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Optimization of Large-Scale Frame Structures by Means of Improved Artificial Rabbits Optimization Algorithm

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ABSTRACT:

With the advancement of intelligent computing systems in recent decades, the optimization process of structures has been significantly improved. These systems provide accurate and fast analysis of complex structures and enable engineers to use more advanced and effective methods in the design and optimization of structures. This ability enables them to obtain optimal solutions in the shortest possible time by analyzing large and complex data. Thus, using intelligent computing systems accelerates and improves the accuracy of structural optimization. The main concern of this study is to investigate the applicability of the Artificial Rabbits Optimization (ARO) algorithm, as one of the recently developed metaheuristic algorithms, in the design optimization of large-scale frame structures. For numerical purposes, three frame structures are selected with different characteristics, an 8-story, single bay frame structure; a 15-story, 3-bay benchmark frame structure; and a 24-story, 3-bay frame structure. In order to improve the overall computational performance of the standard ARO algorithm, an enhanced version of this algorithm is proposed as I-ARO by using the Diagonal Linear Uniform (DLU) initialization process instead of the conventional Brownian random initialization scheme. By comparing the results of I-ARO with those of other approaches in the literature, it can be concluded that the DLU process significantly upgrades the optimization capability of the standard ARO algorithm, such that the improved algorithm provides lower structural weight in the considered design examples.

KEYWORDS:

Optimum design, Improved artificial rabbits optimization, Diagonal linear uniform initialization, Large-scale, Frame structure.

1. Introduction

Reducing building weight is a multi-dimensional endeavor that requires smart design decisions and comprehensive approaches. By using lightweight materials, innovative construction techniques, optimization algorithms, and sustainable practices, experts can create more efficient and sustainable buildings. Reducing building weight offers opportunities to improve construction practices, increase stability, and enhance structural efficiency. As the construction industry moves toward more environmentally friendly and resource-efficient solutions, professionals are tasked with exploring innovative ways to achieve these goals. One of the primary approaches to reducing building weight is the use of lightweight materials such as composite products in the structure. Modification of conventional construction processes can result in significant weight reduction. Strategic spatial planning is very important in reducing building weight while maintaining performance. Efficiently designing layouts that maximize usable space eliminates unnecessary construction, resulting in lighter structures. Integrating energy-efficient systems into buildings not only reduces operating costs but also helps reduce overall weight. Installing smart technologies, such as energy-efficient lighting and air conditioning systems, eliminates the need

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for excessive structural support. These systems enable lighter load-bearing elements and minimize construction materials.

In the domain of sustainable and efficient building construction, recent literature underscores a multifaceted approach to reducing building weight through the utilization of lightweight materials, advanced construction techniques, and integration of energy-efficient systems. Choi et al. (2016) developed a sustainable design model for composite structures, highlighting the potential for CO_2 reduction by optimizing material combinations.

Arkar et al. (2018) demonstrated the development of a composite timber facade wall that balances energy efficiency with dynamic thermal properties using advanced insulating technologies. Fadai and Winter (2017) explored wood lightweight concrete composites, advocating for resource-efficient construction methods that leverage renewable resources. Block et al. (2017) investigated the application of lightweight construction and adaptive energy systems in experimental buildings to enhance lifecycle energy efficiency.

Novais et al. (2020) reported on bi-layered porous/cork-containing waste-based inorganic polymer composites as a novel approach to improving building energy efficiency through material innovation. Chwieduk (2003) emphasized the potential for significant energy savings in residential and tertiary sectors through the adoption of sustainable building practices. Shoubi et al. (2015) assessed the use of Building Information Modeling (BIM) tools to identify material combinations that minimize operational energy consumption.

Rohracher (2001) discussed the socio-technical challenges in transitioning to sustainable construction technologies, highlighting the need for integrating social and technical considerations. Borbon-Almada et al. (2019) evaluated the energy and economic impacts of integrating low-cost lightweight materials in housing, demonstrating significant reductions in energy demand and CO_2 emissions.

Herrmann et al. (2018) reviewed the life cycle engineering of lightweight structures, underscoring the trade-offs and methodological challenges in evaluating their environmental benefits. The use of optimization and engineering algorithms is one of the promising ways to reduce building weight. The implementation of simulation and modeling tools provides the possibility of examining different design possibilities and identifying optimal solutions. These algorithms optimize building structures by analyzing loads, form, and distribution of materials, which leads to significant weight reduction. Achieving weight reduction requires optimizing the use of structural elements. The use of advanced structural analysis techniques can accurately determine the optimal size and position of beams, columns, and trusses. Avoiding excessive dimensions ensures the efficient use of the building profile and reduces the overall weight. The integration of optimization algorithms and engineering techniques into building design processes has been a focal point of recent research, aimed at reducing structural weight while enhancing sustainability and efficiency. Studies have demonstrated the effectiveness of metaheuristic algorithms, including genetic algorithms and biogeography-based optimization, in identifying optimal structural configurations that contribute significantly to weight reduction (Saka, 2016; Çarbaş, 2017). Tools that couple genetic algorithms with building energy simulations enable the optimization of building shapes and envelope features, optimizing energy use and reducing weight (Tuhus, 2010). Multi-objective metaheuristics facilitate the optimization of conflicting objectives, such as weight reduction and increased robustness, demonstrating their applicability in real-world structural design (Zavala et al., 2016). The adoption of metaheuristic optimization for seismic design illustrates the algorithms' capability to minimize both structural cost and ductility demand (Talatahari, 2013).

Strategies like the upper bound strategy enhance computational efficiency in metaheuristic-based optimization, offering potential for significant time and resource savings (Azad et al., 2013). Guided and hybrid metaheuristic algorithms, incorporating design-oriented strategies, have shown promise in optimizing steel truss structures (Azad et al., 2017).

Advanced metaheuristics, such as teaching-learning-based optimization, effectively optimize timber structures under fire, adapting to specific design contexts (Ulusoy, 2022). Game theory-based metaheuristics and the development of general-purpose computing platforms for structural design optimization further underscore the field's evolution, showcasing the adaptability and effectiveness of these algorithms in complex design scenarios (Mahjoubi et al., 2021; Lagaros, 2014).

The hyper-heuristic approach effectively customizes metaheuristics for engineering problems by selecting optimal operators and parameters. It outperforms standard algorithms like PSO, GA, and Cuckoo Search with faster convergence and better solutions (Zambrano, 2023).

The improved multi-objective algorithm IBMSMA, using a chaotic grouping mechanism and dynamic strategies, has achieved better convergence and diversity in truss structure optimization compared to other advanced algorithms. This algorithm has demonstrated high efficiency in solving large-scale engineering problems. (Yin et al., 2023). The application of the Improved Prairie Dog Optimization (I-PDO) algorithm for seismic optimization of steel mega-braced frames demonstrates its effectiveness in enhancing structural stiffness and stability while optimizing bracing topology and size. This metaheuristic approach outperforms conventional methods by efficiently minimizing structural costs and improving seismic performance in tall building designs (Payami Far et al 2024).

The investigations of Saka et al. in 2024 cover a review of algorithms developed for the optimum design of steel skeletal structures, from the first article published in 1960 up to the present date. Collectively, this body of research highlights the transformative potential of computational algorithms and engineering principles in advancing sustainable, efficient, and cost-effective building designs. Building upon the previously highlighted research, additional studies emphasize the critical role and evolving application of optimization algorithms and engineering techniques in structural design (Kashani et al., 2021; Kiani, 2016).

These studies expand upon the use of metaheuristic algorithms and their integration with engineering principles, demonstrating a broadened scope of application and innovation in tackling structural optimization challenges (Greiner, 2013; Lagaros, 2012; Prayogo, 2022).

These additional references not only reinforce the significance of metaheuristic algorithms and advanced simulation tools in structural optimization but also highlight the evolving nature of these technologies. Through the integration of computational intelligence and engineering expertise, the potential for achieving more sustainable, efficient, and cost-effective designs in structural engineering is increasingly realized (Lagaros et al. 2012; Prayogo, 2012).

