Nature-Inspired Metaheuristic Algorithms: A Comprehensive Review

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Abstract: *Recently, the Metaheuristic Algorithms (MAs) field has seen a noteworthy rise in proposed Algorithms. MAs have been picking up ubiquity in a long time due to their capacity to fathom complex optimization issues in different areas, including building, funds, healthcare, and transportation. These Algorithms are based on heuristic methodologies that mirror the behaviour of normal frameworks. For occasion, developmental forms, swarm insights, and mimicked strengthening, among others, this audit presents the foremost productive later algorithms. As well as highlight the instruments and highlights (investigation look procedure, abuse look procedure, and differing qualities) of each algorithm. Moreover, an explanatory investigation has been conducted to show the productivity of each algorithm. This audit will permit interested analysts to select a suitable algorithm to illuminate their issues. In expansion, it'll help the analysts who are looking to propose a recent algorithm.*

Keywords: *Optimization algorithms, metheuristic algorithms, heuristic strategies, local search techniques, global search techniques.*

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1. Introduction

Optimization algorithms are computational methods used to find the best possible solution to a problem by systematically choosing values from a defined set of possible options [8]. Metaheuristic algorithms, a primary category of optimization algorithms, are designed to tackle complex optimization problems, especially those lacking a known closed-form solution or having an exceptionally large search space [1]. Inspired by natural processes, these algorithms can be employed to seek optimal solutions across a wide range of problem domains, including engineering, economics, and science [2].

Metaheuristic Algorithms (MAs) are recognized by their capacity to investigate huge arrangement spaces proficiently and to discover great quality arrangements in a sensible sum of time [58]. Unlike traditional optimization algorithms, such as gradient descent or Newton's method, metaheuristic algorithms do not rely on exact mathematical models of the problem being solved. Instead, they utilize basic rules and heuristics to guide the exploration of ideal arrangements. The victory of metaheuristic algorithms in tackling complex optimization issues has driven their far-reaching utilization in numerous regions of investigation and industry. They are particularly useful in situations where the problem is poorly understood or where traditional optimization methods fail to produce satisfactory results.

Recently, many optimization algorithms have been inspired by natural systems, including human behaviour, animals, plants, and even physical and chemical phenomena as shown in Figure 1. These algorithms are often referred to as nature-inspired or bio-inspired optimization algorithms. Consequently, the Subdivisions of MAs can be divided into several categories based on different criteria [4]. Here are some possible ways to categorize metaheuristic algorithms:

1. Nature-inspired vs. non-nature-inspired: MAs can be motivated by characteristic forms, such as advancement, swarm conduct, or physical marvels. Moreover, the non-nature-inspired, such as tabu search or simulated annealing [7].
2. Single-solution vs. population-based: MAs can work on a single arrangement at a time or keep up a populace of arrangements that advance over time. Illustrations of single-solution metaheuristics incorporate slope climbing and reenacted toughening, whereas illustrations of population-based metaheuristics contain hereditary algorithms and molecule swarm optimization [11].
3. Stochastic vs. deterministic: MAs can utilize stochastic (irregular) or deterministic (non-

random) administrators to produce modern arrangements or adjust existing ones. Examples of stochastic operators include mutation and crossover in genetic algorithms, while examples of deterministic operators include local search and pattern search [35].

4. Trajectory-based vs. memory-based: MAs can be trajectory-based, meaning that they take after a single way through the arrangement space until a ceasing model is met, or memory-based, meaning that they keep up a memory of past arrangements and utilize it to direct their look. Examples of trajectory-based metaheuristics include simulated annealing and tabu search, while memory-based metaheuristics encompass ant colony optimization and adaptive memory programming [20].
5. Combinatorial vs. continuous: MAs can be outlined to settle combinatorial optimization issues, such as travelling sales representative or chart coloring, or ceaseless optimization issues, such as work minimization or parameter optimization [13].
6. Multi-objective vs. single-objective: MAs are designed to optimize either multiple objectives simultaneously or a single target. Multi-objective metaheuristics frequently utilize a Pareto dominance basis to compare arrangements and keep up a set of non-dominated arrangements. Illustrations of multi-objective metaheuristics incorporate NSGA-II and MOEA/D, whereas cases of single-objective metaheuristics incorporate differential advancement and molecule swarm optimization [25].

