Moth Flame Optimization: Developments and Challenges up to 2020

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Abstract Nature-inspired algorithms are the current state-of-the-art optimization algorithms which are quite popular due to their high employability and hence became powerful algorithms for solving unique problems of many research areas. These algorithms have been categorized into swarm intelligence, evolutionary as well as others, etc. On the basis of problem type, these algorithms have been applied to solve and to cope up with such type of complex problems. Many algorithms were simulated and inspired by nature as well as proved to be efficient are mostly swarm intelligence-based algorithms such as ACO, ABC and PSO. Also, novel algorithms are being developed and introduced day by day. Out of such developed algorithms, moth flame optimization (MFO) has gained a wider level popularity due to its significant applicability. In this paper, a comprehensive analysis is made on the applicability of MFO as well as its variants by considering the research related to MFO from its initiation up to the year 2020. The major aim of this survey is to motivate the researchers of optimization community to use MFO for solving unapplied problems.

Keywords Optimization · Nature-inspired algorithms · MFO · Swarm intelligence and evolutionary algorithm

1 Introduction

Process of finding best solution amidst of existing solutions for a specific problem is known as optimization. From the last few decades, we are finding techniques of new optimization due to the raising of problem complexity. Mathematical optimization

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A. K. Das et al. (eds.), *Computational Intelligence in Pattern Recognition*, Advances in Intelligent Systems and Computing 1120,
https://doi.org/10.1007/978-981-15-2449-3_40

methods have been utilized for solving the problems before the suggestion of heuristic optimization methods. Local optima entrapment is a major experienced problem of mathematical optimization techniques those are typically deterministic. A few of them such as gradient-based algorithm need origin of the search space which makes them extremely incompetent in resolving actual problems. Genetic algorithm (GA) [1], which is certainly the most accepted stochastic optimization algorithm, was anticipated to ease the disadvantage of the deterministic algorithms. In recent days, we can find many applications of GA in a broad range of areas. Some famous algorithms like ant colony optimization (ACO) [2], PSO [3] algorithm, differential evolution (DE) [4] and many other have the highest attention after the accompanying of GA.

Individual- and population-based algorithms are the two families for solving optimization problems. Individual-based algorithms requires functional evolution and low computational cost but experiences premature convergence. In different, population-based algorithms have high capability to evade local optima as a set of solutions are concerned in optimization. Simulated annealing (SA) [5] and Tabu search (TS) [6] are some eminent algorithms of individual-based family. Though there are various developments of individual-based algorithms endorse local optima evasion, the population-based algorithms are better in managing such issue. Several population-based algorithms have been anticipated newly. They can be categorized into three major types based on the basis of motivation: swarm, evolution or physic. Evolutionary algorithms (EA) [7] are those who imitate the processes of evolutionary in nature. Biogeography-based optimization (BBO) algorithm [8], human evolutionary model [9] and evolutionary membrane algorithm [10] are some of the newly projected evolutionary algorithms. The amount of freshly anticipated swarm-based (SI) algorithms is better than evolutionary algorithms. Glowworm swarm optimization (GSO) [11], artificial bee colony (ABC) algorithm [12], bat algorithm (BA) [13], cuckoo search (CS) algorithm [14], firefly algorithm (FA) [15], kidney-inspired algorithm (KA) [16], etc. are some of the most recent ones that come under swarm-based algorithms. Chemical reaction optimization (CRO) [17], gravitational search algorithm (GSA) [18], artificial chemical reaction optimization algorithm (ACROA) [19], black hole (BH) algorithm [20], etc. are some other algorithms those are stimulated from physical phenomena in nature. With the aforementioned algorithms, additionally there are some other population-based algorithms with various basis inspirations. Harmony search (HS) optimization algorithm [21], flower pollination algorithm (FPA) [22], soccer league competition (SLC) algorithm [23], mine blast algorithm (MBA) [24], seeker optimization algorithm (SOA) [25], symbiotic organisms search (SOS) [26], etc. are the most new ones. The standing of these algorithms owes numerous causes. Simplicity is the main benefit of population-based algorithm, and these are exceedingly flexible those are willingly appropriate for solving dissimilar optimization problems with no structural alterations. The best part of algorithms in this field tracks an easy structure and has been motivated from effortless perceptions. Local optima prevention of population-based stochastic algorithms is extremely high. These algorithms measure problem as black boxes, so there is a no need of copied data of the search space in compared to mathematical optimization algorithms. In spite of the merits of these optimizers, there is a basic query at this point as if there is any optimizer for resolving all optimization difficulties. According to the no-free-lunch (NFL) theorem [27], there is no such algorithm for resolving all optimization problems. Optimizer may or may not perform well in solving set of problems. So, still some problems are there that can be resolved by novel optimizers enhanced than the existing optimizers.

With this motivation, a new nature-inspired algorithm that has been inspired from the navigation of moths in nature has been suggested to resolve a broad range of unsettled problems. Moths have been progressed to fly in night with the moon light. They used a traverse orientation mechanism for navigation purpose. With this concept, Mirjalili has developed a new algorithm known as moth flame optimization (MFO) in the year 2016 [28]. It is a seminal attempt to simulate the navigation of moths in computer. Nowadays, this algorithm has been widely used in science and industry. This technique has been introduced to compete with the present optimization problems.

The rest of paper has been segmented into the following manner. Section 2 explained about the preliminary concepts of moth flame optimizer as well as structure of MFO algorithm. The variants of MFO in different fields have been confirmed in Sect. 3. The applications those are utilized by MFO have been extensively demonstrated in depth manner in Sect. 4. Section 5 investigates the critique features of MFO in different fields. In Sect. 6, many future directions along with some research challenges have been discussed. This paper was concluded with Sect. 7.

2 Basic Preliminaries

In this section, the structure of moth flame optimization with its preliminaries has been briefly explained.

2.1 Moth Flame Optimizer

The term ‘moths’ are the fancy creatures which are almost similar to the butterfly’s family. Generally, there are more than 160,000 different types of this insect in nature. Larvae and adult are the two major milestones in their life span. The larvae are rehabilitated to moth through cocoons. Special direction-finding (navigation) techniques in the night-time are the major interesting fact of moths. They used a method called transverse orientation for direction-finding purpose.

2.2 Structure of MFO

Mirjalili [28] introduced MFO algorithm in the year 2015, and it was inspired by the mimicking behavior of moths. The insects which are almost parallel to butterflies are moths. These moths make use of unusual technique of night-time triangulation which is named to be transverse orientation, and this technique authorizes moths to hover in the direction of straight line through recollecting the static viewpoint parallel to moon. By concentrating at the source of light, moths hovers in spiral paths in the latency of unreal source of light that is near to the moon.

The structure of MFO contains two important elements: moths as well as flames. The search mediators are the moths which hover in a d-dimensional deeply involved plane. The place of residence is reserved in M matrix. The value of fitness that is related every moth is then kept in array AM.

$$AM = \begin{bmatrix} AM_1 \\ AM_2 \\ \vdots \\ AM_n \end{bmatrix}$$

Here, 'n' is the number of moths.

Both moth and flame are having same dimensions. Both moth and flame act as solution in the algorithm. However, moth indicates the searching agent, and flame indicates the moth's best position. In the search process, flames are acted as flag, and moths drop them. Accordingly, both the positions are being updated, and there is a lesser chance to lose the position. The moth's position is updated as per Eq. 1.

$$M_i = S(M_i, F_j) \tag{1}$$

The i^{th} number moth is indicated by '$M_{i,}$' 'F_j' is the j^{th} flame. 'S' is the spiral function.

The spiral motion as a logarithmic representation is represented in Eq. 2.

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

where,

$b =$ constant for spiral structure
$t =$ Arbitrary number of range $[-1, 1]$
$D_i =$ Euclidean distance in between i^{th} moth and j^{th} flame in d dimension.

