mathematics

Review

Moth Search: Variants, Hybrids, and Applications

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Abstract: Moth search (MS) is a nature-inspired metaheuristic optimization algorithm based on the most representative characteristics of moths, Lévy flights and phototaxis. Phototaxis signifies a movement which organism towards or away from a source of light, which is the representative features for moths. The best moth individual is seen as the light source in Moth search. The moths that have a smaller distance from the best one will fly around the best individual by Lévy flights. For reasons of phototaxis, the moths, far from the fittest one, will fly towards the best one with a big step. These two features, Lévy flights and phototaxis, correspond to the processes of exploitation and exploration for metaheuristic optimization. The superiority of the moth search has been demonstrated in many benchmark problems and various application areas. A comprehensive survey of the moth search was conducted in this paper, which included the three sections: statistical research studies about moth search, different variants of moth search, and engineering optimization/applications. The future insights and development direction in the area of moth search are also discussed.

Keywords: moth search; optimization; metaheuristic; Lévy flights

MSC: 78M50; 80M50

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1. Introduction

Because of the increasing complexity of the optimization problems [1,2], metaheuristic algorithms [3–6] have become increasingly important for solving these complex optimization problems, such as engineering optimization [7], picture processing [8–12], flow shop scheduling [13–15], feature selection [16], path planning [17,18], neural networks [19–22], multi-objective and many-objective optimization [23–27], shape design [28], object extraction [29], cyber-physical social systems [30], classification [31–35], facial micro-expression recognition [36], big data and large-scale optimization [37–39], fuzzy systems [40], and the knapsack problem [41]. These problems have been solved by some well-known methods, such as genetic algorithms (GAs) [42,43], differential evolution (DE) [44–48], particle swarm optimization (PSO) [49–54], monarch butterfly optimization (MBO) [55–59], elephant herding optimization (EHO) [60], artificial bee colonies (ABC) [61], polar bear optimization (PBO) [62], ant colony optimization (ACO) [63], harmony search (HS) [64–67], krill herd (KH) [68–72], cuckoo search (CS) [73–79], earthworm optimization algorithm (EWA) [80], monkey algorithms (MAs) [81,82], firefly algorithms (FAs) [83,84], moth flame optimization (MFA) [85], grey wolf optimization (GWO) [86], biogeography-based optimization (BBO) [87,88], bat algorithms (BAs) [89], wolf pack algorithm (WPA) [90], and moth search [91].

Inspired by characteristics of moths, Wang [91] proposed a novel swarm intelligence method, namely Moth search (MS) algorithm, in 2018. The MS contains two most representative characteristics of moths, phototaxis and Lévy flights. The moths that have a smaller distance from the best one will fly around the best individual by Lévy flights [92]. The best moth individual is seen as the light source in Moth search, which considered the target for the moths. For reasons of phototaxis, the moths, far from the fittest one, will fly towards the best one with a big step. These two features, Lévy flights and phototaxis, correspond to the processes of exploitation and exploration for metaheuristic optimization. In this paper, a comprehensive review of the MS algorithm, including the walk behavior of the historical development of MS, different variants and applications, are presented.

The remainder of this paper is organized as follows. The walk behavior of the historical development of moth search is detailed in Section 2. Different variants of moth search are presented in Section 3. Engineering optimization/applications are presented in Section 4. A conclusion and suggestions for future work was presented in Section 5.

2. Historical Development of Moth Search

2.1. Moth Search Research Studies

Moth search has been around for a long time. Since moth search was proposed, its related studies have been published up to 23 August 2022. A temporal histogram has been given in Figures 1 and 2 for the collected published articles.

