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SURVEY ARTICLE

Moth Flame Optimization: Theory, Modifications, Hybridizations, and Applications

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Abstract
The Moth flame optimization (MFO) algorithm belongs to the swarm intelligence family and is applied to solve complex real-world optimization problems in numerous domains. MFO and its variants are easy to understand and simple to operate. However, these algorithms have successfully solved optimization problems in different areas such as power and energy systems, engineering design, economic dispatch, image processing, and medical applications. A comprehensive review of MFO variants is presented in this context, including the classic version, binary types, modified versions, hybrid versions, multi-objective versions, and application part of the MFO algorithm in various sectors. Finally, the evaluation of the MFO algorithm is presented to measure its performance compared to other algorithms. The main focus of this literature is to present a survey and review the MFO and its applications. Also, the concluding remark section discusses some possible future research directions of the MFO algorithm and its variants.

1 Introduction

Soft computing has various computation techniques such as neural systems, fuzzy systems, evolutionary computing, chaos theory, and many more. Swarm intelligence (SI) is a promising domain of artificial intelligence (AI), and it has become drastically essential and famous in the last few years. Furthermore, natural phenomena have inspired researchers to propose intelligent optimization systems called nature-inspired metaheuristic algorithms and various SI-based algorithms using different inspirations are presented in Fig. 1. Examples include Artificial Bee Colony (ABC) [1], Particle Swarm Optimization (PSO) [2], Fish School Search (FSS) [3], and Ant Colony Optimization (ACO) [4]. The algorithm's optimization process starts with determining the random position of the initial population, updating the positions, calculating the fitness of each population, and finding the optimal solution amongst the candidate solutions. These well-known algorithms follow these logical steps to optimize various complex optimization problems successfully.

Generally, nature-inspired metaheuristic methods mimic different aspects of nature, such as insects, animals, and

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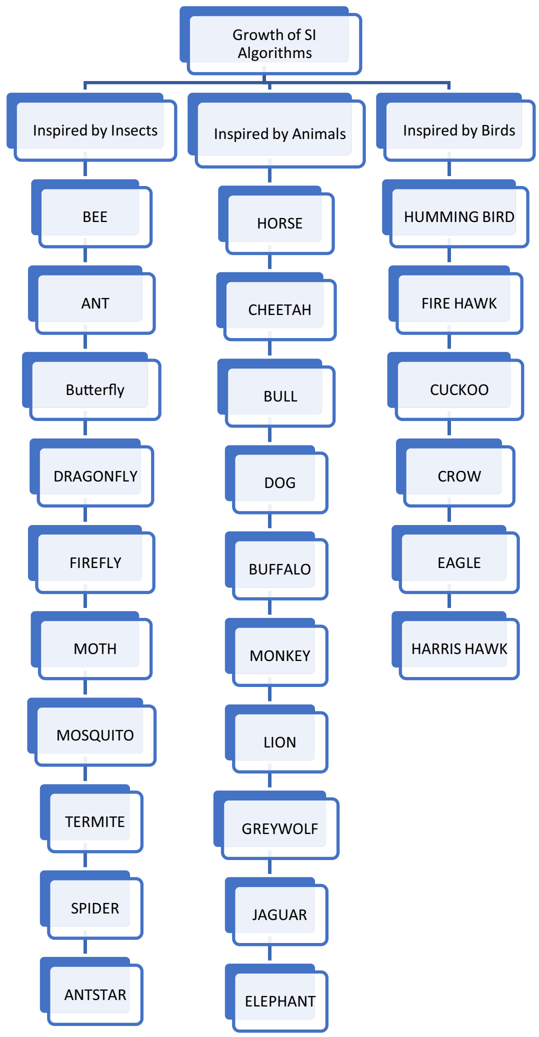

Fig. 1 Various SI-based meta-heuristic algorithms

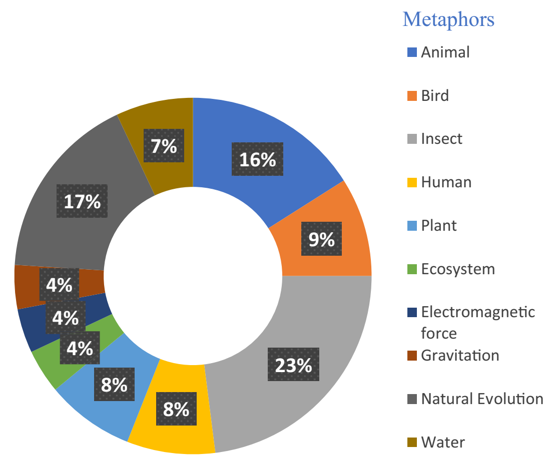

Fig. 2 Top ten leading metaphors for introducing new meta-heuristic algorithms

birds' living and survival systems. The insects are the most common metaphor used to develop efficient optimization algorithms that mimic social behavior to solve optimization problems. The second most used metaphor closely following the insects is the theory of natural evolution (Darwin's evolution theory). Thirdly, metaheuristic designers have also used different aspects of the life of bats, fish, cats, monkeys, and others. Other interesting sources of inspiration for metaheuristic designers include humans, plants, water, ecosystem, electromagnetic force, and gravitation. Figure 2 shows the top ten leading metaphors or frameworks preferred mainly by researchers for developing new metaheuristic algorithms [5].

Metaheuristic algorithms can be broadly divided into single solution-based (SSB) methods and population-based (PB) methods, depending on the number of search agents. The SSB methods use one agent to search the problem space for the optimal solution, whereas the PB methods use many search agents to search the problem space for the optimal solution. Each solution's position is updated in PB methods depending on single and group information about how close they are to the optimal solution. Moreover, the group of agents could easily search the whole problem search space better than a single agent; hence, better results are produced using PB methods than the SSB methods. The PB optimization methods can be classified into four different groups namely evolutionary algorithms [such as, Genetic Algorithm (GA) [6], Differential Evolution (DE) [7], Genetic Programming (GP) [8], Bird Mating Optimizer (BMO) [9], etc.], SI based algorithms [Salp Swarm Algorithm (SSA) [10]**,** Whale Optimization Algorithm (WOA) [11], Symbiotic Organism Search (SOS) [12], Cuckoo Search (CS) [13], Butterfly Optimization Algorithm (BOA) [14], Monarch Butterfly Optimization (MBO) [15], Social Spider Optimization (SSO) [16], Dwarf mongoose optimization algorithm (DMOA) [17], etc.], physical or chemical law-based algorithms [Ray Optimization (RO [18], Multi-Verse Optimizer Algorithm (MVO) [19], Water Evaporation Optimization (WEO) [20] algorithm, Chemical Reaction Optimization (CRO) [21], Atom Search Optimization (ASO) [22], Mine Blast Algorithm (MBA) [23], etc.] and human-based optimization [Teaching–Learning Based Optimization (TLBO) [24] algorithm, Cognitive Behavior Optimization Algorithm (COA) [25], Ebola optimization search algorithm (EOSA) [26],

Coronavirus Herd Immunity Optimizer (CHIO) [27], Socio Evolution and Learning Optimization (SELO) [28] algorithm, and many more]. Some of the works done on these algorithms can be found in Al-qaness et al. [29, 30], Nama et al. [31], Saha [32], Sharma et al. [33], Al-qaness et al. [34], Sharma et al. [35], Chakraborty et al. [36], Elaziz et al. [37], Nama et al. [38].

MFO is a popular SI-based algorithm developed by Mirjalili [11], which imitates the moth's navigation at night, called the transverse navigation mechanism. The moths depend on moonlight to fly at night, maintaining a constant angle to find their direction. This analysis paper offers an inclusive overview of MFO processes for potential MFO-based users. It is a bundle of works of literature consisting of discrete, modified, and hybridization variants. The study also discusses the adaptive parameter settings of different variants of MFO. It also concentrates on the latest MFO applications explaining the methodology, features, and weaknesses. This study exposes readers to the working theory, architecture, and other intricacies of MFO. Finally, significant advantages and limitations of MFO are discussed, and readers are exposed to potential directions for future work.

In [39], the authors published a survey paper on the MFO algorithm from its inception to April 2019. They discussed all the MFO algorithm variants, such as improvements, modifications, or hybridization and application in different fields such as engineering, machine learning, chemical, medical, and so on. The authors of Hussien et al. [41] introduced the latest review paper on the MFO algorithm up to the third quarter of 2019. In the present study, we have discussed all the variants of the MFO algorithm such as modification, hybridization or improvement, binary versions, multi-objective versions, and the applications in various sectors like chemical, medical, engineering, machine learning, image segmentation, networking, fuzzy logic, with the name of the journal along with publishers till today. Therefore, this study provides a more comprehensive review of MFO than the earlier published reviews.

The rest of the present survey paper is designed as follows: a short summary of the classical MFO algorithm is shown in Sect. 2. Then, the development of MFO is elaborated in Sect. 3. Overview of the MFO variants, modifications, and hybridizations are presented in Sect. 4. Further, in Sect. 5, application enhancements in particular fields are presented. Evaluation of the MFO algorithm is shown in Sect. 6. Section 7 illustrates conclusions and a few lines for future research work.

2 Classical MFO Algorithm

In this section, the origin of the MFO algorithm and its working process with the mathematical formulation is presented in Sects. 2.1 and 2.2, respectively.

2.1 Inspiration

Moths belong to the class of insects called the phylum Arthropoda. They have two pairs of broad wings covered in tiny scales, are purely nocturnal, and like all insects, have a head, two antennae, a thorax, six legs, and an abdomen. The moths have unique navigation techniques that have caught metaheuristics researchers' interest. Typically, moths are night travelers using the moonlight for navigation. The navigation pattern of moths can be modeled using the transverse orientation mechanism, as seen in Fig. 3. The flight pattern is such that a crosswise inclination is maintained by keeping a constant angle with the moon to maintain a straight path journey. The moths use the distance from the flame to achieve efficient navigation, meaning as the distance between them decreases, a helix path motion is activated to connect the moth with the flame.

2.2 MFO Algorithm

In basic MFO, the individual moth represents a potential solution, and each position is expressed as a matrix of decision variables given below.

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_N \end{bmatrix} = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,n-1} & x_{1,n} \\ x_{2,1} & \ddots & \cdots & \cdots & x_{2,n} \\ \vdots & \cdots & \ddots & \cdots & \vdots \\ x_{N-1,1} & \cdots & \cdots & \ddots & x_{N-1,n} \\ x_{N,1} & x_{N,2} & \cdots & x_{N,n-1} & x_{N,n} \end{bmatrix} \tag{1}$$

where, $X_i = [x_{i,1}, x_{i,2}, \ldots, x_{i,n}]$, $i \in \{1, 2, \ldots, N\}$.

N represents the number of moths number and n is the dimension of the problem. The fitness of an individual moth is given as a vector shown below:

$$Fit[X] = \begin{bmatrix} Fit[X_1] \\ Fit[X_2] \\ \vdots \\ Fit[X_n] \end{bmatrix} \tag{2}$$

The flame matrix is shown below. The size must be the same as the moth matrix defined earlier because all of the moths fly around a flame.

$$FM = \begin{bmatrix} FM_1 \\ FM_2 \\ \vdots \\ FM_N \end{bmatrix} = \begin{bmatrix} Fm_{1,1} & Fm_{1,2} & \cdots & Fm_{1,n-1} & Fm_{1,n} \\ Fm_{2,1} & \ddots & \cdots & \cdots & Fm_{2,n} \\ \vdots & \cdots & \ddots & \cdots & \vdots \\ Fm_{N-1,1} & \cdots & \cdots & \ddots & Fm_{N-1,n} \\ Fm_{N,1} & Fm_{N,2} & \cdots & Fm_{N-1} & Fm_{N,n} \end{bmatrix} \tag{3}$$

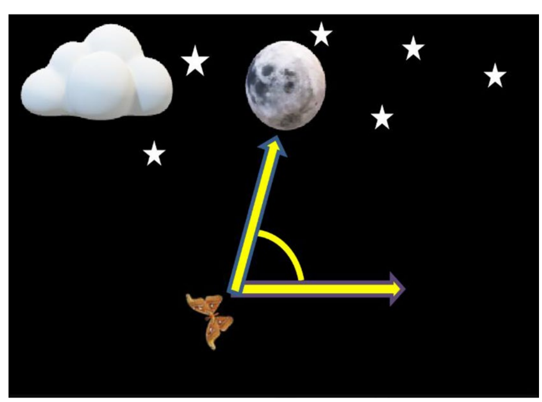

Fig. 3 Navigation pattern of moth at night

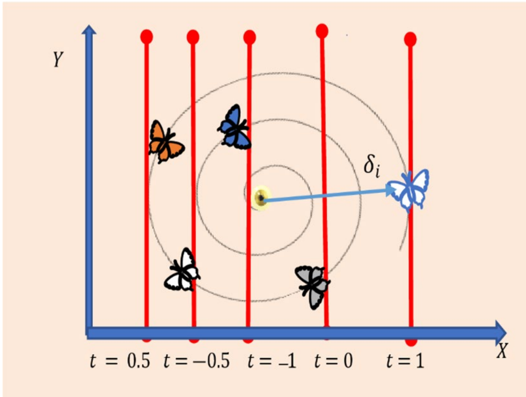

Fig. 4 Logarithm spiral, position w.r.t $'t'$

The corresponding fitness of the flame matrix is given below.

$$Fit[FM] = \begin{bmatrix} Fit[FM_1] \\ Fit[FM_2] \\ \vdots \\ Fit[FM_n] \end{bmatrix} \tag{4}$$

The two key actors in MFO are the moth and the flame. The moth has to move through the flame to obtain desirable results. The logarithmic spiral function is used to model the spiral movement of the moth, and this is defined in the equation below:

$$X_i^{K+1} = \begin{cases} \delta_i \cdot e^{bt} \cdot \cos(2\pi t) + Fm_i(k), i \le N.FM \\ \delta_i \cdot e^{bt} \cdot \cos(2\pi t) + Fm_{N.FM}(k), i \ge N.FM \end{cases} \tag{5}$$

where, $\delta_i = \left| X_i^K - Fm_i \right|$ denotes how far a moth at position X_i is from its corresponding flame (Fm_i). The spiral flight search is determined by b and t (a random number between − 1 and 1) that specifies how close the moth and its flame is presented in Fig. 4. The helix shape flight of a moth towards a corresponding flame is shown in Fig. 5. The value of t decreases over the iterations, thereby balancing the exploration and exploitation at the beginning and end of the iterations.

The mathematical representation t is presented below, and the next position of the moth is shown in Fig. 6.

$$r = -1 + Current_{iter} \left(\frac{-1}{Max_{iter}} \right) \tag{6}$$

$$t = (r - 1) \times k + 1 \tag{7}$$

where, Max_{iter} stands for the maximum number of iterations, k denotes random number between 0 and 1 and r denotes the constant that ensures convergence, and its value decreases linearly from (−1) to (−2) linearly, guaranteeing exploration and exploitation.

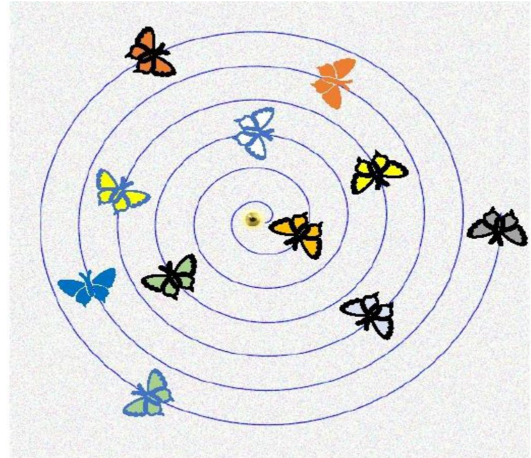

Fig. 5 Spiral movement of Moth around flame

The flame position for the current and last iterations is collected and arranged according to the global and local search fitness value in every iteration. Only the best N.FM flames are preserved, and other flames are wiped away, leading to the one imperfection briefly described in Li et al. [42]. Both first and final flames are the best fitness and the worst fitness. Then, depending in the same order, the moths came to capture the flames one by one.

The last flame will always be captured by the same- and lower-ordered moths over the number of iterations. Figure 7 represents the operational flow of the MFO algorithm for considering twenty initial moths over five hundred iterations (The symbols MO and FM represent moth and flame, respectively, in Fig. 7). The following formula can obtain

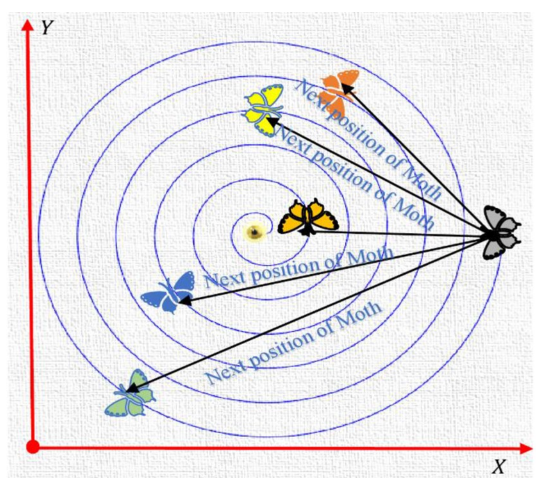

Fig. 6 Position of Moth

the number of flames ($N.FM$) that has been reduced over the iteration.

$$N.FM = round\left(N.FM_{Last\,iter} - Current_{iter} \frac{\left(N.FM_{Last\,iter} - 1\right)}{Max_{iter}} \right) \tag{8}$$

Algorithm 1 and Fig. 8, respectively, represent the pseudo-code and the flowchart of the MFO algorithm.

Algorithm 1: Pseudo-code of MFO Algorithm

1. Input: Objective function $f(X)$, $X = (X_1 X_{2 \ldots\ldots} X_d)$, Number of moths in the population (N), dimension (d), Maximum iteration ($Maximum_{iter}$), Flame number ($N.FM$), b and other related parameters are determined;
2.   for $i = 1{:}\,N$
3.   for $j = 1{:}\,d$
4.   Generate N organism solutions $X_{i,j}$ ($i = 1, 2, \ldots, N$) using following equation
            $X(i,j) = LB(i) + (UB(i) - LB(i)) * rand()$;
5.   end for
6.   end for
7. Calculate fitness value $f(X)$;
8. While $Current_{iter} < Maximum_{iter} + 1$
9.   if Iteration ==1
10.   Enter $N.FM = N$ in initial population
11.   else
            Employ Eqn. (8)
12.   end if
13.   FM = Fitness Function $f(X)$;
14.   if Iteration == 1
15.   arrange the moths according to FM
16.   Update Fm_i
17.   Iteration = 0;
18.   else
            arrange moths based on FM from $Last_{iter}$
19.   Update Fm_i
20.   end if
21.   for $j = 1{:}\,N$
22.   for $k = 1{:}\,d$
23.   Find r and t using Eqn. (6) & Eqn. (7)
24.   Update moths position as to their particular flame using Eqn. (5)
25.   end for
26.   end for
27. $Current_{iter} = Current_{iter} + 1$;
28. end while
29. Output: The best solution with the minimum fitness function value in the ecosystem;

3 Overall Development of the MFO Algorithm

This article presents a conceptual framework of the various improvement efforts made on the basic MFO, enhancements or modifications, and hybridization with the other state-of-the-art problem-solving approaches. Recent studies on the theoretical analysis, variants, and applications of the MFO algorithm in different fields such as chemical, medical, power energy, image processing, economics, engineering, and many more, are discussed with various figures. Figure 9 represents the number of published articles since its inception to January 2021 with the name of the publishers, such as Elsevier, IEEE, Springer, and others. The year-wise articles published on the MFO algorithm from 2015 to 2021 (only in January for 2021) in various domains are presented in Fig. 10, while Fig. 11 represents the number of published articles where MFO has been applied to solve problems in various fields from 2015 to January 2021. Also, the percentage distribution of the articles on the MFO algorithm in various domains is presented in Fig. 12.