D is computed as in Eq. 3.

$$D_i = \left|F_j - M_i\right| \tag{3}$$

Primarily, flames as well as moths remain identical in number which may lead to the reduction in diversification capability of contemporary solution by the way of moth's deliberate 'n' dissimilar locations in search space for updation. The flames are updated by using Eq. 4.

$$\text{no\_Flame} = \text{round}\left(F - i * \frac{F-1}{\text{Max\_gen}}\right) \tag{4}$$

where

i = Contemporary repetition number
F = Extreme number of flames
Max_gen = Maximum number of iterations

3 Variations of MFO

Different discrete versions of MFO with good performance have been urbanized for resolving various problems which have already been utilized in many number of applications. Some investigations have mentioned that modified and binary MFO has better performance. Similarly, some other studies showed that chaotic and opposition-based MFO has solved many problems. However, some other researches aimed to join hybridize MFO with many other algorithms for getting better performance. All these different types of variants have been successfully used to solve some conflicts and to get proper results, respectively. The different variations of MFO have been depicted in Fig. 1.

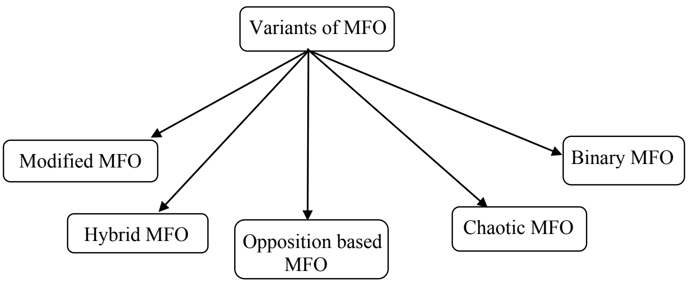


Fig. 1 Variants of MFO

3.1 Binary MFO

MFO was completely affluent in several aspects. One of the variant of MFO named binary MFO has been utilized for resolving some hard yet complicated real-world problems. In the year 2019, Chen et al. [29] have proposed a novel methodology for feature selection and termed the proposed method as SPBMFO (spark parallel binary moth flame optimization) algorithm. The authors have utilized the standard datasets such as wine, ionosphere for evaluating the performance of the proposed method. Later, a comparison has been made with powerful algorithms in the literature such as PSO, GA and CS. They claimed that proposed SPBMFO overcomes the consequence of the MFO (getting stuck into local optima) and yielded a higher performance than the compared ones. In order to solve the problem of UC (unit commitment), in the year 2019, Reddy et al. [30] have developed a new method with the help of MFO and named their method as BMMFO (binary coded modified moth flame optimization) algorithm. By considering test rank, test statistics, etc. as performance factors, the proposed methodology has been compared with BPSO, QEA (quantum evolutionary algorithm), QBPSO (quantum-inspired binary particle swarm optimization) and BFWA (binary fireworks algorithm). The authors claimed that their method yields efficient performance rather the compared ones for solving UC problem. Sayed et al. [31] have proposed a modern method for diagnosing breast cancer with the help of binary variant of MFO and WOA (whale optimization algorithm) which is hybrid intelligence-based algorithm. The authors have utilized clustering algorithms with their proposed method and found that FCM (Fuzzy C-Means) is the perfect algorithm rather than other clustering techniques in terms of computation as well as efficacy. A comparison has been made with some standard algorithms such as FPA (flower pollination algorithm), GWO (grey wolf optimizer) and statistical MFO and claimed a higher performance than the compared methods.

3.2 Modified MFO

Many researchers have tried several methods to improve MFO performance since from its beginning. Some modification like parameter changing, etc. has been considered. According to some literatures, modified MFO has found to be an efficient variant of moth flame algorithm and was applied to solve many problems. In order to tackle with the problems of multi-objective optimization, Vikas and Nanda [32] have proposed a modified version of MFO and named their method as MOMFO (multi-objective moth flame optimization). For the evaluation of performance, the authors have applied their method on six standard problems of mathematical optimization. Later, a comparison has been made with some standard algorithms such as MOPSO (multi-objective particle swarm optimization) and NSAGA-II (non-dominated sorting genetic algorithm-II), and a higher performance with less error rate was observed.

3.3 Chaotic MFO

MFO is a quite efficient SI-based algorithm. However, it is unable to deal some of the complex problems. So, an innovative variant named chaotic-based MFO came into reality which utilizes chaos concept, respectively. For reducing the power loss problem in the active system, in the year 2018, Mawgoud et al. [33] have proposed a variant of MFO and termed it as CMFO (chaotic moth flame optimization) by adding chaos function into statistical MFO. For evaluating the performance, the authors considered a benchmark 33-bus RDS (radial distribution system). Iteration rate, bus system voltage as well as others was concerned as performance metrics, and a comparative analysis was made with MFO as well as GWO (grey wolf optimization) [34]. Later, a high accuracy has been observed rather than the compared methods. Wang et al. [35] have developed a modern method for medical diagnoses using an improved version of MFO along with KELM (kernel extreme learning machine) which is named to be CMFO-KELM (chaotic moth flame optimization-based kernel extreme learning machine). Also, the authors utilized CMFO for feature selection as well as parameter optimization. A comparison has been made over standard algorithms such as PSO, GA and statistical MFO, and they claimed that the intended methodology showed a better performance rather than the compared ones and acts as tool for the medical decision making. Xu et al. [36] have proposed a new method for solving the global optimization problem using a variant of MFO named CMMFO (chaotic mutative moth flame optimizer) and named their proposed method as CLSGMMFO (chaotic local search and Gaussian mutation-enhanced MFO) in the year 2019. With the proper utilization of performance metrics like iteration rate, etc., the authors have considered 25 test functions and compared the method with some state-of-the-art algorithms in literature such as BLPSO and CLPSO and claimed that their method acts as an efficient as well as powerful tool for prediction of finance with improved performance.

3.4 Opposition-Based MFO

OMFO (opposition-based MFO) is the standard variation of MFO which is simulated by introducing the opposition strategies into the statistical MFO and proved its efficacy for solving several issues of various domains of research. Sapre and Mini [37] have proposed a novel method for resolving the issue of global optimization using a new variant of MFO named OMFO. The authors have successfully utilized CM (Cauchy mutation) along with EBCH (evolution boundary constraint handling). CM helped MFO for not getting stuck into local optima. The proposed method later compared with standard algorithms like CSA [38], etc. It is found that the experimentation yields great performance with suitable intensification as well as diversification. OMFO has been utilized to solve the issues of unconstrained optimizations by Apinantanakon and Sunat [39] in the year 2017. The opposition scheme has been used on MFO, and a comparison is made with some standard algorithms such as PSO and DE for evaluating the performance. The authors claimed that their method got higher performance rather than the compared ones. In the year 2019, a novel way of approach for solving the issue of feature selection has been developed by Elaziz et al. [40] with help of OMFO employed by DE. The authors explained that the method has the capability of stopping the local optima stuck as well as high convergence rate. By considering recall rate, accuracy as well as others, etc. as a performance metrics, a comparison has been made over benchmark algorithms such as PSO, DE and GA and claimed that a higher performance has been found with their method rather than the compared ones. A novel method for bidding in USEM (uniform spot energy market) has been developed with the help of OMFO by Jain and Saxena [41] in the year 2019. Twenty-two standard functions have been considered for evaluating the performance and a comparison have been made over original MFO, PSO, etc. with the proposed method. The authors claimed that their method yields high accuracy for solving bidding problem rather the other compared methods.