This paper primarily focuses on examining the effectiveness of the Artificial Rabbits Optimization (ARO) algorithm (Wang et al., 2022), a newly developed metaheuristic algorithm, in optimizing the design of large-scale frame structures. Three different frame structures are chosen for analysis, ranging from an 8-story single bay planar structure to a 24-story, 3-bay frame structure, each with distinct characteristics. To enhance the computational performance of the standard ARO algorithm, an improved version called I-ARO is introduced. This enhancement involves employing the Diagonal Linear Uniform (DLU) (Li et al., 2021) initialization process instead of the conventional Brownian random initialization scheme. The comparison of results between I-ARO and other methods from existing literature suggests that implementing the DLU process notably enhances the optimization capability of the standard ARO algorithm. This enhancement leads to lower structural weight in the design examples considered.

2. Optimization Problem Statement

This section describes the design optimization problem developed for minimizing the weight of frame structures, while adhering to the prescribed design constraints outlined in the relevant codes and standards. The primary goal is to minimize the overall weight of the structure, and discrete design variables are used to assign predefined design sections to the structural elements during the optimization process. Mathematically, the solution method for the developed problem is presented as follows:

$$Weight\,(\boldsymbol{A}) = \sum_{i=1}^{e} \rho_i \, L_i \, A_i\,, \qquad i = 1,2,\dots,e. \tag{1}$$

$$\delta_{min} \le \delta_i \le \delta_{max}, \qquad i = 1,2,\dots,n. \tag{2}$$

$$\sigma_{min} \le \sigma_i \le \sigma_{max}, \qquad i = 1,2,\dots,e. \tag{3}$$

$$A \in S = \{A_1\,, A_2\,,\dots, A_i\} \tag{4}$$

Where, ρ_i represents the density of the material; L_i signifies the length of the structural elements; A denotes a vector containing A_i as the cross-sectional area of the design sections e and n stand for the overall number of structural elements and nodes in the structure; δ_i and σ_i denote the nodal displacement and stress in the structure respectively; and S represents the predefined set of discrete cross-sectional areas.

Given that structural design optimization is a constrained optimization problem, it necessitates the use of a constraint handling approach to carry out the optimization process. To address this, a penalty function is established as part of the penalty-based constraint handling method employed in this study.

$$f_{penalty}(A) = (1 + \varepsilon_1 . v)^{\,\varepsilon_2} \times Weigth\,(A) \tag{5}$$

$$v = \sum_{i=1}^{q} max\{0, g_i(A)\} \tag{6}$$

In this context, v is the aggregate of violated design constraints; g_i (A) signifies the i^{th} design constraint; q stands for the total count of design constraints; and ε_1 and ε_2 are control parameters used to determine the penalty during the optimization process.

3. Artificial Rabbits Optimization (ARO) Algorithm

The inspiration behind the ARO algorithm is inspired by the survival tactics of rabbits in their natural environment. These strategies have evolved over time to help rabbits evade predators. One notable tactic involves avoiding feeding near their nests to prevent detection by predators. Instead, rabbits venture farther away to forage, using their wide field of vision to scan the surroundings. Another survival strategy employed by rabbits is the random selection of shelters. To evade predators or hunters, rabbits construct multiple burrows around their nest and randomly select one as a refuge (Fig. 1).

Fig. 1. Nests and a Rabbit in the nature (Wang et al., 2022)

Their physical characteristics, such as short forelegs and elongated hind legs, along with robust muscles and tendons, enable them to sprint at high speeds. These strategies are incorporated into the ARO algorithm: the latter tactic influences the exploitation phase in the main search loop, while the former guides the exploration phase.

During the initial stage of the ARO algorithm, a random initialization process is performed to establish the initial positions of the search agents as follows:

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_i \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} x_1^1 & x_1^2 & \cdots & x_1^j & \cdots & x_1^d \\ x_2^1 & x_2^2 & \cdots & x_2^j & \cdots & x_2^d \\ \vdots & \vdots & & \vdots & \ddots & \vdots \\ x_i^1 & x_i^2 & \cdots & x_i^j & \cdots & x_i^d \\ \vdots & \vdots & & \vdots & \ddots & \vdots \\ x_n^1 & x_n^2 & \cdots & x_n^j & \cdots & x_n^d \end{bmatrix}, \quad \begin{cases} i = 1,2,\dots,n. \\ j = 1,2,\dots,d. \end{cases} \tag{7}$$

$$x_i^j = x_{i,min}^j + rand.\left(x_{i,max}^j - x_{i,min}^j\right) \quad \begin{cases} i = 1,\dots,n. \\ j = 1,\dots,d. \end{cases} \tag{8}$$

Where xi is position vector of the i^{th} rabbit; n and d refer to the rabbits' total population and dimension of the optimization problem respectively; $x^j_{i,max}$ and $x^j_{i,min}$ relates to the upper and lower bounds of the optimization variables; rand denotes to a random number in the range of 0 and 1. The core mechanism of the ARO algorithm is based on two survival strategies observed in rabbits: detour foraging, utilized for the exploration phase, and random hiding behavior, employed for the exploitation phase. Each rabbit in the swarm is allocated its own territory, which comprises patches of grass and multiple burrows. During foraging, rabbits randomly visit the positions of other rabbits in the swarm and maneuver around food sources, introducing perturbations to their movements to ensure efficient food gathering.

Mathematically, this detour foraging behavior in ARO is represented by each search individual adjusting its position towards another randomly selected search individual within the swarm, while incorporating perturbations into its movements. The mathematical model of this phase in the ARO algorithm is formulated as follows:

$$v_i(t+1) = x_j(t) + R.\left(x_i(t) - x_j(t)\right) + round\left(0.5(0.05 + r_1)\right) n_1 \; ;$$

$$i = 1,2,\dots,n. \tag{9}$$

$$R = L.c \tag{10}$$

$$L = \left(e - e^{\left(\frac{t-1}{T}\right)^2}\right).\sin(2\pi r_2) \tag{11}$$

$$if\ k = g(l)\ then\ c(k) = 1\ else\ c(k) = 0\ ; \quad k=1,\dots,d$$

$$l=1,\dots,\lceil r_3 \cdot d \rceil \tag{12}$$

$$g=randperm(d) \tag{13}$$

$$n_1 \sim N\,(0,1) \tag{14}$$

Where $v(t+1)$ denotes new position of the i^{th} rabbit; T is the total number of optimization iterations; $x_i(t)$ and $x_j(t)$ denote the i^{th} and j^{th} rabbits' position at current iteration; randperm generates integer random numbers between 1 and d; r_1, r_2, and r_3 refers to random numbers of range 0 and 1.

Fig. 2 illustrates the fluctuation of the running length (L) in rabbits, representing the distance traveled during detour foraging. Meanwhile, Fig. 3 displays the variation of R as a running operator, depicted following a standard normal distribution.