4 Variants of MFO Algorithm

In this section, numerous published articles (journal and conference) are presented from different publishers through critical names like "Moth-flame optimization," "MFO," and "Moth flame algorithm." The binary and discrete version of the MFO algorithm is presented in Sect. 4.1. Section 4.2 illustrates various improvements of the MFO algorithm. Hybridization (a combination of two or more optimization algorithms) and multi-objective MFO algorithm methods are discussed in Sects. 4.3 and 4.4, respectively.

4.1 Binary and Discrete MFO Algorithm

Selecting effective features from small and large data sets is crucial for many metaheuristic algorithms. To tackle this challenge, Shahraki et al. [47] introduced an efficient metaheuristic algorithm named binary moth-flame optimization (B-MFO). The goal of B-MFO is to select the smallest possible set of features from small and large medical datasets. The author developed three transfer functions to change

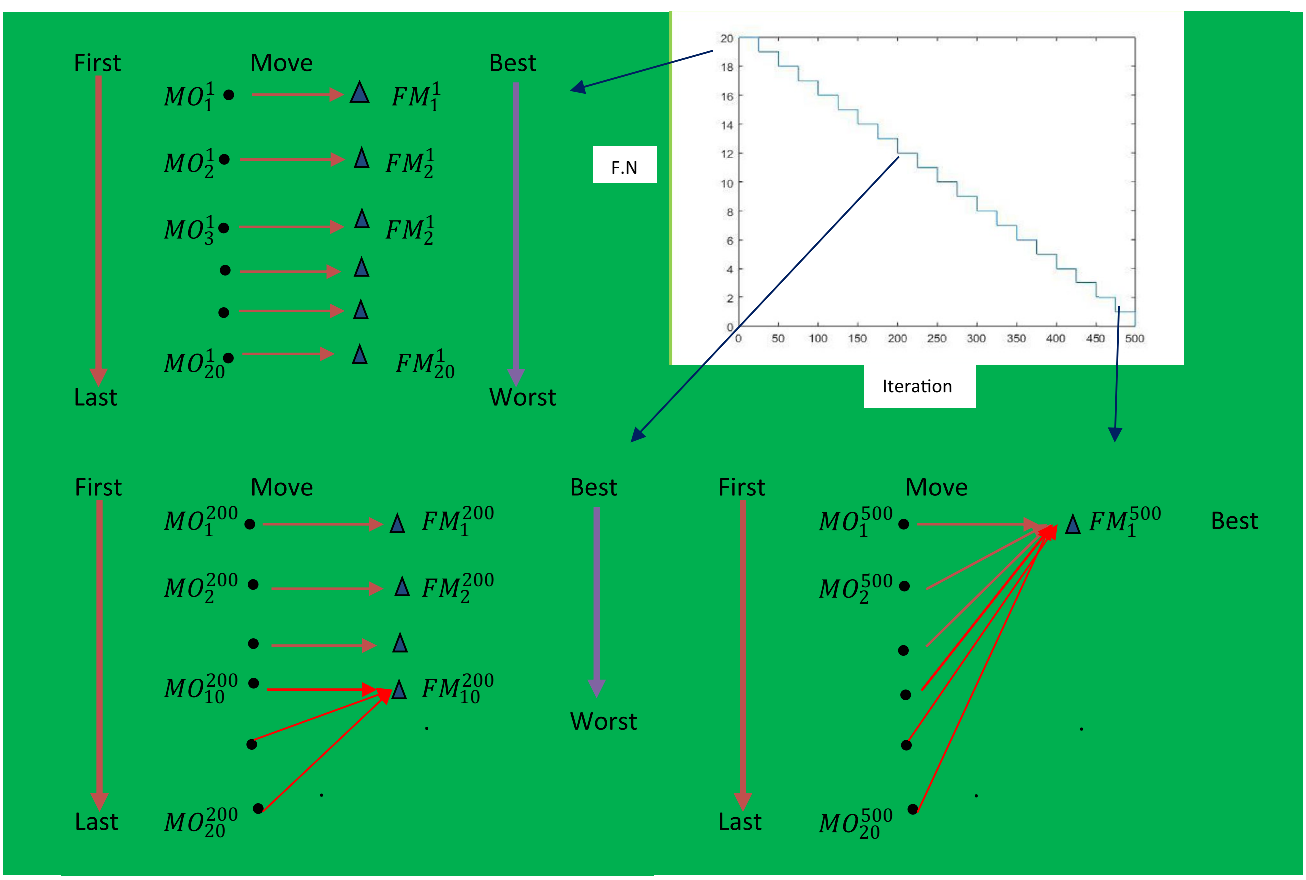

Fig. 7 Visualization of the MFO Algorithm over 500 iterations

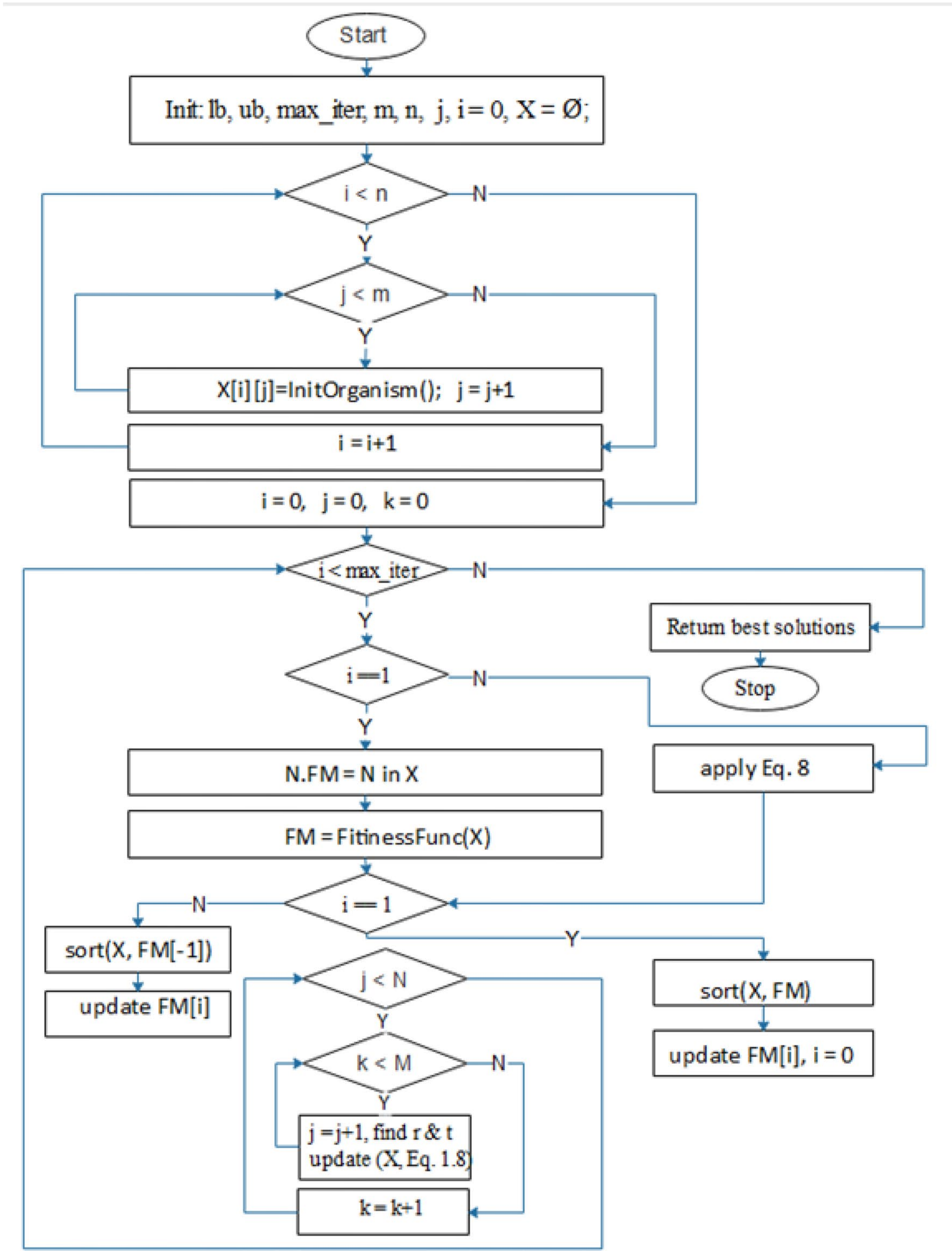

Fig. 8 Flow chart of the MFO Algorithm

the search method used by basic MFO from continuous to binary search space and tested them on seven medical datasets. The obtained results and Friedman rank test prove superior performance of the B-MFO algorithm than the other four meta-heuristic algorithms.

Kigsirisin and Miyauchi proposed an optimization method derived from the basic MFO called alternative binary MFO (BAMFO) [44]. They used it to solve unit commitment (UC) optimization problems. Their goal is to solve the problem of prefixed flame in the MFO algorithm, which causes it to be stocked at local minima. In the proposed BAMFO, four flame generation strategies were introduced to augment the single prefixed flame strategy. The effectiveness and feasibility of BAMFO have been investigated through the total production cost of thermal units in all unit systems (ranging from 5 to 100 companies) as the objective function. Statistical analysis and simulation results prove the superior performance of BAMFO to other algorithms.

The authors [45] proposed a modified MFO called an enhanced binary moth-flame optimization algorithm (EBMFO) using adaptive synthetic sampling (ADASYN) and used it to predict software faults. Three different classifiers (Decision trees, k-nearest neighbors, and linear discriminant analysis) and fifteen real projects (obtained from promise respiratory) are introduced to measure the algorithm's efficiency.

In Reddy et al. [46], the authors designed an algorithm named modified moth–flame binary-coded optimization algorithms (BMMFOA) to improve the unit commitment (UC) problem. The MMFOA (modified MFO algorithm) has been used to enhance the moths' exploitation search and diminish the number of flames. The efficiency of the proposed BMMFOA has been tested on four single-commitment alternatives. The investigation analyzes the effectiveness of the BMMFOA methods concerning the convergence characteristics, execution time, and solution quality terms.

In [47, 48, 49], the authors proposed a discrete version of the MFO algorithm for community detection (In short, DMFO-CD) by mimicking effective techniques, namely representation of solution vectors, initialization, and movement strategy in the classical MFO algorithm. Moths and flames are represented by a locus-based adjacency representation, and the initialization procedure is carried out by examining the community structure and the link between nodes without the requirement for any knowledge of the number of communities. The adapted movement strategy uses a single-point crossover to distance imitate, a two-point crossover to compute the movement and a single-point neighbour-based mutation that can boost exploration and balance exploration and exploitation. DMFO-CD's performance was examined on 11 real-world networks and compared with a few well-known optimization algorithms in terms of modularity, NMI, and the number of detected communities. The comparison findings obtained demonstrate the competitiveness of the proposed DMFO-CD to outperform other algorithms.

Table 1 illustrates the summary of Sect. 4.1.

4.2 Improvements of MFO Algorithm

A new version of the MFO algorithm, EMFO, based on the mutualism phase of symbiotic organism search, has been proposed. The authors added the mutualism phase of SOS after the position update phase of the basic MFO algorithm

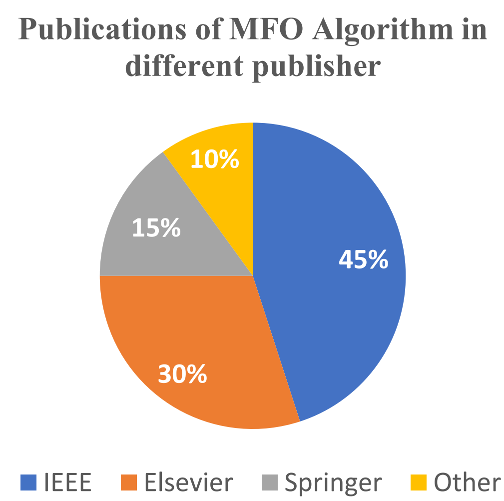

Fig. 9 Percentage of different publishers

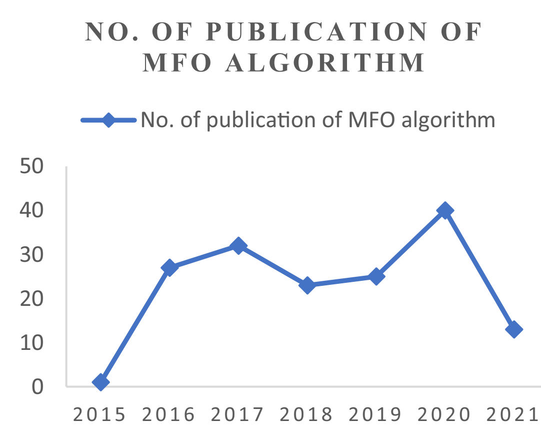

Fig. 10 Year wise publications of MFO algorithm

to get better quality solutions. The suggested EMFO was evaluated against a wide range of other state-of-the-art metaheuristic algorithms and MFO versions. The EMFO has also been used to tackle seven engineering design problems. The obtained results proved that the suggested EMFO outperforms among other competitive algorithms in terms of solution quality and convergence rate.

Sahoo et al. (2022) proposed a novel improved MFO algorithm named m-DMFO by using modified dynamic opposition learning (DOL) strategy to accelerate the convergence rate and helps in removing local optima stagnation. In the beginning, the authors modified the basic DOL strategy with the help of simple quadratic interpolation and embedded it after the position update phase of the MFO algorithm. To measure the efficiency of the newly m-DMFO algorithm, it was tested on a wide range of benchmark functions and a few engineering design problems. Furthermore, the diversity of the m-DMFO algorithm was analysed. From the overall

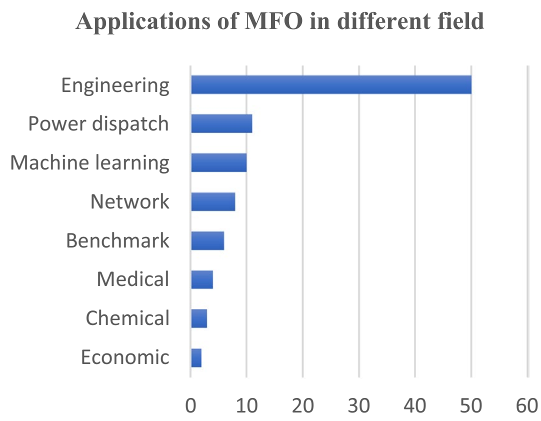

Fig. 11 Distribution of MFO in various fields

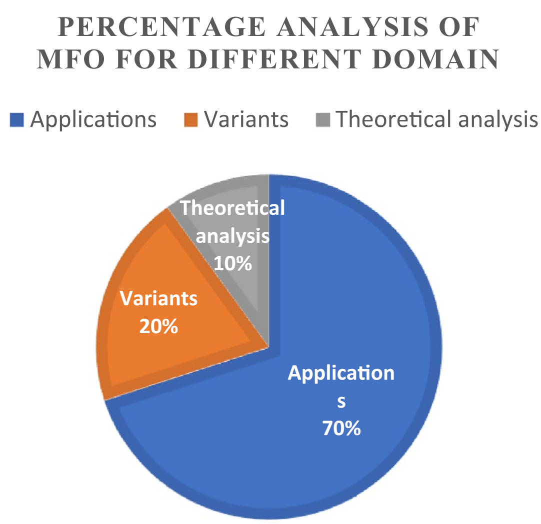

Fig. 12 Modification of MFO in percentage

experimental evaluations and diversity analysis, it can be seen that the suggested algorithm outperforms among other algorithms and achieves a good trade-off between diversification and intensification.

Li et al. [50] attempted to solve some drawbacks associated with MFO by proposing an improvement called ODSMFO. The author combined the OBL mechanism and DE and then combined the resultant method with MFO to obtain quality results through diversity enhancement. The global search was enhanced using a method based on Shuffled Frog Leaping Algorithm (SFLA), and finally, the death mechanism was applied to eliminate unfit individuals. To show how well the proposed algorithm works, the ODSFMFO is tested on 28 benchmark tasks of IEEE CEC 2013 and 30 benchmark tasks of IEEE CEC 2017. Simulations show that the proposed algorithm gets better results than various other algorithms that are competing with it. Further, the suggested ODSMFO helps quicken the convergence rate and makes it easy to jump out of the local optimum.

To overcome the issues of the original MFO algorithm, like slow convergence and convergence to local optima, Ma et al. [51] proposed an improved MFO algorithm. The authors embedded a feedback control for the inertia weight of the population diversity and a probability mutation factor to balance the diversification and intensification of the algorithm. The effectiveness of the suggested approach is thoroughly assessed using four constrained engineering optimization problems and a set of benchmark functions from the IEEE CEC 2014 series. It has been found that the suggested approach performs better as compared to other efficient algorithms in terms of enhancing the algorithm's capacity for convergence. The suggested algorithm also helps in escaping the local minima.

In [52, 53], the authors suggested an improved Moth-Flame Optimization (IMFO) algorithm has been presented to increase the flame variety and moth search ability. The orthogonal opposition-based learning (OOBL) is used to generate the flames in the IMFO, and the moths' location updating method has been updated to include a linear search and mutation operator. According to IMFO's performance evaluation, the IMFO method is compared to other 20 algorithms on 23 benchmark functions, IEEE CEC' 2014 benchmark test set and used for a few engineering design challenges. According to the comparing results, the IMFO is effective and has a good balance of exploitation and exploration abilities.

To improve MFO's performance, Kaur et al. [54] developed an upgraded algorithm of MFO named enhanced moth flame optimization (E-MFO) by adding a few improvements to the original MFO algorithm. The influence of best flame has been introduced to improve exploitation, and adaptive step size and division of iterations are followed to maintain a balance between exploration and exploitation. A Cauchy distribution function is used to improve exploration. To measure the effectiveness of the suggested E-MFO, it has been tested on twenty benchmark functions and has been compared with various meta-heuristic algorithms. MFO and E-MFO performance has also been examined in terms of population and dimension size. In terms of convergence rate and solution quality, the experiments reveal that E-MFO outperforms the competition.

In [55], the authors suggested a new variant of the MFO algorithm opposition-based MFO by differential evolution (OMFODE) for quickening its rate of convergence (OBL technique) and improving the exploitation phase (by DE) by integrating the OBL (opposition based learning) strategy and DE. In order to evaluate our method, we shall conduct a series of experiments. Over a number of CEC2005 benchmark functions, this technique has been tested. As part of the second experimental series, researchers will conduct feature

Table 1 Binary and discrete versions of MFO algorithm

Algorithm name	Used for	Journal/conference	Publisher	References
B-MFO	Used to solve the feature selection problem	Computers	MDPI	[47, 48, 49]
BAMFO	Used to solve unit commitment (UC) problems	IEEE Access	IEEE	[44]
EBMFO	Used for the prediction of software faults	IEEE Access	IEEE	[45]
BMMFOA	Used to improve solving unit commitment (UC) problems	Journal of Computational Science	Elsevier	[46]
DMFO-CD	Used for community detection	Algorithms	MDPI	[47, 48, 49]

selection on ten datasets from UCI repository. Using a genuine dataset that includes photos of different sorts of galaxies, we're also putting our classification algorithm to the test. The results showed that the proposed approach outperforms current state-of-the-art meta-heuristic algorithms using performance metrics.

In Pelusi et al. [56] the authors invented a new PB algorithm called the improved MFO algorithm (IMFO). The proposed IMFO has three phases mimicking exploration, hybrid exploration/exploitation, and exploitation. They used a dynamic crossover operator for flame generation in all three phases, and a weight factor was introduced in the hybrid phase for updating the moth's position,a suitable mutation process has been added for all three phases for the position updating of the moth, which helps in reducing the weakness of the classic MFO algorithm and applied to solve few engineering optimization problems. Six design issues, the CEC 2014 test functions, and a few benchmark functions are used to test IMFO and compare it to more current, well-known optimization techniques. The findings demonstrate that, in terms of search capability and convergence performances, IMFO outperforms the comparative algorithms.

