A modified grasshopper optimization algorithm combined with wavelet functions

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Abstract

The present study analyzes the social interaction function of grasshoppers using five alternative wavelet functions for the original function of grasshoppers. In this research, the Morlet, Polywog1, Polywog3, Rasp1, and Rasp3 wavelet functions have been selected as possible substitutes for the wavelet function. The first structure is a three-member truss, it is optimized under the constraints of tension, deformation, and buckling, to reduce the weight of the truss. The second structure is a cantilever beam, with five hollow square beam sections, with the target function aiming to minimize the total weight of the beam. This research aims to present a proposed model combining the grasshopper algorithm and wavelet functions to improve the convergence speed and results of the grasshopper algorithm. The research results show that replacing the wavelet functions does not change much in the weight of the first benchmark structure, but it provides acceptable accuracy. The Polywog1 algorithm demonstrates superior performance, converging faster than GOA, with a marginal difference of 2.64×10^-8 percent in weight. In addition, the Rasp3 algorithm shows the best result with 6.46×10-10 percent more weight than GOA. In the cantilever beam structure, the optimization has been improved and, in all cases, the convergence speed has been evaluated as appropriate. Moreover, only Morlet wavelet functions have provided a suitable solution while other wavelet functions have not been successful in this field. Adding wavelet functions as the interaction function of the grasshoppers removes the source of error, which includes the l and f parameters, in the new possible functions.

Keywords: Grasshopper optimization algorithm, Modified grasshopper, Wavelet function, Social interaction.

1. INTRODUCTION

Optimizing refers to discovering the maximum or minimum of a function under the title of the target function, but optimization refers to the process of designing the variables in a function to maximize or minimize that function (objective function), taking into account the constraints in the problem is referred to. To start optimization problems, the problem's parameters should be identified first. According to the character of the parameters, problems can be clustered as discrete or continuous. Secondly, the limitations of the problem are also identified at this stage [1].

Constraints divide the problem into two types of constrained and unconstrained problems, as well as the number of objective functions of the problem into single and multi-objective types [2]. Finally, according to the type of problem with the presented divisions, a suitable method should be selected and applied to optimize the problem [3]. The goal of this research is to investigate the effect of using wavelet transform functions as a social interaction function of Grasshoppers, to improve the behavior of the optimization algorithm in terms of convergence speed, eliminating sources of error, and maintaining the required accuracy in the problem.

Meta-heuristic methods are divided into two main class: single-based and population-based algorithms. The basic principle of individual meta-heuristic algorithms, called trajectory algorithms, is to produce a single solution in each run. Unlike individual meta-heuristic algorithms, population-based meta-heuristic algorithms produce a set of multiple solutions (population) in each run [4]. Swarm intelligence (SI) is one of the branches of artificial intelligence that is dynamically developing. This method is a subset of algorithms nature-inspired and population-based meta-heuristic optimization algorithms. Collective intelligence, a novel field within artificial intelligence, focuses on understanding and replicating the group-based intelligent actions seen in natural systems. This field studies the basic actions of individual entities and their self-organizing interactions, such as the coordinated movements of fish schools, bird flocks, or ant colonies.These behaviors inspire the development of artificial colonies of agents that can solve difficult optimization problems. Also, the grasshopper optimization algorithm (GOA) can be introduced as one of the youngest pioneers of this method [5]. The Grasshopper Optimization Algorithm (GOA), proposed by Saremi et al. [3], is a sophisticated optimization technique. This algorithm encompasses social interactions among standard agents, termed Grasshoppers, and the influence of the most exceptional individuals. Swarm-based meta-heuristic optimization methods typically involve a two-fold process: initial exploration, extraction, and exploitation. In GOA, the first step includes searching for food or optimal parameters by grasshoppers or agents, and the extraction step includes finding food or optimal solutions. Preliminary experiments performed by the authors showed the promising heuristic capabilities of the algorithm. GOA incorporates two key elements of the grasshopper movement strategy. It includes the grasshopper's interaction, characterized by slow movements during the larva stage and more dynamic motion in the insect stage. Additionally, it accounts for the grasshopper's inclination to move toward its food source, focusing on decelerating their approach and eventual consumption of the food [6]. The grasshopper optimization algorithm, like all the presented methods and algorithms, has advantages and disadvantages that lead us to choose and use different algorithms for different problems. The mentioned algorithm has a strong ability in exploration and is used in problems due to its simplicity, capability, flexibility, and scalability. Certain complex optimization techniques may encounter challenges, including premature convergence and difficulties in the exploitation phase. Furthermore, the absence of theoretical convergence is another drawback associated with this approach. But this method is easily linked with other meta-heuristic algorithms, has an acceptable execution time, and is also easy to execution and implement. In addition, this algorithm has some numerical and convergence problems, which can be solved by changing and improving the algorithm itself for different problems. The advantages and capabilities of meta-innovative methods make it possible that not only their use is not limited to specific issues, but will also be widely used [4, 7]. Research has been done to solve the basic problems of the grasshopper algorithm and solutions have been presented to improve the algorithm. Hichem et al. [8] introduced a novel approach to feature selection with their New Binary Grasshopper Optimization Algorithm (NBGOA). This algorithm aims to identify a concise subset of features from a larger set, optimizing classification accuracy. The grasshopper algorithm, a chaotic variant, was initially developed by Saxena et al. [9] for 3D truss design. Their findings demonstrated that the chaotic mechanism significantly improves the algorithm's performance. Furthermore, the Wilcoxon rank-sum test results support the efficiency of the chaotic grasshopper algorithm, making it a valuable tool in feature selection processes. Yue et al. [10] introduced a novel approach, the Invasive Weed-Grasshopper Optimization Algorithm (IWGOA), which combines two distinct optimization techniques. This innovative algorithm demonstrated superior performance in various benchmark functions, outperforming other contemporary methods. Furthermore, its application in multi-level image segmentation has yielded encouraging outcomes, further highlighting its effectiveness. These achievements collectively underscore the IWGOA algorithm's advanced capabilities. Sulaiman [11], enhanced the Grasshopper Optimization Algorithm (GOA) by implementing an improved initialization strategy, resulting in the creation of the Improved Grasshopper Optimization Algorithm (IGOA). The primary objective of these algorithms is to identify optimal decision variables for power distribution, aiming to minimize costs, maximize efficiency, and ensure high reliability.

