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SURVEY

Manta Ray Foraging Optimization Algorithm: Modifications and Applications

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ABSTRACT The novel metaheuristic manta ray foraging optimization (MRFO) algorithm is based on the smart conduct of manta rays. The MRFO algorithm is a newly developed swarm-based metaheuristic approach that emulates the supportive conduct performed by manta rays in search of food. The MRFO algorithm efficiently resolves several optimization difficulties in various domains due to its ability to provide an equilibrium between global and local searches during the search procedure, resulting in nearly optimal results. Thus, researchers have developed several variants of MRFO since its introduction. This paper provides an in-depth examination of recent MRFO research. First, the paper introduces the natural inspiration context of MRFO and its conceptual optimization framework, and then MRFO modifications, hybridizations, and applications across different domains are discussed. Finally, a meta-analysis of the developments of the MRFO is presented along with the possible future research directions. This study can be useful for researchers and practitioners in optimization, engineering design, machine learning, scheduling, image processing, and other fields.

INDEX TERMS Global search, local search, manta ray foraging optimization (MRFO), metaheuristic, optimization.

I. INTRODUCTION

The application of optimization algorithms to address numerous complex optimization problems has recently risen. Before this progress, mathematical procedures, such as dynamic, linear, and nonlinear programming, were applied to manage complex optimization problems. These techniques efficiently obtain optimal solutions but cannot be applied to a wide range of nondeterministic polynomial-time complete problems, where the exact solution cannot be obtained in polynomial time, and the time complexity increases exponentially with the input. Thus, these techniques are unsuitable for real-world applications [1], [2].

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Metaheuristic optimization algorithms, which emerged from the study and simulation of intelligent conduct and processes in nature, have been proposed to address these limitations [3], [4]. These algorithms effectively determine nearly optimum solutions to complex optimization problems in polynomial time, especially when managing large-scale problems. Furthermore, metaheuristic algorithms can overcome a significant problem of local search algorithms, the entrapment of solution search agents in local regions far from the intended global solution region. Avoidance of entrapment in local optima is the primary design challenge of metaheuristic algorithms. Global optima are achieved using intelligent stochastic operators for exploring the entire search space. Therefore, the entire search performance of metaheuristic algorithms relies on an adequate balance between exploration and exploitation.

Exploration is a randomization strategy that attempts to drive the algorithm procedure to search the entire search space diversely, whereas exploitation deals with enhancing the current solution to the problem by examining the vicinity of such solutions. Numerous solution areas may be loosely explored if the exploration is high, resulting in a low convergence speed. In contrast, if the exploration is low in the algorithm design, numerous solution areas might be left unsearched, resulting in nonoptimal solutions due to entrapment in local optima. Adequate exploitation is achieved by searching within the vicinity of the acquired solution and adequately tuning the control parameters of the algorithm to the convergence rate [5].

Recently, the development of new advanced metaheuristic algorithms has been on the rise, and they are categorized based on their working methodologies. These procedures have been useful in resolving real-world optimization difficulties arising in various domains, including engineering, medicine, industrial planning, resource scheduling, computer science, and transportation, among others.

Based on the operational working of these algorithms, they are categorized into evolution-based, physics-based, and swarm intelligence algorithms [6], but most fall under swarm intelligence, as they are motivated by simulating intelligent conduct demonstrated by biological agents. Some of these algorithms include the sailfish optimizer [7], salp swarm algorithm (SSA) [8], memetic algorithm [9], genetic algorithm (GA) [10], particle swarm optimization (PSO) [11], differential evolution (DE) [12], ant colony optimization (ACO) [13], bat optimization algorithm [14], tunicate swarm algorithm [15], emperor penguin optimizer [16], symbiotic organism search [17], marine predator algorithm [18], and manta ray foraging optimization (MRFO) [19]. The existing metaheuristic algorithms are distinguished by the balancing strategy between exploration and exploitation, the solution update scheme, or phenomena that inspired the algorithm design. Regardless of their categories, metaheuristic algorithms are primarily placed into two groups based on the literature: single or population based. In the single-based methods, the search usually begins with the solution of one candidate, which is enhanced during each iteration. In contrast, the population-based metaheuristic begins the search process with an initial random population, enhanced during iterations, effectively exploring the search area. The concept of memetic algorithms aims to hybridize the strategies of single- and population-based approaches to provide a decent equilibrium between the exploration and exploitation of the search procedure.

The article suggests that surveying the MRFO algorithm could be a novel approach in several ways. First, it provides a comprehensive review of the literature on MRFO, highlighting areas for future research. Second, it compares the MRFO algorithm with other optimization algorithms to identify its unique features and differences from the others. Third, it identifies the potential practical applications in various fields, such as engineering, machine learning, scheduling, and image processing. Finally, the survey focuses on future directions for researchers aiming to modify, improve, or apply MRFO in other fields. Overall, the survey could provide a valuable contribution to optimization algorithms. Table 1 lists the abbreviations used in the paper.

II. MANTA RAY FORAGING OPTIMIZATION PROCEDURE

The MRFO algorithm is a new population-based metaheuristic approach presented in [19]. This section discusses and analyses the MRFO algorithm from various optimization viewpoints. The motivation behind MRFO is presented, and the practical stages of the MRFO algorithm are provided.

A. MOTIVATION BEHIND THE MRFO ALGORITHM

The MRFO algorithm is a newly developed swarm-based approach that imitates the food-searching behavior of manta rays. The algorithm uses three strategies manta rays employ to search for plankton: chain food searching, cyclone food searching, and somersault food hunting. These strategies identify the location with the highest plankton density, which is returned as the best solution to the optimization problem. This social conduct was imitated to design the MRFO algorithm to handle global optimization problems, in which the location with the highest density is returned as the best solution to the considered problem.

B. PROCEDURAL STAGES OF THE MRFO ALGORITHM

The procedural stages and model of the MRFO algorithm are discussed and presented. These stages are the chain, cyclone, and somersault food-searching approaches. The procedural stages of the MRFO algorithm are presented in Fig. 1. Moreover, Algorithm 1 provides the pseudocode.

1) CHAIN FOOD-SEARCHING APPROACH

In this approach, every manta ray updates its present location using the best solution obtained and the position of the one in front of it, excluding the first one, which updates its location according to the best solution so far achieved. This approach is represented by the mathematical system of equations in (1):

$$p_k^{itr+1} = \begin{cases} p_k^{itr} + rn * \left(Gbest^{itr} - p_k^{itr}\right) + 2 * rn \\ \quad * \sqrt{|\log(r)|} * \left(Gbest^{itr} - p_k^{itr}\right) & k = 1 \\ p_k^{itr} + rn * \left(p_{k-1}^{itr} - p_k^{itr}\right) + 2 * rn \\ \quad * \sqrt{|\log(r)|} * \left(Gbest^{itr} - p_k^{itr}\right) & k = 2, \ldots, N \end{cases} \tag{1}$$

where rn denotes a number between [0, 1], N represents the total number of manta rays (i.e., population size), p_k^{itr} is the location of the k^{th} manta ray in iteration itr, p_k^{itr+1} defines its new location in the coming iteration, and $Gbest$ depicts the best global solution achieved.

TABLE 1. List of abbreviations.

Abbreviation	Meaning	Abbreviation	Meaning
ACO	Ant colony optimization	MOOPF	Multiobjective optimal power flow
ANFIS	Adaptive neuro-fuzzy inference system	MRFO	Manta ray foraging optimization
		MTDC	multiterminal DC
CNN	Convolutional neural network	NM	Nelder–Mead
DE	Differential evolution	NN	Neural network
DG	Distributed generator	Ob-MRFONM	Opposition-based manta ray foraging optimization with Nelder–Mead
ELM	Extreme learning machine	OBL	Opposition-based learning
FLC	Fuzzy-logic control	OPF	Optimal power flow
FLS	Fuzzy-logic system	PD	Proportional-derivative
FFNN	Feedforward neural network	PI	Proportional-integral
GA	Genetics algorithm	PID	Proportional-integral-derivative
GRU	Gated recurrent unit	PV	Photovoltaic
GSA	Gravitational search algorithm	RVFL	Random vector functional link
GWO	Gray wolf optimization	RMSE	Root mean squared error
HHO	Harris hawks optimization	SCA	Sine cosine algorithm
HMRFO	MRFO with a hybrid genetic operator	SHADE	Success history-based parameter adaptive differential evolution
IMRFO	Improved MRFO	SSA	Shark-smell algorithm
MFO	Moth-flame optimization	SMRFO	Spiral-based MRFO
MGEHO	Manta ray foraging and Gaussian mutation-based elephant herding optimization	SQP	Sequential quadratic programming
MHKC	Merkle–Hellman knapsack cryptosystem	WOA	Whale optimization algorithm
MO	Multiobjective	XGBoost	Extreme gradient boosting

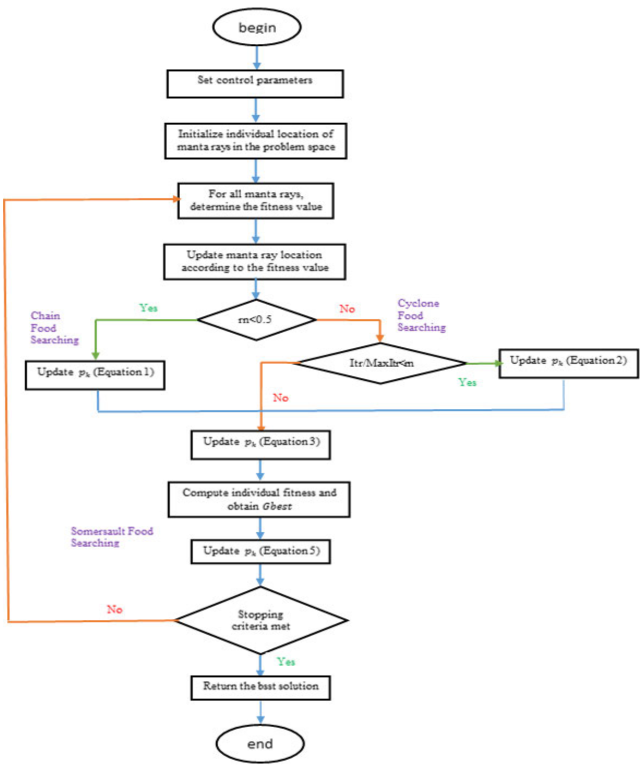

FIGURE 1. Flowchart depicting the manta ray foraging optimization procedure.

2) CYCLONE FOOD-SEARCHING APPROACH

In this approach, the manta rays walk in the search domain cyclically. Subsequently, the cyclone approach is mathematically represented using (2):

$$p_k^{itr+1} = \begin{cases} Gbest + rn * \left(Gbest^{itr} - p_k^{itr}\right) + 2* \\ \quad e^{rn*\frac{MaxItr-itr+1}{MaxItr}} * \sin\left(2*\pi*rn\right) * \left(Gbest^{itr} - p_k^{itr}\right), \\ \quad k = 1 \\ Gbest + rn * \left(p_{k-1}^{itr} - p_k^{itr}\right) + 2* \\ \quad e^{rn*\frac{MaxItr-itr+1}{MaxItr}} * \sin\left(2*\pi*rn\right) * \left(Gbest^{itr} - p_k^{itr}\right), \\ \quad k = 2, \ldots, N \end{cases} \tag{2}$$

where $MaxItr$ indicates the number of iterations to perform by the algorithm, and rn defines the number in the interval of [0, 1]. Manta rays make a random walk by updating their locations based on random positions to enhance diversification, as mathematically performed in (3):

$$p_k^{itr+1} = \begin{cases} p_{rn} + rn * \left(p_{rn}^{itr} - p_{rn}\right) + 2 * e^{rn*\frac{MaxItr-itr+1}{MaxItr}} * \\ \quad \sin\left(2*\pi*rn\right) * \left(p_{rn}^{itr} - p_k^{itr}\right), \\ \quad k = 1 \\ p_{rn} + rn * \left(p_{k-1}^{itr} - p_k^{itr}\right) + 2 * e^{rn*\frac{MaxItr-itr+1}{MaxItr}} * \\ \quad \sin\left(2*\pi*rn\right) * \left(p_{rn}^{itr} - p_k^{itr}\right), \\ \quad k = 2, \ldots, N \end{cases} \tag{3}$$

where p_{rn} represents a reference point in the search domain defined in (4):

$$p_{rn} = LowerBound + rn * (UpperBound - LowerBound). \tag{4}$$

The lower and upper boundaries of the search domain are defined, respectively, as *LowerBound* and *UpperBound.*

3) SOMERSAULT FOOD-SEARCHING APPROACH

Each manta ray adjusts its location in this approach by performing a somersault walk in the direction of the best location discovered thus far. The mathematical description of this strategy is provided in (5):

$$p_k^{itr+1} = p_k^{itr} + Somersault\ factor * (rn_1 * Gbest - rn_2 * p_k^{itr}), i = 1, \ldots, N. \tag{5}$$

The *somersault factor* is given as 2, and rn_1 and rn_2 represent numbers in the interval (0, 1).

III. RECENT VARIANTS OF MRFO

Researchers have proposed improved versions of the MRFO algorithm to address its limitations and improve its performance. These improved versions use various techniques, such as adaptive learning rates, hybridization, multistrategy searches, dynamic parameter adaptation, and dynamic search space partitioning, to enhance the search capabilities of the algorithm. These improved versions of the MRFO algorithm have displayed promising results in solving complex optimization problems. Several versions of the native MRFO have recently been developed since its introduction to guarantee decent stability between the exploration/exploitation and boost the ability and power of classical MRFO. In this review, numerous variations of MRFO are categorized into modified and hybridized variants, as indicated in Fig. 2.

