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An Enhanced Grey Wolf Optimizer for Engineering Design and Multilayer Perceptron

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An Enhanced Grey Wolf Optimizer for Engineering Design and Multilayer Perceptron

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Traditional swarm intelligence optimization methods perform erratically in engineering design due to difficulties in handling nonlinear data, local optimal errors and premature convergence. To address these problems, we developed an enhanced Gray Wolf Optimizer (OGWO) that employs Levy flight and elite adversarial-based learning methods. We evaluated its effectiveness using 20 benchmark functions and compared it with other GWO variants and popular algorithms. The results show that OGWO is superior in terms of convergence speed, accuracy, and freedom from stagnation, as confirmed by the Wilcoxon rank sum test. Furthermore, the effectiveness of OGWO in training Multilayer Perceptron (MLP) has been evaluated using the UCL datasets. Finally, OGWO has been applied to solve the speed reducer design problem, proving its ability to provide optimal solutions in addressing real-life engineering issues.

KEYWORDS: GWO; OGWO; Lévy flight; Elite opposition-based learning; Multilayer Perceptron; OGWO-MLP; speed reducer design.

1. Introduction

Engineering design plays a pivotal role in technological innovation and societal development. Most engineering design problems can be defined as optimization design issues, which necessitate resolution through mathematical optimization [12]. Neural networks, as the foundation of deep learning, have extensive applications in numerous scenarios. In practical problems, traditional deterministic algorithms like gradient descent [8] are prone to fall into high-dimensional local traps. Furthermore, due to factors like time cost, the existence or applicability of precise optimizers often becomes impractical. Hence, a solution capable of finding the optimal solution within an acceptable computational time is required, making heuristic algorithms a suitable method [37]. Concurrently, with societal and technological advancement, an increasing number of complex and challenging optimization problems and demands have emerged. According to the “no free lunch” theorem, the optimal solution for different problems often corresponds to different algorithms [22]. In this context, the improvement of heuristic methods remains, and increasingly so, necessary. Researchers continuously strive to find appropriate improvement schemes to enhance the effectiveness of heuristic algorithms. Specifically, whether in industrial design or neural network optimization, it is a complex task involving many mathematical models and variables, parameters. Ordinary heuristic algorithms have slow convergence speed and are prone to local optima, hence an effective method to find the best solution is needed.

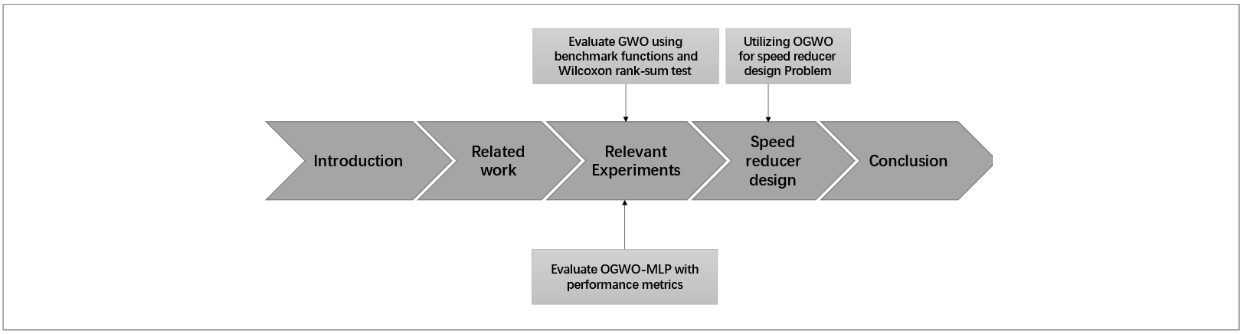
The Grey Wolf Optimizer (GWO), created by Mirjalili in 2014 [30], mimics the social hierarchy and hunting instincts of grey wolves. GWO is widely recognized for its outstanding performance and simple implementation method, distinguishing it from other famous meta-heuristic algorithms such as Particle Swarm Optimization (PSO) [38], Genetic Algorithm (GA) [27], and Differential Evolution (DE) [26]. GWO, as a powerful optimization tool, is relatively simple to implement, with no complex arithmetic or parameter settings, which makes it useful in many complex problems. Therefore, GWO and many other heuristic algorithms are widely favored by researchers and extensively applied in various research fields, including but not limited to engineering design, neural network training, computer vision, and supply chain planning among various complex optimization scenarios. For instance, Yan et al. [15] developed a denoising method in the continuous wave mud pulse transmission process based on GWO. Yu et al. [20] developed a variant butterfly optimization algorithm, effectively solving four mechanical engineering problems and a ten-dimensional process synthesis and design problem. Seetha et al. [36] utilized a novel GWO to regulate the parameters of the neural network model. Xu et al. [40] proposed an Adaptive Particle Swarm Optimization-Triangle Neural Network (PSO-TNN), significantly reducing the error of the neural network. In addition, Prokop and Połap [34] developed a hybrid GWO algorithm for image stitching, demonstrating excellent performance and efficiency.

Despite GWO’s strong competitiveness and wide application in various research fields, like other heuristic algorithms, it still has room for improvement in terms of convergence ratio, stability, and sensitivity to falling into local optima [24]. To mitigate these limitations, researchers have proposed various improvement schemes. Yu et al. [17] combined beetle tentacle search with the gray wolf algorithm for better solutions to high-dimensional problems. Nadimi-Shahraki et al. [32] introduced two gaze clue learning strategies inspired by gray wolves to improve search efficiency. Ahmed et al. [3] developed a new GWO version integrating a memory mechanism, random local search techniques, and evolutionary operators for optimized performance. Although the above ideas improve GWO from different perspectives, there is still room for improvement in terms of increasing the convergence speed and crossing the local optimum.

In order to address these issues for better application to industrial problem solving and training of neural networks, this paper introduces an improved GWO(OGWO), its performance validated through simulations and a Wilcoxon Rank Sum Test against three other GWOs. Further tests using UCL Machine Learning Repository datasets confirmed OGWO’s strong compatibility with Multilayer Perceptron (MLP). OGWO outperformed traditional GWO and other algorithms in precision, convergence speed, stability, and neural network training, showing significant application potential. Lastly, OGWO effectively solved the gear reducer design problem, proving its advantage over traditional methods.

The rest of the paper is organized in the following order: Section 2 introduces GWO, Section 3 introduces OGWO and OGWO-MLP, and Sections 4-5 provide experimental results and discussion. Section 6 applies OGWO to solve gearbox design problems in engineering. Section 7 concludes the paper. Figure 1 shows the entire workflow.

Figure 1
The overall workflow of the whole study



2. Grey Wolf Optimizer

GWO perceives wolf packs as unique particle entities within a search space, thereby enabling the solution of optimization problems. Let α, β, δ and ω represent Alpha, Beta, Delta and member wolves respectively, the procedure for adjusting the gray wolf's location can be articulated in terms of the encircling and hunting stages. The behavior of gray wolves rounding up prey was defined as:

$$\vec{D} = \left|\vec{C}\vec{x}_P(t) - \vec{x}(t)\right| \tag{1}$$

$$\vec{x}(t+1) = \vec{x}_p(t) - \vec{A}\vec{D}, \tag{2}$$

where $\vec{D}$ denotes the distance between the gray wolf and the prey, $\vec{x}$ and $\vec{x}_p$ are the position vectors of the prey and the gray wolf, respectively. $\vec{C}$ and $\vec{A}$ are the coefficient vectors, which are computed by the following equation:

$$\vec{A} = 2\vec{a}\vec{r}_1 - \vec{a} \tag{3}$$

$$\vec{C} = 2\vec{r}_2, \tag{4}$$

where $\vec{a}$ is the convergence factor decreases linearly from 2 to 0 with the number of iterations. $\vec{r}_1$ and $\vec{r}_2$ are random vectors which are modulo random numbers within [0, 1]. Once the prey is identified, the wolf pack will gradually surround it under the command of the three leaders. The distance between each ω and the trio of leaders can be calculated using the following formula:

$$\begin{cases} \vec{D}_a = \left|\vec{C}_1\vec{x}_\alpha - \vec{x}\right| \\ \vec{D}_\beta = \left|\vec{C}_2\vec{x}_\beta - \vec{x}\right| \\ \vec{D}_\delta = \left|\vec{C}_3\vec{x}_\delta - \vec{x}\right| \end{cases} \tag{5}$$

$\vec{x}_\alpha$, $\vec{x}_\beta$, and $\vec{x}_\delta$ denote the current position vectors of α, β, δ respectively. $\vec{C}_1$, $\vec{C}_2$, $\vec{C}_3$ are random vectors.

$$\begin{cases} \vec{x}_1 = \vec{x}_a - A_1\vec{D}_a \\ \vec{x}_2 = \vec{x}_\beta - A_2\vec{D}_\beta \\ \vec{x}_3 = \vec{x}_\delta - A_3\vec{D}_\delta \end{cases} \tag{6}$$

$$\vec{x}(t+1) = \frac{\vec{x}_1+\vec{x}_2+\vec{x}_3}{3} \tag{7}$$

In the wolf pack, the individual's movement towards α, β, and δ is characterized by its step length and direction, as articulated in Equation (6). The culmination of this movement, or in other words, the ultimate position of ω, is determined by Equation (7).

3. Method

3.1. Enhanced Grey Wolf Optimizer

3.1.1. Leader Hunter Mutation Based on Lévy Flights

Lévy flight essentially refers to a Markovian pattern of random movement, governed by the principles of Lévy distribution [11]. In nature, the behavior of many organisms can be described by models of Lévy distributions [39].

Figure 2 illustrates the Brownian motion with a uniform distribution and the Lévy flight with a Lévy distribution, both with a step size of 1500 steps. Figure 3 shows the step trajectory of Levy's flight in 3-dimensions. They clearly demonstrate the case where the object follows a Lévy distribution random walk. The integration of short-range exploratory hops and intermittent long-range ambulation contributes to a more efficient search strategy [25].