The authors of [42, 43] embedded a new PB algorithm denoted as double-evolutionary learning MFO algorithm (DELMFO) by introducing two evolutionary learning strategies viz., dynamic flame guidance (DFG) and DE flame generation (DEFG). The suggested DELMFO proves its superiority over the other six MFO variants, ten stochastic optimization algorithms, and nine algorithms on different benchmark suits. On the CEC2013 test suite, the DELMFO is compared to six MFO algorithms and nine popular stochastic optimization algorithms. Using CEC2017, the DELMFO is also tested against 10 other stochastic optimization techniques. Experiments reveal that DELMFO has the best global search, convergence, and scalability performance of any algorithm tested.

Apinantanakon and Sunat [57] introduced a new variant of the MFO algorithm named OMFO to overcome the method's demerits, such as slow convergence and low-quality solutions. They applied a new opposition-based rule in MFO to add a new moth generating strategy in updating the moths in the position update phase to speed up the algorithm's convergence. A collection of benchmark functions that are frequently used for performance measurement served as the basis for the investigations. The original MFO and four additional well-known algorithms were contrasted with the suggested OMFO. The outcomes unmistakably demonstrated that OMFO performed better than MFO and the other four algorithms tested.

In Bhesdadiya et al. [58], the authors used the MFO algorithm's navigation technique to resolve equality, inequality, and accurate, complex layout problems. In both uncertain and continuous control variables, the MFO algorithm shows a helpful result. Fourteen restricted benchmark functions were compared to the solutions obtained from existing recognized algorithms, and the simulation showed that the algorithm proposed exceeded other techniques.

In Soliman et al. [59], the authors added two new modified algorithms, viz., MFO2 and MFO3, and applied these two algorithms for terrorism prediction. The proposed method has been calculated on several benchmark functions to show its efficiency and compared with other well-known optimization algorithms. Two well-known classification algorithms, the Random Forests (RF) ensemble classifier and the K-nearest neighbour (KNN) algorithm are used to sort the results of the experiments. A set of assessment indicators is used to evaluate and compare the results. This shows that the proposed modified versions of MFO perform better than the original MFO algorithm and are more stable than other searching methods.

The summary of improved MFO algorithms is presented in Table 2.

4.3 Hybridization

In Sahoo and Saha [60], the authors proposed a new hybrid metaheuristic algorithm called h-MFOBOA by integrating MFO and BOA. To enhance the performance and solution quality of the MFO algorithm, the authors added the global and local phases of BOA after the position update phase of the MFO algorithm. To measure the performance of the proposed h-MFOBOA, it has been tested on different benchmark functions and compared with traditional efficient optimization algorithms as well as MFO variants. Furthermore, it has been applied to solve engineering design problems. The experimental results demonstrated that the suggested h-MFOBOA algorithm achieves superior results as compared to other competitive algorithms.

In [61, 62], the MFO algorithm has been integrated with the orthogonal learning (OL) strategy and the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm to alleviate the original MFO algorithm to accelerate convergence rate and stagnation shortcoming. The developed method is called BFGSOLMFO. In this article, the first best solutions have been obtained by applying the OL strategy every month and showing the direction in a good potential area to the entire population; then, the BFGS algorithm is embedded to enhance the potential of the global best moth in the current population. The proposed BFGSOLMFO has been applied to solve a few real-life problems.

In [40], the authors developed an interesting population-based algorithm using a proportional selection scheme to integrate the MFO and Hill climbing (HC) algorithm and named it PMFOHC. The suggested method has two phases: (a) first, integrate HC with MFO to quicken the searching process (b) to improve the solution quality; they add six popular selection schemes. Thirty benchmark functions and five real-world IEEE CEC 2011 challenges are utilised in both stages of enhancement to assess how well the suggested versions work. To compare with the suggested variants, popular and recent meta-heuristic techniques are also used. The experiment's findings show that the proportional selection scheme PMFOHC outperforms other versions and algorithms that have been suggested in the literature.

A new hybrid MFO algorithm has been developed by Wu et al. [64] to obtain the HAPF (Hybrid active power filter). The proposed method is known as ASC-MFO. The author divided the population into two subgroups in this article: exploration and exploitation groups. In contrast, the sine–cosine mechanism of the sine–cosine algorithm (SCA) is used to enhance exploration. The simple flame generation strategy of the MFO algorithm has been used to boost the exploitation ability. In addition, two new strategies have been incorporated into the local and global phases further to improve the diversification and intensification capacity of two subgroups, the personal best flame generation (PFG) and hybrid exemplar (HEM) strategies. An adaptive formula has also been introduced to balance diversification and intensification in each iteration between two subgroups. The two most commonly used HAPF topologies have been framed to measure the ASC-MFO method's efficiency, where each topology includes four real cases. As experimental results showed, ASC-MFO performs better than other competitive algorithms.

To improve the effectiveness of underwater sensor networks (UWSN), the authors [65] suggested a technique by combining the MFO algorithm and fuzzy c means (FCM). The new algorithm is abbreviated as FCMMFO. UWSN suffers from an irreplaceable battery and high communication delay. One of the main techniques for resolving the problem is the clustering method. This article produced FCM energy-efficient clusters and then used the MFO algorithm to select each cluster's head.

Wu et al. [63] introduced a new population-based algorithm by integrating hybrid symbiotic DE and MFO to acquire suitable PV model parameters. The proposed method is known as the HSDE-MFO algorithm and has three stages. The effectiveness of the proposed approach has been tested to solve the parameter identification problem of photovoltaic models. The Simulation results showed that HSDE-MFO has superior performance to other PV models.

To deal with the application of HMGS (hybrid microgrid system), the authors [66] introduced a new technique called HMOMFO (hybrid multi-objective MFO). HMGS contains battery storage/wind/solar/diesel generators and has been applied to three different parts of India. The proposed method has two phases. In the first phase, PSO and Lévy flight method have combined with the MFO algorithm to generate better candidate solutions. Secondly, the authors added a new EDE approach (enhanced DE) to improve the searching capability. From the experimentation, it can be concluded that HMOMFO produces superior results in terms of minimization of PEE (Price of electrical energy), LPSP (Loss of power supply probability), and photovoltaic power with respect to autonomy days, wind turbine generators (WT) and DG (diesel generators).

In Alwerfali et al. [67], the author developed a variant of the MFO algorithm named SSAMFO by integrating MFO with the modified Salp Swarm Algorithm (SSA) to overcome the demerits of the basic SSA. The authors used the operator of MFO in the follower group of SSA to enhance their performance. Eleven images were used to assess the SSAMFO's performance and compared to a number of well-known image segmentation techniques. According to the obtained result analysis, the proposed SSAMFO outperformed the classic SSA and MFO algorithms in terms of PSNR, SSIM, and fitness value.

Khalilpourazari and Khalilpourazary introduced a new hybrid meta-heuristic algorithm WCA-MFO [68], by integrating the MFO algorithm with the water cycle optimization algorithm (WCA) and solved some numerical and constrained engineering optimization problems. In this context, the spiral movement technique of the MFO algorithm has been introduced to enhance the exploitation ability of WCA.

Table 2 Summary of the improved MFO algorithms

Algorithm Name	Used for	Journal/conference	Publisher	References
EMFO	Used to balance the exploration (and exploitation) and optimization performance	Soft Computing	Springer	(Sahoo et al., 2022)
m-DMFO	Used to visualise diversity analysis and accelerate the convergence speed	Artificial Intelligence Review	Springer	(Sahoo et al., 2022)
ODSMFO	Used to obtain good quality optimal value and diversity enhancement	Expert Systems with Applications	Elsevier	[50]
Improved MFO	Used to balance the exploration (and exploitation) and optimization performance	Applied Intelligence	Springer	[51]
Improved MFO	Applied OBL, mutation operator, and linear strategy for better flame generation and position update	Applied Intelligence	Springer	(Zhao et al.., 2020)
E-MFO	Used for best trade-off between diversification and intensification	Neural Computing and Applications	Springer	[54]
OMFODE	Used to quicken the convergence rate and enhance the exploitation ability of the MFO algorithm, respectively	Mathematics and Computers in Simulation	Elsevier	[55]
IMFO	In this context, a weight factor is added to maintain a balance between exploration and exploitation	Knowledge-Based Systems	Elsevier	[56]
DELMFO	Two evolutionary learning strategies, dynamic flame guidance (DFG) and DE flame generation (DEFG), are used	IEEE Access	IEEE	[42, 43]
OMFO	Used to solve the unconstrained optimization problems	Int. Conf. on Computing and Information Technology	Springer	[57]
MFO	Used to solve equality, inequality, and some really challenging layout problems	Advances in computer and computational sciences	Springer	[58]
MFO2 and MFO3	introduced two new population-based algorithms for terrorism prediction	IJAIEM	IJAIEM	[59]

Moreover, the Lévy flight method has been embedded into the WCA-MFO algorithm to improve the exploration phase.

Using the MFO algorithm with the fuzzy logic control (FLC) algorithm, Kamalapathi et al. [69] developed a hybrid technique. The torque tap problem in the BLDC engine was then solved using this information. MFO controls the minimum line stream harmonics and voltage of the motor in the proposed hybrid system. Also, the embedded FLC improved the MFO updating mechanism, thereby increasing the MFO's efficiency. The suggested hybrid algorithm's performance has been tested regarding the torque and stability rate, torque stability, and the torque's variable stability rate analysis. The obtained results proved his superiority among other techniques in the proposed literature.

To overcome the drawbacks associated with the original MFO, such as the quality solutions and slow convergence, Sayed and Hassanien proposed a hybrid algorithm named SA-MFO that combines the simulated annealing (SA) with MFO [70] algorithm. The authors used SA to update the flame phase of the original MFO algorithm to enhance the performance of the MFO approach. Using some unconstrained benchmark functions and few well-known constrained engineering issues, the suggested SA-MFO algorithm is evaluated. The proposed algorithm has been shown to be superior in the experiments as compared to other well-known and recent meta-heuristic algorithms. The results suggest that the suggested SA-MFO is competitive with other meta-heuristic algorithms in terms of overall performance.

In Anfal and Abdelhafid [71], the authors proposed a hybrid of PSO and MFO called PSO-MFO. The PSO accomplishes the exploitation, whereas the MFO accomplishes the exploration. The suggested PSO-MFO minimizes the phasor measurement units (PMU) for power system observability. It has been tested on three standards IEEE-bus 14, 30, and 57 buses, and found that the PSO-MFO algorithm outperforms some other algorithms in this application. In addition, the results are compared to other methodologies that have been documented in the relevant literature on the topic. Results from the simulation reveal that the suggested strategy may ensure good observability of system states by determining optimal PMU placements. 68-bus Algerian network is used for another test of the observability of the complete system.

Bhesdadiya et al. [58] introduced a new hybrid meta-heuristic algorithm HPSO-MFO by combining PSO and MFO algorithms. The proposed method is then applied to the problem of overcurrent relay coordination optimization problems and a few unconstrained optimization problems. PSO has been used for the exploitation phase, and the logarithmic spiral equation of MFO has been used for exploration in this context. In each iteration, the position and velocity of the particle are updated for the moth and flame, respectively. To check the effectiveness of the proposed algorithm, it has been tested on some benchmark functions, and the obtained results proved the superiority of the HPSO-MFO algorithm.

Modern power systems' OPF (optimal power flow) challenge is fascinating. To deal with the OPF issue, they [72] used the hybrid PSO-MFO (HPSO-MFO) technique. Roulette wheel selection is utilised in the exploration phase of HPSO-MFO, which has a faster convergence rate than the standard PSO-MFO algorithm. For the OPF challenge, the author employed an IEEE-30 bus test setup. The results obtained with the hybrid PSO-MFO method is compared with other techniques such as Particle Swarm Optimization (PSO) and Moth Flame Optimizer (MFO). Results show that hybrid PSO-MFO gives better optimization values as compared with PSO and MFO, which verifies the effectiveness of the suggested algorithm.

MFO and GSA were coupled by the authors of Sarma et al. [73], who employed GSA in the exploitation phase and MFO in the exploration phase. These algorithms have tried to model the search agents and altered properties like mass, gravitational constant, fitness, location, etc., to find the most optimal value. The authors used this hybrid algorithm to segment images. It has been suggested to use both an optimised thresholding algorithm and an optimised K-means algorithm. The segmentation results are then used to classify apples into different classes.

The authors [74] proposed a hybrid combining the MFO algorithm and the loss sensitivity factor (LSF) to find optimal solutions to the renewable energy optimization problems. The proposed technique aims to determine the optimum position and size of DG units based on renewables. The invented MFO-LSF algorithm's performance has been measured through the IEEE 69-bus branch distribution system. The acquired results show a significant reduction in power loss, an improvement in system voltage, and an increase in distribution system capacity when compared to the results from previous optimization strategies.

The summary of the above hybrid methods is presented in Table 3.

4.4 Multi-objective MFO Algorithm

The authors [75] developed an improved version of the MFO called the Emulous mechanism-based multi-objective MFO algorithm (EMMFO). They proposed an improvement where competition between the moths is used as the updating mechanism. The efficiency of the suggested EMMFO has been tested on different multi-objective optimization problems (MOOP) and also applied to different engineering problems. The experiment outcomes have been compared with other methods, such as SPEA-2, NSGA-II, PESA2, MOEA/D, MORBABC/D, MOACO, NSMFO, CLPSO-LS, and PAL-SAPSO.

Zhang et al. [61, 62] proposed another multi-objective version of MFO called improved multi-objective optimization (R-IMOMFO). It uses three phases to find the optimal solution for the cascade reservoir model. Firstly, the flame population update strategy, the position update method and the moth linear flight path are used to make the basic MFO avoid being trapped in local minima and named it as IMFO. Then the R-domination method is applied to fine-tune the solutions. Five new evolutionary algorithms are created by combining various multi-objective mechanisms and evolutionary algorithms in order to test the performance of IMFO and R-domination individually. The benchmark functions and reservoir operating model are used to test five brand-new algorithms and five cutting-edge algorithms. The test results demonstrate that the suggested R-IMOMFO method has the capacity to produce a set of solutions to the optimization operation problem of cascade reservoirs with good convergence and strong distribution.

Li et al. [42, 43] introduced a new multi-objective MFO termed the multi-objective MFO algorithm (MOMFA) to improve water resource utilisation efficiency. In this context, consideration is being given to a multi-reservoir system in China's lushui river basin with a range of aims, including meeting ecological water demands, generating electricity, and diverting water. A combination of opposition-based learning and indicator-based selection was applied to increase population variety and speed convergence. The outcome showed that the suggested algorithm is not only able to find the best trade-off between the components and simultaneously achieve a set of well-distributed non-dominated solutions for the multi-objective water resources utilisation problem. This is in addition to obtaining well-pareto solutions on standard problems. The superiority of the suggested MOMFA has also been confirmed when compared to the outcomes produced by other algorithms.

In Savsani and Tawhid [76], the authors proposed non-dominated sorting moth flame optimization (NS-MFO) to solve MOOPs. The searching process of the MFO algorithm was utilized to obtain different non-dominated solutions. The suggested NS-MFO uses the crowding distance approach and elitist non-dominated sorting to acquire various non-dominance levels and maintain the variety of the best possible set of solutions, respectively. Implementing the method on multi-objective benchmark problems and multi-objective engineering design problems with distinctive features allows for evaluating the method's efficacy. This experimental analysis demonstrates that the suggested approach successfully creates the Pareto front.

Nanda [77] introduced a new method called multi-objective moth flame optimization (MOMFO) with the help of local search and global search of the original MFO algorithm. The method aims to reach the optimal solution and preserve diversity. It employs diversification and intensification features of the classical MFO concept, thereby avoiding the domination of outcomes. In comparison to Non-dominated Sorting Genetic Algorithm-II (NSGA-II) and multi-objective PSO (MOPSO), the performance of the proposed MOMFO is illustrated on six mathematical benchmark function optimization problems.

The publisher, journal name, and a few descriptions of the above modifications are presented in Table 4.

5 Applications on MFO Algorithm

The MFO algorithm has been applied in different sectors such as economic, chemical, medical, networking, power dispatch problems, engineering, power energy, machine learning and image processing. In subsection 5.1, applications of MFO in economic, chemical and medical sectors are analysed. Applications of MFO in the field of networking and machine learning are discussed in Sects. 5.2 and 5.3, respectively. In Sects. 5.4 and 5.5, applications of MFO in the field of power energy and power dispatch problems are presented, respectively. Applications of MFO in engineering and image processing are summarized in Sects. 5.6 and 5.7, respectively.

5.1 Applications in the Field of Economical, Chemical and Medical

In this section, we have discussed applications of MFO in economic, chemical and medical fields.

5.1.1 Economical Application

A multi-item, multi-constrictive model for the quantity of non-linear unit holding costs and partial back ordering was proposed [78]. There are various constraints when modelling the relevant problem, such as the total allowable cost, warehouse capacity, and available budget. The essential contribution is the recognition of inventory period lengths, under which the level of inventories decreases as the overall cost of inventories decreases. Moreover, each product's back-ordering rate during the shortage period is considered a significant decision variable to reduce the total inventory cost significantly. The MFO and interior-point methods improve the function fit in multi-size models, given their nonlinearity and complexity.

5.1.2 Chemical Applications

Due to the reduction of carbon footprint and high performance, fuel cell (FC) technologies have been receiving more attention. In Messaoud et al. [79], MFO was used for quantifying the parameter of PEMFC (proton exchange membrane FC), which were used in electrical equations based on I-V (current–voltage) characteristics. The effectiveness of the suggested algorithm was determined through three commercially available PEMFCs and their experimental data, and the obtained results achieved the best performance compared to various other algorithms.

Chauhan and Kotecha developed a strategy using the MFO algorithm to find the optimality of the production planning problem [80] in the chemical industry. The performance of the suggested algorithm has been measured on four hundred eight unique instances of production planning problems mimicking various complex constraints. The production planning problem was observed to be consistently solved by the MFO using the advised approach.

5.1.3 Medical Applications

In order to find diseases and cancer, we need a reliable approach for weeding out genes that are irrelevant, redundant, or just noise in the gene pool. Simplifying the problem by choosing only a small number of genes is important in order to maintain a high level of accuracy, though. Therefore, Dabba et al. [81] developed a novel hybrid metaheuristic algorithm called QMFOA by integrating quantum computation and the MFO algorithm and applied it to identify a small gene subset that can be used to classify samples with high accuracy. The QMFOA features a straightforward two-phase technique. The first phase is a pre-processing that measures gene redundancy and relevance to obtain the relevant gene set. The second step combines MFOA, quantum computing, and support vector machine with leave-one-out cross-validation, etc., to solve gene selection. To measure the efficiency of the proposed QMFOA, it has been examined on thirteen microarray datasets, and obtained results demonstrated the superiority of the proposed QMFOA among other algorithms.

There are various methods used in detecting cancer and disease. The authors [81, 82] first established a modified MFO algorithm called the mMFA. They then used mutual information maximisation (MIM) to classify microarray data using gene selection. The MIM-mMFA has been used to select cancer-predictive genes for classification purposes.