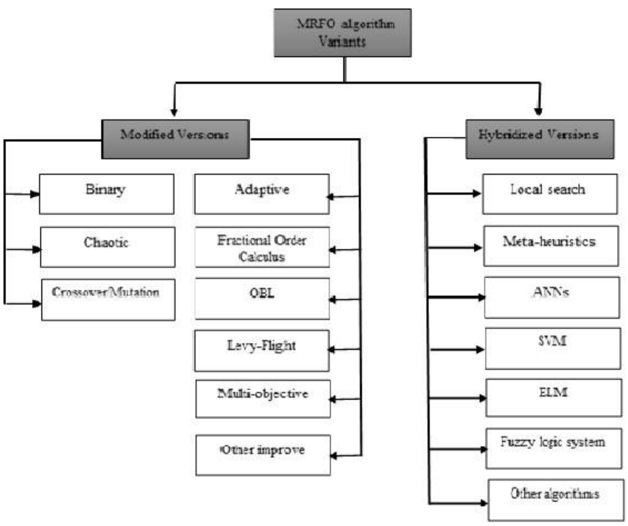

FIGURE 2. **Different manta ray foraging optimization variations.**

Algorithm 1 Manta Ray Foraging Optimization Algorithm

Initialize the manta ray (agents) populations $k = 1, \ldots, N$
while *stopping criteria not satisfied* ***do*** ***for*** $k = 1, \ldots, N$, ***do*** ***if*** $rn < 0.5$, ***then*** ***if*** $\left(\frac{itr}{MaxItr}\right) < rn$ ***then***, ***//Cyclone food searching*** $p_{rn} = LowerBound + rn * (UpperBound - LowerBound)$

$$p_k^{itr+1} = \begin{cases} p_{rn} + rn * (p_{rn}^{itr} - p_{rn}) + 2 * e^{rn * \frac{MaxItr - itr + 1}{MaxItr}} * \\ \sin(2 * \pi * rn) * (p_{rn}^{itr} - p_k^{itr}), \\ k = 1 p_{rn} + rn * (p_{k-1}^{itr} - p_k^{itr}) + 2 * \\ e^{rn * \frac{MaxItr - itr + 1}{MaxItr}} * \\ \sin(2 * \pi * rn) * (p_{rn}^{itr} - p_k^{itr}), \\ k = 2, \ldots, N \end{cases}$$

else

$$p_k^{itr+1} = \begin{cases} Gbest + rn * (Gbest^{itr} - p_k^{itr}) + 2 * \\ e^{rn * \frac{MaxItr - itr + 1}{MaxItr}} * \\ \sin(2 * \pi * rn) * (Gbest^{itr} - p_k^{itr}), \\ k = 1 Gbest + rn * (p_{k-1}^{itr} - p_k^{itr}) + 2 * \\ e^{rn * \frac{MaxItr - itr + 1}{MaxItr}} * \\ \sin(2 * \pi * rn) * (Gbest^{itr} - p_k^{itr}), \\ k = 2, \ldots, N \end{cases}$$

end if *else* //Chain food searching

$$p_k^{itr+1} = \begin{cases} p_k^{itr} + rn * (Gbest^{itr} - p_k^{itr}) + 2 * rn * \sqrt{|\log(r)|} \\ * (Gbest^{itr} - p_k^{itr})\ k = 1 p_k^{itr} + rn * (p_{k-1}^{itr} - p_k^{itr}) \\ +2 * rn * \sqrt{|\log(r)|} \\ * (Gbest^{itr} - p_k^{itr})\ k = 2, \ldots, N \end{cases}$$

end if
// Compute fitness for the k^{th} **manta ray** $f(p_k^{itr+1})$ ***if*** $f(p_k^{itr+1}) < f(Gbest^{itr})$, ***then*** $Gbest^{itr} = p_k^{itr+1}$ ***end if*** ***end for*** **// Somersault food searching** ***for*** $k = 1, \ldots, N$, ***do*** $p_k^{itr+1} = p_k^{itr} + somersaultfactor * (rn_1 * Gbest - rn_2 * p_k^{itr}), i = 1, \ldots, N$ **// Compute fitness for** k^{th} **manta ray** $f(p_k^{itr+1})$ ***if*** $f(p_k^{itr+1}) < f(Gbest^{itr})$, ***then*** $Gbest^{itr} = p_k^{itr+1}$ ***end if*** ***end for***
end while

A. MODIFIED VARIANTS OF MRFO

This section presents the modified versions of MRFO, categorized as binary, chaotic, opposition-based lines, Levy-flight mechanisms, crossover/mutation operators, adaptive, fractional-order calculus (FC), multiobjective (MO), and other methods. The recently improved forms of MRFO are summarized in Table 2, and the details are provided below.

1) BINARY MRFO

The binary version of MRFO has been applied to solve various binary optimization problems, such as binary knapsack problems, binary integer programming, and feature selection problems. One advantage of the binary version of the MRFO is that it can address problems with numerous decision variables, making it suitable for high-dimensional binary optimization problems. For instance, Ghosh et al. [20]

presented a binary MRFO using the V- and S-shaped transfer functions for solving attribute extraction problems. Eight diverse continuous-to-binary conversion functions, four each from S- and V-shaped functions, were applied in the binary MRFO to make it suitable for addressing the attribute extraction problem.

Hassan et al. [21] presented an intrusion detection model using a new binary MRFO algorithm based on the adaptive S-shaped transfer function and the random forest (RF) classifier. The adaptive binary MRFO was proposed to enhance the performance of the MRFO in identifying the most critical features in detecting network intrusions. Based on the selected features, the proposed approach employed the RF classifier to classify the network intrusions. In summary, the binary version of MRFO is a robust metaheuristic algorithm that can efficiently solve a wide range of binary optimization problems by representing the decision variables as binary strings and employing binary selection, crossover, and mutation operators.

2) CHAOTIC MRFO

The chaotic version of the MRFO algorithm introduces chaos theory concepts to improve its exploration and exploitation abilities. Chaotic maps generate random numbers to initialize the population and update the search directions of the manta rays. One standard chaotic map used in the chaotic version of the MRFO algorithm is the logistic map, a one-dimensional (1D) map extensively studied in chaos theory. The chaotic version of the MRFO algorithm uses the logistic map to generate random numbers to initialize the population and update the search directions of the manta rays. The chaotic version of the MRFO algorithm also uses chaotic local search techniques to improve the search process. In a chaotic local search, a chaotic map generates random numbers that determine the direction and magnitude of the search movement. The search process is performed in the local search area around the current solution, and the chaotic map determines the search movement.

Xu et al. [22] designed a modified MRFO called the developed MRFO, where two adjustments were introduced to solve the early convergence problem of the original MRFO. The first adjustment introduced a self-adaptive weighting strategy to update the particle locations in somersault foraging to the random control values. In the second adjustment, a logistic map was incorporated into the cyclone and somersault foraging update location equation to replace the random values and somersault factor to reduce the problem of trapping in the local optima.

Turgut [23] optimized a real-world design problem using chaos-improved MRFO. The author applied more than 20 chaotic maps to MRFO to replace various random numbers required in the update position equations for MRFO and the ten best-performing methods for validation. Additionally, the chaotic MRFO variations were employed to maintain the thermo-economic design optimization of an air-fin cooler to assess the capacity to overcome challenging engineering design problems. The proposed chaotic-based MRFO significantly improved the objective function values for the thermal design problem.

Ćalasan et al. [24] incorporated a logistic map into MRFO to find the parameters of a single phase and two new transformers. Furthermore, the authors proposed a no-load damage function in the assessment procedure as a fitness function. The chaotic MRFO parameters were contrasted with the original MRFO and other approaches from the literature to measure the efficacy of the presented approach using the values obtained by the classical test method suggested by IEEE. The outcomes suggest that the chaotic MRFO-based predicted factors assist output characteristics, which agree with the experimental characteristics.

Qiufeng and Genbei [25] proposed an enhanced MRFO for fiber Bragg grating demodulation, where a tent-chaotic map was used to enhance the initial population, and various DE operators were also incorporated to enhance the individual update location strategy. The experimental outcomes for the multifiber Bragg grating overlapping spectrum indicate that the proposed approach can effectively demodulate the center wavelength of the overlapping spectrum, efficiently reducing the probability of trapping in the local optimum and enhancing the reliability and stability of the algorithm.

In summary, the chaotic version of the MRFO algorithm is a robust metaheuristic algorithm that can efficiently solve optimization problems by introducing chaos theory concepts into the search process. The algorithm can improve the exploration and exploitation abilities of the search process using chaotic maps to generate random numbers and incorporating chaotic local search techniques, leading to better-quality solutions.

3) OPPOSITION-BASED LEARNING MRFO

The opposition-based learning (OBL) MRFO algorithm combines OBL and MRFO to enhance search efficiency and accuracy. In OBL-MRFO, each ray in a group is duplicated, and the duplicate is assigned the opposite position of the original. The opposite position is obtained by inverting the values of each dimension of the original position. The fitness of the original and opposite rays is evaluated, and the best solution is selected to update the position of the original ray. This process is repeated for all rays in the group, increasing the diversity of the population and improving the convergence speed.

Feng et al. [26] suggested improved MRFO (IMRFO) with two adjustments. First, a popular approach, the OBL method, was incorporated to achieve further efficient results in the algorithm. A self-adaptive technique was applied for individual size adjustment in the second adjustment. The IMRFO was applied to reduce energy consumption by constructing shape optimization.

Furthermore, Ekinci et al. [27] suggested an effective approach via an IMRFO to regulate magnetic object deferment. The IMRFO algorithm combined the native MRFO, generalized OBL, and Nelder–Mead (NM) approaches. The enhanced MRFO is the opposition-based MRFO with NM (Ob-MRFONM). In Ob-MRFONM, the NM approach was added to boost the algorithm exploration search capability, whereas generalized OBL provides a better exploitation search capability.

Houssein et al. [28] presented an IMRFO for resolving multilevel thresholding using computed tomography (CT) images of the coronavirus disease 2019 (COVID-19). In this study, to enhance the population diversity of the native MRFO, an OBL mechanism was integrated at the initialization stage of MRFO. This improved algorithm is called MRFO based on OBL. The presented MRFO-OBL was assessed using Otsu's technique and was contrasted using the sine cosine algorithm (SCA), moth-flame optimization (MFO), equilibrium optimizer, whale optimization algorithm (WOA), SSA, and the native MRFO algorithm.

Abdul Razak et al. [29] offered a quasi-oppositional MRFO for proportional-integral-derivative (PID) control of a pendulum system. The study incorporated a quasi-based OBL to improve results by considering the opposite agent fitness positions. Abdul Razak et al. [30] also suggested an enhanced MRFO using an OBL approach called quasi-reflected opposition, which was integrated into MRFO to enhance the ability of MRFO to obtain better result accuracy and a better convergence rate.

In summary, the OBL-MRFO is a robust optimization algorithm combining the strengths of opposition-based learning and MRFO. Its effectiveness has been demonstrated in various applications, and further research may focus on reducing its computational cost to extend its application to larger problems.

4) MRFO WITH LEVY-FLIGHT MECHANISM

In the Levy-flight version of the MRFO algorithm, the manta rays move randomly in the search space by performing a combination of the random walk and Levy flight. The random walk is performed to explore the local search space, whereas the Levy flight explores the global search space. The direction and step size of the Levy flight are determined by a probability distribution function called the Levy distribution. The combination of the Levy flight and MRFO algorithm improves the exploration ability of the search process, enabling the algorithm to escape from local optima and determine better solutions faster. Furthermore, the Levy-flight version of the MRFO algorithm is more suitable for high-dimensional optimization problems because it can explore the search space more efficiently.

Sheng et al. [31] proposed a modified MRFO called balanced MRFO to reduce the sum of the squared error between the simulated and estimated output voltages for better agreement among them to model and experiment with the proton-exchange membrane fuel cell. In the suggested balanced MRFO, a Levy-flight mechanism was incorporated in the update mechanism of the cyclone foraging to improve the convergence ratio of MRFO. Moreover, the constant somersault factor in the original MRFO was replaced with a sinusoidal chaotic map to prevent entrapment in the local optima.

Hao and Xianyu [32] presented an enhanced MRFO via the Levy-flight scheme, enhancing its ability to escape the local minimum and balance its local and global search ability. The proposed MRFO was used to adjust the weight and threshold of the backpropagation neural network (NN), and the Morlet wavelet technique was applied to predict short-term loads. The outcomes demonstrate that the forecasting convergence rate and accuracy of the enhanced model were significantly enhanced.

An IMRFO was presented by Liao et al. [33], implementing a searching control feature based on the MRFO week global search capability, which may efficiently upsurge its global search capability. A Levy-flight scheme with an adaptive weight coefficient was also used to avoid premature convergence. Additionally, the mutation space is flexibly tuned using the Morlet wavelet technique to enhance the capacity of IMRFO to emerge from sluggishness and accelerate convergence.

Zhu et al. [34] proposed a k-means-based image segmentation approach using an IMRFO algorithm. The IMRFO uses a Levy-flight mechanism to enhance the flexibility of individual manta rays and present a random walk strategy to stop the algorithm from local optimum entrapment. Moreover, PSO learning was integrated to enhance the algorithm convergence correctness. The IMRFO optimizes the k-means algorithm to avoid sinking into local optima, improving the stability of the k-means algorithm.

In summary, the Levy-flight version of the MRFO algorithm is a robust metaheuristic algorithm that incorporates the Levy-flight behavior into the search process to enhance the exploration ability of the algorithm. Combining the random walk and Levy flight allows the algorithm to explore the search space more efficiently, leading to better-quality solutions. The Levy-flight version of the MRFO algorithm is particularly useful for high-dimensional optimization problems.

5) MRFO WITH CROSSOVER/MUTATION OPERATORS

In the MRFO algorithm, crossover and mutation operators generate new solutions by combining existing solutions or making minor modifications to existing solutions. The crossover operator combines two parent solutions to generate a new offspring solution. The mutation operator makes slight random modifications to the solution. The crossover and mutation operators in the MRFO algorithm generate new solutions and diversify the population. Combining existing solutions and making slight random modifications allows the MRFO algorithm to explore the search space more efficiently and determine better-quality solutions.

Ahmad et al. [35] incorporated crossover and mutation mechanisms into MRFO to enhance its divergence and convergence actions. Several touchstone functions and an interval Type-2 fuzzy-logic controller of an inverted pendulum model were used to test the proposed modified MRFO. The outcome reveals that the modified MRFO outperforms the GA and original MRFO and offers better parameters for the controller model.

Abdel-Basset et al. [36] incorporated hybrid genetic operators into MRFO (HMRFO) to manipulate the binary outcomes it attained to facilitate its local search ability. This new modified MRFO investigates using the Merkle–Hellman knapsack cryptosystem (MHKC) in the blockchain to enable Internet of Things (IoT) models. The simulation results indicate that, compared to native MRFO and seven other methods, HMRFO is an excellent alternative to the methods for attacking the MHKC with knapsack lengths of more than eight bits to reveal their weak points.

Wu et al. [37] proposed an IMRFO, which hybridizes the properties of the Cauchy mutation and original MRFO to improve the exploration capability and speed of MRFO. The proposed IMRFO was used to determine the best path for path planning for mobile robots. The experimental results indicate that IMRFO attains an effective path with superior efficiency over PSO and MRFO and offers a great tool to handle problems associated with mobile-robot path planning.