Figure 2

Lévy flight and Brownian walk

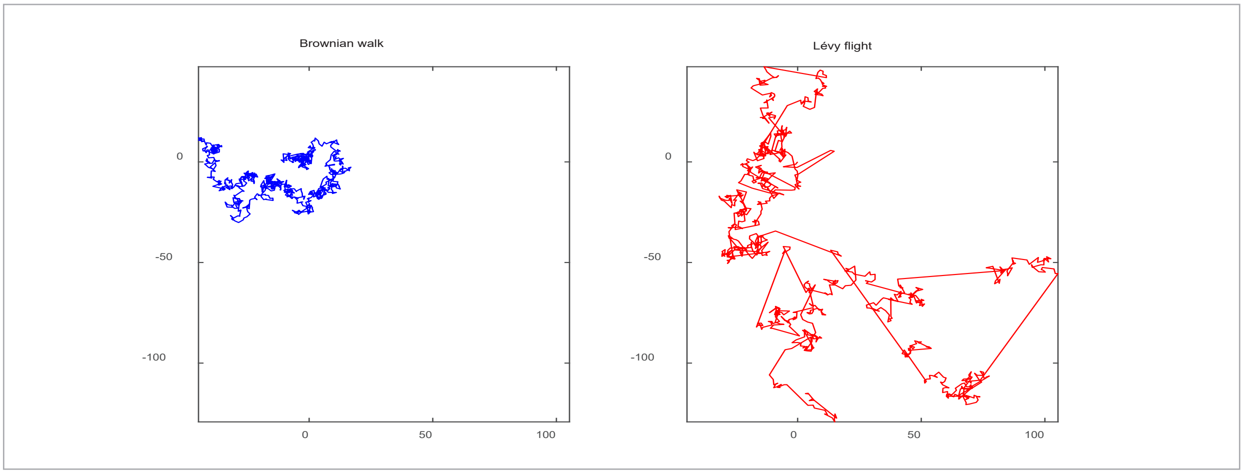


Figure 3

Lévy flight in 3D

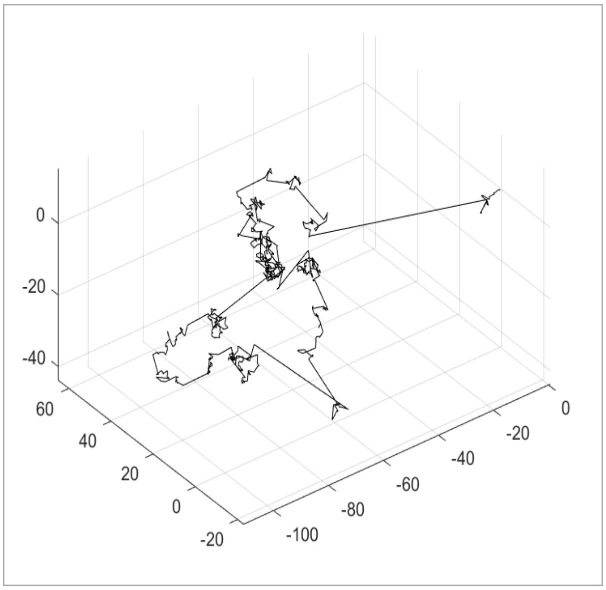
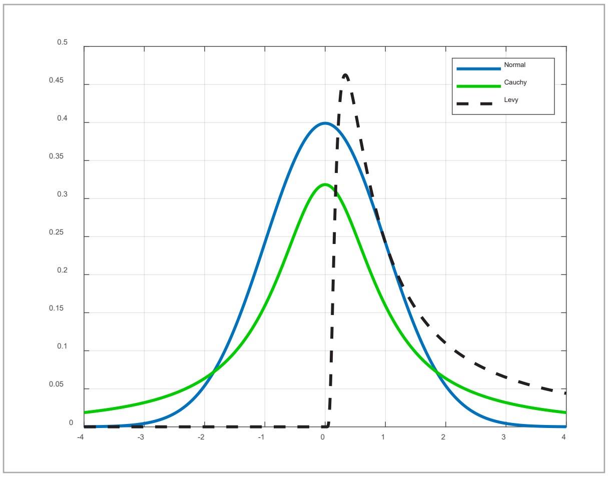


Figure 4

Comparison of stable distribution



$$\vec{x}(t+1) = \frac{\vec{x}_1 + \vec{x}_2 + \vec{x}_3}{3} \quad (7)$$

Figure 4 presents the differences between Lévy, Gaussian, and Cauchy distributions, the Lévy distribution exhibits heavy-tailed characteristics and has a significantly larger search range, making it more suitable for global search [39].

Lévy flight is utilized in the Cuckoo Search algorithm to simulate the flight paths of birds. This Lévy-based flight step length possesses an infinite mean and variance [1], hence effectively enhancing the search efficiency of the algorithm. Inspired by this, Lévy flight can also be utilized to simulate the foraging behavior of grey wolves. In this paper, we introduce the Lévy flight step length into the α individuals among the grey wolf pack. The mutated Alpha wolves can fully integrate the random walk characteristics of Lévy distribution, balancing exploration and exploitation. At the same time, the heavy-tailed property of Lévy flight enhances the exploration capability of the Alpha wolves in the later stage of the search space, preventing premature convergence of the algorithm. Therefore, the introduction of Lévy flight enhances the function of the α wolf as the leader of the wolf pack, and improves the overall exploration capability. The updated position of the mutated α is represented as follows:

$$\vec{x}_\alpha(t+1) = \vec{x}_\alpha\big(1 + r_3 \oplus Gaussion(0,\sigma_v) + + r_4 \oplus \ L(\lambda)\big)\,, \tag{8}$$

where $\oplus$ denotes the multiplication of entries, $\vec{x}_\alpha(t+1)$ is the position before the Alpha mutation, $\vec{x}_\alpha$ is the position after the Alpha mutation, and the value of r_3, r_4 are 0.5.

The novel strategy of α wolf mutation position update, which is based on the Lévy flight mechanism, enhances the range and diversity of the population [41] This approach, leveraging the learning mechanism from the alpha wolf, notably boosts the global search capacity of the wolf population, thereby offering a significant improvement over the original position update method.

3.1.2. Elite opposition-based learning

Elite Opposition-based learning is an innovative technique in intelligent computing [9]. It is based on estimations and respective counter-estimations [10]. This is achieved by creating a counter-population using the elite individuals from the existing population [9]. The definition of the elite inverse solution is predicated on the presumption that the current population's most exceptional individual is the elite [16]:

$$bx_{i\prime}^t = \left(x_{i\prime,1}^t, x_{i\prime,2}^t, \ldots, x_{i\prime,d}^t\right) \tag{9}$$

then for any $x_{i,j}^t$, the inverse result with respect to the elites is:

$$ox_{i,j}^t = \left(ox_{i,1}^t, ox_{i,2}^t, \ldots, ox_{i,d}^t\right) \tag{10}$$

$$ox_{i,j}^t = k\left(pa_j^t + qb_j^t\right) - x_{i,j}^t \tag{11}$$

$i = 1,2,\ldots,n,$

where $k = rand \ (0,1)$, n represents the population size of the stock,d signifies the dimensionality of x. $x_{b,j}^t \epsilon \left[pa_j^t, qb_j^t\right]$, pa_j^t and qb_j^t are the lower and upper bounds of the antagonistic solution and they are obtained by:

$$pa_j^t = \min\left(x_{i,j}^t\right) \tag{12}$$

$$qb_j^t = \max\left(x_{i,j}^t\right). \tag{13}$$

Inspired by the original elite reverse learning, a learning strategy is proposed in this article, with α, β, and δ wolves serving as the elite individuals. The specific program is divided into three plans. The first part is designed to make all individuals learn from the α wolf:

$$o_1 x_{i,j}^t = 2x_\alpha^t - x_{i,j}^t. \tag{14}$$

Equation (20) defines the learning of individuals from α wolves, and all wolves generate reverse individuals based on the alpha wolf, for β and δ, with the following two strategies:

$$o_2 x_{i,j}^t = x_{i,j}^t + L(\lambda) \oplus \left(\frac{x_\beta^t + x_\delta^t}{2} - x_{i,j}^t\right) \tag{15}$$

$$o_3 x_{i,j}^t = x_{i,j}^t + L(\lambda) \oplus \left(pa_j^t + qb_j^t - \frac{x_\beta^t + x_\delta^t}{2} - x_{i,j}^t\right) \tag{16}$$

Equations (21)-(22) determine the two ways in which β and δ co-direct individuals.

The optimal reverse solution will arise between these three approaches. With this approach, all individuals fully reference the position of the leader wolf and generate rich versions of the inverse, which not only maximizes the use of the leader's information but also gives the inverse solution a variety of choices.

3.1.3. Greedy Selection Strategy

Greedy strategy is a strategy that selects the option that currently seems best at each decision point, without considering the long-term implications, and focuses on the best option immediately available. Inspired by the greedy strategy in the DE algorithm and the pitch adjustment method in the cuckoo algorithm [2], Each gray wolf incorporates the following greedy selection:

$$\vec{x}(t+1) = \begin{cases} o_{min}\vec{x}(t), \ f\left(o_{min}\vec{x}(t)\right) < f\left(\vec{x}(t)\right) \\ \vec{x}(t), \ otherwise \end{cases} \tag{17}$$

where $o_{min}\vec{x}(t)$ represents the inverse solution that minimizes the fitness after t iterations and $o_{min}\vec{x}(t)$ is obtained in $o_i\vec{x}(t), i\epsilon\{1,2,3\}$. As we all know, Lévy flight is characterized by long-distance movement and randomness, so as the algorithm iterates, the search space will continue to increase, and elite opposition-based learning will also augment the population. This type of greedy strategy not only balances the diversity of the late-stage population to a certain extent, but also adheres to the "natural selection" law of grey wolves in the natural world. Individuals with superior mutations or better performances will have the chance to survive, continuing to find higher quality solutions.

3.1.4. The Pseudo-Code of the Proposed CGWO Optimizer

The pseudo-code for OGWO is shown as in Algorithm 1

```
Algorithm 1
Determine the initial population size N and number of iterations T
Randomly generate the initial population of wolves
Initialize the position of populations randomly
Get the fitness of each wolf
X_α = the fittest wolf
X_β = the second best wolf
X_δ = the third best wolf
For t = 1 : T
  for i = 1 : N
    Update the position of α by Equation (8)
    Perform Elite Opposition-based learning by Equations (14)-(16)
    Perform Greedy strategy by Equation (17)
  end
  Update the α, β, and δ
  The best fitness = X_α
End
```

3.1.5. Complexity Analysis

For time complexity, For OGWO, suppose we have N grey wolves, each of which needs to optimize a D-dimensional problem and then perform T iterations. In each iteration, each grey wolf needs to update its position, which takes $O(D)$ time. Thus, each iteration takes $(O(N * D)$ time. If T iterations are performed, then the total time complexity will be $(O(T * N * D)$, which is consistent with GWO.