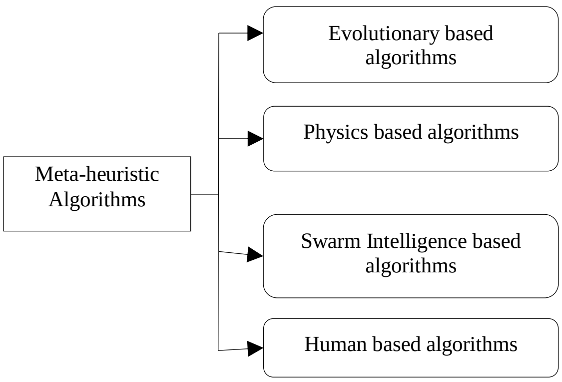

Figure 1. Classifications of metaheuristic algorithms.

This review focuses on recently proposed metaheuristic algorithms, emphasizing the mechanisms, strengths, and weaknesses of each. Moreover, it introduces analytical analysis of the algorithms' properties, such as exploration search techniques, exploitation search techniques, diversity, convergence rate, number of citations, and other relevant factors. Thus, it allows interested researchers to distinguish the differences between algorithms to solve their problems. As well as, the researchers who want to introduce new proposed algorithms by taking advantage of the advantages of the proposed algorithms and avoiding the existing disadvantages.

The structure of the rest of this paper is as follows: Section 2 provides an overview of the MAs. The analytical analysis and comparisons are presented in section 3. The limitations and potential drawbacks are shown in section 4. Section 5 concludes with a conclusion.

2. Overview of Recent Metaheuristic Algorithms

This section introduces a brief overview of the recently proposed MAs. It's worth mentioning that the related works were classified based on the types of MAs discussed previously.

2.1. Evolutionary Based Algorithms

In order to handle optimization issues with various structures, Yapici and Cetinkaya [74] introduced a novel meta-heuristic method called Path-Finder Algorithm (PFA), which simulates the collective movement of animal groups. Because of its ability to efficiently converge to the global search while avoiding local optima, the method can be utilized to difficult real-world issues involving certain search spaces. The suggested PFA outperformed popular meta-heuristics in the literature, including Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), fireflies, and Grey Wolf Optimization (GWO), when tested on benchmark test functions. Furthermore, the PFA was demonstrated to be able to approximate actual Pareto optimal solutions when it was created for multi-objective problems. The study included implementation examples of the suggested PFA and MOPFA algorithms on a number of design challenges as well as a computationally demanding and time-consuming multi-objective engineering problem. The ultimate case study's findings confirm how well the suggested algorithms perform when handling difficult real-world issues. Overall, the study presented a novel and promising meta-heuristic method that got best solution compared the well-known meta heuristics in the literature and can efficiently tackle optimization problems with varying topologies.

Zhao *et al.* [77], stated in their research that a modern optimization algorithm called Artificial Ecosystem-based Optimization (AEO) is presented. The AEO algorithm imitates the behaviours of creation, utilization, and breakdown of living things and is motivated by the control stream in characteristic environments. AEO is population-based and has been tried on 31 capacities and 8 real-world issues. The results of the think about appeared that AEO got the leading arrangements compared to other comparative algorithms in terms of ideal effectiveness, particularly for real-world designing issues. The AEO algorithm has illustrated a prevalent meeting rate and computational effectiveness compared to other strategies. They think about moreover the potential of AEO in settling trouble issues with un-boundary look zones, such as the distinguishing proof of hydrogeological parameters. By and large, the presentation of AEO gives a promising modern optimization algorithm that can be utilized in different applications and spaces. Its nature-inspired approach and capacity to outperform existing strategies propose that it might be an important expansion to the optimization toolkit of analysts and specialists alike.