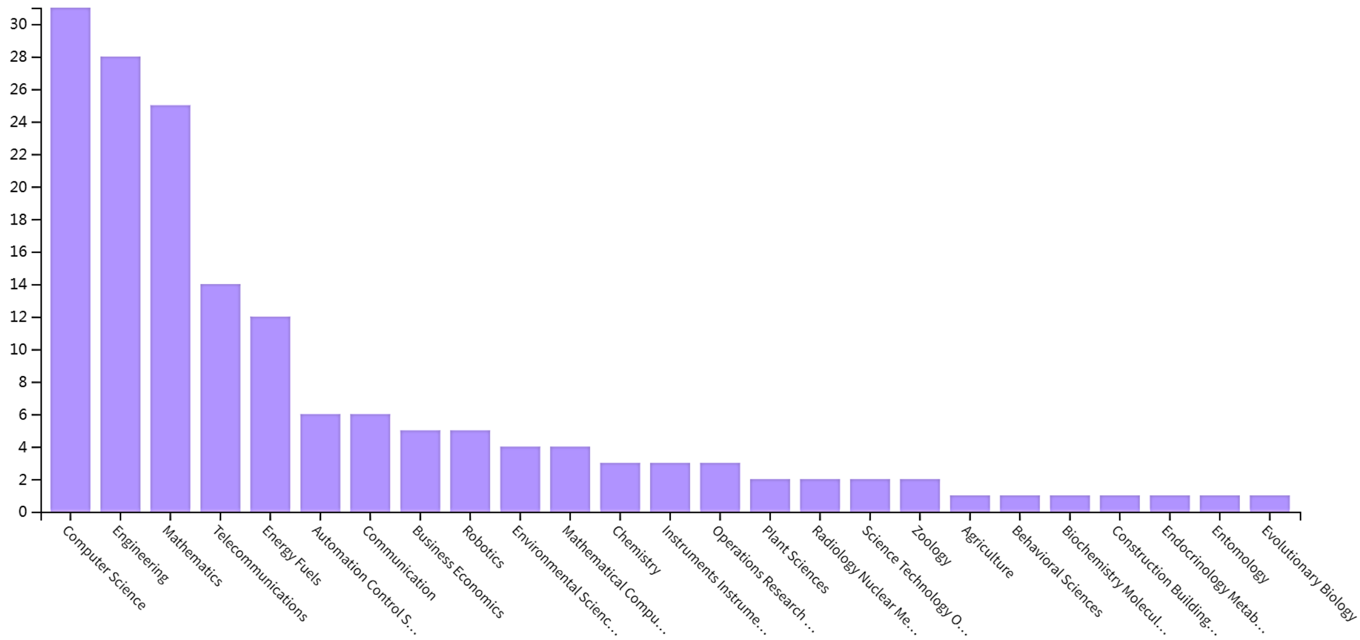

Figure 1. Related MS publications since 2018.

The collected articles are from variety of fields covering mathematics, engineering, telecommunication, energy fuels, automation control systems, communication, business economics, robotics, environmental science, mathematical computational biology, chemistry, instruments instrumentation, operations research management science, plant sciences, radiology nuclear, science technology, zoology, agriculture, behavioral sciences, and biochemistry molecule. Among them, 31 papers were published in computer sciences field, accounting for 59.615%. 28 papers were published in engineering field, accounting for 53.846%. Mathematics field contains 25 papers, accounting for 48.077%. Telecommunication field contains 14 papers, accounting for 26.923%. Energy fuels field contains 12 papers, accounting for 23.077%. Automation control systems field contains 6 papers, accounting for 11.538%. Communication field contains 6 papers, accounting for 11.538%. Business economics field contains 5 papers, accounting for 9.615%. 5 papers were published in robotics field, accounting for 9.615%. Environmental science field contains 4 papers, accounting for 7.692%. Mathematical computational biology field contains 4 papers, accounting for 7.692%. Chemistry field contains 3 papers, accounting for 5.769%. Instruments instrumentation field contains 3 papers, accounting for 5.769%.

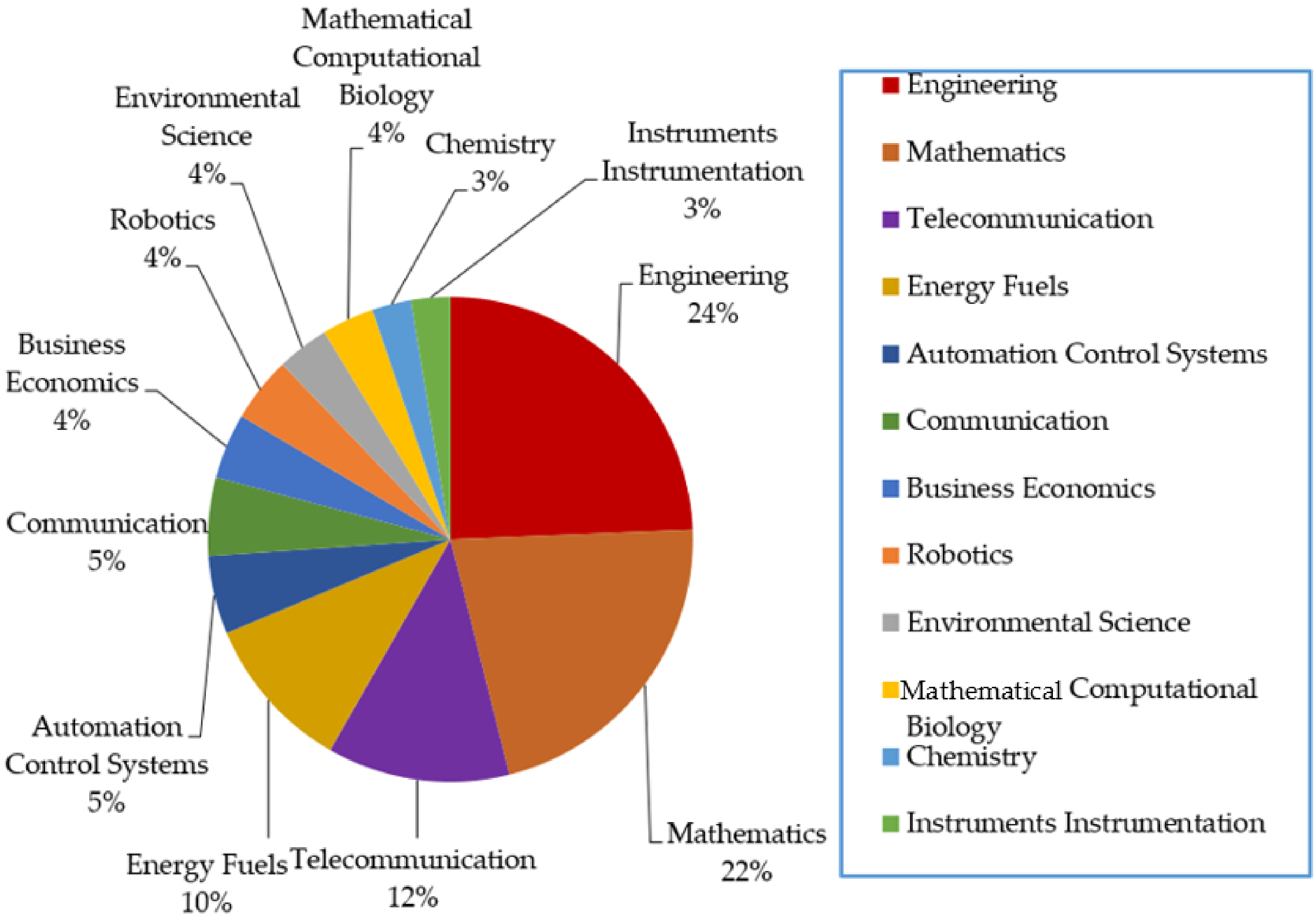

Figure 2. Related MS publications since 2018.