To evade predators during the exploitation phase, a burrow creation process is carried out, modeled by generating d new vectors around the current position of the rabbits. The rabbits then randomly select one of these burrows to reduce the risk of predation. The equation below describes the generation of the j^{th} burrow for the i^{th} rabbit:

$$b_{i,j}(t) = x_i(t) + H.g.x_i(t), \quad \begin{cases} i = 1,2,\dots,n. \\ j = 1,2,\dots,d. \end{cases} \tag{15}$$

$$H = \frac{T-t+1}{T}.r_4 \tag{16}$$

$$n2 \sim N\,(0,1) \tag{17}$$

$$if\ k = j \quad then\ g(k) = 1\,, \quad else\ g(k) = 0\ ;$$

$$k=1,\dots,d \tag{18}$$

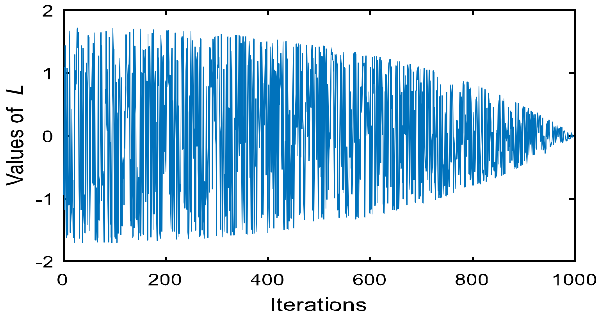

Fig. 2. Variation of *L* values over time

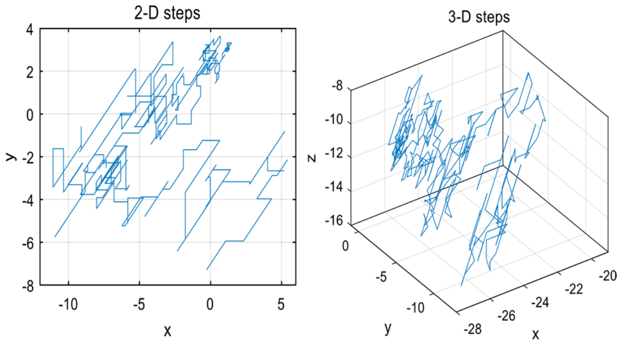

Fig. 3. Variation of *R* values over time

Where *H* refers to a parameter which denotes on hiding with a linear decrease from 1st iteration to T^{th} iteration. Based on the earlier description of rabbits' natural behavior, where they often face threats from pursuing predators, they prioritize finding a secure hiding place. Consequently, they typically choose one of their available burrows at random to seek sanctuary and evade capture. To mathematically model this random hiding behavior, the following equations are employed:

$$v_i(t+1) = x_i(t) + R.\left(r_4.b_i(t) - x_i(t)\right), \quad i = 1,\dots,n \tag{19}$$

$$b_{i,r}(t) = x_i(t) + H.g_r.x_i(t), \quad \begin{cases} i = 1,2,\dots,n. \\ j = 1,2,\dots,d. \end{cases} \tag{20}$$

$$if\ k = \lceil r5 \cdot d \rceil \quad then\ g(k) = 1, \quad else\ g(k) = 0\ ;$$

$$k=1,\dots,d \tag{21}$$

Where $b_{i,r}$ is the burrow which is selected randomly for hiding; r_4 and r_5 are randomly generated numbers in the range of (0, 1). The process of updating the positions of rabbits after executing the procedures for both exploration and exploitation phases is managed in the following manner:

$$x_i(t+1) = \begin{cases} x_i(t) & f(x_i(t)) \le f(v_i(t+1)) \\ v_i(t+1) & f(x_i(t)) > f(v_i(t+1)) \end{cases} \tag{22}$$

In the ARO algorithm, the transition between the exploration and exploitation phases is represented as energy shrink (refer to Fig. 4), wherein a gradual shift is achieved through the following equation:

$$A(t)=4(1-t/T)\ ln1/r \tag{23}$$

Where r is a randomly generated number in the range of 0 and 1; *t* is the current iteration and *T* is the maximum number of considered iterations. Fig. 5 depict the pseudocode and the flowchart of the ARO algorithm, respectively.

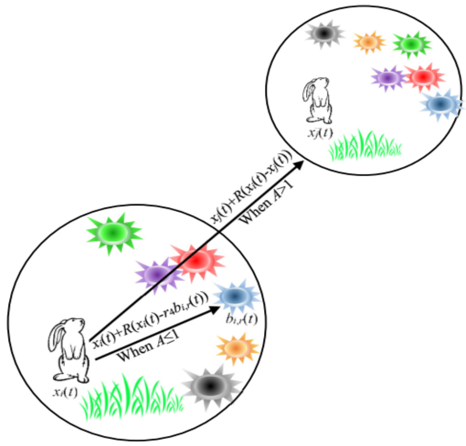

Fig. 4. Conducting energy shrink behavior by rabbits

4. Improved ARO (I-ARO) Algorithm

Random number generation has long been a common method for generating new solution candidates in many metaheuristic algorithms. In the primary loop of these algorithms, determining the initial positions and subsequent movements of candidates often involves a randomization process based on Brownian motion. However, this approach often leads to suboptimal convergence and increases the likelihood of getting trapped in local optima.

In the ARO algorithm, Brownian random generation is employed at various stages, particularly during initialization, where position vectors are randomly determined within the upper and lower bounds of the variables. The quality of the final global optimal solutions and the optimization procedure itself are significantly influenced by the initialization process. However, the random initialization process primarily focuses on the diversity and uniformity of the population distribution but often neglects the algorithm's update mechanism. There is, therefore, a need to develop novel techniques to enhance the initialization process of algorithms, thereby augmenting their search capability.

```
Initialize the parameters of ARO: n, m, and T
——— Initialization of ARO's population
x_{i,j} = x_j^{min} + (x_j^{max} - x_j^{min}) × U(0,1)      ∀i = 1,2,...,n, and ∀j = 1,2,...,m
Calculate f(x_i)      ∀i = 1,2,...,n {Fitness evaluation}
Select the best solution so far x_best
t=1
while (t ≤ T) do
  for i= 1 : n do
    Calculate the energy factor A using
    if A > 1 then
      Selected a random rabbit x_k, where k ≠ i
      Calculate R using
      Perform detour foraging using
    else
      Generate d barrows and randomly select one
      Perform random hiding action using
    end if
    Calculate fitness of x_i
    Update position of x_i
    Update the x_best
  end for
  t = t + 1
end while
Return the best solution x_best
```

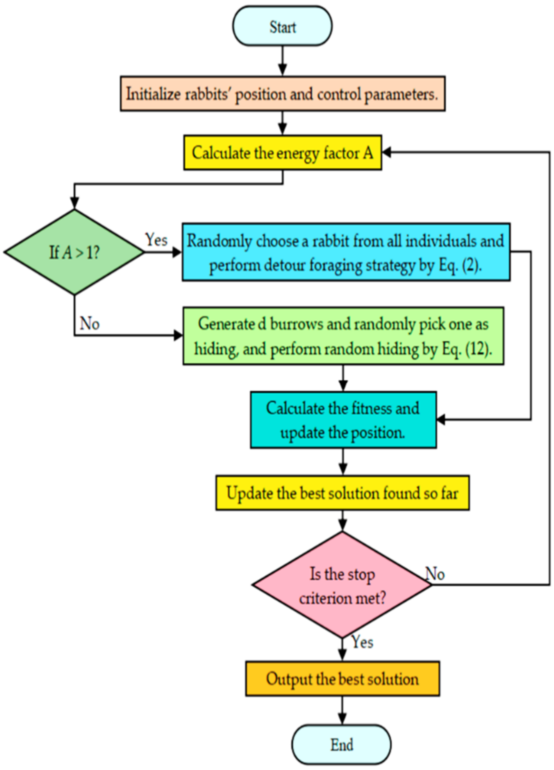

Fig. 5. Pseudo code and flowchart of the ARO algorithm

To address this, an Improved ARO (I-ARO) is proposed in this section, wherein the Brownian random initialization process of the ARO is replaced by a new initialization scheme known as the Diagonal Linear Uniform (DLU) initialization process. In the DLU initialization process, the search space's dimensions are initially divided into *N−1* equal parts, and vertices of the diagonal subspace are subsequently selected accordingly.

This entails choosing uniform points along the "diagonal" of the space (refer to Fig. 6-a), with the total distance between adjacent points calculated as (xu-xl)/(N-1), where xu and xl represent the upper and lower bounds respectively. For example, if five initial individuals are needed in a 3-dimensional space defined by upper and lower bound vectors of (-2, -2, -2) and (2, 2, 2) respectively, the DLU initialization process divides each dimension into four parts. The DLU method then selects the five initial points as (2, 2, 2), (-2, -2, -2), (1, 1, 1), (0, 0, 0), and (-1, -1, -1) (see Fig. 6.b). Initialization via DLU is straightforward and easily applicable. Importantly, its effectiveness remains consistent even in higher dimensions and demonstrates robust performance across various problem types, including multi-objective and multimodal problems. The pseudocode outlining e DLU initialization process is presented in Fig. 7.

