

Frequency Number (Hz)	PSO [6]	CSS [6]	TLBO [6]	GWO [6]	IGWO [6]	MJA	PFJA
1	0.5000	0.5007	0.5000	0.5287	0.5000	0.5354	0.5206
1 *	0.4481	0.5150	0.3529	0.3680	0.4972	0.5354	0.5206
2	1.1083	0.8334	0.8649	1.0505	0.8258	0.8301	0.9015
2 *	0.4496	0.7224	0.5991	0.3762	0.7555	0.8301	0.9015
3	1.2000	1.2012	1.2000	1.2066	1.2000	1.2748	1.2202
3 *	0.5708	0.8989	0.6757	0.6081	0.9630	1.2748	1.2202

* The values of the first three natural frequencies were extracted from SAP2000 v20 [45].

The optimum design obtained with PFJA, along with the results for the first three modes modeled in SAP2000 v20, are presented in Figure 19a–c. As shown in Figure 19, the mode values obtained from PFJA match those from SAP2000 v20.

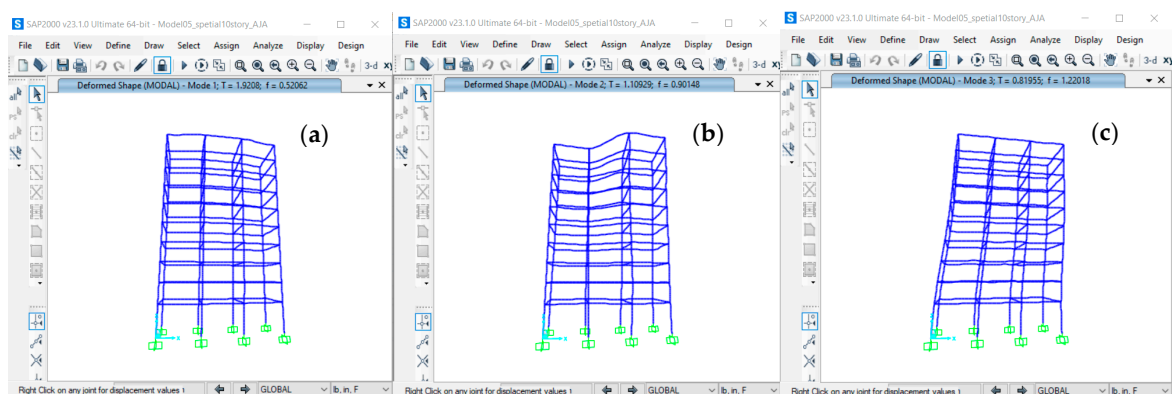


Figure 19. The first 3 modes of spatial one-story steel frame structure (continuous variable) modeled with SAP2000 v20. (a) First mode. (b) Second mode. (c) Third mode.

The convergence curves of PFJA and MJA compared to other methods are shown in Figure 20. Comparing these curves, it can be seen that PFJA and MJA converge to the optimum design faster than other methods.