MS optimization was systematically summarized and studied in this paper. From the various papers collected, 56 representative papers from 1 January 2018 to 23 August 2022 were selected and used for our survey. The classification proportions of MS optimization were showed in Figure 3. Table 1 showed that this paper divides the MS optimization into 2 categories: different variants of moth search and engineering optimization/applications. Different variants of moth search are accounting for 14%. Engineering optimization/applications relatively frequently, with its proportion is 86%.

Table 1. Classification proportions for MS.

Classification	Name	Percentages
Different variants of moth search (14%)	Improved MS algorithms	7%
	Hybrid MS algorithms	5%
	Variants of MS algorithms	2%
Engineering optimization/applications (86%)	Continuous optimization	18%
	Combinatorial optimization	61%
	Constrained optimization	5%
	Multi-objective optimization	2%

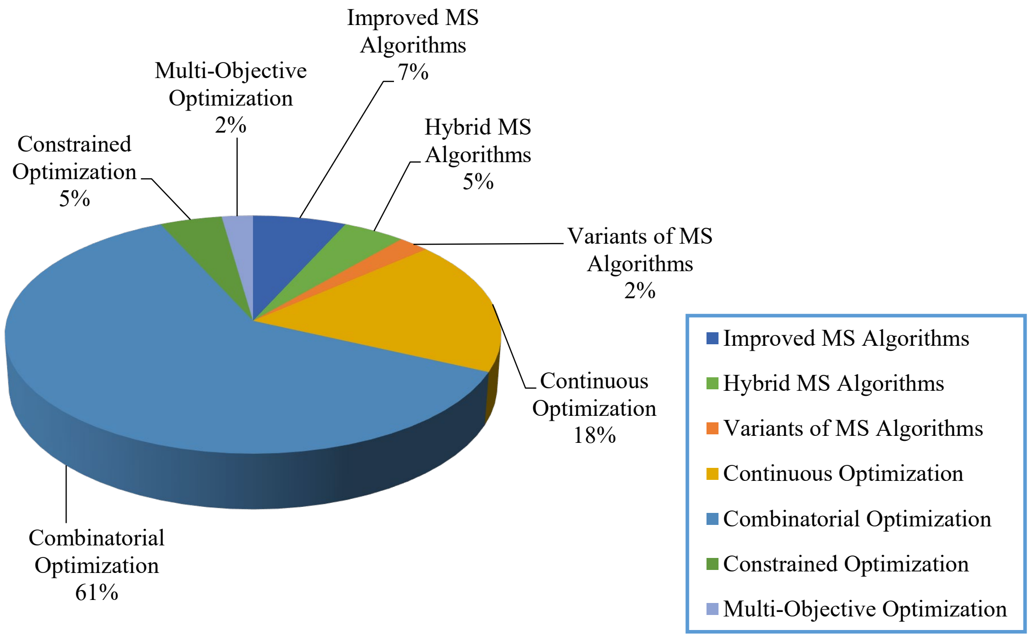

Figure 3. Classification proportions of MS.

2.2. Basics of Moth Search

Moth search (MS) algorithm is a novel swarm intelligence method proposed by Wang in 2018, which inspired by the most representative characteristics of moths [93], Lévy flights and phototaxis. The moths that have a smaller distance from the best one will fly around the best individual by Lévy flights. Others will fly towards the best one in line. According to the fitness, the population was divided into two subgroups in MS algorithm. The moths in subgroup 1 are much closer to the optimal individual than subgroup 2. An offspring of subpopulation 1 and subpopulation 2 is generated by fly straightly and Lévy flights, respectively.

MS is widely used to solve various complex optimization problems in the real world since it was proposed. Despite its searches quickly with high accuracy and wide use, MS suffers from poor balance between exploitation and exploration. Lévy flight with the step size scaling actor is one of the most important parameters for MS algorithm. Lévy flight contains a random walk with continuous heavy tailed distribution. Although Lévy flight can improve performance of the MS algorithm, in the later stage of the algorithm, the MS is easily jumped away from the optimal solution because of the alternate patterns with long and short jumps for the Lévy flight. Therefore, many researchers have proposed some different MS variants of t to improve the global search ability.

2.2.1. Lévy Flights

Lévy flights are a random walk mechanism that satisfies heavy-tailed distribution, which can make large jumps at local locations with a high probability. The probability density distribution of Lévy flight has three characteristics: sharp peaks, asymmetry and trailing. Because of alternated between occasional long-distance jumps and frequent short distance jumps, it can expand the population search area and jump out of local optimal. The moths will fly around the best individual by Lévy flights. For each individual i in subpopulation1, their positions are updated by Lévy flights, as described in Equation (1).

$$x_i^{t+1} = x_i^t + \alpha L(s) \tag{1}$$

where x_i^{t+1} is the updated position, and x_i^t is the original position at generation t. L(s) represent the step drawn for Lévy flights. α indicate the scale factor which can be given as:

$$\alpha = S_{\max}/t^2 \tag{2}$$

where $S_{\max}$ indicated as max walk step. The $L(s)$ can be formulated as follows:

$$L(s) = \frac{(\beta - 1)\Gamma(\beta - 1)\sin\left(\frac{\pi(\beta-1)}{2}\right)}{\pi s^{\beta}} \tag{3}$$

where $L(s)$ is the gamma function, and s be regarded as the position of moth individual which is bigger than 0. β = 1.5.

