# Moth–flame optimization algorithm: variants and applications

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REVIEW ARTICLE

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# Moth–flame optimization algorithm: variants and applications

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**Abstract**

This paper thoroughly presents a comprehensive review of the so-called moth–flame optimization (MFO) and analyzes its main characteristics. MFO is considered one of the promising metaheuristic algorithms and successfully applied in various optimization problems in a wide range of fields, such as power and energy systems, economic dispatch, engineering design, image processing and medical applications. This manuscript describes the available literature on MFO, including its variants and hybridization, the growth of MFO publications, MFO application areas, theoretical analysis and comparisons of MFO with other algorithms. Conclusions focus on the current work on MFO, highlight its weaknesses, and suggest possible future research directions. Researchers and practitioners of MFO belonging to different fields, like the domains of optimization, medical, engineering, clustering and data mining, among others will benefit from this study.

**Keywords** Moth–flame optimization · Metaheuristic algorithms · Optimization problems · Variants of MFO

## 1 Introduction

Metaheuristic algorithms are classified into local search-based algorithms and population-based algorithms. Local search-based algorithms consider one solution at a time and try to enhance it using neighborhood structures [108], such as hill climbing [65], tabu searches [46], $\beta$-hill climbing [7], and simulated annealing [64]. While the main advantage of these methods is rapid search speeds, the main drawback is their tendency to focus on exploitation rather than exploration, which, as a result, increases the likelihood of their getting stuck in local optima. By contrast, population-based algorithms, which consider a population of solutions at a time, recombine the current solutions to generate one or more new solutions at each iteration. These methods are effective in identifying promising areas in the search space but are ineffective in exploiting the search space region being explored [109]. Evolutionary computation and swarm intelligence methods are classifications of population-based methods [3]. Both methods are based on the natural biological evolution or social interaction behavior of natural creatures. Examples of swarm-based algorithms include particle swarm optimization (PSO) [4], krill herd algorithm (KHA) [8], the salp swarm algorithm (SSA) [79], and the moth–flame optimization (MFO) [78].

Swarm intelligence-based methods are inspired by animal societies and social insect colonies [12]. They mimic the behavior of swarming social insects, schools of fish or flocks of birds. The main advantages of these methods are their flexibility and robustness [22]. MFO is a recent metaheuristic population-based method developed by Mirjalili in 2015 [78] that imitates the moths' movement technique in the night, called transverse orientation for navigation. Moths fly in the night depending on the moonlight, where they maintaining a fixed angle to find their path. The behavior of moths has been formulated as a novel optimization technique.

MFO combines a population-based algorithm and local search strategy to yield an algorithm capable of global exploration and local exploitation. Similar to other metaheuristics, MFO is simple, flexible, and easily implemented;

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as such, it can be utilized to solve a wide range of problems [57]. On account of these merits, MFO was successfully applied to various optimization problems, for instance, scheduling [38], inverse problem and parameter estimation [11, 52], classification [134], economic [121], medical [125], power energy [133], and image processing [37].

This review paper provides new MFO-based users with an inclusive overview of the procedures of MFO and shows adequate works of the literature to understand the utilized variants, such as discrete, modified, and hybridization. Also, the adaptive parameters of MFO are discussed. As well as, we focus on the recent applications of the MFO by highlighting their details (i.e., explain the methodology, features, and weaknesses). Based on the above, the review will help the readers to know more about the working principle and the design of MFO. This review paper ends with the major advantages and weaknesses of MFO and proposes possible directions for future work to concerned researchers. While the types of optimization problems considered are generally minimized, some issues introduced in this review are to be maximized. The authors will directly mention if that was necessary. In other words, there are many optimization algorithms have been proposed in the last few years, especially swarm-based algorithms [29]. Therefore, the importance of this review is guidance the researchers who are currently working or will work in this area by leading them toward how the MFO algorithm can be employed to solve the problems, point out its weaknesses and strengths, and prove its effectiveness compared with other algorithms.

The organization of this review is as follows. Section 2 introduces MFO and its framework. Then, the development of MFO is described in Sect. 3. Section 4 presents an overview of the MFO variants and modifications. Application enhancements in particular fields are given in Sect 5. Section 6 illustrates the evaluation of MFO. Finally, Sect. 7 presents some concluding and outlines various lines of interest for future research.

## 2 Moth–flame optimization algorithm

### 2.1 Origin

In nature, over 160,000 different species of moths have been documented, which resemble butterflies in their life cycle (i.e., moth consists of two-level life: larva and adult, where it is converted to moth by cocoons) [116].

In moths' life, their special navigation method at night is the most interesting fact. They have been evolved to fly in the night using the moonlight. Also, they employed a mechanism called transverse orientation for navigation. This mechanism allows the moth to fly by preserving a stable angle with respect to the moon, a very effective mechanism for traveling long distances in a straight path [43]. Figure 1 illustrates a conceptual model of transverse orientation. Since the moon is far away from the moth, this mechanism guarantees flying in a straight line. The same navigation method can be done by humans. Suppose that the moon is in the south side of the sky and a human wants to go the east. If he keeps moon of his left side when walking, he would be able to move toward the east on a straight line.

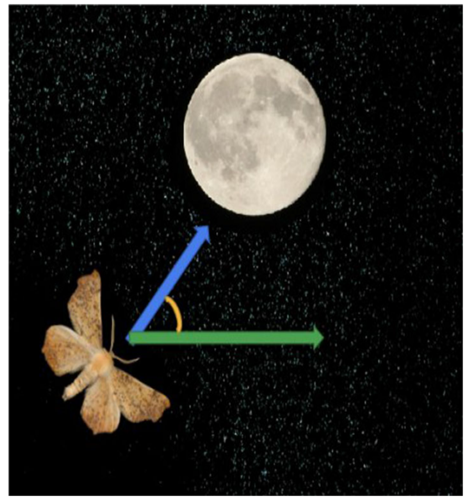

**Fig. 1** Moth's transverse orientation

It can be observed in Fig. 2 the moths don't travel in a forward path, they fly spirally around lights. This is due to the transverse orientation method is efficient just for the light source is very far (moonlight). In the human-made artificial light case, the moths attempt to preserve the same angle with the light source. Consequently, moths moving in spirally paths around lights.

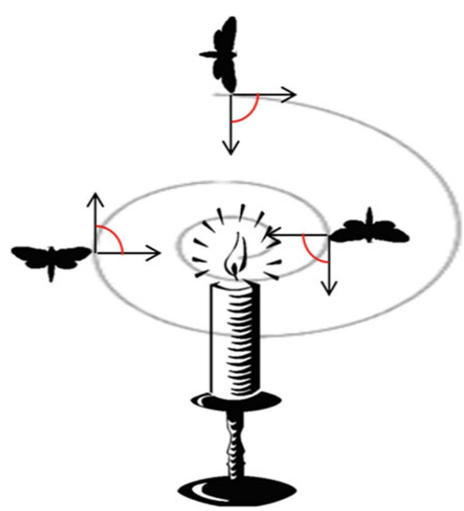

**Fig. 2** Moth's spiral flying path around a light source

## 2.2 MFO algorithm

Moth–flame optimization (MFO) algorithm was proposed by Mirjalili [78]. It is under the population-based meta-heuristic algorithms. As shown in Fig. 3, MFO starts by generating moths randomly within the solution space, then calculating the fitness values (i.e., position) of each moth, and tagging the best position by flame. After that, updating the moths' positions depends on a spiral movement function to achieve better positions tagged by a flame, updating the new best individual positions, and repeating the previous processes (i.e., updating the moths' positions and generating new positions) until the termination criteria are met. Table 1 lists the characteristics of the MFO.

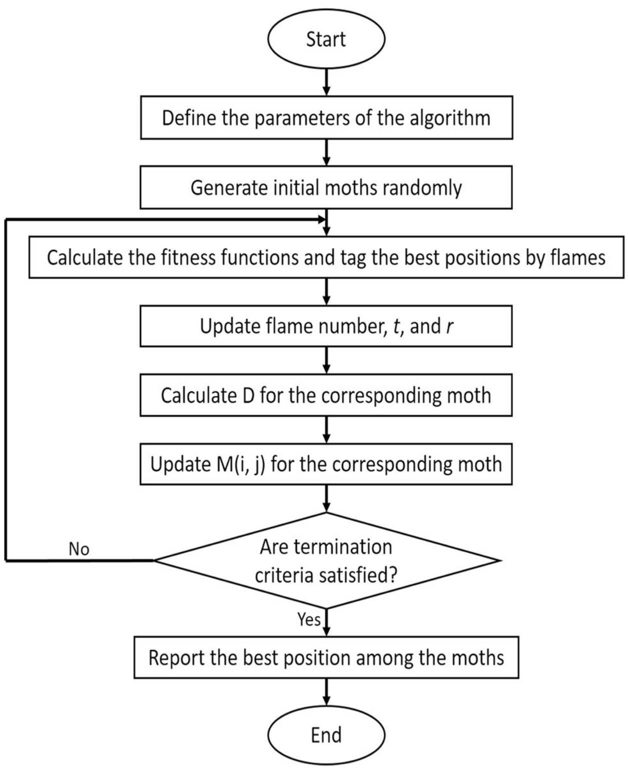


**Fig. 3** Flowchart of the MFO algorithm

The MFO algorithm has three main steps. These steps are shown below. Then, the pseudocode of the MFO as shown in Algorithm 1 and the summary of its parameters setting are illustrated in Table 2.

1. *Generating the initial population of Moths:*
   As mentioned in [78], Mirjalili assumed that each moth can fly in 1-D, 2-D, 3-D, or hyperdimensional space. The set of moths can be expressed:

$$M = \begin{bmatrix} m_{1,1} & m_{1,2} & \cdots & \cdots & m_{1,d} \\ m_{2,1} & m_{2,2} & \cdots & \cdots & m_{2,d} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ m_{n,1} & m_{n,2} & \cdots & \cdots & m_{n,d} \end{bmatrix} \quad (1)$$

   where $n$ refers to the moths' number and $d$ refers to the number of dimensions in the solution space. Also, the fitness values for all moths are memorized in an array as follows:

$$OM = \begin{bmatrix} OM_1 \\ OM_2 \\ \vdots \\ OM_n \end{bmatrix} \quad (2)$$

   The rest elements in the MFO algorithm are flames. The following matrix shows the flames in the D-dimensional space followed by their fitness function vector:

$$F = \begin{bmatrix} F_{1,1} & F_{1,2} & \cdots & \cdots & F_{1,d} \\ F_{2,1} & F_{2,2} & \cdots & \cdots & F_{2,d} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ F_{n,1} & F_{n,2} & \cdots & \cdots & F_{n,d} \end{bmatrix} \quad (3)$$

$$OF = \begin{bmatrix} OF_1 \\ OF_2 \\ \vdots \\ OF_n \end{bmatrix} \quad (4)$$

**Table 1** Characteristic of the MFO algorithm

| Algorithm's description | Moth–flame's elements |
|---|---|
| Decision variable | Moth's position in each dimension |
| Solutions | Moth's position |
| Initial solutions | Random positions of moths |
| Current solutions | Current positions of moths |
| New solutions | New positions of moths |
| Best solution | Flame's position |
| Fitness function | Distance between moth and flame |
| Process of generating new solution | Flying in a spiral path toward a flame |

**Table 2** Summary of parameters setting of MFO algorithm

| Parameter | Common value |
|---|---|
| Number of search agents | 30–50 [101] |
| Number of moths (population) | 10–30 [78] |
| Maximum number of iterations | 100–10,000 [17] |

It should be noted here that moths and flames are both solutions. The difference between them is the way we treat and update them in each iteration. The moths are actual search agents that move around the search space, whereas flames are the best position of moths that obtains so far. In other words, flames can be considered as flags or pins that are dropped by moths when searching the search space. Therefore, each moth searches around a flag (flame) and updates it in case of finding a better solution. With this mechanism, a moth never loses its best solution.

