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REVIEW ARTICLE

Advances in Manta Ray Foraging Optimization: A Comprehensive Survey

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Abstract

This paper comprehensively analyzes the Manta Ray Foraging Optimization (MRFO) algorithm and its integration into diverse academic fields. Introduced in 2020, the MRFO stands as a novel metaheuristic algorithm, drawing inspiration from manta rays' unique foraging behaviors—specifically cyclone, chain, and somersault foraging. These biologically inspired strategies allow for effective solutions to intricate physical challenges. With its potent exploitation and exploration capabilities, MRFO has emerged as a promising solution for complex optimization problems. Its utility and benefits have found traction in numerous academic sectors. Since its inception in 2020, a plethora of MRFO-based research has been featured in esteemed international journals such as IEEE, Wiley, Elsevier, Springer, MDPI, Hindawi, and Taylor & Francis, as well as at international conference proceedings. This paper consolidates the available literature on MRFO applications, covering various adaptations like hybridized, improved, and other MRFO variants, alongside optimization challenges. Research trends indicate that 12%, 31%, 8%, and 49% of MRFO studies are distributed across these four categories respectively.

Keywords Manta ray foraging optimization · Metaheuristic algorithms · Hybridization · Improved · Optimization

1 Introduction

The process of finding the optimum value for a fitness function while subjecting it to several restrictions is known as optimization [1]. The growing complexity and variety of engineering applications demand the evolution of optimization problems that can handle large-scale variable dimensions and intricate functional objectives. Traditional algorithms, including Newton's method, the steepest descent approach, and integer programming, often falter and become trapped in local optima for such multifaceted optimization issues. This is primarily because these canonical algorithms lack random operators in their formulation. Moreover, they impose rigorous conditions on the continuity and differentiability of the fitness function. Consequently, there is a consensus that these traditional methods fall short of promoting modern global optimization techniques. This has led to the infusion of stochastic methods into the optimization process, paving the way for the emergence of metaheuristic algorithms that aptly tackle today's optimization challenges.

Metaheuristics can be characterized as high-level algorithmic strategies inspired by nature. Essentially, these algorithms, rooted in natural phenomena, often incorporate an element of randomness. This intelligent randomness facilitates the generation or evolution of solutions, drawing them closer to the optimal outcome using tactics inspired by nature. Thus, compared to traditional optimization methods, nature-inspired metaheuristics are better equipped to evade situations of suboptimal outcomes [2]. Hence, such metaheuristics do not heavily rely on extensive problem-specific details. Instead, they employ diverse heuristic models to define the spectrum of potential solutions. Metaheuristic algorithms that take their natural cues are excellent replacements for canonical algorithms since they do not rely on gradient information and have a simple central principle [3, 4].

The optimization process of population-based metaheuristics begins with a population of potential solutions that serve

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as a jumping-off point for the algorithm's search mechanism. The technique may yield many solutions in a single iteration. It can avoid local minima in the search space by utilizing a portion of the randomized process to update the starting population [5]. Complex numerical functions and real-world optimization issues are typical applications for many population-based metaheuristic algorithms. Genetic algorithm (GA) [6] and differential evolution (DE) [7] are all examples of well-known population-based methods. In GA, natural selection and reproduction are modeled after the processes described by Darwinian phenomena and simulated using GA. The population is represented by a set of chromosomes, and new candidate solutions are generated by determining which genetic operators should be used. The optimization method for DE uses operators that are analogous to those used by GA. These operators include mutation, crossover, and selection. The mutation and crossover operators locate new areas inside the search space. The selection operator is utilized to preserve the superior individual. The social dynamic of the swarm serves as an inspiration for PSO (fish, birds, bees, etc.). The potential solutions are particles and each particle is given an update that causes it to move toward a new location. The fitness function is then used to determine the new search paths that each particle will take.

Metaheuristic algorithms may solve complicated, nonlinear, and high-level optimization problems in a fair amount of time and resources, unlike deterministic and statistical techniques [8]. Many problems in the real world are amenable to being recast as combinatorial, multi-objective, or single-objective optimization issues. Because of these intricate qualities, conventional mathematical methods such as gradient descent and conjugate gradient are incapable of providing an effective solution to these situations [9]. However, algorithms that take their cues from nature have been shown to have superior performance, particularly when it comes to solving non-continuous, large-scale, and non-differentiable real-world optimization problems [10].

A strategy likely to produce an exceptional possible service but may not necessarily deliver the optimal service for a particular specific situation is an example of a metaheuristic approach [11]. There is no assurance that the answer that is found will be of an exceptionally high standard. Despite this, a well-designed metaheuristic technique may frequently yield a near-optimal answer. The method should also be efficient enough to handle major concerns. Metaheuristics are usually thought of as iterative algorithms that seek a better alternative than the best option identified in previous iterations.

The design of many different systems makes heavy use of these methodologies. In addition, the effectiveness of metaheuristic algorithms is shown by the fact that they can solve various issues in various domains [12]. At the same time, one of the most important recent breakthroughs in optimization is the increasing emphasis placed on the interdisciplinary nature of the subject matter. Several novel swarm intelligence algorithms have been proposed in recent years, such as the Artificial Gorilla Troops Optimizer (AGTO) [13], Starling Murmuration Optimizer (SMO) [14], African Vultures Optimization Algorithm (AVOA) [15], Farmland Fertility Algorithm (FFA) [16], etc. The MRFO was created by Zhao et al. [17]. After witnessing the intelligent foraging behavior of manta rays, a metaheuristic approach to optimization was conceived and developed as a result of these observations. Manta rays have three distinct foraging motions that they use when they are searching for food. These maneuvers are known as the chain, the cyclone, and the somersault. The MRFO algorithm functions similarly to these foraging behaviors to develop a globally optimum solution. In recent years, the research community has shown increased interest in the MRFO as a result of its straightforward construction; as a result, a significant number of papers have been presented to enhance the MRFO's operational capabilities. In Sect. 3, we comprehensively analyze the most recent developments concerning MRFO. It has come to our attention that MRFO does not maintain a healthy equilibrium between the phases of exploration and exploitation in its operations. Therefore, additional work is required to achieve the proper equilibrium in the system.

This review paper's principal purpose is to thoroughly examine all features of the MRFO and how it is luring scholars all over the globe to employ this algorithm in various challenges in multidisciplinary areas. The following is a list of the most important contributions that this paper makes:

- A comprehensive review of MRFO has been done. A thorough and rigorous examination of MRFO and its variations is offered. The limits of current MRFO variations are recognized, and some intelligent proposals for overcoming these shortcomings are presented.
- All modifications to the main MRFO have been highlighted.
- The current review considers two variants of MRFO for review, including Binary and Multi-objective.
- All applications and fields that employed MRFO have been summarized and presented.
- The benefits and drawbacks of MRFO have been examined.
- Several difficulties and concepts have been proposed as potential future work.

The following is the structure of this paper: Sect. 2 describes the motivation for MRFO as well as its mathematical model. In Sect. 3, we will discuss all of the MRFO versions and changes. MRFO methods will be classified into the following four categories: hybridization, improvement, variations of MRFO, and optimization concerns. In Sect. 4, we will talk about MRFO, including its capabilities, benefits, and drawbacks. In the fifth and last section, we shall summarize the upcoming works.

2 MRFO

2.1 Inspiration

Even though they seem terrifying, manta rays are rather beautiful and fascinating animals. They are one of the most significant marine organisms that are currently known. Manta rays have a body that is flat from top to bottom, and they have a pair of pectoral fins that they utilize to propel themselves through the water with the same elegance as birds have when they are flying. In addition to this, each of their large terminal mouths is preceded by a pair of cephalic lobes that project forward in front of the mouth. Figure 1A portrays a manta ray in the process of feeding. and Fig. 1B illustrates the anatomy of a manta ray. They can direct water and prey into their mouths while hunting by using the horn-shaped cephalic lobes on their heads. The modified gill rakers are then used to remove the captured prey from the water. Two different kinds of manta rays may be distinguished from one another. One of them is the reef manta ray, or manta alfredi, which lives in the Indian Ocean as well as the western and southern Pacific and may grow up to 5.5 m wide. The second type is the manta birostris, also known as the giant manta ray. These rays can get as wide as seven meters and live in tropical, subtropical, and mild temperate waters. They have probably been around for at least 5 million years. The average lifespan is 20 years, it does not make it to that age because fishermen are after them [17]. Manta rays feed on plankton daily. Adult manta rays ingest 5 kg of plankton daily. Plankton is most abundant in seas. Plankton is not always concentrated in one place. Tides and seasons create these places. Manta rays are great at finding plankton. Manta rays' food hunting is intriguing. These creatures have evolved numerous impressive foraging methods.

The first method of wild food gathering is called chain foraging. When there are more than 50 manta rays foraging together, they create an organized line by lining up one after the other in a sequential sequence. Smaller male manta rays can ride on top of the backs of more extensive female manta rays and swim in time to the rhythm of the female's beating pectoral fins when they do so. As a direct result of this, manta rays that come after them will be able to consume any plankton that was missed by manta rays that came before them. They receive more food by working together to increase plankton in their gills.

The second method of scavenging that may be carried out is referred to as the cyclone foraging strategy. When there is an unusually high concentration of plankton in the water, a large number of manta rays will congregate together. The water that has been filtered is brought to the surface when their tails come together with their heads to form a swirling vertex in the eye of the cyclone. The plankton is pulled into their open mouths and consumed by them.

Somersault foraging is the last kind of foraging that may be done. It is undoubtedly one of the most beautiful sights that nature has to offer. Manta rays circle plankton and do somersaults backward to attract it. The manta ray's ability to do a movement known as a somersault, unpredictable, frequent, local, and cyclical, allows them to maximize the amount of food they consume. Even though foraging activities like this are uncommon in the wild, their utility cannot be overstated. These foraging habits have been mathematically described, and a novel metaheuristic method called MRFO has been developed to carry out global optimization.

2.2 Mathematical Model

Foraging techniques such as chain foraging, cyclone foraging, and somersault foraging served as inspiration for MRFO. The mathematical models are outlined in the following paragraphs.

Chain foraging: manta rays can use MRFO to pinpoint the exact location of plankton and maneuver their way there. If there is a high concentration of plankton at

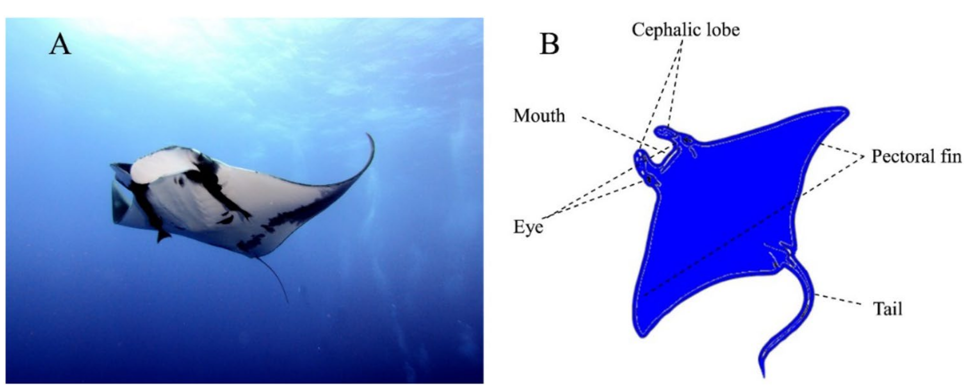


Fig. 1 **A** A foraging manta ray, and **B** structure of a manta ray [17]

a specific location, that location is in a superior position. MRFO hypothesizes that the plankton with the great attention that manta rays desire to approach and consume is the best answer identified so far, even though the optimal solution is unknown. The manta rays will construct a chain of forage by aligning themselves head to tail. Everyone else, except the person who was first, advances towards not just the meal that is currently being served, but also the one that is currently in front of it. That is to say, throughout each iteration, each individual is provided with an up-to-date version of the optimal solution that has been found up to this point as well as the solution that is currently in front of it. the mathematical model of chain foraging is characterized by Eq. (1), and the components of this model are Eqs. (1) and (2) [17].

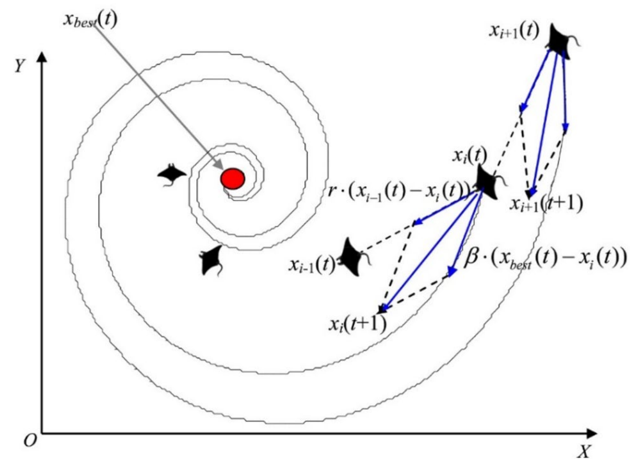


Fig. 3 Cyclone foraging behavior in problem space [17]

$$x_i^d(t+1) = \begin{cases} x_i^d(t) + r \times \left(x_{\mathrm{best}}^d(t) - x_i^d(t)\right) + \alpha \times \left(x_{\mathrm{best}}^d(t) - x_i^d(t)\right) & i = 1 \\ x_i^d(t) + r \times \left(x_{i-1}^d(t) - x_i^d(t)\right) + \alpha \times \left(x_{\mathrm{best}}^d(t) - x_i^d(t)\right) & i = 2, \dots, N \end{cases}, \tag{1}$$

$$\alpha = 2 \times r \times \sqrt{|\log(r)|}, \tag{2}$$

$x_i^d(t)$ is the location of the ith individual at a time t in the dth dimension. r is a random vector with values between 0 and 1. α is a weight coefficient, and $x_{\mathrm{best}}^d(t)$ is the plankton with the highest concentration. Figure 2 shows this foraging behavior in a two-dimensional setting in 2-D. The location $x_{i-1}(t)$ of the $(i-1)$th the current solution is used in in front of it. In other words, manta rays produce a spiral pattern by swarming in lines while they hunt for food. The behavior of a cyclone as it tracks in the problem region is seen in Fig. 3. An individual not only walks in the same direction as the one in front of it but also moves in a spiral pattern as it approaches the food source. The mathematical equation that may be developed to depict the spiral-shaped movement of manta rays across only two-dimensional space can be found by referring to Eq. (3).

$$\begin{cases} X_i(t+1) = X_{\mathrm{best}} + r \times \left(X_{i-1}(t) - X_i(t)\right) + e^{b\omega} \times \cos(2\pi\omega) \times (X_{\mathrm{best}} - X_i(t)) \\ Y_i(t+1) = Y_{\mathrm{best}} + r \times \left(Y_{i-1}(t) - Y_i(t)\right) + e^{b\omega} \times \sin(2\pi\omega) \times (Y_{\mathrm{best}} - Y_i(t)) \end{cases}. \tag{3}$$

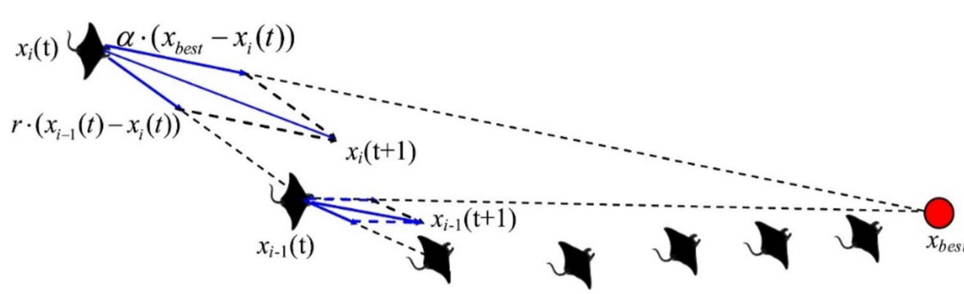
conjunction with the position x_{best} of the food to calculate the position update for the ith individual.