Luo et al. [12] introduced an enhanced GOA for continuous optimization, demonstrating its effectiveness in financial stress prediction. Their study revealed that this improved algorithm ensures a more robust kernel extreme machine learning model, outperforming other methods in prediction accuracy. Taher et al. [13] presented a modified GOA, termed MGOA, to address the OPF problem. The modification focused on enhancing the mutation process to prevent local optima traps. This approach exhibited superior performance in solving various OPF scenarios when compared to established evolutionary optimization techniques. Furthermore, Zhou et al. [14] proposed an enhanced Genetic Optimization Algorithm (GOA) named MOLGOA, addressing the limitations of its predecessor. This advanced algorithm excels in both unconstrained and constrained engineering design challenges, as evidenced by experimental comparisons with existing methods. Goel et al. [15] demonstrated the versatility of the Modified Grasshopper Optimization Algorithm (MGOA) by applying it to autism spectrum disorder (ASD) diagnosis. This advanced algorithm, coupled with a random forest classifier, achieved remarkable accuracy, specificity, and sensitivity in detecting ASD across various life stages. Seifollahi et al. [16] investigated a unique approach by integrating artificial neural networks with wavelet theory to forecast bridge pier scour depth. The findings revealed a significant enhancement, demonstrating an 8.75% improvement when utilizing the Polywog4 wavelet activation function within the neural network framework compared to a conventional neural network model. In a notable case study, Seifollahi et al. [17] employed the Grasshopper algorithm to optimize the Koyna concrete-weight dam. When benchmarked against other optimization techniques, including Particle Swarm Optimization (PSO), Gray Wolf Optimizer (GWO), and LINGO11, the Grasshopper algorithm emerged as the superior method, showcasing its effectiveness in complex engineering scenarios. Seifollahi et al. [18] intelligent methods including artificial neural network (ANN), vector machine optimization (SVM), and their combination of artificial neural network - particle swarm optimization (ANN-PSO), wavelet-artificial neural network (W-ANN) and W-ANN-PSO were investigated to predict the performance of rockfill dam crest settlements. The minimum error values by the neural network method are 1.88%, and the maximum value is 37.44%. the ANN-PSO method, the maximum error is 11.2%, the minimum error value is 1.17%. The db4 wavelet function performs better than other functions in the W-ANN-PSO model.

Mirjalili et al. [19] introduced a novel multi-objective grasshopper algorithm, which demonstrated promising performance when evaluated against various standard multi-objective test problems. This was further supported by Utama et al. [20] through their research, aimed to minimize energy consumption by employing a Hybrid Grasshopper Algorithm (HGAO). The study specifically targeted the permutation flow scheduling problem (PFSSP) and successfully illustrated the HGAO algorithm's ability to reduce energy usage within the context of offset printing operations. Abbasi et al. [21] investigated the application of the Grasshopper Optimization Algorithm (GOA) in enhancing the design of three concrete gravity dams (CGDs) - Pine-Flat, Middle-Fork, and Richard - by optimizing their geometric dimensions and minimizing concrete volume. The GOA proves to be an effective tool in reducing the amount of concrete required, thereby improving the stability and safety of these dams against seismic activities, specifically overturning and sliding. The research highlights GOA's significant role in optimizing the design process of CGDs. Algamal et al. [22] introduced a novel Grasshopper Optimization Algorithm (GOA) by modifying the primary controller parameter function.

This enhancement significantly improved GOA's exploration and exploitation capabilities. The Algamal et al.'s [22] experimental findings demonstrated superior performance in prediction accuracy, feature selection, and execution speed when compared to the mutual validation method. Abbaszadeh et al. [23] investigated the effects of gate openings and different sill widths on the sluice gate's energy dissipation and discharge coefficient (Cd). Finally, non-linear polynomial relationships are presented based on dimensionless parameters for predicting the relative energy dissipation and outflow coefficient. Abbasi et al. [24] investigated the estimation of vertical settlement of earth dams caused by earthquakes using an artificial neural network model and wavelet-artificial neural network combination. The results showed that the rbior 6.8 wavelet function with a correlation coefficient of 83% had the highest accuracy and the best performance, and the dmey wavelet function with a correlation coefficient of 70% showed the least accuracy and the weakest performance. Daneshfaraz et al. [25] worked on the theoretical and experimental analysis of the effects of the gate opening, sill placement with different widths under the gate, and the sill position from under the gate on the discharge coefficient. The results of the present study showed that the discharge coefficient increases with increasing sill width and decreasing total area of the flow passing through the gate.

Furthermore, Qin et al. [26] developed an enhanced grasshopper algorithm, IGOA, with improved convergence speed. Their experimental results confirmed the effectiveness and efficiency of IGOA as an optimization algorithm. Süme et al. [27] Investigated the Clean Energy Production in Drinking Water Networks. In this study, a water distribution network in the Armağan Village of the Maçka district of Trabzon province was used to obtain electrical energy. From this study, it is revealed that electricity can be produced by using a Microturbine instead of Pressure Breaker Valves (PBVs). Abbasi et al. [28] investigated optimizing the geometric dimensions of a Feriant-weighted concrete dam under the influence of earthquake force using the locust algorithm. The study showed that the best optimization results were obtained in the 10th attempt with a 9.18 percent reduction in the weight of concrete consumed, in other words, 658 tons of optimization. The results show the superiority of the optimization of the grasshopper algorithm compared to other methods, including the gray wolf algorithm and the PSO algorithm. Abbaszadeh et al. [29] investigated the experimental and application of soft computing models for predicting flow energy loss in arc-shaped constrictions. The research endeavors to explore the relative energy loss ($\Delta E_{AB}/E_A$) in a constricted flow path of varying widths, employing a Support Vector Machine (SVM), Artificial Neural Network (ANN), Gene Expression Programming (GEP), Multiple Adaptive Regression Splines (MARS), M5 and Random Forest (RF) models. Daneshfaraz et al. [30] investigated the flow pattern and discharge coefficient of sluice gates in free-flow conditions with the non-suppressed sill in experimental and numerical conditions. Experimental results showed that placing a non-suppressed sill under the sluice gate by creating a failure in the flow lines causes a different flow pattern compared to the without sill state.