2. *Updating the Moths' Positions:*

MFO employs three different functions to converge the global optimal of the optimization problems. These functions are defined as follows:

$$MFO = (I, P, T) \tag{5}$$

where $I$ refers to the first random locations of the moths $(I : \phi \rightarrow \{M, OM\})$, $P$ refers to motion of the moths in the search space($P : M \rightarrow M$), and $T$ refers to finish the search process ($T : M \rightarrow true, false$). The following equation represents $I$ function, which is used for implementing the random distribution.

$$M(i,j) = (ub(i) - lb(j)) * rand() + lb(i) \tag{6}$$

where $lb$ and $ub$ indicate the lower and upper bounds of variables, respectively. As mentioned previously, the moths fly in the search space using the transverse orientation. There are three conditions that should abide when utilizing a logarithmic spiral subjected, as follows:

- Spiral's initial point should start from the moth.
- Spiral's final point should be the position of the flame.
- Fluctuation of the range of spiral should not exceed the search space.

Therefore, the logarithmic spiral for the MFO algorithm can be defined as follows:

$$S(M_i, F_j) = D_i \cdot e^{bt}.cos(2\pi t) + F_j \tag{7}$$

where $D_i$ refers to the space between the *i-th* moth and the *j-th* flame (i.e., $D_i = |F_j - M_i|$), $b$ indicates a fix to define the shape of the logarithmic spiral, and $t$ indicates a random number between [−1, 1]. In MFO, the balancing between exploitation and exploration is guaranteed by the spiral motion of the moth near the flame in the search space. Also, to avoid falling in the traps of the local optima, the optimal solutions have been kept in each repetition, and the moths fly around the flames (i.e., each moth flies surrounding the nearest flame) using the OF and OM matrices.

3. *Updating the number of flames:*

This section highlights enhancing the exploitation of the MFO algorithm (i.e., Updating the moths' positions in $n$ various locations in the search space may decrease a chance of exploitation of the best promising solutions). Therefore, decreasing the number of flames helps to solve this issue based on the following equation:

$$flame\ no = round\left(N - l * \frac{N - l}{T}\right) \tag{8}$$

where $N$ is the maximum number of flames, $l$ is the current number of iterations, and $T$ indicates the maximum number of iterations.

**Algorithm 1** Moth-flame optimization algorithm

```
Initialize the parameters for Moth-flame
Initialize Moth position M_i randomly
for i = 1 to n do
  Calculate the fitness function f_i
end for
while iteration ⩽ Max_iterations do
  Update the position of M_i
  Calculate the number of flames using Eq.()
  Evaluate the fitness function f_i
  if iteration ==1 then
    F=sort(M) and OF=sort(OM)
  else
    F=sort(M_{t-1}, M_t) and OF=sort(M_{t-1}, M_t)
  end if
  for i = 1 to n do
    for j = 1 to d do
      Update the values of r and t
      Calculate the value of D respect to its corresponding moth using Eq.()
      Update M(i,j)respect to its corresponding moth using Eq.()
    end for
  end for
end while
Print the best solution
```

## 3 The growth of moth–flame optimization algorithm in the literature

Many articles on MFO have been published. In this review article, two stages use "Moth-Flame Optimization", "Moth flame optimization", "Moth-Flame Algorithm", and "MFO" as a keywords to collect articles. In the first stage, the published MFO articles are gained from highly reputable publishers (journals and conferences). Secondly, the MFO search outcomes are categorized based on the publishing institution, the distribution of publications, variants of MFO, theoretical analysis of MFO, and applications of MFO, as shown briefly in this section. (More details are described in the following sections.)

Measurement of the strength of each algorithm is based on its publication characteristics, such as the number of publications and publishing institutes and whether the article is published in a magazine and a conference. This paragraph is highlighted in the publishing institutes of MFO. Figure 4 shows the number of published articles between 2015 and April 2019.

Figure 5 illustrates the distribution of published research articles on MFO in three main categories: applications 83%, variants 15% and theoretical analysis 2%. It's worth mentioning that Table 3 shows more details about the variants of MFO, while Fig. 5 shows the classification of the MFO's applications.

As mentioned previously, most publications of the MFO were under the application part. Figure 6 illustrates the distribution of the MFO's publication in different fields. It may be observed that the engineering applications have a high percentage of the number of publications compared to the other applications because they contain engineering design, mechanical engineering, electrical engineering, power flow optimization, wind energy, and PID control followed by power dispatch, image processing, machine learning, and other applications. Section 5 shows more details about each applications.

## 4 Different variants of MFO

The MFO has been introduced in 2015 under the meta-heuristic swarm-based algorithms. Various updates have been done on the MFO to comply with the different processes in the search space of the optimization problem. The section ending with Table 3 illustrates the summary of MFO's variants.

### 4.1 Multi-objective

Li et al. [69] applied multi-objective moth–flame optimization algorithm (MOMFA) to improve the efficiency of

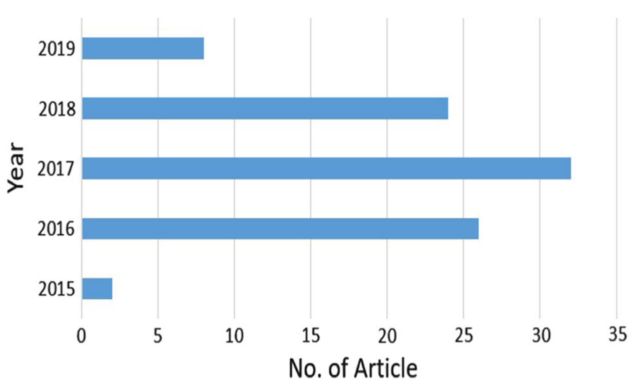


**Fig. 4** Publications of MFO algorithm

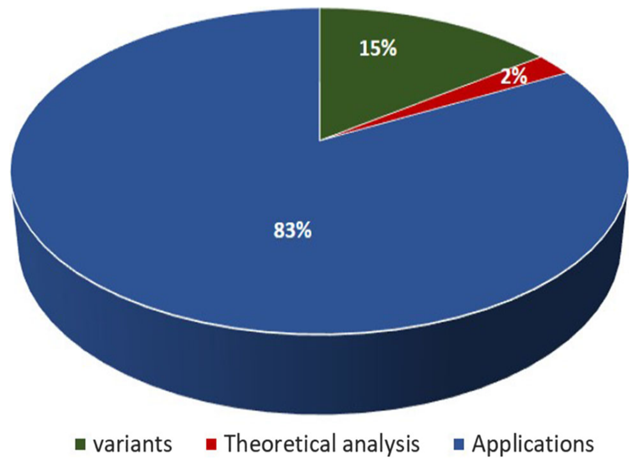


**Fig. 5** The distribution of published research articles

using water resources. The method assisted and utilized the original moth–flame optimization algorithm, opposition-based learning, and indicator-based selection-efficient mechanisms in order to maintain the diversity and accelerate the convergence. The algorithm was tested on the Lushui River Basin and many benchmarks. The algorithm can determine the optimal trade-off of the elements and can distribute non-dominated outcomes for utilization problem of the multi-objective water resources. The result is verified and compared with other algorithms, indicating the ability to obtain well Pareto solutions for standard problems.

A non-dominated moth–flame optimization algorithm (NSMFO) method has been proposed in [100] to solve multi-objective problems. Metaheuristics search techniques are used based on MFO instead of the different optimization techniques like cuckoo search, genetic algorithms, particle swarm optimization, and differential evolutions. The method utilized crowding distance approach and sorting of the elitist non-dominated for preserving the diversity and obtaining variant non-domination levels, respectively, among the optimal set of solutions. It measured the effectiveness by multi-objective benchmark, engineering problems, distinctive feature, and the Pareto front generation. The results of the method were compared with other algorithms and considered closer and better sometimes.

Nanda et al. [86] proposed a new heuristic MFO approach to solve optimization problem. The approach is aimed to reach an optimal destination and sorting the solutions to maintain effective convergence to the Pareto optimal front. It used exploitation and exploration characteristics of the original MFO and other concepts like organize based on the space for separation, archive grid, and non-dominance of outcomes [138]. The new approach was validated on a set of benchmark functions. The performance of the proposed MOMFO was analyzed on a set of benchmark functions over the MOPSO and NSGA-II.

**Table 3** Summary of MFO's variants

| Type | Algorithm | Description | Problem | Reference |
|---|---|---|---|---|
| Multi-objective | MOMFA | Improves the efficiency of using water resources and finds the best trade-off of the components | Maintains the diversity and accelerates the convergence | Li et al. [69] |
| | NSMFO | Measures the effectiveness by multi-objective benchmark, engineering problems, distinctive feature, and generates the Pareto front | Preserves the diversity and obtains variant non-domination levels | Savsani and Tawhid [100] |
| | MOMFO | Uses exploitation and exploration of MFO for sorting, archive grid, non-dominance of solutions | Reaches an optimal destination and sorting the solutions to maintain effective convergence | Nanda et al. [86] |
| Binary | MFOA | Takes the advantages of MFO using exploitation characteristics of moths and reduces the flame number as a function of the iteration count | improves solving UC problem | Reddy et al. [89] |
| Hybridization | MFO-FLC | MFO-FLC is used to control the minimize supply voltage and line current harmonics existing in a motor system | Analyzes the dynamic behavior of the BLDC motor | Kamalapathi et al. [59] |
| | SA-MFO | Integrates SA with MFO aids to slow down the convergence rate and increases the probability to find the best solution | Solves the shortcoming of traditional MFO algorithm in terms of convergence rate and probability to reach best solution | Sayed and Hassanien [101] |
| | PSO-MFO | Increases the exploration search during solving high complex design problem | Solves unconstrained engineering design optimization problems in power system context | Bhesdadiya et al. [20] |
| | WCMFO | Enhances exploitation ability using MFO and enhances the exploration ability using random walk of WCA | Handles constrained engineering optimization problems | Khalilpourazari and Khalilpourazary [62] |
| | MFO-GSA | Takes advantage of the effectiveness of MFO in exploratory nature and the effectiveness of GSA in the team of exploitation | Solves the problem of measuring the degree of food rottenness | Sarma et al. [97] |
| | LSF-MFO | Minimizes the power losses taking into account the effect of annual load growth | Solves renewable energy optimization problems | Abdel-mawgoud et al. [1] |
| | PSO-MFO | Finds optimal placement solution through minimizing the number of PMU installations and maximizes the measurement redundancy | Determines the optimal placement of PMUs | Anfal and Abdelhafid [14] |
| | PSO-MFO | Addresses power flow problems including fuel cost reduction, voltage profile improvement, voltage stability enhancement, active power loss minimization and reactive power loss minimization | Solves optimal power flow problem in power system context | Jangir [58] |
| | MFO-SVR | Proposes an effective solution for the short-term load forecasting in power system and enhances performance by simplifying the intrinsic complexity of the original data | Enhances the forecasting performance | Yang et al. [129] |

For all test functions, MOMFO with Pareto optimal front obtained showed more diversity and better convergence compared with MOPSO which is considered a good alternative in the multi-objective domain.