2.2.2. Fly Straightly

It is well-known that phototaxis is moths tend to fly around the light source. The changes in angle will be clearly discernible when a moth that is close to the light source uses it for navigation with a small distance. The moth will instinctively redirect to move towards the light source, which will lead to a path closer to the light source. In this process, the i-th flights can be formulated as:

$$x_i^{t+1} = \lambda \times (x_i^t + \phi \times (x_{best}^t - x_i^t)) \tag{4}$$

where ϕ indicate an acceleration factor. x_{best}^t represent the best moth at the t-th generation. Λ indicate a scale factor which can improve the diversity of the population and control the convergence speed of the algorithm.

On the other hand, when the moth flies beyond the light source, the position for moth i is formulated as:

$$x_i^{t+1} = \lambda \times (x_i^t + \frac{1}{\varphi} \times (x_{best}^t - x_i^t)) \tag{5}$$

where x_{best}^t and x_i^t are the best and original position for moth i, respectively. λ is a scale factor and φ is acceleration factor.

2.2.3. Schematic Description of MS Algorithm

According to the analyses above, the basic steps of the MS are shown as follows Algorithm 1. Figure 4 designed the corresponding flowchart.

Algorithm 1: Moth search algorithm

(1) **Begin**
(2) **Initialization.** randomly initialize the population P of NP moths randomly, the generation number T = 1, the maximum generation $MaxGen$;
(3) Evaluate each individual as per its position;
(4) **While** $T < MaxGen$ do
(5) Sort all the moth individuals according to per their fitness;
(6) **for** i = 1 to $NP/2$ (subgroup 1) **do**
(7) Evaluate x_i^{t+1} by performing Lévy flights;
(8) **end for** i
(9) **for** $i = NP/2 + 1$ to NP (subgroup 2) **do**
(10) **if** rand > 0.5 **then**
(11) Evaluate x_i^{t+1} by Equation (4);
(12) **else**
(13) Evaluate x_i^{t+1} by Equation (5);
(14) **end if**
(15) **end for** i
(16) Evaluate the population according to the updated positions;
(17) $T = T + 1$;
(18) **end while**
(19) Output the best solution.
(20) **End.**

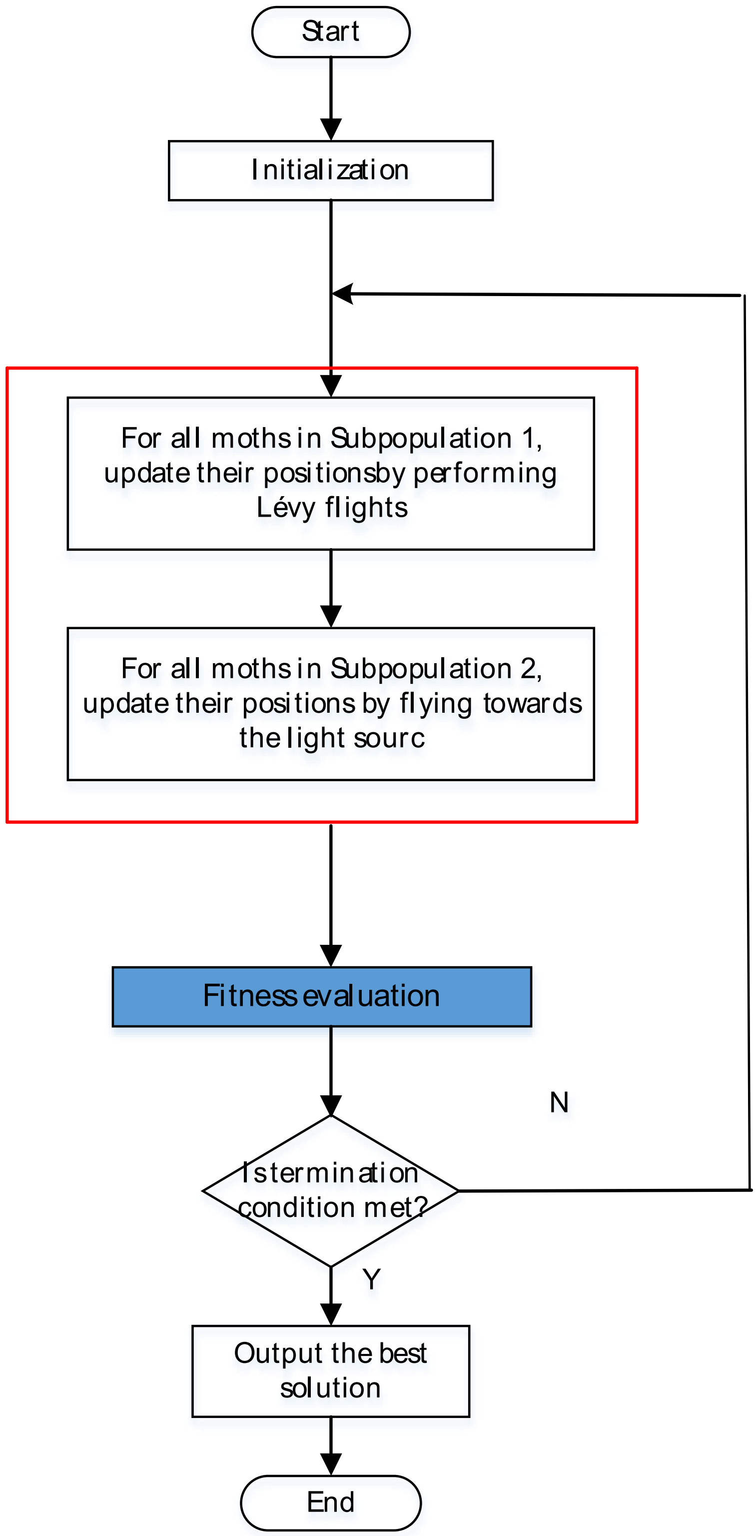

Figure 4. Flowchart of the MS algorithm.