Mohamed et al. [121] presented an integrated variant of MRFO with the triangular mutation operator and orthogonal learning strategy. The two approaches are considered to achieve a robust balance between algorithm cores and provide a reliable mechanism to guide search agents during optimization. The numerical experiments proved the competitive performance of the proposed method in solving all tested CEC optimization and engineering problems.

In summary, the crossover and mutation operators are essential components of the MRFO algorithm. The MRFO algorithm can efficiently explore the search space and determine better-quality solutions using these operators to generate new solutions and diversify the population. The specific types of crossover and mutation operators used in the MRFO algorithm depend on the problem being solved and the characteristics of the search space.

6) MRFO WITH ADAPTIVE STRATEGIES

Adaptive strategies are used in the MRFO algorithm to adjust the parameters based on performance in the search process. The algorithm parameters that can be adjusted adaptively include the step size, angle of turning, size of the vision field, and probability of performing manta ray looping behavior. Tang et al. [38] proposed a modified MRFO for solving global optimization difficulties to address the shortcomings associated with the native MRFO, including the weak global search ability, trapping in the local optima, and decreasing population diversity. To address these problems, the authors incorporated three schemes into the modified MRFO. An elite search pool was used to enhance its local search ability. An adaptive control factor scheme was also integrated to expand the range of the MRFO exploration capability in the initial step and improve the exploitation search capability in the subsequent phase. Moreover, the authors employed a distribution approximation scheme to fine-tune the evolutionary path based on the leading population information to enhance the convergence criteria.

Jena et al. [39] proposed an enhanced MRFO, the attacking MRFO, which includes an additional attacking power, updating itself every iteration and offering the energy needed to prevent early convergence. In addition, Jusof et al. [40] proposed an adaptive-somersault MRFO to boost the global and local search ability of the native MRFO for resolving optimization difficulties. The suggested approach incorporated an adaptive location update sine-based approach into the native MRFO to boost its optimization capabilities. Further, Shaheen et al. [41] designed and improved MRFO with an adaptive penalty function to attain the utmost viable and optimum functioning points for solving cogeneration system economic dispatch problems.

In summary, the adaptive strategies used in the MRFO algorithm are critical for adjusting the algorithm parameters based on performance in the search process. By adjusting the step size, angle of turning, size of the vision field, and probability of performing the manta ray looping behavior adaptively, the MRFO algorithm can efficiently explore the search space and determine better-quality solutions. The specific adaptive strategies used in the MRFO algorithm depend on the problem being solved and the characteristics of the search space.

7) MRFO WITH FRACTIONAL-ORDER CALCULUS

The use of FC in the MRFO algorithm involves the replacement of the traditional integer-order derivatives with fractional-order derivatives. Fractional-order derivatives have more flexibility in capturing the complex behavior of the search space. Using FC in the MRFO algorithm can lead to better exploration and exploitation of the search space, resulting in improved optimization performance.

Abd Elaziz et al. [42] presented a new variant of MRFO to handle complicated optimizations and multilevel image segmentation difficulties. The MRFO was enhanced by incorporating FC in the local search stage in the presented approach.

In addition, Yousri et al. [43] suggested a new variation of MRFO, fractional-order Caputo MRFO, implementing FC based on the Caputo fractional differential operator to improve the manta ray movement in the local search stage. This improvement was made by exploiting the dependency history of FC to enhance searching for the best results by sharing the historical experience through the optimization procedure. Furthermore, the constant somersault factor was adaptively adjusted to avoid untimely convergence.

In summary, using FC in the MRFO algorithm is a promising approach to improve performance in solving complex optimization problems. By replacing the traditional integer-order derivatives with fractional-order derivatives, the algorithm can better capture the complex behavior of the search space, leading to improved optimization performance. However, using FC should be carefully balanced with the computational cost to ensure efficiency.

8) MULTIOBJECTIVE MRFO

The MRFO algorithm is a population-based metaheuristic algorithm for solving single-objective optimization problems. However, many real-world problems involve multiple objectives that must be optimized simultaneously. Researchers have extended the MRFO algorithm to solve MO optimization problems to address this problem. The MO MRFO algorithm is one such extension to solve MO optimization problems. The MO MRFO algorithm maintains a population of solutions representing the trade-offs between different objectives. The algorithm aims to determine a set of optimal solutions concerning all objectives simultaneously.

Elattar et al. [44] proposed a MO MRFO using external storage for the nondominated Pareto particles. This approach adaptively changed the objective function by iteratively varying the weights. In addition, an approach for order preference using the similarity to the best results was employed to mine an appropriate working point between the Pareto outcome set.

Hemeida et al. [45] developed MRFO to handle MO issues of distributed generator (DG) units. The proposed approach optimizes three conflicting objectives: voltage deviation minimization, active power loss minimization, and voltage constancy index maximization.

To create combined AC and multiterminal DC (MTDC) power networks effectively, Shaheen et al. [17] presented a MO MRFO called MO-MRFA. The suggested MO strategy intends to reduce environmental radiation, broadcast power damage, and overall production fuel costs in the AC/MTDC broadcast schemes. An extra Pareto archive was added to the MO-MRFA to preserve the findings that are not dominating. Iteratively altering the form of the active objective function also engages a dynamic adaptation of the objective feature. A fuzzy decision-making process chooses the ideal functioning point for the AC/MTDC power networks.

Sultan et al. [46] adopted MRFO for the best sizing of the combined renewable generating scheme comprising fuel cells, photovoltaics (PVs), and wind turbines under the MO scenario, reducing the power supply loss probability and energy cost. Zouache and Abdelaziz [47] extended the MRFO to handle MO issues. The extended MO MRFO employs a population storing procedure to store the nondominated produced results so far from the global search procedure. The top outcomes are chosen from the population archive to lead the manta ray population to a favorable area. Furthermore, to offer decent stability between convergence and diversity of the acquired possible Pareto set, ε-dominance and distance crowding strategies were added.

Got et al. [48] developed a novel MO algorithm using MRFO to address MO engineering problems. The developed MO MRFO algorithm uses an elitist theory to store the Pareto outcome set by incorporating external storage in the original MRFO. This storage is defined as a warehouse from which an exploration particle is selected based on its degree of density to govern the diversity and convergence of manta rays. Haris and Zubair developed a dynamic load-balancing technique using a hybrid algorithm called the MRFO improved MO Harris hawks optimization (HHO) algorithm (MMHHO) [49]. The study used MRFO to modify the search area of the HHO algorithm by considering resource utilization, cost, and response time. The MMHHO-based load-balancing approach effectiveness was analyzed and compared with MPSO, QMPSO, MRFO, HHO, and Q-learning for the number of variables. The experimental output confirmed that the suggested MMHHO approach outperformed the contrasted algorithms for load balancing in cloud computing.

Kahraman et al. [50] suggested an approach for finding the best solutions for MO optimal power flow (MOOPF). The developed MOOPF was based on a Pareto achieving technique using distance crowding. The statistical analysis revealed that the MOOPF produces a good result on diverse MO problems and can obtain the optimum solution compared with the OMNI, DN-NSGAII, NSGAII, SPEA2, and MO ant lion optimization methods. Ramadan et al. [51] employed the MRFO method to approximate rankings and assignments of renewable DGs for an MO function that reduces the total probable cost, overall radiation, and overall model voltage abnormality, improving the forecasted overall voltage constancy.

Abdul Razak et al. [52] presented an MO variant of MRFO using NSGAII, where MRFO is equipped with a nondominated sorting mechanism, such as crowding distance, and is a sorting procedure established on Pareto's game. It is a quick approach to designing a decent distinctive Pareto front. In contrast, crowding distance is an approach to reserve decent result sharing along the Pareto front. The suggested MO is called NSMRFO, which was validated using several standard functions, and its efficacy was contrasted with other approaches using a statistical study of hypervolume metrics.

The MO MRFO algorithm is effective in solving MO optimization problems. It can determine a diverse set of Pareto optimal solutions in a reasonable time. However, like all MO optimization algorithms, the MO MRFO algorithm requires careful selection of the algorithm parameters and objective functions to ensure good performance. In summary, the MO MRFO algorithm is an extension of the MRFO algorithm to solve MO optimization problems. The algorithm uses Pareto dominance to compare solutions in the population and maintains a set of nondominated solutions, known as the Pareto front. The algorithm uses several techniques to improve the convergence and diversity of the Pareto front, such as the crowding distance and elitist strategy.

9) OTHER IMPROVED MRFO

Hu et al. [53] presented a modified MRFO algorithm, hybridized with quadratic interpolation, wavelet mutation, and control parameter fine-tuning schemes, called wavelet mutation and quadratic interpolation MRFO to improve its ability to escape the local minimum and enhance the computation accuracy of the classical method. This method addresses problems of shape optimization for ball curves.

Shaheen et al. [54] provided a reliable and accurate technique for managing and controlling static volt–ampere–reactive instruments and reconfiguring the distribution system using MRFO. With numerous scenarios of the 33- and 69-bus distribution test systems, the suggested method is employed for the dynamic operation of automated distribution systems, accounting for daily load changes, emission reduction, and loss minimization.

Poobalan et al. [55] presented an enhanced MRFO based on incorporating the Taylor series and MRFO, called Taylor-MRFO. The proposed approach uses diverse objective functions, including bandwidth, latency, load, and power. The Taylor-MRFO with the actor critic NN was used for load distribution and switching of the cloud data center.

Abd Razak et al. [56] suggested an enhanced MRFO, called spiral-based MRFO (SMRFO), to enhance the PID control of a supple manipulator. The spiral scheme was incorporated into the somersault stage of MRFO in the SMRFO to help agents choose the optimal agent for a spiral-based trajectory at each iteration. This scheme also provides a dynamic step-size strategy for all such agents in action. The effectiveness of the SMRFO was validated on arrays of standard functions comprising diverse fitness landscapes and enhanced a PID controller for a flexible manipulator scheme.

B. HYBRIDIZED VERSIONS OF MRFO

Hybrid MRFO (HMRFO): The HMRFO algorithm combines the MRFO algorithm with other metaheuristic algorithms to improve its performance. The HMRFO algorithm uses a hybridization approach combining the search capabilities of MRFO with the local search capabilities of other algorithms, such as simulated annealing (SA) or PSO. This hybridization approach allows the algorithm to explore the search space more efficiently and determine better solutions. The summary of reviewed hybrid MRFO algorithms is presented in Table 3.

1) HYBRIDIZATION WITH LOCAL SEARCH

One of the limitations of the MRFO algorithm is its dependence on the random search process, which can lead to a slower convergence rate and poor performance in solving complex optimization problems. Researchers have proposed hybridizing the MRFO algorithm with local search techniques to address this limitation and improve its convergence rate and solution quality. Hybridization of the MRFO algorithm with local search involves combining the global search capabilities of MRFO with the local search capabilities of an algorithm that explores the neighborhood of the current solution to improve its quality. Local search algorithms, such as hill-climbing or SA, can improve the ability of the MRFO algorithm to explore the search space and refine the solutions it discovers.

For the optimization-damage identification problem of plate structures, Dinh-Cong et al. [57] presented a hybrid global-local algorithm that combines MRFO with sequential quadratic programming (SQP). Moreover, MRFO is used for the global search procedure, whereas SQP is used for the local search operation. The results demonstrated that, compared to artificial ecosystem-based optimization, CS, and MRFO, the damage discovery method established on the hybrid MRFO-SQP algorithm and the iterative order reduction method could achieve the highest correctness and lowest computing cost for damage localization and quantification.

The hybridization of the MRFO algorithm with the local search improves the performance and solution quality of the algorithm in various optimization problems. For example, in a study that applied the hybrid MRFO algorithm to the job shop scheduling problem, the hybrid algorithm outperformed other metaheuristic algorithms, including the basic MRFO algorithm, regarding solution quality and computation time. In summary, hybridizing the MRFO algorithm with local search techniques can improve its ability to explore the search space and refine the solutions it discovers. This approach can improve the solution quality and convergence rate, making the hybrid MRFO algorithm a promising method for solving complex optimization problems.

2) HYBRIDIZATION WITH OTHER METAHEURISTIC ALGORITHMS

Hybridization is a powerful approach to improving the performance of optimization algorithms. Hybridization of the MRFO algorithm with other metaheuristic algorithms involves combining the search capabilities of MRFO with those of another metaheuristic algorithm to create a more effective hybrid algorithm. One popular algorithm to hybridize with MRFO is the GA. The hybrid algorithm, MRFO-GA, uses MRFO to generate the initial population and GA to refine the solutions. In a study that applied the MRFO-GA hybrid algorithm to the task-scheduling problem, the hybrid algorithm outperformed MRFO and GA regarding solution quality and computation time.

Another popular algorithm to hybridize with MRFO is the PSO algorithm. The hybrid algorithm, MRFO-PSO, involves using MRFO to generate the initial population and PSO to refine the solutions. In a study that applied the MRFO-PSO hybrid algorithm to the economic dispatch problem, the hybrid algorithm outperformed MRFO and PSO in terms of solution quality and computation time. Other metaheuristic algorithms that can be hybridized with MRFO include ACO, artificial bee colony, and DE. The hybrid algorithms created by combining these algorithms with MRFO achieve better performance than the individual algorithms in solving a range of optimization problems.

To tune four types of PID controllers for an automatic voltage regulator optimally, Micev et al. [58] devised a hybrid metaheuristic approach combining MFRO and the SA, called SA-MFRO, for an automatic voltage regulator. A novel cost function was also introduced for the optimization of the controller variables. By conducting an evaluation using the controllers adjusted by the many optimizing liaisons, the GA, and PSO, the effectiveness of the acquired best PID, real PID, fractional-order PID, and PID with second-order derivative controllers is validated. The results of the studies reveal that the suggested SA-MRFO algorithm outperforms controllers adjusted by other algorithms for each type of controller. The findings demonstrate that the primary benefit of the SA-MRFO is a significant increase in convergence speed.