## 4.2 Binary

Reddy et al. [89] modified the moth–flame optimization algorithm (MFOA) and examined characteristics of the local and global search of the basic algorithm. The algorithm is aimed to improve solving unit commitment (UC) problem by using the binary coded modified moth–flame optimization algorithms (BMMFOA), the basic MFO is a nature-inspired heuristic search approach that mimics the traverse navigational properties of moths around artificial lights tricked for natural moonlight, the algorithm used position update of a single-based approach between corresponding flame and the moth differently than many other swarm-based approaches. The modified moth–flame optimization algorithm (MMFOA) is used to improve the exploitation search of the moths and reduces the number of flames. The research tested the four additional alternatives based on one

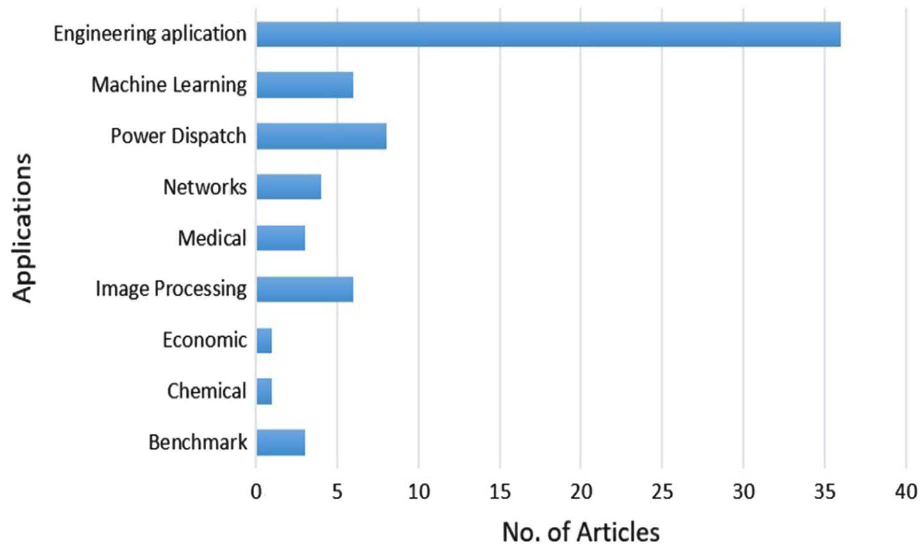


**Fig. 6** Application of MFO

commitment issue of operational scheduling of power system, and it also used the modified sigmoidal transformation to carry out the binary chart of actual moth value and flame positions for fixing unit commitment problem. The research analyzes the efficacy of the proposed approaches for different test systems, in the characteristics of convergence, execution time, and terms of solution quality. The research also used many standard statistical tests to set up statistical significance of BMMFOA among the other approaches.

### 4.3 Hybridization

Kamalapathi et al. [59] presented an optimization framework in the context of electric motor design. The framework was developed to analyze the dynamic behavior of the BLDC motor in order to solve torque ripple problem. Therefore, the presented framework was compromise three components namely, AC voltage, voltage source inverter, integrated MFO and fuzzy logic controller (FLC). AC voltage is used as input source. MFO is used to control the minimize provide voltage and line stream harmonics existing in a motor system, while FLC is applied to improve the performance of MFO algorithm by improving the updating function of MFO and minimization of torque ripple. In the experiment, the performance and applicability of the MFO framework is evaluated under three test situations of rate and torque provisions, which are examination of stability rate and torque, examination of stability torque with rate variation, and examination of stability torque variation with stability rate. The analysis results of the proposed framework are compared with the original MFO and controller. The comparison results show the supremacy of the proposed framework over other techniques.

A new hybrid algorithm based on MFO and simulated annealing (SA) has been proposed in [101]. The proposed algorithm is tested in the context of constrained engineering design optimization problems. SA-MFO hybrid algorithm was proposed to solve the shortcoming of traditional MFO algorithm in terms of convergence rate and probability to reach the best solution. Therefore, the authors argued that integrated SA with MFO will aid to slow down the convergence rate and increases the probability to find the best solution. To validate the performance and effectiveness of the proposed hybrid algorithm (e.g., SA-MFO), the experiment study is performed. The experiment aimed to compare the proposed algorithm with set of traditional optimization algorithm (e.g., particle swarm optimization (PSO), ant bee colony (ABC), moth–flame optimization multi-verse optimization (MVO), and ant lion optimizer (ALO)) to solve on 23 benchmark functions under four well-known engineering problems, namely three-bar truss, welded beam, pressure vessel and tension/compression spring design problems [112]. The experiment results showed the effectiveness of the proposed algorithm in solving constrained engineering design optimization problems. In terms of performance validation, the experiment results showed that SA-based MFO performed better than other compared algorithms.

Bhesdadiya et al. [20] introduced a hybrid optimization algorithm based on integration between particle swarm optimization (PSO) and MFO. The proposed algorithm is used to solve unconstrained engineering design optimization problems in power system context. MFO is applied in order overcome the limitation of PSO algorithm by increasing the exploration search during solving high complex design problem. In the conducted experiment, four benchmarking functions are used to validate the proposed algorithm in terms of exploration and exploitation. Furthermore, the proposed algorithm is compared with the two traditional swarm-based algorithms, namely particle swarm optimization (PSO) and MFO to validate the performance. Overall experiment results illustrate that the performance of the proposed algorithm is better than the compared traditional methods.

Khalilpourazari and Khalilpourazary [62] implemented hybrid algorithm based on population-based algorithm (e.g., Water Cycle Algorithm (WCA)) and swarm-based algorithm (i.e., MFO) in order to handle constrained engineering optimization problems. Specifically, the hybrid optimization algorithm is used to enhance exploitation and exploration ability. For example, to enhance exploitation ability of the hybrid algorithm WCA is introduced to MFO to use the spiral movements of moths, while WCA is used to enhance the exploration ability of the hybrid algorithm by using random walk (Levy flight) of WCA. The performance and efficiency of the proposed hybrid algorithm were measured and validated by using experiment methodology. To measure the performance of hybrid algorithm, twenty-three benchmark functions such as unimodal, multimodal and fixed-dimension multimodal benchmark functions under three test case studies of structural engineering problems including: constraint handling, pressure vessel design, and tension/compression spring design problem, are solved using the proposed hybrid algorithm. The effectiveness of the proposed hybrid algorithm is measured by comparing the experiment results with a wide range of current optimization algorithms (e.g., artificial bee colony algorithm, cuckoo Search, genetic algorithm, PSO, hybrid particle swarm optimization and gravitational search algorithm, gravitational search algorithm, MFO, WCA and dragonfly algorithm). The comparison results revealed that the proposed hybrid algorithm is able to provide competitive results over current optimization algorithms. In the context of image segmentation (automated food quality inspection), Sarma et al. [97] proposed a hybrid algorithm combined between physics-based algorithm (e.g., Gravitational Search Algorithm (GSA)) and Swarm-based Algorithm (i.e., MFO). The proposed algorithm is applied to solve the problem of measuring the degree of food rottenness that cloud help to minimize monetary losses due to food and storage. Both algorithm is combined because they complete each other. For example, MFO is important due to its effectiveness in exploratory nature, while GSA is applied due to its effectiveness in terms of exploitation. The experiment study is designed to test the hybrid optimization algorithm over thirteen unimodal functions and multimodal functions. Then, the experiment results are used to compare the proposed hybrid algorithm with traditional MFO and GSA algorithms. The comparison results showed that the proposed hybrid algorithm is very fast and producing safe results.

In [1], MFO algorithm and loss sensitivity factor (LSF) are integrated to solve renewable energy optimization problems. The hybrid algorithm is used find the degree of optimal location and size of renewable DG units (e.g., solar (PV)- and wind (WTG)-based DG). The main research question of the proposed study is how to minimize the power losses taking into account the effect of annual load growth. Therefore, MFO is applied to find the optimal size and locations for renewable DG units. Meanwhile, LSF is used to decide the adequate buses for installing the DGs. The experiment methodology is used to evaluate the performance of the proposed hybrid algorithm using IEEE 69-bus branch distribution system. The experiment results revealed that the proposed hybrid algorithm is applicable to improve the operating constrains of distribution system to hold out the load growth. This is done by reducing the system power loss, increasing the system capacity, and improving the system voltage profile.

In the context of power system, Anfal and Abdelhafid [14] combined particle swarm algorithm and moth–flame method (PSO-MFO) in order to determine the optimal placement of Phasor Measurement Units (PMUs). PSO-MFO algorithm aims to find optimal placement solution through minimizing the number of PMU installations and maximize the measurement redundancy. In the experiment study, PSO-MFO is was tested on three IEEE bus standards, namely IEEE-14, IEEE-30, IEEE-57 bus systems and 68-bus Algerian system. Then, the testing results were compared with set of optimization methods such as moth–flame optimizer, integer programming, BPSO, GA, tabu search, particle swarm optimization, immunity genetic algorithm, binary search algorithm, imperialistic competition algorithm, and three-stage heuristic method. The comparison results indicate the superiority of PSO-MFO algorithm over other algorithms and could present better solutions in terms of the actual speed.

Jangir [58] integrated two swarm-based algorithms (i.e., particle swarm optimization and moth–flame optimizer) (PSO-MFO) in order to solve optimal power flow problem in power system context. The key problems that PSO-MFO should address power flow problems including fuel cost reduction, voltage profile improvement, voltage stability enhancement, active power loss minimization and reactive power loss minimization. In such uncertain environment, PSO is applied to handle the exploitation phase and MFO is applied to handle exploration phase. The experiment study is designed to test PSO-MFO algorithm under the suggested five power flow problems. The experiment results are then compared with the traditional MFO and PSO algorithms for OPF problems. The compression results indicate the effectiveness of PSO-MFO to solve OPF problem over other algorithm.