For the space complexity, it is obvious that the space complexity in the case of the same N and D are both $(O(N * D)$, occupying the same amount of space. Comprehensive analysis shows that OGWO improves the utilization of time and space.

3.2. OGWO-MLP

3.2.1. Multilayer Perceptron

The Multilayer Perceptron (MLP) is a computational model imitating biological neural systems, adept at handling nonlinear, noise-impacted data [28]. MLP comprises numerous interconnected neurons in a cascading, graph-like structure, divided into input, hidden, and output layers [6]. Each neuron, excluding the input layer, uses a non-linear activation function for information transmission and processing. Heuristic algorithms serve as efficient tools for replacing gradient-based learning algorithms in neural network training [29]. In this research, OGWO fine-tunes the network parameters, including weights and biases, enhancing the network's performance. Figure 7 depicts an MLP's three-layer structure.

Figure 5

Architecture of a multi-Layer perceptron

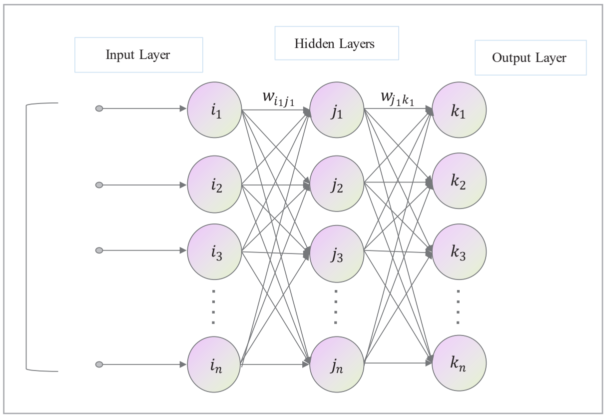


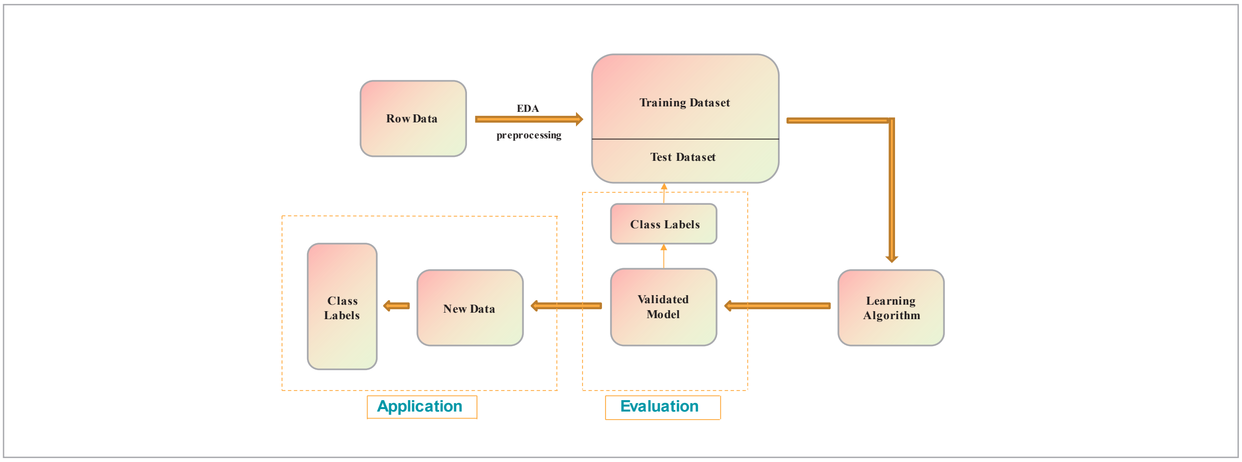
Figure 5 depicts an MLP's three-layer structure,where i, j, k respectively denote the indices of the input layer, hidden layer, and output layer, w_{jk}^{l} is defined as the connection weight from the j^{th} neuron in the $(l-1)^{th}$ layer to the k^{th} neuron in the l^{th} layer.

3.2.2. Combination of OGWO and MLP

The training process unfolds through four pivotal stages: data preprocessing, model training, perfor-

Figure 6

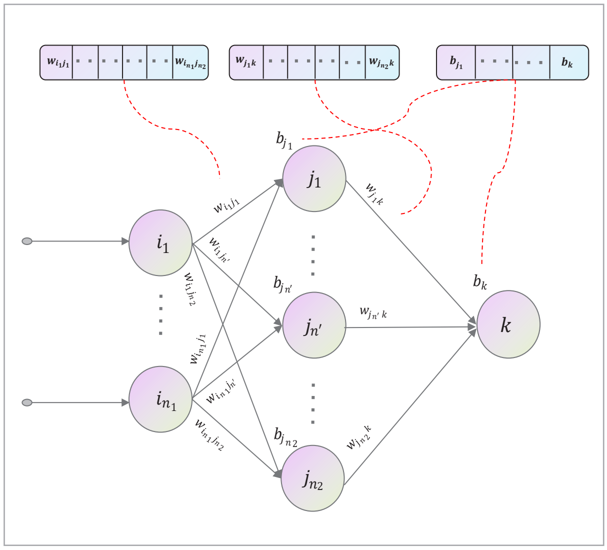
Schematic diagram of OGWO-MLP



mance evaluation, and result prediction [7]. The whole process is shown in the Figure 6. The OGWO-based network training process is employed for a classification task. Once the weights and biases are established, they allow the network to predict outputs for various inputs. The model's performance is enhanced by dynamically adjusting weight parameters and leveraging the unique features of the hidden layer structure, thereby improving classification accuracy. In this approach, the structure of each wolf is mapped to the weights and biases of a neural network, as shown in the Figure 7.

Figure 7

Mapping of an OGWO solution



3.2.3. Performance Evaluation Metrics

The evaluation adopts an array of standard performance metrics, such as accuracy, precision, recall, and the F1 score [5]. These metrics stem from the four components of the confusion matrix, which include True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN). To further illustrate performance, the Area Under the Curve (AUC) for the Receiver Operating Characteristics (ROC) curve is also calculated. The definition formulas are as follows:

- Accuracy: The ratio of correct predictions to the total number of instances.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{18}$$

- Precision: The ratio of correctly predicted positive cases to all predicted positive instances.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{19}$$

- Recall: The percentage of accurately identified positive outcomes from the total pool of actual positive instances.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{20}$$

- F1 Score: The harmonic mean of Precision and Recall, providing a balanced measure between these two metrics.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (21)$$

– AUC-ROC Curve: The ROC curve is a probability graph that illustrates the ability of a model to distinguish between classes.

$$\text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}} \quad (22)$$

4. Simulation Experiment and Result Analysis

The research involves three primary experimental investigations:

1 The first compares the enhanced OGWO with other models and the standard GWO in 30 and 500 dimensions.

2 The second validates OGWO's superior performance against other advanced GWOs.

3 The third uses a Wilcoxon rank-sum test to statistically differentiate OGWO's performance from other algorithms tested in Experiment (1).

4.1. Experimental Setup

Test function selection is pivotal for the validation and comparative analysis of optimization algorithms [19]. This paper utilizes 20 diverse benchmark test functions [13] to evaluate the improved algorithm's performance, including global search capability, convergence precision, and efficiency. f_1 to f_9 test precision as they are unimodal and challenging to converge to the optimum. f_{10} to f_{16}, being multimodal with multiple extrema, test the algorithm's global search capability. The last functions are fixed, low-dimensional ones. This selection strategy ensures a balanced, unbiased assessment of the algorithm's overall performance.

Table 1 lists the names, search ranges, and optimal solutions for all 20 benchmark functions. These tests were conducted using a population size of 20 and a maximum of 250 iterations. Each function was independently tested 25 times on a PC with a 13th Gen Intel Core i9, 16GB RAM, Windows 11, using MATLAB R2023b.

Table 1
The test functions

NO.	Names	Search ranges	Optimal solutions
1	Sphere	[−100, 100]	0
2	Schumer Steiglitz	[−10, 10]	0
3	Powell Sum	[−1,1]	0
4	Rotated hyper-ellipsoid	[−65.536, −65.536]	0
5	SchwefelsP2.21	[−10, 10]	0
6	Quartic	[−1.28, 1.28]	0
7	Rosenbrock	[−30, 30]	0
8	Streched V Sine Wave	[−10, 10]	0
9	Brown	[−1,4]	0
10	Csendes	[−1,1]	0
11	Wavy	[-π, π]	0
12	Ackley	[−32, 32]	0
13	Rastrigin	[−5.12, 5.12]	0
14	Zakharov	[−5, 10]	0
15	Griewank	[−600, 600]	0
16	Pinter	[−10, 10]	0
17	Matyas	[−10, 10]	0
18	Rotated Ellipse	[−500, 500]	0
19	Shekel	[−10, 10]	−10.5364
20	Periodic	[−10, 10]	0.9

4.2. Comparison of OGWO with Other Optimizer

Experiment (1) assesses the performance of OGWO through a comparative analysis with other intelligent algorithms, namely Seagull Optimization Algorithm (SOA), Dandelion-Optimizer (DO), Gravitational Search Algorithm (GSA), Moth-Flame Optimization Algorithm (MFO), Liver Cancer Algorithm (LCA), and the standard GWO. The comparative evaluation is based on each optimizer's highest, average value, and standard deviation. Table 2 encapsulates the results, with the superior outcomes for each function emphasized in bold.

To further illustrate the advantages of OGWO, the convergence curves of all algorithms on each test function are shown in Figure 5.

Table 2
Test results of Experiment (1).