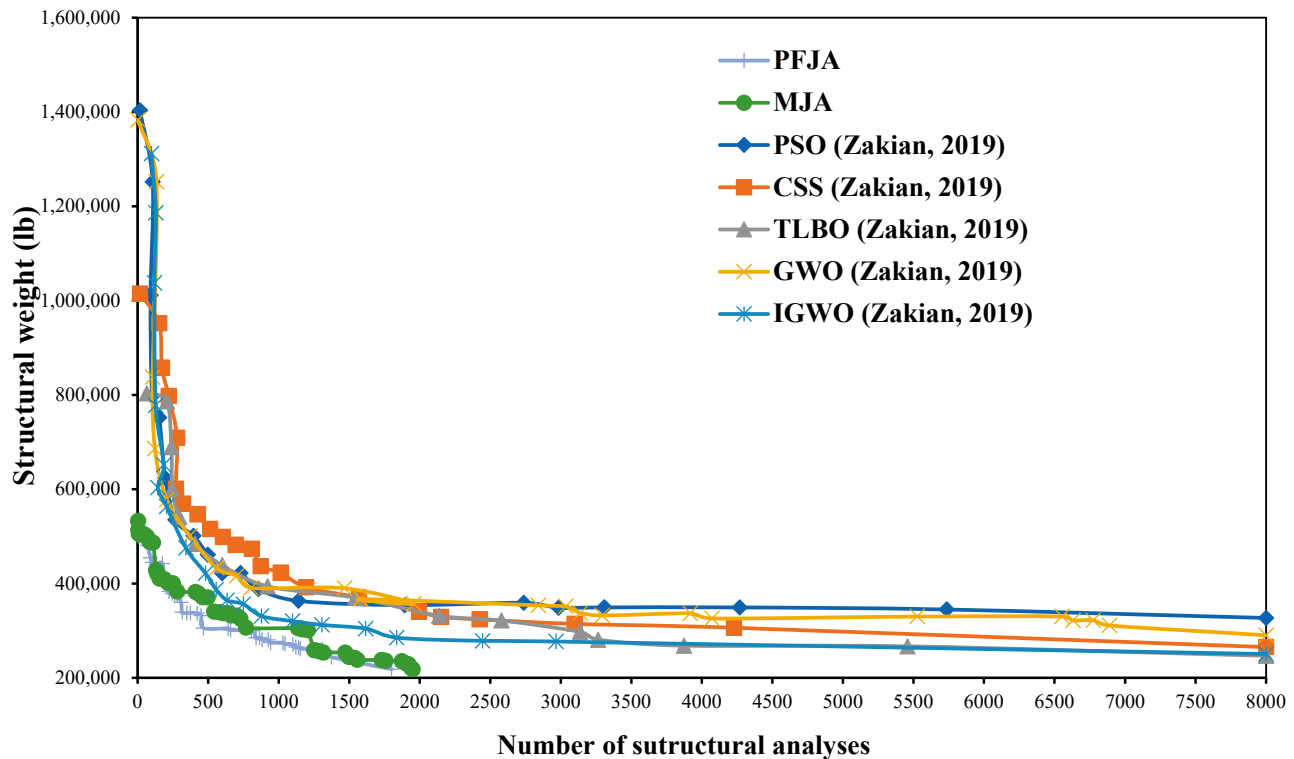


Figure 20. Comparison of the convergence curves recorded for the spatial ten-story frame problem (continuous variable).

The statistical analysis for the continuous formulation of the spatial ten-story frame is shown in Figure 21. The Wilcoxon rank-sum test yields a p -value of 0.5205. In this continuous design domain where variables can take any real value within the bounds, both algorithms exhibit highly stable and equivalent search behaviors. Both methods successfully converge to closely adjacent continuous boundaries, resulting in no statistically significant performance discrepancy.

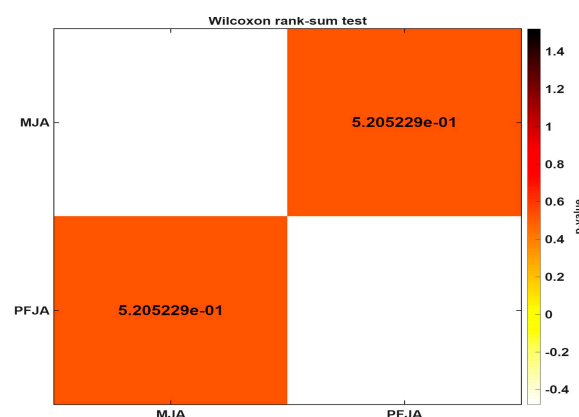


Figure 21. p -values from the Wilcoxon rank-sum test for spatial ten-story frame optimization (continuous variable).

4.5.2. The Spatial Ten-Story Frame Discrete Variable

The sixth steel frame design problem in this paper is identical to the 180-element (continuous design variable) space frame shown in Figure 18. The structure, which was optimized with continuous design variables in Section 4.5, is now optimized with discrete

design variables. The structure has 40 design variables as shown in Figure 18 and given in Table 13. A uniformly distributed load of 1 lb/in is added to all beams of the frame system. The space frame structure was previously optimized by Zakian (2019) [6] using PSO, CSS, TLBO, GWO, and IGWO methods. Table 13 compares the results obtained from PFJA, MJA, and other methods. Table 14 presents the first three natural frequency values from the design results in Table 13.

Table 13 shows that the IGWO and TLBO methods used by Zakian (2019) [6] violate the natural frequency-limiting factors. In contrast, PFJA achieved the best design that satisfied the frequency-limiting factors, with a structural weight of 267,435.5040 lb. Furthermore, Table 13 shows that PFJA required 3550 structural analyses, whereas the reference algorithms required 4000.