Table 3 Summary of hybridization of the MFO algorithm

Method	Hybridized with	Description	Journal/conference	Publisher	References
h-MFOBOA	BOA	Used to enhance the performance of the solution and applied to engineering problems	Journal of Bionic Engineering	Springer	[60]
BFGSOLMFO	Broyden–Fletcher–Goldfarb–Shanno algorithm	Used to enhance the acceleration of convergence rate and stagnation shortcoming	Expert Systems with Applications	Elsevier	[61]
ASC-MFO	SCA	Used to obtain the more accurate parameters of the Hybrid active power filter (HAPF)	IEEE Access	IEEE	[64]
FCMMFO	FCM	Used to improve the performance of the network	IEEE Access	IEEE	[65]
HSDE-MFO	HSDE	Used to acquire suitable parameters for photovoltaic models	IEEE Access	IEEE	[63]
HMOMFO	PSO, Leavy flight, EDE	Used for minimizing the price of electrical energy (PEE)	Applied Soft Computing	Elsevier	[66]
PMFOHC	HC	Applied to improve the quality of solutions and accelerate the search process	Engineering with Computers	Springer	[40]
WCA-MFO	WCA	Used to solve numerical and constrained engineering optimization problems	Soft Computing	Springer	[68]
SSAMFO	SSA	Used to overcome the demerits of SSA and applied in image segmentation	IEEE Access	IEEE	[67]
MFOFLC	FLC	To solve the problem of torque ripple	Electronics	MDPI	[69]
SA-MFO	SA	Used to violate the drawbacks of basic MFO algorithm	Complex and Intelligent Systems	Crossmark	[70]
PSO-MFO	PSO	utilized to minimize the phasor measurement units (PMU) for power system observability	Electrotehnica, Electronica, Automatica	Universita	[71]
HPSO-MFO	PSO	very helpful in solving over current relay co-ordination optimization problems and some unconstrained benchmark functions	In Advances in computer and computational sciences	Springer	[58]
HPSO-MFO	PSO	Used to solve the OPF problem	Global Journal of Research In Engineering	Global Journals Inc. (USA)	[72]
MFO-GSA	GSA	Used to solve food rottenness measurement problems, the cloud helps minimize cash losses caused by food and store	Intelligent Systems Conference (IntelliSys)	IEEE	[73]
MFO-LSF	LSF	Used for image segmentation	International Middle East Power Systems Conference (MEPCON)	IEEE	[74]

mMFA is used in conjunction with MIM to assess the redundancy and significance of the selected genes.

Xia et al. [83] invented a novel MFO variant named GCMFO with the help of a general oppositional-based learning strategy (to enhance the diversity of the population in MFO) and a crisscross search strategy (to enhance the exploration ability of each search agent). In addition, to measure the efficiency of the suggested GCMFO, it has been tested on IEEE CEC 2017 benchmark functions, and then authors integrated GCMFO with kernel extreme learning machine classifier to handle medical diagnosis cases, namely, appendicitis diagnosis, overweight statuses diagnosis, and thyroid cancer diagnosis. Experimental results proved that the suggested algorithm outperforms other competitive algorithms and is best for medical diagnosis cases.

Table 4 A short description of multi-objective versions of the MFO algorithm

Method	Explanations	Journal/conference	Publisher	References
EMMFO	Multi-objective Benchmark functions and Four constrained engineering design problems	Journal of Parallel and Distributed Computing	Elsevier	[75]
R-IMOMFO	Used to solve the Cascade reservoirs problem	Journal of Hydrology	Elsevier	[62]
MOMFA	To accelerate convergence and preserve diversity	Water Resources Management	Springer	[43]
NS-MFO	Used for solving multi-objective engineering design problems	Engineering Applications of Artificial Intelligence	Elsevier	[76]
MOMFO		International Conference on Advances in computing, communications, and informatics (ICACCI)	IEEE	[77]

Effective fatal electrocardiogram (FECG) extraction helps doctors monitor foetal health during pregnancy. Fetal ECG Extraction is difficult since the signal is faint and polluted by sounds, especially maternal ECG. Jibia and Jibia [84] devised an adaptive filter that utilises MFO to maximise the efficiency of the signal extraction process. The mother's body's thoracic and abdominal ECG (AECG) signals are recorded using a non-invasive two-point approach. The two signals are sent to an adaptive filter whose coefficients are best determined by the traditional least means square (LMS) algorithm and MFO. The experimental results indicate that the new approach is suitable for Fetal Electrocardiogram extraction from AECG as compared to other conventional methods.

The authors proposed an enhanced MFO [85], which incorporates Kapur's threshold image segmentation in addition to a modified MFO. After that, they used it to locate the tumour in pictures obtained from clinical-grade MRI slices that had been shot utilising the Flair T2 modality. Their findings demonstrated that the proposed model is superior to the others.

The use of medical imaging technology in the diagnosis and treatment of patients is absolutely essential. Treatment, diagnosis, and early detection are all made possible thanks to their assistance in these three areas. Medical image processing relies heavily on picture segmentation, which has been employed in various contexts. Image segmentation using multi-level thresholding (MLT) is regarded as one of the most straightforward and effective methods available. Elaziz et al. [37] propose a hybrid SI-based approach named MPAMFO by the integration of Marine Predators Algorithm (MPA) and MFO in which MFO is utilized as a local search method for MPA to avoid trapping at local optima. Two experiments were conducted to evaluate the performance of MPAMFO. All that's left is to separate ten images of natural grayscale. In the second experiment, the MPAMFO was tested using CT images of COVID-19, a real-world application. As a result, thirteen CT scans were used to evaluate MPAMFO's performance. An extensive comparison of the MPAMFO's quality and performance with SI methods has been conducted, proving that MPAMFO is a more efficient MLT approach than other methods in terms of efficacy.

Early breast cancer screening with digital mammograms is an important area of medical image analysis. In Muduli et al. [86], the authors combined a CAD model with extreme learning algorithms (ELM) and MFO algorithms to classify malignant mammary masses into the benign or malignant categories. The new algorithm uses a spectral pattern extraction method called lifting wavelet transform (LWT) to obtain essential features from chest X-ray images. MFO's effectiveness is explored to determine the best weights and biases for the ELM, improving generalisation performance with fewer hidden nodes. In order to optimize the efficiency, the algorithm has been designed to work on two datasets (MIAS, DDSM). The simulated results show that the proposed CAD model contains an accuracy of 99.76% for MIAS (normal vs. abnormal) data and 98.80% for DDSM (benign vs. malignant) data. The model we suggest provides superior results over competing approaches.

Sayed et al. [87] proposed a new approach to evaluating breast cancer data that combines the power of cluster analysis with bio-inspired algorithms. They combined the MFO and WOA into a single binary version and adopted two criteria, namely clustering-based measurements and statistics-based measurements, to evaluate the proposed techniques. According to the experimental findings, binary MFO's chosen features are the best at discovering clustering since their performance remains constant as the number of clusters rises, while binary WOA achieves the best results in terms of external validity assessments.

In Hassanien et al. [88], the authors proposed a new algorithm (MFORSFS) by modifying the MFO algorithm to solve the tomato disease problem. The authors used the MFO algorithm and the rough collection for feature selection (RSFS) in this work to find the set of features that maximized classification accuracy. The performance of MFORSFS was compared to that of other feature selection-based algorithms such as PSO and GA. The simulation results show that the MFORSFS algorithm was efficient among other algorithms for Precision, Recall, F-Score, and Accuracy.

The authors [89] proposed a new approach for the kernel extreme learning machine (KELM) with CMFO (Chaotic Moth Flame Optimization). Concerning Parkinson's illness and breast cancer medical diagnosis problems, the methodology proposed was compared with several other competitive KELM models, which rely on basic MFO, PSO, and GA algorithms. From the experiment, it is shown that the proposed algorithm outperforms other existing methods.

Alzheimer's disease detection (AD) is tedious and time-consuming in seniors more than 65. An automatic Diagnostic AD system was suggested by Sayed et al. [90]. The authors used the MFO principle to distinguish between three classes, including Normal, AD, and Cognitive impairment, as the features of selection algorithms. A benchmark data set of 20 patients is also used for each class. The test results show that the method proposed is efficient, accurate, and f-scored.

The overview of the above discussions is shown in Table 5.

5.2 Application in Networking

In Trinh et al. [91], the author presents a distributed fuzzy logic clustering (FLC) approach that leverages two FLCs to cluster wireless sensor networks (WSN). The proposed method considers several mobile sink nodes and gives another FLC for cluster heads (CHs) fuzzy sink selection as CHs cooperate in multi-hop data packet routing to reduce WSN energy usage. After that, they introduced a distance-based variant of random early detection (RED) congestion control to reject data packets more intelligently. To improve the proposed FLCs' effectiveness, authors tune them via MFO and decrease their regulations. Simulation results show that clustering and distance-based RED congestion control improves WSN longevity, reduce retransmissions, and reduce packet loss.

Sapre and Mini [92] embedded a new algorithm by integrating DE with MFO named differential MFO (DMFO) algorithm. The author used an improved mutation strategy in DMFO to place relay nodes (RN) to cluster the wireless sensor networks (WSNs). Further, Sapre and Mini proposed a new technique called the MS (mobile sink) traversal technique to minimize the average trajectory length traversed by MS. It is used to avoid the use of the TSP (traveling salesman problem) solver in MS traversal.

Dash et al. [93] proposed a hybrid of Jaya-based MFO (JMFO) and a basic MFO algorithm to reduce transmission loss in the IEEE network using well-positioned FACTS (flexible alternating current transmission system) devices. The TCSC (thyristor controlled series compensator) and SVC (static VAR compensator) are used as a fitness function for MFO and JMFO algorithms in IEEE 14 and 30 bus systems. The outcomes are contrasted with only PSO and prove its superiority.

To boost the efficiency of the MFO algorithm, Korashy et al. proposed an improved MFO (IMMFO) algorithm [94] and used it to find the optimal coordination between standard and standard directional overcurrent relays (DOCRs). The lead hierarchy concept of the GWO algorithm is used to improve the MFO algorithm in this context. The primary goal is to reduce the total operating time for all primary relays and fulfill the selection criteria between relay pairs without breaking the requirements. Three separate networks have examined the proposed IMMFO algorithm's efficiency (15-bus network, 9-bus network, and 8-bus). This compares the suggested IMFO, the traditional MFOs, and other famous optimization strategies. The results show that both standard and non-standard DOCRs successfully resolve coordination problems without infringing the primary and backup relays proposed by IMFO.

Ameliorated MFO (AMFO) algorithm was projected in Zhao et al. [53] to strengthen the solution efficiency and MFO algorithm's global optimization capability. In this paper, to generate flames for enhancing the MFO algorithm, the opposition learning technique, Gaussian mutation and position updating mechanism were used. The suggested AMFO was then used to refine the parameters of fast learning networks (AMFO-FLN) and to show its supremacy over other models.

Distributed data classification was invented based on the famous K-means algorithm [95]. The biggest downside is that it gets trapped in the local minimum of this algorithm. A new algorithm [96] with robust distributed clustering techniques based on evolution was proposed to solve this issue. MFO was implemented in the literature to minimize the intra-cluster gap and to obtain the optimal partition at each sensor node of the wireless sensor networks. Each data point is assigned a weight based on volume and density for outlier detection for robustness, and a larger weight is known as an outlier. The performance of the proposed method was compared with four algorithms called distributed K-Means (DK-Means), diffusion whale optimization algorithm (DWOA), diffusion particle swarm optimization (DPSO), and diffusion elephant herding optimization in terms of the silhouette index, Dunn's index, and time complexity (DEHO). It is evident from the simulation results that, among others, the proposed approach overflows.

To answer the link prediction problem, the author [97] provides a parallel metaheuristic framework based on moth flame optimization (MFO), clustering, and pre-processed datasets (PMFO-LP). On a high-performance computing cluster, this methodology is implemented and evaluated on various big and complex networks, including social, citation, biological, and information and publication networks,

Table 5 Applications of MFO in economical, chemical and medical field

Applied area	Applied/Used for	Journal/conference	Publisher	References
Economical	Applied to identify the inventory cycles' lengths	Journal of Industrial and Production Engineering	Taylor and Francis	[78]
Chemical	Used to estimate the parameters of PEMFC for their electrical equations	Chemical Engineering Science	Elsevier	[79]
	Applied to improve the single level production technique in a chemical industry	IEEE Region 10 Conference (TENCON)	IEEE	[80]
Medical	Applied for gene selection in microarray data classification	Expert system with applications	Elsevier	[81]
Medical	Used to select cancer-predictive genes	Journal of Ambient Intelligence and Humanized Computing	Springer	[81, 82]
	Applied in appendicitis diagnosis, overweight statuses diagnosis, and thyroid cancer diagnosis	Journal of Bionic Engineering	Springer	[83]
	Applied for fetal ECG extraction from AECG	Advances in Science, Technology and Engineering Systems Journal	ASTESJ	[84]
	Applied for removing Tumor	Evolutionary Intelligence	Springer	[85]
	Applied for CT scan images of COVID-19	IEEE Access	IEEE	[37]
	Applied to classify malignant mammary masses into the benign or malignant categories	Journal of Classification	Springer	[87]
	Intended a CAD model for the classification of breast masses	Biomedical Signal Processing and Control	Elsevier	[86]
	Applied for solving tomato disease problem	Computers and Electronics in Agriculture	Elsevier	[88]
	Applied CMFO strategy for KELM	Neurocomputing	Elsevier	[89]
	Applied MFO algorithm as features selection algorithm for AD diagnosis	International Conference on Genetic and Evolutionary Computing	Springer	[90]

among others. PMFO-LP solves the link prediction problem with more accurate findings in an acceptable amount of time. PMFO-LP surpasses other well-regarded algorithms in error rate, area under curve, and speedup.

Today's social networks are booming. Users choose Twitter, Facebook, microblogs, and YouTube to communicate their opinions and information. With technological advancement and product diversity, online e-commerce firms are competing to improve their business by posting positive product spam reviews. Users' opinions are based on sentiment, ratings, and product attributes. This creates ambiguity for buyers making decisions based on criticism and developing phoney opinions on products. Opinion spam detection helps create opinions from social media reviews. The authors used a unique framework with the help of flower pollination, grey wolf, and moth flame to detect opinion spam is proposed. The Grey wolf method performs better than flower pollination and moth flame optimisation algorithms in terms of convergence speed, mean, standard deviation, variance, and elapsed run time.

The use of relay nodes (RNs) extends the life of a network and reduces data delay. By placing relay nodes in strategic positions throughout the deployment region, we can make sure that the network is always connected. Therefore, it is necessary to locate ideal relay nodes to create a completely interconnected WSN. Various meta-heuristic methods have been developed for RNs positioning problems. In Sapre and Mini [98], the optimal locations for the placement of relay nodes (RNs) have been obtained by utilizing the bat algorithm (BA), MFO algorithm, and ISA (interior search algorithm). The proposed algorithm also uses a fully connected heuristic network to check the network's connectivity. The results of extensive simulations demonstrate that MFO is superior to BA, ISA, and the least spanning tree-based M1tRNP method.

In Strumberger and Sarac [99], the MFO algorithm was applied to solve the static drone location problem (NP-hard optimization problem). The proposed method's main objective is to allow monitoring of all objectives by optimizing the number of drones. The authors used thirty uniformly distributed targets in the network domain to check the proposed algorithm's efficiency. The outcomes of simulations, where the moth search algorithm established full coverage of targets, indicate that this strategy has the potential to handle this kind of issue.

The combinations of wireless access networks and optical networks are fiber-Wireless (FiWi). The optical network unit (ONU) placement problem in FiWi aims to simplify the complex network design and improve the network's general performance through cost efficiency and increased throughput. The authors [100] proposed research based on FiWi. They used the MFO algorithm for multiple optical network unit placement. To strengthen the position of ONU, the proposed approach has been compared to existing annealing and greedy algorithms. It is evident from the experimental findings that MFO algorithms achieve faster convergence than some of the existing greedy algorithms.

In Faris et al. [101] proposes a new algorithm for the radial basis function by applying the MFO algorithm. The authors formulated the MFO algorithm as an RBFN trainer in this literature and then compared it with seven different existing algorithms. The proposed algorithm enhances all network parameters such as widths, centers, and connection weights. The simulation results show that the proposed MFO-trainer can show superior results in most case studies.

In Table 6, a short analysis of the MFO algorithm in the field of networking area are presented.

5.3 Machine Learning Applications

The advancement of the computer, internet, and database technology has accelerated with the velocity of the ocean, the machine learning domain. Techniques such as clustering, feature selection, and classification can successfully manage a vast amount of data (Heidari et al. 2017) [102].

Shan et al. [103] proposed a new algorithm named double adaptive weight mechanism for stabilization of MFO algorithm (WEMFO). The proposed WEMFO enhances searchability and ensures a balance of exploration and exploitation of the basic MFO algorithm. The suggested WEMFO was improved in terms of both efficiency and robustness by employing two weights at various points in the algorithm. This superiority was further demonstrated using KELM and other benchmark optimization problems in the engineering area.

Due to the various font sizes, styles, and noises, Arabic handwritten letter recognition (AHLR) is a difficult area of pattern recognition. In Ewees et al. [104], the authors have introduced a new MFO-based AHLR algorithm called MFO-AHLR to enhance the accuracy of the AHLR with a minimum of feature values. In an MFO-AHLR approach, three phases were used: extraction, binarization, and noise removal. CENPARMI, a benchmark dataset of handwritten Arabic letters, was used. All the experiments showed that the results were better for the chosen features. Also, for all classifiers, the selected feature sets did better than the features that weren't chosen, and the processing time was sped up. The MFO-AHLR was able to classify things correctly 99.25% of the time, which is more than any other published work.

Power load forecasting has become a more complicated undertaking as a result of the growth of the Energy Internet and the ongoing reformation of the electric power market. The MFO-LSSVM model was proposed by Li et al. [25] as a new hybrid (combination of MFO and annual power load forecasting model based on least squares support vector machine (LSSVM)) technique. MFO was employed to determine the optimal use of parameters in the LSSVM model in this proposed strategy. China's annual electricity consumption forecasts show that the proposed MFO-LSSVM model performs much better than single LSSVM, FOA-LSSVM (LSSVM optimised by fruit fly optimization), and PSO-LSSVM (LSSVM optimised by particle swarm optimization).

MFO was employed in the feature selection method to discover the best feature combinations in the wrapper mode. The authors employed MFO methods to increase the classification's performance. The proposed technique was compared to the PSO and GA using a set of UCI data sets. In light of the acquired data, it's clear that the algorithmic approach proposed here works.

In Yamany et al. [105], MFO is used as a multi-layer perceptron (MLP). The proposed method is called MFO-MLP and is utilized to find out the weight and biases of MLP. Three function-approximation data sets are used to measure the efficiency of the proposed method and tested on four popular algorithms named GA, PSO, ACO, and evolution strategy. The outcomes of the simulation results demonstrated that the MFO algorithm achieved higher accuracy than those algorithms.

Table 7 represents an overview of the MFO algorithm in the field of machine learning.

5.4 Power Energy Applications

Overpowering the distribution network is a problem for grid operations because cogeneration plants are inflexible, and wind energy production is unpredictable. To overcome these issues, the authors [106] developed an improved MFO algorithm with the help of three strategies: inertia weight, unified initialization, and the spiral position update strategy. The effectiveness of the newly developed algorithm has been applied in combining heat and power system operation problems and economic dispatch in light load and wind power unpredictability. Moreover, three different instances had been addressed in order to test the algorithm's robustness and resolve the intricate limitations of power systems under difficult circumstances.