Dynamic Differential Annealed Optimization (DDAO), a recent optimization algorithm displayed by Ghafil and Jarmai [34], is aiming to settle an assortment of scientific optimization issues requiring the assurance of the worldwide least or greatest. The DDAO simulates the process of making premium steel by combining classical simulated annealing with random search. The authors compared DDAO to other well cited optimization techniques and benchmarked it for 51 test functions. In several instances, DDAO performed better than some of these algorithms, exhibiting high performance. The authors also used DDAO to fix real-world optimization issues, such as spring design and limited path planning. Both times, DDAO was able to effectively converge to the problem's global minimum; the latter problem, however, found the most practical solution in contrast to other algorithms.

Ahmadianfar *et al*. [15] presented Gradient-Based Optimizer (GBO). The Local Escaping Operator (LEO) and Gradient Search Rule (GSR), the two essential administrators utilized by the GBO to navigate the look space, are modelled after the gradient-based Newton's strategy. In arrange to upgrade the speed meeting rate, and investigation procedure, and secure way better areas within the look space, the GSR utilizes the gradient-based approach. The GBO can break free from nearby optima much appreciated by the LEO. There were two stages to the assessment of the GBO's execution. Amid the primary step, the GBO's highlights were surveyed utilizing 28 numerical test capacities and compared to five other algorithms that were as of now in utilization. The results showed that the GBO created amazingly promising results due to its progressed capacities for Joining, proficiency shirking of neighborhood optima, abuse, and investigation. Six challenging real-world issues were optimized utilizing the GBO within the moment stage, displaying the system's great execution in settling these sorts of issues.

Faramarzi *et al*. [31] presented the Marine Predators Algorithm (MPA), a novel optimization strategy that draws motivation from marine predators' scavenging strategies and their perfect experience rate approach with prey. The viability of MPA has been surveyed by employing an extent of benchmark capacities, irregular scenes, and designing plan issues related to ventilation and building vitality proficiency. The evaluation's discoveries illustrated that MPA outflanked different cutting-edge optimization algorithms in a profoundly competitive way, such as GA, CS, PSO, SSA, GSA, CMA-ES, SHADE, and LSHADE-cnEpSin. In fact, MPA beat GA, CMA-ES, CS, SSA, PSO, and GSA measurably and was put moment by and large. Besides, it was found that MPA's execution was measurably comparable to that of SHADE and LSHADE-cnEpSin, two high-efficiency optimizers and IEEE CEC competition victors.

A modern developmental procedure named Multivariable Grey Prediction Evolution Algorithm (MGPEA) was proposed by Xu *et al*. [73]. It depends on the multivariable grey figure demonstrated by MGM (1, n). A developmental algorithm's populace arrangement is seen by the MGPEA as a time arrangement, and it is changed over into utilizing a guess exponential law for arrangement information. After that, it figures the taking after populace utilizing the MGM (1, n) demonstrate. The objective of MGPEA is to maximize the hereditary data chain's improvement slant inside a populace arrangement. A few benchmark capacities and engineering-constrained plan issues were utilized to evaluate MGPEA's execution. The comes about of comparative tests showed that MGPEA is compelling and prevalent to other strategies. The authors moreover recommended that this approach of building metaheuristics utilizing dim expectation models may rouse the advancement of other metaheuristics based on other expectation models.

Abualigah *et al*. [12] displayed a modern optimization algorithm named Aquila Optimizer (AO) imitating the conduct of Aquila in nature through chasing. The optimization method of AO is based on four diverse strategies of selecting, investigating, abusing, and swooping the look space to discover the ideal arrangement for diverse optimization issues. To approve the viability of AO, 23 well-known capacities, 10 CEC2019 test capacities, 30 CEC2017 test capacities, and 7 genuine issues were utilized within the arrangement of tests. The results of the tests showed that the AO algorithm outflanked well-known meta-heuristic strategies, illustrating its execution in settling complex optimization issues.