In the context of power system, Yang et al. [129] introduced short-term load forecasting algorithm. The proposed algorithm combined complete ensemble empirical mode decomposition (CEEMD), support vector regression (SVR), and moth–flame optimization algorithm (MFO). MFO algorithm is used to improve the forecasting performance. The experiment study is conducted, and the short-term load forecasting results are compared with a set of traditional forecasting algorithms (e.g., ARMA, SVR, CEEMD-SVR, and MFO-SVR). However, the comparison results indicate that each component in the proposed hybrid algorithm is promising and an effective solution is proposed for the short-term load forecasting in power system. In addition, MFO as a prime component of the proposed hybrid algorithm can enhance performance by simplifying the intrinsic complexity of the original data.

## 5 Moth–flame optimization applications

Many applications of MFO to benchmark optimization and real-world problems have been reported. The articles obtained mainly aimed to highlight the efficiency of MFO and compare it with other optimization algorithms. This section shows the discussions of the MFO in various applications, such as benchmark optimization, chemical, economic, image processing, medical applications, networks, power dispatch problem, and engineering optimization. At the end of this section, Table 4 shows the summary of all MFO's applications.

### 5.1 Benchmark functions

MFO algorithm has been developed by Bhesdadiya et al. [21] using navigation approach to solve the inequality and equality constrained optimization, and real challenging layout problems. The navigating strategy of moths in-universe entitles transverse orientation, a well active mechanism for travel so far distance in the straight direction. Moreover, a deadly spiral path has been followed as moths are tricked by artificial lights. MFO algorithm shows a useful result in both discrete and continuous control variables. On the other hand, one of the optimization techniques named real challenging constrained has been proposed to optimize a real function in the presence of constraints on selected variables [105]. MFO solved two types of constrains that are hard- and soft-constrained. The proposed algorithm has been represented statistically to identify the best function in terms of standard deviation and accuracy and compared with some existing optimization algorithms. In terms of real engineering problems, fourteen constrained benchmark functions have been calculated and solution has been gained and compared with solutions that gained from existing recognized algorithms. Results prove that MFO algorithm overcomes the existing algorithms in the field of engineering design problems.

MFO is considered as one of the promising developed nature-inspired optimization algorithms that have direct impact on the optimization problem. However, slow convergence is one of the main drawbacks in MFO. To solve this problem, MFO has been enhanced using ten chaotic maps in order to find the optimum prospectors that help in increasing the process of exploring the best solutions. This method has been implemented to overcome the state-of-the-art test methods [50]. Simulation tests prove that chaotic maps help in improving the performance of the MFO regarding convergence speed. Moreover, simulation test shows that sinusoidal maps significantly improve the performance of the MFO.

### 5.2 Chemical

Chauhan and Kotecha [28] provided a strategy that helps in the evolutionary algorithms in order to improve the single-level production planning efficiently. MFO demonstrates the efficacy of the strategy which also helps in performance evaluation of the proposed technique. It was shown that the MFO has the ability to solve the problem production planning consistently with the suggested strategy. Though demonstrated for production planning in a chemical industry, MFO can be used to determine the optimal production portfolio in many other industries.

### 5.3 Economical applications

Khalilpourazari and Pasandideh [63] proposed a multi-item multi-constrained Economic Order Quantity model with nonlinear unit holding cost and partial backordering. Different technical, strategic, and physical constraints are taken into account to develop an applicable model such as total permissible holding cost, warehouse capacity, available budget, and total permissible backordering cost constraints. The main contribution is to identify the inventory cycles' lengths, where the inventory level is up and down as the total inventory costs are minimized. Moreover, in order to reduce the total inventory costs significantly, backordering rate during shortage period for each product is considered as a decision variable. Because of the nonlinearity and complexity of the proposed model, MFO algorithm and interior-point method are employed to improve the model in multi-sizes. Lastly, the performance of the proposed methods is statistically compared taking into account three measures to identify the superior solution method.

### 5.4 Image processing

Zhou et al. [139] conducted a study to overcome the problem of increasing thresholds during the optimal

**Table 4** Summary of the MFO's applications

| Application | Algorithm | Description | Problem | Reference |
|---|---|---|---|---|
| Benchmark functions | MFO | Using MFO with navigation approach to solve the inequality and equality constrained optimization | Layout problems | Bhesdadiya et al. [21] |
| | MFO | MFO have been enhanced using ten chaotic maps | Slow convergence | Guvenc et al. [50] |
| Chemical | MFO | Using MFO to improve the single-level production planning efficiently | Production planning | Chauhan and Kotecha [28] |
| Economical applications | MFO and interior-point | Applied MFO and interior-point method to identify the inventory cycles' lengths | Cost constraints | Khalilpourazari and Pasandideh [63] |
| Image processing | MFO | MFO employed Kapur's entropy method to improve the thresholds for eight standard test images | Threshold | Zhou et al. [139] |
| | MFO | Utilizing MFO for clustering the abdominal image | MRI images | Said et al. [92] |
| | MTMFO | Using MFO to improve the best multilevel thresholding of satellite images effectively | Image segmentation | Muangkote et al. [84] |
| | MFO-WOA | Employing MFO-WOA to determine the optimal threshold multi-level in image histogram | Image segmentation | El Aziz et al. [37] |
| Medical | MFORSFS | MFORSFS utilizes the high performance of rough sets for the feature selection task | Tomato problems | Hassanien et al. [51] |
| | MFO-SVM | Utilizing MFO-SVM to differentiate between three kinds of classes including AD | Alzheimer's disease | Sayed et al. [102] |
| | CMFO | CMFO utilized optimization parameters and selection strategy | Breast cancer | Wang et al. [125] |
| Networks | MFO | Using MFO for training RBFN algorithm to avoid the convergence to local minima | MLP networks | Faris et al. [41] |
| | MFO | Utilizing MFO for handling local optima avoidance | FiWi | Singh and Prakash [114] |
| | ISA-MFO-BA | ISA-MFO-BA utilizes the heuristic fully connected network | Relay Nodes | Sapre and Mini [96] |
| | MFO | Using MFO to enable monitoring all targets using optimum number of drones | Drone location | Strumberger et al. [118] |
| Power dispatch | MFO | Utilizing MFO for optimization of the data processing strategy and convergence rate | ORPD | Anbarasan and Jayabarathi [13] |
| | MFO | Using MFO to find the best combination of transformers tap setting to achieve minimum voltage deviation | ORPD | Mei et al. [74] |
| | multi-objective MFO | Employing the proposed algorithm to solve the economic dispatch in a radial network and microgrid | ED | Elsakaan et al. [39] |
| | MFOL | Using MFOL to improve the competitiveness results for continuous and discrete control parameters | ELD | Trivedi et al. [121] |
| | MFO | Using MFO to find the best combination of control variables, transformer-tap setting, and voltage magnitude | ORPD | Sulaiman et al. [119] |
| | MFO-ALO | Using MFO-ALO to find the optimal settings of control variables and reactive compensators sizing | ORPD | Mei et al. [75] |
| | EMFO | Implementing MFO to solve the ED by minimizing both fuel cost and emission | ED | Elsakaan et al. [38] |
| | MFO | Using MFO to solve the dynamic and non-convex economic load dispatch electric power system problem | ELD | Bhadoria et al. [19] |

**Table 4** (continued)

| Application | | | Algorithm | Description | Problem | Reference |
|---|---|---|---|---|---|---|
| Machine learning | | | MFO-LSSVM | Using MFO to find the optimal parameters of LSSVM for enhancing the forecasting accuracy of annual power load | Forecasting | Li et al. [68] |
| | | | MFO-AHLR | Using MFO for enhancing the AHLR's accuracy with a minimum number of features | Feature selection | Ewees et al. [40] |
| | | | MFO | Employing MFO to find the minimal number of features and maximizing the performance of the classification | Classification | Zawbaa et al. [134] |
| | | | MFO2, MFO3 | Using MFO2, MFO3 to select the optimal feature subset for classification purposes | Classification | Soliman et al. [117] |
| | | | MFO | Utilizing MFO to search for the weights and biases to train MLP and determining minimum training error | MLP | Yamany et al. [128] |
| | | | MFO | Applying MFO in cluster analysis to obtains superior accuracy and exhibits a higher level of stability | Clustering | Shah et al. [104] |
| Engineering optimization | Engineering design | | MFO | Utilizing MFO for optimizing the designed device performance and ANN for training the FinFET structure | FinFET | Kaur et al. [60] |
| | | | MFO | MFO provides the best solution of expensive, continuous, highly complex constrained | Engineering design | Jangir et al. [57] |
| | | | LMFO | Using LMFO to enhance the population diversity against premature convergence | Convergence rate | Li et al. [71] |
| | | | EMFO | Using EMFO to decrease trapping in local optimal designs | Planar steel | Gholizadeh et al. [45] |
| | | | MFO | Applying MFO to calculate current excitation non-linear values for the synthesis and pattern modeling of a CCAA | CCAA | Das et al. [30] |
| | | | MFO | Using MFO to maximize the profit rate for multi-tool milling procedures | Production industry | Yıldız and Yıldız [132] |
| | Power energy | Electrical engineering | MFO | Utilizing MFO for the simultaneous optimization of the second controller gains | CIPD | Saikia and Saha [93] |
| | | | MFO-FPA | Using MFO-FPA for selecting the best parameters of the Cole-impedance system | Cole-impedance | Yousri et al. [133] |
| | | | MFO | Utilizing MFO to conclude the optimal position and parameter setting of SSSC | SSSC | Abd el sattar et al. [98] |
| | | | MFO | Using MFO for multilevel converters of the harmonic eliminating problem and THD | THD | Ceylan [26] |
| | | | MFO | Using MFO to reduced voltage levels, increased power losses, and enhanced power quality problems | SCBs | Tolba et al. [120] |
| | | | MFO | Proposing MFO to increase the earnings of the market participant regarding twice sided bidding | GSF | Gope et al. [47] |
| | | | MFO | Using MFO to decrease the energy cost by defining the optimal positions and area | RDS | Upper et al. [123] |