Cyclone foraging: manta rays will form a long chain of foragers and spiral toward a plankton concentration in deep water. In the cyclone foraging method used by manta ray swarms, in addition to moving in a spiral motion toward the food, each manta ray swims in the direction of the one

In Eq. (3), ω is a number chosen at random from the range [0, 1]. This kind of motion pattern may be generalized to n-dimensional space.

Equation (4) describes this cyclone foraging model only.

Fig. 2 Chain foraging behavior in a 2-D space [17]



$$x_i^d(t+1) = \begin{cases} x_{\text{best}}^d(t) + r \times \left(x_{\text{best}}^d(t) - x_i^d(t)\right) + \beta \times \left(x_{\text{best}}^d(t) - x_i^d(t)\right) & i = 1 \\ x_{\text{best}}^d(t) + r \times \left(x_{i-1}^d(t) - x_i^d(t)\right) + \beta \times \left(x_{\text{best}}^d(t) - x_i^d(t)\right) & i = 2, \ldots, N \end{cases}, \tag{4}$$

$$\beta = 2e^{r_1 \frac{T-t+1}{T}} \times \sin\left(2\pi r_1\right). \tag{5}$$

In Eq. (5), β is the weight factor, T is the maximum number of iterations, and r_1 is the rand number in the range of 0 to 1. All of the agents search haphazardly, using the location of the food as their point of reference. The cyclone foraging method, the most effective yet, exploits the region heavily. This tendency also boosts exploration. Assigning each person's reference position to a random place in the search region forces them to find a position considerably different from the best one. This mechanism places an emphasis on exploration and gives MRFO the ability to search the entire world; the mathematical equation that describes it is Eq. (7).

$$x_{\text{rand}}^d = Lb^d + r \times \left(Ub^d - Lb^d\right), \tag{6}$$

$$x_i^d(t+1) = \begin{cases} x_{\text{rand}}^d(t) + r \times \left(x_{\text{rand}}^d(t) - x_i^d(t)\right) + \beta \times \left(x_{\text{rand}}^d(t) - x_i^d(t)\right) & i = 1 \\ x_{\text{rand}}^d(t) + r \times \left(x_{i-1}^d(t) - x_i^d(t)\right) + \beta \times \left(x_{\text{rand}}^d(t) - x_i^d(t)\right) & i = 2, \ldots, N \end{cases}, \tag{7}$$

x_{rand}^d is a point generated at random inside the search space, Lb^d and Ub^d are the lower and upper bounds of the dth dimension, respectively, and dth is the dimension being measured.

Somersault foraging: the meal's location is considered the most critical factor in this behavior pattern. Every solution swims in a circle around the pivot before somersaulting into a new position. As a result, they ensure that their locations are continually updated to revolve around the best position identified thus far. One may construct the mathematical model using Eq. (8) as a guide.

$$x_i^d(t+1) = x_i^d(t) + S \times \left(r_2 \times x_{\text{best}}^d - r_3 \times x_i^d(t)\right); i = 1.2. \ldots .N. \tag{8}$$

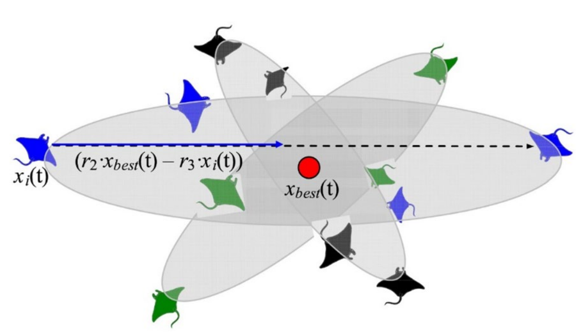


Fig. 4 MRFOs' somersault foraging techniques [17]

In Eq. (8), S is the somersault factor that determines how far manta rays can flip. r_2, and r_3 are two random numbers in the range [0, 1], and $S = 2$ is the somersault factor. Once the somersault range is known, each person is free to move to any point in a new search domain between where they are now and where they would be if they were in the best position so far, as shown by Eq. (8). This can be accomplished by moving to any location in the new search domain. The magnitude of the disturbance imposed on the present location is decreasing with the shrinking distance between the individual location and the best location discovered to date. Every solution gets closer to the best possible answer as they explore the search area. Consequently, the somersault foraging range becomes more constrained as the number of iterations increases. The preliminary sketch of somersault foraging behavior in MRFO is shown in Fig. 4.

According to Eq. (8), Fig. 5 demonstrates that three different solutions developed one hundred times in the search space. The sampled points have a random distribution between their present locations and their symmetrical positions around x_{best}, and as the distance decreases, the sampled points become sparser. Both the dense and the sparse spots in the vicinity of x_{best} have the potential to contribute to the exploitation or exploration of the area significantly.

MRFO begins its process by producing a random population inside the domain of the issue, just as other metaheuristic optimizers do. At the start of each process iteration, each

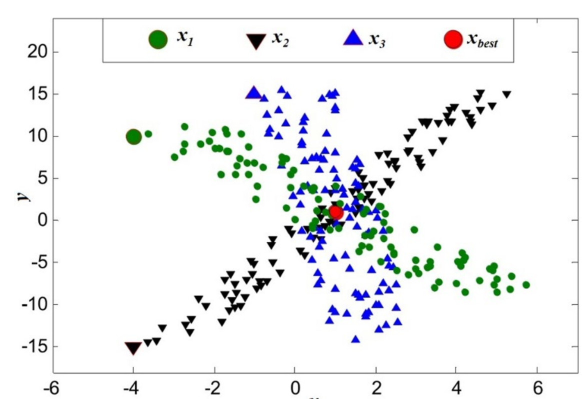


Fig. 5 Three animals foraging somersault-style in a two-dimensional environment

Input:

Initialize the maximum number of generations $tmax$, the size of the population N, and the upper and lower bounds x_{max} and x_{min}.

Output:

The best solution x_{best}.

Initialize the parameters and population→ α, β, S.
Perform a calculation to determine each initialized agent's fitness level, then sort the agents according to their fitness values.
While t < $Tmax$ **do**
IF rand < 0.5 **Then** // **Cyclone Foraging**
IF t/$Tmax$<rand, **Then**
Upgrade x_i according to Eq. (7).
Else
Upgrade x_i according to Eq. (4).
End IF
Else // **Chain Foraging**
Upgrade x_i according to Eq. (1).
End IF
Compute and update the fitness values according to each location.
For i=1: N **do** // **Somersault Foraging**
Upgrade x_i according to Eq. (8).
IF $f[x_i(t+1)] < f(x_{best})$ **Then**
Replace x_{best} with $x_i(t+1)$
End IF
End For
Compute and upgrade the fitness values according to each location.
Sort the new population according to fitness.
t=t+1
End While
Return x_{best}

Fig. 6 Pseudocode of the MRFO algorithm [17]

solution changes its position relative to the one in front of it and the reference position. The value of t/T must be reduced from $1/T$ to 1 before proceeding to do both exploratory and exploitative searches. When t/T is less than or equal to rand, the current best solution is selected as the reference position for the exploitation. If it is greater than or equal to rand, a random position in the search space is chosen at random to be the exploration's starting point.

To locate food, MRFO can switch between chain foraging and cyclone foraging depending on the random number. Afterward, individuals will revise their placements about the optimal position discovered so far via somersault foraging. Every single computation and update is carried out interactively up to the point when the stop condition is reached. In the end, the position and fitness value of the solution with the highest overall fitness is restored. Figure 6 shows the fake code for MRFO.

In a broad sense, the following is a list of the properties of the MRFO and the flowchart is shown in Fig. 7.

(a) The three distinct methods of food acquisition utilized by manta rays, including somersault foraging, chain foraging, and cyclone foraging, served as the impetus for the development of the MRFO. Each of these distinct foraging techniques has the potential to effectively increase the optimization abilities of the MRFO in several different ways, which is something that should be considered before deciding to use any of them.
(b) MRFO can switch between chain and cyclone foraging based on the value of the rand at the moment.
(c) Each solution in chain foraging must update the location of the person in front of them and the optimal global solution.
(d) As the value of t/T steadily becomes higher over time, MRFO is encouraged to make a seamless transition from exploratory search to exploitative search.
(e) Cyclone foraging requires each solution to update its location relative to the person in front of it and the reference position. The reference point will be the best location so far or a random search space position depending on t/T. Both aid in exploitation and exploration.

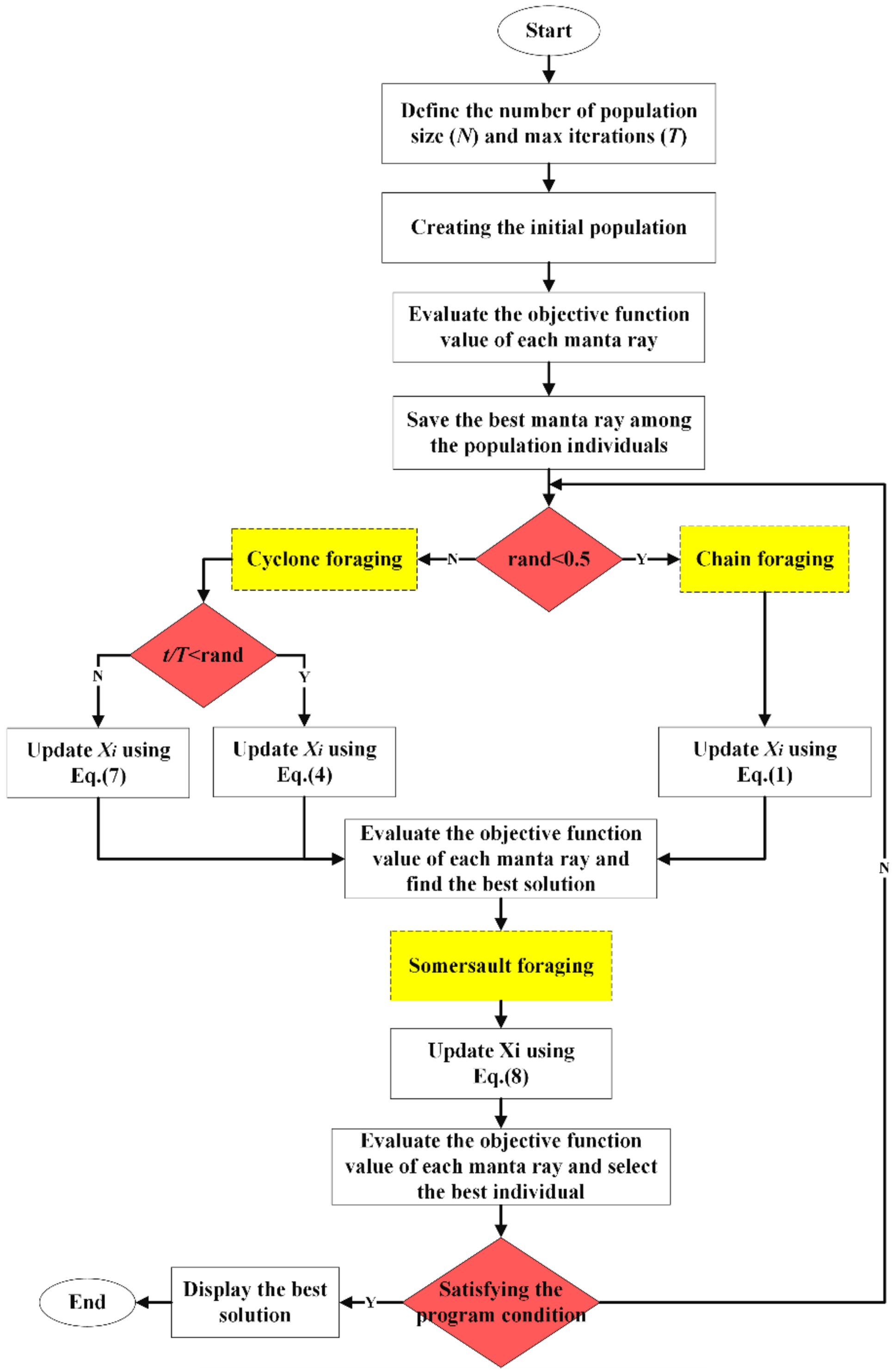


Fig. 7 Flowchart of MRFO algorithm [17]

(f) Individuals can explore in an adaptive manner using the somersault foraging method despite changes in the available search range.

(g) Implementing MRFO is quite simple, as it only requires minor tweaks to a small number of variables.

2.3 Time Complexity MRFO

The amount of time needed to finish MRFO is proportional to the number of participants, as well as the number of variables, and the number of possible iterations. Each cycle includes the execution of the somersault foraging technique

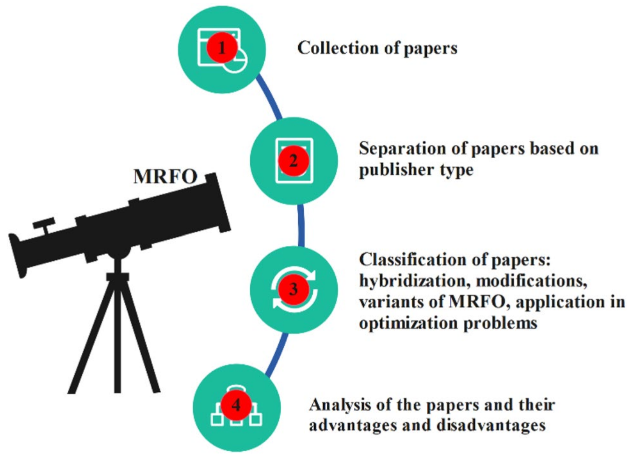


Fig. 8 The steps of collecting and dividing MRFO papers

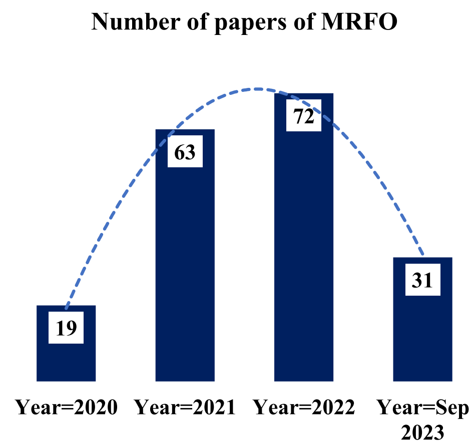


Fig. 9 The average number of publications published by MRFO each year

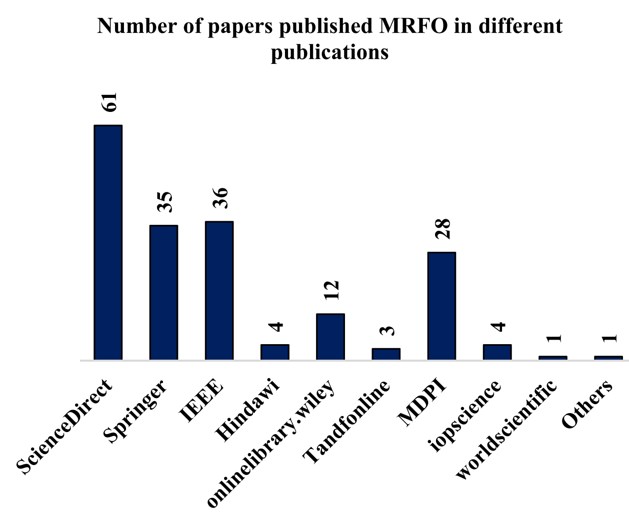


Fig. 10 Number of papers published MRFO in different publications

Table 1 The most crucial queries to search for MRFO papers

No	Keywords to search
1	MRFO + hybrid algorithm
2	MRFO + combining algorithm
3	MRFO + improved algorithm
4	MRFO + modified algorithm
5	MRFO + advanced algorithm
6	MRFO + binary algorithm
7	MRFO + multi-objective algorithm
8	MRFO + optimization problems
9	MRFO + deep learning algorithm
10	MRFO + chaotic algorithm
11	MRFO + levy flight algorithm
12	MRFO + OBL
13	MRFO + fuzzy method
14	MRFO + neuro-fuzzy inference system
15	MRFO + feature selection
16	MRFO + machine learning
17	MRFO + Artificial Neural Networks(ANNs)
18	MRFO + function optimization problems
19	MRFO + continuous optimization problems
20	MRFO + global optimization problems
21	MRFO + global optimization and engineering problems
22	MRFO + strategy search algorithm
23	MRFO + benchmark of global search algorithms
24	MRFO + adaptive local search
25	MRFO + quantum optimization
26	MRFO + structural design optimization
27	MRFO + unimodal and multimodal optimization problems
28	MRFO + Network + Clustering + Routing
29	MRFO + Optimal Parameter
30	MRFO + industrial + analysis

in addition to either the cyclone foraging or the chain foraging technique. As a result, the total amount of time that the MRFO method requires follows Eq. (10) [17].

$$O(MRFO) = O(T(O(\text{cycloneforaging} + \text{chainforaging}) + O(\text{somersaultforaging}))), \tag{9}$$

$$O(MRFO) = O(T(nd + nd)) = O(Tnd). \tag{10}$$

In Eqs. (10) and (11), d represents the total number of variables, T is the maximum number of iterations, and n represents the total number of solutions.