The Artificial Lizard Search Optimization (ALSO) algorithm is a scientific show propelled by the scrounging conduct of Redheaded Agama reptiles [51]. These reptiles have a well-organized and viable way of capturing prey, and the ALSO algorithm looks to capture this conduct in an optimization issue. The motivation for the ALSO algorithm comes from later ponders that appear how Redheaded Agama reptiles control the swing of their tails in a measured way to divert precise force from their bodies to their tails. This allows them to stabilize their body state of mind within the sagittal plane, which is vital for capturing prey in a single shot. Within the optimization issue defined by the ALSO algorithm, a swarm of reptiles is considered that's chasing prey. The algorithm is at that point mimicked and tried on different unimodal, multimodal, and other benchmark capacities to think about its execution compared to other well-known nature-inspired optimization methods. In expansion, the ALSO algorithm was tried on a protest location application, and the outcomes illustrated its adequacy over other state-of-the-art nature-inspired algorithms.

Mohammadi *et al*. [55] presented a swarm-based metaheuristic called Golden Eagle Optimizer (GEO), which is motivated by the chasing conduct of brilliant hawks. The falcons alter their speed and conduct amid diverse stages of chasing, and this conduct is displayed scientifically to form an optimization algorithm that equalizations investigation and misuse. GEO's execution was assessed against six other well-known algorithms and on 33 benchmark test capacities. The results illustrated that GEO performed superior to the other algorithms, illustrating its capacity to find the worldwide ideal and effectively avoid nearby optima. To unravel multi-objective issues, the authors also recommended the Multi-Objective Golden Hawk Optimizer (MOGEO), in expansion to GEO. MOGEO's execution was assessed against two other multi-objective algorithms and tried on ten multi-objective benchmark capacities. The results showed that MOGEO is prevalent to the other two algorithms in its capacity to surmise genuine Pareto ideal arrangements.

A modern optimization procedure, named Run beyond the metaphor (RUN), void of allegories and based on the scientific underpinnings of the Runge Kutta strategy was displayed by Ahmadianfar *et al*. [16]. In arrange to find curiously districts within the highlight space and make advance toward the worldwide ideal arrangement, the RUN algorithm utilizes the rationale of slant varieties computed by the RK strategy as a looking instrument for worldwide optimization. The Expanded Solution Quality (ESQ) component is another procedure utilized by the RUN algorithm to avoid nearby optima and speed up meetings. By differentiating the RUN algorithm from other algorithms on 50 test capacities and 4 real-world circumstances, the creators surveyed the RUN method's proficiency. With its speedy meeting rates, amazing investigation and abuse inclinations, and shirking of neighborhood optima, the RUN algorithm delivered greatly competitive and promising outcomes.

Abualigah *et al*. [6] proposed a modern meta-heuristic optimization algorithm, called the Reptile Search Algorithm (RSA), which is propelled by the chasing conduct of crocodiles. The RSA comprises two primary steps, to be specific encompassing and chasing. The encompassing step is performed by tall strolling or stomach strolling, whereas the chasing step is performed by chasing coordination or chasing participation. The RSA was assessed utilizing different classical and benchmark test capacities, as well as real-world building issues. It appeared that the RSA outflanked other existing optimization algorithms in terms of exactness and joining speed. Particularly, the basis of the benchmark tests demonstrated that the RSA is altogether predominant to other comparative strategies. Moreover, the idea of the building issues illustrated the adequacy of the RSA algorithm in understanding real-world issues.