Table 6 Applications of MFO in networking area

Applied area	Applied/Used for	Journal/conference	Publisher	References
Network	Introduced distributed fuzzy logic clustering and applied in wireless sensor network	Artificial Intelligence Review	Springer	[91]
	Applied to reduce the problems of WSSNs	Peer-to-Peer Networking and Applications	Springer	[92]
	Applied for parameter setting of FACTS devices	Microsystem Technologies	Springer	[93]
	Used to find optimum harmonisation between standard and non-standard DOCR	IEEE Access	IEEE	[94]
	Being used for optimising the training of artificial neural networks	Applied Soft computing	Elsevier	[53]
	Used to minimise the distance in the intracluster and to achieve an optimal WSNsw partition everywhere	Engineering Applications of Artificial Intelligence	Elsevier	[96]
	Applied for link prediction problem	Evolutionary Intelligence	Springer	[97]
	Applied for Email spam detection	International Journal of Web Based Communities	Inder science	(Rani and Sumathy, 2018)
	Applied fully connected heuristic network to monitor network connectivity	Wireless Personal Communications	Springer	[98]
	To enable all targets to be monitored using the optimal drone number	International Journal of Computers	IARAS	[99]
	Required for placement of several optical network units	Optical Fiber Technology	Elsevier	[100]
	Applied in radial basis function	Neural Computation	Elsevier	[101]

The Hybrid Flow Shop with Energy Consumption (HFS-EC) combines the flow shop scheduling and parallel machine scheduling problems to optimise energy utilization, besides regular makespan in the production scheduling. The authors applied the MFO algorithm to optimise the HFS-EC case study, which was conducted in a machine shop concentrating on three machining types; lathe, milling, and deburring. The objectives were to optimise makespan and total energy consumption in the machine schedule. To check the efficiency of the proposed model, it has been compared with a few basic and recent metaheuristic algorithms. The obtained results proved the superiority of the MFO among other competitors.

Abdel-Mawgoud et al. introduced a novel algorithm named hybrid MFO-SCA. They combined MFO with combined power loss sensitivity (CPLS) to determine the optimal allocation of single and multiple distributed generations (DGs). The proposed hybrid MFO-SCA is tested on IEEE-33 and 69 bus radial distributions and proves superior to recent meta-heuristic algorithms.

The moth flame optimization–generalized Hopfield neural network was proposed by Ramachandran et al. (2021) as a hybrid of the MFO technique (MFO-GHNN). FOPID controller with self-adaptation is presented for a multi-area hybrid power system (HPS) with automatic load frequency regulation in the proposed hybrid optimised FOPID controller. The proposed FOPID controller's effectiveness has been experimented with under various changes in HPS like system parameters, load demand, and solar and wind power generation. The obtained results outperform other controllers (GHNN-PID, MFO-FOPID, and PID controller). For stability analysis, the author used Matignon's theorem of stability.

The authors [107] used a new modified MFO algorithm named mMFO for parameter tuning of AFPID of the autonomous power system. The mMFO PID controller's efficiency has experimented on traditional population-based algorithms such as MFO, PSO, GWO, and GSA-based AFPID controller and tested against diverse parameter systems. As per the simulation results, it can be concluded that the proposed method achieved the best results compared to other classic methods.

The finding of the optimum position and sizes of the distributed generators (DG) has been subject to significant interest regarding acquiring several objectives, such as improving voltage profile, power loss, reliability, and efficiency. Recently, Elattar and Elsayed [108] have announced a new algorithm of MFO, named modified MFO algorithm (MMFO), to overcome the drawbacks of the MFO algorithm,two modifications are developed that add unexpected elements to the MFO operation. As a next step, the author presented how a problem formulation was integrated with the objective function to get the optimum position and size of DG units depending on renewable energy sources used to minimize the project's net operating cost considering four distinct objective functions. Finally, the solution to the problem was applied, and the MMFO was used to solve the problem (after converting multi-objective to single-objective optimization). A new algorithm has been created for use in a single-bus test distribution network to measure how efficient and better something is. The results of this algorithm are compared with other algorithms in use.

The authors [109] have used three new algorithms named dragonfly (DFO) [110], the grey wolf (GWO) [111], and the MFO algorithm to find out the optimum position of capacitors in different RDSs (radial distribution system). The LSF (loss sensitivity factor) was used to calculate the most candidate buses then, and the optimum placements and sizes of capacitors were found using DFO, MFO, and GWO algorithms. The 33-bus, 69-bus, and 118-bus RDSs were considered to measure the performance. From the obtained results, GWO, DFO, and MFA are observed to provide accurate convergence at a high convergence speed to the overall minimum objective point of the function.

To evaluate the optimum position and size of the DG (decentralized generators) for RDSs, the authors of Abdelmawgoud et al. [112] propose an algorithm by using PLSF (power loss sensitivity factor) and CMFO (chaotic moth-flame optimization) with aiming of acquiring a maximum reduction in active system loss. The performance of the suggested algorithm has been checked by applying it to three DG installations in thirty 3 RDS busses in the IEEE. The results show the high performance of the suggested algorithm from a comparative study.

In the context [113], authors have applied the MFO algorithm for solving shunt condenser banks (SCBs) optimisation problems and distributed generations (DGs). The authors [114] invented a new approach to obtain the optimal solution for the multi-area hybrid interconnected power problem. Trivedi et al. [115] used the MFO algorithm to find the optimal solution for the optimal power flow problem (OPF). The authors [116] have proposed an efficient hybrid method for finding optimal solutions to the distribution challenges of capacitor banks in the radial distribution system (RDS).

The purpose of the algorithm based on Moth-flame Optimization (MFO) [117] is to ensure an optimized power flow (OPF) by using the existing power system infrastructure in combination with the flexible alternating current transmission (FACTS) devices to reduce losses, maintain a high voltage level in the desired level and ensure the cost-effective operation of the power system. The simulations are conducted to achieve the best parameters for three FACTS devices: devices are placed in a standard IEEE 57-bus system at predefined positions. The experimental findings have shown that the proposed algorithm is superior to other techniques in this literature.

MFO has been applied [118] to solve total harmonic distortion (THD) and harmonic eliminating problems for multilevel converters. This article used the suggested approach on 7-level and 11-level inverters to remove or reduce harmonics and the THD. The findings show that the MFO-model outperforms others in resolving the THD problem and eradicating harmonic distortion.

For single-line contingencies, the authors of developed a new technique for getting the optimal parameter setting and optimal position of SSSC based on the MFO algorithm. The proposed technique has been tested on the IEEE 30-bus system. The experimental findings show that the proposed method effectively prevents transmission lines and bus voltages overload.

Under the deregulated scenario, the authors [119] suggested an automated two-area hydrothermal system control method (namely, cascade integral and proportional-derivative (CIPD)). For the simultaneous optimization of second control gains, the author utilized the MFO algorithm, and the performance of MFO was compared to the performance of PIDs and PRIDs. Compared to PI and PID controllers, the model study MFO-based CIPD controller shows excellent dynamic responses.

Table 7 Applications of MFO in machine learning

Applied area	Applied/Used for	Journal/conference	Publisher	References
Machine learning	Applied to solve Kernel extreme learning machine and numerical optimization problems	Knowledge based systems	Elsevier	[103]
	Applied in arabic handwritten letter recognition	International Conference on Control, Artificial Intelligence, Robotics and Optimization (ICCAIRO)	IEEE	[104]
	Applied in annual power load forecasting	Applied Intelligence	Springer	[25]
	Applied in feature selection problem	IEEE Congress on Evolutionary Computation (CEC	IEEE	(Zawbaa et al., 2016)
	Used to find out the weight and biases of MLP	11th International Computer Engineering Conference (ICENCO)	IEEE	[105]

In order to improve electricity prediction efficiency, a new algorithm (named Rolling-MFO-GM(1, 1)) has been developed [120]. In addition, to increase the performance (forecasting performance of electricity) of the suggested algorithm, the authors added three techniques, including an MFO algorithm, a rolling mechanism, and a GM model of gray prediction (1, 1). The tests display that MFOs can significantly enhance the annual prediction of electrical consumption efficiency to increase GM parameters (1,1). The rolling mechanism could also help the forecast results match the actual data.

In Allam et al. [121], the author used MFO For parameter extraction processes of three models of diodes based on laboratory data. For the performance of the suggested approach named DEIM, the authors collated the results of the proposed approach with the results of the hybrid Evolutionary and flower pollination algorithm. In addition, evaluation analysis was conducted in different environmental conditions for the above algorithms based on three models. The results indicate that MFO's algorithm was the most commonly used in the determination of the minimum mean partial error (MBE), root mean square error (RMSE), and absolute error (AEMPP).

Optimal power flow (OPF) is a well-studied optimization problem in power systems and is defined as a nonlinear programming problem. The primary goal of the OPF problem is to satisfy various system operating conditions, such as power flow equations and inequality constraints, while simultaneously optimizing the chosen objective functions, such as the piecewise quadratic cost function and fuel cost with valve point effects, and voltage profile improvement. In Bentouati et al. [122], MFO was applied by the authors to resolve the OPF problem in the connected power system, considering equal rights and inequality constraints. For various purposes, the suggested algorithm was presented to the Algerian power system grid. Results from the simulation clearly show that the proposed algorithm to resolve the OPF problem is efficacious and robust.

The authors [118] used a recently discovered heuristic, the moth-flame optimization method, to solve the harmonic removal problem and minimise total harmonic distortion. For a seven-level cascaded multilevel inverter, the fifth and seventh order harmonics are eliminated, and for an eleven-level cascaded multilevel inverter, the fifth, seventh, eleventh, and thirteenth order harmonics are eliminated. For various degrees of modulation indexes, simulation results of a seven-level cascaded multilevel inverter and an eleven-level multilevel inverter are reported for various degrees of modulation indexes. The simulation outcomes demonstrate that the moth-flame optimization model effectively addresses the harmonic removal and total harmonic distortion minimization issues.

In Gope et al. [123], MFO proposed an optimal bidding approach to increase market participant earnings by twice bidding on congested systems. The Generator Shift Factor (GSF) generator redesign was used in this paper to reduce the system bottleneck. The optimization of the moth-flame was adopted in order to find the optimal solution to the bidding problem. The proposed system was tested using an amended IEEE 30 bus standard system for the deregulated electricity market.

Table 8 represents an overview of the above discussions MFO algorithm in the field of power energy.

5.5 Application in Power Dispatch Problem

One of these three hybrid approaches, combines an active set algorithm (ASA), an interior point algorithm (IPA), and sequential quadratic programming (SQP). They leveraged the ability of the MFO to control a stochastic window (SW) enabled integrated power plant system. Their hybrids are then applied to find optimal solutions for the economic load dispatch (ELD) problem and a stochastic wind enabled ELD (ELD-SW).

Combined economic and emission dispatch (CEED) challenges aim to meet operational restrictions and load demand while simultaneously reducing operating fuel costs and pollution levels. The authors proposed a new variant of MFO algorithm named MMFO by using path modification of the moth in a new spiral around the flame. Furthermore, the proposed MMFO has been applied to solve the CEED problem, and with various optimization methods, the performance of MMFO is compared. The CEED study includes the valve point effect, environmental emissions, and transmission line losses to produce more useful results. Utilizing various standardised test systems, MMFO is validated. The simulated results demonstrate how effectively the new MMFO outperforms other well-known optimization strategies.

In Sanki et al. [126], the author developed a novel fuzzy proportional integral derivative (PID) controller based MFO and implemented it to improve stability and proper power management in the islanded micro-grid (MG) systems. Further to examine the proposed controller's resilience and sensitivity (RLP), the authors used fluctuations in solar-wind power output under random load perturbation. Additionally, many case studies under various (MG) scenarios are taken into consideration when performing the performance verification of the suggested intelligent controller. The comparative analyses and dynamic responses demonstrated support for the suggested controller's advantages over recently deployed control systems.

Nandi et al. [127] used nonlinearities to improve automated generation control (AGC) for a realistic multi-area multi-source test power system model. Cognizant of damping oscillations in the face of increased load disturbance, this work focuses on the combined unified power flow controller (UPFC) and redox flow battery (RFB). The authors used the MFO algorithm to design UPFC and RFB gains with the help of parameter tuning. MFO's advantages over other metaheuristic optimization methods are demonstrated by comparing its findings with those of other algorithms. Over a range of 25% uncertainty in parametric values and under load, the robustness of the developed controller is examined. The results of the simulations reveal that the integration of UPFC and RFB in a realistic power system is very successful in stabilising the load frequency.

Lal and Barisal [128] applied MFO method to examine the plan and execution of a fractional-order PID (FOPID) controller for simultaneous load frequency and voltage control of a power system. The first section of this study explains how the suggested method for frequency stabilisation of isolated power systems with AVR for excitation voltage control is put into practice. The current research is then expanded to include a multi-unit, multi-area power network. The suggested MFO-tuned PID/FOPID controller's implementation considers recent publications' findings, including ZN- and SA-tuned PID controllers for a related power system. The simulations' results attest to the viability of the MFO-tuned FOPID control method.

The author [129] applied the MFO algorithm to optimise PI/PID controller parameters for automatic generation control (AGC) of power systems in four different ways. At first, simulation is done on a two-area thermal power system. By comparing the results of the proposed MFO optimised PI/PID controller with other recently published metaheuristic algorithm optimised PI/PID controllers for the same power system model followed by a sensitive analysis and the proposed method has also been applied to different realistic multi-area, multi-source power systems with different sources of power. The experimental results demonstrated that the proposed MFO-based model outperforms other algorithms.

In Sahu and Hota [130], the author developed an MFO-based approach and represented a load frequency control method for a two-area, diverse-source power system with non-identical power plants. A brand-new controller called a proportional, integral, derivative (2-DOF PID) controller has been used in the proposed method. Utilizing several optimization techniques, including the genetic algorithm (GA) and cuckoo search algorithm (CSA), the performance of the suggested controller is first evaluated using the objective function Integral time multiplied by absolute error (ITAE). The analysis shows that employing a 2-DOF PID controller is significantly more robust than using a conventional controller for the proposed system.

The authors [131] applied the MFO to find optimal solutions for the ELD problem by utilizing emissions and valve points. The main target is to find the optimality of generating units by minimizing emission cost, generating operator cost, and multi-objective. The proposed method's effectiveness has been checked by an isolated micro-grid and six generating units compared with other algorithms.

The author [132] used two bio-inspired algorithms, ALO and MFO, for the ORPD problem to optimize control variables better. The robustness and effectiveness of the proposed method were tested on the IEEE-57 bus system. However, the authors [133] used the MFO to find optimal solutions for the dynamic and non-convex economic load dispatch (ELD) problem.

The optical reactive dispatch problem is a power system network, mimicking more constraint, non-convex and nonlinear problems. Its target is to diminish the power loss and bus voltages in the power system network. The authors [134] applied the MFO algorithm to overcome this issue and accelerate the convergence rate. IEEE 30 and 57 buses have been taken to check the efficiency of the suggested method.

In Mei et al. [135], the authors applied the MFO algorithm to the ORPD problem to get the best combination (setting of transformer tap, sizing of reactive compensators, and voltage generators) to minimize voltage and loss of total power. IEEE-30, 57, and 118 bus systems have been taken to calculate the effectiveness of the suggested approach. Also, In Sulaiman et al. [136], the authors applied the MFO algorithm to the ORPD problem to get the best combination among the control variables. They opted for loss minimization as an objective function. The author used IEEE 30 bus system to observe the effectiveness of the proposed algorithm.

Table 9 illustrates the overview of applications of MFO algorithm in power dispatch problems.

5.6 In the Field of Engineering

One of the more well-known issues in combinatorial optimization is the knapsack issue. There are numerous knapsack problems, including the 0–1 knapsack problem, the multidimensional knapsack problem, the change-making problem, the generalised assignment problem, the bin-packing problem, and the discounted knapsack problem (DKP01). For those familiar with backpack problems, the discounted {0–1} backpack problem is something fresh. Due to the efficient searching ability of the MFO algorithm, the author [137] used it to solve discounted {0–1} knapsack problem. To accelerate the convergence speed and reduce the gap between best-found and optimal solutions, the author mimicked a greedy procedure in the MFO algorithm. To measure the effectiveness of the suggested algorithm, thirty discounted {0–1} knapsack problem instances are used, and the obtained results proved that the proposed algorithm outperforms the other algorithms.

Table 8 Applications of MFO in power energy

Applied area	Applied/used for	Journal/conference Name	Publisher	References
Power energy	Applied in combine heat and power system operation problems and economic dispatch in light load and wind power unpredictability	Energies	MDPI	[106]
	Applied to the flow shop scheduling and parallel machine scheduling problems	Recent Trends in Mechatronics Towards Industry 4.0	Springer	(Rose and Mohamed 2022)
	Applied to find out the optimal allocation of single and multiple DGs	Electric Power Components and Systems	Taylor and Francis	[124]
	To improve a self-adaptive FOPID controller for multi-area HPS load frequency regulation	IET Renewable Power Generation	Willey	(Ramachandran et al., 2021)
	Applied for parameter tuning of AFPID	International journal of sustainable energy	Taylor and Francis	[107]
	Used to determine the best position and size of DG units in the distribution system	IEEE Access	IEEE	[108]
	Capacitor placement and size can be determined with this tool	Iranian Journal of Science and Technology	Springer	[109]
	Applied for solving AGC	International Journal of Modelling and Simulation	Taylor and Francis	[125]
	Used to determine the optimal locations and sizes of renewable DG in RDS)	International Middle East Power Systems Conference (MEPCON)	IEEE	[112]
	Used to solve the SCBs and DG optimisation issue	Electrical Engineering	Springer	[113]
	Used to solve the interconnected multi area power problem	Optimal Control Applications and Methods	Willey	[114]
	Applied to optimize the optimal power flow (OPF)	Neural Computing and Applications	Springer	[115]
	Used to address RDS condenser banks distribution challenges	International Middle East Power Systems Conference (MEPCON)	IEEE	[116]
	Applied to solve OPF problem	International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS)	IEEE	[117]
	Applied to solve THD and harmonic eliminating problems for multilevel converters	International Symposium on Industrial Electronics (INDEL)	IEEE	[118]
Power energy	Applied for getting the optimal parameter setting and optimal position of SSSC	Eighteenth International Middle East Power Systems Conference (MEPCON)	IEEE	(Abd el-sattar et al., 2016)
	Applied for optimization of CIPD controller	IEEE Region 10 Conference (TENCON)	IEEE	[119]
	Applied for forecasting the electricity consumption of inner Mongolia	Applied Sciences	MDPI	[120]
	Utilized for parameters extraction of the three-diode model for the multi-crystalline solar cell/module	Energy Conversion and Management	Elsevier	[121]
	Applied for optimal power flow problem	Indonesian Journal of Electrical Engineering and Computer Science	IAES	[122]
	Applied for harmonic elimination problem	International Symposium on Industrial Electronics (INDEL)	IEEE	[118]
	Applied for maximize the profit of the market participant considering double sided bidding	2016 IEEE Region 10 Conference (TENCON)	IEEE	[123]

To address the issue of data clustering, this author [138] created a novel heuristic method based on the MFO. The Shape and UCI benchmark datasets have been used in a number of tests to verify the competitiveness of the suggested approach. Over twelve datasets, the suggested method is contrasted with five cutting-edge methods. On ten datasets, the suggested approach performs better on average, and it performs comparably on the remaining two datasets. The examination of experimental findings supports the effectiveness of the proposed strategy.

To address the problems of canonical MFO, the authors [47, 48, 49] developed an improved MFO (I-MFO) algorithm, which helps in finding the trapped moths in local optimums by defining memory for each moth. The trapped moths usually use the adapted walking around search (AWAS) technique to get away from the local optima they have been caught in. The efficiency of the suggested I-MFO has been checked by benchmark functions followed by statistical analysis. In the end, three mechanical engineering issues from the CEC 2020 test suite are used to evaluate the I-MFO algorithm's capacity to discover optimal solutions. Results from experiments and statistical analysis show that the proposed I-MFO method outperforms the competitors and improves upon the canonical MFO's drawbacks in a big way.

Introduced a variant of the MFO called the improved moth-flame optimization (IMFO), which used the flame strategy of the spotted hyena optimization (SHO) algorithm in combination with quasi-opposition-based learning (QOBL). The effectiveness of the proposed IMFO was used to find the optimal path for the mobile robot problem and its results compared with other state-of-the-art algorithms.

Adamu et al. [139] used the MFO algorithm to find the best impulse response coefficients of FIR (Finite Impulse Response). The efficiency of the MFO-based designed FIR filters has been measured with other traditional metaheuristic algorithms. The experimental results have shown superiority compared to the other optimization techniques.