3.5 Hybrid MFO

MFO has turned out to be a trouble solver of NP-hard problems, but still it forces a few challenges according to no-free-lunch theorem [27]. In order to defeat these challenges, hybridized MFO has been enhanced by joining MFO with a new algorithm which tends to generate a novel variation of MFO. Shilaja and Arunprasath [42] introduced a hybrid approach by integrating MSA and GSA for power system by using wind energy resources. In order to represent the irregular nature of wind farm, authors have used Weibull Distribution Function (WDF). They have used both GSA as well as MA for excellent efficiency. Test cases are measured with and without wind power for resolving the objective functions of Fuel cost for condensed power loss. Their anticipated MSA-GSA algorithm offered enhanced outcome when connected with the accessible methods. Singh et al. [43] proposed a method of hybrid optimization for multi-objective optimization that combined ANN with MFO algorithm to forecast optimal procedure parameters of magnetic abrasive finishing process. Authors have combined MFO algorithm with unidentified set of weights for training NN and also predicted the amount of neurons in hidden layers. Their method has established a technique of multi-objective optimization in the fields of significant parameters. They found efficient and exact parameters as a final outcome to improve part quality and surface finish that will be helpful for actual manufacturing environment. A hybrid algorithm based on water cycle algorithm (WCA) and MFO algorithms for explaining numerical and controlled engineering problems has been proposed by Khalilpourazari and Khalilpourazary [44]. In order to improve the ability of exploitation, authors have used spiral association of moths in MFO into the water cycle algorithm. The streams in the WCA were permitted to renew the situation using a Levy flight (random walk) to enlarge the randomization of novel hybrid method. Authors have examined the performance of WCMFO in 23 standard function like fixed dimension multimodal, unimodal as well as multimodal, etc. To recognize the quality of food, Sarma et al. [45] have introduced a method of hybridizing MFO and GSA. Authors have applied their projected hybrid algorithm in the direction of image segmentation. They proposed an optimized k-means as well as thresholding algorithms. Their projected model has been tested by utilizing different test images. Particularly with respect to food substance, smell played an important function in recognizing rottenness, like fruits discharging particular gases when rotten. To get odor information, authors have used Alpha Fox 2000. The outcomes of their segmentation are then utilized to categorize food items into various classes.

4 Applications of MFO

MFO is well-known nature-inspired heuristic paradigm that has been widely used to resolve real-world problems of various application fields. MFO has been effectively applied to image segmentation, feature extraction, power dispatch problem, food processing, health care as well as intrusion detection system, etc. and different variants of MFO has also used to resolve difficult problems.

4.1 MFO in Image Segmentation

Nowadays, multilevel thresholding has obtained more awareness in image segmentation field. Still, it is a hard and complex for segmentation of color image in numerous applications. To ease this situation, a new multilevel thresholding algorithm with two inventive approaches was introduced by Jia et al. [46] on the source of MFO to expand the SAMFO-TH algorithm. Authors have utilized an original self-adaptive inertia weight method to develop both intensification and diversification. Similarly, a recently projected TH heuristic was entrenched into MFO to advance the global recital in multilevel thresholding on the other hand. They have tested their projected algorithm on ten color images that included both natural as well as satellite images. WOA, MVO, PSO, FPA, ACO, SCA, MFO and ABC are the various competitive algorithms compared with their technique. The results revealed that the anticipated SAMFO-TH outperformed other competitive algorithms and has lead concerning constancy, accurateness, and convergence rate that can be utilized to problems of practical engineering. Sikariwal and Chanak [47] have proposed an effective MFOA-based multilevel TH for image segmentation. They have used Otsu as the objective function. Authors have showed the values of PSNR and SSIM by comparing FA and PSO with their projected method. As segmentation of satellite image required advanced quantity of thresholds, their algorithm has executed fit with the similar and capable to section the unclear images better. Multilevel thresholding has efficient processing ability and easy implementation. As the number of threshold standard raises, it subsequently becomes computationally expensive. To defeat this problem, Muangkote et al. [48] have introduced an enhanced description of the MFO algorithm for image segmentation to efficiently develop the optimal multilevel thresholding of satellite images. Authors have tested their projected method on different satellite images against five different existing methods such as DE, ABC, GA, PSO and MFO algorithms for resolving problems of multilevel thresholding. Their investigational outcomes specified that the MTMFO more efficiently and exactly recognizes the values of optimal threshold with respect to the other modern optimization algorithms.

4.2 MFO in Feature Extraction

To know the optimal features as well as to solve the complex problems, a new variant known as feature extraction has been used in MFO. Zawbaa et al. [49] have proposed a feature selection algorithm on MFO and have applied in the machine learning (ML) fields to know the optimal feature grouping by utilizing wrapper-based characteristic selection mode. Reducing number of certain features as well as raising the categorization performance is the main motive behind their projected method. Authors have compared their method to PSO and GA by utilizing various progress criteria on 18 dissimilar data sets from UCI ML repository. Singh et al. [50] have adopted MFO for well-organized land cover feature extraction. In order to get better outcomes, they have applied many number of classification methods in the field of remote sensing. Their outcomes have been contrasted with the active algorithms for the satellite information of Alwar region.

4.3 MFO in Power Dispatch Problem

One more significant variant known as power dispatch problem has been came into existence and focused by many researchers these days. MFO in power dispatch problem has been used to solve major problems. Sulaiman et al. [51] have proposed an application of MFO for resolving optimal reactive power dispatch problem (ORPD). Authors have used loss minimization as ORPD's main function. Whereas best grouping of voltage magnitude which acts as a control variable at transformer-tap setting, voltage magnitude and generator buses have obtained from MFO. The IEEE 30 bus structure has been used to prove the efficiency of their projected algorithm. Ali et al. [52] have introduced multi-area economic dispatch (MAED) problem by using MFO which is a newly developed nature-inspired algorithm. Shape factor as well as search agent number are the two major control parameters. The MFO algorithm was authenticated by applying on two problems of MAED like two-area scheme with forty producing units and four-area scheme with sixteen producing units. Authors have compared the performance of their projected technique with some other newly reported techniques. Levy flight MFO algorithm (MFOL) was applied for economic load dispatch problems through ramp rate limits by Trivedi et al. [53] which have the capability to resolve by extremely difficult ELD problems. Proposed MFOL outperformed the possibility of algorithm in resolving forced problems of ELD and has compared with the PSO, MFO and GA in 16 as well as 15 generating unit schemes. Their enhanced MFOL showed ability of rapid convergence and was maximized the effectiveness of resource investigation in unsure environments. Mustaffa et al. [54] have introduced MFO to resolve ORPD problem. In order to discover the best grouping of control variables like generator voltages and real power generation, overall lowest failure in the networks can be attained. Authors have tested the efficiency of MFO on IEEE-30 bus scheme and were compared with latest algorithms such as ALO, GWO and MVO.

4.4 MFO in Food Processing

Nowadays, researchers demonstrated their attention to pertain MFO in food processing applications. In the year 2019, Lei et al. [55] have developed a novel method for the discovery of protein complexes (PC's) using MFO. The authors have used two-step verification processes and to evaluate the performance, a comparison was made over some algorithms: MCODE, COACH, etc. They claimed that based on the simulated experimentation, a higher performance has been observed rather and it is also proved that MFO acts as an efficient tool for the identification of complexes of protein. Hassanien et al. [56] have developed a novel methodology for the detection of tomato diseases with the help of MFO on the basis of FRS (fuzzy rough sets) and named their method as MFORSFS. The authors have utilized SVM for finding out the feature sets. Various standard datasets from UCI repository have been considered, and some powerful algorithms such as GA and PSO were compared over the proposed methodology. Higher performance has been found for the identification of tomato diseases in terms of classification accuracy, precision rate, etc. In order to detect the quality of food, a hybridization of GSA and MFO has been made by Sarma et al. [45] in the year 2017. The authors have utilized their hybridization method for the segmentation of food images by considering apple dataset. Also, k-means, MSE as well as optimized k-means algorithms were compared among each other. Moreover, a comparison has been made with some benchmark algorithms such as original GA, MFO and GSA. They claimed that better detection rate for the quality of food was found rather than the compared ones.