2.2. Physics Based Algorithms

A new optimization technique called the Equilibrium Optimizer (EO) was motivated by models of monitor size mass balance that are employed in the estimate of equilibrium and dynamic states [32]. Every particle or solution, along with its focusing and location, functions as a explore agent in the EO algorithm. The equilibrium state is the best outcome, and these search agents change their concentrations at random concerning the achieving the best solutions. EO's capacity to avoid local minima, exploit, and explore is improved by the employment of a precise definition of “generation rate”. Three engineering application issues and 58 mathematical functions have been used as benchmarks. Three groups of current optimization techniques have been compared to the outcomes of EO:

1. Popular meta-heuristics like GA and PSO.
2. Newly created algorithms like GWO, GSA, and SSA.
3. High-efficiency optimizers like LSHADE-SPACMA, SHADE, and CMA-ES. The findings demonstrated that, although EO's performance was statistically comparable to that of SHADE and LSHADE SPACMA, it got the best results compared SSA, GWO, PSO, CMA-ES, GA, and GSA.

Transient Search Optimization (TSO), a unique optimization approach was presented, which took into account the transient behavior of switched electrical circuits including storage components like capacitance and inductanced in Qais *et al*. [63]. 23 benchmark issues were utilized to assess the exploitation and exploration abilities of the TSO algorithm, and the statistical outcomes were contrasted with those of 15 other current optimization methods. The TSO algorithm fared better than the other algorithms, as seen by the convergence curves, execution time, p-value test, and non-parametric sign test outcomes. Furthermore, three well-known engineering design problems with constraints were effectively solved using the TSO algorithm.

Motivated by the material science of Archimedes' Guideline, Hashim *et al*. [40] displayed the Archimedes Optimization Algorithm (AOA), a unused metaheuristic strategy. The AOA was differentiated with well known, writing, and prevalent distributed algorithms such as LSHADE-EpSin, L-SHADE, PSO, GA, and differential advancement varieties, WOA, SCA, HHO, and EO. The assessment was conducted on the CEC'17 test suite and four building plan challenges. The testing results demonstrated that AOA is proficient at taking care of troublesome issues and performs way better compared to the other algorithms in terms of exploration-exploitation adjustment and joining speed. The authors advertised a practical strategy for viably settling numerical optimization issues within the real world. More subtle elements concerning the algorithm's operation, parameters, and appropriateness to greater, trickier issues would be useful, even though.

In Hashim and Hussien [38], a modern optimization algorithm named Snake Optimizer (SO) was proposed, which is propelled by the mating conduct of snakes. The SO algorithm models the scrounging and generation conduct of snakes and employments it to perform optimization errands. The proposed strategy was tried on 29 unconstrained Congress on Developmental Computation (CEC) 2017 benchmark capacities and four compelled real-world designing issues. The execution of SO was compared with nine other well-known and recently created optimization algorithms. The comes about of tests illustrated that SO is a viable and proficient optimization algorithm that's able to investigate and abuse distinctive scenes with great adjustment. The meeting bend of SO is speedier than most of the compared algorithms, which appears the adequacy of the proposed strategy. The measurable comparisons to affirm the prevalence of SO over other optimization algorithms in terms of its exploration-exploitation adjustment and meeting speed.

2.3. Swarm Intelligence Based Algorithms

The Coyote Optimization Algorithm (COA) is later population-based metaheuristic algorithms that draw motivation from the canis latrans species [61]. COA was planned to handle the issues related to worldwide optimization, and it presents a novel algorithmic structure and instruments that balance nearby and worldwide look procedures. To assess the execution of COA, in arrange to perform a comparison investigation with other nature-inspired metaheuristics, a collection of benchmarks for boundary-constrained genuine parameter optimization was utilized. The discoveries appear that COA got way better comes about than other metaheuristics on the lion's share of the examined capacities and was able to discover reasonable arrangements. Generally, the COA shows up to be a promising expansion to the field of optimization algorithms, and its utilization of normal motivation seems to lead to assist bits of knowledge into the behaviour of complex frameworks. Future investigations may explore the components basic to the victory of the COA, and explore its potential applications totally different areas.