Amallynda and Hutama [140] applied the MFO algorithm to solve the flow shop problem by taking travel time between machines. To measure the effectiveness of the proposed method, it has been collated with other traditional optimization algorithms. The collated results have proved that the proposed algorithm helps in reducing the makespan by up to 3%.

The authors [141] proposed a modified MFO with an improved performance called the Leavy flight MFO (LMFO) algorithm and applied it to smart grid (SG) systems to solve the issue of power quality. The suggested LMFO could find better optimal solutions that achieve SG systems' objectives.

In Ravuri and Vasundra [142], the author suggests spark-based large data clustering by using the moth-flame optimization-based bat (MFO-Bat) algorithm, which combines MFO and Bat algorithms. The proposed technique clusters huge data in spark's initial cluster nodes using feature selection and clustering. Initial cluster nodes read huge data from dispersed systems, and optimal features are selected and inserted in the feature vector based on the MFO-Bat algorithm. Spark's final cluster nodes employ sparse-fuzzy C-means to produce optimal clustering on the given features. MFO-Bat beat other existing approaches in terms of classification accuracy%, Dice coefficient%, and Jaccard coefficient%.

Gupta et al. [143] developed a variant of the MFO called modified MFO (MMFO), which was used to find the smallest possible feature subset from a high-dimensional dataset. The robustness, effectiveness, and superiority of the proposed algorithm were confirmed by comparing its results with the basic MFO and other existing algorithms.

Within the context of fog computing, the optimization of task scheduling as a demanding topic that pertains to cyber-physical system (CPS) applications has been seen as an NP-hard problem. Using the moth-flame optimization technique, this study Ghobaei-Arani et al. [144] proposes a task-scheduling approach for CPS applications that assigns an ideal set of jobs to fog nodes so that the total execution time of tasks is reduced. To test the proposed approach, we use the iFogSim software. When the technique for scheduling jobs was used in a simulation, the best scheduling solution was determined to ensure equal work distribution to fog nodes while consuming less overall execution time than alternative algorithms.

In Das et al. [145], the MFO algorithm was employed to optimize the set of excitatory weights and the optimal inter-element spacing between the array elements in CCAA design. The suggested method achieves a lower SLL value than the previous one. The MFO optimizes the position of all the elements of the array. The study shows the implications of the algorithm for CCAA design.

Cloud computing exchanges web services and resources with end users through the Internet. Depending on the user's needs, the cloud might supply identical services with varying quality-of-service (QoS) criteria, which must often be integrated. To improve the quality of service (QoS) in a distributed cloud environment, Ghobaei-Arani et al. [146] used the MFO algorithm for the web service composition (WSC) problem termed "MFO-WSC". Model checking is used to ensure that the QoS-aware MFO-WSC algorithm is valid using formal modelling and formal modelling with model checking. The validity of the provided behaviour model is tested using logical problems, including deadlock-free, fairness, and reachability requirements. The results of the experiments show that the proposed method outperforms

Table 9 Applications of MFO in Power dispatch problems

Applied area	Applied/Used for	Journal/conference Name	Publisher	References
Power dispatch problems	Applied to solve ELD Problem	Applied Soft computing	Elsevier	(Khan et al., 2021)
	Applied to solve a non-convex economic dispatch Problem (CEED)	Electric Power Components and Systems	Taylor & Francis	(Hussien et al., 2021)
	to improve stability and proper power management in the islanded microgrid (MG) systems	Journal of The Institution of Engineers (India): Series B	Springer	[126]
	Used MFO algorithm to designing UPFC and RFB	Iranian Journal of Science and Technology, Transactions of Electrical Engineering	Springer	[127]
	applied MFO method to examine the plan and execution of a fractional-order PID controller for simultaneous load frequency and voltage control of a power system	Journal of Electrical Systems and Information Technology	Springer Open	[128]
	applied to optimize PI/PID controller parameters for AGC of power system	International Journal of Energy Optimization and Engineering	IGI Global	[129]
	Applied in load frequency control	2018 Technologies for Smart-City Energy Security and Power (ICSESP)	IEEE	[130]
	Applied to solve ELD problem	Advanced Engineering Forum	Transtech	[131]
	Applied in ORPD problem and used IEE- 57 bus system	Journal of Telecommunication, Electronic and Computer Engineering	UTEM	[132]
	Applied in Economic load dispatch problem	INAE Letters	Springer	[133]
	Applied in ORPD problem and used IEE-30 and 57 bus systems	International Journal of Applied Engineering Research	Research India Publications	[134]
	Applied in ORPD problem and used IEE-30,57 and 118 bus systems	Applied Soft computing	Elsevier	[135]
	Applied in ORPD problem and used the IEE-30 bus system	4th IET clean energy and technology Conference	IET	[136]

other algorithms in terms of convergence, solution quality and local optima stagnation.

The MFO and EMFO algorithms were hybridized to find the optimal values for the discrete design variables in planar and 3D steel frame structures. In this context, various benchmark functions are solved by EMFO and MFO [147]. EMFO proved its superiority from the numerical results compared to other existing oppositional-based methods.

The optimal reactive power dispatch (ORPD) problem was solved using the MFO by the authors [135]. The suggested approach's target is to minimize the total power loss and voltage deviation by selecting the best control variables, including reactive compensators, sizing, transformers tap, and voltage generators IEEE 30, 57 118-bus system, are taken to check the efficiency of the algorithm. The outcomes of the algorithm's experimental results proved its superiority compared to other algorithms.

In Yıldız and Yıldız [148], the authors have applied the MFO algorithm in the production industry to solve optimization problems. The effectiveness of the proposed algorithm has been tested by solving a milling optimization problem. The results show that the MFO can better solve production optimisation problems.

The MFO algorithm has been applied to solve the constrained benchmark optimization problem and five engineering design problems [149]. The obtained results demonstrated that the MFO algorithm provides superior results to other meta-heuristics algorithms.

Table 10 represents applications review of MFO algorithm in the engineering field.

5.7 Applications in Image Processing

Segmenting a colour image based on regions is a fundamental step in image processing and computer vision. Multidimensionality has been an issue for region-based (RGB) colour image segmentation. Three dimensions (in colour) and two dimensions (Geometry) are used to solve five-dimensional colour image challenges (luminosity layer and chromaticity layer). For the segmentation of RGB colour images, a bio-inspired technique known as the "modified moth flame optimization" (MMFO) algorithm was presented by the authors [150]. The author has been used L*a*b color space conversion to reduce the one dimension geometrically and to measure the effectiveness of the suggested MMFO algorithm, and it has been compared with a few algorithms. The experimental results showed that the newly developed MMFO outperforms among other algorithms.

For image segmentation, the author [151] applied a newly invented algorithm by modifying the MFO algorithm to multilevel thresholding. Also, the author used the MSSIM index to observe the quality of the suggested algorithm and compared it with WOA, BFO, PSO, and MFO. The results of the suggested MFO algorithm outperform other existing algorithms for stability and quality image segmentation.

In Said et al. [152], the authors developed a novel approach for liver segmentation with the help of the MFO algorithm, which helps cluster the abdominal image. It has two phases (a) the Initial segmented phase of the liver (user picks up the required clusters) and (b) the Final segmented image of the liver (morphological operations). The effectiveness of the algorithm has been tested by applying seventy MRI images. The algorithm was found to be 95.66% efficient in the experiments.

Determining the optimal thresholding for image segmentation has received more attention in recent years since it has many applications. In multilevel thresholding, more time is taken to decide the best thresholds. To determine the optimal thresholds, the authors of Aziz et al. [153] applied two population-based algorithms, WOA and MFO. In the proposed method, the candidate solutions are utilized for creating image histograms, and then the procedure of basic algorithms updates positions. Several benchmark images were used to measure how well the proposed algorithms worked and compared to five different swarm algorithms. The best fitness values, PSNR, and SSIM measures, as well as time complexity and the ANOVA test, were used to analyse the results. The tests showed that the proposed methods were better than the other swarm algorithms.

In the author proposed a new method for multilevel thresholding based on the Moth-Flame Optimization (MFO) algorithm. Kapur's entropy or Otsu's between class variance function was used to judge how good the thresholds were. The proposed method was tested on a set of benchmark test images, and its performance was compared to several algorithms. Using the fitness function and the Peak Signal to Noise Ratio (PSNR) values, the results are looked at in a fair way. The MFO-based multilevel thresholding method has been found to work better than the PSO-based and BFO-based methods.

To improve satellite image thresholding (multilevel), the authors [154] utilized an improved version of the MFO algorithm called MTMFO for image segmentation. The suggested method has been tested on five different methods, namely, GA, DE, PSO, ABC, and MFO, for image segmentation for efficiency. In contrast to other existing algorithms, the MTMFO correctly identifies the optimal threshold values according to the results of the experiments.

Table 11 represents applications of MFO in the image segmentation area.

6 Evaluation of MFO Algorithm

To measure the efficiency of the MFO algorithm, many researchers compared the performance of the basic MFO algorithm with the traditional algorithms like SOS, GA, PSO, DE, and ABC. In this section, twenty-five benchmark functions in which fifteen unimodal (from U1 to U15) and ten multimodal functions (From M16-M25) have been taken to measure the efficiency of the MFO algorithm and compared the performance with five other metaheuristics algorithms SOS, PSO, DE, JAYA and WOA.

The MFO algorithm is implemented using MATLAB R2015a. The computer has a Windows 2010 operating system, an Intel i5 processor, and 8 GB RAM. At most, the MFO iterates 10,000 times, and it is the stop criteria. Other existing stop criteria include a fixed error tolerance value, the maximum number of iterations having zero improvements, and maximum use of CPU time. The number of independent function runs is set at 30, and results are rounded up to decimal points to reduce statistical errors and produce statistically significant results. The results are collated using the 'average (M)' and 'standard deviation (SD)' performance indicators. The MFO parameters settings include: powers exponent constant $b = 1$, t is defined between $[-1, 1]$, and the number of moths is thirty (50).

The comparative results of both unimodal and multimodal functions are presented in Tables 12 and 13, respectively. Similarly, Tables 14 and 15 represent the details of mathematical formulation values obtained by the MFO algorithm and illustrate that MFO achieves global solutions for seventeen benchmark functions out of twenty-five. Out of twenty-five benchmark functions, MFO provides 11, 18, 23, 17, and 10 superior results, 10, 4, 0, 3, and 12 equal results, and 4, 3, 2, 5, and 5 inferior results than SOS, PSO, JAYA, DE and WOA algorithms, respectively.

Table 10 Applications of MFO in the field of engineering

Applied area	Applied/Used for	Journal/conference Name	Publisher	References
Engineering	Used it to solve discounted {0–1} knapsack problem	Mathematical Problems in Engineering	Hindawi	[137]
	Used to address the issue of data clustering	Sensors	MDPI	[138]
	Used to solve numerical optimization problems	Entropy	MDPI	[47, 48, 49]
	Used to find out the optimal global path of the mobile robot problem	IEEE Access	IEEE	(Dai and Wei, 2021)
	Used for finding the best impulse response coefficients of FIR	International Journal of Intelligent Systems and Applications	IJISA	[139]
	Applied to solve the flow shop problem	Journal Teknik Industri	JTI	[140]
	Used in SG system to improve the performance	Journal of Ambient Intelligence and Humanized Computing	Springer	[141]
	Used in spark-based large data clustering	Big Data	Mary Ann Liebert, Inc	[142]
	Applied for suitable feature selection	Microsystem Technologies	Springer	[143]
Engineering	Applied in task scheduling problem	Transactions on Emerging Telecommunications Technologies	Wiley	[144]
	Applied in the CCAA design 3-ring structure to find the optimum inter-element separation	International Journal of Electronics and Communications	Elsevier	[145]
	Applied to solve web service composition (WSC) problem	Transactions on Emerging Telecommunications Technologies	Wiley	[146]
	Applied in 3D steel frame structures with discrete variables	Steel and Composite Structures	Techno press	[147]
	Applied to solve ORPD problem	Applied Soft Computing	Elsevier	[135]
	Applied for solving optimization issues in the production industry	Materials Testing	De Gruyter	[148]
	Applied to solve constrained and engineering optimization problem	IEEE Students' Conference on Electrical, Electronics and Computer Science (SCEECS)	IEEE	[149]

Table 11 Applications of MFO in the field of image processing

Applied area	Applied/used for	Journal/conference Name	Publisher	References
Image processing	Applied in region-based (RGB) colour image segmentation	International Journal of Electrical and Computer Engineering (IJECE)	Elsevier	[150]
	Applied to check stability and quality of image segmentation by the modified MFO algorithm through multilevel thresholding approach	International Journal of Swarm Intelligence Research (IJSIR)	IGI Global	[151]
	Applied for liver segmentation	International Conference on Advanced Intelligent Systems and Informatics (ICAISI)	Springer	[152]
	Applied for creating image histograms	Expert Systems with Applications	Elsevier	[153]
	Applied for image segmentation by classical benchmark image	International Journal of Applied Metaheuristic Computing (IJAMC)	IGI Global	(Khairuzzaman and Chaudhury, 2017)
	Used for satellite image segmentation	international joint conference on computer science and software engineering (JCSSE)	IEEE	[154]

Table 12 Comparison of unimodal functions with SOS, PSO, JAYA, DE, and WOA

Function		MFO	S0S	PSO	JAYA	DE	WOA
U1	M	0	6.03E−173	1.76E−51	1.39E+04	2.61E−165	0
	SD	0	0	1.12E−50	3.54E+03	0	0
U2	M	0	0	3.10E−53	1.86E+12	1.40E−172	0
	SD	0	0	2.10E−52	2.08E+11	0	0
U3	M	0	0	1.31E−31	1.47E+04	1.30E−01	0
	SD	0	0	6.65E−31	2.91E+03	4.85E−01	0
U4	M	2.89E+001	− 1	2.57E+02	2.83E+07	2.35E+01	2.42E+01
	SD	6.44E−002	0	3.73E+02	1.20E+07	4.98	0
U5	M	0	2.27E−74	1.20E+03	6.54E+04	1.14E−175	0
	SD	0	2.41E−74	5.44E+02	1.57E+04	0	0
U6	M	0	1.24E−86	1.05E−01	6.56E+01	1.02	1.10
	SD	0	1.26E−86	6.53E−02	6.69	4.59E−01	0
U7	M	0	− 4.19E+02	7.28E+01	4.58E+02	8.15E−91	0
	SD	0	0	2.27E+01	8.32E+02	1.23E−90	0
U8	M	1.04	3	0	6.22	0	6.44E−08
	SD	1.78	1.94E−15	0	6.18	0	0
U9	M	0	7.51E−13	0	2.51E−01	0	0
	SD	0	3.99E−12	0	2.33E−01	0	0
U10	M	0	4.62E−03	3.36E+03	1.02E+02	1.30E+02	5.38E−07
	SD	0	6.45E−03	9.52E+02	7.95E+01	1.85E+02	0
U11	M	− 3.18E−003	1.26E−07	7.67E+05	1.53E−01	− 4.89E+03	− 3.79E−03
	SD	8.43E−004	3.29E−07	4.01E+05	1.21E−01	2.72E+01	0
U12	M	8.63E−002	9.98E−01	− 3.79E−03	4.51E−01	− 3.79E−03	3.55E−10
	SD	1.02E−001	2.92E−16	0	4.12E−01	4.57E−19	0
U13	M	0	0	6.19E+01 3.44E+01	3.57E+04	5.11E+04	0
	SD	0	0		6.22E+03	0	0
U14	M	0	0	8.40E+05 3.23E+05	1.00E+06	1.00E+06	0
	SD	0	0		8.60E+01	1.36E+01	0
U15	M	8.09	1.74	3.74	3.74	2.61E−03	8.54
	SD	3.68	2.05E−01	1.02	2.19	1.05E−03	0

Table 13 Comparison of multimodal functions with SOS, PSO, JAYA, DE, and WOA

Function		MFO	S0S	PSO	JAYA	DE	WOA
M16	M	0	0	3.03E−02	3.04E+02	0	0
	SD	0	0	2.61E−17	2.69E+02	0	0
M17	M	8.88E−016	1.00E−15	1.81E+01	1.96E+01	1.71	4.44E−15
	SD	0	6.38E−16	5.48	6.58E−01	0	0
M18	M	0	0	4.05E+01	1.26E+02	9.22E−17	0
	SD	0	0	4.13E+01	3.41E+01	2.04E−17	0
M19	M	0	0	1.44E+02	1.19E+02	1.24E+01	0
	SD	0	0	3.79E+01	1.26E+01	3.30	0
M20	M	0	1.82E−01	0	3.50E+02	0	0
	SD	0	1.20E−01	0	1.24E+02	0	0
M21	M	−4.11E−001	8.84E+01	− 1.00E+00	−7.24E−14	− 1.00	− 1
	SD	3.69E−001	1.22E−03	0.00E+00	4.03E−13	0	0
M22	M	−4.05E+02	7.04E−25	− 7.57E+03	−4.03E+02	− 4.56E+12	− 4.18E+02
	SD	3.58E+01	9.02E−25	8.88E+02	3.69E+01	3.19E+12	0
M23	M	0	0	0	1.57E+02 1.86E+01	6.49E+02	2.56E+03
	SD	0	0	0		3.48E+01	9.83E−02
M24	M	0	0	0	1.06E+01 7.62E−01	1.97E+01	3.34E+01
	SD	0	0	0		4.17E−01	2.98E−01
M25	M	0	0	9.98E−02 1.99E−13	2.81E+01 1.35	4.20E+01	5.25E+01
	SD	0	0			5.20E−01	4.53E−01

Table 14 List of unimodal benchmark functions

Sl. no	Functions	Formulation of objective functions	D	Min. of Unimodal Function	MFO minimum value	Search space
U1	Sphere	$f(x) = \sum_{j=1}^{d} x_j^2$	30	0	0	[−100, 100]
U2	Cigar	$f(x) = 10^6 \sum_{j=1}^{d} x_j^2$	30	0	0	[−100, 100]
U3	Step	$f(x) = \sum_{j=1}^{d} \left(x_j + 0.5\right)^2$	30	0	0	[−100, 100]
U4	Rosenbrock	$f(x) = \sum_{j=1}^{d} [100\left(x_{j+1} - x_j^2\right)^2 + \left(x_j - 1\right)^2]$	30	0	2.89	[−2.048,2.048]
U5	Schwefel 1.2	$f(x) = \sum_{j=1}^{d} \sum_{k=1}^{j} x_j^2$	30	0	0	[−100, 100]
U6	Schwefel 2.21	$f(x) = max\left\{ \left\|x_j\right\|, 1 \le j \le d \right\}$	30	0	0	[−100, 100]
U7	Schwefel 2.22	$f(x) = \sum_{i=1}^{d} \left\|x_j\right\| + \prod_{i=1}^{d} \left\|x_j\right\|$	30	0	0	[−10, 10]
U8	Booth	$f(x) = \left(2x_1 + x_2 - 5\right)^2 + \left(x_1 + 2x_2 - 7\right)^2$	2	0	1.04	[−10, 10]
U9	Matyas	$f(x) = 0.26\left(x_1^2 + x_2^2\right) - 0.48x_1x_2$	2	0	0	[−10, 10]
U10	Powell	$f(x) = \sum_{j=1}^{d/4} \left(x_{4j-3} + 10x_{4j-2}\right)^2 + 5\left(x_{4j-3} + 10x_{4j-2}\right)^2 + \left(x_{4j-2} + 2x_{4j-1}\right)^4 + 10\left(x_{4j-3} - x_{4j}\right)^4$	32	0	0	[−4, 5]
U11	Zettl	$f(x) = \left(x - 1^2 + x - 2^2 - 2x_1\right)^2 + 0.25x_1$	2	− 0.00379	− 3.18	[−1, 5]
U12	Leon	$f(x) = 100\left(x_2 - x_1^3\right)^2 + \left(1 - x_1\right)^2$	2	0	8.63	[−1.2, 1.2]
U13	Zakhrov	$f(x) = \sum_{j=1}^{d} x_i^2 + \left(0.5 \sum_{j=1}^{d} jx_j\right)^2 + \left(0.5 \sum_{j=1}^{d} jx_j\right)^4$	2	0	0	[−5, 10]
U14	Tablet	$f(x) = 10^6 \times x_1^2 + \sum_{j=1}^{d} x_j^6$	30	0	0	[−1, 1]
U15	Quartic	$f(x) = \sum_{j=1}^{d} jx_j^4 + random(0, 1)$	30	0	8.09	[−1.28, 1.28]