4.5 MFO in Health Care

MFO has been used in detail by researchers to pertain in the significant application area like health care. Sayed et al. [31] have developed a novel approach for the diagnosis of breast cancer disease on the basis of MFO as well as WOA. The authors used clustering algorithms such as FCM and found that it is the perfect one among all the clustering algorithms. High diagnosis efficacy has been found when compared to FPA and GWO. In this way, the authors have successfully utilized MFO for breast cancer diagnosis. A disease named diabetes was one of the reasons of causing deaths of people all over the world. Various researchers were developed for detecting the type of diabetes. Likewise, in order to classify the data of diabetes, Majhi [57] has proposed a novel approach with the help of MFO. A standard dataset named Wisconsin hospital has been utilized for the evaluation of performance. Later, a comparison has been made with some current published techniques such as GA-NB [58] and SIM [59]. High classification accuracy has been found with the proposed method for classifying diabetes data rather than the compared ones. Sayed et al. [60] have developed a modern way of approach for the diagnosis of Alzheimer's disease using MFO along with SVM. Recall, precision as well as accuracy rate have been used as performance metrics and algorithms such as GWO and GA have been compared over the proposed methodology for which the authors claimed that higher detection rate has been found for the diagnosis of Alzheimer's disease.

4.6 Global Optimization with MFO

Global optimization has played a vital role and known to be one of the variant of MFO for solving several optimization problems. Li et al. [61] have proposed a novel method with the help of the recent swarm intelligence-based MFO algorithm for solving the problem of global optimization (GO) of actual parameters. The authors named their method as DELMFO (double evolutionary learning MFO) algorithm. For evaluating the performance, they compared the method with six standard algorithms such as MFO, LMFO, CCMFO, WCAMOF, MFO and MMFO3. Also, the algorithms such as WCA, ABC and PSO were compared. They claimed that the developed technique got higher performance rather than the all compared ones in terms of accuracy, global searchability, etc. In order to solve the problems of global optimization, Xu et al. [36] have proposed a method using MFO which is named to be CLSGMMFO in the year 2019. Comparison has been made with some algorithms: BLPSO, CLPSO, etc. and claimed that their method yields higher performance in terms of accuracy rate, iteration rate as well as less error rate. Xu et al. [62] have proposed a novel strategy for solving the problem of global optimization with the help of MFO along with mutation strategy. The authors combined the three techniques: LM, CM as well as GM with MFO and compared it with fifteen benchmark algorithms. CM has been utilized for improving global exploration, while GM and CM were concerned for enhancing informed and search agent movement capabilities, respectively. They claimed that the method explored great intensification and diversification and reduced the GO problem.

4.7 MFO in Intrusion Detection

Apart from above mentioned application areas, one more important field is known to be intrusion detection system where problems of security threats will be identified and solved properly. Due to this reason, researchers have attained their interest on MFO in intrusion detection. In order to enhance the capabilities of precision, stability in NIDS (network intrusion detection system), Xu et al. [63] have proposed a DWKNN (distance weighted k-nearest neighbor) improved with the help of standard swarm intelligence-based algorithm named MFO. For predicting the performance, some techniques such as GWO-KNN, PSO-KNN and SVM were compared with the proposed method. Later, they claimed that MFO-KNN employed a higher precision rate as well as stability rather than the compared ones.

4.8 Other Applications

Some of the other applications of MFO that have been done since from 2015 to 2019 are depicted in Table 1.

5 Critical Analysis

MFO is an ongoing powerful nature-inspired meta-heuristic swarm intelligence-based algorithm that has been used for solving major complex problems since from the year 2015 (initiated year). Several research areas were utilized with the help of MFO have been discussed in various sections and some contemporary areas such as food processing and health care are in growing stage. Almost the areas that have been discussed in Sect. 4 were the most frequently applicable and solvable and concerned interested fields of various researchers. On the basis of key word search in IEEE explore, it has been found that most of the issues were solved that are related to image segmentation, feature extractions, power dispatch problems and global optimizations. The papers those were concerned for the study have been extracted from the online standard databases such as: Springer, Science Direct, Wiley as well as IEEE explore.

As the main theme of our research work is on the usage levels as well as enhancements of MFO, we used a keyword ‘moth flame optimization’ and found 95 papers. We considered 24 papers for applications and 15 papers for variants. Among those

Table 1 Some other applications of MFO in literature

S. No	Algorithm used	Application area	Compared method	Year	Ref
1.	AMFO	–	–	2018	[64]
2.	Enhanced MFO	RBF evolution	–	2017	[65]
3.	Enhanced MFO	Economic dispatch problem	PSO, GA, HS, BSA, etc.	2018	[66]
4.	NS-MFO	Multi-objective problem	MOABC, MTS, MOEAD, etc.	2017	[67]
5.	MFO	Lobe suppression of CCAA (concentric circular antenna array)	FA, BBO, MFO, SOS, etc.	2018	[68]
6.	MFO	Wind energy conversation system	GA, SA as well as ZN based PID controllers	2018	[69]
7.	MFO	Power dispatch solution by loss minimization	PSO, HAS, GWO, SGA	2017	[70]
8.	MFO	Parameter extraction	FPA, DEIM	2016	[71]
9.	MFO	ONU (optical network unit) placement in Wi-Fi	SA as well as Greedy Algorithms	2017	[72]
10.	WMO and MFO	Image segmentation	–	2017	[73]
11.	MFO	Nonlinear feedback control design	WMO	2020	[74]
12.	MFO	Load frequency stabilization	GA	2019	[75]
13.	PMFO-LP	Link prediction problem	GA, PSO, DE	2019	[76]
14.	AMFO	Power flow optimization	MFO, GWO	2019	[77]
15.	MFO	Design of channel equalizer	AIS, APSO, BGA and LMS	2019	[78]
16.	MFO, GWO, DFO	Radial distribution system	PSO, fuzzy-GA, heuristic, DSA, TLBO, DA-PS, FPA and CSA	2019	[79]
17.	CMFO	Global optimization	SCA, ABC, CS	2019	[80]
18.	MFO	Controlling of automatic generation	PSO-tuned PI, GA-tuned PI, etc.	2019	[81]
19.	MFSTERP	Wireless sensor networks	TEEN, SEP, etc.	2019	[82]
20.	EMFO	Enhancement in statistical MFO	DE, FA, FPA, BA, GA, PSO	2018	[83]

(continued)

Table 1 (continued)

S. No	Algorithm used	Application area	Compared method	Year	Ref
21.	MFO	AMBS (active magnetic bearing system)	PSO, DE, GWO, NBA, COA, MFO.	2018	[84]
22.	RF-MFO-ELM	Forecasting	MFO-ELM, RF-PSOELM, RF-ELM, and RF-BP	2018	[85]
23.	MFO	Optimal allocation of DG (distributed generations)	SPEA, NSGA, ICA/GA, MODE	2018	[86]
24.	EMFO	Cultural learning	Original MFO	2018	[87]
25.	MFO	Optimization	PSO, FA, GSA	2015	[28]
26.	MFO	Economic load dispatch problem	BBO, RGA	2018	[88]
27.	–	Visual tracking	–	2018	[89]
28.	MFO-LSSVM	Power load forecasting	LSSVM, FOA-LSSVM, and PSO-LSSVM	2016	[90]
29.	–	Simulated Annealing	–	2018	[91]
30.	MFO	Side lobe reduction	SOS, BBO, PSO, etc.	2019	[92]
31.	IMFO	Optimal power flow reduction	TLBO, GA, PSO, MFO	2019	[93]
32.	MFO	AGC system	PSO, GA-tuned DMC and others, etc.	2018	[94]
33.	MFO-WSC	Cloud computing	CSA-WSC, GAPSO-WSC	2018	[95]
34.	AMFO	Enhancement of global exploration of original MFO	PSO, MFO	2018	[96]
35.	MFO	Automatic generation control	PI as well as PID controllers	2016	[97]
36.	MMFO	Optimal capacitor placement	–	2017	[98]
37.	MFO	Constrained engineering optimization	DE, GA, FA, CS, MFO	2016	[99]
38.	MFO	Performance evaluation of original MFO	–	2016	[100]
39.	MFO	Bidding in deregulated power market	ABC	2016	[101]
40.	MFO	PSS tuning	BF, FA	2018	[102]