**Table 4** (continued)

| Application | Algorithm | Description | Problem | Reference |
|---|---|---|---|---|
| | MFO | Employing MFO to determine the optimal proportional-integral controller and DMC | multiarea hybrid interconnected power | Mohanty et al. [82] |
| | MFO | Using MFO to minimize the loos and warranty the cost-effective power system process | OPF | Saurav et al. [99] |
| | MFO | Using MFO to find optimal capacitor position and sizing in spreading distribution systems | spreading distribution | Ceylan and Paudyal [27] |
| | CMFO | Utilizing MFO to determine the optimal positions and sizes of renewable DG in RDS | RDS | Abdel-mawgoud et al. [2] |
| | GWO-DFO-MFO | Using GWO-DFO-MFO to determine the optimal sitting of capacitors in different RDSs | RDS | Diab and Rezk [33] |
| | MFO | Using MFO to extract the maximum parameter's operation for three examined models | Solar cells | Allam et al. [11] |
| | MFO | Applying MFO to solve AGC by a comprehensive study of PIDD controller | AGC | Mohanty [81] |
| | Rolling-MFO-GM | Using Rolling-MFO-GM to improve the forecasting efficiency of yearly electricity consumption | Electricity consumption | Zhao et al. [137] |
| Power flow | MFO | Using MFO to address the voltage profile improvement, active power loss minimization and reactive power loss minimization | OPF | Trivedi et al. [122] |
| | MFO | Using MFO to improve the ability of exploration and exploitation, also adaptive spiral motion and Gaussian walks | OPF | Mohamed et al. [80] |
| | MFO | Applying MFO to minimize emission, fuel cost, and power loss reduction | various non-convex | Buch et al. [23] |
| Wind energy | MFO-CCOPF | Using MFO to increase the profit and mitigate the contingency situations and to find the critical line in the system | LOCI | Gope et al. [48] |
| | SMFO | Utilizing MFO to achieve MPPT, and to improve the capability of FRT | DFIG | Huang et al. [55] |
| | MVO-MFO | Using MVO-MFO to obtain the optimal design of the power sources | HPGS | Mekhamer et al. [76] |
| PID Control | MFO-tuned PI | Using MFO-tuned PI to optimize the controller gains | AGC | Acharyulu et al. [9] |
| | MFO | Utilizing MFO to optimize the scaling parameters of the fuzzy-PID controller | AMB | Dhyani et al. [32] |
| | MFO | Using MFO to optimize the load frequency control system of two areas | Non-identical power | Sahu and Hota [91] |

threshold determination; for that purpose, a multi-threshold image segmentation method has been proposed based on the MFO. The proposed algorithm employed Kapur's entropy method to improve the thresholds for eight standard test images. Simulation results have been conducted according to image segmentation results and numerical experimental results. Results prove that the proposed algorithm is more effective and robust than other state-of-the-art algorithms.

A successful approach for liver segmentation based on MFO algorithm has been proposed by Said et al. [92]. This algorithm is employed for clustering the abdominal image. In this algorithm, the required clusters have been picked up by the user that shows the liver to gather the initial segmented image. Next, the final segmented liver has been produced using morphological operations. In order to test the proposed approach and segment the liver, a set of 70 MRI images were employed. The experimental results prove that the overall accuracy of the proposed approach is 95.66%.

In order to improve the best multilevel thresholding of satellite images effectively, Muangkote et al. [84] proposed an optimized algorithm of the MFO algorithm for image segmentation. Regarding image segmentation, multilevel thresholding is considered that is widely used as it is easy implement and works efficiently in processing. However, it consequently becomes expensive computationally since the number of threshold values increases. Therefore, authors developed a multilevel thresholding moth–flame optimization algorithm (MTMFO) for multilevel thresholding. The proposed method was evaluated on different satellite images tested verses five existing algorithms: the particle swarm optimization (PSO) algorithm, the genetic algorithm (GA), the artificial bee colony (ABC) algorithm, the moth–flame optimization (MFO) algorithm for solving multilevel satellite image thresholding problems, and the differential evolution (DE) algorithm. Experimental results prove that the MTMFO works more efficiently and accurately detects the optimal threshold values in comparison with the state-of-the-art optimization algorithms.

El Aziz et al. [37] introduced a comparison between two nature-inspired optimization algorithms (MFO and Whale Optimization Algorithm (WOA)) to determine the optimal threshold multi-level in image segmentation. The proposed algorithms have been designed and considered as candidate solutions utilizing the image histogram. Then, the status has been updated using the characteristics of each algorithm. The authors employed the Otsu's fitness function to design the solutions through the optimization stage. A set of benchmark images have been using to evaluate the performance of both proposed algorithms, then comparing them with the existing algorithms in the literature, such as social spider optimization (SSO), firefly algorithm (FA), harmony search (HS) algorithm, and sine cosine algorithm (SCA). The experimental results showed that the performance of MFO is better than WOA and other algorithms in both high and small threshold numbers.

### 5.5 Medical

In agricultural production, plant diseases are considered as main challenges that have direct influences on the countries' economies. Automatic detection of such disease could minimize these effects. A usual pre-processing step named features selection employed for automatic infection discovering systems. In this field, it is an essential operation for identifying and handling sharp, redundant, and irrelevant information leading to maximize the detection performance. In order to automatically discover tomato problems, an improved moth–flame approach was introduced in [51]. The fitness function of the moth–flame employed is based on dependency rough groups level taking into observance the total of selected features. MFO utilizes the high performance of rough sets for the feature selection task, as well as the power of exploration of the moth–flame in order to determine the features set of maximizing the precision of the categorization that examined with support vector machine (SVM). The evaluation process of MFORSFS algorithm has been done utilizing a set of benchmark used in UCI machine learning data repository. After that, it has been compared with GA and PSO.

At the age of 65 and above, people start affected by Alzheimer's disease (AD) as it is considered one of the most causes of dementia. Recent studies show that the main criterion for identifying AD is time consuming and tedious. Therefore, Sayed et al. [102] proposed an automatic AD diagnosis system. The main concepts of MFO are utilized as selection creation algorithm along with the adaptive of SVM classifier in order to differentiate between three kinds of classes including AD, Normal, and Cognitive Impairment. The objective is to help physicians in identifying AD and to compare two different anatomical views of the brain and detect the optimal representative one. the results of this work have been evaluated and benchmarked with genetic algorithm and grey wolf optimizer. A dataset is composed of 20 patients. The experimental results prove the efficiency of the proposed algorithm in terms of Precision Recall, F-Score, and Accuracy.

Wang et al. [125] introduced a novel learning scheme based on the chaotic moth–flame optimization (CMFO) strategy for the kernel extreme learning machine (KELM). In this algorithm, CMFO utilized optimization parameters and selection strategy. The methodology of the proposed scheme is compared to other KELM scheme that is utilized with the use of genetic algorithms, particle swarm optimization, and the original moth–flame optimization. The evaluation is done using the medical diagnosis problems of breast cancer and Parkinson's disease. Moreover, the proposed scheme has been utilized in practical medical diagnosis cases. The experimental results showed that the proposed method obtains better classification performance with the smaller feature subset. Moreover, CMFOFS-KELM becomes an efficient and effective computer-aided tool in the field of medical decision making used in medical diagnosis.

### 5.6 Networks

MFO has been proposed in [41] for training RBFN algorithm based on the application of nature-inspired metaheuristic algorithm. Generally, MFO is considered as a population-based algorithm that detected mainly using the nature of special navigation paths of moths. According to previous works, MFO, when training the MLP networks, has obtained high tendency in terms of low dependency to the initial solutions when applied to complex and challenging problems, and avoiding the convergence to local minima. Moreover, MFO obtains a promising result. This problem attracts authors to investigate the effectiveness of this metaheuristic in terms of training RBFNs. The presented method in this paper is developed based on enhancing all parameters of the network such as widths, centers, and the connection weights. In this context, this optimizer is promising and utilized for training RBFNs. The evaluation process of this work has been conducted in two phases, first, a comparison of MFO with other well-known metaheuristic algorithms. Second, it is compared with well-known classical training algorithms in the literature for training RBFNs. Moreover, authors utilized seven popular datasets to compare and benchmark the training algorithms.

Singh and Prakash [114] conducted a study based on the deployment of FiWi and then introduced a novel nature-inspired heuristic paradigm for multiple optical network units' placement called MFO algorithm. In this field, MFO is a population-based algorithm as it is better in terms of handling local optima avoidance. Simulation results are conducted with comparison with the existing greedy and annealing algorithms in order to enhance the position of ONUs. MFO algorithm is considered as the first algorithm in this field. It has the ability to obtain competitive and promising results. An analysis of the performance of MFO algorithm has been done by varying the 'b' parameter. Simulation results showed that MFO algorithm obtains faster convergence than the existing greedy algorithms. Moreover, the results prove the dependence of the objective function on the base of users' distribution of wireless.

In [96], Sapre and Mini found the optimal positions for the placement of Relay Nodes (RNs) using interior search algorithm (ISA), MFO algorithm, and bat algorithm (BA). In order to check the connectivity of the network, the proposed algorithm utilizes the heuristic fully connected network. Simulation results have shown the improvement of MFO compared to ISA, BA, and minimum spanning tree based M1tRNP approach.

In order to solve static drone location problem, an implementation of the MFO has been proposed by Strumberger et al. [118]. The optimum position location of drones can be considered as one of the major issues in this area. Moreover, it can be categorized in the NP-hard optimization. The main contribution of the proposed model in this paper is to enable monitoring all targets using optimum number of drones. Regarding testing, authors employ 30 uniformly distributed targets as a problem instance in the network domain. Simulation results prove that moth search algorithm obtains full coverage of targets, and this approach obtains better results that can deal with this part of problem.

### 5.7 Power dispatch problem

Anbarasan and Jayabarathi [13] developed MFO to fix the optimal reactive power dispatch (ORPD) problem. The algorithm aims to quick convergence rate for method of roulette wheel election. It illustrates non-linear, continuous and discrete variable, reactive power optimization problems, and numerous non-convex problems. Standard IEEE-30 bus and IEEE-57 bus system are employed to attain the optimal settings of regulating variables from reactive power compensating components. The algorithm demonstrated data processing optimization strategy, the convergence characteristics, the number of iterations, and handling constraints by efficient method.

MFO has been utilized in [74] to solve the optimal reactive power dispatch (ORPD) problem. The technique investigated the best combination of transformers tap setting, control variables including generators voltage, and reactive compensators sizing to achieve minimum voltage deviation and total power loss. The technique compared the effectiveness of MFO algorithm with other optimization techniques using three case studies that are IEEE 118-bus system, IEEE 30-bus system, and IEEE 57-bus system. The statistical analysis of this research illustrated that MFO is able to produce competitive results by yielding lower power loss and lower voltage deviation than the selected techniques from the literature. Moreover, the minimum total transmission loss of MFO algorithm results will benefit the secure operation and power system economic dispatch.

Elsakaan et al. [39] implemented a multi-objective MFO to solve the economic dispatch (ED) problem in radial network and microgrid with valve point effects and emissions. Three criteria are minimized and determined to generate the optimal schedule units. The algorithm used two test systems to illustrate the effectiveness of the new method, and test systems consist of six generating units and isolated microgrid. The results give better optimum solution and show better global convergence through reducing system generation cost and emission cost.

