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Optimizing Northern Goshawk Algorithm with Fuzzy Logic and Whale Algorithm Strategies

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ABSTRACT

Scientists have initiated the examination of living behavioral patterns of organisms, with a primary focus on their quest for sustenance and evasion of predators to ensure their survival. This research endeavors to formulate mathematical models capable of emulating these behaviors, thereby empowering these models to address intricate and demanding mathematical quandaries. In this investigation, two distinct strategies were employed to enhance problem-solving capabilities. The first strategy entailed synergizing the North Goshawk Optimization Algorithm (NGOA) with fuzzy logic (FL). Fuzzy logic was leveraged to impart fuzziness to the initial population and allocate membership grades to all community elements within the confines of the fuzzy logic framework. The second strategy involved the integration of two hybridization approaches: the first through the community and the second via equations between the Fuzzy North Goshawk Optimization Algorithm (NGOA) and the Whale Optimization Algorithm (WOA). The proposed methodology was implemented across ten fundamental functions, revealing a marked superiority of the proposed algorithm when compared to the original version.

1. INTRODUCTION

The Meta-Heuristic Algorithm (MHA) relies on the characteristics and behaviours of organisms in their search for food and predation avoidance, including those of solitary and swarming animals [1]. Where scientists developed these behaviours into mathematical models, which are used to address complex mathematical problems and problems of improvement and search for optimal solutions [2].

In 2021, the North Goshawk Optimization Algorithm (NGOA) was introduced by Dehghani et al. [3]. This algorithm was designed based on the behavior of the North Goshawk in its search for food, where it seeks optimal solutions to various problems and efficiently addresses issues to find the most effective solutions [4]. The algorithm is characterized by its high accuracy in finding the best solutions and is considered modern in terms of community processing and obtaining optimal solutions [5].

Whale Optimization Algorithms (WOA) are heuristic algorithms used for optimization problems, inspired by the hunting behavior of whales, such as humpback whales [6]. WOA utilizes whale behaviors in searching for prey, encircling it, and attacking it [7]. These behaviors are explored and leveraged in the search space for optimization problems. WOA has been successful in solving optimization problems in engineering and data sciences efficiently [8]. The algorithm is known for its high-speed performance in finding the best solutions in a short amount of time [9]. Fuzzy logic (FL) fuzzy units, which are units with no specific constraints, are utilised in theories and techniques as a appropriate opportunity for the classical set, which not meets the needs of the brand new arithmetic and logical information in our cutting-edge medical ideas [10]. Lotfi Zadeh, an Azerbaijani researcher on the University of California, advanced this approach in 1965 with the goal of improving facts processing by means of using a more human-like manner of thinking in records programming [11]. When managing complex troubles, accuracy is not usually required, however it is probably crucial whilst working with essential structures. Figure 1 depicts fuzzy logic's behaviours.

Many methods have been used to reach the optimal solution. Essentially, Table 1 summarizes the key results from past studies, in improving and hybridizing the algorithms utilized by Shehab et al. [12].

In this manuscript, two methods for improving algorithms in terms of achieving high precision are presented. This approach is considered one of the latest methods in hybridization using tri-hybridization for artificial intelligence algorithms [13].

The first method involves using the Fuzzy Logic technique as an initial enhancement for the North Goshawk Optimization Algorithm (NGOA) to find the best solution. The triangular fuzzy function was used to determine the best radius of the search space to avoid deviating from the solution, in addition to reducing the time.

The second method is performed by hybridizing the Fuzzy North Goshawk Optimization Algorithm (NGOA). The hybridization process here is done in two ways, first method by creation of an initial community in the first algorithm and fuzzifying it, where the results of this community become inputs for the second algorithm. The 2nd hybridization is executed with the aid of replacing the velocity equations of the first algorithm after fuzzification with the velocity equations of the second set of rules, as the second one set of rules is faster in searching for the choicest answer. The main goal of the work lies in reaching the optimal solution by obtaining zero results in most functions, which represent the optimal solution, or results close to zero, which represent the locality of the solution. These results can be compared in tables in Section 5.