By reviewing the theory of the grasshopper algorithm, it can be seen that this function causes problems such as convergence problems and getting stacked in the local optimum. Therefore, this function should be modified. As mentioned in the research literature, researchers have provided solutions to solve these problems, but none of the solutions have been provided in general for all problems and can only be used in a specific area. Therefore, this research presents a solution to improve and optimize the main Grasshopper Algorithm. This algorithm is improved based on modifying the social interaction function of grasshoppers and a wavelet transform replaces the exponential function.

2. METHODOLOGY

2.1. THEORY of GRASSHOPPER OPTIMIZATION ALGORITHM (GOA)

The field of nature-inspired computing has developed algorithms that categorize search processes into two distinct phases: exploration and exploitation. The algorithm promotes rapid and diverse movements in the exploration phase, while the exploitation phase focuses on localized and precise actions. These algorithms emulate the natural behavior of grasshoppers, which inherently exhibit both exploratory and exploitative tendencies in their search for targets [31]. A mathematical model has been developed to simulate grasshopper swarming behavior, adhering to the outlined steps and the findings of Saremi et al. [3]. This model is presented below, detailing the intricate grasshopper aggregation and movement process.

$$X_i = S_i + G_i + A_i \tag{1}$$

An alternative relationship can be employed to describe the erratic movements of grasshoppers, where r_1, r_2, and r_3 are arbitrary values within the range of [0,1]. This relationship offers a more comprehensive understanding of their unpredictable behavior.

$$X_i = r_1 S_i + r_2 G_i + r_3 A_i \quad (2)$$

In relation (1), X_i, the position of the *i* th grasshopper, S_i, G_i, and A_i models the effects of the social interaction of the grasshoppers, the effects of gravity and wind force on the movement, attraction, and repulsion of the *i* th grasshopper in the algorithm. The available parameters are defined as follows:
Relation (1), incorporates various factors to model the movement and interactions of grasshoppers. The position of each grasshopper, denoted as X_i, is influenced by social interactions represented by S_i, and the forces of gravity and wind, indicated by G_i and A_i, respectively. These parameters collectively define the intricate behavior of the *i* th grasshopper within the algorithm.

$$S_i = \sum_{\substack{j=1 \\ j \neq 1}}^{N} s(d_{ij}) \hat{d}_{ij} \quad (3)$$

$$G_i = -g\widehat{e_g} \quad (4)$$

$$A_i = u\widehat{e_w} \quad (5)$$

In the aforementioned equations (3), (4), and (5), the variable *dij* represents the spatial separation between the *i* th and *j* th grasshoppers, which is mathematically defined as $d_{ij}=|x_j-x_i|$. The function s governs the strength of the social interactions, while $\widehat{d_{ij}} = \frac{|x_j - x_i|}{d_{ij}}$ denotes the unit vector pointing from grasshopper *i* towards *j*. In addition, *g* and *u* are the earth's gravitational constant and the amount of drift force, respectively. $\widehat{e_g}$ and $\widehat{e_w}$ are the unit vectors towards the center of the earth and in the direction of the wind, respectively.

The exponential function that governs social interaction, denoted by *s*, can be expressed as follows:

$$s(r) = f e^{\frac{-r}{l}} - e^{-r} \quad (6)$$

where *f* symbolizes the intensity of attraction, and *l* represents the scale or range over which this attraction operates.

Figure 1 shows that the repulsive interactive force of grasshoppers is the dominant force inside the indicated area, and attraction is the dominant force outside this area. In addition, grasshoppers do not show any interaction in the mentioned area. The region referred to as the comfort zone is influenced by the variations of f and l in equation (6), which consequently impact the interactive conduct exhibited by the grasshoppers.

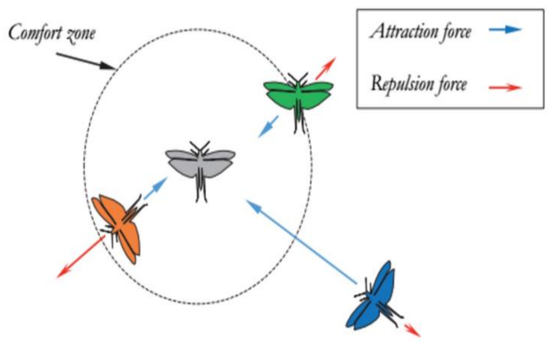


Figure 1. The force of gravitation and repulsion of the grasshoppers' interaction inside and outside the convenience zone [3].

The mathematical representation expressed in equation (1) is ultimately reformulated as equation (7) to quantify the number N of grasshoppers, after specifying the relevant parameters. Nonetheless, this mathematical model cannot be directly employed to address optimization problems, primarily due to the rapid attainment of the comfort zone by grasshoppers, resulting in the swarm's failure to converge towards a specific point. To overcome this limitation, a modified version of the equation is proposed, as follows, to facilitate the resolution of optimization problems.

$$X_i = \sum_{\substack{j=1 \\ j \neq 1}}^{N} s(|x_j - x_i|) \frac{|x_j - x_i|}{d_{ij}} - g\widehat{e_g} + u\widehat{e_w} \quad (7)$$

$$X_i^d = c\left(\sum_{\substack{j=1 \\ j \neq 1}}^{N} c \frac{ub_d - lb_d}{2} s(|x_j^4 - x_i^4|) \frac{x_j - x_i}{d_{ij}}\right) + \widehat{T_d} \quad (8)$$