(continued)

Table 1 (continued)

S. No	Algorithm used	Application area	Compared method	Year	Ref
41.	MFO	Production planning in petro-chemical industry	–	2016	[103]
42.	MFO	Load frequency control	GA, CSA	2018	[104]
43.	CAMONET	VANET	CACONET, CLPSO	2018	[105]
44.	MFO-AHLR	Arabic handwritten letter recognition	LDA, SVM, etc.	2017	[106]
45.	MFO	Power loss reduction	PSO, BTS, FA, etc.	2017	[107]
46.	MFO	Capacitor bank allocation	DSA, TLBO	2017	[108]
47.	MFO	Harmonic elimination	–	2016	[109]
48.	MFCA-IoV	Internet of Vehicle	CLPSO, MOPSO, CACONET, etc.	2018	[110]
49.	MFO	Air-conditioning control	PSO, BP, BOA	2018	[111]
50.	MFO	Profit maximization	–	2016	[112]
51.	MFO	Power dispatch problem	FPA, PSO	2016	[113]
52.	MFO	Automatic test generation	GA	2016	[114]
53.	MFO-MLP	Training of MLP	PSO, ACO, ES	2015	[115]
54.	MFO	Power loss minimization	PSO	2016	[116]
55.	MFO	Security enhancement of power systems	–	2016	[117]
56.	MFO	Accurate simulation	PSO, GA	2018	[118]
57.	MFO	OPN placement	–	2017	[119]
58.	MFO	Allocation in power system	DE, PSO	2017	[120]
59.	MFO	Fault-tolerant wireless sensor networks	BBO, BA, DE	2018	[121]
60.	MFO	Multi-area power system	GA, PSO, DE, FA	2016	[122]

39 papers, those were considered for both applications and variations, seven papers were used twice. For the whole study, we considered 124 papers from the literature.

In our survey, we found that 15 papers are related to variants and usability of MFO (Fig. 2). Among those 15 papers, three papers are related to binary, one paper was

Fig. 2 Usage levels of mostly used variants of MFO

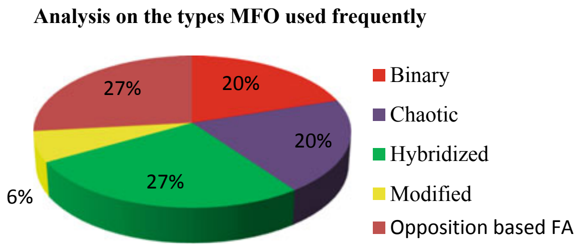
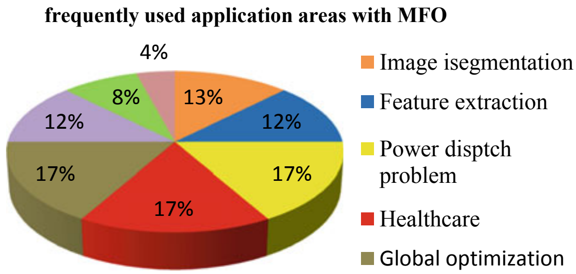


Fig. 3 Usage levels of mostly used applications of MFO



related to modified and three, four and four papers are related to chaotic, opposition and hybrid variations, respectively.

Similarly, an analysis has been made on the percentage of frequently used applications of MFO and the results are depicted in Fig. 3. We found that out of 95 papers, 24 papers are related to frequently used applications and rest of the 71 papers are related to other application areas.

Likewise, out of 71 papers (which are other applications), the applications such a wireless sensor networks, cloud computing, forecasting, cultural learning, bidding, IoV, visual tracking and some other applications have been found and those applications are depicted in Fig. 4.

6 Research Challenges

Obviously, MFO is a current trendy as popular powerful algorithm, and it was attractable to use by the researchers for resolving distinct issues. It is clearly found that MFO has been extensively used for the applications those were mentioned in Figs. 3 and 4. Although, MFO proved its efficacy toward these application areas, still some problems need to be noticed. MFO was not used for solving the issues of several domains such as data mining, cloud computing, resource allocation, task scheduling and work flow scheduling. Apart from these, research challenges such as convergence analysis and parameter tuning are need to be resolved.

Also, it has been found that MFO was hybridized with some standard algorithm such as GSA and WCA, and some clustering algorithms like k-means have also been

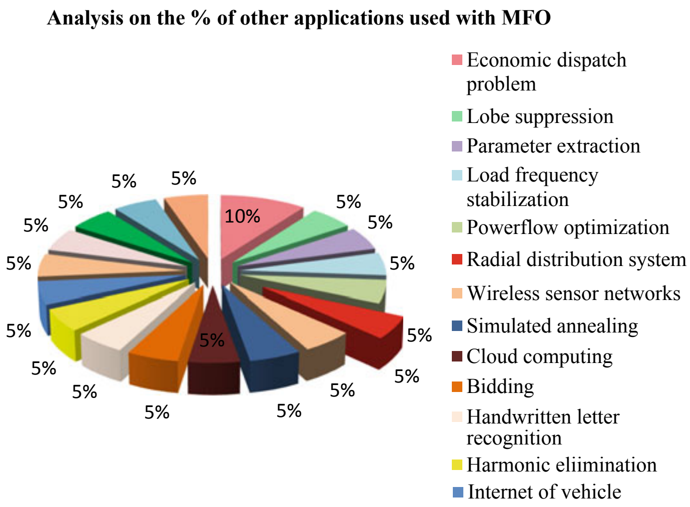


Fig. 4 Applications of MFO in several areas of research

hybridized. There may be an interest that MFO can be hybridized with powerful algorithms in literatures such as FA, PSO, ACO, ABC, KA and many more. There may be also a chance that many variants of MFO may come into existence like Cauchy mutated MFO [37]. By concerning the expanded literatures of MFO, still there is a need of advanced researches to cope up with many issues of several fields of research.

7 Conclusion

Moth flame optimization is latest count to the area of evolutionary algorithms and widely used in many applications from its beginning. Nowadays, moth flame optimization has been concerned in almost all fields. In addition to this, new applications are also being enhanced day by day. MFO has been effectively applied on a variety of real-world problems with dissimilar areas of research. MFO has been used in many application areas like image segmentation, feature extraction, power dispatch problems, intrusion detections, food processing, health care, global optimization problems and many more are the major concern behind the interest of various researchers. Examining of previous articles those are extracted from standard databases confirmed that MFO and its variants were used as powerful tool for solving many number of real-world complex problems. In this present paper, we have concerned different variants like modified, hybrid, oppositional based, binary and adaptive MFO as well as mostly used application areas in depth manner. There is a sudden possibility of improvement using MFO that can influence the progress research in works in the vicinity point of view, and it may be an apprehension of future research. It cannot be exaggerated to tell that additional number of advancements with the assist of MFO and its variants will be instigated and developed for solving real and difficult problems in approaching days.