2.2.4. Analysis of Algorithm Complexity

The computational complexity of the MS algorithm is analyzed according to the steps for MS algorithm. The dimension is D and population size is NP. Sort the population in step (5) with time complexity $O(NP)$. Execute x_i^{t+1} by performing Lévy flights for subgroup 1 in steps (6)–(8)with time complexity $O(NP/2 \times D)$. In steps (9)–(15), execute x_i^{t+1} by performing Lévy flights in Subpopulation 2 with time complexity $O(NP/2 \times D)$. In step (16), evaluate the population as per the newly updated positions with time complexity $O\ (NP)$. In summary, the total time complexity of MS algorithm is $O(T \times NP \times D)$. From the above analysis, the total time complexity of the MS algorithm is $O(T \times NP \times D)$ after omitting the low-order terms, which are only related to T, NP, and D.

3. Different Variants of Moth Search

Several MS variants have been proposed to solve different optimization problems. The variants of MS are divided into three groups: improved MS, hybrid MS, and variants of MS, as shown in Table 2.

Table 2. The classification proportions for different variants of MS.

Name	Percentages	Literatures
Improved MS	43%	[94–96]
Hybrid MS	43%	[97–99]
Variants of MS	14%	[100]

3.1. Improved MS Algorithms

Feng et al. [94] proposed a binary MS algorithm for solving the 0–1 multidimensional knapsack problem (MKP). The self-learning flight straightly was introduced into the enhanced MS, which aims to make each individual learn. Through testing 89 different widely used benchmark instances, the results concluded that the proposed SLMS can enhance global search ability and population diversity for solving the MKP problem.

Feng et al. [95] established nine novel MS-based algorithms for DKP namely de MS1–MS9. In order to verify the influence of fly straightly operator and Lévy flights operator in MS algorithm, Lévy flights operator was replaced with nine types of new mutation operator based on the global harmony search. The experiment results showed that the proposed new MS-based approaches showed better comprehensive performance.

Mariyappan et al. [96] proposed a game model-combined improved MS optimization (GMMSO) to explore the design space and optimize the system space. The GMMSO comprised the game model notion in the input portion, was employed to explore the design space of the system structure effectively for various possible configurations, which ultimately find the best solution in a reasonable time. This experiment is implemented in the field Programma Ble gate array (FPGA) Xilinx Zynq and Virtex platforms, the simulation results revealed that the GMMSO obtained outstanding performance in delay measurement, data rate, and static power consumption compared with the traditional heuristic mixed integer linear programming methods.

3.2. Hybrid MS Algorithms

Any algorithm has its limitations. Although the moth search algorithm is a new optimization method, which can solve many problems in different fields, we noticed that MS is easy to fall into local optimization for solving complex optimization problems by analyzing basic moth search. The hybrid of MS algorithm and other metaheuristicsm algorithms, such as the mutation and explosion operators, are introduced into the MS. This approach can not only strong exploitation capability and preserve the advantages of fast convergence but also significantly enhance the exploration capability.

Starnberger et al. [97] presented a hybridized moth search algorithm with an artificial bee colony to tackle constrained optimization problems. According to the results obtained during experiments on a set of 13 classic constrained benchmarks, the hybridized MS algorithm has potential in dealing with constrained functions optimization.

Han et al. [98] designed a new hybrid moth search-fireworks algorithm (MSFWA) which introduced the explosion and mutation operators from the fireworks algorithm to solve constrained engineering optimization problems. The simulation results using 23 benchmark functions showed that the MSFWA not only preserved the strong exploitation capability but also enhanced the exploration capability.

Chaudhary et al. [99] studied an improved search technique to reduce the range of uniform random movement for MS algorithm, which enhanced overall efficiency and convergence capabilities. In the improved method, uniform and Lévy distributions, as well as Cauchy distribution, have been employed to apply different swarm algorithms, including MS algorithm. The experimental results indicated that improved method has a positive influence by employing different random distributions.

3.3. Variants of MS Algorithms

Srivani et al. [100] studied a dragonfly moth search (DMS) optimization to reveal the efficiency of the classification model using spark architecture. Features selection is accomplished by employing the DMS algorithm. The performance of the classification method is carried out in two different phases, offline and online. The parameters, such as sensitivity, accuracy and specificity metrics, are evaluated on the DMS method.

4. Engineering Optimization/Applications

MS optimization is a search optimization method inspired by things in nature. It has two properties, Lévy flight and phototaxis. The moths that have a smaller distance from the best one will fly around the best individual by Levy flights. Compared with traditional optimization methods, MS optimization has significant advantages in solving speed and accuracy, which can obtain the solution closest to the optimal solution in the shortest time. Therefore, it has been widely used in many engineering fields, as shown in Table 3.

Table 3. The classification of engineering optimization/applications.