The steps involved in collecting and sorting MRFO papers are illustrated in Fig. 8.

Table 1 lists the crucial search queries for MRFO papers.

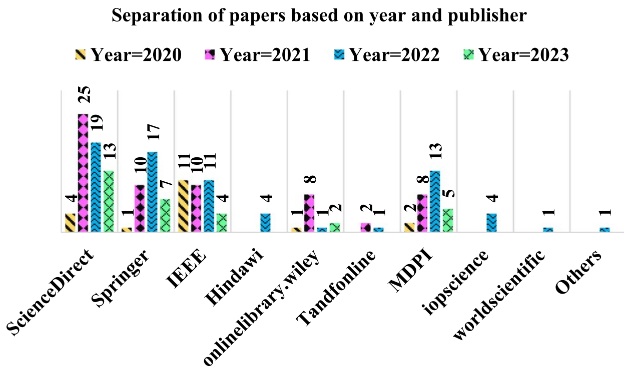


Fig. 11 Separation of papers of MRFO based on year and publisher

The total number of papers related to MRFO published in certain years is shown in Fig. 9. The total number of MRFO papers that were published in the year 2020 was 19. Beginning in the year 2020 and continuing beyond, several studies focusing on the application of MRFO to the resolution of optimization issues have been conducted. First, all of the papers that MRFO has worked on have been downloaded. After that, the reliability of a category that was established based on the proportion of documents that were included in a variety of publications and the amount of MRFO papers that were distributed each year were evaluated. MRFO paper counts can be calculated. Figure 9 illustrates an annual rise in published documents after 2020. It is not hard to see that the number of papers published in the year 2022 (up to September of that year) is much larger than that of prior years. The number of papers published until 5 September 2023 is about 31 paper.

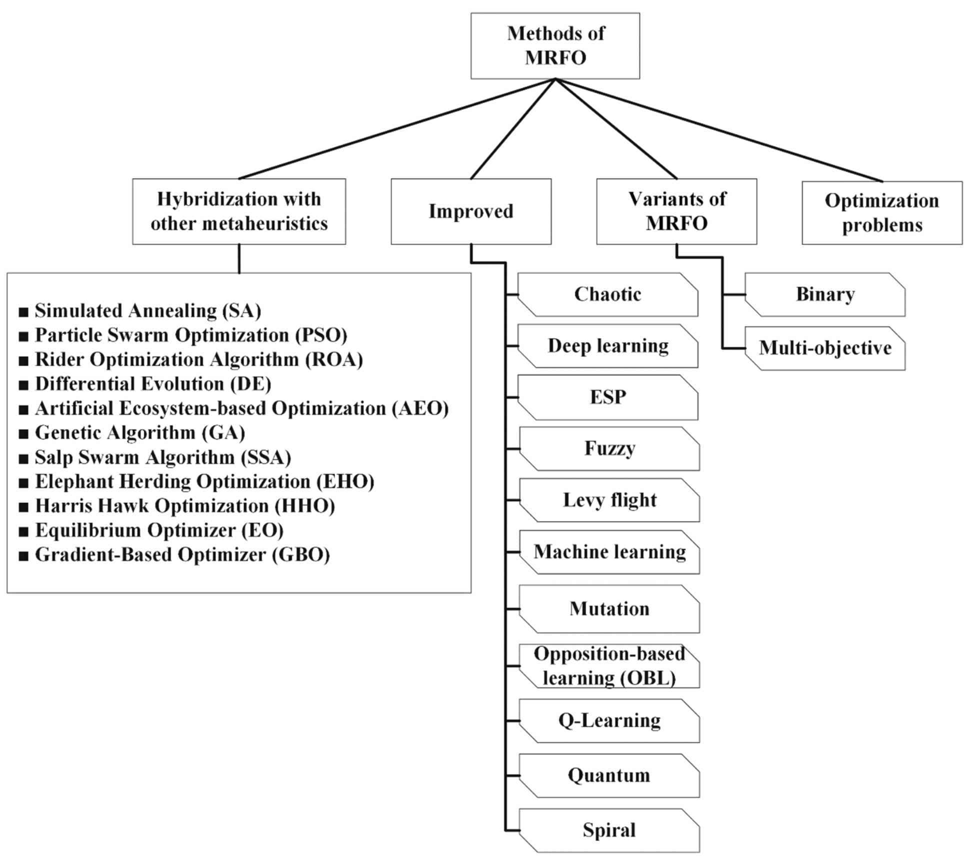
Figure 10 displays the total number of papers that MRFO has released in a variety of publications over the years (10). The number of papers published in the ScienceDirect publication is much higher than that of other publications in Fig. 10.

Figure 11 depicts the categorization of MRFO papers by year and publisher.

3 Methods of MRFO

This paper's principal objective is to provide a comprehensive synopsis of the fundamental technique followed by the MRFO and its sources. The several MRFO approaches are broken down and categorized in Fig. 12. MRFO's methodologies are offered in hybridization, enhanced, variant, and optimization issues.

Fig. 12 Classification of MRFO methods



3.1 Hybridization

3.1.1 MRFO-Simulated Annealing (SA)

A model of the visual question answering (VQA) system has been suggested. The model has two attention modules. These two modules collaborated to create more powerful attention modules that extracted features from the foreground object and background region. These characteristics can answer queries about both. The hybrid Simulated Annealing-MRFO (SA-MRFO) [18] finds the best weight parameter for the specified model, improving the proposed architecture's performance. This is accomplished by selecting the optimal weight parameter. The use of simulated annealing, which is incorporated in the very first step of the MRFO method, helps to cut down on the amount of time spent on analysis by the optimization process. The accuracy of the suggested VQA was increased due to this hybridization.

The rotational speed of a direct current (DC) motor was controlled by a fractional-order proportional-integral-derivative (FOPID) controller. Using a novel metaheuristic method known as the OBL hybrid MRFO with Simulated Annealing (SA) [19] algorithm, the variables of the controller have been optimally set so that they can perform their intended functions. This algorithm that has been suggested aims to enhance the performance of the traditional MRFO algorithm in two different ways. To begin, it enhances MRFO's potential for exploration by providing support for OBL. By doing so, it is possible to prevent the stagnation of the local minimum. Second, it allows MRFO to have a higher exploitation capacity by using hybridization in conjunction with a simulated annealing process. It benefits the organization in two ways. The hybridization contributes to hastening the pace of convergence achieved by MRFO. It outperforms other optimization algorithms in exploration and exploitation.

A hybrid metaheuristic approach was used to tune four PID controllers for an automated voltage regulator (AVR) system. The MRFO, combined with the SA algorithm, serves as the foundation for this strategy [20]. The results of the simulations give irrefutable proof that every kind of controller tuned using the proposed SA–MRFO algorithm achieves more excellent performance compared to controllers tuned utilizing other approaches. This conclusion can be drawn from the outcomes of the simulations. In addition, a comparison investigation is carried out to identify the ideal controller for use in AVR systems. The model achieves a significant acceleration of convergence. A modified MRFO, or MMRFO, is a methodology that improves the characteristics of the MRFO method [21]. SA was added to the MRFO strategy to improve exploitation. It created a modified MRFO. Second, the technology is used to size and place Multiple Photovoltaic (PV) and Wind Turbine (WT) units in a Radial Distribution System (RDS). A single-fitness function minimizes system loss due to stochastic PV and WT output production and variable load demand. To minimize value. QLSF is used to find sites for up to 50% of system buses to narrow the search. PV and WT alone or together have been extensively studied to improve system performance. The solution method addresses IEEE 69 bus RDS. Installing PV and WT in RDS together offers better results than installing either PV or WT individually. The simulation showed that reactive power-capable PV inverters could reduce system losses. The convergence feature demonstrates that the modified MRFO generates solutions of greater quality than those generated by the conventional MRFO.

3.1.2 MRFO-PSO

To achieve a healthy balance between exploitation and exploration capabilities, MRFO-PSO, a novel hybrid MRFO with PSO, has been developed [22]. The idea of velocity from the PSO is implemented into the MRFO-PSO algorithm so that it may drive the searching process of the MRFO. This algorithm's velocity is updated based on the first-best and second-best answers. The difficulty of balancing the exploratory phase and the capacity to utilize resources has been significantly reduced. The MRFO-PSO is evaluated based on its performance on 23 benchmark equations to show its robustness and efficiency. The MRFO-PSO is compared against six contemporary metaheuristic approaches using a variety of statistical measures in addition to a non-parametric test based on Wilcoxon's test. The results of these comparisons are shown below. Consequently, the performance evaluations that were carried out validated the superiority of the suggested MRFO-PSO and the achieved competitive outcomes.

It is recommended that a hybrid MRFO algorithm with PSO should be used [23]. The PSO algorithm is well-known and regarded for its excellent performance. The elitism and social interaction processes in PSO have been included in MRFO via the hybrid algorithm introduced in this study. The methods assist the search agents in determining the new path that they should take in their search. Tests using completions on evolutionary computing (CEC) 2014 benchmark function dimensions and fitness landscapes confirm the proposed technique. Optimizing a PD controller for an inverted pendulum system solves an engineering problem. The strategy improved the accuracy of most test functions. The proposed technique outperformed MRFO in PD control optimization.

An essential component of environmentally responsible groundwater management of productive aquifers is modeling the groundwater's reliable and accurate quality. In this topic, individual and integrative machine learning, Adaptive

Neuro-Fuzzy Inference Systems (ANFIS), and nonlinear mathematical models estimate groundwater-specific conductance. The well-known PSO and the innovative MRFO heuristic algorithms have been included in the models to facilitate the development of integrative models [24]. The models were developed and validated using groundwater level, salinity, and water temperature at a Florida city observation site. Univariate, bivariate, and multivariate scenarios are described. ANFIS models predict SC more accurately than mathematical models (IA = 0.933). PSO and MRFO algorithms improved ANFIS models' prediction accuracy by 13 and 5 percentage points, respectively, as evaluated by Root-Mean-Squared Error (RMSE).

3.1.3 MRFO-Rider Optimization Algorithm (ROA)

Early glaucoma detection reduces the risk of irreversible visual loss. An excellent glaucoma detection approach is the ROA-MRFO-based general adversarial network [25]. Segmenting optical discs uses fuzzy local information C-means clustering (FLICM clustering). This glaucoma detection method uses sparking to identify blood vessels. As a result, the Rider MRFO-based GAN model possesses the highest accuracy, with a score of 0.96, the highest sensitivity, with a score of 0.94, and the highest specificity, with a score of 0.89.

3.1.4 MRFO-DE

The challenge of economic load dispatch (ELD), which has to be solved to realize the thermal units' cleaner and more economical purpose, led to the development of an improved IMRFO algorithm [26]. The following are some of the distinguishing features of the innovative method: The MRFO method's adaptability was presented by introducing sine and cosine adaptations, the algorithm's convergence speed was presented by introducing a nonlinear convergence factor, and its robustness was presented by introducing a DE algorithm. To demonstrate that the IMRFO-based solution technique is effective, three typical ELD testing systems were chosen. According to the findings, the IMRFO algorithm provided the most advantageous scheduling technique when compared to the other possible methods that were taken into consideration. To accomplish cleaner and more sustainable power generation, improving the economics of the operation of power systems is important.

3.1.5 MRFO–Artificial Ecosystem-Based Optimization (AEO)

A unique hybrid approach based on MRFO and AEO has been presented to determine the variables of the battery [27]. The MRFO–AEO algorithm eliminates the MRFO cyclone foraging operator's random search operation to improve battery parameter identification precision and stability. The MRFO–AEO algorithm dynamically coordinates the AEO decomposition operator and the improved MRFO tumble foraging operator with the iterative process. This is done to strike a balance between exploration and exploration throughout the global search. The validity of the battery model, as well as the method's practicability, are evaluated and validated with the use of experimental data on battery discharge gathered at the Kunbei converter station in Yunnan, China.

3.1.6 MRFO–GA

It is proposed to combine MRFO and GA using a pseudo parameter [28]. The GA can assist the MRFO in staying above the local minimum. When combined with MRFO, it is referred to as a pseudo-GA (PGA–MRFO). The proposed method is not a traditional MRFO–GA fusion. Each algorithm must be performed on all system variables, conventional hybridization would make the search procedure lengthy. Additionally, traditional hybridization produces an extended search algorithm, which is particularly problematic in settings with many variables. The PGA–MRFO algorithm is a hybrid that hybrids the pseudo-parameter-based GA with the MRFO algorithm to provide a more efficient approach that includes the benefits of both algorithms without becoming caught in a local minimum or requiring a great deal of time to do computations. Because the GA only has to be applied to a subset of the system's variables thanks to the pseudo parameter, the amount of time spent computing and the required work are cut down significantly. The technique that was made also used an estimate for the fitness function's gradient. It made it possible to skip the derivatives calculations. Also, the PGA–MRFO algorithm uses the pseudo-inverse of matrices that are not square, which makes calculations go faster. After testing the suggested algorithm on the test functions, the principal MRFO could not find the optimal solution, which is needed to prove the algorithm's competence and efficacy. As further evidence of the method's usefulness, it was used to the resolution of the unit commitment issue, which was one of the most significant challenges facing the power systems.