References

1. Holland, J.H.: Genetic algorithms. Sci. Am. **267**(1), 66–73 (1992)
2. Colorni, A., Dorigo, M., Maniezzo, V.: Distributed optimization by ant colonies. In: Proceedings of the First European Conference on Artificial Life, vol. 142, 1992
3. Eberhart, R.C., Kennedy, J.: A new optimizer using particle swarm theory. In: Proceedings of the Sixth International Symposium on Micro Machine and Human Science, pp. 39–43, 1995
4. Storn, R., Price, K.: Differential evolution—a simple and efficient heuristic for global optimization over continuous spaces. J. Global Optim. **11**(4), 341–359 (1997)
5. Kirkpatrick, S., Gelatt, C.D., Vecchi, M.P.: Optimization by simulated annealing. Sci. **220**(4598), 671–680 (1983)
6. Glover, F.: Tabu search—part I. ORSA J. Comput. **1**(3), 190–206 (1989)
7. Branke, J.: Memory enhanced evolutionary algorithms for changing optimization problems. In: Proceedings of the 1999 Congress on Evolutionary Computation-CEC99 (Cat. No. 99TH8406), vol. 3. IEEE, 1999
8. Simon, D.: Biogeography-based optimization. IEEE Trans. Evol. Comput. **12**(6), 702–713 (2008)
9. Montiel, O., et al.: Human evolutionary model: a new approach to optimization. Inf. Sci. **177**(10), 2075–2098 (2007)
10. Liu, C., Han, M., Wang, X.: A novel evolutionary membrane algorithm for global numerical optimization. In: 2012 Third International Conference on Intelligent Control and Information Processing. IEEE, 2012
11. Krishnanand, K. N., Ghose, D.: Glowworm swarm optimisation: a new method for optimising multi-modal functions. Int. J. Comput. Intell. Stud. **1**(1), 93–119 (2009)
12. Karaboga, D., Basturk, B.: A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm. J. Glob. Optim. **39**(3), 459–471 (2007)
13. Yang, X.-S. A new metaheuristic bat-inspired algorithm. In: Nature Inspired Cooperative Strategies for Optimization (NICSO 2010), pp. 65–74. Springer, Berlin, Heidelberg, 2010
14. Yang, X.-S., Deb, S.: Cuckoo search via Lévy flights. In: 2009 World Congress on Nature & Biologically Inspired Computing (NaBIC). IEEE, 2009
15. Yang, X.-S.: Firefly algorithm. In: Engineering Optimization, pp. 221–230. Wiley, Hoboken, 2010
16. Jaddi, N.S., Alvankarian, J., Abdullah, S.: Kidney-inspired algorithm for optimization problems. Commun. Nonlinear Sci. Numer. Simul. **42**, 358–369 (2017)
17. Lam, A.Y.S., Li, V.O.K.: Chemical-reaction-inspired metaheuristic for optimization. IEEE Trans. Evol. Comput. **14**(3), 381–399 (2009)
18. Rashedi, E., Nezamabadi-Pour, H., Saryazdi, S.: GSA: a gravitational search algorithm. Inf. Sci. **179**, 2232–2248 (2009)
19. Alatas, B.: A novel chemistry based metaheuristic optimization method for mining of classification rules. Expert Syst. Appl. **39**(12), 11080–11088 (2012)
20. Hatamlou, A.: Black hole: a new heuristic optimization approach for data clustering. Inf. Sci. **222**, 175–184 (2013)
21. Geem, Z.W., Kim, J.H., Loganathan, G.V.: A new heuristic optimization algorithm: harmony search. Simul. **76**(2), 60–68 (2001)
22. Yang, X.-S.: Flower pollination algorithm for global optimization. In: International Conference on Unconventional Computing and Natural Computation. Springer, Berlin, Heidelberg, 2012

23. Moosavian, N., KasaeeRoodsari, B.: Soccer league competition algorithm: a novel metaheuristic algorithm for optimal design of water distribution networks. Swarm Evol. Comput. **17**, 14–24 (2014)
24. Sadollah, A., et al.: Mine blast algorithm: a new population based algorithm for solving constrained engineering optimization problems. Appl. Soft Comput. **13**(5), 2592–2612 (2013)
25. Dai, C., et al.: Seeker optimization algorithm for optimal reactive power dispatch. IEEE Trans. Power Syst. **24**(3), 1218–1231 (2009)
26. Cheng, M.-Y., Prayogo, D.: Symbiotic organisms search: a new metaheuristic optimization algorithm. Comput. & Struct. **139**, 98–112 (2014)
27. Wolpert, D.H., Macready, W.G.: No free lunch theorems for optimization. IEEE Trans. Evol. Comput. **1**(1), 67–82 (1997)
28. Mirjalili, S.: Moth-flame optimization algorithm: a novel nature-inspired heuristic paradigm. Knowl.-Based Syst. **89**, 228–249 (2015)
29. Chen, H., et al.: Feature selection of parallel binary moth-flame optimization algorithm based on spark. In: 2019 IEEE 3rd Information Technology, Networking, Electronic and Automation Control Conference (ITNEC). IEEE, 2019
30. Reddy, S., et al.: Solution to unit commitment in power system operation planning using binary coded modified moth flame optimization algorithm (BMMFOA): a flame selection based computational technique. J. Comput. Sci. **25**, 298–317 (2018)
31. Sayed, G.I., Darwish, A., Hassanien, A.E.: Binary whale optimization algorithm and binary moth flame optimization with clustering algorithms for clinical breast cancer diagnoses. J. Classif. **37**, 1–31 (2019)
32. Nanda, S.J.: Multi-objective moth flame optimization. In: 2016 International Conference on Advances in Computing, Communications and Informatics (ICACCI). IEEE, 2016
33. Abdel-mawgoud, H., et al.: Optimal installation of multiple DG using chaotic moth-flame algorithm and real power loss sensitivity factor in distribution system. In: 2018 International Conference on Smart Energy Systems and Technologies (SEST). IEEE, 2018
34. Mirjalili, S., Mirjalili, S.M., Lewis, A.: Grey wolf optimizer. Adv. Eng. Softw. **69**, 46–61 (2014)
35. Wang, M., et al.: Toward an optimal kernel extreme learning machine using a chaotic moth-flame optimization strategy with applications in medical diagnoses. Neurocomputing **267**, 69–84 (2017)
36. Xu, Y., et al.: An efficient chaotic mutative moth-flame-inspired optimizer for global optimization tasks. Expert. Syst. Appl. **129**, 135–155 (2019)
37. Sapre, S., Mini, S.: Opposition-based moth flame optimization with Cauchy mutation and evolutionary boundary constraint handling for global optimization. Soft Comput. **23**(15), 6023–6041 (2019)
38. Askarzadeh, A.: A novel metaheuristic method for solving constrained engineering optimization problems: crow search algorithm. Comput. Struct. **169**, 1–12 (2016)
39. Apinantanakon, W., Sunat, K.: OMFO: a new opposition-based moth-flame optimization algorithm for solving unconstrained optimization problems. In: International Conference on Computing and Information Technology. Springer, Cham, 2017
40. Elaziz, M.A., et al. Opposition-based moth-flame optimization improved by differential evolution for feature selection. Math. Comput. Simul. **168**, 48–75 (2019)
41. Jain, P., Saxena, A.: An opposition theory enabled moth flame optimizer for strategic bidding in uniform spot energy market. Eng. Sci. Technol., Int. J. **22**, 1047–1067 (2019)
42. Shilaja, C., Arunprasath, T.: Optimal power flow using Moth Swarm Algorithm with Gravitational Search Algorithm considering wind power. Futur. Gener. Comput. Syst. **98**, 708–715 (2019)
43. Singh, R.K., et al.: A novel hybridization of artificial neural network and moth-flame optimization (ANN–MFO) for multi-objective optimization in magnetic abrasive finishing of aluminium 6060. J. Braz. Soc. Mech. Sci. Eng. **41**(6), 270 (2019)
44. Khalilpourazari, S., Khalilpourazary, S.: An efficient hybrid algorithm based on water cycle and moth-flame optimization algorithms for solving numerical and constrained engineering optimization problems. Soft. Comput. **23**(5), 1699–1722 (2019)