Table 13. Comparison of optimization results for the spatial ten-story frame problem (discrete variable).

Design Variables (in ²)*	PSO [6]	CSS [6]	TLBO [6]	GWO [6]	IGWO [6]	MJA	PFJA
1	W21X48	W14X48	W27X94	W24X68	W18X76	W4X13	W6X9
2	W44X230	W14X257	W10X100	W4X13	W44X335	W4X13	W18X97
3	W33X118	W36X135	W27X84	W27X146	W24X55	W44X335	W40X327
4	W36X135	W36X135	W40X199	W44X230	W33X118	W30X108	W30X124
5	W14X90	W18X76	W14X43	W30X90	W18X76	W4X13	W24X104
6	W14X22	W16X67	W33X201	W14X30	W44X290	W18X55	W8X24
7	W33X118	W36X135	W27X84	W27X146	W24X55	W14X211	W16X67
8	W36X135	W36X135	W40X199	W44X230	W33X118	W24X84	W8X21
9	W16X36	W24X117	W24X162	W14X145	W27X84	W16X50	W10X15
10	W14X311	W21X44	W12X120	W44X335	W40X183	W18X106	W12X45
11	W33X118	W36X135	W27X84	W27X146	W24X55	W18X119	W33X201
12	W36X135	W36X135	W40X199	W44X230	W33X118	W21X57	W36X262
13	W44X230	W27X146	W12X136	W14X61	W21X48	W18X40	W18X97
14	W18X76	W14X455	W44X335	W44X335	W44X290	W14X145	W24X131
15	W33X118	W36X135	W27X84	W27X146	W24X55	W40X324	W33X152
16	W36X135	W36X135	W40X199	W44X230	W33X118	W33X118	W18X158
17	W14X26	W24X62	W14X132	W18X60	W8X31	W33X118	W21X50
18	W21X44	W30X132	W14X193	W40X215	W44X335	W4X13	W18X76
19	W33X118	W36X135	W27X84	W27X146	W24X55	W30X191	W16X67
20	W36X135	W36X135	W40X199	W44X230	W33X118	W33X318	W21X44
21	W24X84	W16X67	W4X13	W4X13	W10X49	W21X147	W6X15
22	W36X231	W16X45	W4X13	W4X13	W6X8.5	W18X46	W10X39
23	W33X118	W36X135	W27X84	W27X146	W24X55	W10X88	W16X100
24	W36X135	W36X135	W40X199	W44X230	W33X118	W14X53	W40X392
25	W6X8.5	W18X46	W14X68	W4X13	W14X61	W12X30	W21X44
26	W14X145	W14X257	W14X48	W44X335	W12X14	W5X19	W18X40
27	W33X118	W36X135	W27X84	W27X146	W24X55	W6X16	W21X201
28	W36X135	W36X135	W40X199	W44X230	W33X118	W16X89	W12X65
29	W24X104	W14X74	W4X13	W4X13	W8X31	W4X13	W4X13
30	W21X48	W18X86	W4X13	W4X13	W10X12	W16X77	W8X10
31	W33X118	W36X135	W27X84	W27X146	W24X55	W14X74	W10X45
32	W36X135	W36X135	W40X199	W44X230	W33X118	W27X102	W10X49
33	W6X8.5	W14X34	W4X13	W12X87	W10X12	W24X146	W8X28
34	W6X8.5	W18X46	W4X13	W4X13	W12X14	W8X58	W18X119
35	W33X118	W36X135	W27X84	W27X146	W24X55	W21X111	W27X129
36	W36X135	W36X135	W40X199	W44X230	W33X118	W40X277	W16X100
37	W6X8.5	W14X34	W4X13	W8X28	W6X8.5	W5X19	W4X13

38	W16X40	W18X46	W4X13	W4X13	W6X8.5	W4X13	W4X13
39	W33X118	W36X135	W27X84	W27X146	W24X55	W4X13	W30X191
40	W36X135	W36X135	W40X199	W44X230	W33X118	W4X13	W6X16
Best weight (lb)**	359,127.2160	411,126.9120	367,534.9440	429,660.0000	333,367.7760	290,578.1760	267,435.5040
Mean weight (lb)**	445,682.2256	514,455.8208	416,019.1541	477,983.1175	425,415.4022	308,344.80106	280,026.36616
SD (lb)**	54,610.9907	68,397.9754	36,324.0672	27,496.7118	59,154.2569	9390.08942	7480.07615
CV (%)	0.0000	0.0000	5.5160	0.0000	17.5381	0.0000	0.0000
NSA	4000	4000	4000	4000	4000	3860	3550

* 1 in² = 6.4516 cm² ** 1 lb = 0.4536 kg.