NO.	Dimension	Results	SOA	DO	GSA	MFO	LCA	GWO	OGWO
1	30	Best	1.2059e-04	6.3479e-03	2.8101e+02	3.7780e+02	3.3326e-03	1.0944e-10	2.3478e-129
		Mean	1.2065e-03	2.3211e-02	1.3474e+03	3.5061e+03	1.0998e+00	1.3853e-09	1.8054e-102
		Std	1.1196e-03	1.3864e-02	6.3360e+02	4.4108e+03	2.5628e+00	2.4579e-09	9.0120e-102
	500	Best	1.5895e+02	4.5892e+04	2.6298e+05	1.2358e+06	2.7912e-01	9.4378e+01	1.2768e-118
		Mean	4.9532e+02	7.2025e+04	2.7755e+05	1.3213e+06	8.9029e+00	1.5831e+02	3.9848e-93
		Std	2.2300e+02	1.3131e+04	6.7875e+03	3.7116e+04	1.1911e+01	3.6832e+02	1.6435e-92
2	30	Best	3.7301e-11	1.1929e-08	3.0545e-02	1.1744e+01	3.5864e-11	1.0794e-22	8.0414e-245
		Mean	2.0429e-08	5.0143e-07	8.9497e-01	8.8287e+01	4.0911e-06	1.8674e-18	2.9529e-206
		Std	5.3805e-08	8.0078e-07	1.2132e+00	7.4943e+01	9.2785e-06	7.1588e-18	0
	500	Best	6.0507e+01	2.6205e+04	2.5216e+03	6.6907e+05	2.3540e-10	2.7001e-01	3.1794e-224
		Mean	4.7411e+02	5.2470e+04	3.2953e+03	7.3586e+05	1.7179e-04	1.2161e+00	1.6413e-171
		Std	4.5989e+02	1.7024e+04	4.9397e+02	3.0672e+04	6.9723e-04	7.8817e-01	0
3	30	Best	1.3116e-26	2.7435e-12	7.9290e-08	4.2408e-07	6.0845e-10	6.8726e-48	1.5993e-236
		Mean	4.0619e-13	4.5624e-11	4.0396e-05	3.8193e-03	2.34506e-06	5.6250e-40	2.8045e-200
		Std	2.0213e-12	7.2546e-11	9.5883e-05	1.4963e-02	6.2423e-06	1.6578e-39	0
	500	Best	1.0289e+00	2.0654e-02	5.5243e-03	4.3216e-01	2.1142e+00	1.8449e-09	2.8830e-239
		Mean	2.3208e+00	1.3621e-01	2.0786e-01	1.2179e+00	6.3413e+00	1.2609e-07	3.1436e-207
		Std	6.8121e-01	7.5303e-02	3.1601e-01	4.8503e-01	6.7224e-01	2.1455e-06	0
4	30	Best	3.1592e-04	4.4673e+02	2.6853e+02	9.3973e+02	1.1257e+02	8.6593e+00	6.4926e-126
		Mean	1.0057e-02	3.6825e+02	2.0242e+03	2.7533e+04	3.1656e+03	1.1257e+01	1.4044e-99
		Std	1.8116e-02	2.3439e+02	1.9032e+03	3.5069e+04	3.3822e+03	8.8870e+02	7.0214e-99
	500	Best	1.3875e+04	1.5347e+06	7.8193e+06	1.2439e+08	1.9354e+02	8.4484e+03	2.0538e-115
		Mean	4.3885e+04	2.1979e+06	8.8189e+06	1.3581e+08	6.2351e+05	1.2771e+04	3.2464e-89
		Std	2.1213e+04	3.4820e+05	5.6275e+05	4.4541e+06	7.6904e+05	3.0796e+03	1.6229e-88
5	30	Best	2.4918e-02	1.2905e-01	2.1632e+00	5.7451e+00	2.3213e+00	2.5205e-03	1.8487e-63
		Mean	2.0841e-01	1.0655e+00	3.4579e+00	7.5052e+00	5.5091e+00	2.4181e-02	5.3256e-52
		Std	2.5127e-01	6.6695e-01	7.3941e-01	7.1413e-01	1.3682e+00	1.0243e-02	2.5086e-51
	500	Best	9.8932e+00	9.3087e+00	3.2678e+00	9.8118e+00	3.0013e-03	6.5897e+00	3.7436e-59
		Mean	9.9352e+00	8.8225e+00	3.5491e+00	9.9102e+00	1.3820e-02	7.5603e+00	3.0194e-43
		Std	2.1051e-02	1.3641e+00	2.0246e-01	3.9006e-02	8.2015e-03	4.7679e-01	1.3810e-42
6	30	Best	9.5758e-04	1.4090e-02	5.3834e-01	5.9375e-01	1.0907e-04	1.9020e-03	1.0273e-04
		Mean	1.1427e-02	6.4081e-02	9.4812e+00	4.4384e+00	1.6489e-04	6.9048e-03	1.8110e-03
		Std	8.5948e-03	8.2544e+02	9.7105e+00	7.9760e+00	1.4899e-03	3.5274e-03	1.1289e-03
	500	Best	2.2794e+00	8.5250e+02	7.8452e+03	4.1907e+04	2.3481e-04	5.5929e-01	3.1604e-04
		Mean	1.5313e+01	2.4391e+03	1.1332e+04	4.7361e+04	7.0332e-03	8.8042e-01	6.3332e-03
		Std	8.9996e+00	2.2031e-02	1.6336e+03	2.3750e+03	1.0442e-02	1.8828e-01	5.5553e-03
7	30	Best	2.7829e+01	3.2533e+02	3.4588e+02	5.7035e+04	7.8129e+03	2.6563e+01	2.6058e+01
		Mean	8.3642e+01	2.8698e+02	3.7250e+03	7.5285e+06	1.5242e+06	1.3140e+01	2.7830e+01
		Std	4.8253e-01	4.3014e+02	4.3445e+03	2.2066e+07	1.7726e+06	1.6145e-01	8.7745e-01
	500	Best	1.8046e+05	1.4869e+08	2.0361e+07	5.5608e+09	1.8121e+09	2.8486e+00	4.9794e+02
		Mean	3.7201e+06	3.6559e+08	2.7674e+07	6.0062e+09	2.7491e+09	1.0203e+02	4.9816e+02
		Std	3.6734e+06	2.325e+08	3.9734e+06	2.2534e+08	5.0624e+08	1.3390e+02	1.4213e-01

Table 2 (continuation)

NO.	Dimension	Results	SOA	DO	GSA	MFO	LCA	GWO	OGWO
8	30	Best Mean Std	1.1492e+01 1.1754e+01 1.5213e-01	4.2873e+00 8.6653e+00 2.2086e+00	4.4161e+00 6.8893e+00 1.6049e+00	7.9337e+00 1.1716e+01 2.0048e+00	2.0238e-01 1.0975e+00 7.9016e-01	2.3267e+00 7.1220e+00 4.0482e+00	1.3633e-30 1.1427e-04 5.7134e-04
	500	Best Mean Std	2.0964e+02 2.0986e+02 6.7348e-02	3.1860e+02 4.1597e+02 6.2931e+01	2.4800e+02 2.6775e+02 1.1764e+01	5.3405e+02 5.7688e+02 1.8564e+01	4.5249e+00 1.5205e+01 7.0196e+00	1.3739e+02 2.0782e+02 4.0630e+01	2.3382e-28 5.9727e-14 2.9222e-13
9	30	Best Mean Std	3.6482e-08 9.7361e-07 6.7524e-07	2.1004e-05 9.0549e-05 6.3605e-05	5.9571e+01 1.3395e+01 1.7083e+01	4.2123e+00 2.1005e+01 2.3158e+01	3.8640e-05 1.0912e-03 1.1579e-03	7.1168e-13 3.5534e-12 4.1363e-12	8.8864e-120 5.8272e-88 2.9136e-87
	500	Best Mean Std	1.5490e+02 9.3033e+12 3.0403e+13	1.4004e+04 3.4667e+08 8.6968e+08	1.1029e+05 2.3596e+05 8.3566e+04	4.5945e+13 4.3618e+15 1.2664e+16	1.7168e-03 1.8775e-02 1.2533e-02	4.2640e+00 4.6231e+01 5.9921e+01	3.6929e-110 1.5796e-77 7.8981e-77
10	30	Best Mean Std	1.0516e-20 6.4550e-15 2.3065e-14	4.2958e-13 7.7261e-11 1.7789e-10	1.2280e-05 2.4234e-01 4.1946e-01	1.8736e-04 5.0595e-02 2.3107e-01	4.2707e-21 1.5538e-14 6.1583e-14	3.1620e-33 1.1884e-28 5.0709e-28	0 1.2087e-307 0
	500	Best Mean Std	2.6548e-02 3.4970e-01 2.9017e-01	3.5213e+00 6.7958e+00 2.3393e+00	1.8289e+01 3.3769e+01 1.0407e+01	8.6660e+01 9.7434e+01 4.7388e+00	1.5513e-17 3.8818e-13 1.6277e-12	3.4632e-06 3.8083e-05 3.4257e-05	0 9.9589e-264 0
11	30	Best Mean Std	6.7306e-03 1.7838e-01 1.4585e-01	1.2178e-01 2.2215e-01 7.2864e-02	5.3656e-01 6.8194e-01 7.6946e-02	3.7309e-01 4.7446e-01 5.8337e-02	5.5686e-06 3.4021e-01 3.9463e-01	5.1573e-02 1.6520e-01 8.5145e-02	0 0 0
	500	Best Mean Std	1.4030e-02 1.2218e-01 1.6852e-01	4.1653e-01 4.9593e-01 6.2433e-02	6.9596e-01 7.2713e-01 1.7761e-02	8.0549e-01 8.2880e-01 1.2499e-02	1.1813e-06 1.1150e-01 3.1624e-01	2.5998e-01 3.1999e-01 4.7609e-02	0 0 0
12	30	Best Mean Std	1.9959e+01 1.9962e+01 1.4294e-03	1.7288e-02 3.1333e-01 5.5123e-02	1.3479e+00 2.8017e+00 8.5535e-01	4.9861e+00 1.5066e+01 5.0890e+00	1.0069e-02 2.4145e-01 2.2597e-01	2.0583e-06 6.2656e-06 3.1054e-06	4.4409e-16 4.4409e-16 0
	500	Best Mean Std	1.9967e+01 1.9967e+01 6.0907e-05	1.0996e+01 1.2620e+01 7.9673e-01	1.2053e+01 1.2641e+01 2.7325e-01	2.0337e+01 2.0508e+01 7.3743e-02	1.3809e-02 2.6924e-01 2.8926e-01	1.5075e+00 1.9696e+00 2.0700e-01	4.4409e-16 4.4409e-16 0
13	30	Best Mean Std	5.1480e-04 1.5671e+01 1.5822e+01	8.8398e+00 5.4401e+01 3.4467e+01	3.9821e+01 6.7961e+01 2.0934e+01	1.2835e+02 1.7915e+02 3.6781e+01	5.8635e-04 1.0259e+01 5.0334e+01	2.5815e+00 2.0656e+01 3.1685e+01	0 0 0
	500	Best Mean Std	7.1157e+01 1.6539e+02 7.0852e+01	2.6992e+03 3.4299e+03 3.7456e+02	3.4638e+03 3.6317e+03 9.7054e+01	7.3556e+03 7.5392e+03 9.0560e+01	8.6293e-02 7.2332e+00 1.7225e+01	4.8255e+02 7.0714e+02 1.1080e+02	0 0 0
14	30	Best Mean Std	1.9086e-02 8.8565e-01 1.2135e+00	1.6903e+00 1.3371e+01 1.1454e+01	1.6711e+02 2.4385e+02 6.8951e+01	2.7648e+02 4.9884e+02 1.1122e+02	2.7553e-01 1.1800e+01 2.1325e+01	3.5335e-02 7.8302e-01 7.9381e-01	2.5166e-118 1.1491e-76 5.4611e-76
	500	Best Mean Std	4.0472e+03 7.9745e+03 1.9045e+03	4.6316e+03 5.6907e+03 5.9319e+02	5.0447e+19 8.7816e+19 2.4647e+19	1.7956e+04 1.9673e+04 9.8494e+02	1.2938e+04 1.7249e+11 4.5311e+11	3.1465e+03 4.1563e+03 4.6377e+02	6.5231e-104 3.0630e-65 1.5199e-64