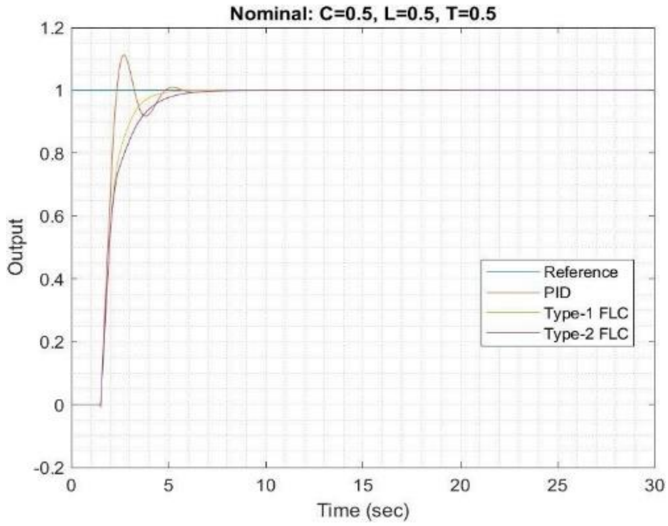

Figure 1. The fuzzy logic technique

Table 1. Literature survey

No.	Function	GOT [14]	GWO [15]	ENGO [16]	CLNGOA [17]	MGTO [18]
I.	Sphere	13e-176	3.66e-61	16.3498	1.6951-e303	0
II.	Schwefel 2.22	2.96e-85	1.36e-35	36.2778	1.16e150	0
III.	Schwefel 1.2	3.8e-167	3.09e-19	18.0688	9.03 e303	0
IV.	Schwefel 2.21	8.11e-88	1.28e-15	32.4697	3.46e297	0
V.	Step	4.82e-05	25.25594	13.9053	0	1.30-e10
VI.	Quartic	1.28e-07	2.06e-05	36.2515	1.01e62	1.99-e9
VII.	Rastrigin	5.83e-06	0.000149	15.7787	0	2.37-e6
VIII.	Ackley	-1909.05	–7464.67	31.2109	1.52 e01	−1.26-e4
IX.	Griewank	0.000616	0	1.1626	3.94e02	0
X.	Penalized	8.88e16	1.51e-14	1.0218	1.85e15	8.88e-16

2. THE NORTH GOSHAWK OPTIMIZATION ALGORITHM (NGOA)

Linnaeus first recognized the northern goshawk, a medium-sized bird, in 1758 [19]. This raptor is known to prey on an expansion of fowl species, each big and small, which include small birds of prey, the northern goshawk has an extensive geographic variety that extends throughout Eurasia and North America. Interestingly, the adult males are an awful lot larger than the ladies [20].

The male northern goshawk is usually 46 to 61 cm long, has a wingspan of 89 to 105 cm, and weighs about 780 grams [20]. On the contrary, the female usually has a length between 58 and 69 cm, a weight of 1220 grams, and a wingspan of 108 to 127 cm. Figure 2 provides a visual representation of a northern goshawk, the bird's hunting strategy consists of two steps:

First, it lunges at its prey as soon as it sees it. Second, it follows a swift pursuit to catch the prey.

In the pursuit and capture of its prey, the northern goshawk implements a crafty method [21]. The inspiration behind the program's development was primarily the mathematical representation of the described tactic. This strategy reproduces two core actions performed by the northern goshawk. First, identifying prey and initiating attack, and second, a sequential chase and evasion process.

Figure 2. The northern goshawk

The hunting behaviors and tactics of the northern goshawk are observable in a natural setting. In the initial stages of random hunting, the northern goshawk (NGOA) chooses a target randomly and strikes swiftly. This stage, thanks to the random prey selection in the search area, enhances exploration capabilities [22].

This process facilitates an in-depth exploration of the search field to identify the optimal spot, inclusive of selecting and attacking the prey.

$$P_n = X_i, n = 1,2, \dots, K, i = 1,2, \dots, n-1, n+1, \dots, K \tag{1}$$

$$x_{n,k}^{new,p1} = \begin{cases} x_{n,k} + r\left(p_{n,k-Ix_{n,k}}\right), F_{p_n} < F_n \\ x_{n,k} + r\left(x_{n,k-p_{n,k}}\right), F_{p_n} \geq F_n \end{cases} \tag{2}$$

$$x_n = \begin{cases} x_n^{new,p1}, F_n^{new,p1} < F_n, \\ x_n, F_n^{new,p1} \geq F_n, \end{cases} \tag{3}$$

wherein, P_n is wherein the ith northern goshawk hunts for prey, F_{p_n} is the fee of its objective function, it's far a chance natural quantity that falls among [1, K]. $x_n^{new,p1}$ is the updated scenario for the most updated idea. $x_{n,k}^{new,p1}$) is its jth dimension, $F_n^{new,p1}$ is the goal feature price primarily based on the primary segment of the NGO, and r is a random integer within the variety [0, 1], wherein I is a random number, which can be either 1 or 2 [3].