Dey et al. [59] suggested a hybrid feature selection method called the manta ray foraging-based golden ratio optimizer to choose the more crucial feature set from COVID-19 datasets. Three datasets, including the MOSMED, SARS-COV-2, and COVID-CT datasets, were used to test the model. The findings demonstrate that this method is highly effective compared to the local texture descriptors employed for COVID-19 detection from chest CT images. Attiya et al. [60] proposed a hybrid metaheuristic approach using MRFO and SSA. In the proposed approach, the SSA was integrated into the MRFO as a local search operator to improve the convergence capability of MRFO. The MRFO SSA was applied for task scheduling IoT applications in the cloud. The MRFO SSA was evaluated using several real-world and synthetic datasets with different sizes. The outcome indicates the dominance of MRFO SSA over the HGSWC, MRFO, SSA, HHO, and artificial ecosystem optimization SSA concerning the throughput and span.

Duan et al. [61] created a hybrid algorithm known as MGEHO—manta ray foraging and Gaussian mutation-based elephant herding optimization. The manta ray somersault foraging strategy, which adjusts patriarch positions, replaces the clan updating component of the native elephant herding optimization algorithm. A dynamic convergence element is also in place to balance exploitation and exploration. The Gaussian mutation increases population diversity and helps MGEHO maintain a robust local search capability.

Ekinci et al. [62] introduced a hybrid optimization technique called OBL-MRFO-SA to manage the speed of DC motors using fractional-order PIDs. The hybridization helps hasten the MRFO convergence ratio. The fractional-order PID-based speed control system for a DC motor using the OBL-MRFO-SA algorithm was designed using a time domain objective function that considers the performance criteria (steady-state error, maximum overshoot, settling time, and rising time).

Firouz et al. [63] presented two discrete algorithms, comprising discrete MRFO and discrete SSA, to handle controller placement problems. The two discrete algorithms were designed using a random insert, half-point crossover operators, and two-point swaps. The succeeding discrete MRFO and SSA algorithms were effectively merged. The performance of this approach was validated using six popular software-defined networks with a diverse number of controllers.

To resolve problems with economic emission dispatching, Hassan et al. [64] suggested an optimization approach combining MRFO with a gradient-based optimizer (GBO). These issues, related to single and multiple targets, were handled using the suggested MRFO-GBO. A fuzzy set theory approach was used to determine the best compromise between the Pareto optimal outputs to solve the MO economic emission dispatch problem.

Saravanan and Anbalagan [65] proposed a hybrid meta-heuristic algorithm, merging MFRO and the dragonfly algorithm for the best generator arrangement of congestion management in a deregulated control market. The proposed method is implemented in the adjusted IEEE 30- and 57-bus models, and the efficacy is contrasted with the native dragonfly algorithm, MRFO, and other metaheuristic methods from the literature.

Jain et al. [66] developed an effective glaucoma discovery method combining MRFO, the rider optimization algorithm, and the generative adversarial network (GAN), called the rider MRFO-based GAN. In the developed approach, the fuzzy local information C-means clustering (FLICM clustering) simulation outcomes indicate that the proposed glaucoma discovery approach reveals superior effectiveness using such measures as sensitivity, accuracy, and specificity. Furthermore, the rider MRFO-based GAN provides an enhanced outcome with the maximum correctness of 0.96%, 0.94% sensitivity, and 0.89 specificity, in contrast to the GSO, convolutional NN (CNN), modified U-net CNN, GAN, MRFO-based GAN, and rider optimization algorithm-based GAN.

Abdel-Mawgoud et al. [67] presented a modified MRFO algorithm to improve the MRFO features. In the modified MRFO, an SA approach was integrated to improve the local search to explore the feasible region in the search location effectively. Additionally, the modified MRFO was exploited to find the optimum dimensions and positions of PV units in radial distribution systems and multiple wind turbines.

In addition, Jusof et al. [68] combined MRFO and PSO. The hybrid approach incorporates the PSO social contact strategy and elitism into the MRFO plan. The tactic helps search agents choose a new search direction. The algorithm was evaluated on various dimensions and fitness landscapes of CEC 2014 touchstone functions. It optimizes a proportional-derivative (PD) controller for an inverted pendulum system to solve a practical engineering problem.

Changting et al. [122] presented a hybrid MO success history-based parameter adaptive DE (SHADE) with MRFO for structural design problems, where the updating rules of SHADE, a variant of DE with superb performance, are combined with the operators from MRFO, which can balance the exploration and exploitation of the hybrid algorithm for structural design problems. Furthermore, MO-SHADE-MRFO uses the external archive to save and update the Pareto fronts during optimization. According to the experimental results, MO-SHADE-MRFO can provide the best statistical values of hypervolume, inverted generational distance, and spacing-to-extent, in most cases ranking first among the compared algorithms.

Mohammed et al. [123] proposed a hybridization of MRFO and the GA based on a pseudo-parameter, where the GA can help MRFO escape the local minimum. This hybridized algorithm is a pseudo-GA with MRFO, which hybridizes the pseudo-parameter-based GA and MRFO algorithm to produce a more efficient algorithm that combines the advantages of both algorithms without becoming trapped in a local minimum or taking a long time to calculate.

Rizk et al. [124] presented a hybrid metaheuristic algorithm called MRFO-PSO that hybridizes the MRFO and PSO. In the MRFO-PSO, the concept of the PSO velocity is incorporated to guide the searching process of the MRFO, where the velocity is updated by the best and the second-best solutions. This integration further improved the balancing problem between the exploration phase and exploitation ability.

In summary, the hybridization of MRFO with other metaheuristic algorithms can improve its search capabilities and solution quality. The specific hybridization approach depends on the characteristics of the optimization problem and the strengths and weaknesses of the combined algorithms.

3) MRFO WITH THE NEURAL NETWORK

The hybridization of the MRFO algorithm with NNs is a promising approach combining the strengths of both techniques to solve optimization problems. The idea behind this hybridization is to use the MRFO algorithm to optimize the weights and biases of the NN, which is used to solve the optimization problem. The hybridization of MRFO with NNs has been applied to various optimization problems, such as feature selection, image classification, and financial forecasting. In a study that applied the MRFO-NN hybrid algorithm to the problem of feature selection in high-dimensional datasets, the hybrid algorithm outperformed other state-of-the-art algorithms in terms of feature selection accuracy and computation time. Similarly, in a study that used the MRFO-NN hybrid algorithm to solve the image classification problem, the hybrid algorithm achieved higher accuracy and lower error rates than other algorithms.

Gokulkumari [69] proposed a brain tumor classification approach combining MRFO and the deep CNN (MRFO-based DeepCNN), where MRFO trains the DeepCNN to classify the brain tumor as an edema, core, malignant, or benign tumor. The proposed MRFO-based DeepCNN was validated using accuracy, specificity, and sensitivity measures. Moreover, in contrast with existing approaches, the MRFO-based DeepCNN achieved higher accuracy, specificity, and sensitivity. Kamil and Shaymaa [70] employed MRFO to obtain the best CNN hyperparameters, including weights and biases. The efficacy of the enhanced CNN using MRFO was demonstrated on the Cifar_10 standard dataset. The outcome proved the superiority of the MRFO-based CNN over the vanilla CNN.

Elmaadawy et al. [71] hybridized MRFO with the random vector functional link (RVFL) to forecast the vital efficiency parameters of a complete water management plant functioning with an initiated sludge management procedure. The MRFO obtains the optimum RVFL variables to enhance the model prediction efficiency. The MRFO-RVFL approach was compared with the traditional RVFL based on a dataset measured for 222 days to discover the significance of MRFO. The outcomes indicate that the hybrid approach exhibited greater efficiency and validity for prediction, according to the root mean squared error (RMSE) and R^2.

Nguyena et al. [72] presented a new hybrid technique of MRFO and a deep NN (DNN) for flood vulnerability planning for the Quang Ngai region of Vietnam. An analytical method using geospatial distribution was employed, comprising 2176 flood area points and 13 influencing parameters to generate input data. The outcome indicates that hybridizing the DNN and MRFO enriched the flood vulnerability forecasting accuracy with an area under the curve of 0.98 compared to DNN gray wolf optimization (GWO), DNN-SSO, support vector machine (SVM), and GBR. The study findings are crucial for helping policymakers comprehend and identify problems, which helps them improve their adaptation plans.

Duman et al. [73] presented a combined model comprising the feedforward NN (FFNN) and MRFO for forecasting electric energy consumption. The MRFO trains the FFNN. The trained FFNN model predicts the electric consumption rate in Burs, Turkey. Experimental trials were performed to discover the ideal values of weight and bias factors in diverse network arrangements. The experimental outcomes were statistically validated and compared with an arithmetic optimization algorithm, HHO, SSA, improved GWO, SHO, and hierarchical PSO with time-varying acceleration coefficients. The results reveal that the FFNN trained with the MRFO algorithm outperformed models trained with the compared algorithms in predicting electrical energy consumption.

Zhang et al. proposed the MRFO-based method for choosing the wavelength of the soil moisture characteristic [74]. In the suggested method, spectral data of various soil moisture levels that were manually adjusted were obtained using a high-resolution spectrometer. Afterward, outliers from the data were purged using the isolation forest technique (iForest). Finally, the backpropagation NN and MRFO were employed to choose the characteristic wavelength for soil moisture. The analysis findings demonstrated that, compared to the slime mold algorithm, GA, and PSO, MRFO displayed the best predictive capability. The findings also demonstrated that MRFO performed better in identifying the distinctive spectra of soil moisture.

Ayub et al. [75] presented a theft detection model, combining the CNN and gated recurrent unit (GRU) fined tuned using MRFO. Furthermore, the proposed study implemented a preprocessing approach using the local value associated with missing instances to compute the missing values in the dataset. In addition, the synthetic minority oversampling technique was used to balance the classes in the dataset. The analysis using power consumption data from China National Grid Co., Ltd. reveals that the proposed CNN-GRU-MRFO reached 6% higher detection accuracy than the CNN-GRU alone.

Kamil and Al-Shammari [76] combined MRFO with the CNN for brain tumor classification, where the MRFO adjusts the parameters of the CNN for effective classification of extracted variables from brain magnetic resonance imaging (MRI) scans. The proposed MRFO-based CNN has an accuracy of 98.57% and is better than other CNN-based models optimized with MRFO.

Shinde [77] proposed a hybrid approach, combining the DeepCNN with enhanced MRFO for lane detection. The enhanced MRFO was based on the OBL method. The enhanced MRFO optimized the weights of the DeepCNN. In comparison with conventional models, the proposed models displayed superior performance.

Bahgat et al. [78] adapted MRFO to adjust 12 CNN architecture network hyperparameters for the effective automatic detection of COVID-19 using chest x-ray images. An experimental study was performed on eight public datasets to assess the efficacy of this method. The outcomes indicate that the DenseNet121 optimized network obtained the optimum performance.

Karuppusamy [79] combined MRFO with the CNN to identify early-stage brain tumors in MRI scans. The MRFO extracted relevant attributes from brain tumor MRI images. The obtained attributes were tested using the CNN and detected early-stage brain tumors. The simulation outcome produced by the proposed approach was contrasted with existing artificial NNs and PSO, obtaining a higher classification and detection accuracy.

In conclusion, the hybridization of MRFO with NNs is a promising approach that can improve the search capabilities and solution quality of the MRFO algorithm. The specific design of the NN depends on the characteristics of the optimization problem, and the hybrid algorithm can be applied to a wide range of optimization problems in various fields.

4) MRFO WITH ELM

Hybridizing the MRFO algorithm with an extreme learning machine (ELM) is a promising approach to solving optimization problems efficiently. The ELM is a machine learning algorithm that has gained attention recently for its fast and accurate performance in solving various real-world problems. In the hybrid MRFO-ELM algorithm, the MRFO algorithm is used to optimize the parameters of the ELM algorithm.

Wang and Wang [80] developed a hybrid prediction model, combining the ELM and MRFO, denoted as MRFO-ELM. Following this approach, the mean impact value technique assesses and distinguishes the significance of the 13 best parameters. Moreover, three setups were established to forecast transport carbon dioxide emissions in China. The experiential outcomes specify that the hybrid MRFO-ELM provides outstanding performance concerning the searching velocity and forecasting accuracy compared with other approaches.

Sharma et al. [81] used MRFO to train a bidirectional ELM. A four-level dual-tree complex wavelet transform is applied to each training image to generate approximation coefficients. The intended outputs for bidirectional-ELM training are the relevant MES values obtained via MRFO using imperceptibility and robustness as the optimization criteria, whereas the approximation coefficients serve as input features.

Panagiotis et al. [125] presented ELM models developed using MRFO to predict the compressibility of clay for soft ground improvement. The results demonstrate that the developed MRFO-ELM model predicts the compressibility of clay with less than $\pm$ 20% deviation of the data for 67% of the specimens and outperforms the prediction accuracy of simple or multiple regression correlations and advanced NN models reported in the literature.

In conclusion, the hybridization of MRFO with ELM is a promising approach that can improve the search capabilities and solution quality of the MRFO algorithm. The specific design of the ELM algorithm depends on the characteristics of the optimization problem, and the hybrid algorithm can be applied to a wide range of optimization problems in various fields. The hybrid MRFO-ELM algorithm is a fast, efficient, and accurate optimization technique that can solve complex optimization problems in real-world applications.

5) MRFO WITH FUZZY-LOGIC SYSTEM

The hybridization of the MRFO algorithm with the fuzzy-logic system (FLS) is a promising approach to solving optimization problems that involve uncertainty and imprecision. Fuzzy logic is a mathematical technique that deals with vague and imprecise information using linguistic terms and fuzzy sets. The MRFO-FLS hybrid algorithm combines the strengths of MRFO and the FLS to solve optimization problems efficiently.

Mishra and Bhoi [82] hybridized MRFO with the adaptive neuro-fuzzy inference system (ANFIS) to improve categorizing cancerous and noncancerous cells from a microarray dataset. In this study, an ensemble Kal-man filter approach initially preprocessed the microarray dataset. Subsequently, similar genes were grouped based on the adaptive density-based spatial clustering with noise method.

Zounemat-Kermani et al. [83] applied MRFO and PSO for the parameter optimization of ANFIS to predict the specific conductance of groundwater effectively. Different parameters were used to design and evaluate the predictive model, including water temperature, salinity, and groundwater level. The ANFIS-based model was compared with a nonlinear mathematical model to buttress the efficacy of the machine model. The outcome indicates that, although the mathematical model provides competitive performance for the specific conductance prediction, the ANFIS presents a better prediction. Moreover, the results also indicate that the MRFO and PSO enhanced the ANFIS model with RMSE values of 13% and 5%, respectively.