Trivedi et al. [121] used MFO to solve highly complex constrained of economic load dispatch (ELD) problems. The method combined MFO algorithm with levy flights (MFOL) to improve the competitiveness results for continuous and discrete control parameters. MFOL integrated Levy flights and distribution with MFO used to solve constrained economic load dispatch (ELD) problem, and three different standard case studies used to treat MFOL are (1) thirteen-unit system with valve point effect loading outperforms compared with CEP, FEP, MFEP, and IFEP, (2) prohibited operating zones (POZ), (3) out performance to standard MFO, PSO and GA in six- and fifteen-unit system without valve point effect including ramp rate limits (RRL). Integration of Levy flight technique MFO optimization algorithms attains faster convergence and optimal solution.

An application for MFO has been proposed by Sulaiman et al. [119] to solve the optimal reactive power dispatch (ORPD) problem, and the application used loss minimization as objective function of the problem. It is obtained by best combination of control variables like injected mega volt-amps reactive MVAR, transformer-tap setting and voltage magnitude at generator buses. The algorithm utilized and compared the IEEE 30 bus system with other nature algorithms to show the effectiveness of the algorithm. The simulation results compared to other algorithms showed MFO is better for obtaining less total system loss.

Mei et al. [75] implemented both MFO and ant lion optimizer (ALO) algorithms to solve optimal reactive power dispatch (ORPD) problems and minimize power loss in the transmission system. For this, the algorithm determines the optimal settings of control variables, transformers tap setting, reactive compensators sizing, and value of generator buses voltage. To show the effectiveness of MFO and ALO algorithms, the application utilized IEEE 57-bus system. The algorithm results indicate that MFO algorithm losses a lower power than ALO algorithm and other algorithms. However, ALO algorithm can produce more consistent results than MFO throughout the 30 simulations.

Elsakaan et al. [38] implemented MFO to solve the economic dispatch (EMFO) of non-convex problem continuing emissions and valve point effects, which minimizes both fuel cost and emission. The EMFO combines the levy flight and traditional MFO. The proposed algorithm used ten benchmark functions and three standard test systems to prove effectiveness of EMFO algorithm, and the benchmark and test systems consisted of 6, 40 and 80 of generating units with non-convex fuel cost functions. The algorithm is also verified for single- and multi-objective cases compared with other techniques. The EMFO method results at acceptable low emission levels confirm high performance in order to find the scheduling of optimal economic generation. To solve problem of non-smooth economic dispatch, the results are compared with other algorithms that reflect capability and robustness.

MFO has been presented in [19] to solve the dynamic and non-convex economic load dispatch electric power system problem. The application tested the performance of MFO algorithm for dynamic, non-convex and convex economic load dispatch (ELD) problem, the test applied on standard IEEE bus system consisting of 3, 5, 6, 10, 13 and 40 generating model of units. Lambda iteration method is used to verify seven benchmarks are particle artificial bee colony, evolutionary programming (EP), genetic algorithm (GA), swarm optimization algorithm, and grey wolf optimizer (GWO). The results show that MFO solves ELD problems and is able to lower transmission loss and minimize total fuel cost. It is also considered very fast compared with other algorithms. The application considered the renewable energy sources like wind and solar with the conventional thermal power generating units.

### 5.8 Machine learning

Recently, the advance of computer and database technologies led to data pile in a speed unmatch-able to the human's ability of data processing [24]. Machine learning techniques (such as feature selection, clustering, and classification) have the capability to deal with the mountains of data, efficiently [53, 115].

Li et al. [68] introduced a new combination annual power load forecasting model which consists of FMO and least squares support vector machine (LSSVM), called MFO-LSSVM. The proposed method was used for enhancing the forecasting accuracy of annual power load by determining the optimal parameters of LSSVM using MFO. The experimental results showed that the performance of MFO-LSSVM outperformed PSO-LSSVM (LSSVM optimized by particle swarm optimization), FOA-LSSVM (LSSVM optimized by fruit fly optimization), and single LSSVM.

Arabic handwritten letter recognition (AHLR) has various font styles, noises, and sizes. Thus, it is difficult to recognize its patterns with high accuracy. Therefore, Ewees et al. [40] introduced a new approach based on MFO for enhancing the AHLR's accuracy with a minimum number of features, namely MFO-AHLR. There are three phases have been used in MFO-AHLR approach: (i) binarization and remove the noise, (ii) feature extraction, and (iii) classification. It's worth mentioning that the MFO has been utilized as a feature selector before the classification phase.

Zawbaa et al. [134] used MFO to determine the optimal feature set (i.e., find the minimal number of features) and maximize the performance of the classification (i.e., achieve better classification accuracy). 18 various datasets from the UCI machine learning repository have been employed to evaluate the performance of MFO.

Tow modified versions of MFO (i.e., MFO2 and MFO3) have been introduced in [117]. The authors used the proposed versions to select the optimal feature subset for classification purposes. For instance, it is utilized as a prediction method for terrorist groups based on Random Forest (RF) to enhance the classification accuracy and Wrapper feature selection approach. The results showed that MFO2 and MFO3 achieved better performance compared with other state-of-the-art methods.

Feedforward neural networks (FFNNs) have many types, such as multi-layer perceptron (MLP). In [128], the authors used MFO to search for the weights and biases to train MLP which is significant to find minimum training error. For evaluation of the performance of MFO, five standard classification datasets (i.e., breast cancer iris, XOR, heart, and balloon) and three function-approximation datasets (i.e., sine, cosine, and sigmoid) have been applied.

K-means clustering algorithm is most common and widely used compared with the many clustering algorithms [104]. However, it has drawbacks in dealing with large computational complexity. Therefore, Yang et al. [130] applied MFO in cluster analysis to obtain superior accuracy and exhibit a higher level of stability. Two types of datasets (i.e., artificial and real) have been utilized to prove the performance of MFO.

## 5.9 Engineering optimization

Engineering optimization process is a set of steps that engineers follow to achieve a solution to a problem, and often, the solution includes designing a product (e.g., a computer code or a machine) that meets certain criteria and/or accomplishes a particular task.

### 5.9.1 Engineering design

Kaur et al. [60] analyzed the fin field-effect transistor (FinFET) structures with trapezoidal and rectangular shape. The paper presents a FinFET structure a compact fin shape that the gate controls over it, and this structure reduces short channel effects in comparison with existing structures. The technique performed simulations for FinFET in the tool of Technology Computer Aided Design (TCAD), the technique designed FinFET with Broadwell-Y shape proposed by Intel, and it compares existing rectangular and trapezoidal structures for the same input design parameters with the performance of broadwell-Y shaped FinFET. The results indicated that Broadwell-Y FinFET surpassed the last two structures in terms of short channel effects. The technique used artificial neural network (ANN) for training and MFO for optimizing the designed device performance. For training the neural network, the fin thickness and gate oxide thickness are used as input parameters. In additional, short channel effects are improved as subthreshold swing (SS); this makes the designed structure better for applications at nanoscale.

MFO has been applied by Jangir et al. [57] to solve problems of engineering design and constrained optimization. Five constrained benchmark functions of engineering problems are calculated and compared with other algorithms. According to the extracted results, MFO provides best solution compared to different design problems of other optimization algorithms; many kinds of problems are investigated such as expensive, continuous, highly complex constrained, and discrete control parameters. The results prove that the method is effective to solve problems with unknown search space.

Li et al. [71] improved MFO based on Levy-flight strategy moth–flame optimization (LMFO) to handle the slow in convergence and precision. LMFO makes the results more effectiveness by enhancing the population diversity against premature convergence, it obtains a better trade-off between exploitation and exploration, and this makes the algorithm more robust and faster. The approach is compared based on nineteen benchmark functions with many algorithms such as BA, ABC, PSOGSA, DA, and MFO. Two constrained engineering design problems are also tested, and the reasons for poor their performances are identified. The approach also observed that swarm algorithms suffer from low exploration. Gholizadeh et al. [45] developed a new MFO. The main objective of the study is to enhance the MFO algorithm performance in order to solve the optimization problems of benchmark steel frame using the MFO and EMFO algorithms. To enhance the moth–flame optimization (EMFO), the algorithm employs a new equation for position updating using the information collected by the search agents during the optimization process. The algorithm also implements the optimization process of 3D and planar steel frame structures. The optimizer uses the navigation method of moths in nature termed transverse orientation and adds a mutation operator in order to decrease trapping in local optimal designs. The results of the proposed EMFO are converged to better performance compared with other existing metaheuristics and need less structural analyses during search process.

Calculating current excitation nonlinear values for the synthesis and pattern modeling of a concentric circular antenna array using MFO has been introduced in [30]. As well the authors utilized the MFO to design a non-uniform Concentric Circular Antenna Array (CCAA). The approach achieves lower Side Lobe Level (SLL) value. The MFO calculates the inter-element spacing optimally and excitation weights of all the array elements. It shows comprehensive results and confirms the superiority of the algorithm for CCAA design. The algorithm specifies MFO parameters, generates population of moths, evaluates moths and flames fitness, then updates the number of flames, list of flames, and position of moths, and stores them. The results of the algorithm show a good improvement of SLL of the uniform array pattern.

A new MFO is introduced in [132] for solving optimization obstacles in the production industry. A milling optimization problem is resolved to maintain the effectiveness of the MFO in the optimization of production difficulties. The main purpose of this paper is to maximize the profit rate for multi-tool milling procedures regarding complex restrictions. The results show that the MFO is an efficient optimization scheme for the solution of production optimization difficulties.

### 5.9.2 Power energy

1. *Electrical engineering:*

   Saikia and Saha [93] proposed a new method to automated generation control of a two-area hydrothermal system under the deregulated scenario. A new proportional derivative (CIPD) controller and cascade integral are proposed as secondary controllers for the system. For the simultaneous optimization of the second controller gains, the author uses a nature-inspired MFO model. The proposed model is compared with the performance of proportional-integral-derivative (PID) controllers and proportional integral (PI). The analysis of the CIPD model shows great dynamic responses than PI and PID controllers. MFO-optimized CIPD controller is examined by poolco, poolco bilateral and contractual violation situations to evaluate its performance.

   Metaheuristic optimization algorithms have been proposed in [133] for selecting the parameters of the Cole-impedance system. These algorithms motivated by nature are known as MFO and Flower Pollination Algorithm (FPA). To measure the performance of the algorithms, an experimental model and simulation have been studied. In addition, the proposed algorithms compared Bacterial Foraging Optimization (BFO) algorithm and nonlinear least square (NLS) algorithm. The result showed a much fit in the sum of absolute error sense (SAE) which strengthens the effectiveness of proposed algorithms in the extraction process.