Name	Percentages	Area	Literatures
Continuous optimization	5%	Neural networks	[101–107]
		Big data processing	[108]
Combinatorial optimization	7%	Knapsack	[109,110]
		Power systems	[111–114]
		Static drone localization	[115]
		Wireless sensor network	[116–118]
		Scheduling	[119–121]
		Energy	[122–126]
		Water quality monitoring	[127]
		Computer vision	[128]
		Information security	[129–131]
		Text mining	[132,133]
		Information metasearch	[134]
		Path optimization	[135]
Constrained optimization	7%	Linear and nonlinear constrained optimization	[136]
		Bridges design	[137]
		Industry design	[138]
Multi-objective optimization	81%	Multi-objective optimization	[139]

4.1. Continuous Optimization

4.1.1. Neural Networks

Fri et al. [101] integrated data envelopment analysis (DEA) and artificial neural network (ANN) in a single framework to evaluate the performance of operations for the container terminal. In the proposed framework, MS is employed to train the feed forward neural network (FNN) for determining the efficiency scores. The efficacy of the proposed framework was demonstrated on two container terminals of tangier and casablanca.

Reshma et al. [102] integrated chicken swarm optimization (CSO) and moth search algorithm to train optimally deep convolutional neural network (DCNN) classifier for pixel identification in image steganography. The inverse Tetrolet transform is applied to extract the secret message from an embedded image. The performance of image steganography is established based on the dataset. The results showed that the proposed method achieved excellent results for three correlation parameters, such as correlation coefficient, structural similarity index, and peak signal-to-noise ratio.

Shankar et al. [103] developed a new MS algorithm based on classification and detection model for diabetic retinopathy images (DNN-MSO). Different processes, such as preprocessing, segmentation, feature extraction, and classification, are involved with DNN-MSO. The analysis of the computational validated on diabetic retinopathy dataset indicated that the DNN-MSO has superior characteristics for curacy, sensitivity and specificity.

Srivastava et al. [104] developed a novel method, namely moth monarch optimization-based deep belief neural network (MMO-DBN) for deception detector. Two phases of feature extraction and classification were undergone in MMO-DBN classifier. Deep belief neural network (DBN) was used to subject these extracted features for classification. Monarch butterfly optimization (MBO) and MS algorithm were integrated to train. The MMO-DBN obtained the higher accuracy, which showed the superiority of the proposed MMO-DBN in deception detection.

Xu et al. [105] considered a novel optimized method containing five main types of noise reduction, tumor segmentation, morphology, feature extraction and gray-level co-occurrence matrix, and classification for early diagnosis of the brain tumor, in which an enhanced MS algorithm is utilized to optimize the classifier network. The simulation results are applied to three different datasets, revealed that the reposted method has good achievements toward the other methods.

Rekha et al. [106] considered novel method combining water wave optimization (WWO) and the MS, namely the water moth search algorithm (WMSA) for the detection of intrusion and malicious activities. The deep recurrent neural network (RNN) classifier effectively was detected by using the selected features. The research results showed that the proposed WMSA showed improved results with maximal specificity, accuracy, and sensitivity.

Sophia et al. [107] demonstrated an advanced multi-resolution algorithm (MRA) for optimally identifying and classifying pathologies, in which the vocal regions are acquired by using the genetic k-means algorithm. In addition, moth search-rider optimization-based deep convolutional neural networks (MRA-based DCNN) are used for pathology classification, and the local directional pattern (LDP) fed is used to generate pathology features. The hybrid optimization (MRA) is integrated by adopting the rider optimization algorithm (ROA) and moth search algorithm (MS). The experimentation is conducted by using the real databases regarding the performance metrics divulge, and the results indicated that the proposed module obtained the accuracy, specificity, and sensitivity.

4.1.2. Big Data Processing

Srivani et al. [108] illustrated a technique based on the integration of dragonfly algorithm (DA) and MS, namely DMS algorithm, which handled the concept drift effectively for the big data stream classification without any concept drift. The DMS algorithm aimed at feature selection and optimal tuning of the stacked auto-encoder (SAE). The effective feature selection-based SAE ensured the classification of the data and enhanced the classification accuracy.

4.2. Combinatorial Optimization

4.2.1. Knapsack

Feng et al. [109] combined twelve transfer functions divided three families (S-shape, V-shaped, and other shape) with MS to solve set-union knapsack problem (SUKP). Through the evaluation for three groups of fifteen SUKP instances, the simulation results showed that the transfer function demonstrated excellent performance and convergence rate.

Feng et al. [110] investigated an improved MS for solving SUKP, in which Lévy flight is replaced by enhancing the interaction operator (EIO). The mutation operator (MO) of differential evolution (DE) is employed into EIO to enhance the ability of information interaction among individuals. The analysis of the computational results indicated that the improved MS is superior to the other metaheuristic algorithm.

4.2.2. Power Systems

Singh et al. [111] designed MS for solving optimal distributed energy resources (DERs) integration problems of distribution systems. An optimal DERs integration problem with MS is formulated at annual energy loss minimization considering multiple distributed generations. The optimal DERs allocation is determined for minimization of annual energy loss at three different load levels. The simulation experimental results demonstrated that MSO has a better searching ability to determine optimal solutions for optimal DERs allocation problems.

Dhillon et al. [112] considered MS to address frequency control problem, which was caused by sudden source and load fluctuation in a three-area test power system. The experiments were simulated on MATLAB (R) and Simulink (R) platform. The effectiveness and accuracy of the proposed method were demonstrated in load frequency control problem.

Singh et al. [113] introduced MS for solving the distributed energy resources integration problems (DER). In order to verify the performance of the proposed method, two benchmark test distribution networks of 33 and 118 buses are implemented; the experimental results indicated that the proposed method optimally utilized the distribution system resources and generated higher deployment benefits at lesser DER penetration.

Srivastava et al. [114] introduced a new hybrid algorithm which termed lion algorithm with moth-based mutation (LA-MM) hybridized both lion algorithm and moth search. LA-MM is used to optimize the generating power of added generators with the bus system, which managed the congestion with minimized rescheduling cost. Experimentally, it has been proved that the LA-MM took the benefits of different optimization algorithms for fast convergence, which reduced grave damage caused by the congestion causes.