The linear initialization method with uniform coverage of the search space samples different regions of the search space for the initial points, whereas the random approach may generate points close to each other and enter the first iteration of calculations. In other words, it creates greater diversity in the initial population, enhances global search, and reduces the likelihood of getting trapped in local optima. Diagonal initialization, due to the uniform distribution of initial points across the entire response range, improves the algorithm's performance by strengthening the exploration or global search phase in the first step, reducing the required iterations, and increasing accuracy.

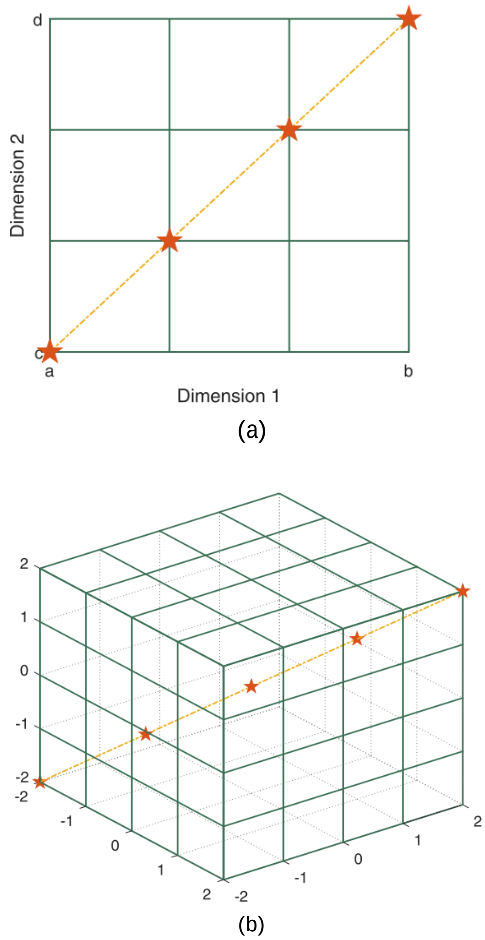

Fig. 6. DLU initialization process for: **a)** 2D, **b)** 3D, spaces

Input: the range $[x_{i\_\min}, x_{i\_\max}]$ for each dimension x_i.
the population size N, the dimension of problem D.
$X_{init} = zeros(N, D)$ // allocate memory space
for $j = 1, 2, \ldots, N$ **do**
  for $i = 2, \ldots, D-1$ **do**
    $X_{init}(j, 1) = x_{i\_\min}$,
    $dx = \frac{x_{i\_\max} - x_{i\_\min}}{N-1}$ // length of each interval in i-th dimension
    $X_{init}(j, i) = x_{i\_\min} + (i-1) * dx$
    $X_{init}(j, D) = x_{i\_\max}$
  end for
end for
return X_{init} as a vector.

Fig. 7. Pseudo code of the DLU initialization process

4.1. Validation of I-ARO

Validation of optimization algorithms is a vital process for assessing their accuracy, reliability, and efficiency. This is achieved through various methods such as standard benchmark functions, comparison with reference algorithms, statistical analysis, asymptotic approaches, and real-world applications. The validation process ensures that the algorithm can effectively solve optimization problems and that its results are trustworthy.

In this study, the performance of the proposed algorithm was evaluated using 23 mathematical benchmark functions from CEC2017 and the results were validated by comparison with well-known algorithms. To ensure fairness, all algorithms were executed 30 times, with the initial population size and the number of iterations set to 30 and 1000, respectively. Performance indicators including mean, standard deviation, maximum, and best results across the 30 runs were reported in Table 1.

The findings clearly indicate the high efficiency and robustness of the proposed algorithm. Comparative analysis with other algorithms also confirms its effectiveness in solving optimization problems. Furthermore, examination of the convergence plots in Fig. 8 demonstrates that the proposed approach significantly improves the convergence behavior of the Artificial Rabbits Optimization algorithm.

Table 1. Validation of I-ARO

		GA	PSO	ARO	I-ARO
F1	Best	3.13E-300	1.32E-09	7.49E-09	0
	Worst	4.37E-242	1.90E-06	2.20E-08	0
	Mean	1.46E-243	9.24E-07	1.26E-08	0
	Std	0	4.92E-07	3.67E-09	0
F2	Best	5.37E-151	4.53E-08	4.51E-06	2.68E-200
	Worst	1.73E-98	0.003429355	3.87E-05	2.29E-189
	Mean	5.77E-100	0.000451193	9.72E-06	7.74E-191
	Std	3.16E-99	0.000767668	7.68E-06	0
F3	Best	3.94E-301	5.26E-06	6.08E-10	2.20E-307
	Worst	1.25E-197	0.000874834	3.27E-09	8.43E-288
	Mean	4.16E-199	0.000326517	1.89E-09	3.87E-289
	Std	0.00E+00	0.000224414	8.24E-10	0
F4	Best	7.70E-154	1.79E-05	8.29E-06	1.98E-172
	Worst	2.56E-97	0.035142677	2.66E-05	3.98E-164
	Mean	8.74E-99	0.009083961	1.62E-05	2.10E-165
	Std	4.68E-98	0.007472062	4.09E-06	0
F5	Best	3.35E-06	26.75076727	0.624898405	21.93583048
	Worst	6.55E-03	28.07344896	1090.954969	26.22815407
	Mean	1.09E-03	27.495159	84.14202415	24.52684086
	Std	0.001619295	0.359168123	208.1314924	1.085685936
F6	Best	1.59E-07	1.384029948	2.47E-10	0.000112543
	Worst	0.00034795	2.177535768	1.16E-09	0.26089617
	Mean	5.63E-05	1.720228239	6.93E-10	0.026168086
	Std	9.13E-05	0.180469716	2.54E-10	0.076532005
F7	Best	3.74E-06	1.18E-06	0.0004845	1.33E-05
	Worst	2.11E-04	8.33E-05	0.022215827	0.000681939
	Mean	6.00E-05	3.16E-05	0.006420786	0.000157451
	Std	5.44E-05	2.28E-05	0.004336444	0.000141794
F8	Best	-1.26E+04	-6108.287233	-3419.968821	-11748.82531
	Worst	-4454.76281	-4789.848948	-2367.600692	-5356.307059
	Mean	-9.87E+03	-5438.862167	-2860.698924	-8271.636958
	Std	3602.770098	320.9542892	261.8541017	2037.872321
F9	Best	0.00E+00	0	5.969754343	0
	Worst	4.09E-07	1.07E-06	33.82848667	0
	Mean	1.36E-08	3.14E-07	17.77657189	0
	Std	7.47E-08	3.47E-07	7.296133342	0
F10	Best	4.44E-16	5.55E-07	6.89E-06	4.44E-16
	Worst	4.44E-16	0.000357466	2.579927557	4.44E-16
	Mean	4.44E-16	0.000185204	0.672278655	4.44E-16
	Std	0	0.000110479	0.958397214	0
F11	Best	0	2.64E-06	0.073766397	0
	Worst	0.00E+00	1.34E-05	0.580395357	0
	Mean	0.00E+00	6.85E-06	0.258365675	0
	Std	0.00E+00	2.75E-06	0.122077156	0
F12	Best	1.30E-09	0.533896601	4.89E-12	3.35E-05
	Worst	4.80E-06	0.673489616	4.390221787	0.112179351
	Mean	4.50E-07	0.60035013	0.410222833	0.008397946
	Std	8.97E-07	0.031134013	0.923839097	0.027770677
F13	Best	2.81E-08	2.909689137	1.23E-11	0.011503796
	Worst	3.32E-05	2.966081647	0.021023766	1.467820239
	Mean	4.71E-06	2.964197557	0.00253202	0.40466719
	Std	9.43E-06	0.010294997	0.005424326	0.34711147
F14	Best	0.998003838	1.9920309	0.998003838	0.998003838
	Worst	12.67050581	12.67050581	0.998003838	2.982105157
	Mean	2.109545159	10.7717628	0.998003838	1.19667749
	Std	2.73E+00	3.455166075	2.59E-16	0.480835503