In the equation $s(r) = f e^{\frac{-r}{l}} - e^{-r}$, the upper limit of the *D* dimension is represented by ub_d, while the lower limit is denoted by lb_d. The value of the *D* dimension in the optimal solution discovered thus far is symbolized by T_d. Furthermore, *c* serves as a scaling factor responsible for contracting the comfort zone, repulsion zone, and attraction zone. It is noteworthy that *S* bears a striking resemblance to the *S* component present in equation (1). Nonetheless, the altered formulation disregards the gravitational force, excluding the G component, and operates under the assumption that the wind vector (A component) is perpetually oriented towards the intended target (T_d). To strike an equilibrium between exploration and exploitation, the parameter c ought to be diminished in proportion to the number of iterations. This approach enhances utilization by augmenting the iteration count. The coefficient c contracts the comfort zone in accordance with the repetition frequency, and its calculation is as follows:

$$c = cmax - l\frac{cmax - cmin}{L} \tag{9}$$

Where *cmax* denotes the highest value, *cmin* signifies the lowest value, *l* symbolizes the current iteration, and *L* represents the maximum number of iterations permissible.

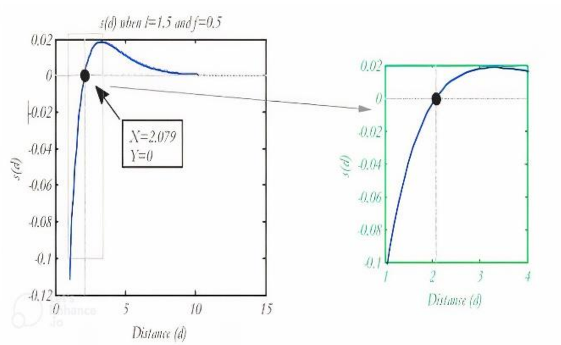


Figure 2. The right picture: the social interaction function with *l*=1.5 and *f*=0.5 in the interval x=[0,15] and the left picture: interval x=[1,4].

```
Initialize the swarm X_i (i = 1, 2, ..., n)
Initialize cmax, cmin, and maximum number of iterations
Calculate the fitness of each search agent
T=the best search agent
while (l < Max number of iterations)
    Update c using Eq. (2.8)
    for each search agent
        Normalize the distances between grasshoppers in [1,4]
        Update the position of the current search agent by the equation (2.7)
        Bring the current search agent back if it goes outside the boundaries
    end for
    Update T if there is a better solution
    l=l+1
end while
Return T
```

Figure 3. Grasshopper optimization algorithm [3].

The primary optimization procedure of the principal GOA is depicted in Figure 3. This algorithm initiates the optimization process by employing random solutions, and the agents (grasshoppers) revise their positions based on equation (8). The location of the optimal solution attained is updated with each iteration. This cycle is reiterated until a specific criterion is met to terminate the process, at which point the best solution is retrieved from among the computed answers.

2.2. MODIFIED GRSSSHOPPER ALGORITHM (W-GOA)

The basic grasshopper algorithm consists of some errors due to the existence of a lot of trial-and-error process and the involvement of human error in choosing the correct values of *l*, *f*, and many other combinations for these parameters. To reduce the effects of this problem and improve the speed of convergence, this research has changed the social interaction function of the grasshopper. In this regard, the exponential function that represents social interactions has been replaced with different functions of the mother wavelet. The choice of the mother wavelet is crucial in wavelet analysis. For instance, when employing a wavelet to eliminate noise, the judicious selection of the mother wavelet results in the concentration of a significant portion of the signal's power on a limited number of wavelet coefficients, thereby facilitating the separation of noise and signal components through straightforward thresholding.

Mother wavelets are classified into various groups based on their distinct attributes. These properties encompass orthogonality, compression capabilities, symmetry, and vanishing moments. The inherent characteristics of the mother wavelet are pivotal in determining the appropriate selection. Nonetheless, encountering multiple mother wavelets with identical properties is not uncommon. Numerous techniques exist to assess the degree of resemblance between the signal and the mother wavelet, employing qualitative and quantitative methodologies. However, a universally accepted or standardized approach to this selection process remains elusive. Certain attributes of the mother wavelet, such as symmetry, periodicity, vanishing moment, degree of shift variation, orthogonality, and compression, are taken into account as selection criteria in qualitative approaches. Furthermore, the choice of the appropriate mother wavelet is made by assessing these characteristics. In other research endeavors, visual inspection of the signal shape's conformity with the mother wavelet is carried out as part of the selection criterion. The selection of the mother wavelet in quantitative methodologies is governed by rigorous mathematical principles. Certain criteria are employed in the process of wavelet selection, which are outlined herein.

- Minimum Description Length (MDL): One of the optimal selection criteria for the mother wavelet is the evaluation of the minimum description length (MDL). The approach of this criterion is to create a compromise between the accuracy of the data estimation results and the quality of signal display.

- The Maximum cross-correlation coefficient: Is a widely recognized metric employed in research to determine the most suitable mother wavelet.

- Symmetric Distance Coefficient (SDC): The mother wavelet's resemblance to a signal's transient state is determined through this coefficient calculation. Thus, it is evident that the wavelet coefficients of a transient state, when structurally akin to a mother wavelet, exhibit symmetry.

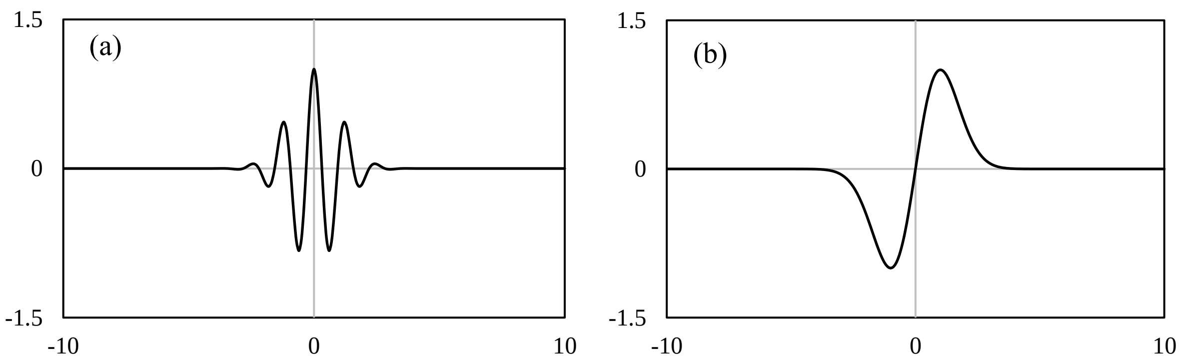
- Compression Ratio (CR): Another technique, the calculation of the maximum compression ratio in certain applications and for some signals is mentioned in some sources as a criterion for choosing the best mother wavelet.