4.2.3. Static Drone Localization

Strumberger et al. [115] devised the MS algorithm to adjust static drone location problem. The MS algorithm is applied to establish monitoring all targets with the least possible number of drones. Instances with 30 uniformly distributed targets were tested, and the results indicated that MS algorithm full coverage of targets, which showed potential in dealing with this kind of problem.

4.2.4. Wireless Sensor Network

Strumberger et al. [116] developed hybridized moth search algorithm adapted to solve localization problem for wireless sensor networks. According to test on the same problem instances of node localization problem, the research results showed that hybridized MS algorithms are promising to deal with wireless sensor network localization.

Tandon et al. [117] modified bio-inspired cross-layer routing protocol (BiHCLR) combining MS and slap swarm optimization, to achieve effective and energy preserving routing in wireless sensor networks (WSN) for the Internet of Things (IoT). In BiHCLR, in order to enable energy preservation, the fuzzy logic approach was executed to select the cluster head for every grid. The experimentation was conducted in six indicators. The experimental results showed that the performance of the BiHCLR outperformed all other conventional techniques.

Boursianis et al. [118] applied MS to derive the final geometry of the proposed antenna for triple-band single-layer Rectenna for radio frequency (RF) energy harvesting (EH). The proposed rectifier is designed based on the Greinacher topology. The experiments showed that the proposed Rectenna can efficiency harvest RF energy from outdoor sources.

4.2.5. Scheduling

Elaziz et al. [119] devised an improved MS algorithm to minimize the makespan that required to schedule a number of tasks on different virtual machines for cloud task scheduling problem. In the proposed method, the DE is introduced into MS for improving the exploitation ability. The experiment was compared with other metaheuristic algorithms for synthetical and real trace data, respectively. It was concluded that the proposed algorithm outperformed other algorithms for cloud task scheduling problems.

Zade et al. [120] proposed a hybrid algorithm, namely hybrid multi-objective fuzzy hitchcock bird (MOHFHB) with moth search algorithm to solve multi-objective scheduling problems. Two concepts, crowding distance and ranking non-dominated solution, are added to determine the optimal Pareto front in MOHFHB. The experiments showed that the makespan and resource utilization have been improved.

Gokuldhev et al. [121] developed a hybridization of moth search algorithm (MSA) and flower pollination algorithm (FPA), namely local pollination moth search algorithm (LPMSA) for proper task scheduling in the cloud. FPA algorithm is used to improve the exploitation capacity of MSA. The experimentation is simulated under the platform of JAVA, and the results indicated that the LPMSA reduced the makespan and energy consumption during proper task scheduling.

4.2.6. Energy

Fathy et al. [122] developed an enhanced moth search algorithm (EMSA) to identify the optimal parameters of triple-junction (TJS) photovoltaic panel under different operating conditions. In order to avoid MS from being stuck in the local point, the disruptor operator is introduced into MS, which improved the diversity of the algorithm. The panel is tested under different solar radiation conditions. The results compared with other metaheuristic optimization showed that the EMSA extracted the optimal parameters of TJS based module operated at different operating conditions.

Boursianis et al. [123] introduced moth search algorithm to design a modified micros trip patch antenna of three varying slots. The proposed antenna with MS exhibited tuning operation in the long range and the cellular communications frequency. The experimental results indicated excellent performance for RF energy harvesting applications.

Huang et al. [124] devised the hybrid system based moth search algorithm, to analyze regarding the smoothness of the energy generation trend. In order to reduce the variance of electricity generation annually, MS is used for calculating the output of the PV voltage. The hybrid system is evaluated via three different hydrological periods, such as wet, drought, and normal. The research results showed that hydropower and PV are complementary, which can compensate for shortcomings and reduce energy in different conditions.

Sun et al. [125] presented a novel modified moth search algorithm namely converged moth search algorithm (CMSA) for minimizing the total of the squared deviations (TSD) between the experimental data and the output voltage in proton exchange membrane Fuel cells (PEMFCs). The CMSA method is applied to two different test cases, NedStack PS6 and BCS 500-WPS6. The simulation results revealed that the CMSA has the minimum values for both case studies toward the other compared algorithms, which showed that the CMSA has a good data agreement with the experimental data.

Shobana et al. [126] studied a dispatch strategy with fitness sorted moth search algorithm (FS-MSA) to enhance the economy of the micro grid system, which minimized the cost of system operation and environmental control for meeting system load requirements. The experimental results indicated that the FS-MSA model obtained excellent performance.

4.2.7. Water Quality Monitoring

Hussein et al. [127] proposed a new alternative machine learning method, namely MSA-RVFL, to predict the missing values of total algal count. The method combined the advantage of the random vector functional link network (RVFL). The performance results showed that the MSA-RVFL reduced the processing time and minimized the input variables, compared with GA-RVFL and PSO-RVFL methods whenever the number of inputs is large or small during water quality monitoring programs.

4.2.8. Computer Vision

Wagdarikar et al. [128] presented an improved chronological-moth search (Chronological-MS) for video watermarking based on interesting regions. Chronological concept is used in chronological-MS to select the optimal regions for the video watermarking. The chronological-MS is used to carry out for interesting regions identified. The simulation results showed that chronological-MS showed superior performance with correlation coefficient.