		GA	PSO	ARO	I-ARO
F15	Best	3.10E-04	0.000310624	0.000422979	0.000307486
	Worst	6.57E-04	0.046231698	0.001621365	0.022553327
	Mean	4.42E-04	0.005223639	0.000874561	0.005628281
	Std	7.82E-05	0.010876221	0.000271227	0.008472899
F16	Best	-1.03E+00	-1.031628453	-1.031628453	-1.031628453
	Worst	-1.03E+00	-1.031628453	-1.031628453	-1.031628453
	Mean	-1.03E+00	-1.031628453	-1.031628453	-1.031628453
	Std	2.16E-04	7.42E-12	8.77E-15	6.78E-16
F17	Best	0.39788783	0.556509834	0.397887358	0.397887358
	Worst	0.398742933	8.756369965	0.397887358	0.397887358
	Mean	0.397998855	2.428547078	0.397887358	0.397887358
	Std	0.000168612	1.737985169	5.75E-14	0
F18	Best	3.00087027	3	3	3
	Worst	3.067040078	30	3	3
	Mean	3.015375507	8.4	3	3
	Std	0.016608471	10.98462876	6.36E-14	2.25E-15
F19	Best	-3.862767353	-3.862782018	-3.862782148	-3.862782148
	Worst	-3.85E+00	-3.862778591	-3.862782148	-3.089764163
	Mean	-3.85960911	-3.862781327	-3.862782148	-3.837014882
	Std	0.002636484	8.57E-07	6.70E-14	0.141133129
F20	Best	-3.317082587	-3.321994956	-3.321995172	-3.321995156
	Worst	-2.930910448	-3.203079336	-3.194243302	-3.197377007
	Mean	-3.209898501	-3.294250713	-3.225103277	-3.301934802
	Std	0.098325225	0.051149366	0.0493378	0.045608024
F21	Best	-10.153181	-10.15317377	-10.15319968	-10.15319968
	Worst	-10.12609174	-2.630463646	-2.630471668	-10.15319868
	Mean	-10.1485866	-8.049783709	-8.648419106	-10.15319962
	Std	0.006555551	2.656562185	2.837221482	2.04E-07
F22	Best	-10.40285967	-10.40293027	-10.40294057	-10.40294057
	Worst	-10.38867867	-2.765892977	-2.751933564	-3.724300347
	Mean	-10.39997246	-7.980360379	-9.717534966	-10.18031923
	Std	0.00365955	3.06357822	2.122012957	1.219347301
F23	Best	-10.53632852	-10.53633983	-10.53640982	-10.53640982
	Worst	-10.50868384	-2.421723252	-2.421734027	-1.859480301
	Mean	-10.53207146	-8.332619399	-8.165053327	-8.224634567
	Std	0.00624807	3.482800752	3.478475609	3.614669811

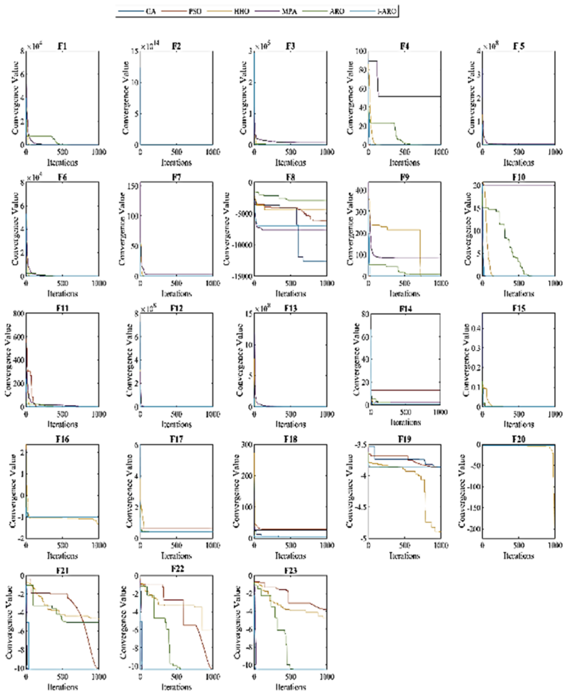

Fig. 8. Validation of I-ARO

5. Numerical Investigations

This section presents the results of numerical investigations conducted using the ARO algorithm and its improved version, I-ARO, in the design optimization of large-scale frame structures.

Given the inherent nature of large-scale structural design problems, uncertainties arising from unforeseen parameters (such as the precise characteristics of seismic records or the degree of connection semi-rigidity) can influence optimization results. In this study, an indirect yet effective approach has been adopted to investigate the robustness and efficiency of the I-ARO algorithm in confronting such uncertainties. The selection of three frame structures with significantly different characteristics (including variations in the number of stories, bays, and geometric complexities) was meticulously performed to cover a broad spectrum of structural behaviors and design challenges. This diversity in case studies implicitly serves as a test for evaluating the algorithm's resilience to wide-ranging variations in problem inputs. Furthermore, the introduction of the Diagonal Linear Uniform (DLU) initialization process in the I-ARO algorithm plays a crucial role in reducing the algorithm's sensitivity to initial fluctuations and uncertainties related to the search space. This enhancement not only accelerates convergence but also, by more uniformly and strategically distributing the initial population, helps the algorithm discover optimal solutions with greater confidence in a space that might be influenced by uncertain parameters. Therefore, although explicit modeling of uncertainties (such as through complex probabilistic analyses) was not the primary objective of this study, the judicious selection of case studies and the inherent improvement of the algorithm allow I-ARO to demonstrate strong and reliable performance across a broad range of conditions and common uncertainties encountered in real-world structural design.

Although the analysis does not explicitly perform detailed nonlinear structural analysis, the nonlinear behavior of the structures is implicitly accounted for through these code-based design criteria, such as limits on strength, stability, and deformation. The intelligent optimization algorithms effectively handle the complex, nonlinear relationships between design variables and performance criteria by exploring the design space thoroughly.

5.1. 8-Story, single-bay frame structure

Fig. 9 depicts the schematic view of an 8-story, single-bay frame structure and the applied loads. The structure's 24 members are divided into eight groups, as shown in Fig. 9. The sole performance constraint is the lateral drift at the structure's apex, which must not exceed 2 inches.

The material properties include a modulus of elasticity (E) of 200GPa (29×10^3ksi) and a material density (ρ) of 76.8KN/m3 (2.83×10^{-4}Kip/m^3). A series of eight-digit binary numbers are used to represent 268 W-sections sourced from the AISC-ASD.

Fig. 10 represents the optimization process for the 8-story frame structure using two different methods: ARO and the newly developed I-ARO method in this study. Both curves start at a higher objective function value and decrease as the number of function evaluations increases, which suggests an optimization process where the goal is to minimize the overall weight of the frame structure. The convergence curve of both the ARO and I-ARO methods decreases sharply and then levels off, indicating that a solution was rapidly found, which did not significantly improve with further evaluations after about 10,000 function evaluations. However, the I-ARO method decreases more gradually, suggesting a more incremental optimization process. A close-up view of the last iterations shows that the I-ARO method achieves a lower objective function value than the ARO method and maintains this lead. Overall, the results suggest that the I-ARO method was able to find a better objective function value (lower weight) more quickly than the ARO method in optimizing the 8-story frame structure.