Table 2 (continuation)

NO.	Dimension	Results	SOA	DO	GSA	MFO	LCA	GWO	OGWO
15	30	Best Mean Std	2.4711e-04 5.2305e-02 8.2999e-02	3.2735e-02 7.9883e-02 3.2052e-02	1.3847e+02 2.0645e+02 3.4185e+01	2.7688e+00 3.0674e+01 3.7657e+01	1.2929e-02 4.9993e-01 3.2324e-01	5.3100e-10 1.2591e-02 1.6339e-02	0 0 0
	500	Best Mean Std	2.1772e+00 4.4565e+00 2.0190e+00	4.9738e+02 6.9746e+02 1.3934e+02	1.0551e+04 1.1228e+04 2.4017e+02	9.7295e+02 1.1085e+04 1.1909e+04	1.3173e-01 7.7338e-01 4.1203e-01	2.0299e+00 2.5189e+01 3.4874e-01	0 0 0
16	30	Best Mean Std	5.0540e-04 5.9091e+00 2.9470e+01	6.8484e+01 9.7768e+02 7.3526e+02	1.1883e+03 1.9675e+03 5.8223e+02	3.2928e+03 5.7820e+03 1.6184e+03	1.8043e-01 2.2117e+01 2.8285e+01	1.2635e-08 4.2587e-07 5.7638e-07	1.9304e-126 3.9669e-99 1.9703e-98
	500	Best Mean Std	2.1131e+04 5.9258e+04 2.4290e+04	2.9357e+06 3.5119e+06 3.6427e+05	1.3038e+06 1.4146e+06 5.8097e+04	4.8318e+06 5.0745e+06 1.4205e+05	1.0465e+04 3.5060e+04 3.4759e+04	4.0788e+04 7.5742e+04 2.0589e+04	1.3278e-115 5.5672e-93 2.7834e-92
17	2	Best Mean Std	3.7656e-42 3.2694e-32 1.4798e-31	1.0898e-22 2.0977e-16 6.4720e-16	1.1118e-22 3.8090e-20 3.1679e-20	9.3309e-41 7.7350e-09 2.3585e-08	6.0832e-08 3.9446e-06 4.8125e-06	2.7076e-54 2.2043e-40 8.4076e-40	3.4730e-189 2.1780e-151 1.0888e-150
18	2	Best Mean Std	6.5811e-49 8.1686e-32 3.1480e-41	8.7132e-18 3.5542e-15 6.2006e-15	2.7562e-19 1.1413e+02 3.6398e+02	1.2246e-47 5.9586e-41 2.2435e-40	8.0594e-02 2.0359e+00 1.9245e+00	1.1751e-84 2.9234e-64 1.1060e-64	2.2036e-209 2.0874e-165 0
19	4	Best Mean Std	1.1143e-02 1.1143e-02 1.7705e-18	1.1143e-02 1.1143e-02 1.7705e-18	1.1143e-02 1.1164e-02 1.0398e-04	1.1143e-02 1.1164e-02 1.0398e-04	1.1143e-02 1.1143e-02 1.7705e-18	1.1143e-02 1.1393e-02 2.6509e-04	2.2205e-77 1.2697e-58 5.9572e-58
20	2	Best Mean Std	0.9 9.5634e-01 5.0971e-02	0.9 9.6800e-01 4.7609e-02	9.3195e-01 9.9485e-01 1.6751e-02	0.9 9.8000e-01 4.0825e-02	0.9 1.0104e+0 8.3111e-02	0.9 9.2826e-01 4.6253e-02	0.9 0.9 3.3993e-16

Figure 8

Convergence diagrams of Experiment (1)

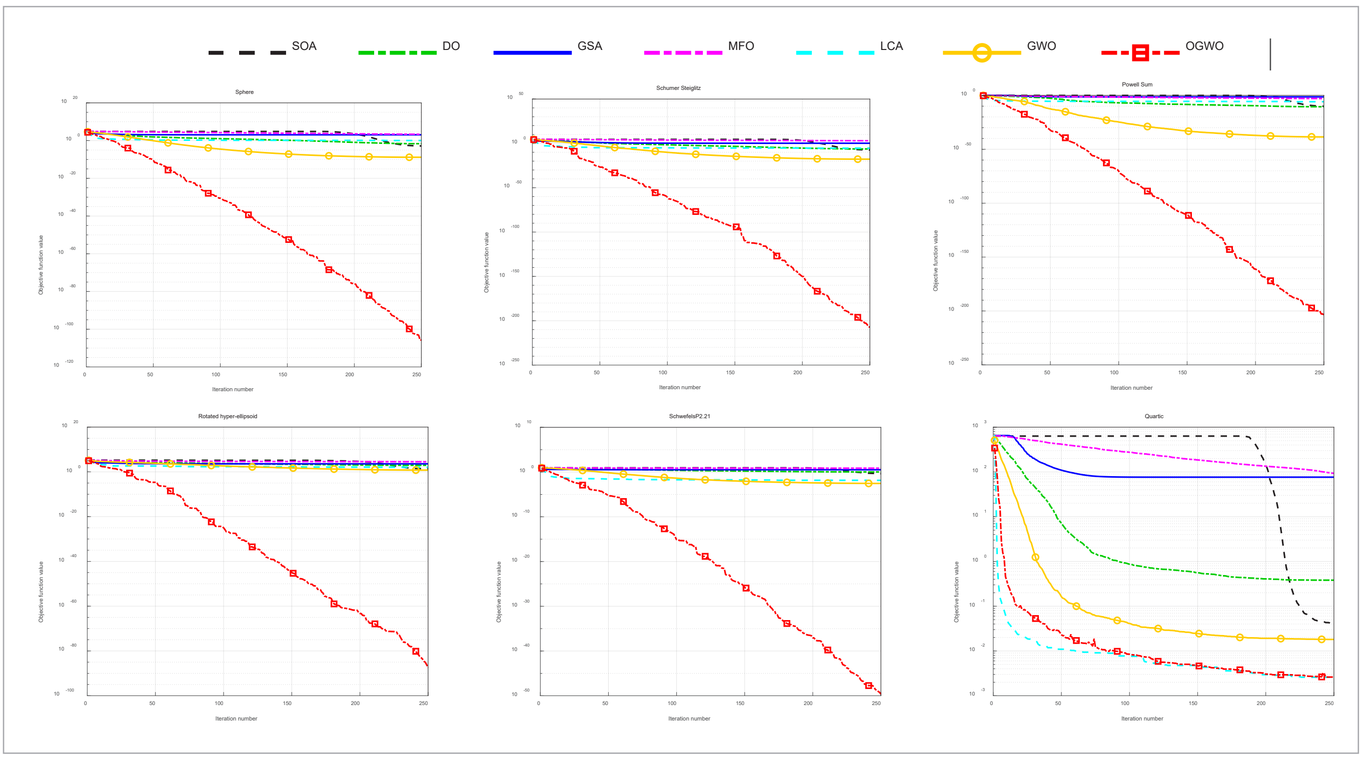
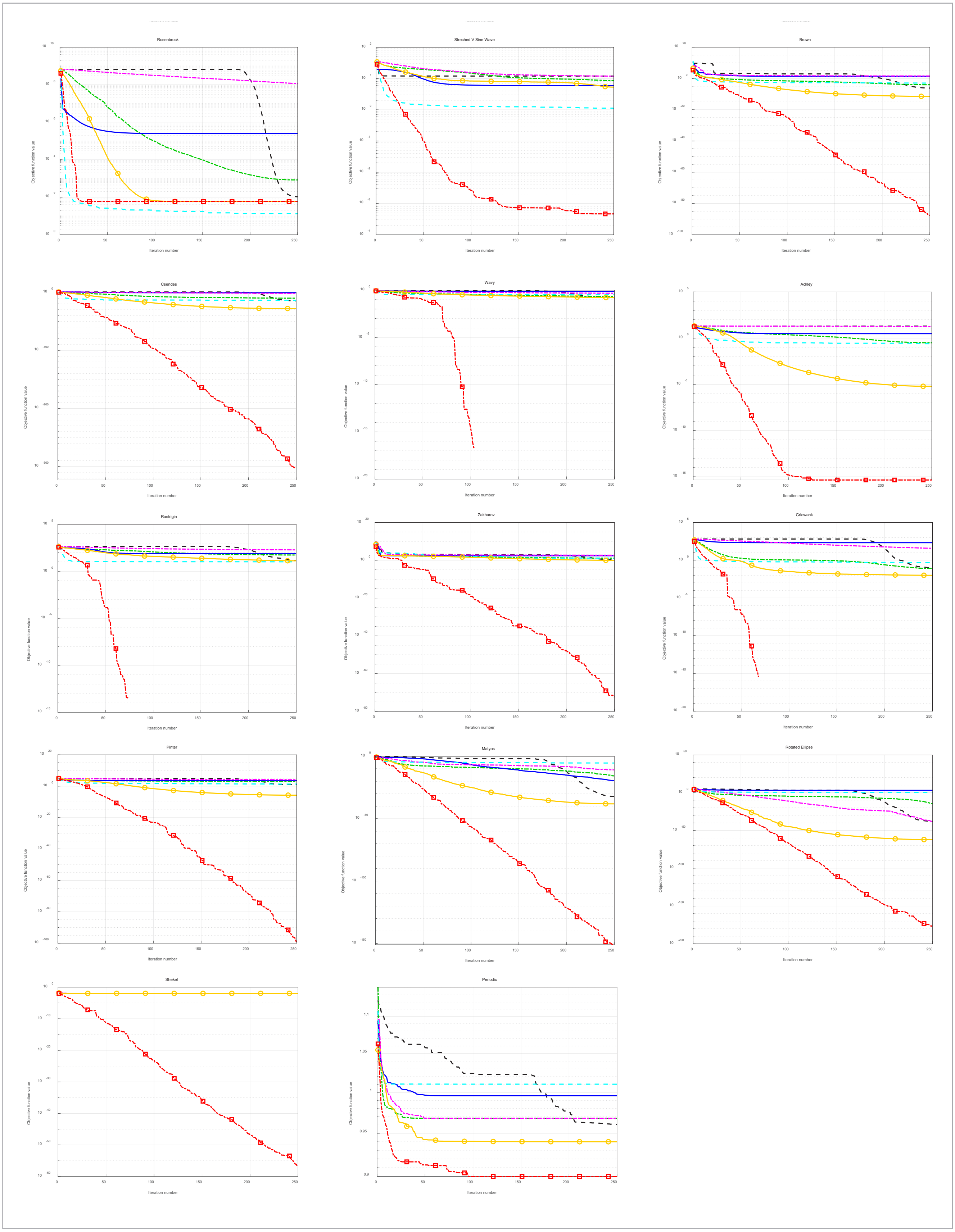