4.2.9. Information Security

Kumar et al. [129] proposed more secure data encryption combined moth search algorithm (MSA) with elliptic curve cryptography (ECC), in which optimal value of the elliptic curve was selected. Multi-level security with less computational power was provided by combining DNA encoding with the ECC encryption algorithm. The experimental is conducted based on safety, decryption time, and encryption time. The results indicated that the proposed two-layer security with minimum key size and less storage space, which protected different attacks effectively.

Alotaibi et al. [130] designed an effective attack detection method based on moth elephant herding optimization (MEHO), which is developed by integrating the MS algorithm and the elephant herding optimization (EHO), to resolve the vulnerabilities in the computing devices. The data is cleaned via removing the noise and artifacts at the stage of the pre-processing. Then, the auto encoder classifier was used to perform the attack detection. In order to verify the performance of the method, the metrics, like accuracy, false acceptance rate (FAR) and detection rate is evaluated. The results indicated that the MEHO showed excellent performance.

Varghese et al. [131] deployed the hybridized concepts combining monarch butterfly optimization with moth search algorithm to optimally tune the weight of deep convolutional neural network (DCNN). A new intrusion detection system (IDS) model based on machine learning (ML) technology in cloud networks is established. The results showed that the method provided better outcomes compared to exciting methods.

4.2.10. Text Mining

Venkata Sailaja et al. [132] used MS algorithm to select optimal weights in support vector neural network (SVNN). The proposed classifier, namely MS-SVNN, performed incremental learning using SVNN, and the weights were bounded in a limit using rough set theory. 20 News group dataset and the Reuters dataset are used for simulation experimentation. Moreover, the text categorization is done by using the rough set MS-SVNN classifier and the optimal weights based on the MS. The analysis of the computational results indicated that the online text categorization scheme-based MS-SVNN can identify the unique words from the dataset and obtain the features like semantic word-based features from the keyword set.

Yarlagadda et al. [133] demonstrated Modsup-based frequent item set and rider optimization-based MS (Rn-MSA) for clustering the documents. The Rn-MSA is designed for document clustering by combining the MS and rider optimization algorithm. The performance of the proposed Rn-MSA is evaluated in precision, recall, F-Measure, and accuracy. The study results showed that the developed document clustering method indicated its superiority.

4.2.11. Information Metasearch

Kaur et al. [134] considered MS approach along with two distance measure methods for the rank aggregation (RA) module, which merged the output derived from distinct search engines. In order to select the best optimized document, the novel method assigns a relevance rank to similar documents from different search engines. The experimental results indicated that the approach outperformed than another conventional algorithm.

4.2.12. Path Optimization

More et al. [135] investigated a novel algorithm, namely moth whale optimization algorithm (MWOA), to determine the optimal multipath for the transmission of the videos from one vehicle to other in the vehicular ad hoc network (VANET). The MWOA is designed for the integration of whale optimization algorithm (WOA) and MS algorithm. The VANET is simulated based optimal selection of the multipath under geographic routing scheme. The simulation results revealed that MWOA showed the superiority-based packet delivery ratio (PDR), throughput, and packet end-to-end delay for effective video transmission.

4.3. Constrained Optimization

4.3.1. Linear and Nonlinear Constrained Optimization

Razmjooy et al. [136] proposed an optimal design for control of the synchronous machine, which is a 4th order linear Philips-Heffron synchronous machine. A controller is utilized for stability by minimizing a fitness function, which removed the unstable Eigen-values to the left-hand side of the imaginary axis. The considered parameters of the controller are optimized by moth search algorithm. The simulation experimental results demonstrated that the proposed method gave better efficiency for comparing particle swarm optimization.

4.3.2. Bridges Design

Carrasco et al. [137] applied moth search algorithm to optimize the process of calculating the hanger magnitudes and the order for obtaining one or several satisfactory solutions. The experimental results are obtained for an arch bridge and three hangers. The efficiency and effectiveness are compared with the black hole algorithm.

4.3.3. Industry Design

Ong et al. [138] utilized a soft computing technique for optimizing the performance of the electrical discharge machining (EDM). The MS was introduced to determine the optimal machining parameters which maximized the MRR and minimized the EWR. The EDM experiment was conducted, and the effectiveness was evaluated in material removal rate (MRR) and electrode wear rate (EWR). The experimental results indicated that the optimization capability of MS was validated based on the obtained optimal parameters.

4.4. Multi-Objective Optimization

Thokar et al. [139] proposed multi-objective nested optimization framework based involved two-layered structure for the simultaneous optimal allocation of multiple solar photovoltaics (SPVs) and battery energy storage system (BESS) in the distribution networks. Moth search is combined with a new weighted sum approach in the proposed method. The experimental results indicated that the proposed model ensured the high penetration of SPVs and the optimal utilization of BESSs, which enhanced energy efficiency and absorbed the excess renewable power generation during light load hours.

5. Conclusions and Future Directions

This paper systematically summarized moth search. We searched through Google scholar with the keyword "moth search". We selected 56 representative papers from 1 January 2018 to 23 August 2022 from the various papers. We found that the development trend and space of MS is promising from the summary analysis of these papers. A large number of researchers improved the MS algorithm and successfully applied them to various optimization fields. However, some problems still are worth study.

(1) Up to now, there is still not sufficient explanation for theoretical analysis about MS. Therefore, strengthening the theoretical analysis study of MS will be an important research direction in the future.

(2) Constrained optimization and multi-objective optimization have always been important research problems. Therefore, MS is worth further study to solve the problems in these fields.
(3) Lowing proportion of engineering applications is undoubtedly a shortcoming of MS, which will be an important challenge.
(4) MS is used to solve continuous and discrete optimization problems should be considered in future research [140,141].
(5) MS has a lower proportion combining with machine learning methods than the others [142,143].

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