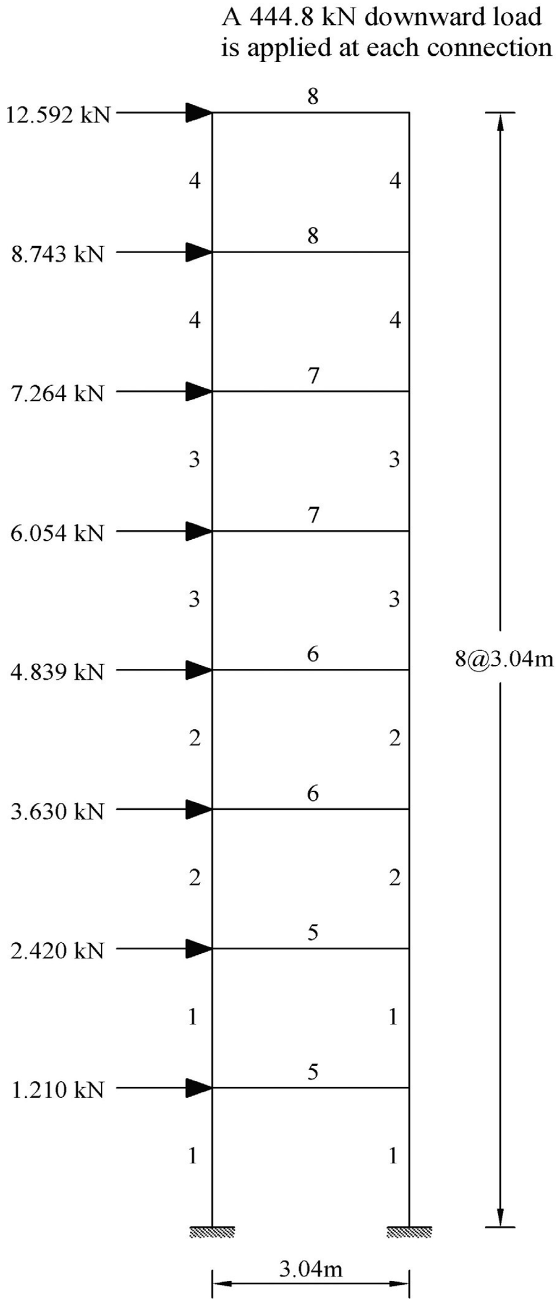

Fig. 9. Schematic view of the 8-story single bay frame structure

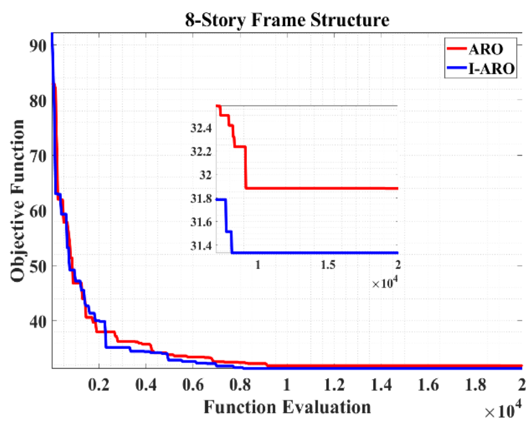

Fig. 10. Optimization process for the 8-Story frame structure

Table 2 presents a comparison of different optimization methods in terms of the optimum structural steel sections selected for the design of an 8-story benchmark structure. It also shows the corresponding total weight of the structure. The methods compared include Optimum Criteria (OC), Genetic Algorithm (GA), Differential Evolution (DE), Evolution Strategies with Differential Evolution (ES-DE), ARO, and Improved ARO (I-ARO). The total weight of the structure is a significant indicator of the efficiency of the design in terms of material usage. A lower total weight often indicates a more cost-effective and material-efficient design.

The I-ARO method resulted in the lightest structure at 31.33kN, which is marginally lighter than the ARO method (31.88kN) and the other methods. This suggests that I-ARO is potentially more efficient in material usage while likely maintaining the necessary structural integrity. In several design groups, the I-ARO method selected lighter sections compared to ARO. For example, in group 2, both ARO and I-ARO chose W16X31, which is lighter than the sections chosen by the other methods except for DE and ES-DE. In group 7, I-ARO opted for a lighter section (W18X35) compared to ARO's choice (W18X40).

Table 2. Optimum weight and design sections of the 8-Story frame structure

Groups	OC (Khot, 1976)	GA (Camp, 1998)	DE (Talatahari, 2015)	ES–DE (Talatahari, 2015)	ARO	I-ARO
1	W21X68	W18X35	W16X36	W18X40	W18X35	W18X35
2	W24X55	W18X35	W16X36	W18X35	W16X31	W16X31
3	W21X50	W18X35	W14X22	W14X22	W16X31	W14X22
4	W12X40	W18X26	W12X22	W12X14	W12X14	W14X22
5	W14X34	W18X46	W18X35	W18X46	W18X35	W18X35
6	W10X39	W16X31	W16X31	W18X35	W18X35	W18X40
7	W10X33	W16X26	W18X40	W18X35	W18X40	W18X35
8	W8X18	W12X16	W14X30	W12X19	W16X26	W14X22
Weight kN	41.02	32.83	32.76	31.77	31.88	31.33

OC: Optimality Criterion
GA: Genetic Algorithm
DE: Differential Evolution
ES–DE: Hybrid eagle strategy algorithm with differential evolution

5.2. 15-Story, 3-bay frame structure

Fig. 11 illustrates the schematic view of a 15-story frame structure, detailing the various groups of elements and the forces exerted on the structure. Optimization constraints included both displacement limits and AISC combined strength guidelines. The top floor's lateral movement is restricted to under 23.5 cm. The material's modulus of elasticity is specified at E=200GPa, with a yield stress of Fy=248.2MPa. It's assumed that columns are unbraced for their entire length, and the unbraced length for each beam is calculated to be one-fifth of its span length.

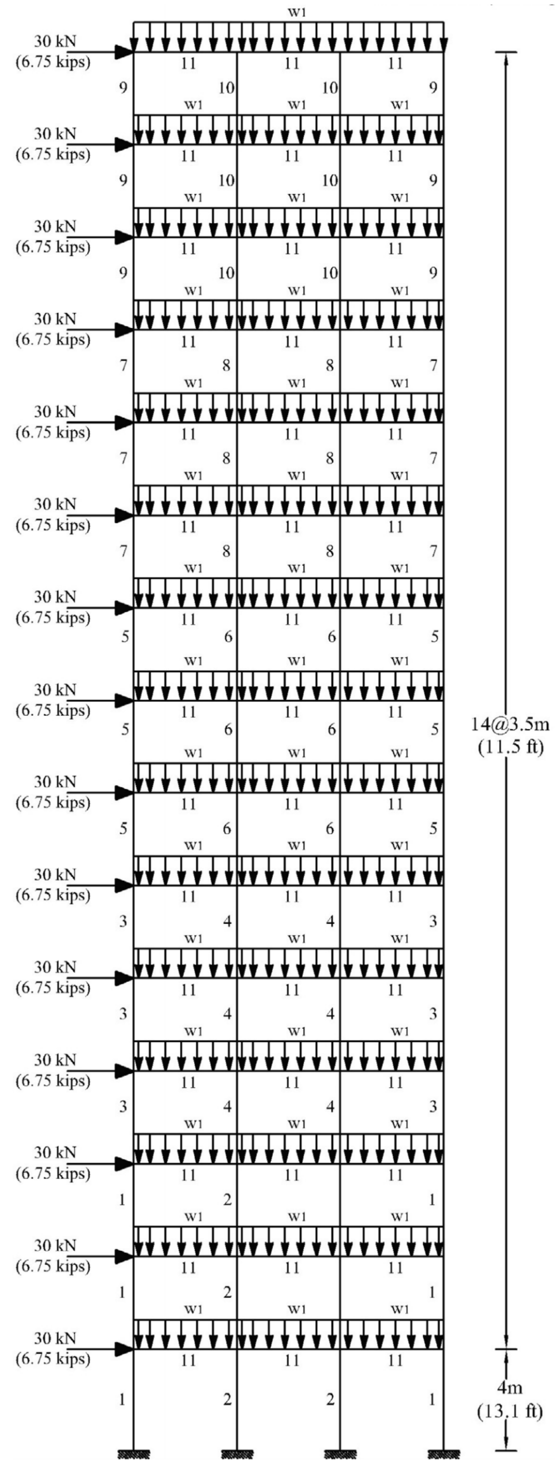

Fig. 11. Schematic view of the 15-story, 3-bay frame structure

Fig. 12 presents a performance comparison between the ARO and I-ARO algorithms, as applied to the optimum design of a 15-story frame structure. In this case, both ARO and I-ARO exhibit a rapid initial decrease in the objective function value, with the curve flattening out as the number of evaluations increases, a trend typical of optimization algorithms. It is evident that I-ARO is more efficient and effective, as its curve consistently lies below that of ARO, indicating lower objective function values for a given number of function evaluations. This demonstrates that, for the 15-story frame structure, the I-ARO algorithm can reach more optimal solutions more quickly than ARO, suggesting that the improved I-ARO performs better in addressing this structural optimization problem.