A revised version of the MRF, the O algorithm that uses GA's building blocks has been suggested [29]. This optimization technique, however, has room for improvement in its approach, which would increase its accuracy. As a result, in this suggested enhancement, the mutation and crossover technique used in GA was implemented into MRFO. The crossover operation lures agents to an optimal location. Mutation diverges agents to a wider viable range during this time. The algorithms were then tested on several benchmark functions using the Wilcoxon signed-rank test. The algorithms were tested with a real-world scenario on an interval type 2 fuzzy logic controller of an inverted pendulum system. GMRFO outperformed MRFO and GA on benchmark functions. It shows a superior control system parameter and excellent response.

3.1.7 MRFO–Salp Swarm Algorithm (SSA)

The fast development of applications that are based on the Internet of Things (IoT) has contributed to the increased demand for cloud computing services. To effectively utilize the other potential of cloud computing, advanced scheduling techniques are required. IoT services must also be scheduled on cloud resources optimally using these approaches. In this paper, a task scheduler is used as a substitute for the CCE in arranging IoT application jobs. A hybrid swarm intelligence strategy using MRFO and SSA is presented as a solution for scheduling IoT tasks in cloud computing [30]. MRFOSSA approach is predicated on the use of SSA to enhance the local search capability of MRFO, which in most cases accelerates the pace of convergence towards the global solution. In numerous experimental series, various real-world and synthetic datasets of varying sizes are utilized. MRFOSSA is verified after it has been constructed. It is evaluated and compared with several other metaheuristics. Several performance metrics, including the makespan time and cloud throughput, show that MRFOSSA is superior to its competitors.

3.1.8 MRFO–Elephant Herding Optimization (EHO)

EHO algorithm is a revolutionary metaheuristic optimizer inspired by elephant populations' behavior regarding renewing their clans and separating groups [31]. It contains a minimal number of variables and is easy to build, but it suffers from under-exploitation, which causes delayed convergence. MRFO and Gaussian mutation-based EHO (MGEHO) and for global optimization, an enhanced version of the EHO method, have been presented as solutions [31]. It included in the first version of the EHO algorithm has been replaced with the somersault foraging technique used by manta rays. It seeks to alter patriarch placements in the most effective way possible. Additionally, a dynamic convergence factor is established to preserve a healthy balance between exploration and exploitation. MGEHO can maintain its robust local search capabilities by adopting the Gaussian mutation to increase population diversity and satisfy this demand. Thirty-three traditional benchmark functions have been selected to determine how well various algorithms work. These functions will prove MGEHO's superiority. The enhanced paradigm is evaluated using 32 benchmark functions from the IEEE CEC 2014 and CEC 2017 conferences and several advanced metaheuristic algorithms. Scalability, convergence, statistical, diversity, and running time analyses show that MGEHO is beneficial in multiple contexts and context-specific ways. MGEHO outperforms other algorithms in precision and stability, according to the findings. Finally, MGEHO solves three engineering problems. The comparison shows that this approach helps solve complex problems.

3.1.9 MRFO–Harris Hawk Optimization (HHO)

The scheduling of tasks in the cloud is a challenging problem for optimization. The load distributed over the cloud system is determined by the design of the cloud as well as the requirements of the users. On the other hand, underloading or overloading scenarios may lead to several system failures, including increased power consumption, broken machines, and other issues. As a result, task load-balancing on Virtual Machines (VMs) is regarded as an essential component of cloud task scheduling. As a dynamic load balancing algorithm, MRFO-Modified Multi-objective HHO (MMHHO) was presented as a hybrid optimization approach [32]. The hybridization procedure updates the search space of HHO by using the MRFO and taking into account, among other things, cost, reaction time, and resource consumption. The hybrid scheme proposed in this study improves system performance by increasing VM throughput, balancing VM load, and maintaining task priority balance by adjusting the waiting time of the functions involved. The recommended model's efficiency has been examined in terms of several factors, and the results have been compared to those of other algorithms already in use. According to the findings of the simulations, the MMHHO load-balancing scheme performs better than other algorithms in terms of overall performance.

3.1.10 MRFO–Equilibrium Optimization (EO)

Cancers of the lung and colon are fatal illnesses that may appear in organs simultaneously and negatively impact human life in some exceptional circumstances. Even though the likelihood of having both of these forms of cancer simultaneously is low, there is a significant risk of metastasis occurring between the organs if the disease is not detected in its early stages. Examining histopathological images and making diagnoses of cancer patients has traditionally been a laborious and time-consuming process for specialists; however, with the advancements in technology that have been made in recent years, it is now possible to complete this procedure in a shorter amount of time. To classify the histopathological pictures of lung and colon cancer, researchers turned to methodologies backed by artificial intelligence models and optimization techniques. The dataset that was employed has five classes of histopathological pictures. There are two classes dedicated to colon cancer and three classes devoted to lung cancer. According to the suggested strategy, the picture classes were trained using the DarkNet-19 model, one of the deep learning models. The EO and MRFO algorithms were used to pick the inefficient features from the feature set taken from the DarkNet-19 model [33]. After that, the collection that included the ineffective features was separated from the remainder of the features, resulting in an efficient feature set (complementary rule insets). A technique known as Support Vector Machine (SVM) is used to aggregate and classify the effective features produced by combining the results of the two applied optimization methods. The categorization procedure yielded an average accuracy rating of 99.69 percent across all categories. According to the findings of this investigation, it was found that using the complementary approach in conjunction with various optimization methods resulted in an improvement in the classification performance of the dataset.

3.1.11 MRFO–Gradient-Based Optimizer (GBO)

A grand strategy based on MRFO merged with GBO is developed [34] to handle the Economic Emission Dispatch (EED) issues effectively. This strategy is given the name MRFO–GBO. The objective of the MRFO–GBO that has been designed is to hasten the process of finding a solution while simultaneously lowering the likelihood that the original MRFO would get mired in a local optimum. The best EED delivers all necessary electrical loads at the lowest cost while reducing emissions and meeting operational equality or inequality constraints. Both single- and multi-objective EED issues may be handled using the suggested MRFO–GBO in conjunction with the traditional MRFO. The fuzzy set theory is modified in the process of multi-objective EED to figure out which of the Pareto optimum solutions is the best compromise option. Well-known CEC 2017 test functions first verify the suggested approach. After that, it is implemented to address numerous scenarios of EED issues for three electrical systems with three generators, five generators, and six generators, respectively. The suggested method's resilience is tested by applying varying amounts of load to the systems being examined as part of the validation process. Comparisons are made between the results achieved by the newly suggested MRFO–GBO and those obtained by previously published optimization approaches, in addition to the results obtained by the traditional MRFO and GBO. The MRFO–GBO solved single and multi-objective EED problems with accuracy, robustness, and convergence characteristics.

Table 2 shows the primary motivation for combining MRFO with metaheuristic algorithms. Each algorithm has its own set of benefits, which collectively contribute to an improved MRFO.

3.2 Improved

In this subsection, we examine the procedures associated with improvement. These techniques include Fuzzy, Levy Flight, Mutation, Spiral, OBL, Quantum, Deep Learning, Elite Search Pool (ESP), Q-Learning, Chaotic, and Machine Learning. All of these techniques aim to enhance the MRFO. The proportion of strategies based on improved MRFO is seen in Fig. 13.

3.2.1 Chaotic

Even though the native MRFO has shown strong competitive capacity compared to popular metaheuristic algorithms, it still tends to become stuck in local optima. It has a poor convergence rate when dealing with certain complex issues. A new elite chaotic MRFO has been created and given the name of the CMRFO algorithm to make up for the MRFO's flaws. This method incorporates the population's chaotic initialization and an OBL technique. To start the population, fourteen distinct types of chaotic maps, each with a distinctive set of attributes, are employed. This way, the chaotic map that produces the most significant effect is chosen. The elite confusing searching strategy's sensitivity analysis to the CMRFO is being worked on in the meantime [36]. The MRFO is benefiting from the coordinated efforts of these strategies to improve efficiency.

Several methods, including chaotic sequences, have been tried and tested to address this deficiency and enhance the capability of doing global searches. In MRFO, ten distinct chaotic maps are offered. The effectiveness of the suggested messy method CMRFO was initially assessed using the IEEE CEC 2017 benchmark functions [37]. Chaotic searching is carried out to improve the MRFO's ability for exploitation. It involves carrying out chaotic operations on people to achieve additional renewal.

It is hypothesized that a real-world design challenge may be solved using chaos-MRFO augmented versions [38]. MRFO is a bio-inspired swarm intelligence-based metaheuristic program that replicates the various food-seeking behaviors of manta rays. It has several inherent algorithmic flaws, such as delayed and premature convergence as well as unforeseen trapping to the search domain's local optimum points, which causes it to be inefficient overall. Recent developments in chaos theory have led to the incorporation of random number generation into the metaheuristic algorithms used to tackle these issues. The basic algorithm is given more than twenty chaotic maps to apply, and the ten approaches that perform the best on high-dimensional optimization test issues are considered for performance assessment. A comprehensive statistical study is carried out, and chaotic forms of MRFO

Table 2 The main reason for hybridizing MRFO and metaheuristic algorithms

Refs	Application	Advantages	Disadvantages	Publisher	Year
[18]	MRFO–SA	The variety level of the starting population is improved through SA, which ultimately results in an increased convergence rate	High computational complexity	Springer	2022
[22]	MRFO–PSO	The MRFO search behaviors of exploration and exploitation are more balanced because of PSO's contributions	The model gets stuck in the best possible solution for the immediate area	Springer	2022
[25]	MRFO–ROA	The ROA works effectively and can continually increase the MRFO architecture's performance	Relatively slow convergence speed	ScienceDirect	2022
[26]	MRFO–-DE	The DE algorithm accelerates convergence with adaptive mutation	High computational complexity	ScienceDirect	2022
[27]	MRFO–AEO	AEO decreases the likelihood of premature convergence due to improvements in global search capabilities	The high tendency of the MRFO-AEO to suffer with rapid loss of population diversity during the initialization stage	IEEE	2022
[28]	MRFO–GA	The mutation scheme improves the balancing of exploration and exploitation search behaviors of MRFO	The convergence rate is low, The model becomes stuck in the optimal local solution	MDPI	2022
[23]	MRFO–PSO	The PSO technique helped improve our capacity to search the world over	Relatively slow convergence speed	Springer	2022
[30]	MRFO–SSA	SSA maximizes convergence while balancing exploration and exploitation	High computational complexity	IEEE	2022
[19]	MRFO–SA	Increases convergence speed and searchability	The model becomes stuck in the optimal local solution	Springer	2021
[35]	MRFO–SSA	The SSA strategy enhanced the global search ability	High computational complexity	Springer	2021
[31]	MRFO–EHO	EHO can produce a faster convergence rate speed than the traditional initialization method	Trapped locally, the Random searching feature	Springer	2021
[20]	MRFO–SA	Accelerates convergence and improves searchability	High computational complexity	ScienceDirect	2021
[32]	MRFO–HHO	HHO leads to strengthening solutions and exploring the entire problem space	High computational complexity	ScienceDirect	2021
[33]	MRFO–EO	EO has the potential to boost both exploration and exploitation searches at the same time, all without compromising the convergence speed	The model becomes stuck in the optimal local solution	ScienceDirect	2021
[34]	MRFO–GBO	MRFO-GBO is more effective than other approaches in locating initial populations of high-quality specimens	High computational complexity	ScienceDirect	2021
[21]	MRFO–SA	Increases convergence speed and searchability	Trapped locally, the Random searching feature	IEEE	2021
[24]	MRFO–PSO	The PSO technique helped improve our capacity to search the world over	During the start period, there is a high risk of the MRFO-PSO experiencing a significant reduction in the variety of its population	Online library.Wiley	2021
[29]	MRFO–GA	Using a mutation operator selection system, better preservation of population diversity was achieved	High computational complexity	iopscience	2020

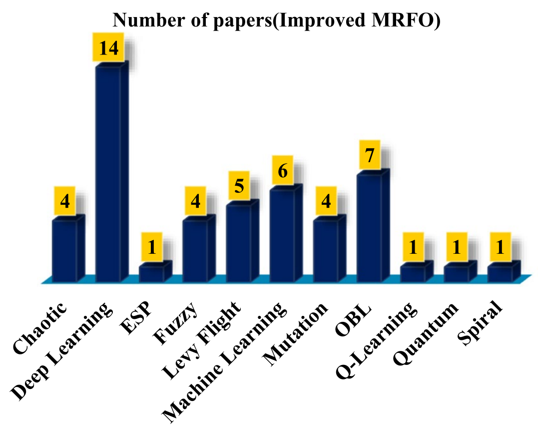


Fig. 13 Number of papers by improved MRFO

have been used to successfully handle all forty test issues, including unimodal and multimodal functions. The chaotic MRFO variants also preserve the thermo-economic design optimization of an air-fin cooler to test their optimization skills across complex engineering design constraints. Ten important air fin cooler design variables are tuned for total annual cost rates. Comparing the preliminary design to the five best chaotic MRFO algorithms' optimum solutions. MRFO with chaotic operators improves this thermal design issue's fitness function. The MRFO chaotic algorithm was used to estimate transformer variables in the model presented [39]. The assessed variables acquired using the suggested optimization methods and fitness function are compared to the values obtained using the IEEE-recommended traditional test approach. The related values are derived using the approaches previously described in the literature. It is done to see if there is a statistically significant difference between the two sets of findings. The fitness function given guarantees that the natural copper and no-load losses are reflected in the predicted transformer variables and that the estimated transformer output characteristics coincide with the empirically acquired curves. This is accomplished by ensuring that the estimated transformer variables are represented accurately. Experimental parameter identification tests are carried out to demonstrate that the proposed parameter estimation algorithms are practical. The experimentally determined transformer variables are then compared to the estimated variables, and the correlation between the two is examined.

3.2.2 Deep Learning

Deep learning neural networks using MRFO are broken down and discussed in this section. The convolutional neural network (CNN), long short-term memory (LSTM) network, and gated recurrent units (GRU) networks are broken down and examined in this section. CNN is analogous to ANNs, which often use multi-layered perceptron to reduce the amount of data that must be processed beforehand. This kind of network comprises neurons with weights and biases that may be modified via training (adjusted) [40]. Each neuron takes many inputs, calculates the product of the consequences associated with those inputs, and then eventually uses a nonlinear transformation function to provide a result. A loss function, often an SVM or a Softmax, is typically implemented in the topmost layer of this kind of network (fully connected). CNN often includes convolutional layers, pooling layers, and fully linked layers in its structure. The purpose of the convolution process is to extract patterns from the input data; as the number of layers increases, the network can extract more difficult habits from the practices it has already extracted. The characteristics derived from the convolutional layer have many dimensions in total. The pooling layer is in charge of lowering the number of dimensions. The fully connected layer combines all the local features and produces the final feature as the output. In a broad sense, an LSTM is understood to be a modified form of RNN that circumvents the restrictions of the conventional RNN. LSTM can learn dependencies and memorize vast volumes of data for extended periods [41]. It also has a significant potential for learning new information. Table 3 outlines the benefits and drawbacks of using MRFO for Deep Learning.

3.2.3 Elite Search Pool (ESP)

The random selection of reference locations hinders the exploitation potential of MRFO during the early iterations of the process. When used, chain foraging often leads the algorithm to a locally optimal solution. Furthermore, the method has the disadvantage of decreasing population diversity in subsequent iterations of the procedure. A modified version of the MRFO that uses three different techniques is being presented as a solution to these issues [56]. This study establishes an elite search pool (ESP) to increase exploitation. Using adaptive control parameter (ACP) techniques, MRFO's exploration range was broadened in early iterations while exploitation precision was increased in later iterations, balancing exploring and exploiting capabilities. A distribution estimating approach (DES) was employed to assist convergence by shifting evolutionary change utilizing dominant population information. Twenty-three conventional test functions and the CEC 2017 test suite validated the M-MRFO. The Friedman, Wilcoxon, and Iman-Davenport tests verified the findings. By tackling three engineering design obstacles, they showed that M-MRFO could solve real-world problems. Its findings show that the performance of MRFO may be significantly enhanced by using the enhancement technique outlined in this study. The M-MRFO market is quite competitive.