Figure 8 (continuation)



The results of Experiment (1) show that OGWO performs well in both high and low dimensional cases. Basically, it exhibits the smallest values in the results of all the tested functions and even reaches the theoretical optimum in some of the tested functions. This highlights the effectiveness of the proposed improvements to OGWO.

4.3. Comparison of OGWO with Other Improved GWOs

To delve deeper into the performance of OGWO, this section selects three improved GWO algorithms, namely G-NHGWO [4], I-GWO [33], and VAGWO [35], for performance comparison experiments with OGWO. The experimental (2) results are shown in Table 3, and the best experimental results are highlighted in bold.

Figure 9 provides a visual representation of the performance comparison among the four enhanced GWO algorithms.

The analysis of the results of Experiment (2) shows that OGWO has excellent performance compared with the other three improved GWOs, such as being able to break through the local optimum, converging significantly faster and reaching the theoretical optimum, and maintaining the highest solution accuracy and stability even for fixed low-dimensional benchmark functions. This shows that OGWO has a great improvement in the overall performance.

Table 3
Test results of Experiment (2)

NO.	Dimension	Results	G-NHGWO	I-GWO	VAGWO	OGWO
1	30	Best Mean Std	1.2906e-03 5.5781e-03 3.3315e-03	3.6175e-11 1.7010e-10 1.4864e-10	5.7695e+00 1.3718e+01 4.9219e+00	2.3478e-129 1.8054e-102 9.0120e-102
2	30	Best Mean Std	5.5550e-09 6.0182e-08 7.0857e-08	2.2276e-11 1.2187e-18 2.5770e-18	1.4664e-03 2.3017e-02 2.5987e-02	8.0414e-245 2.9529e-206 0
3	30	Best Mean Std	2.4276e-23 1.0643e-19 3.3339e-19	1.2159e-47 3.5437e-39 1.7434e-38	4.7884e-13 4.3400e-11 9.1353e-11	1.5993e-236 2.8045e-200 0
4	30	Best Mean Std	5.2884e-03 2.0787e-02 1.0557e-02	8.1975e-11 1.2150e-09 1.2934e-09	4.1375e+01 8.2467e+01 3.5986e+01	6.4926e-126 1.4044e-99 7.0214e-99
5	30	Best Mean Std	1.0180e-01 1.8330e-01 5.4715e-02	2.3287e-03 9.8167e-03 7.7014e-03	4.1569e-01 8.0730e-01 2.4849e-01	1.8487e-63 5.3256e-52 2.5086e-51
6	30	Best Mean Std	3.9811e-03 1.0130e-02 4.5175e-03	2.3950e-03 7.6234e-03 3.4619e-03	3.0991e-02 8.0270e-02 3.5034e-02	1.0273e-04 1.8110e-03 1.1289e-03
7	30	Best Mean Std	2.8560e+01 3.0239e+01 2.9384e+00	2.5149e+01 2.6632e+01 9.8596e-01	2.3200e+02 5.8741e+02 2.8849e+02	2.6058e+01 2.7830e+01 8.7745e-01

Table 3 (continuation)

NO.	Dimension	Results	G-NHGWO	I-GWO	VAGWO	OGWO
8	30	Best Mean Std	5.4818e+00 9.4810e+00 2.1266e+00	3.7778e+00 1.0445e+01 2.6799e+00	5.5583e+00 1.4516e+01 6.1995e+00	1.3633e-30 1.1427e-04 5.7134e-04
9	30	Best Mean Std	5.2562e-06 2.0480e-05 1.4278e-05	1.3123e-14 7.1230e-13 6.6773e-13	5.4780e-03 2.2748e-02 1.0015e-02	8.8864e-120 5.8272e-88 2.9136e-87
10	30	Best Mean Std	2.3921e-16 2.4103e-14 5.6388e-14	2.0754e-32 6.9283e-27 1.7412e-26	9.9150e-09 1.7685e-07 1.8796e-07	0 1.2087e-307 0
11	30	Best Mean Std	5.8868e-01 6.5696e-01 3.2208e-02	2.4695e-01 5.3808e-01 1.3007e-01	2.5611e-01 5.1071e-01 1.4723e-01	0 0 0
12	30	Best Mean Std	8.9525e-03 1.5437e-02 3.5886e-03	1.0715e-06 3.5040e-06 2.8578e-06	1.9324e+00 2.4549e+00 3.3400e-01	4.4409e-16 4.4409e-16 0
13	30	Best Mean Std	2.9110e+01 4.9728e+01 2.8611e+01	1.2002e+01 3.2753e+01 1.3127e+01	4.2236e+01 1.1358e+02 7.4374e+01	0 0 0
14	30	Best Mean Std	3.2019e+01 7.5139e+01 2.7508e+01	2.9809e-02 2.7065e-01 3.1064e-01	1.9211e+01 5.0174e+01 2.0277e+01	2.5166e-118 1.1491e-76 5.4611e-76
15	30	Best Mean Std	3.9478e-03 4.7360e-02 6.8535e-02	7.4573e-11 6.0799e-03 7.0999e-03	1.0448e+00 1.1562e+00 7.9401e-02	0 0 0
16	30	Best Mean Std	8.0661e-02 1.5934e+01 5.3275e+01	1.3323e-08 1.0947e+01 3.7888e+01	5.2269e+02 1.5438e+03 6.8380e+02	1.9304e-126 3.9669e-99 1.9703e-98
17	2	Best Mean Std	3.5294e-23 2.8110e-15 9.5772e-15	2.9399e-88 5.7150e-65 2.0734e-64	2.3368e-57 2.8555e-18 1.4228e-17	3.4730e-189 2.1780e-151 1.0888e-150
18	2	Best Mean Std	8.0436e-38 2.4705e-23 1.2164e-22	9.0985e-124 3.2005e-79 1.1701e-78	8.9677e-71 1.3520e-29 6.1021e-29	2.2036e-209 2.0874e-165 0
19	4	Best Mean Std	1.1143e-02 1.1143e-02 1.7705e-18	1.1143e-02 1.1143e-02 1.4395e-04	1.1143e-02 1.1407e-02 5.1146e-04	2.2205e-77 1.2697e-58 5.9572e-58
20	2	Best Mean Std	0.9 9.0365e-01 1.4581e-02	0.9 9.0400e-01 2.0000e-02	0.9 9.7036e-01 4.5907e-02	0.9 0.9 3.3993e-16

Figure 9

Convergence diagrams of Experiment (2)