Table 14. Natural frequencies of the ten-story frame designs (discrete variable).

Frequency Number (Hz)	PSO [6]	CSS [6]	TLBO [6]	GWO [6]	IGWO [6]	MJA	PFJA
1	0.5026	0.5021	0.6301	0.5014	0.5063	0.5544	0.5884
1 *	0.7321	0.7366	0.8282	0.6424	0.6127	0.5544	0.5884
2	1.1220	1.1434	1.0678	0.9645	1.1108	0.8012	0.8338
2 *	0.9118	1.0194	0.8895	0.8817	0.6597	0.8012	0.8338
3	1.2051	1.2107	1.1999	1.2494	1.2120	1.2375	1.2547
3 *	1.5895	1.7736	1.1338	1.4179	1.0411	1.2375	1.2547

* The values of the first three natural frequencies were extracted from SAP2000 v20 [45].

The optimum design obtained with PFJA, along with the results for the first three modes modeled in SAP2000 v20, are presented in Figure 22a–c. As shown in Figure 22, the mode values obtained from PFJA match those from SAP2000 v20.

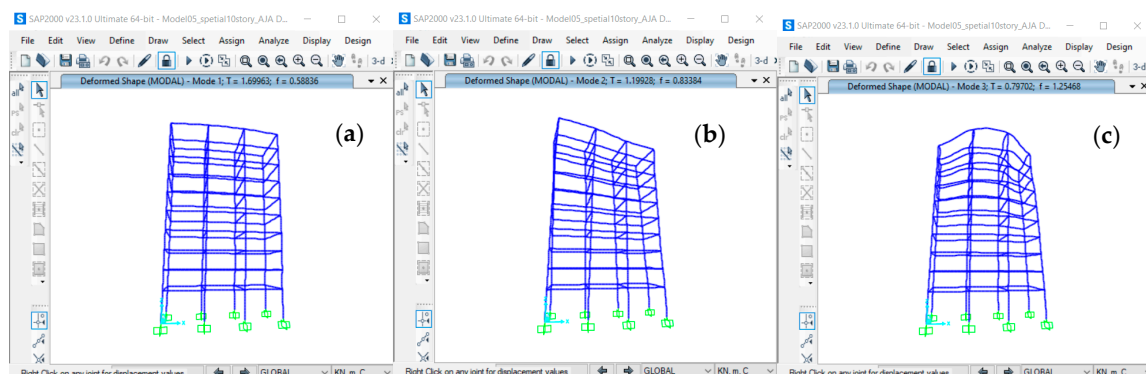


Figure 22. The first 3 modes of spatial ten-story steel frame structure (discrete variable) modeled with SAP2000 v20. (a) First mode. (b) Second mode. (c) Third mode.

The convergence curves for PFJA and MJA, compared with other methods, are shown in Figure 23. Comparing these curves, it can be seen that PFJA and MJA converge to the optimum design faster than other methods.