Table 3 Advantages and disadvantages of deep learning with MRFO

Refs	Model	Application	Advantages	Disadvantages	Publisher	Year
[42]	MRFO–CNN	Image enhancement	MRFO is responsible for training the CNN approach, which involves optimizing the computational weights and biases	High iterations, High execution time	World scientific	2022
[43]	MRFO–CNN	Prediction	The CNN approach is trained using the MRFO algorithm, which optimizes the computational weights and biases in the process	High execution time, Non-optimal updates of individual	Springer	2022
[44]	MRFO–CNN	brain tumor detection	Finding a technique for detecting brain tumors with the lowest mean squared error, relative means squared error, and mean absolute percentage error proved challenging	Slow convergence rate, High iterations	Springer	2022
[45]	MRFO–CNN	Pneumonia diagnosis	MRFO is responsible for training the CNN approach, which involves optimizing the computational weights and biases	Slow convergence rate, Achieve a solution in the final iterations	Springer	2022
[46]	MRFO–CNN	Brain tumor classification of MRI images	The CNN approach is trained using the MRFO algorithm, which optimizes the computational weights and biases in the process	Slow convergence rate, High iterations	Springer	2022
[47]	MRFO–LSTM	Predicting	The best weights and parametric values for the LSTM, including the number of hidden neurons and the choice of training technique, are calculated concurrently	High iterations, Achieve a solution in the final iterations	ScienceDirect	2022
[48]	MRFO–LSTM	Watermark	The MRFO algorithm optimizes the learning variables of the LSTM	High iterations, Achieve a solution in the final iterations	ScienceDirect	2022
[49]	MRFO–LSTM	Daily Solar Radiation Prediction	The best weights and parameter values (the number of hidden neurons and the training algorithm) for the LSTM are found simultaneously	Slow convergence rate, Achieve a solution in the final iterations	MDPI	2022
[50]	MRFO–GRU	Classification	The MRFO algorithm optimizes the learning variables of the GRU	High execution time, Non-optimal updates of individual	MDPI	2022
[51]	MRFO–CNN	Short-term wind power prediction	The MRFO algorithm trains the CNN technique by optimizing the computational weights and biases	Achieve a solution in the final iterations, High iterations	Iopscience	2022
[52]	MRFO–CNN	Big Data Electricity Theft Detection	The MRFO algorithm trains the CNN technique by optimizing the computational weights and biases	Slow convergence rate, High iterations	MDPI	2021
[53]	MRFO–CNN	Flood susceptibility mapping	The MRFO algorithm trains CNN by optimizing system weights and biases	High iterations, Achieve a solution in the final iterations	Tandfonline	2021
[54]	MRFO–GRU	Electricity Theft Detection	GRU variable and neuron weight optimization	High iterations, Achieve a solution in the final iterations	IEEE	2020
[55]	MRFO–CNN	Images classifications	The MRFO method optimizes the computational weights and biases to train the CNN approach	High iterations, Achieve a solution in the final iterations	Conscience	2020

3.2.4 Fuzzy

In recent years, several techniques for frequent item sets and association rule mining (ARM) have been shown; nevertheless, the performances based on scalability and processing time are still regarded to be a severe shortcoming, which results in the solutions obtained having inferior quality. This paper presents three key stages as a solution to such drawbacks. These phases are the pre-processing data phase, frequent item set mining, and ARM. Each of these phases is designed to overcome a specific limitation. During the pre-processing data phase, the acquired Twitter datasets are pre-processed to eliminate excessive data and transform them into a suitable format for further mining. The data mining phase follows this phase. An Apriori algorithm mines frequent item sets during the process phase. It allows for the precise mining of standard item sets. The Fuzzy MRFO (FMRF) [57] optimization technique is used during the ARM phase of the process. This approach includes the development of association rules from the enormous item sets, with the end goal being to achieve the lowest confidence and minimum support value. The experimental analysis and the comparative performances are carried out for various simulation measures, and the findings indicated that the suggested technique gives compelling performances when compared with a variety of other current approaches.

It is necessary to have a method that is both effective and capable of producing precise results when classifying cancers. Enhanced ANFIS (EANFIS) is employed to detect cancer genes to circumvent this problem. The amount of time it takes for ANFIS to converge on a solution increases throughout the learning process; hence, to circumvent this issue and enhance the overall classification performance, MRFO is hybridized along with ANFIS. The MRFO, like the ANFIS, is a hybrid to select the optimum variables [58]. The performance of the ANFIS-based cancer detection was significantly improved due to these ideal settings. The Ensemble Kalman Filter (ENKF) method is used in the first phase of the classification procedure to perform pre-processing on the data that will later serve as an input to the process. After the preprocessing stage has been completed, an adaptive density-based spatial clustering with noise (ADBSCAN) clustering method is applied to group genes with similar features. In the final phase, the performance of the developed and improved ANFIS is evaluated using a variety of metrics, such as f-measure, recall, accuracy, sensitivity, precision, and specificity. The findings demonstrated that ANFIS-MRFO is superior to the competition. As a result, Maximum PowerPoint Tracking (MPPT) control is significant to continually monitor the ideal operating point despite changes in operating conditions. A Maximum Power Point Tracking (MPPT) method based on enhanced fuzzy logic control (FLC) is proposed [59]. The freedom and flexibility offered by FLC systems are used in the suggested technique, which aims to produce an accurate and quick-tracking controller of maximal PowerPoint for TEG applications. Through the use of MRFO, the variables of the optimal FLC have been determined. The gains of the membership functions are employed as choice variables throughout the optimization method, and the integral of the error is used as a cost function. To demonstrate the improved FLC's dependability, many situations in which the differential temperature is altered are run through. The results that were acquired through the use of the optimized FLC are compared to those that were obtained via the use of traditional FLC and hill-climbing techniques. The preliminary results demonstrate that the suggested design, which incorporates characteristics of both MRFO and FLC, provides a potential solution for MPPT in TEG systems. The proposed improved FLC technique delivers higher performance by reducing the variations in the output power in the different analyzed situations. It allows the approach to be used in a broader range of applications. In addition, the suggested improved FLC approach can continuously monitor the maximum power from TEG at various temperatures on both the hot and cold sides, in addition to fluctuations in the output load.

An improved version of the MRFO is offered as a method for estimating the Optimal Power Flow (OPF) in electric power networks, with or without the inclusion of newly designed VSC stations. The planned IMRFO has as its goal the reduction of total expenditures on fuel, as well as total emissions into the environment and actual losses in electrical output [60]. The manta ray feeding activities are modeled in the MRFO so researchers can study them. MRFO has been enhanced to deal with several goals by adding an outer store for those whom Pareto does not dominate. Adaptive variation in the shape of the fitness function is achieved by repeatedly altering the participants' weights. To select an appropriate operating point from the Pareto set that was generated, a TOPSIS method is also implemented. Both the traditional IEEE 30-bus system, which operates as an AC meshed power system, and the modified IEEE 30-bus system, which operates as a hybrid AC/MDC interwoven power system that incorporates developing VSC stations, are used here to demonstrate several applications of the proposed IMRFO. The traditional IEEE 30-bus system functions as an AC meshed power system. The simulation findings indicate that the suggested algorithm has superior efficiency and resilience characteristics compared to the other algorithms. In addition, the proposed method may find several well-distributed Pareto solutions that meet the necessary criteria regarding technology, economics, and the environment.

3.2.5 Levy Flight

Accurate short-term load forecasting has the potential to cut down on the shutdown reserve and rotational reserve of generating units, which has direct repercussions on the economic advantages, stability, and safety of the power system. A load forecasting technique based on an enhanced manta ray algorithm to optimize the BP neural network is suggested to address the drawbacks of BP neural networks, which include their sensitivity to beginning value and propensity to slip into local optimization easily. The Levy Flight strategy [61] is used to improve the MRFO location update formula, the algorithm's regional and global search performance, the algorithm's ability to leap out of the local optimization, the weight and threshold of the BP network, and the creation of an optimization model for short-term load forecasting. The results show that the updated prediction model has higher accuracy and faster convergence.

Image segmentation is beneficial in many aspects of day-to-day living. The problem of unpredictability plagues traditional K-means image segmentation. It is prone to settling into a local optimum, decreasing the quality of the segmentation generated by the approach somewhat. A K-means picture segmentation approach using Improved MRFO (IMRFO) has been offered as a means of making the occurrences that were discussed before more accessible. IMRFO employs Levy Flight as a means of enhancing the adaptability of individual manta rays and then proposes random walk learning as a means of preventing the algorithm from arriving at its optimal local state [62].

In conclusion, the learning principle of PSO is incorporated to increase the model's convergence accuracy. This, in turn, significantly enhances the algorithm's capacity to optimize both globally and locally at the same time. Because there is less of a chance that K-means may settle on a local optimum, the optimized version of K-means maintains a higher level of stability. Within the context of the 12 standard test functions, comparisons are made between IMRFO, seven fundamental algorithms, and four variation algorithms. IMRFO has a better ability for optimization, according to the results of both the optimization index and the statistical test. In the course of the investigation, they looked at eight different underwater pictures using eleven different algorithms. The PSNR, FSIM, and SSIM of IMRFO in each picture, are all greatly improved, according to the findings. In the meanwhile, the performance of the enhanced K-means picture segmentation is much improved.

In [63], they propose a novel technique for MRFO that employs Latin hypercube sampling and collaborative learning to overcome the challenges caused by the MRFO's faults. A sluggish convergence rate and trouble breaking out of a local optimum are two examples of these issues. Latin hypercube sampling, often known as LHS, is applied first to the population. The results of the testing show that the improved algorithm can significantly improve the initial method's convergence time and optimization accuracy. In addition, the revised approach is used to optimize the coverage of wireless sensor networks (WSNs). The findings of the experiments show that the modified form enhances network coverage by about 3% compared to the technique used initially. Additionally, the improved approach leads to a more appropriate optimized node distribution.

An improved MRFO, abbreviated IMRFO, has been suggested to more precisely determine MR damper models' control variables. The new algorithm constructs a searching control factor following MRFO's limited capacity for exploration, which has the potential to expand the algorithm's worldwide exploration effectively. An adaptive weight coefficient based on the Levy Flight has been created [64] to avoid the early convergence of the optimal local solution. The IMRFO is also used to determine the control variables of MR dampers. The simulation results confirmed the IMRFO's efficiency and usefulness in a wide range of technological applications.

A better method than the one currently in use has been developed to model and simulate a proton exchange membrane fuel cell (PEMFC) system. The primary goal is to attain the highest possible level of agreement between the experimental and predicted output voltages by reducing the sum of squared error (SSE) as much as possible. A modified metaheuristic with the working title Balanced MRFO (BMRFO) has been devised to reduce the error value to its absolute minimum. It is likely that, in certain cases, premature convergence happened as a result of the random population selection in each iteration, causing the running time to rise. The MRFO algorithm may be improved via the use of a variety of different approaches. The Levy Flight mechanism is the first one that is used [65]. The provision of the local search location is accomplished via the use of this mechanism utilizing a random walk behavior. It is recommended that the devised algorithm be used to resolve the issue of premature convergence and increase the method's variety. After executing 30 separate iterations of the suggested BMRFO algorithm and contrasting it with other algorithms found in the literature, it was discovered that the proposed technique produced greater convergence in speed and accuracy. In most studies, Levy Flight has been used for optimization [66, 67]. Levy Flight leads to finding the best solutions by fully searching the problem space [68].

The most important Levy Flight objectives in MRFO are illustrated in Fig. 14.

3.2.6 Machine Learning

To simulate the ultrasonic welding of a polymeric material mix, a novel approach based on a hybrid kind of artificial

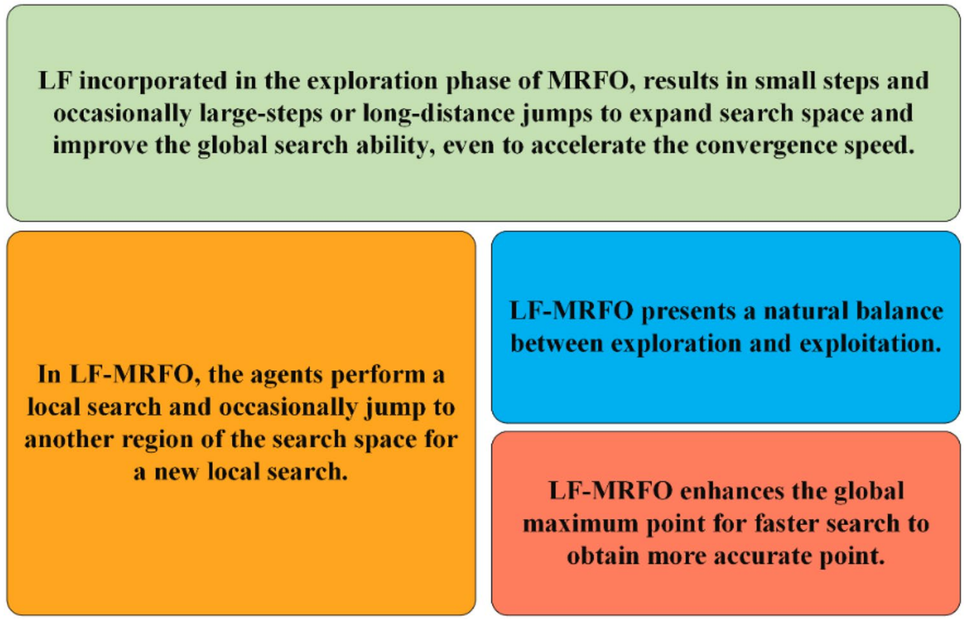


Fig. 14 The most critical Levy Flight goals in MRFO

intelligence has been devised. In the proposed approach, an Ensemble Random Vector Functional Link (ERVFL) model is combined with a GBO. A series of welding studies were carried out on injection-molded combinations of Acrylonitrile Butadiene Styrene (ABS) and polycarbonate. The tests were planned using the L27 orthogonal array, which took into account three process variables (vibration amplitude, welding duration, and applied pressure,) and two reactions (joint strength and average temperature). The data from the trials were then used to “train” the model that had been created. It was compared to both pure ERVFL and two fine-tuned ERVFL models (ERVFL-SCA and ERVFL-MRFO), in which ERVFL is paired with either the Sine Cosine Algorithm (SCA) or the MRFO [69]. It was done so that the correctness of the model could be verified. Five different statistical methods were used to assess the four models. ERVFL-GBO has the highest coefficient of determination, the lowest root-mean-square error, and the lowest mean relative error, coefficient of variance, and mean absolute error when compared to other models. It indicates that it has a higher level of accuracy than other models that have been tested.

In other areas, such as solar generating units, MRFO has achieved success that augurs well for the company's future. SVM provides findings with a high level of accuracy, this classification technique is the one that is used the most often in cancer research, mainly when dealing with microarray data. A hybrid approach is presented to choose the best predictive and informative genes for cancer classification [70]. It is done to capitalize on the benefits offered by both the MRFO and the SVM algorithms. The great dimensionality and complexity of the microarray data provide particular challenges for the MRFO optimization method, just as they do for other optimization approaches. The minimal redundancy maximum relevance (MRMR) approach is used as a preprocessing step to resolve issues of this kind and enhance overall performance. The experiments' results show that our proposed method delivers the most significant degree of precision with the least amount of labor required and the fewest number of informative genes.

