Seismic Design Optimization Using an Improved Starfish Optimization Algorithm Integrated with Grey Wolf Optimizer Strategy

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ABSTRACT

This study proposes an improved version of the Starfish Optimization Algorithm (SFOA) by integrating strategies from the Grey Wolf Optimizer (GWO) algorithm to address the entrapment in local minima and enhance its exploitation capabilities. Through benchmark tests on two asymmetrical steel frame structures, the proposed Improved SFOA (ISFOA) demonstrated superior performance compared to the original SFOA, Particle Swarm Optimization (PSO), GWO, and Stellar Oscillation Optimizer (SOO). The algorithm successfully optimized the benchmark steel frames, achieving the lightest structural designs among the tested algorithms. Specifically, for the four-story structure with a 132-member steel space frame, ISFOA obtained lighter designs by 34%, 10%, 7%, and 11% compared to the best solutions achieved by PSO, GWO, SOO, and SFOA, respectively. Similarly, for the four-story with 428-member steel frame, the optimized design generated by the ISFOA suggested lighter designs by 42%, 17%, 9%, and 12%, for PSO, GWO, SOO, and SFOA, respectively. The ISFOA complied with displacement and geometric constraints according to the LRFD-AISC standard.

Keywords-optimization; seismic design; metaheuristics; Sfoa; Gwo; steel frame

I. INTRODUCTION

The research on the seismic design optimization of structures has gained extensive attention due to severe damage caused by earthquakes. The effectiveness of different optimization methods in improving the seismic resilience of structures has been thoroughly investigated. Authors in [1] developed a sensitivity analysis formulation of displacement with respect to the changes in member sizes for performance-based design optimization of steel moment-resisting frames, employing an equivalent static analysis for a three-story frame. A similar three-story frame structure optimization was conducted with constraints on inter-story drift and member stability, utilizing welded box sections for columns and hot-rolled I-sections for beams [2]. Their findings indicated that the PSO algorithm was not highly efficient in assessing the fabrication costs, as these costs mainly depended on structural weight. Authors in [3] applied a gradient-based optimization method to minimize the weight of nonlinear frame structures under displacement constraints, examining both the linear and nonlinear structural behavior in the optimization process.

The minimum-weight design of steel frames in seismic structural optimization must be carefully considered. In this nonlinear optimization problem, the design variables—cross-sectional areas—are discretely selected from a predefined catalog of available sections, ensuring compliance with the structural design standards and minimizing the construction costs. The performance-based optimization was investigated for concentrically braced steel frames, integrating size and topology optimization with Incremental Dynamic Analysis (IDA) to construct fragility curves and compute collapse margin ratios [4]. In [5], seismic design optimization of multi-story composite buildings was conducted, consisting of concrete-encased steel columns, steel beams, and steel bracing systems. A discrete algorithm was applied to simultaneously optimize the size and topology of structural elements, aiming to minimize the total cost of steel and concrete materials while controlling the seismic response through constraints on inter-story drift and fundamental vibration periods according to Eurocode provisions.

Metaheuristic optimization algorithms, such as Genetic Algorithm (GA), PSO, Cuckoo Search (CS), and their hybrid variants, have demonstrated high efficiency in solving complex optimization problems [6-9]. These algorithms are characterized by large search spaces, multi-modal objective functions, and nonlinear constraints, particularly in structural optimization for seismic design [10-13]. Authors in [14] employed charged system search and improved Harmony Search (HS) algorithms to optimize the design of planar steel shear and moment-resisting frames using linear elastic dynamic time-history analysis, incorporating stress and inter-story drift constraints. In [15], the quantum PSO algorithm was improved for performance-based optimization, aiming to minimize the structural weight. Simultaneously, the algorithm complies with the inter-story drift constraints according to FEMA-356 guidelines' performance levels, including Immediate Occupancy (IO), Life Safety (LS), and Collapse Prevention (CP). Authors in [16] studied a hybrid methodology combining HS with other optimization techniques to enhance the efficiency of seismic analysis and design. A hybrid method based on GA and PSO was proposed in [17] for the topology optimization of large-scale truss bridges. On this basis, the present study proposes an enhanced version of SFOA by improving its exploitation phase through strategies inspired by GWO [18, 19].