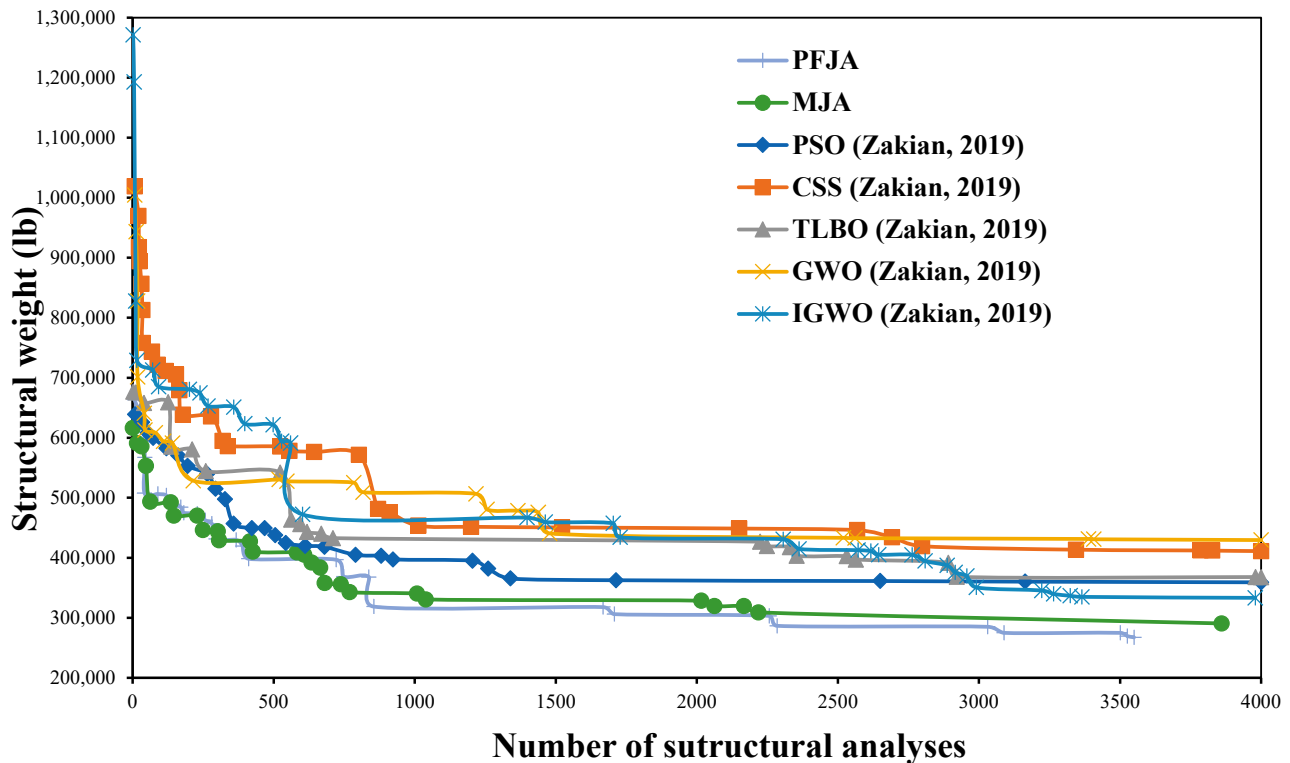


Figure 23. Comparison of the convergence curves recorded for the spatial ten-story frame problem (discrete variable).

Figure 24 illustrates the p -value heatmap for the discrete formulation of the spatial ten-story frame. In stark contrast to the continuous model, the discrete optimization where design variables must be selected from commercial profile databases yields a p -value of 0.0001827. Since $p < 0.01$, the superiority of the proposed PFJA is highly significant. Discrete frame optimization presents a demanding combinatorial problem prone to local minima. This extremely low p -value mathematically confirms that the parameter-free adaptive search mechanism of PFJA successfully bypasses local optimum traps, proving its exceptional efficacy in solving realistic, discrete structural engineering design problems.

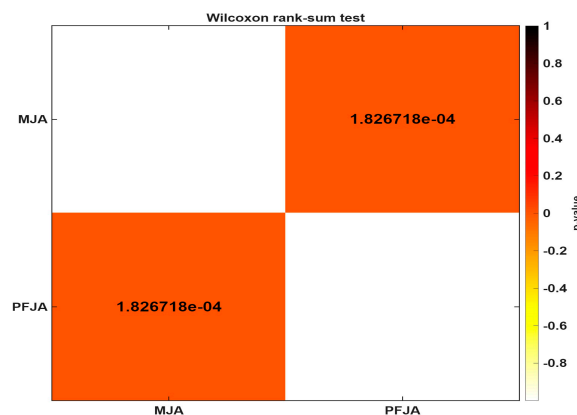


Figure 24. p -values from the Wilcoxon rank-sum test for spatial ten-story frame optimization (discrete variable).

4.6. Discussion on Algorithmic Mechanisms and Limitations

To fully understand the computational trajectory of the parameter-free Jaya algorithm (PFJA) in structural weight minimization, it is essential to evaluate how it navigates the design space under varying constraint conditions and problem scales.