Aly and Rezk [84] combined MRFO and fuzzy-logic control (FLC) for maximum power point tracking, finding the best FLC parameters using MRFO. The choice of variables in the suggested method was derived from membership function gains, and the integral error was the cost function. The results using the MRFO-based FLC are superior to the hill-climbing method and native FLC. The main findings confirm that using hybrid MRFO and FLC features is a promising remedy for maximum power point tracking in thermoelectric generator systems.

Lakshmi and Krishnamurthy [85] proposed an association rule mining-based fuzzy MRFO approach for frequent item set generation from social media, where MRFO adjusts the FLS parameters. In the study, the association rule mining stage exploits the optimized fuzzy-based MRFO algorithm, generating association rules from massive item sets, attaining the least confidence and support value.

In conclusion, the hybridization of MRFO with FLS is a promising approach that can efficiently solve optimization problems with uncertainty and imprecision. The MRFO-FLS hybrid algorithm combines the strengths of MRFO and FLS to search efficiently for the optimal solution to optimization problems. The specific design of the FLS depends on the characteristics of the optimization problem, and the hybrid algorithm can be applied to a wide range of optimization problems in various fields. The MRFO-FLS hybrid algorithm is a fast, efficient, and accurate optimization technique that can solve complex optimization problems in real-world applications.

6) MRFO WITH MACHINE LEARNING ALGORITHMS

The hybridization of the MRFO algorithm with machine learning algorithms, such as SVM, RF, and extreme gradient boosting (XGBoost), is a promising approach to solving complex optimization problems that involve large datasets and nonlinear relationships between the variables. These hybrid algorithms can also handle multiple objectives or constraints in optimization problems. The specific design of the machine learning model depends on the characteristics of the optimization problem, and the hybrid algorithm can be applied to various fields, such as finance, health care, and engineering.

Houssein et al. [86] suggested a novel combined electrocardiogram classification technique called MRFO with SVM. In this hybrid approach, the MRFO adjusts the SVM parameters and determines the most relevant attribute subset for optimum classification efficiency. The adjusted SVM is applied for the electrocardiogram classification, and the MIT-BIH arrhythmia dataset comprises four abnormal and one abnormal heartbeat to train the SVM. The outcome proves its dominance with an accuracy of about 98% over other metaheuristics approaches.

Sumathi and Umasankar [87] suggested combining the RF classifier and MRFO for power flow administration. The main goal of the RF MRFO is the optimum operation of renewable energy sources to reduce the electricity generation cost by hourly day-ahead real-time scheduling. In this approach, the RF predicts the load constraint, and MRFO produces the optimum control signals reliant on the power difference within the source and load sides.

Datar and Kulkarni [88] presented a hybrid PV-wind solar energy model using a static synchronous compensator. The model combines the XGBoost package and MRFO and is called the XGBoost-MRFO control strategy. The MRFO algorithm enhances the XGBoost learning procedure using the minimum error as the objective function. The XGBOOST-MRFO is a control algorithm to produce position signals for the static synchronous compensator.

In summary, hybridizing MRFO with machine learning algorithms, such as SVM, RF, and XGBoost, is a promising approach that can efficiently solve complex optimization problems. The hybrid algorithms combine the strengths of MRFO and machine learning algorithms to search for the optimal solution to optimization problems efficiently. The specific design of the machine learning model depends on the characteristics of the optimization problem, and the hybrid algorithm can be applied to a wide range of optimization problems in various fields. Hybrid algorithms are fast, efficient, and accurate optimization techniques that can solve complex optimization problems in real-world applications.

IV. APPLICATIONS OF THE MRFO ALGORITHM

The MRFO algorithm is a relatively new optimization technique inspired by the foraging behavior of manta rays. It has displayed promising results in various applications, including energy and power, image processing, PID control, PV parameter optimization, feature selection, scheduling, and other areas. The applications of the MRFO algorithm and its variants are summarized in Table 4. The summary of the applications of the MRFO algorithm in diverse domains is presented in the subsection below.

A. ENERGY AND POWER

The MRFO algorithm has been used for power system optimization, economic dispatch, load forecasting, and energy management in energy and power applications. Further, MRFO-based algorithms can optimize building energy consumption, reduce energy costs, and improve the efficiency of renewable energy systems.

El-Hameed et al. [3] employed MRFO to determine the best three-diode equivalent model variables of solar generating units. The three-diode equivalent model consists of nine resolution parameters, which can accurately define the features of the solar generating units when chosen wisely. The MRFO is applied to determine the resolution parameters of the three-diode equivalent model using the Kyocera polycrystalline KC200GT solar component and simulation setup under diverse altered settings for the Ultra 85-P. The cost functions for the feature selection for the solar generator are enhanced successively via MRFO, defined using RSE and mean absolute error between the measured and projected data.

Fathy et al. [89] developed a novel global maximum power point tracking system using MRFO. The developed tracking system mines the global maximum power point from the triple-junction solar-made array under shadow operation settings.

Hemeida et al. [90] applied MRFO to decrease power damage by sizing and sharing Type I DGs joined in a radial distribution network. The presented approach was validated using IEEE 33, 69, and 85 test models.

Alturki et al. [91] implemented MRFO as a control approach for adjusting the proportional-integral (PI) controllers of DC/DC and DC/AC converters to incorporate the PV scheme into the grid. The efficacy of the proposed method was considered under irradiance disparity and compared with five other metaheuristics algorithms.

Mohamed et al. [92] applied MRFO to adjust power system controller factors to determine the best factors of the load frequency control model and superconducting energy storage model controllers. The strength of the suggested MRFO-based controllers was examined over the disparity of the power system parameters.

Shaheen et al. [93] developed an MRFO to address economic power heat dispatch in the cogeneration energy system combined with nonconvex controller point effects. Test models consisting of five, seven, and ten units were used to estimate the efficacy of MRFO in handling the stated problem.

Arya et al. [94] proposed an energy-based routine protocol using a deep belief network and the MRFO algorithm for effective data transmission in fifth-generation wireless sensor network communications. In the proposed technique, the nodes in the entire network are grouped as clusters via the reinforcement learning approach. Furthermore, the MRFO selects the required cluster head for effective data communication. Then, the data are transmitted to the sink node through the selected cluster head using the deep belief network.

Akdag and Yeroglu [95] adapted MRFO to the organization of directional overcurrent relays combined with a fitness function to maintain the best relay organization by maintaining the relay organization margin among the relay pairs. The successful method was applied to 9- and 15-bus validation models, and the outcome was contrasted with four other methods. Additionally, this study suggests an adaptive defense architecture, offering the best organization of directional overcurrent relays with the MRFO algorithm according to changing power system conditions. The adaptive protection architecture was applied to the virtual system of a cross section of 10-bus distribution networks, such as wind-powered DGs in the Hatay region of Turkey.

Ben et al. [96] examined the potential and efficacy of employing MRFO to evaluate the system parameters of 2D dike-like magnetic profile inconsistencies. The simulation data include magnetic anomalies created artificially and corrupted with noise at 5%, 10%, 15%, and 20% for case studies from two mining sites in China and Peru.

Hemeida et al. [97] proposed a Monte Carlo simulation-based diverse metaheuristic algorithm to enhance the positions of three-DG units under load uncertainties considering 500 situations. In addition, Ramadan and Helmi [98] considered using MRFO for optimal distribution network reconfiguration for vulnerable radial smart grids in uncertain working situations. The performance of the MRFO was measured in a diverse working environment for IEEE 33- and 85-bus models, and the results were compared with GWO and PSO.

Elattar et al. [99] used the MRFO approach to create distribution model controls that minimize lost energy and provide quantitative and qualitative power amenities to satisfy customers. The IEEE practical distribution networks of 33-, 69-, and 84-bus were subjected to the MRFO-based approach at the Taiwan Power Company.

To reduce damage and consider raising the voltage profile, Vahid et al. [100] offered an ideal distribution and design of power-generating assets, such as DGs with scheduling ability in a smart location using MRFO. The DGs with scheduling ability were distributed using a weighted coefficient approach, and their configuration was conducted in a 69-bus distribution network.

Fathy et al. [101] applied MRFO to identify the best factors of the optimized fractional maximum power point tracking scheme. The outcomes were contrasted with ten other metaheuristics algorithms to authenticate the strength of the MRFO-based approach. Alasali et al. [102] applied MRFO to discover single-objective and MO issues associated with optimal power flow (OPF) integrating stochastic renewable energy sources. The MRFO algorithm was applied to resolve OPF issues, improve energy productivity, and enhance the cost and environmental performance of the power network.

Eida et al. [103] used the MRFO algorithm for the optimal distribution of numerous DG units attached to radial distribution systems. The DG units were improved to operate with a unity power factor and OPF during 24 hours of time-varying demand. The single-, two-, and three-DG units were optimized by the MRFO algorithm. The time-varying demand energy loss and savings were calculated, and the results were compared to the baseline. The MRFO behavior was compared to the behavior of the PSO and atom search optimization regarding energy loss and energy-saving values using the 69-bus radial distribution system standard.

Tiwari et al. [104] developed a renewable microgrid-based MRFO. As DG running costs primarily rely on their kind, the load dispatch was established to evaluate the operating costs of various DGs within their respective parameters. The best technique to lower the overall operating costs was determined using MRFO. A comparison with the PSO, DE, crow search algorithm, and SHEPO established the effectiveness of MRFO.

The influence of cost reduction from solar and energy storage system integration has also been studied for electric power demand. Abou El-Ela [105] proposed an MRFO-based solution for resolving the problem of the maximum hosting capacity of renewable energy resources, such as wind turbines and PVs in distribution systems. Regarding the conductors' current carrying capacity and voltage deviation performance metrics, the results of the proposed technique employing the IEEE 33-bus benchmark distribution were compared to those of PSO.

Guvenc et al. [106] applied MRFO to address the problems with OPF and consider restricted operating zones. The success of this method was confirmed using the IEEE 30-bus validation system, and the experimental analysis results were evaluated compared with those of other widely used approaches to OPF difficulties. The comparison study revealed that the MRFO-based strategy guarantees excellent outcomes for OPF problems.

B. FEATURE SELECTION

The MRFO algorithm can be used to select the most relevant features in a dataset, improving the accuracy and efficiency of machine learning algorithms. Chattopadhyay et al. [107] applied MRFO to attribute selection to enhance speech recognition. The approach was assessed using the Emo-DB and SAVEE datasets with the multilayer perceptron and k-nearest neighbor algorithms concerning accuracy. The simulation results affirmed the superiority of the method in contrast to the GA, GWO, and PSO.

Ghimire et al. [108] used MRFO to choose parameters for daily global solar radiation prediction. The chosen attributes were input into a 1) deep learning model with a sequence-to-sequence sequence autoencoder with long short-term memory and 2) a long short-term memory model for the final forecasting. The effectiveness of this model was evaluated using data from six solar power farms and was compared to RF regression, gradient boosting regression, much-randomized trees, adaptive boosting regression, and DNNs.

Sasank and Venkateswarlu [109] used MRFO to choose the most crucial characteristics for classifying brain tumors. The chosen characteristics were used to classify the grades of brain tumors using a hybrid DNN and adaptive rain optimizer. The accuracy was evaluated and compared to logistic regression and other methods. The results support the superiority of the method with reasonable accuracy and effectiveness.

Norfadzlia et al. [110] developed a swarm-based intelligence attribute extraction approach in a wrapper-based technique using BMRFO, BWOA, and BPSO metaheuristic algorithms and the k-nearest neighbor classifier to select appropriate descriptors for the effective classification of amphetamine-type stimulus drugs. The effectiveness of the approaches was assessed and compared using different criteria. The findings revealed that BMRFO was outperformed by BWOA, with the highest accuracy and fewer feature dimensions.

Chattopadhyay et al. [111] demonstrated the applicability of MRFO in speech-emotion recognition tasks. The method combined MRFO, Mel frequency cepstral coefficients, and linear predictive coding for feature extraction. The performance of the approach was validated using the Emo-DB and SAVEE datasets, reaching a classification accuracy of 97.49% and 97.68% on the two datasets, respectively.

C. IMAGE PROCESSING

The MRFO algorithm has been used in image segmentation, feature extraction, and image classification and can improve the performance of image processing algorithms by optimizing the parameters and weights. Karuppusamy [79] combined MRFO with the CNN to identify early-stage brain tumors in MRI scans. The MRFO algorithm extracts relevant attributes from brain tumor MRI images, which are tested using the CNN to detect early-stage brain tumors. The simulation produced by this approach was contrasted with existing artificial NNs and PSO, obtaining a higher classification and detection accuracy.

Togacar [112] applied an artificial intelligence model and optimization approaches to classify histopathological images of lung and colon cancers. In this study, the image labels were trained using the DarkNet-19 model to extract image features. The inefficient features were selected using MRFO, and an equilibrium optimizer from the DarkNet-19 model extracted features. The remaining features in the set were separated from the set containing inefficient features to create an efficient feature set (complementary rule insets). The SVM combined and categorized the effective features produced by the two optimization techniques.

Alkhliwi [113] presented a new encryption technique and image steganography system for COVID-19 diagnosis. The method consists of three steps. A multilayer discrete wavelet was employed for picture decomposition in the initial step. Then, MRFO identified the best pixels, and a double logistic chaotic map was used for the encrypted secret image.

The effectiveness of the performance of the MRFO-based encryption model was confirmed with a thorough analysis, and the results were reviewed using evaluation criteria. The outcome demonstrates that the model surpassed previous approaches, such as WOA and GWO.

D. SCHEDULING

The MRFO algorithm can optimize the scheduling of tasks in a system, such as scheduling production processes or transportation routes. In addition, MRFO can improve the efficiency and reduce the costs of these processes.

Wang et al. [114] suggested an MRFO-based approach to solving reactive power optimization scheduling problems in the power grid system. The simulation results of the MRFO-based approach were contrasted with those of four other metaheuristic algorithms. According to the results, MRFO can generate a practical, steady configuration with strong convergence and high reliability to solve optimization problems involving reactive power optimization.

E. PID CONTROLLER AND PV PARAMETER OPTIMIZATION

The MRFO algorithm has been used to optimize the parameters of the PID controller, commonly used in control systems. Further, MRFO can also optimize the parameters of PV systems to improve their performance and efficiency.

Houssein et al. [115] applied MRFO to extract the parameters of single-, double-, and three-diode PV models. The simulation analysis revealed that the parameters extracted by the proposed method provide the best values with the least difference between the computed and measured data in contrast to six other metaheuristic approaches.