- Information Quality Ratio (IQR): The recently introduced metric, known as the Ratio, offers a novel approach to identifying Mother wavelets. Its concept is founded on the principle that the reconstructed signals must retain the critical data present in the initial signal.

- Peak Signal to Noise Ratio (PSNR) + Mean Squared Error (MSE): Known as the method of combining the maximum noise ratio to the signal and the mean square error and the maximum error report is also proposed to choose the best mother wavelet. In this method, weight should be assigned to each criterion based on the recursive processes of analysis.

When selecting a mother wavelet for research, it is crucial to acknowledge that the chosen wavelet may not be universally applicable across all research contexts and wavelet analyses. This consideration follows the process of employing specific methods to identify the most suitable mother wavelet. As in each research, the type of input signal is different. In other words, in any research, different mother wavelets depending on the input signal and the similarity of that signal to the mother wavelet should be considered. For example, for processing EEG signals, the Danish wavelet may be a good choice, but for applications such as removing image noise, the Haar wavelet may provide better results.

In this research, 5 wavelets (Figure 4) acting as representatives of the whole family of wavelets have been chosen instead of the exponential social interaction function, then the results are obtained with the optimization algorithm of grasshoppers (Saremi et al. [3], and compared with the results obtained from other algorithms including, ALO [32], DEDS [33], PSO-DE [34], MBA [35], Ray and Sain [36], Tsa [37], CS [38].



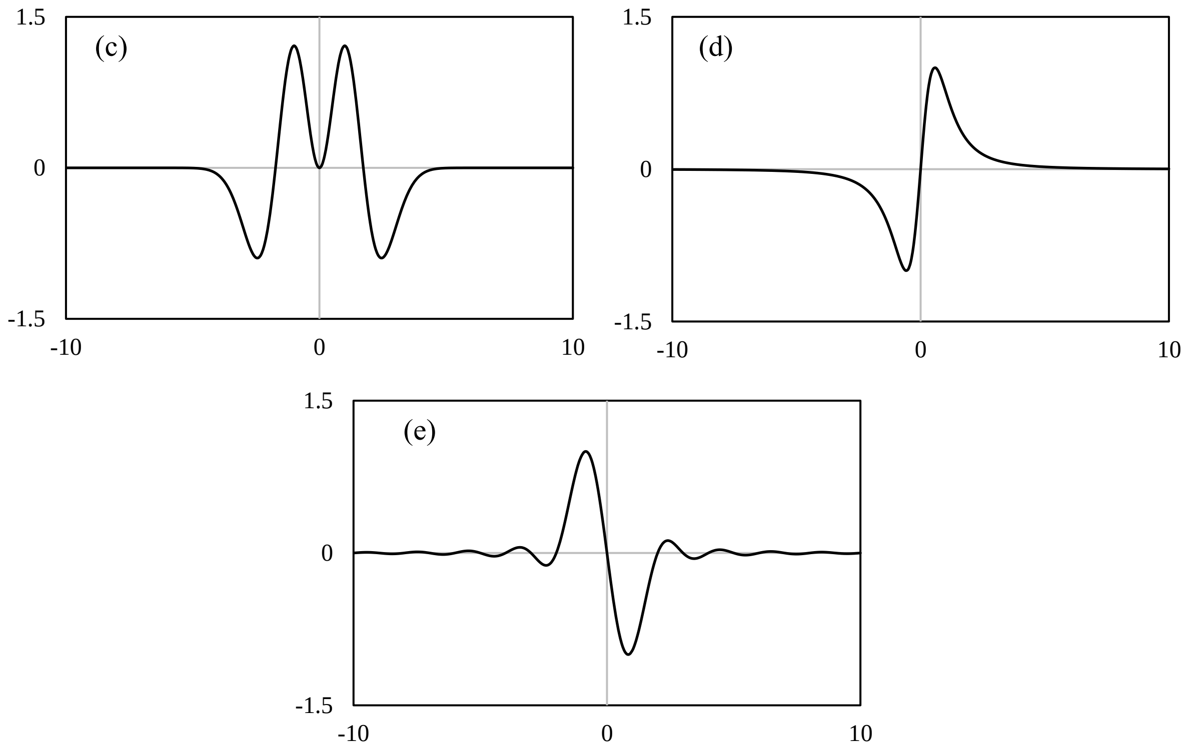


Figure 4. Mother wavelet functions (a) Morlet, (b) polywog1, (c) polywog3, (d) Rasp1, (e) Rasp3

The relations of Morlet, Polywog1, Polywog3, Rasp1, and Rasp3 wavelets are specified in relations (10) to (14), respectively. In these relations, *t* represents the time and *e* represents Euler's number

$$Morlet = \cos(5t)\, e^{(-t^2/2)} \tag{10}$$

$$Polywog1 = \sqrt{e}(t)e^{(-t^2/2)} \tag{11}$$

$$Polywog3 = (3t^2 - t^4)e^{(-t^2/2)} \tag{12}$$

$$Rasp1 = \frac{3.0778t}{(t^2+1)^2} \tag{13}$$

$$Rasp3 = \frac{0.6111 \sin(\pi t)}{(t^2-1)} \tag{14}$$

3. VERIFICATION of the RESULTS

To demonstrate the viability and practicality of the W-GOA model, a comprehensive evaluation is required. This involves assessing the algorithm's performance and comparing it to the outcomes of the GOA and other referenced optimization techniques. In this regard, two structures have been selected for the sake of comparison. The two proposed structures for verification of the combined model have also been used for verification in the original GOA article by Saremi et al. [3].