The present study aims to enhance the algorithm's ability to escape local minima and efficiently exploit the design space, thereby effectively solving seismic structural optimization problems. An ISFOA algorithm integrated with GWO-inspired strategies is proposed. In addition, experiments are conducted to evaluate and compare the performance of the proposed method against existing optimization algorithms. Finally, the superior performance and effectiveness of the proposed method are demonstrated in seismic design optimization problems.

II. ISFOA ALGORITHM

The SFOA described in [18] consists of two phases: exploration and exploitation. In the first phase, the exploration behavior is simulated, employing a hybrid search model. The model combines five-dimensional and one-dimensional search patterns to improve computational efficiency and maintain effective search capability. Furthermore, the selection of the search pattern depends on the dimensionality (D) of the optimization problem. Specifically, if the D exceeds 5, the SFOA emulates the starfish's simultaneous movement of its five arms to explore the surrounding environment, guided by the best-known positions within the population. The position-update formula for an individual i at dimension p at iteration t, denoted as $\mathbf{Y}_{i,p}^t$, is expressed in:

$$\mathbf{Y}_{i,p}^t = \begin{cases} \mathbf{X}_{i,p}^t + a_1 \cdot \left(\mathbf{X}_{\text{best},p}^t - \mathbf{X}_{i,p}^t\right) \cdot \cos(\theta), r \le 0.5 \\ \mathbf{X}_{i,p}^t - a_1 \cdot \left(\mathbf{X}_{\text{best},p}^t - \mathbf{X}_{i,p}^t\right) \cdot \sin(\theta),\ r > 0.5 \end{cases} \quad (1)$$

where $\mathbf{X}_{i,p}^t$ is the p component of the position vector of individual i at iteration t. $\mathbf{X}_{\text{best},p}^t$ is the p component of the globally best-known position; $a_1 = 2r - 1$ is a directional oscillation coefficient; $\theta = \frac{\pi}{2} \cdot \frac{t}{T}$ is the modulation angle, with T being the maximum number of iterations; $r \sim \mathcal{U}(0,1)$ is a uniformly distributed random number; and $p \in \{1,2,\dots,D\}$ are five randomly selected dimensions within the problem dimension D. Conversely, when $D \le 5$, the SFOA adopts a one-dimensional search model, mimicking the movement of a single starfish arm in search of food sources. The mathematical representation of this search strategy is provided by:

$$\mathbf{Y}_{i,q}^t = E_t \cdot \mathbf{X}_{i,q}^t + A_1 \cdot \left(\mathbf{X}_{k_1,q}^t - \mathbf{X}_{i,q}^t\right) + A_2 \cdot \left(\mathbf{X}_{k_2,q}^t - \mathbf{X}_{i,q}^t\right) \quad (2)$$

where $\mathbf{X}_{k_1,q}^t$ and $\mathbf{X}_{k_2,q}^t$ represent the positions of two randomly selected starfish; $A_1, A_2 \sim \mathcal{U}(-1,1)$ are random numbers drawn from a uniform distribution; and $E_t = \frac{(T-t)}{T} * \cos(\theta)$ denotes the energy level of the starfish at iteration t. Dimension $q \in \{1,2,\dots,D\}$ is randomly selected from the problem's dimensions.

Moreover, during the exploitation phase, starfish engage in predatory and regenerative behaviors. The SFOA utilizes a parallel two-directional search strategy that simulates the hunting behavior, guiding candidate solutions toward better positions based on information from two randomly selected starfish and the current global best position. Despite its effectiveness, this method may fail to recognize suitable candidates already identified. Therefore, an integrating strategy inspired by GWO is proposed to enhance algorithm performance. Specifically, for the top three selected candidates, the strategy of GWO is applied to identify the three best individuals—alpha, beta, and delta—as described in:

$$\begin{aligned} \mathbf{D}_\alpha &= |\mathbf{C}_1 \cdot \mathbf{X}_\alpha - \mathbf{X}_i|,\ \ \mathbf{X}_1 = \mathbf{X}_\alpha - \mathbf{A}_1 \cdot \mathbf{D}_\alpha \\ \mathbf{D}_\beta &= |\mathbf{C}_2 \cdot \mathbf{X}_\beta - \mathbf{X}_i|,\ \ \mathbf{X}_2 = \mathbf{X}_\beta - \mathbf{A}_2 \cdot \mathbf{D}_\beta \\ \mathbf{D}_\delta &= |\mathbf{C}_3 \cdot \mathbf{X}_\delta - \mathbf{X}_i|,\ \ \mathbf{X}_3 = \mathbf{X}_\delta - \mathbf{A}_3 \cdot \mathbf{D}_\delta \end{aligned} \quad (3)$$

where $\boldsymbol{A}_k = 2ar_{1k} - a$, $\boldsymbol{C}_k = 2r_{2k}$, with $k = 1,2,3$ and $r_{1k}, r_{2k} \sim U(0,1)$. Subsequently, (4) describes the position update for the next two selected individuals. These two individuals utilize the SFOA strategy by leveraging parallel information from two randomly selected starfish. Denoting these randomly selected individuals as $\mathbf{X}_\epsilon$ and $\mathbf{X}_\zeta$, their updated positions are computed using:

$$\begin{aligned} \mathbf{d}_\epsilon &= \mathbf{X}_{\text{gbest}} - \mathbf{X}_\epsilon,\quad \mathbf{X}_4 = \mathbf{X}_i + r_4 \cdot \mathbf{d}_\epsilon \\ \mathbf{d}_\zeta &= \mathbf{X}_{\text{gbest}} - \mathbf{X}_\zeta,\quad \mathbf{X}_5 = \mathbf{X}_i + r_5 \cdot \mathbf{d}_\zeta \end{aligned} \quad (4)$$

Finally, all obtained positional information is combined through a weighted average approach, utilizing weights $w_{GWO} = 0.6$ for the GWO group and $w_{SFOA} = 0.4$ for the SFOA group. The mathematical representation of this strategy is presented in:

$$\mathbf{X}_i^{t+1} = w_{GWO} \cdot \frac{\mathbf{X}_1 + \mathbf{X}_2 + \mathbf{X}_3}{3} + w_{SFOA} \cdot \frac{\mathbf{X}_4 + \mathbf{X}_5}{2} \quad (5)$$

Additionally, the regeneration strategy originally introduced by SFOA is maintained, as presented in:

$$If\ i = N:\quad \mathbf{X}_i^{t+1} = \exp\left(-\frac{tN}{T_{max}}\right) \cdot \mathbf{X}_i \quad (6)$$

The probability of executing exploration and exploitation phases is controlled by a fixed algorithm parameter, GP=0.5. To enhance algorithm performance, this study proposes a dynamic GP coefficient, as shown in (7). This represents a significant practical improvement over the fixed GP, enabling the algorithm to automatically adapt its search strategy over time:

$$GP_t = r \cdot GP_0 \cdot \left(1 - \frac{t}{T_{max}}\right) \quad (7)$$

The pseudocode of the proposed algorithm is:

```
Begin
Step 1: Initialize starfish positions X
randomly within the bounds [LB, UB].
Evaluate fitness F(x) for each starfish.
Set X_best as the global best position
```

```
Step 2: Repeat until stopping criteria are met
For t = 1 to T:
Calculate dynamic GP_t value using (7):
If rand() < GP_t: Exploration phase
If D > 5:
For i=1 to n:
Select 5 dimensions randomly
Update position according to (1)
End for
Else
For i=1 to n:
Select randomly two starfish positions k1, k2
Update position according to (2)
End for
End if
Else: Exploitation phase
Sort population based on fitness and identify
α, β, δ
Randomly select two additional starfish
positions (ϵ, ζ)
For i=1 to n:
Calculate new positions X1, X2, X3 using GWO-
based (3)
Calculate new positions X4, X5 using SFOA-
based (4)
Update position X_i using weighted average
strategy (5)
If i=n:
Apply regeneration strategy using (6)
End if
End for
Check and correct positions violating bounds
[LB, UB]
Evaluate fitness F(x) for updated positions
Update X_best if a better solution is found
End for: Until the maximum number of
evaluations or iterations is reached.
Return X_best and F(X_best)
End
```