Table 15 List of multimodal benchmark functions

Sl. No	Functions	Formulation of objective functions	D	Min. of Multimodal Function	Minimum Value of MFO	Search space
M16	Bohachevsky	$f(x) = x_1^2 + 2x_2^2 - 0.3\cos\left(3\pi x_1\right) - 0.4\cos\left(4\pi x_2\right) + 0.7$	2	0	0	[−100, 100]
M17	Ackley	$f(x) = 20 + e - 20e^{\frac{1}{d}\left(\sqrt{\left(\frac{1}{d}\sum_{j=1}^{d} x_j^2\right)}\right)} - e^{\frac{1}{d}\left(\sum \cos\left(2\pi x_j\right)\right)}$	30	0	8.88E−01	[−32.768, 32.768]
M18	Griewank	$f(x) = \sum_{j=1}^{d} \frac{x_j^2}{4000} - \prod_{j=1}^{d} \cos\left(\frac{x_j}{\sqrt{j}}\right) - 1$	30	0	0	[−600, 600]
M19	Rastrigin	$f(x) = 10D + \sum_{j=1}^{d} [x_j^2 - 10\cos\left(2\pi x_j\right)]$	30	0	0	[−5.12, 5.12]
M20	Schaffers	$f(x) = 0.5 + \frac{sin^2\left(x_1^2+x_2^2\right)-0.5}{\left[1+0.001\left(x_1^2+x_2^2\right)\right]^2}$	2	0	0	[−100, 100]
M21	Easom	$f(x) = -\cos(x_1)\cos(x_2)exp\left[-\left(x_1-\pi\right)^2 \times 9\left(x_2-\pi\right)^2\right]$	2	0	− 4.11	[−100, 100]
M22	Schwefel 2.26	$f(x) = -\sum_{j=1}^{d} x_j \sin\left(\sqrt{\lvert x_j \rvert}\right)$	30	− 418.982	− 4.05	[−500, 500]
M23	Csendes	$f(x) = \sum_{j=1}^{d} x_i^6\left(2 + \sin 1/x_j\right)$	30	0	0	[−1, 1]
M24	Inverted cosine mixture	$f(x) = 0.1 \times 30 - \left[0.1 \times \sum_{j=1}^{d} 5\pi x_j - \sum_{j=1}^{d} x_j^2\right]$	30	0	0	[−1, 1]
M25	salomon	$f(x) = 1 - \cos\left(2\pi\sqrt{\sum_{j=1}^{d} x_j^2}\right) + 0.1\sqrt{\sum_{j=1}^{d} x_j^2}$	30	0	0	[−100, 100]

7 Conclusion with Future Research Work

Many nature-inspired optimization methods, including the MFO algorithm, have been proposed over the last two decades to solve complex optimization problems where gradient-based techniques cannot be used. The increased number of algorithms and literature has led to increased surveys and studies on these algorithms. All these surveys aim to provide adequate and appropriate benchmarks for selecting the best choice of algorithms in literature reviews of these optimization techniques. Therefore, we must critically review the most promising algorithms that fit these characteristics. In this paper, more than a hundred papers were gathered, reviewed, and evaluated for this analysis to illustrate the robustness, shortcomings, benefits, and drawbacks of MFO to serve as a repository for MFO research enthusiasts. In the pursuit of optimality of optimization algorithms, it is impossible to design an algorithm that optimizes every single optimization problem [155]. This ensures that MFO might require a variety of enhancements to solve different optimization problems in many domains. The specific drawback of MFO is that it is complex to implement, but the number of parameters is fewer than other schemes [156, 157]. A few issues for future research are as follows:

- Parameter settings are pretty static in the proposed MFO methods. We suggest integrating another system of MFO methods to scale up the dynamism in the associated parameters. Integration with other computer technologies, such as parallel calculation, requires reducing the time elapsed transaction.
- To experiment to determine if the MFO algorithm performs better than random search and determine how better the MFO algorithm is than random search.
- More literature is required to solve dynamic problems.
- Parameter tuning is required to solve real-life problems. Unfortunately, the investigators do not make any effort to look into the MFO parameters.
- In order to be more stable, further research on the theoretical aspect of MFO is needed.
- Extensive research is required to solve more complicated large-scale multi-objective optimization problems.

Finally, we believe that this manuscript will help researchers improve or apply MFO and its variants to various problems.

Declarations

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

Ethical approval This article does not contain any studies with human participants or animals performed by the authors.

References

1. Yi Y, He R (2014) A novel artificial bee colony algorithm. In: 2014 sixth international conference on intelligent human-machine systems and cybernetics, vol 1, pp 271–274.
2. Kennedy J, Eberhart R (1995) Particle swarm optimization. In: Proceedings of ICNN'95-international conference on neural networks, vol 4, pp 1942–1948
3. Bastos Filho CJ, de Lima Neto FB, Lins AJ, Nascimento AI, Lima MP (2008) A novel search algorithm based on fish school behavior. In: 2008 IEEE international conference on systems, man and cybernetics, pp 2646–2651
4. Dorigo M, Maniezzo V, Colorni A (1996) Ant system: optimization by a colony of cooperating agents. IEEE Trans Syst Man Cybern B 26(1):29–41
5. Dokeroglu T (2019) A survey on new generation metaheuristic algorithms. Comput Ind Eng 137:106040
6. Holland JH (1992) Genetic algorithms. Sci Am 267(1):66–73
7. Storn R, Price K (1997) Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces. J Global Optim 11(4):341–359
8. Koza JR, Koza JR (1992) Genetic programming: on the programming of computers by means of natural selection, vol 1. MIT Press, Cambridge
9. Askarzadeh A (2014) Bird mating optimizer: an optimization algorithm inspired by bird mating strategies. Commun Nonlinear Sci Numer Simul 19(4):1213–1228
10. Abualigah L, Shehab M, Alshinwan M, Alabool H (2019) Salp swarm algorithm: a comprehensive survey. Neural Comput. Appl. 1–21.
11. Mirjalili S, Lewis A (2016) The whale optimization algorithm. Adv Eng Softw 95:51–67
12. Cheng M-Y, Prayogo D (2014) Symbiotic organisms search: a new metaheuristic optimization algorithm. Comput Struct 139:98–112
13. Gandomi AH, Yang X-S, Alavi AH (2013) Cuckoo search algorithm: a metaheuristic approach to solve structural optimization problems. Eng Comput 29(1):17–35
14. Arora S, Singh S (2019) Butterfly optimization algorithm: a novel approach for global optimization. Soft Comput 23(3):715–734
15. Wang G-G, Deb S, Cui Z (2019) Monarch butterfly optimization. Neural Comput Appl 31(7):1995–2014
16. Cuevas E, Cienfuegos M, Zaldívar D, Pérez-Cisneros M (2013) A swarm optimization algorithm inspired in the behavior of the social-spider. Expert Syst Appl 40(16):6374–6384
17. Agushaka JO, Ezugwu AE, Abualigah L (2022) Dwarf mongoose optimization algorithm. Comput Methods Appl Mech Eng 391:114570
18. Kaveh A, Khayatazad M (2012) A new meta-heuristic method: ray optimization. Comput Struct 112:283–294
19. Mirjalili S, Mirjalili SM, Hatamlou A (2016) Multi-verse optimizer: a nature-inspired algorithm for global optimization. Neural Comput Appl 27(2):495–513
20. Kaveh A, Bakhshpoori T (2016) Water evaporation optimization: a novel physically inspired optimization algorithm. Comput Struct 167:69–85
21. Lam AY, Li VO (2009) Chemical-reaction-inspired metaheuristic for optimization. IEEE Trans Evol Comput 14(3):381–399
22. Zhao W, Wang L, Zhang Z (2019) Atom search optimization and its application to solve a hydrogeologic parameter estimation problem. Knowl-Based Syst 163:283–304
23. Sadollah A, Bahreininejad A, Eskandar H, Hamdi M (2013) Mine blast algorithm: a new population based algorithm for solving constrained engineering optimization problems. Appl Soft Comput 13(5):2592–2612
24. Zou F, Wang L, Hei X, Chen D (2015) Teaching–learning-based optimization with learning experience of other learners and its application. Appl Soft Comput 37:725–736
25. Li M, Zhao H, Weng X, Han T (2016) Cognitive behavior optimization algorithm for solving optimization problems. Appl Soft Comput 39:199–222
26. Oyelade ON, Ezugwu AES, Mohamed TI, Abualigah L (2022) Ebola optimization search algorithm: a new nature-inspired metaheuristic optimization algorithm. IEEE Access 10:16150–16177
27. Al-Betar MA, Alyasseri ZAA, Awadallah MA, Doush IA (2020) Coronavirus herd immunity optimizer (CHIO). Neural Comput Appl 1–32
28. Kumar M, Kulkarni AJ, Satapathy SC (2018) Socio evolution & learning optimization algorithm: a socio-inspired optimization methodology. Futur Gener Comput Syst 81:252–272
29. Al-qaness MAA, Ewees AA, Fan H, AlRassas AM, Abd Elaziz M (2022) Modified aquila optimizer for forecasting oil production. Geo-Spatial Inf Sci. https://doi.org/10.1080/10095020.2022.2068385
30. Al-qaness MA, Ewees AA, Fan H, Abualigah L, Abd Elaziz M (2022) Boosted ANFIS model using augmented marine predator algorithm with mutation operators for wind power forecasting. Appl Energy 314:118851
31. Nama S, Sharma S, Saha AK, Gandomi AH (2022) A quantum mutation-based backtracking search algorithm. Artif Intell Rev 55(4):3019–3073
32. Saha AK (2022) Multi-population-based adaptive sine cosine algorithm with modified mutualism strategy for global optimization. Knowl-Based Syst 251:109326. https://doi.org/10.1016/j.knosys.2022.109326
33. Sharma S, Chakraborty S, Saha AK, Nama S, Sahoo SK (2022) mLBOA: a modified butterfly optimization algorithm with lagrange interpolation for global optimization. J Bionic Eng 19:1161
34. Al-qaness MAA, Ewees AA, Abd Elaziz M (2021) Modified whale optimization algorithm for solving unrelated parallel machine scheduling problems. Soft Comput 25(14):9545–9557. https://doi.org/10.1007/s00500-021-05889-w
35. Sharma S, Saha AK, Majumder A, Nama S (2021) MPBOA-A novel hybrid butterfly optimization algorithm with symbiosis organisms search for global optimization and image segmentation. Multimedia Tools Appl 80(8):12035–12076
36. Chakraborty S, Saha AK, Chakraborty R, Saha M (2021) An enhanced whale optimization algorithm for large scale optimization problems. Knowl-Based Syst 233:107543
37. Elaziz MA, Ewees AA, Yousri D, Alwerfali HSN, Awad QA, Lu S, Al-Qaness MAA (2020) An improved marine predators algorithm with fuzzy entropy for multi-level thresholding: real world example of COVID-19 CT image segmentation. IEEE Access 8:125306–125330. https://doi.org/10.1109/ACCESS.2020.3007928

38. Nama S, Saha AK, Ghosh S (2017) Improved backtracking search algorithm for pseudo dynamic active earth pressure on retaining wall supporting c-Φ backfill. Appl Soft Comput 52:885–897
39. Shehab M, Abualigah L, Al Hamad H, Alabool H, Alshinwan M, Khasawneh AM (2020) Moth–flame optimization algorithm: variants and applications. Neural Comput Appl 32(14):9859–9884. https://doi.org/10.1007/s00521-019-04570-6
40. Shehab M, Alshawabkah H, Abualigah L, AL-Madi N (2020) Enhanced a hybrid moth-flame optimization algorithm using new selection schemes. Eng Comput. https://doi.org/10.1007/s00366-020-00971-7
41. Hussien AG, Amin M, Abd El Aziz M (2020) A comprehensive review of moth-flame optimisation: variants, hybrids, and applications. J Exp Theor Artif Intell 32(4):705–725. https://doi.org/10.1080/0952813X.2020.1737246
42. Li C, Niu Z, Song Z, Li B, Fan J, Liu PX (2018) A double evolutionary learning moth-flame optimization for real-parameter global optimization problems. IEEE Access 6:76700–76727
43. Li WK, Wang WL, Li L (2018) Optimization of water resources utilization by multi-objective moth-flame algorithm. Water Resour Manag 32(10):3303–3316. https://doi.org/10.1007/s11269-018-1992-7
44. Kigsirisin S, Miyauchi H (2021) Short-term operational scheduling of unit commitment using binary alternative moth-flame optimization. IEEE Access 9:12267–12281
45. Tumar I, Hassouneh Y, Turabieh H, Thaher T (2020) Enhanced binary moth flame optimization as a feature selection algorithm to predict software fault prediction. IEEE Access 8:8041–8055
46. Reddy S, Panwar LK, Panigrahi BK, Kumar R (2018) Solution to unit commitment in power system operation planning using binary coded modified moth flame optimization algorithm (BMMFOA): a flame selection based computational technique. J Comput Sci 25:298–317
47. Nadimi-Shahraki MH, Banaie-Dezfouli M, Zamani H, Taghian S, Mirjalili S (2021) B-MFO: a binary moth-flame optimization for feature selection from medical datasets. Computers 10(11):136. https://doi.org/10.3390/computers10110136
48. Nadimi-Shahraki MH, Fatahi A, Zamani H, Mirjalili S, Abualigah L, Abd Elaziz M (2021) Migration-based moth-flame optimization algorithm. Processes 9(12):2276. https://doi.org/10.3390/pr9122276
49. Nadimi-Shahraki MH, Moeini E, Taghian S, Mirjalili S (2021) DMFO-CD: a discrete moth-flame optimization algorithm for community detection. Algorithms 14(11):314. https://doi.org/10.3390/a14110314
50. Li Z, Zeng J, Chen Y, Ma G, Liu G (2021) Death mechanism-based moth–flame optimization with improved flame generation mechanism for global optimization tasks. Expert Syst Appl 183:115436. https://doi.org/10.1016/j.eswa.2021.115436
51. Ma L, Wang C, Xie N, Shi M, Ye Y, Wang L (2021) Moth-flame optimization algorithm based on diversity and mutation strategy. Appl Intell. https://doi.org/10.1007/s10489-020-02081-9
52. Zhao X, Fang Y, Liu L, Li J, Xu M (2020) An improved moth-flame optimization algorithm with orthogonal opposition-based learning and modified position updating mechanism of moths for global optimization problems. Appl Intell 50(12):4434–4458. https://doi.org/10.1007/s10489-020-01793-2
53. Zhao X, Fang Y, Liu L, Xu M, Zhang P (2020) Ameliorated moth-flame algorithm and its application for modeling of silicon content in liquid iron of blast furnace based fast learning network. Appl Soft Comput 94:106418
54. Kaur K, Singh U, Salgotra R (2020) An enhanced moth flame optimization. Neural Comput Appl 32(7):2315–2349
55. Abd Elaziz M, Ewees AA, Ibrahim RA, Lu S (2020) Opposition-based moth-flame optimization improved by differential evolution for feature selection. Math Comput Simul 168:48–75
56. Pelusi D, Mascella R, Tallini L, Nayak J, Naik B, Deng Y (2020) An improved moth-flame optimization algorithm with hybrid search phase. Knowl-Based Syst 191:105277
57. Apinantanakon W, Sunat K (2017) Omfo: a new opposition-based moth-flame optimization algorithm for solving unconstrained optimization problems. In: International conference on computing and information technology, pp 22–31
58. Bhesdadiya RH, Trivedi IN, Jangir P, Kumar A, Jangir N, Totlani R (2017) A novel hybrid approach particle swarm optimizer with moth-flame optimizer algorithm. In: Advances in computer and computational sciences. Springer, pp 569–577
59. Soliman GM, Khorshid MM, Abou-El-Enien TH (2016) Modified moth-flame optimization algorithms for terrorism prediction. Int J Appl Innov Eng Manag 5(7):47–58
60. Sahoo SK, Saha AK (2022) A hybrid moth flame optimization algorithm for global optimization. J Bionic Eng. https://doi.org/10.1007/s42235-022-00207-y
61. Zhang H, Li R, Cai Z, Gu Z, Heidari AA, Wang M, Chen H, Chen M (2020) Advanced orthogonal moth flame optimization with Broyden–Fletcher–Goldfarb–Shanno algorithm: framework and real-world problems. Expert Syst Appl 159:113617
62. Zhang Z, Qin H, Yao L, Liu Y, Jiang Z, Feng Z, Ouyang S (2020) Improved multi-objective moth-flame optimization algorithm based on R-domination for cascade reservoirs operation. J Hydrol 581:124431
63. Wu Y, Chen R, Li C, Zhang L, Cui Z (2020) Hybrid symbiotic differential evolution moth-flame optimization algorithm for estimating parameters of photovoltaic models. IEEE Access 8:156328–156346
64. Wu Y, Chen R, Li C, Zhang L, Dai W (2020) An adaptive sine-cosine moth-flame optimization algorithm for parameter identification of hybrid active power filters in power systems. IEEE Access 8:156378–156393
65. Fei W, Hexiang B, Deyu L, Jianjun W (2020) Energy-efficient clustering algorithm in underwater sensor networks based on fuzzy C means and Moth-flame optimization method. IEEE Access 8:97474–97484
66. Bandopadhyay J, Roy PK (2020) Application of hybrid multi-objective moth flame optimization technique for optimal performance of hybrid micro-grid system. Appl Soft Comput 95:106487
67. Alwerfali HSN, Abd Elaziz M, Al-Qaness MAA, Abbasi AA, Lu S, Liu F, Li L (2019) A multilevel image thresholding based on hybrid salp swarm algorithm and fuzzy entropy. IEEE Access 7:181405–181422. https://doi.org/10.1109/ACCESS.2019.2959325
68. Khalilpourazari S, Khalilpourazary S (2019) An efficient hybrid algorithm based on water cycle and moth-flame optimization algorithms for solving numerical and constrained engineering optimization problems. Soft Comput 23(5):1699–1722
69. Kamalapathi K, Priyadarshi N, Padmanaban S, Holm-Nielsen JB, Azam F, Umayal C, Ramachandaramurthy VK (2018) A hybrid moth-flame fuzzy logic controller based integrated cuk converter fed brushless DC motor for power factor correction. Electronics 7(11):288
70. Sayed GI, Hassanien AE (2018) A hybrid SA-MFO algorithm for function optimization and engineering design problems. Complex Intell Syst 4(3):195–212
71. Anfal M, Abdelhafid H (2017) Optimal placement of PMUs in Algerian network using a hybrid particle swarm–moth flame optimizer (PSO-MFO). Electrotehnica Electron Autom 65(3)
72. Jangir P (2017) Optimal power flow using a hybrid particle Swarm optimizer with moth flame optimizer. Glob J Res Eng
73. Sarma A, Bhutani A, Goel L (2017) Hybridization of moth flame optimization and gravitational search algorithm and its