3.1. TRUSS WITH THREE ELEMENTS

This structure is one of the most famous structures used for optimization problems. This issue can be expressed as follows (Relations 15 to 21):

$$consider \quad \vec{x} = [x_1\ x_2] = [A_1\ A_2] \tag{15}$$

$$Minimize \quad f(\vec{x}) = \left(2\sqrt{2}x_1 + x_2\right) \times l \tag{16}$$

$$subjected\ to \quad g_1(\vec{x}) = \frac{\sqrt{2}x_1 + x_2}{\sqrt{2}x_1^2 + 2x_1x_2}P - \sigma \leq 0 \tag{17}$$

$$g_2(\vec{x}) = \frac{x_2}{\sqrt{2}x_1^2 + 2x_1x_2}P - \sigma \leq 0 \tag{18}$$

$$g_3(\vec{x}) = \frac{1}{\sqrt{2}x_2 + x_1}P - \sigma \leq 0 \tag{19}$$

$$Variable\ range \quad 0 \leq x_1, x_2 \leq 1 \tag{20}$$

$$Where \quad l = 100cm, P = 2\, {}^{KN}/_{cm^2}, \sigma = P = 2\, {}^{KN}/_{cm^2} \tag{21}$$

The configuration of this truss and the forces acting on it are shown in Figure 5. According to the optimization problem and the shape of the truss, there are two structural variables to evaluate, the first variable is the cross-sectional area of rods 1 and 3 and the second variable is the cross-sectional area of rod 2. The optimization aims to minimize the truss structure's weight while maintaining specific requirements, including stress, deformation, and buckling constraints.

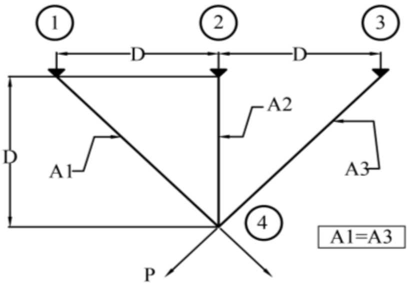


Figure 5. Three-member truss problem configuration

The empirical parameters for the three-node truss analysis include a grasshopper algorithm with a population cap of twenty and a repetition threshold of five hundred. This structured approach ensures a methodical exploration of the design space.

However, in the study of Saremi et al. [3] the search factor and the number of repetitions are 20 and 650 respectively. The study introduces a novel approach, the Death Penalty method, which significantly impacts search agents by imposing substantial penalties for constraint violations. This method effectively discourages agents from breaching constraints at any level, ensuring adherence to rules.

The findings are validated by comparing them with established methods: ALO, DEDS, PSO-DE, MBA, Ray, GOA, Tsa, and Cs. These comparative outcomes are presented in Table 1, offering optimal variable and weight values.

In a comparative analysis of algorithm performance, the W-GOA algorithm demonstrates superior maximum performance evaluation when compared to ALO, DEDS, PSO-DE, and MBA. The W-GOA algorithm demonstrates superior performance, effectively addressing the challenges posed by a restricted search space. This achievement highlights its potential as a valuable tool for tackling similar issues in various domains.

3.2. CANTILEVER BEAM DESIGN and OPTIMIZATION

The optimization problem under consideration is a well-known challenge, with its theoretical foundations outlined in relations 22 to 25. These relations provide a comprehensive understanding of the problem's theoretical aspects.

$$consider \quad \vec{x} = [x_1\ x_2\ x_3\ x_4\ x_5] \tag{22}$$

$$Minimize \quad f(\vec{x}) = 0.6224(x_1 + x_2 + x_3 + x_4 + x_5) \tag{23}$$

$$subjected\ to \quad g_1(\vec{x}) = \frac{61}{x_1^3} + \frac{27}{x_2^3} + \frac{19}{x_3^3} + \frac{7}{x_4^3} + \frac{1}{x_5^3} - 1 \leq 0 \tag{24}$$

$$Variable\ range \quad 0 \leq x_1, x_2, x_3, x_4, x_5, \leq 100 \tag{25}$$

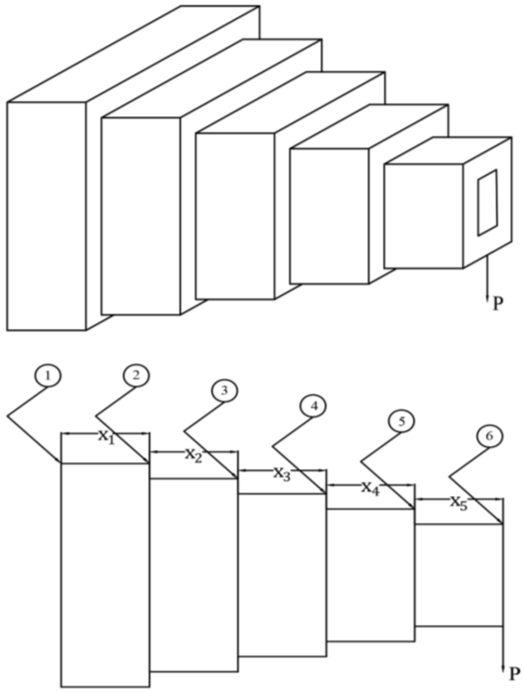


Figure 6. Cantilever beam problem configuration

The configuration of the beam problem is evident in Figure 6. In this study the population of grasshoppers and the maximum repetition are considered equal to 20 and 30 respectively.

The research conducted by Saremi et al. [3] utilized the Grasshopper Optimization Algorithm (GOA) with a configuration of 20 search factors and a maximum iteration limit of 650 to identify the optimal solution for the problem under investigation. The objective function exhibited progressive enhancement with each successive iteration, leading to a more accurate approximation of the global optimal solution, proportional to the number of iterations performed.

As depicted in Figure 6, the cantilever beam structure comprises five hollow square-sectioned beams, with the length of these beams serving as the design parameters for this particular problem.