III. BENCHMARK STORIES

This study evaluates ISFOA against SFOA, SOO, PSO, and GWO using two benchmark problems, including a four-story 132-member frame and a four-story 428-member frame. All algorithms selected sections from a standardized W-section list of 273 cross-sections (W6×8.5 to W14×730), treated as discrete variables [20]. The loadings followed 2010 LRFD-AISC and 2019 ASCE 7-10 guidelines, with gravity loads 2.88 kN/m², 2.39 kN/m², 0.755 kN/m² referring to dead, live, and snow loads, respectively. In addition, seismic loads are 1.05 for SDS, full in one direction + 30% orthogonal, including vertical effects. The inter-story drift limit is 8.75 cm. Each story is 3.5 m high and members are modeled as A992 steel (E = 200 GPa, F_y = 250 MPa, ρ = 7.85 kN/m³) with linear elastic beam elements. The direct analysis method is employed with second-order effects and the tau-b stiffness reduction approach.

A. The 132-Member Steel Frame of the Four-Story Structure

The steel frame, as illustrated in Figure 1, is an asymmetrical model with 70 nodes and 132 members, systematically arranged by story and position. These members are divided into 16 design groups according to geometry, location, and function, reducing the design variables and simplifying optimization while preserving analysis accuracy.

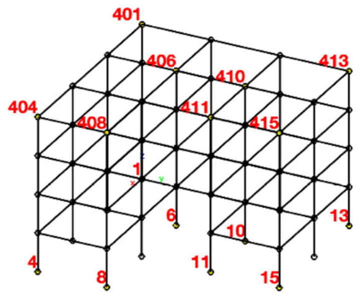


Fig. 1. 132-member steel frame of the four-story structure.

B. The 428-Member Steel Frame of the Four-Story Structure

The second example considers a larger four-story steel frame with 215 nodes and 428 members, as depicted in Figure 2. Members are classified into column types (corner, side, inner) and beam types (side, slide, inner) according to geometry, location, and function. In total, 20 design groups are defined, notably increasing optimization complexity.

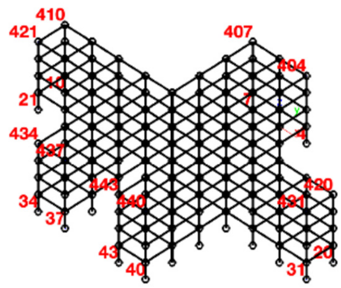


Fig. 2. 428-member steel frame of the four-story structure.

C. Seismic Design Objective Function

The primary objective of the structural optimization problem is to identify the minimum-weight design solution ($W(\mathbf{X})$), formulated by (8). Simultaneously, all relevant technical constraints should be satisfied, as depicted in (9):

$$W(\mathbf{X}) = \sum_{i=1}^{N_g} x_i \sum_{j=1}^{n_{m(i)}} \rho_j L_j \quad (8)$$

$$\begin{cases} g_j(\mathbf{X}) \leq 0, j = 1, 2, 3, \ldots, n_c \\ x_{i,\min} \leq x_i \leq x_{i,\max} \end{cases} \quad (9)$$

where $\mathbf{X} = \left[x_1, x_2, \ldots, x_{N_g}\right]$ denotes the vector of the design variables; $W(\mathbf{X})$ represents the total structural weight; N_g is the number of the design groups; $n_{m(i)}$ indicates the number of elements in the i; design group; ρ_j and L_j, respectively, denote the material density and length of the j element. The variables

$x_{i,\min}, x_{i,\max}$ represent the lower and upper bounds of the design variable x_i, respectively. $g_j(\mathbf{X})$ denotes the constraint functions, and n_c is the total number of constraints. The technical constraints in this study include strength, serviceability, and geometry requirements. Specifically, members must resist design loads, deflections and drifts must remain within code limits, and geometric rules are imposed on column depth and beam-to-column connections, including the condition that the beam flange width does not exceed $D - 2t_b$ of the supporting column.