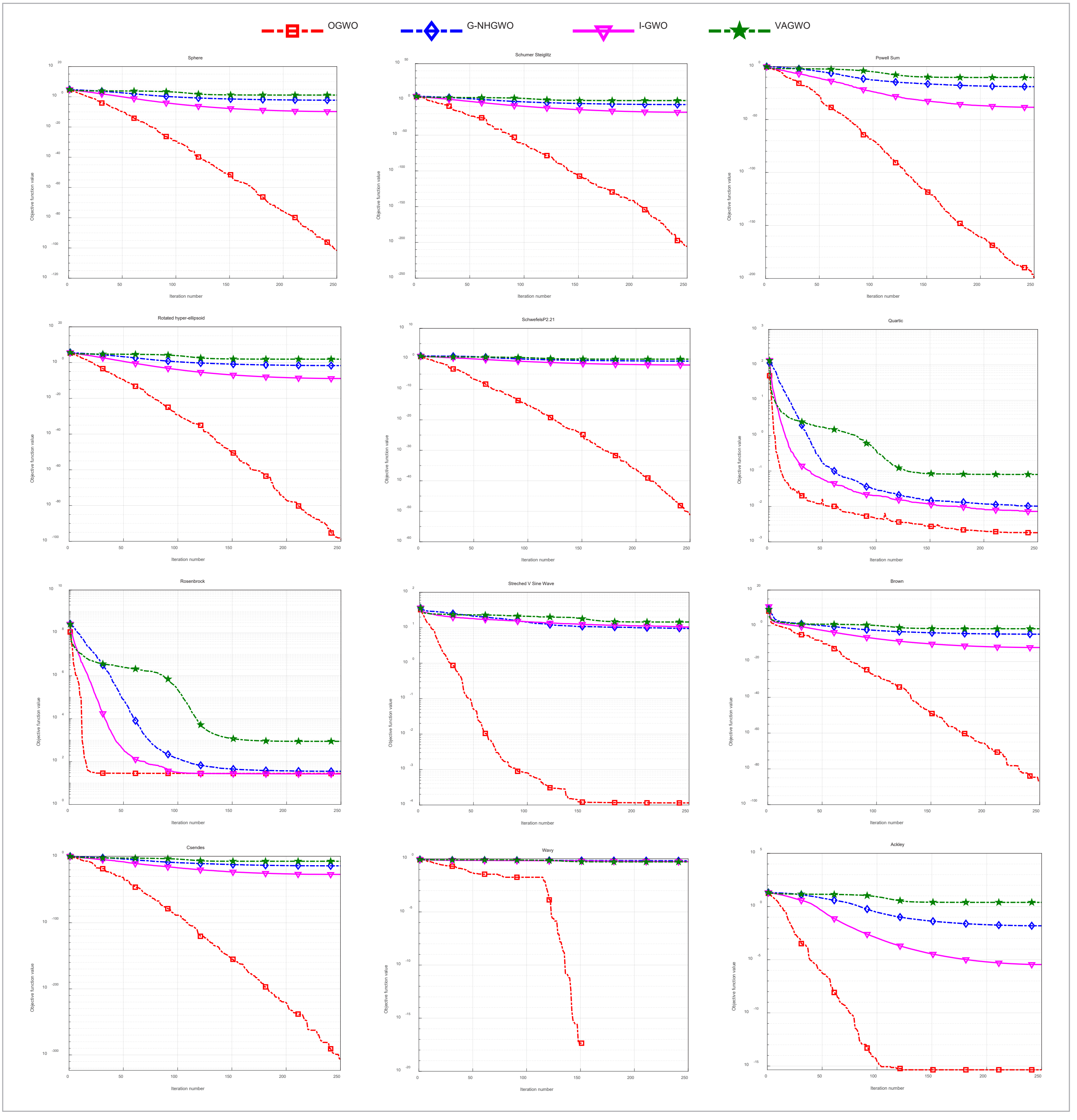
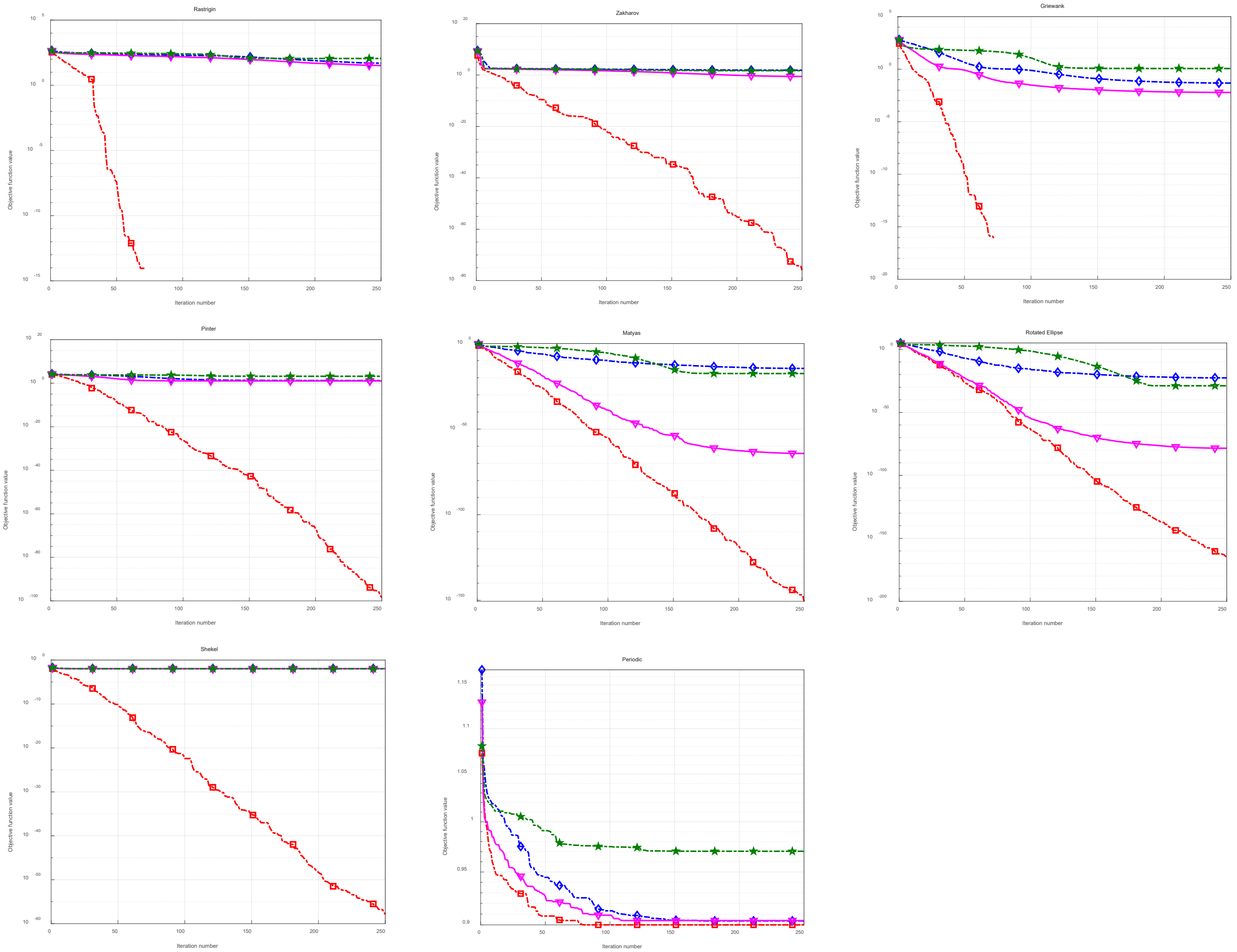


Figure 8 (continuation)



4.4. Wilcoxon Rank Sum Test

The Wilcoxon rank-sum test [21], a non-parametric hypothesis test, was employed in this study to compare the OGWO algorithm's performance and feasibility against other intelligent optimization algorithms. The test was executed at 5% significance level (α=5%) to ascertain if a significant disparity existed between the outcomes generated by OGWO and the other algorithms. Table 4 exhibits the test results comparing OGWO and the algorithms used in Experiment (1).

Based on the data in Table 4, we observe that the p-values associated with the OGWO are predominantly lower than the significance level α. This suggests a statistically significant variance between the outcomes of this algorithm and those of its counterparts.

Table 4
The results of Experiment (3)

Functions	OGWO vs. SOA	OGWO vs. DO	OGWO vs. GSA	OGWO vs. MFO	OGWO vs. LCA	OGWO vs. GWO
1	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+
2	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+
3	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+
4	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+
5	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+
6	6.1473e-07+	1.4157e-09+	1.4157e-09+	1.4157e-09+	4.3415e-03+	2.0536e-08+
7	6.1473e-07+	2.1060e-04+	1.4157e-09+	1.4157e-09+	2.5677e-08 +	6.4145e-01-
8	1.4157e-09+	1.4648e-08+	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+
9	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+
10	2.4712e-10+	2.4712e-10+	2.4712e-10+	2.4712e-10+	2.4712e-10+	2.4712e-10+
11	9.7285e-11+	9.7285e-11+	9.7285e-11+	9.7285e-11+	9.7285e-11+	9.7285e-11+
12	9.7285e-11+	9.7285e-11+	9.7285e-11+	9.7285e-11+	9.7285e-11+	9.7285e-11+
13	9.7285e-11+	9.7285e-11+	9.7285e-11+	9.7285e-11+	9.7285e-11+	9.7285e-11+
14	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+
15	9.7285e-11+	9.7285e-02+	9.7285e-11+	9.7285e-11+	9.7285e-11+	9.7285e-11+
16	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+
17	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+
18	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+	1.4157e-09+
19	9.7285e-11+	9.7285e-11+	1.3762e-10+	1.3762e-10+	9.7285e-11+	7.7271e-10+
20	7.6102e-06 +	1.1013e-06+	9.7283e-12+	2.0357e-08+	9.7285e-11+	5.1455e-03+

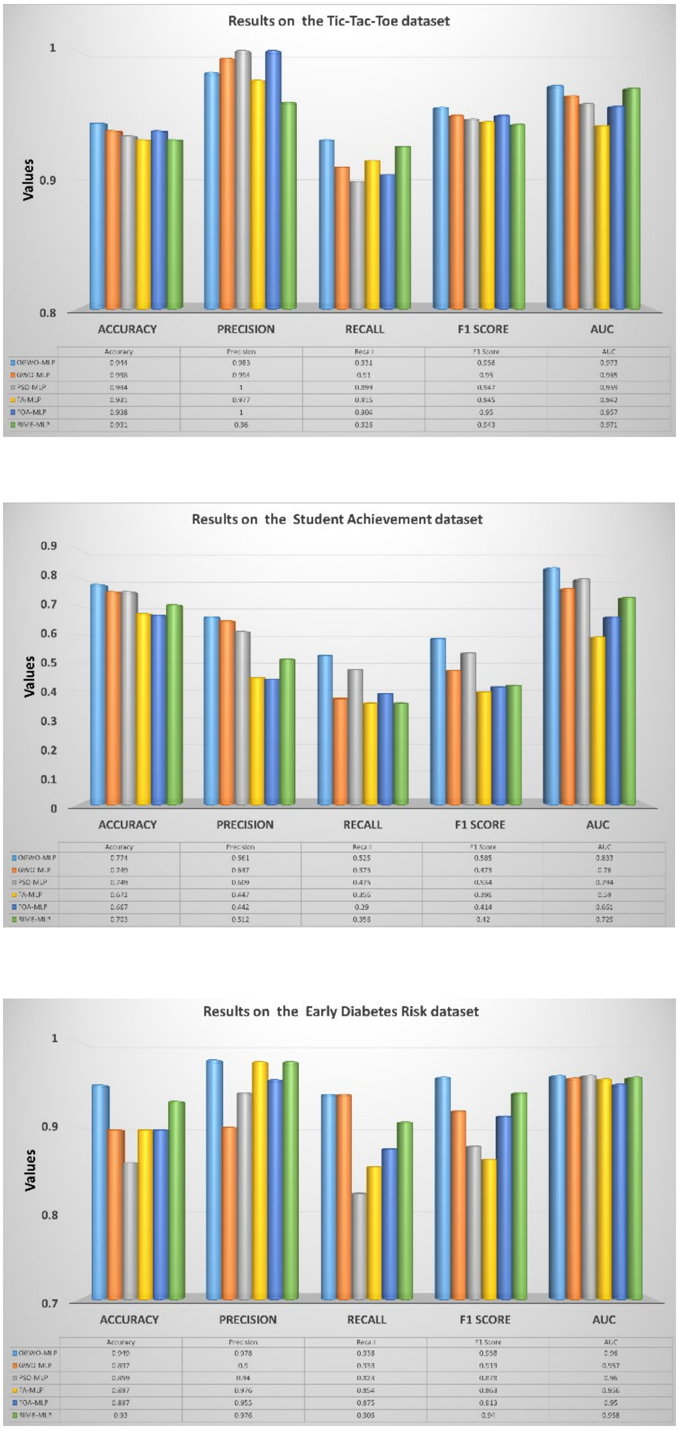
5. OGWO-MLP Classification Model

This study employed three unique standard classification datasets from the UCL Machine Learning Repository to assess the efficacy of the MLP optimized through OWGO. The three datasets are the Tic-Tac-Toe dataset, the Student Performance dataset and the Early Diabetes Risk Dataset, with sample sizes of 958, 649, and 520, respectively, all of which are binary categorical datasets.