Ben et al. [116] implemented MRFO to assess model parameters from prospective field irregularities initiated from 2D dipping faults. The inversion process was first tested on magnetic abnormalities from simulated datasets before contamination. Then, the process was examined using profiles collected from mining areas in Australia and the United States. The outcomes demonstrated how admirably steady and adaptable the design process is, particularly when working with noisy data. It also solves quantitative geophysical inverse problems with astonishing efficiency. Even when compared to background data, the consistency of the conclusions drawn from the analysis of deep-seated and shallow field cases is outstanding. In addition, the novel method exhibits substantial improvements over existing methods, such as PSO, ACO, and GA, particularly regarding the convergence rate, cost, and quality of resolved anomaly parameters. Therefore, the modeling of other geophysical data, such as resistivity and self-potential data, and the interpretation of other structures are advised.

Saleh et al. [117] enhanced the dynamic security of an islanded microgrid using a frequency control method based on virtual inertia control. The virtual inertia control loop was built using a PI controller optimally designed using the MRFO technique. Different operating scenarios were considered to compare the performance of the MRFO-based PI controller with that of the GA and PSO-based PI controllers. Realistic simulation settings were created using wind and solar power statistics and random load changes. The results indicated that the MRFO-based PI controller outperforms optimization methodologies regarding frequency disturbance reduction and reference frequency tracking.

To estimate the model parameters of 2D gravity profile irregularities, including depth and shape over geologic structures with faultless geometries, Ben et al. [118] employed MRFO. The simulation dataset includes instances gathered from mining sites in various regions and artificially created gravity anomalies that were then tainted with 5%, 10%, and 15% white Gaussian noise. The results demonstrate the consistency and stability of the algorithm regarding its capacity to determine the best solution globally for each geophysical inverse problem. Additionally, the algorithm efficiency was superior to that of PSO and DE when confronted with constrained multiparameter nonlinear inversion challenges, and it displayed impressive strength even in the presence of noise.

Amr et al. [126] applied MRFO to control the virtual inertia of islanded microgrids, including renewable energy sources. The control in the virtual inertia control loop was based on a PI controller optimally designed using the MRFO algorithm. The performance of the MRFO-based PI controller was investigated under various operating conditions and was compared with other evolutionary optimization algorithm-based PI controllers. The results demonstrate that the MRFO-based PI controller performs better in frequency disturbance alleviation and reference frequency tracking than the other considered optimization techniques.

F. OTHER APPLICATIONS

The MRFO algorithm has also been used in other areas, such as clustering, classification, optimization of NNs, and swarm robotics. Singh et al. [119] presented a cooperative spectrum-detecting method using MRFO, where MRFO adjusts the weighting vector at the fusion center, and the spectrum distribution is achieved using the ideal weight vector for secondary users. This MRFO method was contrasted with the PSO, dragonfly algorithm, and GA, and the outcomes indicate that MRFO can be applied effectively for spectrum allocation by cognitive radios.

Gölcük and Ozsoydan [120] suggested a recommendation architecture based on Q-learning and hyperheuristic methods to aid decision-makers in selecting the best bio-inspired approach for a given problem. Four low-level optimizers, including WOA, SSA, artificial bee colony, and MRFO, were used for Q-learning and hyperheuristics to select the optimizer in each optimization procedure automatically.

The method was applied in dynamically multidimensional knapsack problems. The effectiveness of the solo bio-inspired algorithm and recommender was evaluated using a thorough simulation analysis. The MRFO and Q-learning algorithm recommender successfully managed the dynamic multidimensional knapsack problem.

V. STUDY OF MRFO ALGORITHM GROWTH

A. RATE OF MRFO GROWTH

The number of publications of the MRFO algorithm per year from 2020 to 2022 was analyzed, and the outcome is presented graphically in Fig. 3 and by percentage in Fig. 4. The outcome indicates that research on MRFO has been growing since its development. The analysis indicates that the highest number of publications of MRFO and its variants was in 2021 at 59 (57%), followed by 2020 at 26 (25%) and 2022 at 19 (18%).

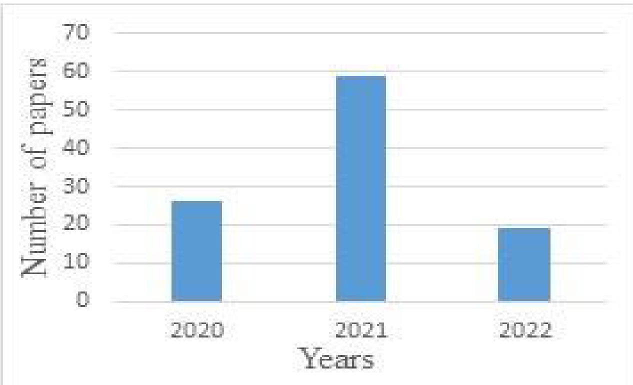

FIGURE 3. Number of published papers by year.

B. DEVELOPMENT OF MRFO

The distribution of published study papers in terms of models of MRFO algorithms comprises classical, modified, and hybrid MRFO. The total number in each category is presented in Fig. 5, and the percentage is in Fig. 6. The analysis reveals that modified MRFO has the most publications at 38 (36%), followed by original MRFO at 34 (33%), and hybridized MRFO at 32 (31%).

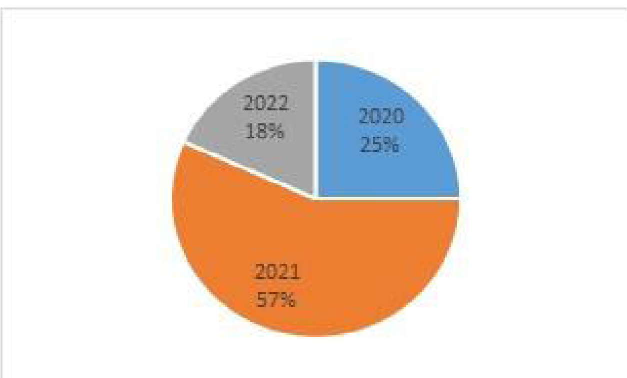

FIGURE 4. Percentage of publications by year.

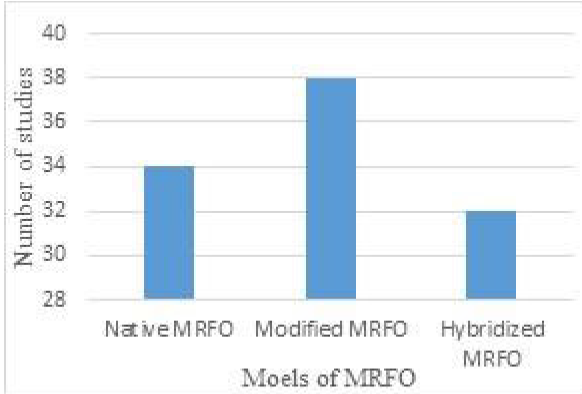

FIGURE 5. Distributions of manta ray foraging optimization (MRFO) studies.

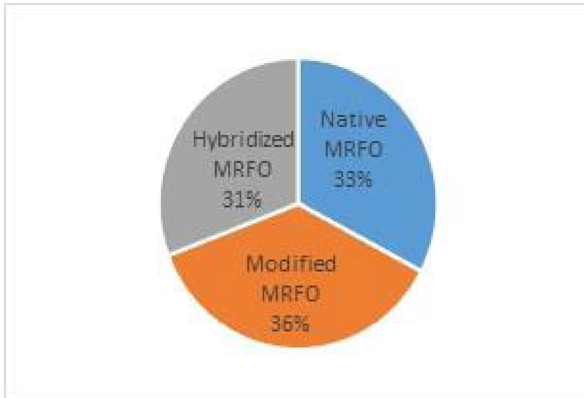

FIGURE 6. Percentage distribution of manta ray foraging optimization (MRFO) studies.

C. ANALYSIS OF MRFO APPLICATIONS

The study areas exploring MRFO are listed in Fig. 7, and the percentage is provided in Fig. 8. This study indicates that MRFO has been frequently explored in the fields of engineering and function optimization, power and energy, feature selection, PID controllers and PV parameter optimization, image processing, and other applications. The analysis results in these figures indicate that energy and power have the highest MRFO algorithm applications at 41 (39%), followed by function and engineering optimization at 14 (13%), function optimization at 13 (12%), image processing at 12 (12%), other applications at 12 (12%), feature selection at 11 (11%), parameter optimization at nine (9%), and scheduling at four (3%).

D. META-ANALYSIS OF MRFO

The number of publications of MRFO algorithms was reviewed in valid databases, including Elsevier, IEEE, Springer, Wiley Online Library, MDPI, Taylor and Francis, and others. The number and percentage of MRFO algorithm publications in each database are depicted in Figs. 9 and 10, respectively. The analysis results in these figures indicate that Elsevier has the highest number of MRFO algorithm publications at 32 (31%), followed by Springer at 18 (17%), IEEE at 17 (16%), other publishers at 17 (16%), Wiley at

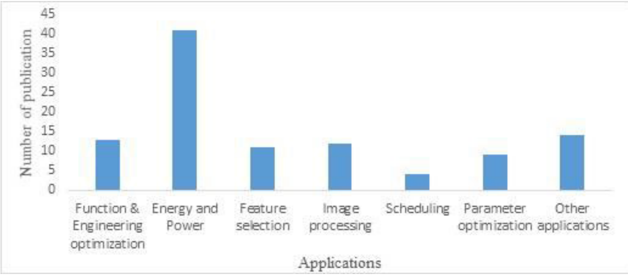

FIGURE 7. Number of applications by field.

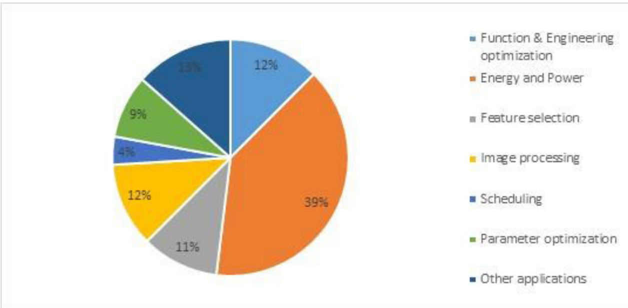

FIGURE 8. Percentage of studies by application.

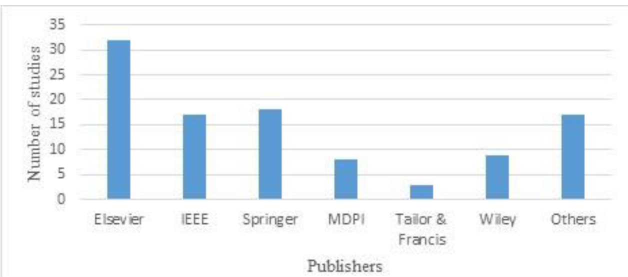

FIGURE 9. Number of published studies by publisher.

nine (9%), MDPI at eight (8%), and Taylor and Francis at three (3%).

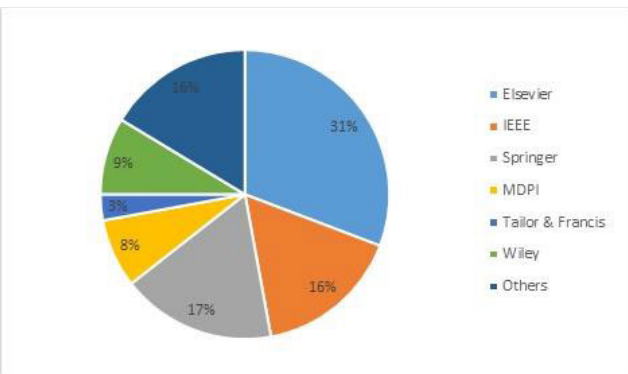

FIGURE 10. Percentage of published studies by publisher.

VI. CONCLUSION AND FUTURE DIRECTIONS

This study offers a review of the MRFO algorithm, presenting a discussion of the inspiration, mathematical model, and analysis of MRFO. Then, the performance of MRFO is discussed concerning its exploration and exploitation. After the presentation of the MRFO framework, various modifications of MRFO in terms of new operators, encoding schemes, parameter turning, hybridization, and binary optimization were reviewed and analyzed. Application areas of MRFO were reviewed, such as power and energy optimization, economic load dispatch, clustering, feature selection, training NNs, image processing, medical and health applications, and scheduling. Summaries of the review of MRFO studies are provided in Tables 2, 3, and 4.

This study considers MRFO research published by various publishers, such as Elsevier, IEEE, SpringerLink, Wiley, MDPI, and others. Most publications on MRFO studies were published through Elsevier, IEEE, and SpringerLink. The power optimization and engineering field explored more applications of the MRFO algorithm. Moreover, when compiling this review, 2021 had the most published MRFO studies. Overall, the survey provides a valuable resource for researchers and practitioners interested in using or further developing MRFO and demonstrates the algorithm's potential as a powerful optimization tool.

The MRFO algorithm has garnered the attention of researchers in solving various optimization problems since its introduction. However, numerous aspects of MRFO must be studied further, such as its development and applications. The following are some potential future research directions:

- The ability of the MRFO algorithm to solve large-scale optimization problems can be explored, especially its ability to cope with solution diversity and escape from entrapment in local optima when dealing with an ample search space.
- The hybridization of the MRFO algorithm with the local search or other metaheuristic algorithms can be designed to improve the convergence rate. Various operators from other techniques can be employed to improve the exploration and exploitation capacity of the MRFO algorithm.
- Subpopulation mechanisms for initialization can be studied to improve the performance of the MRFO algorithm when handling challenging optimization problems.
- The design of the MRFO algorithm for solving dynamic optimization problems can be assessed. The MRFO algorithm must be modified using operators, such as multiswarm, to cope with the dynamic search space due to changes in the global optimum over time.
- The design of an efficient MO MRFO algorithm, especially for dynamic MO optimization problems, can be evaluated. More modifications of MO MRFO are needed to efficiently update the nondominated solutions and generate a dynamic Pareto optimal front.
- The proposed MO MRFO in the literature used an archive mechanism to solve MO problems. However,

TABLE 2. Summary of various manta ray foraging optimization (MRFO) modifications.