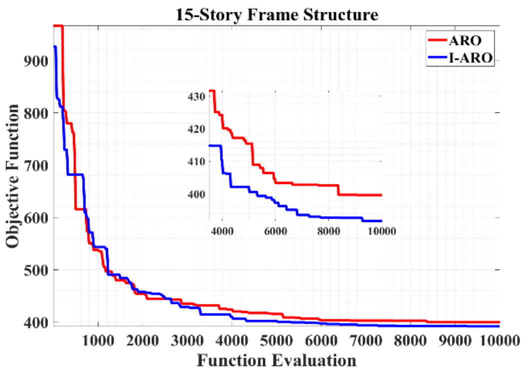

Fig. 12. Optimization process for the 15-story, 3-bay frame structure

Table 3 compares the optimum weight and design sections of a 15-story frame structure obtained using various optimization algorithms. Notably, the I-ARO algorithm achieves the lowest total weight of 391.72kN, demonstrating its superior efficiency in optimizing structural design to reduce weight while maintaining structural integrity.

This comparison highlights the critical role of selecting an appropriate optimization algorithm based on project-specific goals, such as minimizing weight, as well as meeting safety and performance criteria. The variability in design section choices and total optimized weights across different algorithms underscores the trade-offs and unique strengths each method offers in structural design, emphasizing the importance of algorithm selection in achieving optimal structural solutions.

Table 3. Optimum weight and design sections of the 15-story frame structure

Groups	HPSACO (Kaveh et al. 2009)	HBB-BC (Kaveh et al. 2010)	DE (Talatahari et al. 2015)	PSO (Kaveh et al. 2015)	PSOPC (Kaveh et al. 2010)	ARO	I-ARO
1	W21X111	W24X117	W21X122	W33X118	W27x129	W12X96	W21X122
2	W18X158	W21X132	W33X141	W33X263	W24x131	W36X160	W18X143
3	W10X88	W12X95	W14X82	W24X76	W24x103	W30X90	W18X76
4	W30X116	W18X119	W30X108	W36X256	W33x141	W18X97	W24X104
5	W21X83	W21X93	W30X108	W21X73	W24x104	W12X72	W12X72
6	W24X103	W18X97	W12X79	W18X86	W10x88	W18X86	W30X90
7	W21X55	W18X76	W14X61	W18X65	W14x74	W12X58	W18X65
8	W27X114	W18X65	W18X71	W21X68	W27x94	W14X61	W18X60
9	W10X33	W18X60	W6X25	W18X60	W21x57	W8X28	W8X24
10	W18X46	W10X39	W24X62	W18X65	W18x71	W10X33	W14X38
11	W21X44	W21X48	W21X48	W21X44	W21x44	W21X48	W21X44
Weight (kN)	426.36	434.54	423.83	496.68	452.34	399.65	391.72

PSO: Particle Swarm Optimization
HPSACO: Hybrid algorithm based on particle swarm, ant colony and harmony search algorithms
HBB–BC: Hybrid big bang–big crunch and particle swarm optimization algorithms
ICA: Imperialist Competitive Algorithm

5.3. 24-Story, 3-bay frame structure

The third structure in this study is a 24-story steel frame building, featuring three bays and comprising 168 structural components. The steel's modulus of elasticity and yield strength are set to 205GPa and 230.3MPa, respectively. The frame's 168 components are organized into 20 distinct design categories. A diagram illustrating this framework is provided in Fig. 13.

Fig. 14 demonstrates a comparison between the ARO and the newly proposed I-ARO in the optimum design of the 24-story, 3-bay frame structure. As the number of function evaluations increases, both algorithms appear to find better solutions, as indicated by the decrease in the objective function value. However, the I-ARO tends to find better solutions more quickly than the ARO, descending to lower objective function values sooner. The inset graph zooms in on a section of the plot (from 4,000 to 10,000 function evaluations) to show the differences in more detail. It illustrates that beyond a certain point (around 4,000 evaluations), the I-ARO maintains a consistent lead over the ARO, achieving lower objective function values and thus indicating better performance according to the optimization criteria.

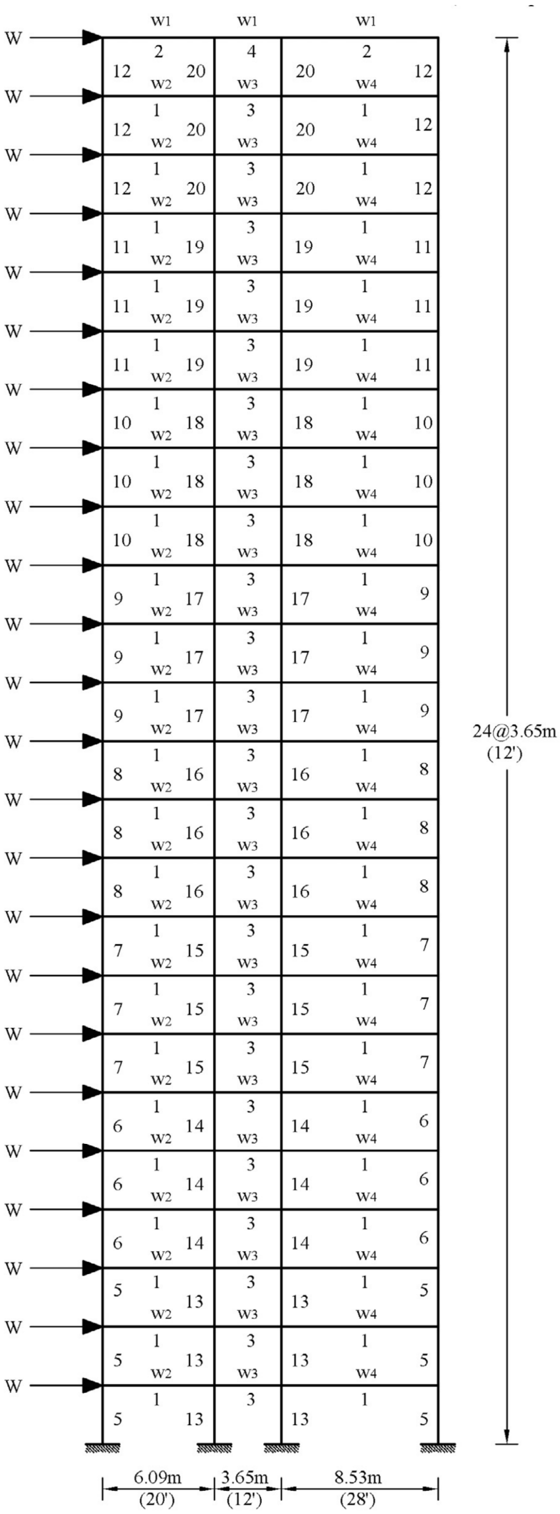

Fig. 13. Schematic view of the 24-story, 3-bay frame structure

Table 4 showcases the superiority of the I-ARO algorithm by highlighting its consistently favorable selection of steel sections across multiple groups. Compared to other algorithms, I-ARO consistently chooses sections with competitive weights, suggesting a more efficient utilization of materials without compromising structural integrity.