The GWO-MLP, PSO-MLP, Firefly algorithm-MLP (FA-MLP), Fruit fly optimization algorithm- MLP (FOA-MLP) and Rime-ice optimization algorithm-MLP (RIME-MLP) were compared with the proposed OGWO-MLP model to validate the accuracy of the latter in prediction tasks more effectively. Each model underwent a comprehensive process of training, optimization, and evaluation. As observed in Figure 10, the OGWO-MLP model outperformed the others in all prediction tasks. This suggests that the MLP trained through OGWO establishes more ideal weights and biases [31]. The population size and maximum number of iterations for all algorithms were set to 5 and 30, respectively.

Figure 10

Comparison of test performance on datasets.



6. Solving a Speed Reducer Design Problem

With the development of industry, the need for optimal design of gearboxes is constantly improving. The design of a speed reducer is a time-consuming and complex problem as it is a analysis that must be repeated after designing based on dynamic constraints, and is currently targeted at minimizing the weight of the gear set [14, 18]. Figure 11 shows a typical speed reducer, which is a major key component in the gearbox of a mechanical system and can also be used in various other applications. This task incorporates seven key variables: the face width z_1, the teeth's module z_2, the number of pinion teeth z_3, the length of the first shaft between bearings z_4, the second shaft between bearings z_5, and the diameter of the first z_6 and second z_7 shafts.

Figure 11

Speed reducer

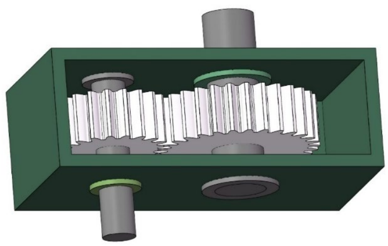
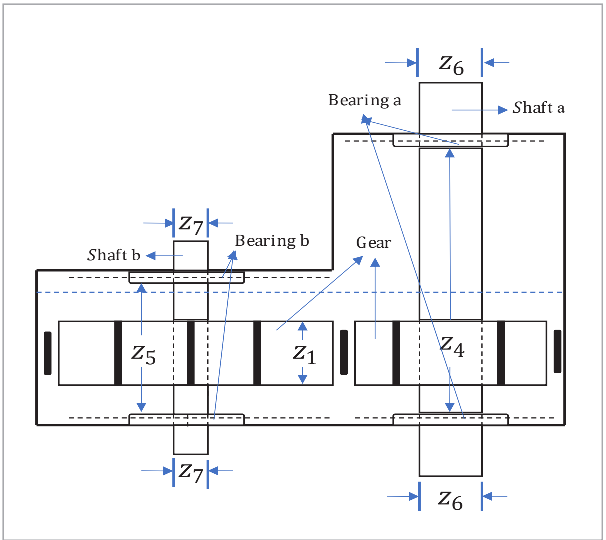


Figure 12 provides a cross-sectional diagram, clearly labeling these variables.

The objective of the issue is to minimize the total weight of the speed reducer, while conforming to eleven specific conditions. The restrictions encompass the boundaries on the flexural stress of the cog teeth, surface

Figure 12

Cross-sectional diagram of a speed reducer



strain, lateral distortions in shafts a and b from the imparted force, and pressure in shafts a and b [23]. The quantitative programming representation of the speed reducer issue, as evaluated in this research, is articulated in the subsequent manner.

$$\textit{Consider} \quad \bar{z} = [z_1\, z_2\, z_3\, z_4\, z_5\, z_6\, z_7] \tag{31}$$

$$f(\bar{z}) = 0.7854 z_1 z_2{}^2 (3.3333 z_3{}^2 + 14.9334 z_3 - 43.0934) - 1.508 z_1 (z_6{}^2 + z_7{}^2) + 7.4777 (z_6{}^3 + z_7{}^3) + 0.7854 (z_4 z_6{}^2 + z_5 z_7{}^2) \tag{32}$$

$$\textit{Subject to:} \quad g_1(\bar{z}) = \frac{27}{z_1 z_2{}^2 z_3} - 1 \le 0, g_2(\bar{z}) = \frac{397.5}{z_1 z_2{}^2 z_3{}^2} - 1 \le 0, g_3(\bar{z}) = \frac{1.93 z_4{}^3}{z_2 z_3 z_6{}^4} - 1 \le 0, g_4(\bar{z}) = \frac{1.93 z_5{}^3}{z_2 z_3 z_7{}^4} - 1 \le 0 \tag{33}$$

$$g_5(\bar{z}) = \frac{\left[\left(745(z_4/z_2 z_3)\right)^2 + 1.69\times10^6\right]^{1/2}}{110 z_6{}^3} - 1 \le 0, g_6(\bar{z}) = \frac{\left[\left(745(z_5/z_2 z_3)\right)^2 + 157.5\times10^6\right]^{1/2}}{85 z_7{}^3} - 1 \le 0 \tag{34}$$

$$g_7(\bar{z}) = \frac{z_2 z_3}{40} - 1 \le 0, g_8(\bar{z}) = \frac{5 z_2}{z_1} - 1 \le 0, g_9(\bar{z}) = \frac{z_1}{12 z_2} - 1 \le 0 \tag{35}$$

$$g_{10}(\bar{z}) = \frac{1.5 z_6 + 1.9}{z_4} - 1 \le 0, g_{11}(\bar{z}) = \frac{1.1 z_7 + 1.9}{z_5} - 1 \le 0 \tag{36}$$

Where

$2.6 \le z_1 \le 3.6$, $0.7 \le z_2 \le 0.8$, $17 \le z_3 \le 28$, $7.3 \le z_4 \le 8.3$, $7.3 \le z_5 \le 8.3$, $2.9 \le z_6 \le 3.9$, $5 \le z_7 \le 5.5$

Equation (32) constitutes the objective function for the traditional speed reducer design problem. This research substantiates the exceptional efficacy of OGWO in addressing real-world engineering challenges. It does so by juxtaposing the solutions of this design issue obtained using OGWO with those derived from PSO, FA, GSA, FOA, SCA and GWO.

Table 5 presents the experimental findings. A close examination of the data reveals that the OGWO scheme outperforms all others by achieving the minimum total weight. This outcome underscores OGWO's remarkable effectiveness in addressing real-world engineering challenges.

7. Conclusions

This study describes an enhanced grey wolf optimization algorithm, called OGWO, which employs random steps extracted from Lévy flights during alpha wolf mutations, thereby improving population mobility through the random walk property inherent in Lévy flights. Subsequently, an elite opposition-based learning approach was deployed across the population. This strategy in this paper in taken three inverse methods to maximize the search capability of the wolf pack, expand the diversity of the population, and further improve the convergence speed of the algorithm by discarding the poorer versions through a greedy selection strategy. The organic combination of these strategies can fully enhance the hunting ability of the

Table 7
Results for the speed reducer design problem

Algorithm	Optimal Variables							Optimum weight
	z_1	z_2	z_3	z_4	z_5	z_6	z_7	
OGWO	3.4885	0.6894	16.5980	7.4756	7.7900	3.4624	5.3360	2940.6751
GWO	3.5294	0.7005	17.0028	7.6368	7.9605	3.3701	5.2869	3022.3979
MFO	3.6000	0.7000	17.0000	7.3000	7.7153	3.3505	5.2867	3033.7016
SOA	3.5043	0.7000	17.3000	7.3000	8.1369	3.4296	5.2967	3032.3660
GSA	3.5958	0.7045	20.8220	8.2318	8.1771	3.8167	5.3790	4024.6013
WOA	3.5979	0.7000	18.0550	7.3926	8.0410	3.6178	5.2866	3306.8296
SCA	3.5932	0.7045	17.1748	7.4166	8.2325	3.6230	5.3396	3205.2214
DO	3.5150	0.7000	17.0063	7.5259	7.8968	3.3582	5.2884	3010.6227

grey wolf and the hierarchical structure of the wolf pack, so that the algorithm is more comfortable in dealing with practical problems.

The effectiveness of the proposed OGWO was evaluated by comparing it with various versions of GWO, traditional algorithms, and prevalent algorithms across 20 benchmark test functions. Additionally, the Wilcoxon rank-sum test was employed at a 95% confidence level, revealing OGWO's significant superiority. Moreover, the efficacy of OGWO-MLP was affirmed using three standard classification datasets. The findings consistently indicated that OGWO surpassed other models in MLP training.

This study proves that proposed improvements notably boost the algorithm's convergence speed, accuracy, and precision. These enhancements help OGWO evade local optima, confirming its reliability and effectiveness in diverse scenarios. When used in speed reducer design, OGWO showed significant superiority, indicating its potential for complex engineering issues and a promising future.

Future research intends to conduct an in-depth and comprehensive evaluation of OGWO's performance. Further exploration will also be dedicated to unlocking OGWO's potential in the machine learning domain. This will include conducting comparative experiments of OGWO-MLP against other algorithms such as random forest and support vector machines.

Data Availability

The dataset used to support the findings of this study have been deposited in the [UC Irvine Machine Learning] repository.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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Supplementary Materials

This research has no supplementary materials.

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