Variants	Reference	Name	Problem solved	Results
Binary	[20]	Binary MRFO	Feature selection	The binary MRFO obtained the highest accuracy with fewer attributes than other approaches in the literature.
	[21]	Binary MRFO	Feature selection	This approach was validated using NSL-KDD and the CIC-IDS2017 intrusion detection dataset and compared with the genetic algorithm (GA), particle swarm optimization (PSO), gray wolf optimization (GWO), and grasshopper optimization algorithm. A statistical significance test reveals a significant difference between the presented model and the compared methods in the F-measure.
Chaotic	[22]	Chaotic MRFO	Function optimization	The developed MRFO has the utmost dependability compared to the improved whale optimization algorithm (WOA), KH, original MRFO, and crow search algorithm.
	[23]	Chaotic MRFO	Function optimization and maintaining the thermo-economic scheme optimization of an air-fin cooler	A substantial enhancement was detected in the objective function values using the chaotic-based MRFO in thermal design problems over contrasted algorithms, including barnacle-mating optimization, Harris hawks optimization (HHO), and seagull optimization algorithm.
	[24]		Finding parameters of a single phase and two new transformers	The chaotic MRFO-based predicted factors assist output characteristics in agreement with the experimentally obtained characteristics compared to the PSO, GA, gravitational search algorithm (GSA), ICA, coyote optimization algorithm, and original MRFO.
	[25]		Energy fiber Bragg grating demodulation	The experimental outcomes for the multiple fiber Bragg grating overlapping spectrum indicate that the proposed approach can effectively demodulate the center wavelength of the overlapping spectrum, efficiently reducing the probability of trapping in local optima and enhancing the algorithm's reliability and stability.
Opposition-based learning (OBL) MRFO	[26]	Improved MRFO	Applied for reducing energy intake through constructing shape optimization	The exploited method implements properly in contrast to PSO, approaching nearly optimal results in less than 50% of the experiments.
	[27]	Opposition-based manta ray foraging optimization with Nelder–Mead (Ob-MRFONM)	Multimodal and unimodal touchstone function optimization and identification of the best features of an actual PID controller	The proposed Ob-MRFONM was contrasted with the Levy-flight distribution, artificial ecosystem-based optimization, arithmetic optimization algorithm, and native MRFO concerning convergence, disturbance rejection, signal effects, transient response, and controller effort. The validated outcomes similarly affirm the modest competency of Ob-MRFONM in handling complex magnetic object suspension scheme problems.
	[28]	MRFO-OBL	Multilevel thresholding using COVID-19 computed tomography images	The MRFO-OBL achieved suitable and precise outcomes in quality and stability. The MRFO-OBL technique overtakes the native MRFO and other compared procedures using Otsu's technique for the metrics.
	[29]	OMRFO	Function optimization and PID control of an inverted pendulum model	The efficiency of the presented OMRFO was statistically validated on various touchstone functions and compared with the original MRFO in terms of accuracy using the Wilcoxon statistical test. Moreover, OMRFO was used for handling PID control of an inverted pendulum model, and the outcomes confirm the superiority of OMRFO over the native MRFO.
	[30]	QR-MRFO	Function optimization	The QR-MRFO performs better than the native MRFO concerning accuracy measures.
MRFO with Levy-flight	[31]	Balanced MRFO	Fuel cell with a proton-exchange membrane modeling and testing	The balanced MRFO provides the highest value for the touchstone functions and obtains the highest accuracy with good convergence speed in contrast to the KH, GSA, crow search algorithm, and classical MRFO.
	[32]	Improved MRFO	Fine-tune the weight and threshold of the backpropagation neural network	The convergence ratio and accuracy of the enriched forecasting system were significantly enhanced.
	[33]	Improved MRFO	Function optimization and finding the control features of magnetorheological dampers (engineering)	The solution confirms the feasibility and ability of the IMRFO in resolving engineering application difficulties compared with PSO, whale optimization algorithm (WOA), GSA, MRFO, comprehensive learning PSO, evolution strategy with covariance matrix adaptation, improved GWO, and hybrid PSO and GSA.

TABLE 2. ***(Continued.)*** **Summary of various manta ray foraging optimization (MRFO) modifications.**

	[34]	IMRFO	Function optimization and image processing	The touchstone functions and statistical validation confirm that IMRFO achieved higher optimization than the MRFO, honey badger algorithm, PSO, GWO, WOA, teaching-learning-based optimization, flower pollution algorithm, multistrategy serial cuckoo search algorithm, firefly algorithm with courtship learning, self-adaptive cuckoo search, and Cssin. For each image, the IMRFO is stronger than the feature similarity index measure, structural similarity index measure, and peak signal-to-noise ratio, and the improved *k*-means image analysis efficacy is also better.
MRFO with crossover/mutation operators	[35]	Modified MRFO	Function optimization of an inverted pendulum model with an interval Type 2 fuzzy-logic controller	The modified MRFO outperforms GA and the original MRFO and offers better parameters for the controller model.
	[36]	MRFO with a hybrid genetic operator (HMRFO)	Utilization of Merkle–Hellman Knapsack cryptosystem (MHKC) in blockchain, enabling IoT models	In contrast to the slime mold algorithm, pathfinder algorithm, generalized normal distribution optimization, WOA, MRFO, marine predator algorithm, equilibrium optimizer, and GA, the simulation analysis indicates that HMRFO is a good alternative to the current approaches for addressing the MHKC with knapsack dimensions larger than eight bits to reveal the vulnerability points.
	[37]	Improved MRFO	Finding the best path for mobile-robot path planning	The improved MRFO attains an effective path with superior efficiency over PSO and MRFO and offers an excellent tool to address problems associated with mobile-robot path planning.
MRFO with adaptive strategies	[38]	Modified MRFO	Function and engineering optimization	The incorporated schemes efficiently enhance the efficacy of the MRFO, and the modified MRFO is highly competitive among its counterparts, such as the GSA, WOA, PSO, SSA, sine cosine algorithm (SCA), MVO, moth-flame optimization (MFO), biogeography-based optimization, and flower pollution algorithm.
	[39]	Attacking MRFO	Function optimization and image processing	The outcome reveals the dominance of the attacking MRFO over other methods for function optimization and confirms that the approach is suitable for multispectral color image classification.
	[40]	Adaptive-somersault MRFO	Function optimization and parameter adjustment of a proportional-derivative (PD) controller	The test indicates that the suggested improvement has considerably higher results than the native MRFO for accuracy. Moreover, the method achieved better performance control in optimizing PD control.
	[41]	Improved MRFO	Solving economic dispatch in cogeneration system problems	The solution demonstrates the competence, viability, and ability of MRFO to achieve improved results in reducing the fuel cost compared to the GA, HS, WVO, TVAC-PSO, CPSO, and WVO-PSO at a tolerable convergence speed. Furthermore, the outcomes prove the capacity of MRFO performance on large-scale 96-unit systems.
MRFO with fractional-order calculus (FC)	[42]	Function optimization MRFO	Function optimization and image processing	Based on diverse quality metrics, the function optimization MRFO overtakes the contrasted algorithms in image segmentation and global optimization.
	[43]	Fractional-order Caputo MRFO	Function optimization and image processing	The simulation and statistical analyses confirm the excellence and efficacy of the fractional-order Caputo MFRO compared with the MRFO, slime mold algorithm, HHO, SCA, differential evolution with composite trial vector, and others in resolving engineering and image segmentation issues.
Multiobjective (MO) MRFO	[44]	MO MRFO	Applied to solve various multiobjective power optimization problems	The approach achieved excellent efficacy and strength attributes in contrast to the artificial bee colony, krill herd algorithm, stud krill herd algorithm, adaptive real-coded biogeography-based optimization, teaching-learning-based optimization (TLBO), and modified TLBO, grasshopper optimizer, and adaptive grasshopper optimizer. Similarly, this approach achieved numerous dispersed Pareto outcomes with sufficient techno-economic environmental features.
	[45]	MO MRFO	MO problems of distributed generator (DG) units	Voltage buses were enhanced, and power damage was reduced in 33- and 69-bus IEEE models. Moreover, MRFO provides noble outcomes with fewer iterations, saving the time required for resolving difficulties and saving energy compared with the flight algorithm (QODELFA), MRFO, stochastic fractal search algorithm, comprehensive teaching learning-based optimization, MO HHO, MO improved HHO, MO PSO, and MO WOA.

TABLE 2. *(Continued.)* **Summary of various manta ray foraging optimization (MRFO) modifications.**

	[46]	MO-MRFA	Development of combined AC and multiterminal DC power networks	Statistical outcomes using IEEE 30- and 57-bus test power models prove that MO-MRFA achieved higher efficiency and strength above the bat optimization algorithm, MPO, dragonfly algorithm, CSOA, SSA, MVO, GWO, and PSO.
	[47]	MO MRFO	Sizing of the combined renewable generating system consisting of photovoltaics (PVs), fuel cells, and wind turbines under MO scenarios	The experimental outcome confirms the quality of MRFO in handling the presented problem with reliable output and fast convergence.
	[48]	MO MRFO	Function optimization and structural engineering problems	The outcome demonstrates the superiority of MO MRFO by providing enhanced convergence with improved outcome diversity over the MO evolutionary algorithm based on the decomposition, MO GWO, MO PSO, and MO SSA.
	[49]	MO MRFO	Engineering and function optimization	The outcome was satisfactory for diversity and convergence and demonstrated promise in handling MO problems.
	[50]	MRFO improved MO Harris hawks optimization (MMHHO)	Load balancing in cloud computing	The experimental output confirms that the suggested MMHHO approach outperformed MPSO, Q-learning, QMPSO, HHO, and MRFO algorithms for load balancing in cloud computing.
	[51]	MO optimal power flow (MOOPF)	Power optimization problems	The statistical analysis revealed that the MOOPF produced a good result on diverse MO problems and obtained the optimum solution compared with the OMNI, DN-NSGAII, NSGAII, SPEA2, and MO ant lion optimizer.
	[52]	MO MRFO	Optimum DG distribution	The MRFO approach resolved the optimum DG distribution issues better than the PSO, ant lion optimization, WOA, and SCA.
	[53]	NSMRFO	Function optimization	The results of NSMRFO on standard functions indicate its dominance over NSGAII, and it acceptably enhances PD control for the IPS.
Other improved MRFO	[54]	Wavelet mutation and quadratic interpolation (WMQ)-IMRFO	Address the shape optimization concerns for Ball curves	Numerical illustrations demonstrate the capacity of the WMQ-IMRFO in resolving shape optimization problems with complex CCG-Ball curves regarding strength, precision, and convergence features.
	[55]	MRFOA	Dynamic operation of automated distribution systems	The efficacy of MRFOA as a tool in modern automated distribution system control centers is demonstrated by a comparison with related techniques.
	[56]	Taylor-MRFO	Cloud data center load-balancing and switching	The strategy performed better than the artificial bee colony, AP-ACO, and ELORM. Therefore, the dual technique improves cloud infrastructure performance while more efficiently condensing parallel workloads in data centers.
	[57]	Spiral-based MRFO (SMRFO)	Improving flexible manipulator PID control	The SMRFO-based PID controller tracks bang-bang validation input better than the MRFO-based PID.

other operators, such as nondominated sorting, aggregation, and niching, should be studied.

- The investigation and integration of various transfer functions should be explored to solve binary and combinatorial optimization problems, investigating various S-shaped, V-shaped, tapper, and other transfer functions.
- New and emerging forms of data will influence the future development of the MRFO algorithm. The MRFO algorithm must be adapted to handle extensive, unstructured, real-time, and multimodal data to solve complex optimization problems in various domains effectively [130]. For instance, with the explosion of big data, algorithms that can efficiently process and analyze numerous data have become increasingly important. The foraging behavior in MRFO can guide the search process in large datasets, facilitating optimal solutions in a shorter time. However, the scalability of MRFO with large datasets and the ability to handle complex data structures has yet to be explored.
- Finally, no work has provided a theoretical analysis of the MRFO framework. A theoretical analysis would provide an in-depth understanding of MRFO and can be studied in terms of population structure, fitness landscape, and parameters.

The mentioned future work on the MRFO algorithm make it a good prospective optimization algorithm for solving optimization problems. Moreover, this review paper can serve as a guide for researchers in the optimization community interested in applying MRFO algorithm to solve various optimization problems.

TABLE 3. **Summary of various hybridizations of mata ray foraging optimization (MRFO).**

Variants	Reference	Name	Problem solved	Results
Hybridization with a local search	[58]	MRFO sequential quadratic programming (SQP)	Resolving the plate structure optimization-damage identification problem	Compared to artificial ecosystem-based optimization, CS, and MRFO, the damage identification approach based on the hybrid MRFO-SQP algorithm and the iterative order reduction method achieves the highest accuracy and lowest computing cost for damage localization and assessment.
Hybridization with other metaheuristic algorithms	[59]	Simulated annealing (SA) MFRO	Adjusting four types of PID controllers to the optimal settings for an automatic voltage regulator	The main benefit of SA-MRFO is the substantial rise in the convergence speed
	[60]	Manta ray foraging-based golden ratio optimizer (MRFGRO)	Choosing the most critical feature subset from coronavirus disease 2019 (COVID-19) datasets	The MRFGRO is more effective than the local texture features applied for COVID-19 discovery from chest computed tomography images.
	[61]	MRFO SSA	Scheduling problem	The outcomes indicate the dominance of MRFO SSA over the HGSWC, MRFO, SSA, Harris hawks optimization (HHO), and artificial ecosystem-based optimization SSA concerning the throughput and makespan.
	[62]	Manta ray foraging and Gaussian mutation-based elephant herding optimization (MGEHO)	Function and engineering optimization problems	Regarding solution correctness and reliability, MGEHO is superior to EEHO15, EHO, OEHO, improved gray wolf optimization (GWO), LFEHO, equilibrium optimizer, whale optimization algorithm (WOA), sailfish optimizer, and HHO. Furthermore, three actual engineering problems were solved using MGEHO. The comparison demonstrates this strategy's effectiveness as a support tool for solving challenging issues.
	[63]	OBL-MRFO-SA	DC motor speed control using fractional-order proportional-integral-derivative (PID)	The global and local search capabilities of OBL-MRFO-SA are superior to those of GWO/fractional-order PID, atom search optimization/fractional-order PID, sine cosine algorithm (SCA)/PID, and SFS/PID. Using a practical setup has also demonstrated that the designed algorithm is more effective.
	[64]	Discrete MRFO SSA	Handling controller placement problems	The findings demonstrate the efficacy of the influences and the advantage of this approach over the MVO, SCA, SSA, WOA, moth-flame optimization (MFO), and MRFO.
	[65]	MRFO gradient-based optimization (GBO)	Effectively handling problems associated with economic emission dispatch	The outcome is contrasted with native MRFO, GBO, SCA, WOA, HHO, MFO, and BWO. The findings demonstrate the capability of the MRFO-GBO in handling economic emission dispatch problems with single and multiple objectives concerning robustness, convergence features, and precision.
	[66]	MRFO with the dragonfly algorithm	For the best generator arrangement of congestion management in the deregulated control market	The proposed method is implemented in adjusted IEEE 30- and 57-bus models, and the efficacy is contrasted with the native dragonfly algorithm, MRFO, and other metaheuristic methods from the literature.
	[67]	Rider MRFO-based generative adversarial network (GAN)	Effectively discovering glaucoma	Compared to the GSO, convolutional neural network (CNN), modified U-net CNN, GAN, MRFO-based GAN, and rider optimization algorithm-based GAN, the rider MRFO-based GAN offered an improved result with a maximum accuracy of 0.96%, sensitivity of 0.94%, and specificity 0.89.
	[68]	Modified MRFO	Determining the optimum dimensions and positions of multiple wind turbines and photovoltaic (PV) units in a radial distribution system	The overall model damage could be abridged, allowing the reactive power ability of PV inverters. The convergence features demonstrate that the modified MRFO offers the optimum results over the native MRFO approach.
	[69]	MRFO and particle swarm optimization (PSO)	Function and engineering optimization	This method was applied to improve a proportional derivative (PD) controller for an inverted pendulum system to address a real-world engineering challenge. A statistical analysis was performed on the touchstone function test results. For most of the validation functions, the accuracy of the proposed hybrid technique improved. Compared to the native MRFO, the technique improves control performance for PD control.