The velocity of northern goshawk i is updated using the following relationship:

$$V_i = \delta V_i + \mu(x_{n,k}^{new,p1} - x_n), \tag{4}$$

where, V_i is velocity of northern goshawk I, δ and μ represent update coefficients, and $x_{n,k}^{new,p1}$ is the best solution found so far.

$$x_{n,k}^{new,p2} = x_{n,k} + R(2r-1)x_{n,k} \tag{5}$$

$$R = 0.02\left(1 - \frac{t}{T}\right) \tag{6}$$

$$x_n = \begin{cases} \{x_n^{new,p2}, F_n^{new,p2} < F_n \\ x_n, F_n^{new,p2} \geq F_n \end{cases} \tag{7}$$

In which, t is the iteration counter, T is the maximum number of iterations, $x_n^{new,p2}$ is the brand-new repute for ith proposed answer. $x_{n,k}^{new,p2}$) is its jth size, $F_n^{new,p2}$ is its objective feature value based on 2nd phase of NGO.

3. WHALE OPTIMIZATION ALGORITHM (WOA)

The Whale Optimization Algorithm (WOA), which is inspired by the hunting strategies of whales [23]. The algorithm generates a population of potential solutions and updates them based on the behaviors of whales during their hunts [24]. The algorithm goes through three phases: searching, surrounding, and attacking. In the search phase, the solutions are moved randomly to explore the search space. In the surrounding phase, the optimal solution is chosen, and other solutions move towards it, which reduces the search space. In the attack phase, the optimal solution updates other solutions [25]. WOA has been successfully used in various fields to solve optimization problems.

3.1 Mathematical model and optimization algorithm

The behavior of whales that can be seen in Figure 3 served as the inspiration for WOA. Within the framework of the WOA model, the current optimal solution is represented by the target prey, and other whales aim to adjust their location to reach the best possible outcome based on Eq. (8).

$$F = |SX^*(t) - X(t)| \tag{8}$$

$$X(t+1) = X^*(t) - AF. \tag{9}$$

Figure 3. The whale

In the given equation, the variable t represents the present iteration, while S and A refer to vectors of coefficients [8]. The position vector of the optimal solution is denoted as X^*, and the position vector being evaluated is X. The values of A and S are determined through the following equations:

$$A = 2av - a \tag{10}$$

$$S = 2v. \tag{11}$$

The variable a is gradually reduced in a linear manner from a value of two to zero throughout the iterations [26]. The value v is within the range of 0 to 1 ($v \in [0, 1]$). The process of exploitation is mathematically emulated in the following manner:

(1) Obtaining shrinking encircling: lowering a value in accordance with Eq. (11). Mention that the value of an in $[-a, a]$ is random.

(2) Spiral updating: determines the separation between the whale and its prey [27]. The spiral that simulates the spiral movement is calculated using Eq. (12) as follows:

$$X(t+1) = F^k e^{bk} cos\,(2\pi k) + X^*(t). \tag{12}$$

The value of b is constant, while k is a randomly generated number within the range of negative 1 and positive 1([−1, 1]). In order to select between the spiral model and the shrinking encircling mechanism model, a 50% chance is assumed using the following method:

$$X(t+1) = \begin{cases} X^*(t) - AF \; if \; p < 0.5 \\ F^k e^{bk} cos\,(2\pi k) + X^*(t) \text{ if } p \geq 0.5, \end{cases} \tag{13}$$

where, p is a uniformly distributed random number. On the other hand, $1 \prec A \prec -1$ is employed during the exploration phase to compel the agent to leave this area. Eq. (14) and Eq. (15) mathematically depict the exploration phase as follows:

$$F = |S.X_{rand} - X| \tag{14}$$

$$X(t+1) = X_{rand} - A.F \tag{15}$$

4. FUZZY LOGIC

Concepts and methods primarily based on fuzzy sets, which are sets without clear obstacles, are taken into consideration as a capacity alternative for classical units that now not healthy the criteria of up to date mathematical and logical viewpoints in contemporary medical research [10]. Lotfi Zadeh initially proposed this belief in 1965, when he integrated an extra human-centric style to questioning into records programming, growing its efficacy in records processing. While precision is vital while coping with primary structures, it is frequently redundant and pointless whilst handling complex troubles [28].