   Abd el sattar et al. [98] used MFO to conclude the optimal position and parameter setting of Static Synchronous Series Compensator (SSSC) for improving power system security under single line contingencies. Contingency analysis is executed on the power system to discover the most critical line blackout contingencies using achievement index which is based on the number of voltage levels violation and thermal overloads. The IEEE 30-bus standard test system is used to verify the effectiveness of contingency analysis. The results show the effectiveness of the proposed technique moreover, and placing of the SSSC in its optimal location can improve the security of the power system by decreasing the violation of bus voltages and overloading of transmission lines.

   In [26], harmonic eliminating problem has been solved and total harmonic distortion (THD) problem for multilevel converters by using MFO. The optimization algorithm trying to eliminate the harmonics and reduce the THD tested on 7-level and 11-level inverters. The simulation results of a seven-level and eleven cascaded multilevel inverters are given for various levels of modulation indexes. The simulation results show that moth–flame optimization model solves the harmonic eliminating problem and total harmonic deformation minimization problem effectively.

   MFO has been proposed in [120] to solve the optimization problem of shunt capacitor banks (SCBs) and also the distributed generations (DGs). The authors aim to reduced voltage levels, increased power losses, and enhanced power quality problems. In addition to the MFO, a loss-voltage-cost index (LVCI) method was included to improve the voltage and reduce the system power consumption. Regarding the execution, the work has been divided into two main steps: (1) Utilizing loss sensitivity factors (LSFs) to evaluate the maximum candidate buses for installing DGs and SCBs; (2) Employing the MFO to determine the optimal position of DGs- and SCBs-based objective function (i.e., LVCI). The proposed system is tested on 69-bus and 33-bus. Also, Moscow district network has been used as a case study. To prove the validity and efficiency of the MFO performance, the obtained results were compared with other algorithms and systems. The numerical analysis shows that the MFO has flame with high efficiency to determine the best solution of DGs and SCBs allocation for reducing the system power consumptions, maximizing the net savings and enhancing the voltage profile.

In [47], an optimal bidding approach of supplier under congested system with MFO has been proposed to increase the earnings of the market participant regarding twice sided bidding. Generator rescheduling based on the Generator Shift Factor (GSF) has been used in this paper for reducing the bottleneck of the system. To get the optimal solution of the bidding difficulty, the moth–flame optimization has been adopted. The proposed system has been tested on a modified IEEE 30 bus standard system to analyze the proposed approach to the deregulated electricity market.

Upper et al. [123] proposed an effective hybrid approach to fix the distribution challenges of capacitor banks in the radial distribution system (RDS). The proposed approach consisted of two parts: the first part using the loss sensitivity factor (LSF) to determine the most candidate positions for joining of shunt capacitors and the second part decreasing the energy cost by defining the optimal positions and area using MFO. The proposed approach is verified utilizing the IEEE 69-bus standard RDS under the light, low, and top load ranks. The collected outcomes using the proposed approach are compared with results achieved from various optimization methods. The proposed approach shows superior result over other methods for reducing the cost in the RDS.

In [82], determining the optimal proportional-integral controller and dual-mode controller (DMC) using MFO has been proposed to solve the multiarea hybrid interconnected power problem. The proposed method has been extended to two different regions of a 6-unit hybrid-sources interconnected power model. The optimum gain of DMC and sliding mode controller (SMC) is optimized with MFO algorithm. The performance of an MFO tuned DMC is compared with particle swarm optimization and genetic algorithm tuned DMC, MFO tuned SMC, and teaching-learning–based optimization optimized SMC for the same system. Moreover, robustness analysis is made by changing the system variables based on their low rates. It's worth to mention that the optimal earns obtained for the nominal situation are required to reset for a completely change in system variables.

To increase the economically and secure working of the power system, Saurav et al. [99] attained to the Optimal Power Flow (OPF) using MFO. The proposed approach involved the Flexible Alternating Current Transmission System (FACTS) devices with the current base of the power system, to minimize the loss and warranty the cost-effective power system process with monitoring the voltage level of the system. The monitor variable for the problem contains a generator's reactive result, parameters of FACTS devices and settings of tap swapping transformers. The experiment results of the proposed approach achieved the optimal parameters of three FACTS devices (i.e., Static Var Compensator (SVC), Thyristor Controlled Phase Angle Regulator (TCPAR), and Thyristor Controlled Series Compensator (TCSC)). It is noted that the IEEE 57-bus system has been utilized to determine the position of all previous devices.

A new mathematical model has been introduced by Ceylan and Paudyal [27] for optimal capacitor position and sizing in spreading distribution systems. The optimization model finds position and sizes of capacitors regarding differences on load profiles with 15-min resolution. The modified MFO and a developed heuristic algorithm have been used to solve the model. The proposed model is examined on a remodeled 33-node distribution feeder. The optimization model tested over two simulations: the first simulation presumes a fixed tap location of the regulators. Second simulation sets the tap locations optimally to some fixed daily values. The simulation results confirm the enhancement of the voltage profiles with the modified moth–flame optimization.

In [2], the optimal positions and sizes of renewable decentralized generation (DG) in the radial distribution system (RDS) are defined using chaotic moth–flame optimization (CMFO) algorithm and the maximum reduction in active system power loss defined by real power loss sensitivity factor (PLSF). The goal of this system to face electric grid concerns. Integration of renewable spread generation such as solar (PV) and wind (WTG) in RDS have gained high regard in many countries over the world due to its impact in reducing the distribution feeders' losses and the greenhouse gas radiation. The proposed system is implemented on three decentralized generations installation in IEEE 33-bus RDS standard. The results show that the proposed system demonstrates high performance compared with other systems.

In [33], a comparison study between various optimization algorithms has been done, to determine the optimal sitting of capacitors in different radial distribution systems (RDSs). The algorithms are the grey wolf (GWO), dragonfly (DFO), and MFO. The absence of the allergy factor is utilized to find out the most applicant buses. Next, each optimization method is used to determine best positions and volume of capacitors for suitable Buses. IEEE 118-, 69- and 33-bus RDSs standard are considered for verifying the efficiency of considered models. The convergence execution is estimated to examine RDSs utilizing MATLAB software. The acquired outcomes approve that GWO, DFO, and MFO show exact convergence to the global minimum point of the objective function with a strong convergence rate. A comparison study between each reviewed algorithm with each other and with other algorithms like CSA, FPA, DA-PS, TLBO, DSA, heuristic, fuzzy-GA, and PSO has been carried out. The results of the comparison showed that the MFO achieved the optimal accurate convergence capacitor banks and location. Also, it obtained the best performance compared with the other algorithms.

Three-diode methods have been proposed in [11] as an accurate sample to match the comparatively compound physical process of the multi-crystalline silicon solar cells. To validate the ability of this sample, it is matched with an enhanced double-diode method of the same cell/module and the double diodes. The author proposes to use MFO to extract the parameter's operation for three examined models based on the information described at previous research and data measured at the laboratory. The performance of the proposed model compared with Flower Pollination (FPA) algorithms and Hybrid Evolutionary (DEIM). Moreover, the evaluation study is shown for the three algorithms of the chosen algorithms at various area requirements. The outcomes demonstrate that MFO algorithm performs the smallest Root Mean Square Error (RMSE), Absolute Error at the Maximum Power Point (AEMPP), best Coefficient of Determination and Mean Bias Error (MBE). Moreover, the result shows that the MFO is giving the best solution with the lowest running time compared with the other measured methods.

Mohanty [81] applied MFO to solve automatic generation control (AGC) by a comprehensive study of proportional-integral-double derivative(PIDD) controller. At first two unequal areas of the thermal system are considered and the gains of the PIDD controller are optimized using MFO. Considering the undershoot and overshoot of space frequency, deviations, and settling time in tie-line power, the simulation result shows that the MFO algorithm improves the PIDD controller and gives better performance compared with other algorithms. The generation rate constraint (GRC) is added for two-region thermal framework, and effective stability is tested and compared with modern competing algorithms. Moreover, the research is continued to nonlinear AGC model with a different exporter of production. Sensitivity test shows that the MFO-optimized PIDD controller parameter acquired at low situation requires to exchange for comprehensive exchanges in system parameters and with diversity in random rank load perturbation.

Zhao et al. [137] proposed a new hybrid optimized grey system called Rolling-MFO-GM (1,1) proposed for improving the efficiency of electricity consumption prediction. The proposed model uses the rolling mechanism, MFO and grey forecasting model GM (1,1). Therefore, this paper attempts by this combination to improve the forecasting efficiency of yearly electricity consumption. The result shows that applying MFO to optimize the parameters of GM (1,1) can improve the efficiency of yearly electricity consumption prophecy significantly. In addition, using the rolling mechanism can make the forecasting results very closer to the real data.

2. *Power flow optimization:*

Trivedi et al. [122] employed MFO to optimize the optimal power flow (OPF). Standard IEEE-30 bus test system is used for the OPF solution and applied flower pollination algorithm, MFO and particle swarm optimization algorithm. The algorithm addressed many OPF functional problems such as voltage profile improvement, voltage stability enhancement, active power loss minimization, and reactive power loss minimization. The results showed effectiveness of MFO that gives better optimization values and optimal settings of control compared with particle swarm optimizer (PSO) and Flower Pollination Algorithm (FPA), and the algorithm gave best results when the population size is 40 with the 10 trials. As well, Bentouati et al. [18] used MFO for solving OPF problem that used in the interconnected power system. The algorithm minimizes the total fuel cost, improves the voltage power, and minimizes the total emission. The results are compared with many algorithms such as artificial bee colony (ABC). The algorithm tested system on 59 bus system, and it showed robustness effectiveness of the algorithm for solving the OPF problem.

Mohamed et al. [80] presented and applied MFO to solve constrained OPF problem in three test power systems. The authors proposed associative learning mechanism with population diversity crossover and immediate memory to improve ability of exploration and exploitation, also adaptive spiral motion and Gaussian walks. The MFO mechanism implemented and compared with four heuristic search FPA, MFO, MDE, and MPSO algorithms on power systems IEEE 30-bus, 57-bus and IEEE 118-bus. Applying these approaches aim to load tap changer ratios, optimize the control variables like real power generations, values of bus shunt and voltages capacitance. The approaches executed Fourteen different environmental pollution emission, cases on various curves of fuel cost such as multi-fuels options quadratic, valve-loading effects, active power loss, voltage stability and voltage profile for contingency and normal conditions. The algorithm also investigated the impacts of the optimizers updating mechanism and concluded that MFO demonstrated the effectiveness and superiority in comparison with many OPF solutions.

MFO have been demonstrated suitability in [23] to solve objective functions of nonlinear optimum power flow (OPF) and various non-convex problems. The paper solved OPF problem by five objective functions, these functions are real power loss reduction, emission minimization, and generator fuel cost minimization under deference realistic conditions. The paper shows the efficiency of the method, and the simulations are performed on the IEEE 30-bus system. As results, MFO considers appropriate for solving the complex problems and non-smooth and rapid convergence. To proof the effectiveness of the MFO, many statistical tests are executed such as Friedman test, Friedman aligned test, Wilcoxon test, and Quade test. Comparison of MFO with other stochastic algorithms demonstrates the superiority of MFO in terms of solution excellency and solution feasibility, substantiating its effectiveness and competence.