TABLE 3. ***(Continued.)*** **Summary of various hybridizations of mata ray foraging optimization (MRFO).**

MRFO with neural networks	[70]	MRFO-based DeepCNN	Brain tumor classification	The proposed MRFO-based DeepCNN was validated using accuracy, specificity, and sensitivity measures, achieving higher accuracy, specificity, and sensitivity than existing approaches.
	[71]	MRFO-CNN	Brain tumor classification	The outcome proved the superiority of the MRFO-based CNN over the CNN without MRFO.
	[72]	MRFO-RVFL	Forecasting of the vital efficiency parameters of a complete water management plant functioning with a sludge management procedure	The outcome indicates that the proposed hybrid approach exhibited greater efficiency and validity for prediction regarding the RMSE and R^2 metrics.
	[73]	Deep neural network (DNN) and MRFO	For flood vulnerability planning for the Quang Ngai region of Vietnam	Hybridizing MRFO and the DNN enriched the flood vulnerability forecasting accuracy with an area under the curve of 0.98 compared to DNN-GWO, DNN-SSO, support vector machine (SVM), and GBR. The findings are crucial for helping policymakers comprehend and identify problems, which can help them improve their adaptation plans.
	[74]	Feedforward neural network (FFNN) and MRFO	Forecasting electric energy consumption	The FFNN trained with the MRFO algorithm outperformed the version trained by other algorithms in predicting electric energy use.
	[75]	Backpropagation neural network and MRFO	Selection of soil moisture characteristic wavelength	Compared to the slime mold algorithm, genetic algorithm (GA), and PSO, MRFO had the best predictive capability. Moreover, MRFO performed better in terms of identifying the distinctive spectra of moisture in the soil.
	[76]	CNN-gated recurrent unit (GRU)-MRFO	Electricity theft detection	The analysis using power consumption data from the China National Grid Co., Ltd. reveals that the proposed CNN-GRU-MRFO obtained 6% higher detection accuracy than the CNN-GRU alone.
	[77]	MRFO-based CNN	Brain tumor classification	The proposed MRFO-based CNN has an accuracy of 98.57% and better results than other CNN-based models optimized with MRFO.
	[78]	Enhanced MRFO-based DCNN	Lane detection	In comparison with conventional models, the proposed model exhibited superior performance.
	[79]	MRFO-CNN	Direct discovery of COVID-19 using chest x-ray images	The DenseNet121 optimized network obtains the optimum performance.
	[80]	MRFO-based CNN	Identifying early-stage brain tumors in magnetic resonance imaging (MRI)	The simulation outcome produced by the proposed approach was contrasted with the existing artificial neural networks and PSO, obtaining a higher classification and detection accuracy.
MRFO with extreme learning machine (ELM)	[81]	MRFO-ELM	Forecasting of transport CO_2 emissions in China	The hybrid MRFO-ELM has outstanding performance concerning the examining velocity and forecasting accuracy compared with the PSO-ELM, cat swarm optimization algorithm-SVM, PSO-SVM, ELM, PSO-backpropagation neural network (BPNN), SVM, BPNN, and long short-term memory.
	[82]	MRFO-based bidirectional ELM	Using watermarking that is based on image adaptive multiple embedding strength optimization	Due to its speed, the suggested approach could be used in several multimedia applications.
MRFO with the fuzzy-logic system	[83]	MRFO with the adaptive neuro-fuzzy inference system (ANFIS)	Categorization of cancerous and noncancerous cells from a microarray dataset	The approach is superior to similar methods, such as GK-SVD, ALRFC, iKGGE, RFACO, CSC, EMPAGA, ANFIS, and KF-FANN.
	[84]	MRFO and PSO-based ANFIS	Predicting specific conductance of groundwater	Although the mathematical model provides competitive performance for the specific conductance prediction, the ANFIS presents better prediction. Moreover, MRFO and PSO enhanced the ANFIS models with an RMSE of 13% and 5%, respectively.
	[85]	MRFO with fuzzy-logic control (FLC)	Maximum power point tracking	The strategy using hybrid features of MRFO and FLC offers an encouraging solution for maximum power point tracking in thermoelectric generator systems.
	[86]	Association rule mining-based fuzzy MRFO	Frequent item set generation from social media	The strategy performs effectively compared to current methods.
MRFO with other machine learning algorithms	[87]	MRFO-SVM	Electrocardiogram classification	The model has an accuracy of about 98% over the ant lion optimization, PSO, SSA, GWO, GOA, HHA, and dragonfly algorithm.
	[88]	Random forest (RF) MRFO	Optimum operation of renewable energy sources, reducing electricity generation costs	The RF MRFA method is a successful implementation of renewable energy sources and cost-effective power generation for the smart grid.
	[89]	Extreme gradient boosting (XGBoost)-MRFO	Hybrid PV-wind solar energy model using a static synchronous compensator	By offering reactive power compensation, the proposed XGBoost-MRFO technique provides the optimal control of a static synchronous compensator that attempts to recover the damping of the power system and direct line voltage.

TABLE 4. Summary of applications of manta ray foraging optimization (MRFO).

Application	Reference	Problem solved	Results
Energy and power	[90]	Determining the ideal solar power system's three-diode equivalent model parameters (solar generating units)	The MRFO-based three-diode equivalent model variable selection is superior to the genetic algorithm (GA), SA, whale optimization algorithm (WOA), sailfish optimizer, and coyote optimization algorithm. The MRFO-based method performs better than the compared methods and should be employed in resolving other massive-scale engineering problems.
	[91]	System for tracking global maximum power points	The findings establish the dominance of the MRFO-based maximum power point tracking in mining the global maximum power point under diverse partial shadow arrangements.
	[92]	Reducing power damage, Type I dispersed generators connected in a radial distribution network are sized and shared	The outcomes were contrasted with GA and the hybrid WOA-sine cosine algorithm (SCA). The findings indicate that MRFO is an efficient, fast method that can reach the optimum results in fewer iterations.
	[93]	Controlling the DC/DC and DC/AC converters' proportional-integral (PI) controllers to include a photovoltaic (PV) system in the grid	The attained transient outcome reveals the functionality and capability of the MRFO method.
	[94]	Adjusting power system controller factors to determine the best factors of the load frequency control model and superconducting energy storage model controllers	The strength of the suggested MRFO-based controllers was examined over the disparity of the power system parameters. The authors did not compare it with other metaheuristic-based methods.
	[95]	Combining nonconvex controller point effects with the economic power heat dispatch in the cogeneration energy system	The best outcomes achieved with the MRFO demonstrate its ability, viability, and effectiveness of better outcomes in reducing fuel costs in contrast to HS, FA, TVAC-PSO, WVO, WVO-PSO, GSO, IWO, EDHS, and CPSO.
	[96]	Effective data transmission in fifth-generation wireless sensor network communications	This approach was evaluated using the packet delivery ratio, energy consumption, number of live nodes, and network lifetime as evaluation measures and was compared with the TTDFP, deep neural network (DNN), CLONALG-M, and EADCR. The approach attains a superior network lifetime.
	[97]	Organization of directional overcurrent relays	The outcome was contrasted with MWCA, MEFO, biogeography-based optimization, and HS.
	[98]	Assessing system parameters of 2D dike-like magnetic profile inconsistencies	The MRFO approach is advised for use in modeling other geophysical problems, such as vertical electrical sounding, gravity, self-potential, and magnetotelluric datasets, because it is accurate and trustworthy for solving inverse geophysical problems.
	[99]	Enhancing positions of 3 DG units under load uncertainties in 500 situations	The outcome reveals that the SBO outperforms the remaining algorithms in nearly all situations, followed by GWO, which offers decent outcomes. Conversely, the good efficacy achieved by MRFO consumes double the time of other compared approaches.
	[100]	Optimal distribution network reconfiguration for vulnerable radial smart grids in uncertain working situations	The MRFO method offers effective and exceptional conduct in various working conditions.
	[101]	For the best control and working of distribution models that diminish the lost energy and present quantitative and qualitative power amenities to meet users' satisfaction	The MRFO-based approach has great efficacy and strength over the GA, TSA, PSO, slime mold algorithm, cat swarm optimization algorithm, and ITSA.
	[102]	Optimal distribution and design of power generation assets as distributed generators (DGs) with scheduling ability	The outcomes verified the dominance of the MRFO in contrast with PSO in the distribution of the DGs with scheduling ability.

TABLE 4. ***(Continued.)*** **Summary of applications of manta ray foraging optimization (MRFO).**

Application	Reference	Problem solved	Results
	[103]	Identification of the best factors of the enhanced fractional maximum power point tracking scheme	The key findings demonstrated the advantage of the MRFO-based enhanced fractional maximum power point tracking scheme in contrast to other approaches for dynamic and steady-state responses.
	[104]	To discover single-objective and MO issues associated with optimal power flow (OPF) integrating stochastic renewable energy sources	The results were compared with the moth-flame optimization (MFO), chaotic gravitational search algorithm, improved PSO, supply-demand optimization, autonomous groups PSO, and ant lion optimization. The MRFO-based approach resolves OPF difficulties and outperforms the compared algorithms.
	[105]	Optimum distribution of multiple DG units attached to radial distribution systems	With one-, two-, and three-DG units with unity power factor allocations, the MRFO algorithm produces efficiency gains of 817.91, 751.08, and 730.25 kWh, respectively. In contrast, the MRFO obtains efficiency gains of 233.24, 142.08, and 106.79 kWh using the same number of DG units when the DG units are designed to function with OPF.
	[106]	A renewable microgrid to meet the electric power demand	The effectiveness of the MRFO was established through comparison with the PSO, differential evolution, crow search algorithm, and SHEPO. The influence of cost reduction from solar and energy storage system integration was also studied for various electric power demands.
	[107]	Problems associated with the maximum hosting capacity of renewable energy resources	The findings indicate that the MRFO-based approach obtained better efficacy than the PSO-based approach, where the MRFO reaches the largest hosting capacity with the minimum computation time.
	[108]	Problems associated with optimal power flow	The comparison study found that the MRFO-based strategy guarantees excellent outcomes for OPF problems.
Feature selection	[109]	Attribute selection enhancing speech recognition	The simulation results affirm the superiority of the proposed method in contrast to GA, GWO, and PSO.
	[110]	An attribute extraction approach to select parameters for daily global solar radiation prediction	The effectiveness of the proposed model using six solar energy farms was contrasted with random forest regression, gradient boosting regression, enormously randomized trees, DNNs, and adaptive boosting regression.
	[111]	Optimally select the most critical attributes for classifying brain tumors	The findings confirm the dominance of this approach by providing better accuracy and efficacy.
	[112]	Selects appropriate descriptors to classify amphetamine-type stimulus drugs effectively	The findings reveal that the BMRFO was outperformed by BWOA, with the highest accuracy and fewer feature dimensions.
	[113]	Speech-emotion recognition tasks	The proposed approach achieved a classification accuracy of 97.49% and 97.68% on the two datasets.
Image processing	[114]	Extracting relevant attributes from brain tumor magnetic resonance imaging scans	The simulation produced by the approach was contrasted with existing artificial neural networks and PSO, obtaining a higher classification and detection accuracy.
	[115]	Image processing	The accuracy of the classification procedure was 99.69%. Using the complementary technique with MRFO and equilibrium optimizer algorithms enhanced the classification efficiency of the dataset.
	[116]	Safe transmission of data for coronavirus disease 2019 (COVID-19) diagnosis	The proposed model has outperformed other methods, such as WOA and GWO.
Scheduling	[117]	Power grid scheme reactive power optimization planning problems	The MRFO can produce steady, robust convergence, excellent dependability, and viable configuration of the desired space in resolving optimization difficulties with sensitive power optimization.
PID controller and PV parameter optimization	[118]	Excavating the factors of single-, double-, and three-diode PV models	The factors extracted using the suggested approach offer the best values with the least difference between the computed and measured data in contrast to the ant lion optimization, WOA, MVO, GWO, SCA, and MFO.
	[119]	Assessing model parameters from prospective field irregularities initiated from 2D dipping faults	This approach demonstrated outstanding dominance over other techniques, such as the PSO, GA, and ACO, concerning the convergence rate, quality of handled anomaly variables, and cost. Subsequently, this method was suggested to analyze other configurations and model other geophysical data, such as self-potential and resistivity data.
	[120]	Proportional-integral (PI) controller parameter optimization	According to the findings, the MRFO-based PI controller performs better than optimization strategies at reducing frequency disturbances and tracking reference frequencies.
	[121]	Calculating the model parameters of anomalous 2D gravity profiles	The algorithm efficiency was outstanding when challenged with constrained multiparameter nonlinear inversion difficulties and displayed commendable strength, even with noise, compared with PSO and differential evolution.
Other applications	[122]	Adjust the weighting vector at the fusion center	The MRFO method was contrasted with the PSO, dragonfly algorithm, and GA, and the outcomes indicate that MRFO can be applied effectively for spectrum allocation by cognitive radios.
	[123]	Applied in dynamically multidimensional knapsack problems	The Q-learning algorithm with MRFO effectively handles the dynamic multi-dimensional knapsack problem.

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