4.1 Fuzzy set

A fuzzy set (FS) is a concept in mathematics and computer science that deals with a kind of set where the boundaries are not clearly defined, differing from traditional sets where elements either belong or don't belong to the set (binary or crisp sets) [29]. In a fuzzy set, elements have degrees of membership, meaning that they can partly belong to a set. This is particularly useful in modelling and dealing with real-world situations where boundaries are often ambiguous and not sharply delineated.

For example, the concept of "tallness" can be considered a fuzzy set because there's no precise height where someone becomes definitively "tall". It has the following form in definition:

$$A = \{x\,, \mu_A(x)\} \tag{16}$$

for each element x in X, where $\mu_A(x)$ is the membership function of the element x in A and that: $\mu_A(x) \in [0, 1]$.

4.2 Membership function

A membership function (MF) is a key concept in the theory of fuzzy sets and fuzzy logic. It's a mathematical function that defines the degree to which elements belong to a fuzzy set. In other words, the membership function quantifies the uncertainty or fuzziness associated with whether an element belongs to a set or not [30].

Unlike in classical set theory, where an element either fully belongs to a set or does not belong at all (binary logic), a membership function allows for degrees of membership [31]. These degrees are usually represented as values between 0 and 1, where 0 signifies no membership and 1 signifies full membership. Intermediate values represent partial membership.

For example, in a fuzzy set representing the concept of "tall people," a membership function might assign a membership value of 1 to someone who is 6 feet tall (fully belongs to the set of tall people), a value of 0.5 to someone who is 5 feet 5 inches tall (partially belongs to the set of tall people), and a value of 0 to someone who is 4 feet tall (does not belong to the set of tall people). this ability to handle degrees of truth makes membership functions very useful in a wide range of applications, including control systems, decision-making, and artificial intelligence, which is that there is no total affiliation to groups or elements, or vice versa. The set, and the basic condition for this function is that its range is between zero and one, and it has multiple forms of it:

4.2.1 Triangular function

The mathematical formula of this function can be given as:

$$\mu(x) = \begin{cases} 0; \; x \leq a, \\ \dfrac{x-a}{b-a}; \; a \leq x \leq b, \\ \dfrac{c-x}{c-b}; \; b \leq x \leq c, \\ 0; \; c \leq x. \end{cases} \tag{17}$$

The parameters of the function are *a*, *b*, and *c*. *A* and *c* stand for the lists of the trigonometric characteristic, while *b* stands for the vertices of the triangle.

4.2.2 Trapezoidal function

The mathematical formula of this function can be given as:

$$\mu(x) = \begin{cases} 0; \; x \leq a, \\ \dfrac{x-a}{b-a}; \; a \leq x \leq b, \\ 1; \; b \leq x \leq c, \\ \dfrac{d-x}{d-c}; \; c \leq x \leq d, \\ 0; \; d \leq x. \end{cases} \tag{18}$$

where, $a, b, c,$ and d are the function's parameters, and a and d stand for the figure's lower and higher vertices, respectively [32, 33]. More details about this function and its associated applications can be found from the studies of Alalhareth et al. [34] and Nadimi-Shahraki et al. [35].

4.2.3 Gaussian function

The mathematical formula of this function can be given as:

$$\mu(x) = e^{-\frac{(x-c)^2}{2\sigma^2}}. \tag{19}$$

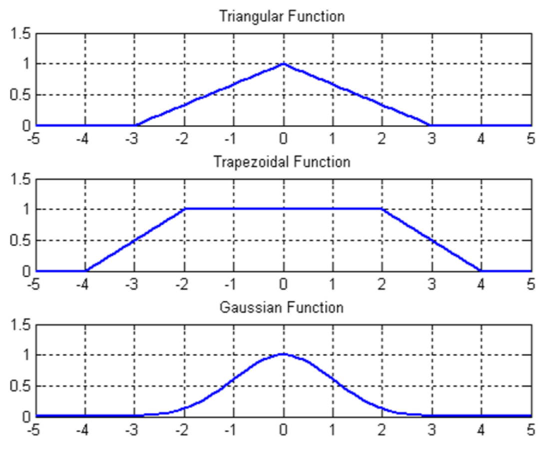

Figure 4. The form of each type of membership functions

The parameters c and σ respectively represent the upper vertex of the figure and the distance of the edges from the center. Figure 4 includes the form of each type of the membership functions.