3. *Wind energy:*

Wind farm (WF) energy algorithm is used to increase the profit and mitigate the contingency situations by reducing the cost of fuel [34]. It aims to improve the security under N-1 contingency case in the deregulated power market. The algorithm used line outage contingency index (LOCI) in order to find the critical line in the system. To solve the problem, the algorithm is also used MFO and Contingency Constraint Optimal Power Flow (CCOPF) algorithm [48]. Modified IEEE 30 bus system is tested for the proposed algorithm, effect wind farm of the system is also analyzed. The result of algorithm showed generation of wind farm is very useful to minimize the value of LOCI, this leads to minimize the cost and losses system, and overall results maximize the profit in the market of deregulated electricity.

Huang et al. [55] proposed a swarm moth–flame optimizer (SMFO) algorithm, and algorithm obtained four optimal proportional-integral (PI) parameters tuning of doubly fed induction generator (DFIG)-based wind turbine using in order to extract the optimal wind energy, to achieve maximum power point tracking (MPPT), and to improve capability of fault ride-through (FRT), whereas the higher brightness of flame will attract more moths compared with adjacent flames. Two new mechanisms of SMFO helps to determine an appropriate trade-off between exploration and exploitation by encircling each flame by multiple moths and represent the flame with a higher brightness. For achieving a wider exploration, the design constructed a ring network among the flames for guiding moths to effectively look for a brighter flame. The algorithm is conducted three case studies to verify enhanced FRT capability and more optimal power tracking, and an improved global convergence can be achieved by the metaheuristic techniques compared with SMFO algorithm.

A new design of the hybrid power generation systems (HPGS) has been presented in [76], which includes SB, PV, WT, and gas turbine (GT). HPGS integrated for natural gas distribution network. The design dealing with two modes, stand-alone mode and utility connected mode, where each mode is discussed under two condition includes winter and summer scenarios. The design used modern metaheuristic optimizations techniques to keep the results efficiency and effectiveness, and it used also multi-verse optimization (MVO) and MFO to obtain the optimal design of the power sources. A detailed comparison between all scenarios is presented considering the emission and total annual cost, and it tested and compared with the results of flower pollination algorithm (FPA) and cuckoo search algorithm (CSA).

A distributed optimization and control algorithm are explored and developed for wind energy conversion system (WECS). Ebrahim et al. [35] used MFO and proportional-integral-differential (PID) technique for design of blade pitch controllers (BPCs) to improve the oscillations damping in the voltage output and power and realize the advantage of the MFO technique. The algorithm utilized single wind turbine system equipped with blade pitch controllers BPC-PID (MFO). MFO is used to find the optimal controller parameters by reducing a candidate time-domain. The result of the proposed controller performance is compared with basic PID controller and optimized by genetic algorithms (GA). Simulation results of the proposed design show better performance of BPC-PID (MFO) compared to GA-based BPC-PID controllers. In addition, referential integrity via MFO (RI-MFO) approach shows accuracy in defining the optimal BPC-PID. It guarantees the stability of the system under a wide range of operating conditions such as excessive wind speed with uncertainties of controller parameters and increasing of mechanical torque perturbations.

4. *PID control:*

Acharyulu et al. [9] presented a general research of automatic generation control (AGC) framework with a corresponding integral derivative filter (PIDF). The MFO has been employed to optimize the controller

**Table 5** Differences between MFO, CSA, GA, PSO, HS, and TS

| Properties | Algorithm | | | | | |
|---|---|---|---|---|---|---|
| | MFO | CAS | GA | PSO | HS | TS |
| Proposed | Mirjalili [78] | Yang and Deb [131] | Holland [54] | Kennedy [61] | Geem et al. [44] | Glover [46] |
| Parameter | Three [31] | Three [107] | Three [85] | Five [88] | Three [25] | Four [135] |
| Complexity | $O(nlogn)$ [71] | $O(n.D.t_{max})$ [95] | $O(m^2)$ [10] | $O(nm^2)$ Wang et al. [126] | $O(HMS \times M + HMS \times log(HMS))$ [124] | $O(mn^2)$ [90] |
| Convergence | Smooth convergence with fast rate [71] | Slow convergence rate [110] | Fast convergence [127] | Quickly converge [72] | Suffer from premature convergence [49] | Rapidly converged [135] |
| Strength | Balance between exploration and exploitation [37] | Balance between intensification and diversification [87] | Deal with the complex fitness landscape [16] | Don't have overlapping and mutation calculation [15] | Increases the diversity of the new solutions [77] | Avoid trapped at local optimum [66] |
| Weaknesses | Relaxed convergence [56] | Trapped in a local optimum [113] | Evaluation is relatively expensive [140] | Suffers from partial optimism [15] | Get stuck on local optima [77] | Needs huge memory resources [66] |

gains. The MFO-tuned PI controller is investigated on the two-area non-reheat connected thermal energy system, and the best performance is realized. In addition, the job is extended to a three-region connected hybrid method with traditional production rate constraint. The result shows that MFO-tuned PIDF controller executes efficiently compared to the other controllers studied in the literature. To evaluate the robustness of the proposed model, sensitivity analysis has been used.

The optimal control of an active magnetic bearing (AMB) model has been determined by using the MFO [32]. The active magnetic bearings model is recognized to be very nonlinear multivariable models. AMB system has a lot of applications in turbines, generators, motors and several other types of machinery in various industries to produce an active suspension to the rotor shafts. This paper presents a comparative study of the controlled responses of multiple closed-loop systems occurring from the use of current PID and fuzzy logic-based creative control approaches. The MFO is employed to optimize the scaling parameters of the fuzzy-PID controller. The proposed system shows superior performance in terms of different time response parameters, compared with the famous controller like fuzzy-PID and PID controller. Authors apply three performance criteria to design the optimization problem: integral time absolute of error (ITAE), integral square error, and integral time absolute of error plus Integral time absolute of control action (ITAE + ITAU).

Sahu and Hota [91] proposed a controller to base on the MFO to optimize the load frequency control system of two areas, diverse-source power model consisting of non-identical power plants. The controller called 2 two degrees of freedom proportional-integral-derivative (2-DOF PID). The Integral time multiplied by absolute error (ITAE) function is applied to measure the performance of the proposed controller. Then, the result compares with performance and PID controller applying different optimization algorithms specifically cuckoo search algorithm (CSA) and genetic algorithm (GA). The result shows that the robustness of the proposed controller is better with 2-DOF PID controller as compared to current controllers.

## 6 Evaluation of MFO

As explained above, MFO has been widely used to solve various problems in different fields since it has been proposed in 2015. Like the many metaheuristic algorithms, simple in nature, flexibility and easily implemented are the main reasons for the success of the MFO. Furthermore, there are specific advantages of the MFO. For example, it provides very quick convergence at a very initial stage by switching from exploration to exploitation, which leads to an increase in the efficiency of MFO for applications such as classifications when a quick solution is needed [42]. By contrast, MFO facing some limitations and drawbacks.

As known no free lunch theorems for Optimization. Thus, MFO is shared this limitation with all optimization algorithms, which states that it's impossible to be an optimization algorithm eligible to solve all optimization problems [136]. This means MFO might require some enhancements to be performed in order to fix different kinds of optimization problems. The specific limitation of MFO is a complicated implementation as the number of parameters is more in comparison with other schemes [73, 103].

In community detection problem, MFO performance is suitable for small size networks. However, for large size networks, the performance of MFO is not efficient and could be degraded compared to other community detection algorithms, because the MFO accepts new solution only if it is better than the current global best. This may constrain the number of flames in the search space [94]. Furthermore, the drawback of MFO summarizes in the stagnation after the initial stage because the algorithm is diverging to the exploitation stage by changing the number of flames [83]. Also, it suffers from a slow speed convergence which leads to stuck at local optima [67].

Finally, Table 5 illustrates the comparisons between the MFO and the other algorithms using various properties, such as the proposed date, number of the parameters, time complexity, convergence rate, strengths, and weaknesses of each algorithm. It's worth to mention that the algorithms have been selected from evolutionary algorithms (EAs) (i.e., GA and HS), swarm-based algorithms (i.e., CSA and PSO), and trajectory-based algorithms (i.e., TS) [111].

## 7 Concluding remarks

In this review, around 100 articles were collected, studied, and analyzed to highlight the robustness, weaknesses, advantages, and disadvantages of MFO for researchers interested in working with the algorithm. This review comprehensively summarizes references published from 2015 until April 2019. The majority of these articles described MFO applications in different fields. For instance, medical research, image processing, ELD, engineering design, robotics, and data clustering. Furthermore, introduced MFO variants such as binary, multi-objective, and hybridization where the proposed versions of MFO helped to enhance the performance of MFO for solving various types of optimization problems.

MFO is a very promising and interesting algorithm that has already been successfully applied to several problems [84]. Its advantages over other optimization algorithms contain simplicity, speed in searching, and simple hybridization with other algorithms. However, MFO is getting stuck in bad local optima because it focuses on exploitation rather than exploration. Therefore, it is of great significance to research and put forward swarm intelligence optimization algorithms with better performance to enrich the algorithm and expand the application field of the algorithm [70]. This issue can be observed in terms of the hardness of perception why and when the algorithm used and how improves its performance. For instance, parameter tuning one of the important components that used to enhance the performance of the algorithm [36].

Based on the above discussion, MFO has the ability to stay strong in the various fields. This review guides researchers and students who are working or plan to work in this field by describing how MFO can be utilized to fix problems, pointing out its strengths, weaknesses, and proving its efficiency.

Finally, we suggest topics for future research on MFO. BA and MFOA in [89] could be combined with relative reduction as the fitness function to achieve better performance. If relative reduction is used for feature selection, the computational time of the feature selection model increases. Consequently, this requires an integration with other computational technologies, such as parallel computations, to reduce the elapsed processing time. In addition, applying feature selection methods, such as IG, hinders the classifier's results on testing MFO for classification tasks. In the proposed methods of MFO, parameter setting is rather static. We recommend that the proposed methods of MFO be integrated with another method to flexibly tune the related parameters and make them mutable or dynamic. From [50], the MSA algorithm can applied to engineer optimization problems and develop new metahybrid approaches to solve more complex optimization problems. In [5, 7], there are several hybridization strategies that would be useful to apply on BA for improve its performance [6]. In [86], two ways to create new works are provided: employing MOMFO to real-life industry cases and extensive research on methods to solve multi-objective optimization problems. In addition, improve the performance of the MFO by utilizing various of selection schemes, such as tournament selection, linear rank selection, exponential rank selection, etc [106].

## Compliance with ethical standards

**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 any of the authors.

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