Fiber-reinforced polymer, also known as FRP, in addition to its high tensile strength and low self-weight, also possesses several additional benefits. These advantages include resistance to corrosion, high durability, and ease of construction, which positions FRP as one of the ideal choices for restoring concrete structures. Calculating the bond strength between the two materials is difficult due to the complicated binding behavior of the FRP-Concrete (FRPC) interface. As a result, a good modeling framework is required. The accuracy of these models in predicting binding strength is evaluated using a large database of 969 distinct experimental samples. The RUN-ANN model more precisely evaluates interfacial-bond strength than the BES-ANN and DFDB-MRFO techniques. Furthermore, the Shapley Additive Explanations (SHAP) approach is employed to aid comprehension of the best model and to study how the model’s features influence its output[71]. The RUN-ANN algorithm outperformed mechanically based methods. According to SHAP and the sensitivity analysis technique, the length and width of FRP linkages have a greater effect on the final prediction conclusions.

The model in question is the Extreme Learning Machine (ELM) optimized by MRFO, referred to in the following as MRFO-ELM [72]. Following the guidelines of this hybrid model, the mean impact value approach is used to assess and distinguish the significance of the thirteen elements that influence the outcome. In addition, three different scenarios will be used to undertake the projection of China's CO2 emissions from its transportation sector. According to the empirical findings, the suggested MRFO-ELM has outstanding performance in terms of both the optimization seeking velocity and the prediction accuracy. While this is happening, it has been shown that the degree to which vehicles are electrified is one of the main elements determining China's total CO2 emissions from transportation. Under the conditions of the baseline model, the CO2 emissions from transport in China would reach their highest point in 2039. Under sustainable development and fast growth scenarios, emissions would peak by 2035 or 2043. The peak years put China under enormous pressure to cut its existing carbon emissions from transportation. At the same time, active policy modifications can potentially encourage the emission peak to occur sooner and successfully. These results demonstrated that China must improve its energy mix and encourage the replacement of traditional energy sources with electric energy in line with urbanization to reduce transport sector CO2 emissions.

It was suggested that a feed forward neural network (FFNN) model based on the MRFO algorithm be used to predict the rates of electric energy consumption in Bursa, a Turkish industrial city with a rapidly rising economy [73]. Data collection is required for the proposed model, which includes mean values for environmental conditions, days of the week, and electric energy consumption rates. The results of these simulations determined the appropriate weight and bias coefficient values for the various network topologies. The proposed technique was validated by applying it to five categorization difficulties reported in recent years, which varied in complexity. The findings of the simulation were statistically examined and compared to those of other approaches. Simulation findings from both datasets reveal that the MRFO-trained neural network model outperformed the other strategies in the five classification tasks and the prediction of electrical energy consumption.

For feature extraction, many electrocardiogram signal descriptors based on one-dimensional local binary patterns, and higher-order statistical, wavelet, and morphological information have been presented. A novel hybrid electrocardiogram arrhythmia classification technique called MRFO–SVM has been developed for use in feature selection and classification procedures [74]. These approaches combine the MRFO metaheuristic algorithm and the SVM. The novel MRFO–SVM approach was trained using data from the MIT-BIH Arrhythmia database, which included six aberrant and one normal heartbeat. In experimental findings of electrocardiogram arrhythmia classification, the MRFO–SVM demonstrated superior performance than seven well-known metaheuristic algorithms, with an overall classification accuracy of 98.26%.

3.2.7 Mutation Strategy

The primary challenge in several metaheuristic strategies is becoming stuck in local solutions. A changed search strategy becomes a more appealing method as a solution to such limitations since it improves the performance of the search agents. It offers a novel update to MRFO to address that algorithm's most significant flaws while simultaneously addressing engineering and global optimization issues. The recommended version depicts an integrated form of MRFO that comprises the triangular mutation operator and an orthogonal learning technique [75]. This variant is given the name MRTMO. It is believed that the two strategies will produce a stable equilibrium between the algorithm cores and provide a dependable mechanism for directing the search agents during optimization. Six engineering problems and CEC 2005 and CEC 2017 benchmark functions were used to show the performance of the proposed MRTMO. In addition, many evaluation criteria were employed to ensure the efficacy and robustness of the proposed MRTMO. In addition, a comprehensive analysis was conducted to evaluate MRTMO against other optimization algorithms already in existence to validate its superiority. The computational studies demonstrated that the MRTMO offered a competitive performance in resolving all investigated CEC optimization and engineering issues.

An updated MRFO is employed to provide optimal outcomes in the form of Complex Composite Cubic Generalized Ball (CCG-Ball) curves. First, a new class of cubic generalized Ball basis was developed to address the issues of form optimization for Ball curves. Next, the CCG-Ball curves with various shape variables based on the developed basis functions were displayed. One can modify and optimize the curves' shapes using the shape variables. Second, the optimization of the form of CCG-Ball curves is mathematically an issue of optimization, which a swarm intelligence algorithm is perfectly capable of solving in a timely and effective manner. An improved version of the MRFO known as WMQIMRFO has been developed for this purpose. It uses control parameter modification, wavelet mutation, and a quadratic interpolation method to improve the accuracy of the native algorithm's computations and its ability to escape local minima [76]. In addition, the superiority of the WMQIMRFO is proven by comparisons with nature-inspired optimization algorithms on the well-known CEC 2014 and CEC 2017 test suites and four engineering optimization tasks, respectively. These experiments were conducted to validate the performance of the WMQIMRFO.

The MRFO algorithm is an effective technique for performance optimization in terms of finding a theoretically optimal solution to several different optimization benchmark functions. Compared to other algorithms considered to be state-of-the-art, it performs quite well in terms of accuracy. An adaptive position update sine-based formula was included to make the original MRFO's exploration and exploitation techniques more effective [77]. It is evaluated using evolutionary benchmark functions known as CEC to demonstrate the proposed algorithm's accuracy performance. A flexible manipulator system is also used to improve proportional-derivative (PD) control. The performance test results showed that the proposed adaptive algorithm performed much better in terms of accuracy than the MRFO that was previously used. The technique of PD control optimization has been used, and the results demonstrate that the control strategy improved by the recommended adaptive-somersault algorithm surpasses the strategy improved by the original algorithm.

The efficiency of a high-temperature proton exchange membrane fuel cell was investigated. This was accomplished by estimating the output voltage of the cell under a variety of different operating circumstances by making use of semi-experimental relationships. A customized iteration of the MRFO is responsible for carrying out the system optimization. However, it has been created in certain instances. In certain cases, The MRFO exhibited excellent results in addressing the optimization problems, but this was a cause for concern. The self-adaptive weighting strategy is used as the mutation mechanism [78]. The rate at which the algorithm converged was sped up by this method. The early candidates swim by a big step size in the MRFO, but the later iterations lower the step size to conduct a local search inside the solution space. Balances local and worldwide searches. The newly developed method is then evaluated in light of previously published algorithms and the outcomes of computer simulations, both of which demonstrated a high level of congruence with one another.

3.2.8 Opposition-Based Learning (OBL)

Tizhoosh [79] came up with the idea for the machine learning technique known as OBL. To improve an algorithm's capacity for optimization, OBL may acquire knowledge in the opposite direction of a present solution and investigate areas of search space unfamiliar to it. When using OBL, it is possible to increase the variety of solutions within a population, and the algorithm has a greater chance of breaking free from a locally optimal solution. Numerous research has shown that OBL–MRFO can improve both the convergence rate of algorithms and the quality of the solutions they produce. The objective of presenting the OBL approach is to provide a method that can improve the performance of optimization algorithms. It is required for the candidate solutions generated by a stochastic iteration technique as well as their

Table 4 A general review of OBL-MRFO in the optimization problems

Refs	Application	Advantages	Disadvantages	Publisher	Year
[80]	The magnetic ball suspension system	It has been suggested that OBL-MRFO might be a suitable solution and an accelerated coefficient	High execution time	Springer	2022
[81]	PID Control	Utilizing OBL to improve local search capabilities (exploitation) to get optimal and more appropriate solutions	High iterations, High execution time	Springer	2022
[82]	Global Optimization	Exceptional performance and rapid convergence toward discovering the best solution	High iterations	Springer	2022
[83]	Detection of fault location in the Distribution Network	Combining the MRFO algorithm's strengths of robust exploitation and high exploration capacity in the search space to provide a competitive edge	High iterations, High execution time	MDPI	2022
[84]	Multi-level threshold using COVID-19 CT images	This one has a rapid convergence rate compared to previous optimization methods published	High execution time	Springer	2021
[85]	Minimization of energy consumption	Utilizing OBL to improve local search capabilities (exploitation) to get optimal and more appropriate solutions	High execution time, High iterations	ScienceDirect	2021
[86]	Optimization Problems	superior functionality and quick convergence while selecting the best option	High execution time	IEEE	2020

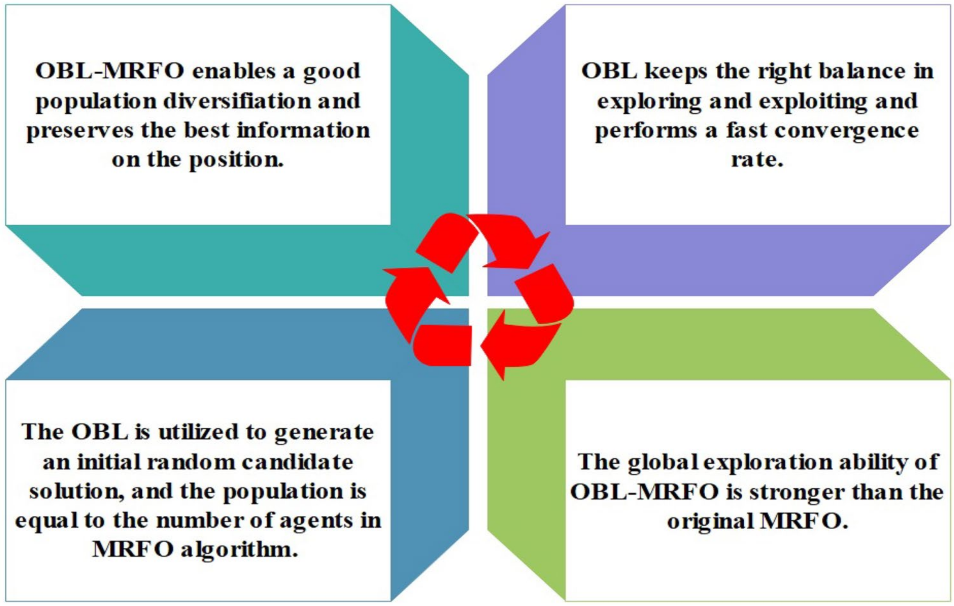


Fig. 15 Shows the most important OBL targets for the MRFO

inverse solutions identified in contrasting parts of the search space. These solutions approach the global optimum more closely than a random solution. Table 4 provides a detailed review of OBL-role MRFOs in optimization algorithms.

The most important OBL targets for the MRFO are displayed in Fig. 15.

3.2.9 Q-Learning

In the Q-Learning algorithm, the agent uses a value-based method to determine what would be the most beneficial course of action given the present state of the system. The agent acquires new knowledge as a result of its activities and conditions. Because an agent conducts random acts, and then receives a reward or penalty. Eventually, an experience is formed for the agent based on the behaviors that lead to rewards; this algorithm eliminates the need for a predefined policy. In the Q-Learning method, a table with the name Q-Table is constructed. The agent then makes an effort to update its state so that it can choose the optimal action based on the values in the Q-Table, taking into account the many activities it can do. As a result, every agent in action must choose whether to investigate or benefit from the surrounding environment.

3.2.10 Quantum Computing

The increased usage of photovoltaic systems in recent years has sparked interest in investigating their efficiency, particularly in manufacturing these systems. In [87], a modification of the MRFO technique is provided to extract the variables of the Three-Diode photovoltaic Model (TDM). In the evaluation process, many assessment methods are utilized, such as the Root-Mean-Square-Error (RMSE) metric for accuracy and statistical analysis for establishing robustness. The results produced by MRFO and any other optimization technique explored are not as accurate as those obtained by a modification of the MRFO technique.

3.2.11 Spiral

A spiral-based MRFO (SMRFO) was developed to maximize the efficacy of PID control over a flexible manipulator [88]. The first version of MRFO offers performance comparable to others regarding its precision in determining the best possible solution. The system's performance may improve even more if the balanced exploration and exploitation strategies

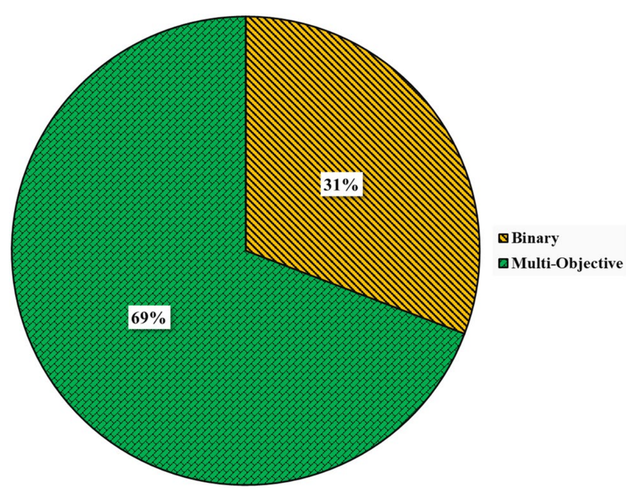


Fig. 16 Two distinct approaches are used to calculate the proportion of MRFO variations

utilized throughout a search operation can be improved. It has been suggested that the MRFO's Somersault phase might need some revisions. A spiral approach is employed as part of the procedure during the Somersault phase of the MRFO. It is done to direct all agents in a spiral-based trajectory toward the best agent in each trajectory iteration. The spiral approach also offers a dynamic step size scheme that may be used by all search agents throughout the process. The SMRFO is evaluated based on benchmark functions, each comprising a different fitness landscape. A PID controller for a flexible manipulator system is optimized using the SMRFO to resolve an engineering issue. It is carried out to enhance the system. The SMRFO performs significantly better than the original MRFO, according to the accuracy performance test results on benchmark functions. SMRFO and MRFO both optimize the PID control to an acceptable level to address the technical problem. Compared to the MRFO-PID, the SMRFO-PID control does a better job of following the bang-bang test input. This evidence shows the advantage of the SMRFO over the MRFO.

3.3 Variants of SSA

In this section, Binary and Multi-objective are checked with the MRFO algorithm. Figure 16 displays the proportion of MRFO variations using two alternative approaches. It indicates that the binary and multi-objective percentages are 31% and 69%, respectively.

3.3.1 Binary

There is a unique time-varying modified sigmoid transfer function with two time-varying updating techniques that have been offered as a strategy for binarization for WOA, PSO, GWO, and HHO, in addition to MRFO. This function can be used for all of these things. The unique binary algorithms BWOA, BPSO, BGWOA, and BMRFO have been implemented to solve the problem of choosing descriptors for the supervised Amphetamine Type Stimulants (ATS) drug classification task. This was done to address the problem [89]. These algorithms are all of the binary variety. This investigation aims to enhance both the rate of convergence and the precision of categorization. Experiments were run on a particular chemical dataset comprising molecular descriptors of non-ATS and ATS medications to assess the performance of the proposed algorithms. The compiled findings provided evidence that the suggested methods displayed promising performances on the chemical dataset. One of these outcomes was near-optimal convergence, as well as enhanced classification accuracy, quicker processing, and a size decrease in the descriptors that was rather significant.