5. THE PROPOSED MODEL

The crystallization of the idea behind improving algorithm performance and achieving optimal solutions is crucial, as each algorithm in this research paper often does not lead us to the optimal solution on its own. The basic idea of this manuscript the primary concept of this manuscript is divided into main levels. The first stage includes improving the North Goshawk Optimization Algorithm (NGOA). The algorithm starts with an initial random community consisting of 30 birds, and the number of iterations is set to 1000. By using fuzzy logic, constraints were imposed on the initial community, and membership grades were assigned to all elements of the initial community within the boundaries of the fuzzy logic, which range from $(0, 1)$, using the triangular membership function with a parameter related to the NGOA algorithm. This enhancement had a clear impact, as we used ten basic functions, each of which is explained with its mathematical formula and range in Table 2.

Table 3 demonstrates the use of the North Goshawk Optimization Algorithm (NGOA) and its enhancement using fuzzy triangular and trapezoidal functions, we observed that the enhanced F-NGOA model achieved better results than NGOA alone. The second stage focuses on hybridizing the mentioned algorithms in two ways:

First Method: In this method, a hybrid population is formed. The best individuals are selected from the fuzzy-enhanced F-NGOA algorithm, which starts with initial random populations. After applying the F-NGOA algorithm, the best individuals obtained after 1000 iterations are taken from the fuzzy-enhanced F-NGOA and considered as the initial population for the second algorithm, WOA. This way, a blend of the two algorithms is obtained, called "F-NGOA-WOAO1." The ten basic functions are executed using this hybrid approach. The results obtained from this strategy are shown in Table 4, which clearly demonstrates the superiority of the hybrid method over the conventional ones.

Table 2. The fundamental functions of the algorithms

No.	Name	Function	D	Range
I.	Sphere	$f_1(x) = \sum_{i=1}^{n} x_i^2$	30	[-100, 100]
II.	Schwefel 2.22	$f_2(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	30	[-10, 10]
III.	Schwefel 1.2	$f_3(x) = \sum_{i=1}^{n} (\sum_{j=1}^{n} x_j)^2$	30	[-100, 100]
IV.	Schwefel 2.21	$f_4(x) = -\sum_{i=1}^{n} (x_i \, sin \, sin \left(\sqrt{\lvert x_i \rvert}\right))$	30	[-500, 500]
V.	Step	$f_5(x) = \sum_{i=1}^{n} (\lfloor x_i + 0.5 \rfloor)^2$	30	[-100, 100]
VI.	Quartic	$f_6(x) = \sum_{i=1}^{n} i x_i^4 + random[0,1)$	30	[-1.28, 1.28]
VII.	Rastrigin	$f_7(x) = -\sum_{i=1}^{n} [x_i^2 - 10 \, cos \, cos \, (2\pi x_i) + 10]$	30	[-5.12, 5.12]
VIII.	Ackley	$f_8(x) = -20exp \, (-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2})$	30	[-32, 32]
IX.	Griewank	$f_9(x) = \frac{1}{4000}\sum_{i=1}^{n} (x_i - 100)^2 - \prod_{i=1}^{n} cos \, cos \, \left(\frac{x_i - 100}{\sqrt{i}}\right) + 1$	30	[-600, 600]
X.	Penalized	$f_{10}(x) = \frac{\pi}{2}\{10sin^2(\pi y_1) + \sum_{i=1}^{n-1} (y_i - 1)^2 \times [1 + 10sin^2(\pi y_i + 1)] + (y_n - 1)^2\} + \sum_{i=1}^{30} u(x_i, 10,100,4)$	30	[-50, 50]