To ensure compliance with the constraints, a penalty method is employed. Accordingly, the extended objective function or penalty function is defined by:

$$\boldsymbol{P}(\mathbf{X}) = (1 + \varepsilon_1 \cdot v)^{\varepsilon_2} \times W(\mathbf{X}) \quad (10)$$

where v represents the degree of constraint violation, ε_1 is a fixed coefficient, and ε_2 is a dynamic coefficient computed as: $\varepsilon_2 = 1.5 + 1.5 \times \frac{t}{T}$. Here, t denotes the current iteration and T represents the total number of iterations. The penalty function equals the structural weight if all constraints are satisfied, and significantly increases upon constraint violations, guiding the optimization algorithm towards feasible optimal solutions.

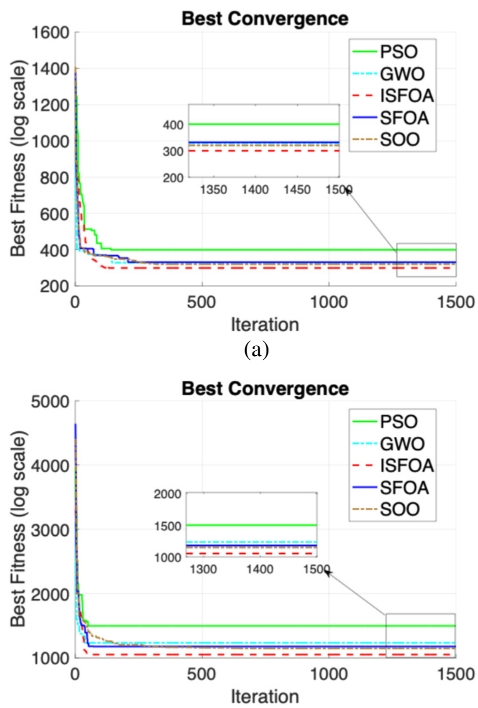
IV. RESULTS AND DISCUSSION

The selected algorithms include SFOA, SOO, PSO, and GWO. Across all experiments, the setup entailed a population size (N_{pop}) of 30, 1500 as the number of maximum iterations ($Iter_{max}$), and a number of runs (N_{runs}) equal to 30 independent trials. The candidate designs are initialized uniformly over $[LB, UB]$ and mapped to a discrete catalog of 273 W-sections. The objective is to achieve the minimum structural weight subject to strength, serviceability, and geometric constraints in accordance with LRFD-AISC, ASCE 7-10 load combinations, and an inter-story drift limit of 8.75 cm for a 3.5 m story height. The penalty function, as indicated in (10), is employed with a fixed penalty factor and a dynamic coefficient to enforce constraints.