The intrusion detection system (IDS) is one of the most important fundamentals for establishing and maintaining security measures in network settings. It is typically used to identify, monitor, and detect malicious threats. The most current trend delivers an enhanced detection rate by detecting intruders using metaheuristics and machine-learning approaches. Consequently, the objective of this study was to develop an enhanced binary MRFO approach for intrusion detection based on an adaptive S-shape function and a Random Forest (RF) classifier [90]. It is intended to determine which characteristics are the most important for intrusion detection and then exclude features from the datasets that are redundant or not relevant. In addition, the RF is used in the process of feature assessment as well as the construction of the IDS model. The suggested technique was verified and compared to existing methods by utilizing two benchmark IDs, namely CIC-IDS2017 and NSL-KDD datasets. The researchers used these datasets. According to the findings, the given model picked 38 features for the CIC-IDS2017 dataset with an accuracy of 99.3 percent, 99.6 percent precision, 94.3 percent recall, and 96.9 percent f-measure. In addition, the given model chose 22 features for the NSL-KDD dataset with precision, recall, F-measure, and accuracy scores of 98.8 percent, 96.2 percent, and 96.5 percent, respectively.

This study implements swarm intelligence-based feature selection strategies to boost classifier performance when classifying medicines as amphetamine-type stimulants (ATS). A recent study has recommended that 3D Exact Legendre Moment Invariants (3D-ELMI) molecular descriptors be used to show the 3D molecular structure of anti-tuberculous drugs. These characteristics make up the dataset that is used. However, a classifier's performance could degrade if it has a lot of descriptors. Three swarm methods are integrated with a K-Nearest Neighbor (KNN) classifier in the wrapper feature selection technique. This technique selects only pertinent descriptors for the ATS drug categorization challenge [91]. In this work, three swarm algorithms are employed. Binary versions of swarm algorithms, such as the new Binary MRFO and the binary whale optimization Algorithm (BWOA), have been developed for feature selection. These binary swarm methods are aided by an S-shaped or sigmoid transfer function. Their performance is reviewed and graded using seven distinct performance evaluation criteria. In addition, the best feature subset was tested using a total of seven distinct classifiers. The findings of this research have shown that BWOA is superior to other methods because it achieves maximum classification accuracy while maintaining a modest feature size.

In machine learning and data mining, feature selection is regarded as one of the most popular fundamental concepts because of its significant influence on the classification model's overall performance. Eliminating characteristics that are unimportant or just partly relevant may be accomplished by feature selection, which, in turn, contributes to an improvement in the model's overall performance. Researchers have used various metaheuristic optimization methods during their careers for the aim of feature selection because these strategies circumvent the restrictions associated with traditional optimization methodologies. A new approach to feature selection has been created based on a newly presented metaheuristic algorithm termed MRFO [92]. MRFO is helpful for problems involving continuous search space, they modified a binary version of MRFO so that it could be applied to the problem of feature selection. They utilized eight different transfer functions, each of which belonged to either the S-shaped family or the V-shaped family. They tested the eight different binary variants of MRFO on the 18 different standard datasets from UCI. MRFO is superior to other approaches considered to be state-of-the-art in terms of both the classification accuracy and the number of features chosen.

3.3.2 Multi-Objective Optimization

Low measurement frequency trend prediction data are often needed by wind power plants, however, the old multi-step prediction approach had poor forecast accuracy due to error accumulation. They offer a novel approach for predicting future trends in wind speed that employs fuzzy information granulation for data preprocessing and coupled neural network prediction, an enhanced Multi-Objective MRFO (MOMRFO) based on Tent chaotic mapping and T-dist. This system is intended to predict wind speeds in the future. The improved MOMRFO demonstrates that breaking out of the local optimum solution is possible and provides theoretical evidence that the Pareto optimal solution has been reached [93]. As a result of simulating four sets of tests, it has been abundantly clear that the model satisfies the requirements for stability, generalization, and accuracy. As a result of testing the model's capacity to produce point and interval predictions, it has been demonstrated that the model greatly improves the accuracy of trend forecasts, and it also makes a contribution, however little, toward finding a solution to the problem of accurately forecasting wind speeds.

Search algorithms that use a strategy based on Pareto's archival hierarchy are the most successful ways to resolve multi-objective problems characterized by high degrees of complexity. Recently, the crowding distance method has been used to enhance the efficiency of the Pareto-based archiving technique. The MOMRFO is a technique that can determine the optimal solution set for a Multi-Objective Optimal Power Flow (MOOPF) problem [94], even when the fitness functions of the problem are at odds with one another. A technique using the Pareto archiving strategy based on crowding distance that is both powerful and efficient was created to accomplish this goal. The effectiveness of the newly devised approach was evaluated using twenty-four benchmark problems with varying structures and degrees of challenge, and the results were compared to those produced by competing algorithms. Statistical testing techniques were used to analyze the data gathered from the experimental trials and the four distinct performance indicators. The investigation demonstrated that the MOMRFO generated competitive results on a variety of multi-objective optimization problems and discovered the best solutions in the literature for the practical MOOPF problem. In addition, the MOMRFO found the best solutions in the literature.

It is suggested to create a MOMRFO using components from the Non-dominated Sorting GA (NSGAII) [95]. It is only capable of solving problems with a single objective, but it has the potential to handle situations with multiple objectives as well. Therefore, Crowding Distance (CD) tactics and non-dominated sorting (NS) strategies were included in MRFO. The NS method is a sorting strategy derived from Pareto's Front. It is a quick method that may help you establish a positive quality of Pareto's Front (PF). The CD is a mechanism that assures a good distribution of solutions along the PF while this is occurring. NSMRFO is the name of the algorithm that has been proposed. Its performance is evaluated using a variety of benchmark functions, and by statistically analyzing the hypervolume indicator, its performance is contrasted with that of its parent. Then, to evaluate its performance in a real-world setting, it is put via a proportional-derivative controller for an inverted pendulum system. When applied to benchmark functions, the NSMRFO beats NSGAII and optimizes proportional-derivative control for the inverted pendulum system to a satisfactory degree.

The MOMRFO method is used to tackle the Energy Management (EM) problem [65]. This approach is utilized for posture prediction and incorporates an uncertainty-weighted measurement error of the target feature. An enhanced strategy for the management of energy is provided by the multi-objective optimization problem, which takes into account the reduction of both costs and pollution as fitness functions. The model reduces overall cost and emissions by 3.5% and 21.33.3%, respectively. MOMRFO is the starting point for developing a novel algorithm for managing multi-objective engineering design problems [96]. The elitist notion has been used to preserve the whole list of Pareto solutions by including an external archive in the conventional MRFO to accomplish this objective. This archive is also regarded as a repository. Depending on the degree of density, a search agent is selected from it to manage the convergence and variety of the manta ray population. In the first step of the MOMRFO efficiency validation process, comprehensive experiments are performed on ten test functions. The results of these studies were highly satisfying in terms of convergence and diversity in virtually all situations. After that, it was applied to four engineering challenges with numerous objectives. The results revealed that it had a lot of potential for addressing real-world problems with multiple goals.

MOMRFO employs a population archive to keep the non-dominated solutions discovered thus far in the exploration phase [97]. The population archive is combed through to pick the solutions proposed by the leader to direct the Manta Rays population towards potentially fruitful search zones. Crowding distance and -dominance balanced variation and convergence in the likely Pareto set. Five bi-objective and seven three-objective test functions confirmed the MOMRFO. It has also been used for structural design challenges such as the design of welded beams, speed reduction designs, and disk brake designs. The method is evaluated in light of its performance compared to four established multi-objective metaheuristics. According to the study's findings, the MOMRFO surpasses existing multi-objective metaheuristics by giving superior convergence behavior with a broader variety of solutions.

A unique MRFO algorithm is proposed based on a non-dominated sorting strategy and calls it NSMRFO [98]. This strategy aims to solve optimization issues with several criteria. In the search and target space, the strong optimizer may achieve high convergence and dispersion. The NSMRFO algorithm uses an exclusive technique for sorting data. The Pareto front is archived, and the coverage of optimal solutions is increased by including a crowding distance and a non-dominated ranking strategy. They put it through a battery of tests on a variety of issues, including classic unconstrained and restricted functions; a recent benchmark suite dubbed Completions on Evolutionary Computing 2020 (CEC 2020) includes 24 multimodal optimizations and a few engineering design tasks. Wind/solar/small-hydro power generation is used in a modified real-world problem known as the IEEE 30-bus optimum power flow.

The adoption of a MO-MRFO is recommended to improve the efficiency of hybrid alternating current and Multi-Terminal DC (MTDC) power grids [99]. The MO framework aims to achieve economic, technical, and environmental reasons in the AC/MTDC transmission systems by reducing overall production fuel costs, transmission power losses, and environmental pollutants. These three objectives can be met by environmental pollutants, and environmental pollutants, lowering transmission power losses, and lowering overall production fuel costs. The MRFO is modeled after three unique and autonomous manta ray foraging groups. It has been improved by incorporating an additional Pareto archive to keep the non-dominated solution possibilities. It is modifying the form of the fitness function being employed repeatedly, resulting in the dynamic adaptation of the fitness characteristic. Furthermore, a fuzzy decision-making technique is employed to determine the ideal operating point of the AC/MTDC power grids. The apps are evaluated on three distinct platforms. These systems, in addition to being an integral component of the Egyptian grid in the West Delta area, are also tested power systems for the IEEE 30-bus and IEEE 57-bus standards. According to the numerical results, the proposed MO-MRFO has much greater effectiveness and robustness indices than the other choices. The IEEE 33-bus and 69-bus systems, two well-known radial distribution power systems, have been integrated with Distributed Generation (DG) to be optimized [100]. These radial distribution power systems are examples. The simulation results were compared to many alternative optimization methodologies, depending on the circumstance. The MRFO produced satisfactory outcomes while requiring a reduced number of iterations, which resulted in significant time and resourced savings throughout the issue resolution process.

3.4 Optimization Problems

Academics study high-precision algorithms for optimization problems because they can explain a wide range of complicated biological issues. For traditional mathematical optimizations (TMO), the fitness function of the optimization problem must frequently satisfy both convexity and differentiability. This need assures, at least in theory, that TMO approaches may get closer and closer to the best possible answer [101]. TMO cannot handle more complex optimization problems because their fitness functions are multimodal, discontinuous, non-differentiable, and non-convex. Swarm intelligence algorithms are computer programs that replicate the behavior of species found in nature and are frequently used to solve optimization problems to achieve predetermined goals.

The optimization issues are of utmost importance from a scientific and manufacturing point of view. It is an essential and demanding field, particularly in engineering design, which focuses on creating precise and efficient forms [102]. In addition, the viable area could only make up a small part of the search domain. In addition, optimization issues are separated into restricted and unconstrained problems according to whether or not they include equality or inequality restrictions. The various approaches for solving unconstrained optimization issues were classified as direct search and gradient-based methods. Simultaneously, strategies for constrained optimization problems may be separated into indirect and natural approaches. These traditional optimization algorithms are not robust enough to perform well in discontinuous, multimodal, huge, and noisy search spaces. MRFO was developed as an alternative to more conventional optimization strategies to deal with optimization issues due to the inadequacies of such methods. The use of MRFO for various optimization issues is outlined in Table 5.

Table 5 Application of MRFO to various optimization problems

Refs	Application	Convergence speed	exploration	exploitation	Changing Position	Publisher	Year
[103]	Engineering problems	High	High	Medium	Extra high	ScienceDirect	2023
[104]	Economic Dispatch	Medium	Medium	Extra high	Medium	ScienceDirect	2023
[105]	solar photovoltaic	High	High	High	Low	ScienceDirect	2023
[106]	Engineering problems	Medium	High	High	High	ScienceDirect	2023
[107]	Engineering problems	High	High	High	High	ScienceDirect	2023
[108]	image processing	High	Extra high	Low	Medium	ScienceDirect	2023
[109]	prediction	High	High	Medium	Extra high	ScienceDirect	2023
[110]	Engineering problems	Medium	Medium	Extra high	Medium	ScienceDirect	2023
[111]	Engineering problems	Medium	Low	Medium	Medium	ScienceDirect	2023
[112]	Engineering problems	High	High	Low	Extra high	ScienceDirect	2023
[113]	Engineering problems	High	High	High	Extra high	ScienceDirect	2023
[114]	Engineering problems	High	Extra high	Extra high	High	ScienceDirect	2023
[115]	solar photovoltaic	Medium	Low	High	Medium	ScienceDirect	2023
[116]	Engineering problems	Medium	Medium	High	Medium	IEEE	2022
[117]	Engineering problems	Low	Low	High	High	ScienceDirect	2022
[118]	Energy Management	High	High	High	Extra high	MDPI	2022
[119]	PID controlled	Low	Low	Low	Medium	Springer	2022
[120]	Engineering problems	Low	Low	Medium	High	Springer	2022
[121]	prediction	Low	Low	High	High	ScienceDirect	2022
[122]	solar photovoltaic	High	High	Extra high	Extra high	ScienceDirect	2022
[123]	image processing	Low	Low	Medium	High	IEEE	2022
[124]	Scheduling	Medium	Medium	Low	High	IEEE	2022
[125]	Engineering problems	High	High	Extra high	Medium	tandfonline	2022
[126]	optimal Allocation	Low	Low	Medium	High	IEEE	2022
[127]	Energy Management	Low	Low	High	Medium	IEEE	2022
[128]	Engineering problems	Extra high	Extra high	High	High	IEEE	2022
[129]	solar photovoltaic	High	High	Extra high	Extra high	ScienceDirect	2022
[130]	Feature Selection	High	High	High	High	MDPI	2022
[131]	WSNs	High	High	High	Extra high	Hindawi	2022
[132]	Image processing	Low	Medium	Medium	Medium	Hindawi	2022
[133]	cryptanalysis	Medium	Low	High	High	ScienceDirect	2022
[134]	Engineering problems	High	High	Medium	High	IEEE	2022
[135]	Engineering problems	Extra high	Medium	High	High	IEEE	2022
[136]	Engineering problems	Medium	High	Extra high	Low	MDPI	2022
[137]	Engineering problems	Low	Extra high	High	Medium	MDPI	2022
[138]	Engineering problems	High	High	Extra high	High	MDPI	2022
[139]	Engineering problems	High	High	Medium	Extra high	ScienceDirect	2022
[140]	Classification	Medium	Medium	Extra high	Medium	ScienceDirect	2022
[141]	Solar photovoltaic	High	High	High	Low	MDPI	2022
[142]	Engineering problems	Medium	Medium	High	High	Others	2022
[143]	Prediction	High	High	High	High	ScienceDirect	2021
[144]	Engineering problems	Medium	Extra high	Low	Medium	ScienceDirect	2021
[145]	Engineering problems	High	High	Medium	High	Springer	2021
[146]	Energy management	high	Extra high	High	High	IEEE	2021
[147]	Estimation	Low	Medium	Extra high	High	ScienceDirect	2021
[148]	solar photovoltaic	High	Extra high	Medium	High	MDPI	2021
[149]	Estimation	Medium	Medium	High	Extra high	IEEE	2021
[150]	Energy Management	High	High	High	High	ScienceDirect	2021
[151]	Engineering problems	Medium	Extra high	High	High	IEEE	2021
[152]	Engineering problems	High	High	High	Medium	ScienceDirect	2021

Table 5 (continued)