Table 3. Comparison of F-NGOA and NGOA

No.	Function	NGOA	F-NGOA
I.	Sphere	7.4792e-182	9.3239e-210
II.	Schwefel 2.22	4.5824e-94	3.7343e-109
III.	Schwefel 1.2	1.182e-229	1.182e-229
IV.	Schwefel 2.21	7.3984e-78	2.7729e-109
V.	Step	2.2975e-08	4.9876
VI.	Quartic	8.3188e-03	4.7828e-05
VII	Rastrigin	0.0895	0
VIII.	Ackley	4.4409e-15	8.8818e-16
IX.	Griewank	-6.3711	0
X.	Penalized	0.096105	2.6657e-07

Table 4. Comparisons of all studied algorithms

No.	Function	NGOA	F-NGOA	F-NGOA-WOAO1	F-NGOA-WOAO2
I.	Sphere	7.4792e-182	9.3239e-210	0	0
II.	Schwefel 2.22	4.5824e-94	3.7343e-109	4.1245e-271	0
III.	Schwefel 1.2	1.182e-229	1.182e-229	0	0
IV.	Schwefel 2.21	7.3984e-78	2.7729e-109	2.8366e-272	0
V.	Step	2.2975e-08	4.9876	7.045e-63	0
VI.	Quartic	8.3188e-03	4.7828e-05	1.0733e-55	0
VII	Rastrigin	0.0895	0	0	0
VIII.	Ackley	4.4409e-15	8.8818e-16	8.8818e-16	0
IX.	Griewank	-6.3711	0	0	0
X.	Penalized	0.096105	2.6657e-07	3.8405e-49	0

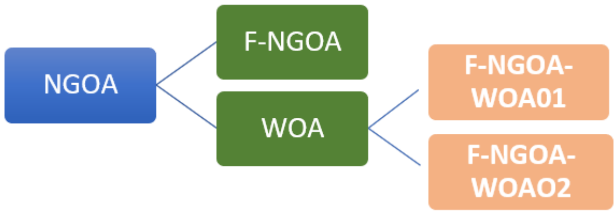

Figure 5. Flowchart for showing the work stages

Second Method: This method involves hybridizing the equations. The velocity equation of the NGOA algorithm Eq. (4) is enhanced by replacing it with the velocity equation of the WOA algorithm Eq. (12), known for its high speed. This results in a second hybrid model called "F-NGOA-WOAO2," which is characterized by both accuracy and speed in execution. The basic algorithms rely on finding the optimal solution for all functions, leading to a new type of hybridization that guides us toward optimal solutions for the entire set of functions. The workflow stages are presented in Figure 5.

These two methods represent innovative approaches to hybridization, combining the strengths of both algorithms to achieve optimal solutions across a range of functions.

6. CONCLUSION AND FUTURE WORK

In this study, we introduced the F-NGO algorithm to enhance the performance of the original Goshawk Optimization Algorithm. The original algorithm, inspired by the behavior of the North Goshawk, initially found solutions for basic functions, often resulting in local solutions. By incorporating fuzzy logic, we improved the algorithm's performance, enabling it to find optimal solutions for a wide range of functions.

To achieve optimal solutions, we developed a novel hybridization strategy that combined the Goshawk algorithm with fuzzy logic and the Whale algorithm. This hybridization occurred through two distinct approaches:

First, Community-based Hybridization (F-NGOA-WOAO1): In this approach, we utilized the best solutions from the fuzzy-enhanced F-NGOA algorithm to form the initial population for the Whale Optimization Algorithm (WOA). This method consistently produced optimal solutions for all tested functions.

Second, Equation-based Hybridization (F-NGOA-WOAO2): We enhanced the velocity equation of the F-NGOA algorithm by replacing it with the velocity equation of the WOA algorithm, known for its speed and efficiency. This fusion resulted in a hybrid model that quickly and accurately achieved optimal solutions.

Comparing the results obtained from F-NGOA-WOAO1, F-NGOA-WOAO2, and the original F-NGOA algorithm, as demonstrated in Table 4, our experimental findings indicate that the proposed algorithm, F-NGOA-WOAO2, consistently outperforms the other approaches in terms of both the speed and the accuracy. This makes it a promising solution for various optimization problems.

We suggest that further research explores innovative approaches to finding optimal solutions in hybridization processes. This could involve combining multiple swarm algorithms or incorporating numerical analysis and feature selection techniques to identify the best values and achieve minimal results. Additionally, considering the success of algorithms inspired by other sciences, such as the planetary motion algorithm in physics and hybridization processes could open up new avenues for improving optimization results.

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