4.6.1. Handling of Active vs. Passive Constraints

In frame optimization problems subjected to dynamic criteria, natural frequency constraints (ω_i) typically dictate the boundaries of the feasible design space. When these dynamic constraints are highly active—meaning structural frequencies are bounded tightly near excitation zones—the PFJA exhibits a robust self-correcting behavior. The algorithm's self-adaptive vector update equation automatically scales down its step sizes as the population approaches the constraint boundaries. If a candidate design violates these boundaries, the algorithm utilizes physical variable limits (cross-sectional areas A_i and moments of inertia I_i) to project the violating components back into the feasible region, effectively isolating non-compliant solutions. Conversely, passive constraints (such as upper-bound frequencies far from the dynamic excitation spectrum) are processed with minimal computational overhead, allowing the algorithm to focus its exploitation capacity on the critical design boundaries and avoid local optima stagnation.

4.6.2. Active Influence of Scale and Dimensionality

The scaling of the structural design space introduces significant topographic complexity. As the optimization problem shifts from lower-dimensional systems (e.g., a two-story planar frame) to more complex environments (e.g., a 10-story spatial frame involving numerous structural members), the PFJA maintains a robust convergence trajectory. In high-dimensional optimization, typical metaheuristics often suffer from premature convergence due to a rapid loss of population diversity. The PFJA mitigates this risk through its self-adaptive population resizing mechanism. Without requiring manual hyperparameter tuning, this mechanism dynamically regulates diversity based on the feedback from the evolutionary search space, preserving exploration capabilities in dense design environments.

4.6.3. Methodological Limitations

Despite the computational advantages of the proposed framework, certain boundaries must be acknowledged:

1. **Scalability to Ultra-Large Systems:** While the PFJA demonstrates high computational efficiency and a low number of function evaluations (NSAs) for standard benchmarks, its scaling performance on extremely large systems (such as high-rise skyscraper frames with thousands of elements) requires further investigation and potential parallel computing integration.
2. **Integration with Code-Based Rules:** The current active optimization loop operates primarily on dynamic frequency criteria (ω_i) and cross-verification via SAP2000 v20 [45] database properties. It does not yet directly embed standard code-based design regulations such as regulatory demand-to-capacity ratios, allowable stress checks, or wind/seismic drift limits directly inside the active search loop. Future work will focus on co-simulating these ultimate limit state provisions alongside dynamic targets.

5. Conclusions

This paper presented the development and application of the parameter-free Jaya algorithm (PFJA) for the weight minimization of planar and spatial steel frames under

dynamic frequency constraints. Based on the numerical results, statistical analyses, and independent structural verifications, the following conclusions are made:

- The proposed PFJA converges to feasible optimum or near-optimum designs across all evaluated planar and spatial frame problems. In terms of minimum design weight, standard deviation of runs, and the number of structural analyses (NSAs) required for convergence, the parameter-free formulation shows better or highly competitive performance compared to the standard JA, MJA [44], and other algorithms in the literature [6].
- The non-parametric Wilcoxon rank-sum test ($\alpha = 0.05$) verifies the statistical significance of the algorithm's performance. While PFJA and MJA perform similarly on low-dimensional search spaces (e.g., Planar Two-Story and Seven-Story frames with $p > 0.05$), PFJA yields a decisive statistical superiority ($p < 0.01$) in complex, high-dimensional combinatorial design spaces, such as the discrete Spatial Ten-Story frame ($p = 0.0001827$). This confirms that the parameter-free adaptive mechanism effectively avoids local minima in discrete domains.
- Cross-verification of all optimal designs using independent SAP2000 v20 [45] finite element models showed that several lighter designs previously reported in the literature actually violate the prescribed frequency constraints. This highlights that structural optimization algorithms must be evaluated not only by raw weight minimization but also by strict constraint feasibility.
- By employing an adaptive population-size strategy and a convergence-based termination criterion, PFJA eliminates manual algorithm-specific parameter tuning. This self-adaptive capability reduces the trial-and-error overhead in computationally intensive structural optimization.

Although the current study focuses on classic frequency-constrained weight-minimization benchmarks, practical structural design must simultaneously satisfy multi-criteria regulatory design limits. Future research will focus on extending the PFJA framework to handle multi-constraint layouts under realistic dynamic loads. This will involve integrating code-based strength requirements (AISC [46] and Eurocode section capacities), serviceability limits (beam deflections and lateral drift envelopes under wind or seismic actions), and complex dynamic loading scenarios (equivalent lateral force or time-history analyses) alongside local and global buckling verification modules.

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