45. Sarma, A., Bhutani, A., Goel, L.: Hybridization of moth flame optimization and gravitational search algorithm and its application to detection of food quality. In: 2017 Intelligent Systems Conference (IntelliSys). IEEE, 2017
46. Jia, H., Ma, J., Song, W.: Multilevel thresholding segmentation for color image using modified moth-flame optimization. IEEE Access **7**, 44097–44134 (2019)
47. Sikariwal, P., Chanak, P.: An efficient moth flame optimization algorithm based multi level thresholding for segmentation of satellite images. In: 2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS). IEEE, 2018
48. Muangkote, N, Sunat, K., Chiewchanwattana, S.: Multilevel thresholding for satellite image segmentation with moth-flame based optimization. In: 2016 13th International Joint Conference on Computer Science and Software Engineering (JCSSE). IEEE, 2016
49. Zawbaa, H.M., et al.: Feature selection approach based on moth-flame optimization algorithm. In: 2016 IEEE Congress on Evolutionary Computation (CEC). IEEE, 2016
50. Singh, A., Chhablani, C., Goel, L.: Moth flame optimization for land cover feature extraction in remote sensing images. In: 2017 8th International Conference on Computing, Communication and Networking Technologies (ICCCNT). IEEE, 2017
51. Sulaiman, M.H., et al.: Application of moth-flame optimization algorithm for solving optimal reactive power dispatch problem. In: 4th IET Clean Energy and Technology Conference (CEAT 2016), pp. 1–5, 2016
52. Ali, M.A., Dubey, H.M., Pandit, M.: Moth-flame optimization for multi area economic dispatch: a novel heuristic paradigm. In: 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS). IEEE, 2017
53. Trivedi, I.N., et al.: Economic Load Dispatch problem with ramp rate limits and prohibited operating zones solve using Levy flight moth-flame optimizer. In: 2016 International Conference on Energy Efficient Technologies for Sustainability (ICEETS). IEEE, 2016
54. Mustaffa, Z., et al.: Solving the optimal reactive power dispatch problem based on moth-flame optimizer for power system operation and planning. In: 2018 19th IEEE/ACIS International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD). IEEE, 2018
55. Lei, X., Fang, M., Fujita, H.: Moth–flame optimization-based algorithm with synthetic dynamic PPI networks for discovering protein complexes. Knowl.-Based Syst. **172**, 76–85 (2019)
56. Hassanien, A.E., et al.: An improved moth flame optimization algorithm based on rough sets for tomato diseases detection. Comput. Electron. Agric. **136**, 86–96 (2017)
57. Majhi, S.K.: How effective is the moth-flame optimization in diabetes data classification. In: Recent Developments in Machine Learning and Data Analytics, pp. 79–87. Springer, Singapore, 2019
58. Choubey, D.K., et al.: Classification of Pima Indian diabetes dataset using naive bayes with genetic algorithm as an attribute selection. In: Communication and Computing Systems: Proceedings of the International Conference on Communication and Computing System (ICCCS 2016), 2017
59. Luukka, P.: Feature selection using fuzzy entropy measures with similarity classifier. Expert Syst. Appl. **38**(4), 4600–4607 (2011)
60. Sayed, G.I., et al.: Alzheimer's disease diagnosis based on moth flame optimization. In: International Conference on Genetic and Evolutionary Computing. Springer, Cham, 2016
61. Li, C., et al.: A double evolutionary learning moth-flame optimization for real-parameter global optimization problems. IEEE Access **6**, 76700–76727 (2018)
62. Xu, Y., et al. Enhanced moth-flame optimizer with mutation strategy for global optimization. Inf. Sci. **492**, 181–203 (2019)
63. Xu, H., et al.: Application of a distance-weighted KNN algorithm improved by moth-flame optimization in network intrusion detection. In: 2018 IEEE 4th International Symposium on Wireless Systems within the International Conferences on Intelligent Data Acquisition and Advanced Computing Systems (IDAACS-SWS). IEEE, 2018

64. Liu, D., et al.: Projection pursuit evaluation model of regional surface water environment based on improved chicken swarm optimization algorithm. Water Resour. Manag. **32**(4), 1325–1342 (2018)
65. Faris, H., Aljarah, I., Mirjalili, S.: Evolving radial basis function networks using moth–flame optimizer. In: Handbook of Neural Computation, pp. 537–550. Academic Press, London, 2017
66. Elsakaan, A.A., et al.: An enhanced moth-flame optimizer for solving non-smooth economic dispatch problems with emissions. Energy **157**, 1063–1078 (2018)
67. Savsani, V., Tawhid, M.A.: Non-dominated sorting moth flame optimization (NS-MFO) for multi-objective problems. Eng. Appl. Artif. Intell. **63**, 20–32 (2017)
68. Das, A., et al.: Concentric circular antenna array synthesis for side lobe suppression using moth flame optimization. AEU-Int. J. Electron. Commun. **86**, 177–184 (2018)
69. Ebrahim, M.A., Becherif, M., Abdelaziz, A.Y.: Dynamic performance enhancement for wind energy conversion system using moth-flame optimization based blade pitch controller. Sustain. Energy Technol. Assess. **27**, 206–212 (2018)
70. Mei, R.N.S., et al.: Optimal reactive power dispatch solution by loss minimization using moth-flame optimization technique. Appl. Soft Comput. **59**, 210–222 (2017)
71. Allam, D., Yousri, D.A., Eteiba, M.B.: Parameters extraction of the three diode model for the multi-crystalline solar cell/module using moth-flame optimization algorithm. Energy Convers. Manag. **123,** 535–548 (2016)
72. Singh, P., Prakash, S.: Optical network unit placement in Fiber-Wireless (FiWi) access network by moth-flame optimization algorithm. Opt. Fiber Technol. **36**, 403–411 (2017)
73. El Aziz, M.A., Ewees, A.A., Hassanien, A.E.: Whale optimization algorithm and moth-flame optimization for multilevel thresholding image segmentation. Expert Syst. Appl. **83**, 242–256 (2017)
74. Mehne, S.H.H., Mirjalili, S.: Moth-flame optimization algorithm: theory, literature review, and application in optimal nonlinear feedback control design, pp. 143–166. In: Nature-Inspired Optimizers. Springer, Cham, 2020
75. Nandi, M., Shiva, C.K., Mukherjee, V.: A moth–flame optimization for UPFC–RFB-based load frequency stabilization of a realistic power system with various nonlinearities. Iran. J. Sci. Technol., Trans. Electr. Eng. **43**(1), 581–606 (2019)
76. Barham, R., Sharieh, A., Sleit, A.: Multi-moth flame optimization for solving the link prediction problem in complex networks. Evol. Intell. **12**, 563–591 (2019)
77. Buch, H., Trivedi, I.N.: An efficient adaptive moth flame optimization algorithm for solving large-scale optimal power flow problem with POZ, multifuel and valve-point loading effect. Iran. J. Sci. Technol., Trans. Electr. Eng. **43**, 1–21 (2019)
78. Nanda, S.J., Garg, S.: Design of supervised and blind channel equalizer based on moth-flame optimization. J. Inst. Eng. (India): Ser. B **100**(2), 105–115 (2019)
79. Diab, A.A.Z., Rezk, H.: Optimal sizing and placement of capacitors in radial distribution systems based on Grey Wolf, Dragonfly and moth–flame optimization algorithms. Iran. J. Sci. Technol., Trans. Electr. Eng. **43**(1), 77–96 (2019)
80. Wang, P., et al.: A complex-valued encoding moth-flame optimization algorithm for global optimization. In: International Conference on Intelligent Computing. Springer, Cham, 2019
81. Acharyulu, B.V.S., Mohanty, B., Hota, P.K. Comparative performance analysis of PID controller with filter for automatic generation control with moth-flame optimization algorithm. In: Applications of Artificial Intelligence Techniques in Engineering, pp. 509–518. Springer, Singapore, 2019
82. Mittal, N.: Moth flame optimization based energy efficient stable clustered routing approach for wireless sensor networks. Wireless Pers. Commun. **104**(2), 677–694 (2019)
83. Kaur, K., Singh, U., Salgotra, R.: An enhanced moth flame optimization. Neural Comput. Appl. **30**, 1–35 (2018)
84. Dhyani, A., Panda, M.K., Jha, B.: Moth-flame optimization-based fuzzy-PID controller for optimal control of active magnetic bearing system. Iran. J. Sci. Technol., Trans. Electr. Eng. **42**(4), 451–463 (2018)