For the PSO algorithm, a constriction-style configuration is adopted. Specifically, inertia is initialized at $w[0] = 1$ and reduced linearly by $w^{(t)} = w^{(t-1)} \cdot w_{\text{damage}}$ with $w_{\text{damage}} = 0.9$. The cognitive and social coefficients are set to $c_1 = c_2 = 1.5$, while the maximum velocity is limited to $V_{\max} = 0.2(UB - LB)$. For GWO, the control schedule is $a(t) = 2 - 2t/T$, with $\text{A} = 2ar_1 - a$ and $\text{C} = 2\text{r}_2$ where $\text{r}_1, \text{r}_2 \sim U(0,1)$, and the three leaders α, β, δ guided the search. In SOO, the endogenous hyperparameters comprised the oscillation period $P(t) = P_0 + \Delta P t$ (with $P_0, \Delta P$ specified), angular frequency $\omega(t) = 2\pi/P(t)$, and a scaling factor $S(t) = 2 - 2t/T$ to gradually shrink the step sizes. At each iteration, given the current best and the elite centroid x_{avg} (mean of the three best solutions), two candidates $x_{\text{osc1}}, x_{\text{osc2}}$ are generated via sinusoidal/cosinusoidal oscillations with $r_1, r_2, r_3 \sim U(0,1)$, then combined by a random weighted average to produce x_{new}. For SFOA, the exploration-exploitation switch is fixed at $p = 0.5$; exploration used a 5D pattern when $d > 5$ and a 1D pattern when $d \leq 5$; the exploitation applied a two-directional search with two random peers and the global best, retaining the regeneration scheme. Additionally, for ISFOA, the regeneration scheme is retained, the fixed parameter GP is replaced by a dynamic coefficient, represented by (7). In addition, GWO-style updates are applied to α, β, δ, and SFOA-style updates to two random individuals. The results are aggregated by a weighted average with 0.6 and 0.7 for w_{GWO} and w_{SFOA}, respectively. These weights are selected empirically through preliminary sensitivity tests, where ratios in the range [0.5–0.7] for w_{GWO} provided stable convergence, and the chosen values yielded the best balance between exploitation and exploration. All optimized designs are verified against $\text{IDR}_{\max} \leq 2.5\%$ (8.75 cm at 3.5 m).

A. *The 132-Member Steel Frame Four-Story Structure*

Figure 3(a) shows the convergence behavior of different algorithms for the 132-member, four-story frame. The horizontal axis denotes iterations, while the vertical axis indicates the best fitness value at each step.



(a) (b)

Fig. 3. Best convergence curve for: (a) 132-member and (b) 428-member steel frames.

ISFOA achieves the best convergence, consistently reaching the lowest objective values with both high efficiency and solution quality, in comparison to SOO, PSO, and GWO. A clear gap exists with the original SFOA, which converges quickly at first but stagnates later. Thanks to the GWO-inspired exploitation strategy, ISFOA sustains convergence and reliably attains better solutions.

While the qualitative results show the proposed algorithm's superiority, the quantitative analysis highlights the performance gap. As displayed in Table II, ISFOA attains the lightest weight of 299.134 kN, reducing about 7%, 11%, 34%, and 10% for

SOO, SFOA, PSO, and GWO, respectively. The 11% improvement over SFOA underscores the impact of the GWO-inspired exploitation mechanism, confirming ISFOA's advantage in structural weight optimization.

TABLE I. PERFORMANCE COMPARISON OF THE 132-MEMBER FRAME

Metrics	Algorithms				
	SFOA	*ISFOA*	*PSO*	*GWO*	*SOO*
Best	331.130	299.134	399.441	328.103	319.647
Worst	334.581	327.848	407.793	371.940	342.165
Mean	325.684	300.604	391.665	336.845	330.906
Std.	14.349	25.566	15.265	33.134	15.923
Best Dif.	11%	0%	34%	10%	7%
Mean Dif.	8%	0%	30%	12%	10%

TABLE II. DISPLACEMENT OPTIMIZATION PERFORMANCE OF THE 132-MEMBER FRAME

Algorithms	ISFOA	SFOA	PSO	GWO	SOO
Max Displacement (cm)	8.750	8.491	7.311	8.742	8.740
Performance (%)	100.00	97.04	83.54	99.91	99.89

Table II indicates that ISFOA reaches the maximum displacement exactly at the 8.75 cm limit (100.00%), fully utilizing the allowable drift, and therefore producing the lightest design. GWO and SOO exhibited similar results (~99.9%), whereas the original SFOA (97.04%) and PSO (83.54%) leave a considerable margin, indicating designs that are stiffer, and thus heavier than necessary. In short, ISFOA not only minimizes structural weight but also meets the displacement requirements for earthquake-resistant frames, in comparison to the GWO, SOO, and SFOA algorithms.

B. The 428-Member Steel Frame Four-Story Structure

The convergence behavior of the 428-member frame is portrayed in Figure 3(b). All algorithms start with high objective values that gradually decrease, reaching different final results. ISFOA indicated the best performance, combining fast early decline with steady progress to the lowest final value. In contrast, SFOA stabilizes earlier but converges with a suboptimal solution.