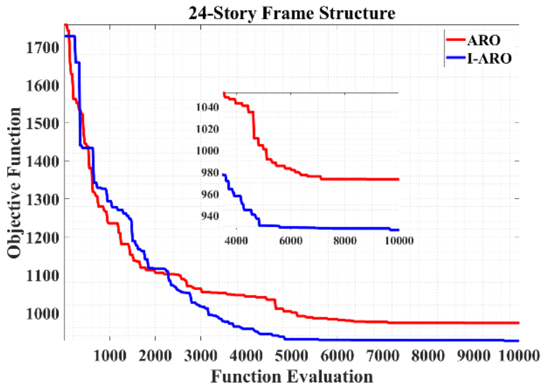

Fig. 14. Optimization process for the 24-story frame 3-bay frame structure

Furthermore, I-ARO achieves this superior performance while reducing the overall weight of the structure, indicating its effectiveness in optimizing structural designs for weight reduction. These results underscore the effectiveness and potential superiority of the I-ARO algorithm in achieving an optimal structural weight of 926.85kN, making it a compelling choice for structural engineering optimization tasks.

6. Conclusion

This paper primarily focuses on examining the suitability of the Artificial Rabbits Optimization (ARO) algorithm, a recently developed metaheuristic approach, for optimizing the design of large-scale frame structures. For numerical investigations, three frame structures with varying characteristics are selected: an 8-story single bay frame structure; a 15-story, 3-bay benchmark frame structure; and a 24-story, 3-bay frame structure. To enhance the computational performance of the standard ARO algorithm, an improved version termed I-ARO is introduced, which employs the Diagonal Linear Uniform (DLU) initialization process instead of the conventional Brownian random initialization scheme. Comparative analysis of the results obtained using I-ARO and other methods documented in the existing literature clearly shows that the DLU process significantly enhances the optimization capability of the standard ARO algorithm. Specifically, the improved algorithm demonstrates the ability to achieve lower structural weights for the considered design examples.

Table. 4. Optimum weight and design sections of the 24-story frame structure

Groups	ACO (Camp et al. 2005)	HS (Degertekin et al. 2008)	IACO (Kaveh et al. 2010)	ICA (Kaveh et al. 2010)	DE (Talatahari et al. 2015-a)	ES-DE (Talatahari et al. 2015-b)	ARO	I-ARO
1	W30X90	W30X90	W30X99	W30X90	W30X90	W30X90	W30X108	W30X90
2	W8X18	W10X22	W16X26	W21X50	W21X48	W21X55	W21X48	W21X50
3	W24X55	W18X40	W18X35	W24X55	W21X44	W21X48	W21X48	W21X48
4	W8X21	W12X16	W14X22	W8X28	W27X129	W10X45	W12X22	W12X19
5	W14X145	W14X176	W14X145	W14X109	W14X176	W14X145	W14X159	W14X109
6	W14X132	W14X176	W14X132	W14X159	W14X120	W14X109	W14X145	W14X109
7	W14X132	W14X132	W14X120	W14X120	W14X132	W14X99	W14X109	W14X132
8	W14X132	W14X109	W14X109	W14X90	W14X132	W14X145	W14X74	W14X74
9	W14X68	W14X82	W14X48	W14X74	W14X109	W14X109	W14X68	W14X68
10	W14X53	W14X74	W14X48	W14X68	W14X53	W14X48	W14X43	W14X38
11	W14X43	W14X34	W14X34	W14X30	W14X61	W14X38	W14X34	W14X30
12	W14X43	W14X22	W14X30	W14X38	W14X30	W14X30	W14X34	W14X30
13	W14X145	W14X145	W14X159	W14X159	W14X99	W14X99	W14X30	W14X132
14	W14X145	W14X132	W14X120	W14X132	W14X132	W14X132	W14X82	W14X132
15	W14X120	W14X109	W14X109	W14X99	W14X109	W14X109	W14X90	W14X99
16	W14X90	W14X82	W14X99	W14X82	W14X74	W14X68	W14X82	W14X120
17	W14X90	W14X61	W14X82	W14X68	W14X82	W14X68	W14X82	W14X85
18	W14X61	W14X48	W14X53	W14X48	W14X82	W14X68	W14X61	W14X82
19	W14X30	W14X30	W14X38	W14X34	W14X48	W14X61	W14X33	W14X43
20	W14X26	W14X22	W14X26	W14X22	W14X82	W14X22	W14X26	W14X22
Weight (kN)	980.63	956.13	967.33	946.25	997.56	945.15	973.37	926.85

ACO: Ant Colony Optimization
HS: Harmony Search Algorithm
IACO: Improved Ant Colony Optimization

6. Conclusion

This paper primarily focuses on examining the suitability of the Artificial Rabbits Optimization (ARO) algorithm, a recently developed metaheuristic approach, for optimizing the design of large-scale frame structures. For numerical investigations, three frame structures with varying characteristics are selected: an 8-story single bay frame structure; a 15-story, 3-bay benchmark frame structure; and a 24-story, 3-bay frame structure. To enhance the computational performance of the standard ARO algorithm, an improved version termed I-ARO is introduced, which employs the Diagonal Linear Uniform (DLU) initialization process instead of the conventional Brownian random initialization scheme. Comparative analysis of the results obtained using I-ARO and other methods documented in the existing literature clearly shows that the DLU process significantly enhances the optimization capability of the standard ARO algorithm. Specifically, the improved algorithm demonstrates the ability to achieve lower structural weights for the considered design examples.

The enhancement of the Artificial Rabbits Optimization (ARO) algorithm through the substitution of Brownian initialization with the Diagonal Linear Uniform (DLU) initialization may, at first glance, appear to be a relatively modest modification. Nonetheless, even ostensibly straightforward alterations in initialization strategies can exert a substantial influence on the convergence characteristics and overall efficacy of metaheuristic algorithms. The DLU approach facilitates the generation of a more uniformly distributed and well-dispersed initial population, thereby enabling the improved ARO (I-ARO) algorithm to more effectively explore the search space and mitigate the risk of premature convergence.

While this study primarily demonstrates the effectiveness of the proposed enhancement through numerical experiments on benchmark problems, the findings are nonetheless significant, showcasing notable improvements in performance within complex engineering optimization scenarios. The algorithm's performance was assessed using 23 mathematical benchmark functions from CEC2017, and the results were validated by comparing them against well-established algorithms. To ensure a fair evaluation, each algorithm was executed 30 times, with an initial population size of 30 and 1000 iterations per run. Overall, the validation conducted in this research offers robust empirical evidence, highlighting a simple yet effective strategy to enhance algorithmic performance and contributing meaningfully to the optimization field.

In conclusion, the numerical investigations conducted using the ARO and its improved version, I-ARO, have provided significant insights into the design optimization of large-scale frame structures. The results obtained from optimizing 8-story, 15-story, and 24-story frame structures demonstrate the effectiveness and superiority of the I-ARO method over the traditional ARO and other optimization techniques. Key findings from these investigations include:

• The optimization process for the 8-story frame structure revealed that the I-ARO method achieved a lower objective function value (i.e., lower weight) more rapidly than the ARO method, showcasing its efficiency in finding optimal solutions.

• The comparative analysis of optimization methods for the 8-story frame structure highlighted I-ARO's ability to select lighter structural steel sections, resulting in a slightly lower total weight compared to ARO and other methods, thereby emphasizing its potential for cost-effectiveness and material efficiency.

• Similarly, for the 15-story frame structure, the I-ARO algorithm consistently outperformed the ARO in reaching more optimal solutions faster, as evidenced by lower objective function values for a given number of function evaluations.

• I-ARO is superior to various optimization algorithms in achieving the lowest total weight for the 15-story frame structure, underscoring its efficiency in reducing structural weight while maintaining structural integrity.

• The optimization process for the 24-story frame structure reaffirmed the effectiveness of I-ARO over ARO, as it consistently found better solutions more quickly.

• I-ARO's competitive selection of steel sections across multiple groups for the 24-story frame structure leads to a significantly reduced total weight compared to other algorithms, thus establishing its compelling advantage in structural engineering optimization tasks.

Overall, the results indicate that the I-ARO algorithm offers a promising approach for optimizing the design of large-scale frame structures, with implications for enhancing structural efficiency, reducing material usage, and achieving cost-effective solutions. These findings contribute valuable insights to the field of structural engineering and underscore the importance of improvement techniques in enhancing the overall performance of metaheuristic algorithms in dealing with the complex optimization challenges in structural design.

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