85. Wei, S., Yuwei, W., Chongchong, Z.: Forecasting CO_2 emissions in Hebei, China, through moth-flame optimization based on the random forest and extreme learning machine. Environ. Sci. Pollut. Res. **25**(29), 28985–28997 (2018)
86. Tolba, M.A., et al.: LVCI approach for optimal allocation of distributed generations and capacitor banks in distribution grids based on moth–flame optimization algorithm. Electr. Eng. **100**(3), 2059–2084 (2018)
87. Xu, L., et al.: Enhanced moth-flame optimization based on cultural learning and Gaussian mutation. J. Bionic Eng. **15**(4), 751–763 (2018)
88. Tripati, P., et al.: Solution of economic load dispatch problems through moth flame optimization algorithm. In: Advances in Communication, Devices and Networking, pp. 287–294. Springer, Singapore, 2018
89. Zhang, H., et al.: A novel visual tracking method based on moth-flame optimization algorithm. In: Chinese Conference on Pattern Recognition and Computer Vision (PRCV). Springer, Cham, 2018
90. Li, C., Li, S., Liu, Y.: A least squares support vector machine model optimized by moth-flame optimization algorithm for annual power load forecasting. Appl. Intell. **45**(4), 1166–1178 (2016)
91. Zhang, Q., et al.: Moth-flame optimization algorithm based on adaptive weight and simulated annealing. In: International Conference on Intelligent Science and Big Data Engineering. Springer, Cham, 2018
92. Das, A., et al.: Moth flame optimization based design of linear and circular antenna array for side lobe reduction. Int. J. Numer. Model.: Electron. Netw., Devices Fields **32**(1), e2486 (2019)
93. Taher, M.A., et al.: An improved moth-flame optimization algorithm for solving optimal power flow problem. Int. Trans. Electr. Energy Syst. **29**(3), e2743 (2019)
94. Mohanty, B., Acharyulu, B.V.S., Hota, P.K.: Moth-flame optimization algorithm optimized dual-mode controller for multiarea hybrid sources AGC system. Optim. Control. Appl. Methods **39**(2), 720–734 (2018)
95. Ghobaei-Arani, M., et al.: A moth-flame optimization algorithm for web service composition in cloud computing: simulation and verification. Softw.: Pract. Exp. **48**(10), 1865–1892 (2018)
96. Zhao, X.-D., et al.: An Ameliorated moth-flame optimization algorithm. In: 2018 37th Chinese Control Conference (CCC). IEEE, 2018
97. Saikia, L.C., Saha, D.: Automatic generation control in competitive market conditions with moth-flame optimization based cascade controller. In: 2016 IEEE Region 10 Conference (TENCON). IEEE, 2016
98. Ceylan, O., Paudyal, S.: Optimal capacitor placement and sizing considering load profile variations using moth-flame optimization algorithm. In: 2017 International Conference on Modern Power Systems (MPS). IEEE, 2017
99. Jangir, N., et al.: Moth-flame optimization algorithm for solving real challenging constrained engineering optimization problems. In: 2016 IEEE Students' Conference on Electrical, Electronics and Computer Science (SCEECS). IEEE, 2016
100. Kommadath, R., Kotecha, P.: Performance evaluation of moth flame optimization on real parameter single objective optimization and computationally expensive optimization. In: 2016 IEEE Region 10 Conference (TENCON). IEEE, 2016
101. Gope, S., et al.: Moth Flame Optimization based optimal bidding strategy under transmission congestion in deregulated power market. In: 2016 IEEE Region 10 Conference (TENCON). IEEE, 2016
102. Dey, P., Bhattacharya, A., Das, P.: Tuning of power system stabilizers in multi-machine power systems using moth flame optimization. In: 2018 International Electrical Engineering Congress (iEECON). IEEE, 2018
103. Chauhan, S.S., Kotecha, P.: Single level production planning in petrochemical industries using moth-flame optimization. In: 2016 IEEE Region 10 Conference (TENCON). IEEE, 2016
104. Sahu, A., Hota, S.K.: Performance comparison of 2-DOF PID controller based on moth-flame optimization technique for load frequency control of diverse energy source interconnected

power system. In: 2018 Technologies for Smart-City Energy Security and Power (ICSESP). IEEE, 2018
105. Shah, Y.A., et al.: CAMONET: moth-flame optimization (MFO) based clustering algorithm for VANETs. IEEE Access **6**, 48611–48624 (2018)
106. Ewees, A.A., Sahlol, A.T., Amasha, M.A.: A Bio-inspired moth-flame optimization algorithm for Arabic handwritten letter recognition. In: 2017 International Conference on Control, Artificial Intelligence, Robotics & Optimization (ICCAIRO). IEEE, 2017
107. Das, A., Srivastava, L.: Optimal placement and sizing of distributed generation units for power loss reduction using moth-flame optimization algorithm. In: 2017 International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICICT). IEEE, 2017
108. Upper, N.A., Hemeida, A.M., Ibrahim, A.A.: Moth-flame algorithm and loss sensitivity factor for optimal allocation of shunt capacitor banks in radial distribution systems. In: 2017 Nineteenth International Middle East Power Systems Conference (MEPCON). IEEE, 2017
109. Ceylan, O.: Harmonic elimination of multilevel inverters by moth-flame optimization algorithm. In: 2016 International Symposium on Industrial Electronics (INDEL). IEEE, 2016
110. Khan, M.F., et al.: Moth Flame Clustering Algorithm for Internet of Vehicle (MFCA-IoV). IEEE Access **7**, 11613–11629 (2018)
111. Zhong, Y., Xia, Y., Wang, Y. Moth flame optimized adaptive fuzzy refrigeration control algorithm and modeling in air conditioning control refrigerated system. In: 2018 IEEE 4th Information Technology and Mechatronics Engineering Conference (ITOEC). IEEE, 2018
112. Gope, S., et al.: Profit maximization with integration of wind farm in contingency constraint deregulated power market using moth flame optimization algorithm. In: 2016 IEEE Region 10 Conference (TENCON). IEEE, 2016
113. Parmar, S.A., et al.: Optimal active and reactive power dispatch problem solution using moth-flame optimizer algorithm. In: 2016 International Conference on Energy Efficient Technologies for Sustainability (ICEETS). IEEE, 2016
114. Metwally, A.S., et al. "WAP: A novel automatic test generation technique based on moth flame optimization." 2016 IEEE 27th International Symposium on Software Reliability Engineering (ISSRE). IEEE, 2016
115. Yamany, W., et al.: Moth-flame optimization for training multi-layer perceptrons. In: 2015 11th International Computer Engineering Conference (ICENCO). IEEE, 2015
116. Ebeed, M., Kamel, S., Youssef, H.: Optimal setting of STATCOM based on voltage stability improvement and power loss minimization using moth-flame algorithm. In: 2016 Eighteenth International Middle East Power Systems Conference (MEPCON). IEEE, 2016
117. Abd el-sattar, S., Kamel, S., Ebeed, M.: Enhancing security of power systems including SSSC using moth-flame optimization algorithm. In: 2016 Eighteenth International Middle East Power Systems Conference (MEPCON). IEEE, 2016
118. Talaat, M., et al.: Moth-Flame algorithm for accurate simulation of a non-uniform electric field in the presence of dielectric barrier. IEEE Access **7**, 3836–3847 (2018)
119. Singh, P., Prakash, S.: Performance evaluation of moth-flame optimization algorithm considering different spiral paths for optical network unit placement in fiber-wireless access networks. In: 2017 International Conference on Information, Communication, Instrumentation and Control (ICICIC). IEEE, 2017
120. Saurav, S., Gupta, V.K., Mishra, S.K.: Moth-flame optimization based algorithm for FACTS devices allocation in a power system. In: 2017 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS). IEEE, 2017
121. Sapre, S., Mini, S.: Moth flame based optimized placement of relay nodes for fault tolerant wireless sensor networks. In: 2018 9th International Conference on Computing, Communication and Networking Technologies (ICCCNT). IEEE, 2018
122. Lal, D.K., Bhoi, K.K., Barisal, A.K.: Performance evaluation of MFO algorithm for AGC of a multi area power system. In: 2016 International Conference on Signal Processing, Communication, Power and Embedded System (SCOPES). IEEE, 2016