Refs	Application	Convergence speed	exploration	exploitation	Changing Position	Publisher	Year
[153]	Engineering problems	Low	Extra high	High	High	ScienceDirect	2021
[154]	solar photovoltaic	Medium	Medium	Low	Medium	ScienceDirect	2021
[155]	complex problems	High	Medium	Medium	Extra high	Wiley	2021
[156]	Engineering problems	Extra high	High	High	High	ScienceDirect	2021
[157]	Optimal allocation	High	Extra high	Extra high	High	ScienceDirect	2021
[158]	Engineering problems	Low	High	Medium	Medium	ScienceDirect	2021
[159]	complex problems	Medium	Extra high	Low	High	ScienceDirect	2021
[160]	Image processing	Low	medium	High	Medium	ScienceDirect	2021
[161]	Estimation	High	Medium	Extra high	High	MDPI	2021
[162]	Estimation	High	High	High	Extra high	MDPI	2021
[163]	PID controlled	Low	High	High	High	Wiley	2021
[164]	prediction	Medium	High	Extra high	Extra high	Others	2021
[165]	Global optimization problems	Medium	Low	Medium	Medium	ScienceDirect	2021
[166]	Energy Management	High	Medium	High	Extra high	IEEE	2021
[167]	Engineering problems	High	High	High	Extra high	ScienceDirect	2021
[168]	Estimation	High	Extra high	Extra high	High	MDPI	2021
[169]	Optimal allocation	Medium	Medium	High	High	MDPI	2021
[170]	Engineering problems	High	Low	High	Medium	MDPI	2021
[171]	Economic Dispatch	High	High	Medium	High	IEEE	2021
[172]	Engineering problems	Extra high	High	High	High	ScienceDirect	2021
[173]	Energy Management	Medium	Medium	Medium	High	IEEE	2021
[174]	solar photovoltaic	High	High	High	Low	ScienceDirect	2021
[175]	Energy Management	Extra high	High	Extra high	Medium	online library.Wiley	2021
[176]	Economic Dispatch	Medium	High	High	High	IEEE	2021
[177]	Energy Management	High	High	Extra high	Extra high	online library.Wiley	2021
[178]	Engineering problems	High	High	Medium	Medium	Springer	2021
[179]	image processing	Extra high	Low	Extra high	Low	ScienceDirect	2021
[180]	solar photovoltaic	High	Medium	Medium	High	ScienceDirect	2020
[181]	Energy Management	Medium	Extra high	High	Medium	IEEE	2020
[182]	Energy Management	High	Medium	Extra high	High	MDPI	2020
[183]	Engineering problems	Medium	Low	High	High	IEEE	2020
[184]	Economic Dispatch	High	High	High	High	IEEE	2020
[185]	Engineering problems	Extra high	High	Medium	High	IEEE	2020
[186]	solar photovoltaic	High	Medium	High	Low	IEEE	2020
[187]	Engineering problems	Extra high	High	Medium	Medium	IEEE	2020
[188]	Engineering problems	Medium	High	High	High	ScienceDirect	2020
[189]	Estimation	High	High	Extra high	Extra high	Online library.Wiley	2020

To perform global numerical optimization, many MRFO models have been presented in the research literature; each model seeks to profit from certain subdimensions of the search space intelligently. In every one of the difficulties, optimization methods have been used to locate the best possible design and save costs in some way (such as the amount of material, operational cost, precision, and reduced error). The number of papers that pertain to optimization issues in various domains is shown in Fig. 17. Most of the publications found on optimization problems are related to engineering issues.

4 Results and Discussion

Even though MRFO is often regarded as the best method for a wide variety of optimization applications, it cannot strike a healthy equilibrium between exploration and exploitation. When it comes to multimodal functions, MRFO does not adequately investigate the whole area, and as a result, it often suffers from early convergence or loss of variety. Several different models have been proposed as a solution to this issue to address it. Most strategies, including exploration and exploitation, may be altered by the appropriate control

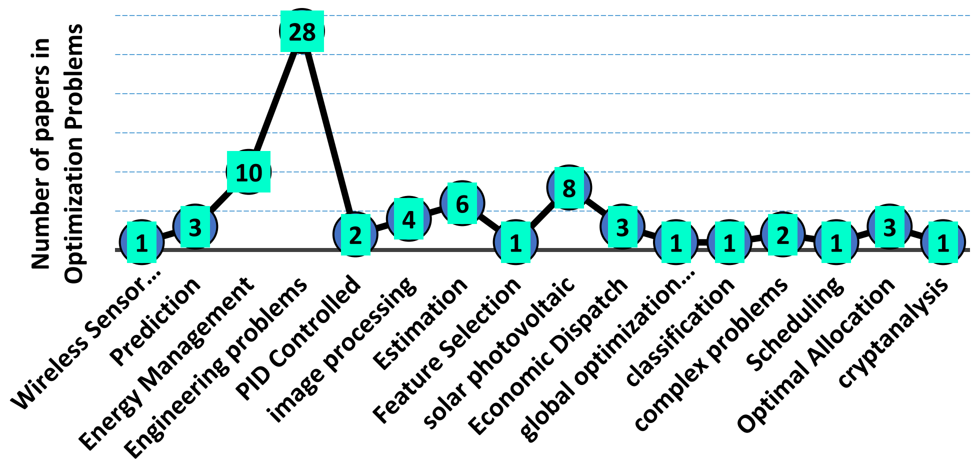


Fig. 17 Shows the number of papers belonging to optimization problems in different fields

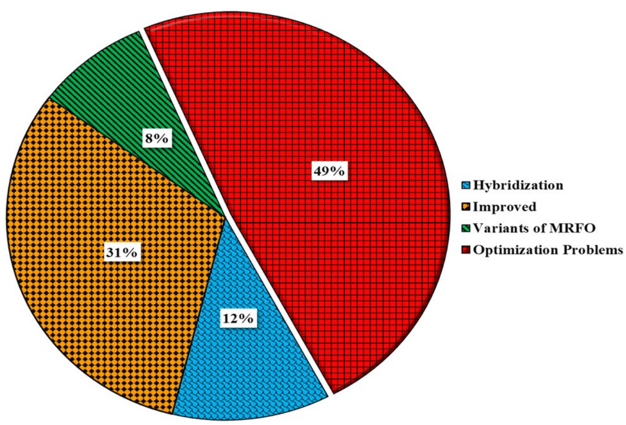


Fig. 18 A percentage breakdown of MRFO procedures according to four distinct categories

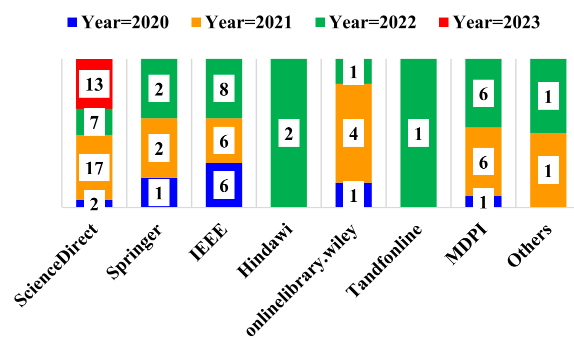


Fig. 19 Graph of the number of papers based on the year and type of publisher for optimization problems

variables, affecting the algorithm's search capabilities. Exploration should be the initial focus of MRFO's strategy, with exploitation coming later on as a natural progression. It is a systematic approach. In other models, the population size is used to alter the proportion of resources allocated to exploration and use. A lower population size necessitates a more focused investigation, whereas a more significant population needs a more comprehensive one. Although this method provides a more straightforward means to maintain variety, its answer is often unsatisfying. Incorrect management of huge populations may cause data to converge to a single point, despite adding more function evaluations. In Fig. 18, the categories with the most significant percentages are Optimization and Improved, which both have a value of 49 percent. Improved came in third with a value of 31 percent. In light of this, the MRFO algorithm is more beneficial in these two domains.

The most current research in this field demonstrates that MRFO can tremendously resolve intricate engineering optimization issues. The current research community in a variety of fields, including engineering problems, electrical and power systems, training ANNs, prediction, applied mathematics, WSNs, path planning, data mining and machine learning, and structure design, has shown an outstanding amount of interest in this method due to its apparent benefits, which include simplicity, flexibility, a fast convergence speed, and stochastic nature. These benefits include the following: simplicity, flexibility, a fast convergence speed, and stochastic nature. It has received an extraordinary amount of attention from the scientific community. The MRFO is notable for several reasons, including that it implements both the exploration (global search) and exploitation (local search) searching strategies equitably and that it can successfully carry out its operations despite having a smaller number of variables. Consequently, it constructs a highly robust framework that takes advantage of a special convergence rate.

In contrast to many other metaheuristic algorithms, MRFO is known to have a few shortcomings. According to the current body of research, the global exploration phase of basic MRFO is where its strength rests. However, there are instances when it may get mired in an optimal local solution and fail to perform the global search fully. Due to these limitations, researchers are urged to modify it and combine it with other tactics or metaheuristics to address high-dimensional problems. The graph of the number of papers for optimization problems is shown in Fig. 19. The chart is based on the year and the kind of publication.

They summarize the most significant advantages and disadvantages connected with the MRFO. Advantages of the MRFO algorithm are:

Low parameter count and simple implementation
Other than the population size and the number of repeats, there are no specific control elements. In addition, the structure is simple, and its implementation takes low computational work.
The straightforwardness of MRFO may be seen by examining the amount of computing complexity it entails.
High-quality solutions
Low generating costs and good convergence qualities
SSA is highly competitive in finding optimal values
balance rule between exploration and exploitation
Diversity of the population
Obtaining reliable answers efficiently while spending less time computing
Prevent premature convergence
Contributes to a better overall balance between local and global searches
short computational time computational time

And disadvantages of the MRFO algorithm are:

Inconsistency in the local and global search
premature convergence
Increase iteration with increasing the size of the problems
trapping into the local optima

However, in the same way, that other metaheuristics do, MRFO has a few flaws, the most notable of which are its early convergence, the propensity to become stuck in an optimal local solution, and lackluster exploration. Many researchers have resorted to diverse methodologies, including chaotic, fuzzy, Lévy flight, and OBL, to increase the effectiveness of MRFO in the current field of research.

The chaotic MRFO is offered to attain a more incredible convergence speed to preserve the variety of particles and produce an initial population that is evenly distributed. During the exploration phase, chaotic unpredictability and ergodicity may be used to prevent becoming stuck in local optimum places. It is one of the ways that the shortcomings of the basic MRFO algorithm can be mitigated. One of the most typical issues confronted by group intelligence algorithms is the coordination between global and local investigations. A strong capacity for global exploration may help guarantee a community's demographic variety. In addition, the high local exploration capability may help to ensure that the findings are accurate and precise. Therefore, it is vital to compromise the MRFO algorithm's global exploration and local exploration capabilities. The linear convergence factor is unable to provide an accurate representation of the actual optimization process. Therefore, a nonlinear convergence factor such as chaos has been established to achieve an equilibrium between global and local investigation capabilities. The MRFO method is improved to include the chaotic algorithm to preserve population variance and provide an initial population with uniform distribution. This modification ultimately results in a higher convergence speed. An increased capacity to explore globally indicates that the population has the appropriate amount of variety, and a solid ability to explore locations leads to greater accuracy.

Two primary benefits come along with using Lévy Flight for MRFO. The Lévy Flight is a variation of a unique kind of random walk with many small excursions interspersed with a few longer ones. The Lévy flight follows a power-law step-length distribution with a long tail, allowing MRFO to build possibly improved solutions. It enables MRFO to develop solutions that are far removed (i.e., by large jumps) from the present best answer. A significant number of iterations allows the Lévy fly to discover every critical point in the search region, which means that it always finds the best solution. Second, there are fewer control variables in MRFO than in other optimization algorithms; this implies that MRFO-LF is significantly better suited to a wider variety of optimization issues than other optimization techniques.

In machine learning, feature selection has proven to be a substantial difficulty. Feature selection is regarded as an NP-hard task because of the ever-increasing amount of time needed to find the most relevant characteristics within a dataset with a high dimension. MRFO is a highly effective and efficient method for selecting the optimal subset of a dataset, and they can do it while preserving the model's accuracy.

5 Conclusion and Future Works

The advantages and disadvantages of the MRFO for metaheuristic optimization algorithm researchers have been collected from over 154 research articles. The references published between the beginning of 2020 and the beginning of 2022 are summarized in this study in an all-encompassing and complete manner. The majority of these papers detailed the various iterations of the MRFO, where the proposed versions of the MRFO support enhancing the original MRFO's ability to address various types of optimization problems, including multi-objective, binary, chaotic, modification, hybridization, and optimization problems. The majority of these papers were written in the form of academic papers. In addition, describe how the MRFO can be utilized in a variety of contexts and engineering applications. In the areas where researchers considered it helpful and advantageous to handle optimization problems, the findings gained through studies and evaluations of these references provide supporting evidence. As a result of this, it is considered that this review paper might be suitable and valuable for students, academic researchers, professionals, and engineers. In addition to this, it has the potential to serve as an original and exhaustive reference for forthcoming academic papers and books that deal with the MRFO, optimization techniques, and metaheuristic optimization algorithms.

In conclusion, it can be said that there is still room or chance for performance enhancement and that the MRFO has the potential to be expanded into other hybridizations, modifications, modified versions, and variations depending on the requirements of the specific challenges. As a consequence, the findings of this review paper could be used by interested researchers to demonstrate various methods for achieving an improvement goal. These methods need to consider the applications, benefits, and drawbacks of other methodologies that researchers have introduced. There are some limitations to this paper, which are as follows:

Lack of empirical studies: although the paper mentions the effectiveness of the MRFO algorithm in solving real-world problems, it does not provide any empirical studies to validate its claims. The paper only provides a statistical analysis of the studies that have used the MRFO algorithm.

Limited scope: the paper only focuses on the MRFO algorithm and does not compare it with other meta-heuristic algorithms. It also does not provide a comprehensive analysis of the strengths and weaknesses of the MRFO algorithm. Limited discussion on parameter tuning: The paper briefly mentions the impact of different parameters and operators on the performance of the MRFO algorithm. However, it does not provide a detailed discussion on how to tune these parameters to achieve better results.

Lack of practical examples: the paper does not provide practical examples of the MRFO algorithm's application in solving real-world problems. It only provides a brief overview of the engineering applications of the MRFO algorithm.

This paper suggests that researchers should focus on developing hybrid versions of the MRFO algorithm by combining it with other meta-heuristic algorithms to improve its performance and overcome its limitations. The paper also recommends exploring the application of the MRFO algorithm in dynamic environments and multi-objective optimization problems. Additionally, the paper suggests that researchers should investigate the impact of different parameters and operators on the performance of the MRFO algorithm. In terms of potential paths for the future, we propose making use of and improving the MRFO by including additional method components to make more advancements in the resolution of a variety of optimization issues. In our following study, we are going to concentrate on the following points of view:

Using MRFO to solve multi-objective optimization problems.

Changing the MRFO to address outstanding optimization problems

MRFO adaptation to address unsolvable optimization problems via MRFO

The MRFO is used to address multi-objective optimization problems.

It involves adopting the MRFO to deal with real-world challenges such as NP-hard and discrete optimization problems.

It combines the MRFO with additional metaheuristic algorithms to meet real-world challenges such as NP-hard and discrete optimization problems.

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Data Availability This paper is a survey paper, that why there is not any data used in this paper.

Declarations

Conflict of Interest The authors declare that they have no conflict of interest.

Ethical Approval No human or animal studies were conducted by any of the authors.

Replication of Results The only results presented in this paper are in Figures, Tables, and in Sect. 4.

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