TABLE III. PERFORMANCE COMPARISON OF THE 428-MEMBER FRAME

Metrics	Algorithms				
	SFOA	*ISFOA*	*PSO*	*GWO*	*SOO*
Best	1179.110	1053.177	1500.089	1235.293	1148.754
Worst	1254.977	1209.704	1691.639	1309.599	1258.914
Mean	1222.010	1111.778	1605.242	1275.711	1203.834
Std.	54.494	89.836	110.972	52.452	77.895
Best Dif.	12%	0%	42%	17%	9%
Mean Dif.	10%	0%	44%	15%	8%

Table III confirms the performance gap among the algorithms. ISFOA attains the lightest weight (1001.456 kN), reducing about 10–12% compared to SFOA (1295.463 kN). While SOO improves over SFOA, it still weighs 9% more than ISFOA. The advantage is even greater against PSO (1500.089 kN, +42%) and GWO (1235.293 kN, +17%), underscoring the effectiveness of the GWO-based enhancement. According to Table IV, ISFOA achieves a displacement of 8.747 cm (99.97%), nearly reaching the 8.75 cm limit, and thus maximizing drift capacity while minimizing weight. SOO ranks second with 8.652 cm (98.88%), whereas SFOA (8.454 cm; 96.62%) and GWO (8.305 cm; 94.91%) produce stiffer, heavier designs. In contrast, PSO yields 12.21 cm (139.54%), exceeding the drift limit and failing to satisfy the seismic requirements.

TABLE IV. DISPLACEMENT OPTIMIZATION PERFORMANCE OF THE 428-MEMBER FRAME

Algorithms	ISFOA	SFOA	PSO	GWO	SOO
Max Displacement (cm)	8.747	8.454	12.21	8.305	8.652
Performance (%)	99.97	96.62	139.54	94.91	98.88

Beyond weight minimization, the optimization results are evaluated for seismic performance. As shown in Tables II and IV, ISFOA fully exploits the inter-story drift capacity (99.9–100% of the 8.75 cm limit), proving its ability to balance efficiency and seismic demand. In contrast, GWO and SOO yield feasible but overly stiff designs with higher weight, while PSO even violates the drift limit in the larger frame. These results highlight that ISFOA not only reduces material usage but also ensures compliance with structural and seismic constraints, offering practical and reliable solutions for earthquake-resistant design.

To further validate the convergence reliability, all algorithms are executed over 30 independent runs, and the reported statistics (best, mean, worst, and standard deviation) in Tables I–IV are calculated across all these. In addition, a non-parametric Wilcoxon signed-rank test is conducted at the 5% significance level. The results confirmed that the improvements achieved by ISFOA over SFOA, PSO, GWO, and SOO are statistically significant, thereby ensuring the observed superiority of ISFOA.

V. CONCLUSION

This paper proposes an improved optimization algorithm for the design of earthquake-resistant steel frame structures. Two benchmark problems involving asymmetric steel frame optimization were considered, with stress constraints defined according to LRFD-AISC standards, limitations on maximum lateral displacement, and geometric constraints applied to all structural configurations. In addition to the proposed method, four well-established metaheuristic algorithms—Starfish Optimization Algorithm (SFOA), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Stellar Oscillation Optimizer (SOO)—are employed. The algorithms are compared in terms of minimizing the structural weight using discrete design variables.

The numerical results demonstrate that the proposed Improved SFOA (ISFOA) consistently achieved the lightest designs across all examined cases. The algorithm effectively validates the integration of the GWO-inspired exploitation strategy into the original SFOA, significantly enhancing its performance and convergence stability. In the first case study involving a four-story structure with a 132-member steel frame, the best solution obtained by ISFOA resulted in a structural weight reduction of 34%, 10%, 7%, and 11% compared to those found by PSO, GWO, SOO, and SFOA, respectively. In the second case, involving a more complex 428-member frame, the optimized design produced by ISFOA was lighter by 42%, 17%, 9%, and 12%, respectively, further confirming the algorithm's superior capability in solving complex structural optimization problems.

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