4. RESULT and DISCUSSION

The studied problems are optimized using the algorithms reviewed in the literature, the main GOA algorithm, and the W-GOA algorithm, and their results are presented in this section. According to Table 1, in the three-member truss optimization problem, the results (i.e., the total weight of the structure, according to the constraints of the problem) are equal to the results presented in GOA with a pretty negligible approximation. The analysis of the data in Table 1 and Figure 7 reveals a significant finding. The Polywog1 algorithm demonstrates superior performance, converging faster than GOA, with a marginal difference of 2.64×10^-8 percent in weight. In addition, the Rasp3 algorithm shows the best result with 6.46×10^{-10} percent more weight than GOA. According to the percentage of final changes for each wavelet function that has been replaced as a function of social interaction. The findings demonstrate a close alignment with the work of Saremi et al. [3], as

indicated by the relative error analysis. When compared to the original grasshopper algorithm, the results exhibit remarkable precision, ranging from one hundred million to ten billion, as presented in Tables 1 and 2.

By evaluating the results of W-GOA and GOA, and comparing with the other algorithms; it can be concluded that ALO, DEDS, PSO-DE, MBA, and Tsa methods have calculated the weight of the structure less than the mentioned methods, but this difference can be distinguished with an accuracy of one hundred thousandth. The part of the different wavelet functions illustrated in Figure 7 shows the influence of the type of the wavelet function in optimization. Considering the weight distribution along the vertical axis and the frequency of responses on the horizontal axis, the wavelet functions exhibiting vertical symmetry, namely Polywog3, and Morlet, demonstrated superior performance when evaluated against the wavelet function shape depicted in Figure 4.

Wavelet functions with symmetry compared to the bisector of the vertical and horizontal axis had a weaker performance than other functions.

Table 1. Comparison of the results of W-GOA, the original GOA and other algorithms introduced in Benchmark 1

Algorithm	Parameters optimal values		Optimal weight
	X_1	X_2	
W-GOA-Morlet	0.7888	0.4076	263.8958
W-GOA-Polywog1	0.7888	0.4076	263.8958
W-GOA-Polywog3	0.7888	0.4076	263.8958
W-GOA-Rasp1	0.7888	0.4076	263.8958
W-GOA-Rasp3	0.7888	0.4076	263.8958
GOA [3]	0.7888	0.4076	263.8958

ALO [32]	0.7886	0.4082	263.8958
DEDS [33]	0.7886	0.4082	263.8958
PSO-DE [34]	0.7886	0.4082	263.8958
MBA [35]	0.7885	0.4085	263.8958
Ray [36]	0.7950	0.3950	264.3000
Tsa [37]	0.7880	0.4080	263.6800
CS [38]	0.7886	0.40902	263.9716

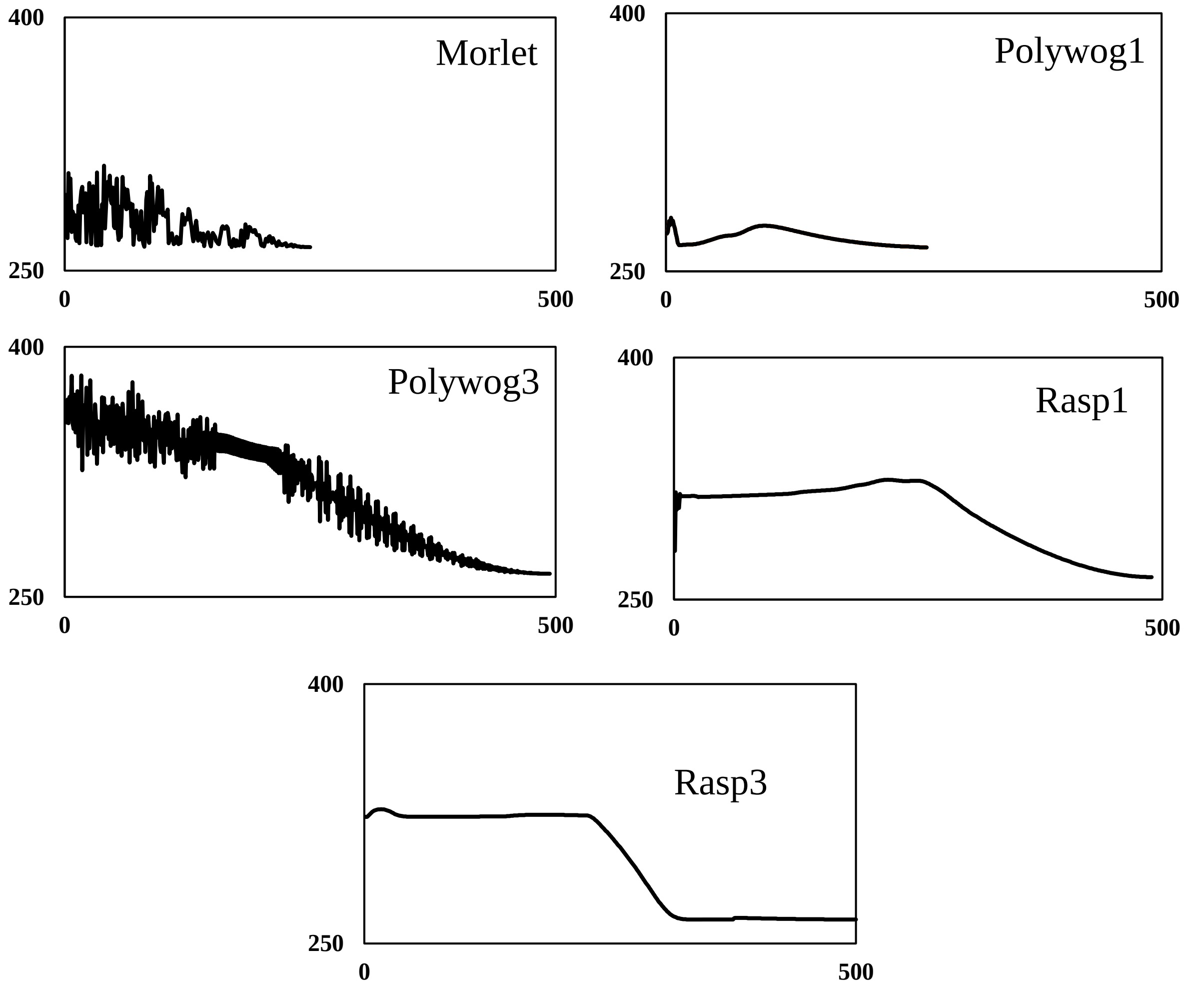


Figure 7. The optimization process in each of the presented algorithms for benchmark 1