application to detection of food quality. Intell Syst Conf (IntelliSys) 2017:52–60
74. Abdel-mawgoud H, Kamel S, Ebeed M, Youssef A-R (2017) Optimal allocation of renewable dg sources in distribution networks considering load growth. In: 2017 Nineteenth International Middle East Power Systems Conference (MEPCON), pp 1236–1241.
75. Sapre S, Mini S (2021) Emulous mechanism based multi-objective moth–flame optimization algorithm. J Parallel Distrib Comput 150:15–33
76. Savsani V, Tawhid MA (2017) Non-dominated sorting moth flame optimization (NS-MFO) for multi-objective problems. Eng Appl Artif Intell 63:20–32
77. Nanda SJ (2016) Multi-objective moth flame optimization. In: 2016 international conference on advances in computing, communications and informatics (ICACCI), pp 2470–2476
78. Khalilpourazari S, Pasandideh SHR (2017) Multi-item EOQ model with nonlinear unit holding cost and partial backordering: moth-flame optimization algorithm. J Ind Prod Eng 34(1):42–51
79. Messaoud RB, Midouni A, Hajji S (2021) PEM fuel cell model parameters extraction based on moth-flame optimization. Chem Eng Sci 229:116100
80. Chauhan SS, Kotecha P (2016) Single level production planning in petrochemical industries using Moth-flame optimization. In: 2016 IEEE region 10 conference (TENCON), pp 263–266
81. Dabba A, Tari A, Meftali S (2021) Hybridization of Moth flame optimization algorithm and quantum computing for gene selection in microarray data. J Ambient Intell Humaniz Comput 12(2):2731–2750
82. Dabba A, Tari A, Meftali S, Mokhtari R (2021) Gene selection and classification of microarray data method based on mutual information and moth flame algorithm. Expert Syst Appl 166:114012
83. Xia J, Zhang H, Li R, Chen H, Turabieh H, Mafarja M, Pan Z (2021) Generalized oppositional moth flame optimization with crossover strategy: an approach for medical diagnosis. J Bionic Eng 18(4):991–1010
84. Jibia MS, Jibia AU (2021) Fetal electrocardiogram extraction using moth flame optimization (MFO)-based adaptive filter. Adv Sci Technol Eng Syst J 6(2):303–312. https://doi.org/10.25046/aj060235
85. Kadry S, Rajinikanth V, Raja NSM, Hemanth DJ, Hannon NM, Raj ANJ (2021) Evaluation of brain tumor using brain MRI with modified-moth-flame algorithm and Kapur's thresholding: a study. Evol Intell 14:1053
86. Muduli D, Dash R, Majhi B (2020) Automated breast cancer detection in digital mammograms: a moth flame optimization based ELM approach. Biomed Signal Process Control 59:101912
87. Sayed GI, Darwish A, Hassanien AE (2020) Binary whale optimization algorithm and binary moth flame optimization with clustering algorithms for clinical breast cancer diagnoses. J Classif 37(1):66–96. https://doi.org/10.1007/s00357-018-9297-3
88. Hassanien AE, Gaber T, Mokhtar U, Hefny H (2017) An improved moth flame optimization algorithm based on rough sets for tomato diseases detection. Comput Electron Agric 136:86–96
89. Wang M, Chen H, Yang B, Zhao X, Hu L, Cai Z, Huang H, Tong C (2017) Toward an optimal kernel extreme learning machine using a chaotic moth-flame optimization strategy with applications in medical diagnoses. Neurocomputing 267:69–84
90. Sayed GI, Hassanien AE, Nassef TM, Pan J-S (2016) Alzheimer's disease diagnosis based on moth flame optimization. In: International conference on genetic and evolutionary computing, pp 298–305
91. Trinh C, Huynh B, Bidaki M, Rahmani AM, Hosseinzadeh M, Masdari M (2022) Optimized fuzzy clustering using moth-flame optimization algorithm in wireless sensor networks. Artif Intell Rev 55(3):1915–1945. https://doi.org/10.1007/s10462-021-09957-3
92. Sapre S, Mini S (2021) A differential moth flame optimization algorithm for mobile sink trajectory. Peer-to-Peer Netw Appl 14(1):44–57
93. Dash SP, Subhashini KR, Satapathy JK (2020) Optimal location and parametric settings of FACTS devices based on JAYA blended moth flame optimization for transmission loss minimization in power systems. Microsyst Technol 26(5):1543–1552. https://doi.org/10.1007/s00542-019-04692-w
94. Korashy A, Kamel S, Alquthami T, Jurado F (2020) Optimal coordination of standard and non-standard direction overcurrent relays using an improved moth-flame optimization. IEEE Access 8:87378–87392
95. Bandyopadhyay S, Giannella C, Maulik U, Kargupta H, Liu K, Datta S (2006) Clustering distributed data streams in peer-to-peer environments. Inf Sci 176(14):1952–1985
96. Kotary DK, Nanda SJ (2020) Distributed robust data clustering in wireless sensor networks using diffusion moth flame optimization. Eng Appl Artif Intell 87:103342
97. Barham R, Sharieh A, Sleit A (2019) Multi-moth flame optimization for solving the link prediction problem in complex networks. Evol Intel 12(4):563–591. https://doi.org/10.1007/s12065-019-00257-y
98. Sapre S, Mini S (2018) Optimized relay nodes positioning to achieve full connectivity in wireless sensor networks. Wirel Pers Commun 99(4):1521–1540. https://doi.org/10.1007/s11277-018-5290-8
99. Strumberger I, Sarac M (2018) Moth search algorithm for drone placement problem. Int J Comput 3:6
100. Singh P, Prakash S (2017) Optical network unit placement in Fiber-Wireless (FiWi) access network by Moth-Flame optimization algorithm. Opt Fiber Technol 36:403–411. https://doi.org/10.1016/j.yofte.2017.05.018
101. Faris H, Aljarah I, Mirjalili S (2017) Evolving radial basis function networks using moth–flame optimizer. In: Handbook of neural computation. Elsevier, pp 537–550. https://doi.org/10.1016/B978-0-12-811318-9.00028-4
102. Singh U, Singh SN (2019) A new optimal feature selection scheme for classification of power quality disturbances based on ant colony framework. Appl Soft Comput 74:216–225. https://doi.org/10.1016/j.asoc.2018.10.017
103. Shan W, Qiao Z, Heidari AA, Chen H, Turabieh H, Teng Y (2021) Double adaptive weights for stabilization of moth flame optimizer: balance analysis, engineering cases, and medical diagnosis. Knowl-Based Syst 214:106728. https://doi.org/10.1016/j.knosys.2020.106728
104. Ewees AA, Sahlol AT, Amasha MA (2017) A bio-inspired moth-flame optimization algorithm for arabic handwritten letter recognition. In: 2017 international conference on control, artificial intelligence, robotics & optimization (ICCAIRO), pp 154–159. https://doi.org/10.1109/ICCAIRO.2017.38
105. Yamany W, Fawzy M, Tharwat A, Hassanien AE (2015) Moth-flame optimization for training multi-layer perceptrons. In: 2015 11th international computer engineering conference (ICENCO), pp 267–272. https://doi.org/10.1109/ICENCO.2015.7416360
106. Wang F, Liao X, Fang N, Jiang Z (2022) Optimal scheduling of regional combined heat and power system based on improved MFO algorithm. Energies 15(9):3410. https://doi.org/10.3390/en15093410
107. Mohanty D, Panda S (2021) A modified moth flame optimisation technique tuned adaptive fuzzy logic PID controller for frequency regulation of an autonomous power system. Int J Sustain

Energ 40(1):41–68. https://doi.org/10.1080/14786451.2020.1787412

108. Elattar EE, Elsayed SK (2020) Optimal location and sizing of distributed generators based on renewable energy sources using modified moth flame optimization technique. IEEE Access 8:109625–109638. https://doi.org/10.1109/ACCESS.2020.3001758
109. Diab AAZ, Rezk H (2019) Optimal sizing and placement of capacitors in radial distribution systems based on grey wolf, dragonfly and moth-flame optimization algorithms. Iran J Sci Technol Trans Electr Eng 43(1):77–96. https://doi.org/10.1007/s40998-018-0071-7
110. Mirjalili S (2016) Dragonfly algorithm: a new meta-heuristic optimization technique for solving single-objective, discrete, and multi-objective problems. Neural Comput Appl 27(4):1053–1073. https://doi.org/10.1007/s00521-015-1920-1
111. Rezaei H, Bozorg-Haddad O, Chu X (2018) Grey wolf optimization (GWO) algorithm. In: Bozorg-Haddad O (ed) Advanced optimization by nature-inspired algorithms, vol 720. Springer, Singapore, pp 81–91
112. Abdel-mawgoud H, Kamel S, Tostado M, Yu J, Jurado F (2018) Optimal installation of multiple DG using chaotic moth-flame algorithm and real power loss sensitivity factor in distribution system. In: 2018 International Conference on Smart Energy Systems and Technologies (SEST), pp 1–5. https://doi.org/10.1109/SEST.2018.8495722
113. Tolba MA, Diab AAZ, Tulsky VN, Abdelaziz AY (2018) LVCI approach for optimal allocation of distributed generations and capacitor banks in distribution grids based on moth–flame optimization algorithm. Electr Eng 100(3):2059–2084. https://doi.org/10.1007/s00202-018-0684-x
114. Mohanty B, Acharyulu BVS, Hota PK (2018) Moth-flame optimization algorithm optimized dual-mode controller for multiarea hybrid sources AGC system. Optim Control Appl Methods 39(2):720–734. https://doi.org/10.1002/oca.2373
115. Trivedi IN, Jangir P, Parmar SA, Jangir N (2018) Optimal power flow with voltage stability improvement and loss reduction in power system using Moth-Flame Optimizer. Neural Comput Appl 30(6):1889–1904. https://doi.org/10.1007/s00521-016-2794-6
116. Upper N, Hemeida AM, Ibrahim AA (2017) Moth-flame algorithm and loss sensitivity factor for optimal allocation of shunt capacitor banks in radial distribution systems. In: 2017 nineteenth international middle east power systems conference (MEPCON), pp 851–856. https://doi.org/10.1109/MEPCON.2017.8301279
117. Saurav S, Gupta VK, Mishra SK (2017) Moth-flame optimization based algorithm for FACTS devices allocation in a power system. In: 2017 International conference on innovations in information, embedded and communication systems (ICIIECS), pp 1–7. https://doi.org/10.1109/ICIIECS.2017.8276010
118. Ceylan O (2016) Harmonic elimination of multilevel inverters by moth-flame optimization algorithm. In: 2016 international symposium on industrial electronics (INDEL), pp 1–5. https://doi.org/10.1109/INDEL.2016.7797803
119. Raju M, Saikia LC, Saha D (2016) Automatic generation control in competitive market conditions with moth-flame optimization based cascade controller. In: 2016 IEEE region 10 conference (TENCON), pp 734–738. https://doi.org/10.1109/TENCON.2016.7848100
120. Zhao H, Zhao H, Guo S (2016) Using GM (1,1) optimized by MFO with rolling mechanism to forecast the electricity consumption of inner Mongolia. Appl Sci 6(1):20. https://doi.org/10.3390/app6010020
121. Allam D, Yousri DA, Eteiba MB (2016) Parameters extraction of the three diode model for the multi-crystalline solar cell/module using moth-flame optimization algorithm. Energy Convers Manag 123:535–548. https://doi.org/10.1016/j.enconman.2016.06.052
122. Bentouati B, Chaib L, Chettih S (2016) Optimal power flow using the moth flam optimizer: a case study of the algerian power system. Indones J Electr Eng Comput Sci 1(3):431. https://doi.org/10.11591/ijeecs.v1.i3.pp431-445
123. Gope S, Dawn S, Goswami AK, Tiwari PK (2016) Moth flame optimization based optimal bidding strategy under transmission congestion in deregulated power market. In: 2016 IEEE region 10 conference (TENCON), pp 617–621. https://doi.org/10.1109/TENCON.2016.7848076
124. Abdel-Mawgoud H, Kamel S, El-Ela AAA, Jurado F (2021) Optimal allocation of DG and capacitor in distribution networks using a novel hybrid MFO-SCA method. Electric Power Comp Syst 49(3):259–275. https://doi.org/10.1080/15325008.2021.1943066
125. Mohanty B (2019) Performance analysis of moth flame optimization algorithm for AGC system. Int J Model Simul 39(2):73–87. https://doi.org/10.1080/02286203.2018.1476799
126. Sanki P, Mazumder S, Basu M, Pal PS, Das D (2021) Moth flame optimization based fuzzy-PID controller for power–frequency balance of an islanded microgrid. J Inst Eng B 102(5):997–1006. https://doi.org/10.1007/s40031-021-00607-4
127. Nandi M, Shiva CK, Mukherjee V (2019) A moth-flame optimization for UPFC–RFB-based load frequency stabilization of a realistic power system with various nonlinearities. Iran J Sci Technol Trans Electr Eng 43(S1):581–606. https://doi.org/10.1007/s40998-018-0157-2
128. Lal DK, Barisal AK (2019) Combined load frequency and terminal voltage control of power systems using moth flame optimization algorithm. J Electr Syst Inf Technol 6(1):8. https://doi.org/10.1186/s43067-019-0010-3
129. Barisal AK, Lal DK (2018) Application of moth flame optimization algorithm for AGC of multi-area interconnected power systems. Int J Energy Optim Eng 7(1):22–49. https://doi.org/10.4018/IJEOE.2018010102
130. Sahu A, Hota SK (2018) Performance comparison of 2-DOF PID controller based on Moth-flame optimization technique for load frequency control of diverse energy source interconnected power system. In: 2018 Technologies for smart-city energy security and power (ICSESP), pp 1–6. https://doi.org/10.1109/ICSESP.2018.8376686
131. Elsakaan AA, El-Sehiemy RA-A, Kaddah SS, Elsaid MI (2018) Economic power dispatch with emission constraint and valve point loading effect using moth flame optimization algorithm. Adv Eng Forum 28:11
132. Mei RNS, Sulaiman MH, Daniyal H, Mustaffa Z (2018) Application of moth-flame optimizer and ant lion optimizer to solve optimal reactive power dispatch problems. JTEC 10(1):6
133. Bhadoria A, Kamboj VK, Sharma M, Bath SK (2018) A solution to non-convex/convex and dynamic economic load dispatch problem using moth flame optimizer. INAE Lett 3(2):65–86. https://doi.org/10.1007/s41403-018-0034-3
134. Anbarasan P, Jayabarathi DT (2017) Optimal reactive power dispatch using moth-flame optimization algorithm. Int J Appl Eng Res 12(13):12
135. Mei RNS, Sulaiman MH, Mustaffa Z, Daniyal H (2017) Optimal reactive power dispatch solution by loss minimization using moth-flame optimization technique. Appl Soft Comput 59:210–222. https://doi.org/10.1016/j.asoc.2017.05.057
136. Sulaiman MH, Mustaffa Z, Aliman O, Daniyal H, Mohamed MR (2016) An application of moth-flame optimization algorithm for solving optimal reactive power dispatch problem. 5.

137. Truong TK (2021) A new moth-flame optimization algorithm for discounted ${$0–1$}$ knapsack problem. Math Probl Eng 2021:1–15
138. Singh T, Saxena N, Khurana M, Singh D, Abdalla M, Alshazly H (2021) Data clustering using moth-flame optimization algorithm. Sensors 21(12):4086. https://doi.org/10.3390/s21124086
139. Adamu ZM, Dada EG, Joseph SB (2021) Moth flame optimization algorithm for optimal FIR filter design. Int J Intell Syst Appl 13(5):24–34. https://doi.org/10.5815/ijisa.2021.05.03
140. Amallynda I, Hutama B (2021) The moth-flame optimization algorithm for flow shop scheduling problem with travel time. Jurnal Teknik Industri 22(2):224–235
141. Suja KR (2021) Mitigation of power quality issues in smart grid using levy flight based moth flame optimization algorithm. J Ambient Intell Hum Comput 12:9209
142. Ravuri V, Vasundra S (2020) Moth-flame optimization-bat optimization: map-reduce framework for big data clustering using the moth-flame bat optimization and sparse fuzzy C-means. Big Data 8(3):203–217. https://doi.org/10.1089/big.2019.0125
143. Gupta D, Ahlawat AK, Sharma A, Rodrigues JJPC (2020) Feature selection and evaluation for software usability model using modified moth-flame optimization. Computing 102(6):1503–1520. https://doi.org/10.1007/s00607-020-00809-6
144. Ghobaei-Arani M, Souri A, Safara F, Norouzi M (2020) An efficient task scheduling approach using moth-flame optimization algorithm for cyber-physical system applications in fog computing. Trans Emerg Telecommun Technol. https://doi.org/10.1002/ett.3770
145. Das A, Mandal D, Ghoshal SP, Kar R (2018) Concentric circular antenna array synthesis for side lobe suppression using moth flame optimization. AEU-Int J Electron C 86:177–184. https://doi.org/10.1016/j.aeue.2018.01.017
146. Ghobaei-Arani M, Rahmanian AA, Souri A, Rahmani AM (2018) A moth-flame optimization algorithm for web service composition in cloud computing: Simulation and verification. Softw Pract Exp. https://doi.org/10.1002/spe.2598
147. Gholizadeh S, Davoudi H, Fattahi F (2017) Design of steel frames by an enhanced moth-flame optimization algorithm. Steel Compos Struct 24(1):129–140. https://doi.org/10.12989/SCS.2017.24.1.129
148. Yıldız BS, Yıldız AR (2017) Moth-flame optimization algorithm to determine optimal machining parameters in manufacturing processes. Mater Test 59(5):425–429. https://doi.org/10.3139/120.111024
149. Jangir N, Pandya MH, Trivedi IN, Bhesdadiya RH, Jangir P, Kumar A (2016) Moth-flame optimization algorithm for solving real challenging constrained engineering optimization problems. In: 2016 IEEE students' conference on electrical, electronics and computer science (SCEECS), pp 1–5. https://doi.org/10.1109/SCEECS.2016.7509293
150. Jaiswal V, Sharma V, Varma S (2020) MMFO: modified moth flame optimization algorithm for region based RGB color image segmentation. IJECE 10(1):196. https://doi.org/10.11591/ijece.v10i1.pp196-201
151. Khairuzzaman AKM, Chaudhury S (2020) Modified moth-flame optimization algorithm-based multilevel minimum cross entropy thresholding for image segmentation. Int J Swarm Intell Res 11(4):123–139. https://doi.org/10.4018/IJSIR.2020100106
152. Said S, Mostafa A, Houssein EH, Hassanien AE, Hefny H (2018) Moth-flame optimization based segmentation for MRI liver images. In Hassanien AE, Shaalan K, Gaber T, Tolba MF(eds) Proceedings of the international conference on advanced intelligent systems and informatics 2017, vol 639. Springer, pp 320–330
153. Aziz MAE, Ewees AA, Hassanien AE (2017) Whale optimization algorithm and moth-flame optimization for multilevel thresholding image segmentation. Expert Syst Appl 83:242–256. https://doi.org/10.1016/j.eswa.2017.04.023
154. Muangkote N, Sunat K, Chiewchanwattana S (2016) Multilevel thresholding for satellite image segmentation with moth-flame based optimization. In: 2016 13th international joint conference on computer science and software engineering (JCSSE), pp 1–6. https://doi.org/10.1109/JCSSE.2016.7748919
155. Wolpert DH, Macready WG (1997) No free lunch theorems for optimization. IEEE Trans Evol Comput 1(1):67–82. https://doi.org/10.1109/4235.585893
156. Luo J, Chen H, Zhang Q, Xu Y, Huang H, Zhao X (2018) An improved grasshopper optimization algorithm with application to financial stress prediction. Appl Math Modell 64:654–668. https://doi.org/10.1016/j.apm.2018.07.044
157. Sayed GI, Soliman M, Hassanien AE (2016) Bio-inspired swarm techniques for thermogram breast cancer detection. In: Dey N, Bhateja V, Hassanien AE (eds) Medical imaging in clinical applications, vol 651. Springer, Cham, pp 487–506