In the second benchmark structure cantilever beam, all 5 wavelets used in the previous problem were examined on behalf of all wavelet families. Nonetheless, considering the intricacy of the issue and the substantial quantity of functions involved, no single wavelet function can provide a comprehensive solution. Consequently, within this framework, the Morlet function emerges as the sole viable option to effectively address the problem at hand. In other functions the answer is undefined. Therefore, by limiting the above tasks to a specific interval, this problem is solved. Still, because we are searching for the answer in the length of the problem in question, we refrained from changing its interval and finding the solution. In Table 2, the values obtained from the optimizations are compared. Based on this table, it can be seen that the W-GOA-Morlet algorithm has a lower optimized weight than the algorithm of grasshopper Saremi et al. [3] and other methods. In other words, the lightest weight of the structure presented in the cantilever beam benchmark problem was obtained by the GOA with the social interaction function of the Morlet wavelet function type, which is unique. The W-GOA-Morlet model has optimized and designed the weight of the structure to be lighter than the model presented by Saremi et al. [3].

Figure 8 depicts the optimization process for the Morlet function. In this figure, the vertical axis is the weight of the beam, and the horizontal axis is the number of repetitions to reach the answer. In this image, the process of convergence is evident, which requires optimization and convergence, and this process happens quickly. The main reason for the good performance of the Morlet function is its symmetry for the vertical axis.

Table 2. Comparison of the results of W-GOA, the original GOA and other algorithms introduced in Benchmark 2

Algorithm	X_1	X_2	X_3	X_4	X_5	Optimal Weight
W-GOA-Morlet	6.0395	5.3524	4.4801	3.4137	2.2326	1.3393
GOA [3]	6.0116	5.3129	4.4830	3.5027	2.1633	1.3399
ALO [32]	6.0181	5.3114	4.4883	3.4975	2.1583	1.3399
MMA [39]	6.0100	5.3000	4.4900	3.4900	2.1500	1.3400
GCA_I [40]	6.0100	5.3000	4.4900	3.4900	2.1500	1.3400
GCA_II	6.0100	5.3000	4.4900	3.4900	2.1500	1.3400
CS [38]	6.0089	5.3049	4.5023	3.5077	2.1504	1.3399
SOS [41]	6.0187	5.3034	4.4958	3.4989	2.1556	1.3399

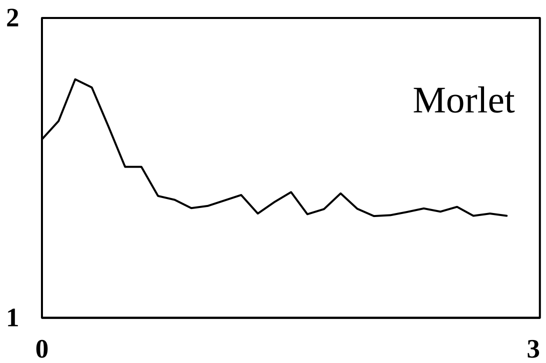


Figure 8. Optimization process of the presented algorithm for benchmark 2

By examining two benchmark structures, a three-membered truss, and the cantilever beam, it was determined that the social interaction function in the grasshopper algorithm offered by Saremi et al. [3] can be changed exponentially with two fixed numbers *(f, l)* Considered replaceable. Of course, the replacement of this function has conditions such as continuity of the function and derivability, and all these conditions are satisfied in the mother functions and derived from the mother functions of the wavelet. The results of the wavelet functions were checked on the benchmark structures. If the mother wavelet function is used as a Morlet sample, there is no need to change or check the *f*, *l* variables in the social interaction function, and by default, these functions calculate the reference values. The calculation factor of checking the effect of fixed variables is time-consuming, causes time loss and sometimes reduces the reliability of design and optimization, which can be eliminated by replacing it with a wavelet function.

5. CONCLUSION

- The Grasshopper algorithm is used in many fields, and it can be changed and improved according to the user.

- In this research, the social interaction function, which in the original grasshopper algorithm is an exponential function with variable parameters f and l, showed effective results in the behavior of the algorithm and the speed of convergence, has been replaced with five Wavelet-Morlet functions, Polywag1, Polywag3, Rasp1, and Rasp3.
- The two benchmark structures, the three-membered truss, and the five-membered cantilever were optimized by the modified algorithm, the original algorithm, and several other algorithms in this research.
- the results showed that: In the first benchmark, the weight of the structure by applying the W-GOA algorithm is equal to the values of the weight of the structure optimized by the original grasshopper algorithm in all wavelet functions with an acceptable error. This difference is the largest for the Polywog1 wavelet and equals 2.64*10-6. This mother wavelet has the fastest convergence among the presented algorithms, and the Rasp3 wavelet has the lowest weight among the presented algorithms.
- Among the functions examined for the first benchmark, the Ray algorithm (Ray and Saini, [36]), has the highest weight among the constructs. Comparing the results, it can be seen that the second benchmark could only answered by the function related to the Morlet wavelet. The Morlet wavelet exhibits a marginal 0.048% reduction in structural weight compared to the GOA algorithm, and its convergence rate is deemed satisfactory.
- It can be concluded that the new algorithm provides satisfactory results in all structures if all five wavelet functions are used, and the Morlet wavelet function can also analyze larger structures.
- The use of wavelet functions can eliminate two factors that cause errors in the original GOA, parameters l and f. In addition, it has satisfactory behaviors in terms of analysis time, the number of repetitions, and the speed of convergence.

Statements and Declarations

All authors confirm that they have no conflict of interest in publishing this manuscript.

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