It is interesting to see how nature can rouse us to make modern and inventive arrangements for issues, as illustrated by the farmland ripeness metaheuristic algorithm displayed by Shayanfar and Gharehchopogh [65]. The utilization of metaheuristic algorithms has developed in notoriety over the past long time, as they offer an effective apparatus for tending to troublesome optimization issues in a run of disciplines, counting science, building, and financial matters. The farmland ripeness algorithm is unique in its approach because it separates the optimization issue into smaller parts and optimizes each area utilizing two sorts of memory: inner and outside. By mirroring the way that farmland is organized and overseen in nature, the algorithm can optimize arrangements more effectively and successfully than other metaheuristic algorithms, as illustrated by the recreations performed on 20 scientific optimization issues. assessing the agrarian richness algorithm's execution against that of other well-known metaheuristic algorithms, like improved PSO, ABC, FA, HS, PSO, DE, and BA, the results clearly showed that the farmland ripeness algorithm performs superior in general. This is often particularly genuine for issues with bigger measurements, where the proficiency of other algorithms diminishes altogether, but the farmland ripeness algorithm is still able to get superior comes about.

A novel sort of metaheuristic optimization method to be specific the Moth Search (MS) algorithm was persuaded through the require flights and of phototaxis moths [72]. In this algorithm, the fittest moth person is considered as the light source, and other moths are pulled in towards it either through coordinate development or require flights. This approach combines both investigation and abuse forms, making it a flexible optimization strategy. The MS algorithm was compared with five comparable metaheuristic optimization algorithms utilizing fourteen fundamental benchmarks, a set of IEEE CEC 2005 benchmarks, and a set of IEEE CEC 2011 real-world issues. The results outline that the MS algorithm got the finest arrangements for the foremost capacities and real problems compared to the other strategies. Subsequently, the MS algorithm could be a promising approach to optimization issues, particularly in cases where conventional optimization strategies may not perform ideally. The algorithm's execution is due to its capacity to use the phototaxis and exact flights of moths, which are normal forms that have advanced to help moths in exploring their environment.

Kallioras *et al*. [45] displayed that the Pity Beetle Algorithm (PBA) draws motivation from the conduct of the Pityogenes chalcographus creepy crawly to illuminate optimization issues and has appeared to be successful in deciding worldwide optima for uni-modal and multi-modal capacities. It is additionally empowering that PBA can handle NP-hard optimization issues in any case of their scale, recommending its potential for real-world applications. Comparing PBA against other metaheuristic algorithms, particularly those that were inspected on the CEC 2014 benchmark, could be a thorough way to evaluate its proficiency and competitiveness. It would be accommodating to know more about the particular execution measurements and assessment criteria utilized in this comparison, as well as any impediments or challenges experienced in applying PBA to these benchmark issues. Generally, this work includes the extending corpus of information on bio-inspired optimization algorithms and their capacity to resolve challenging optimization issues. It would be captivating to watch PBA's execution on distinctive sorts of issues and in down-to-earth settings.

The Butterfly Optimization Algorithm (BAO) could be a new nature-inspired metaheuristic algorithm that mirrors the rummage around for nourishment and mating state of mind of butterflies [23]. ABO depends on the way butterflies scavenge, utilizing their sense of scent to discover conceivable accomplices or nectar sources. ABO is outlined to settle worldwide optimization issues and has appeared superior execution than conventional approaches and other metaheuristic algorithms. The victory of ABO can be credited to its capability to execute worldwide the look space by mirroring the scrounging conduct of butterflies. ABO can bargain with the exploration and exploitation of the look space, which empowers it to discover superior arrangements. Besides, it could be a plain and easy-to-implement algorithm that is utilized to assist address an assortment of optimization issues. ABO was inspected and assessed utilizing a set of 30 benchmark capacities and differentiated with other metaheuristic algorithms. The comes about outlined that ABO is more effective than other metaheuristic algorithms in settling these test capacities. Moreover, ABO has been connected to settle common designing problems(i.e., spring plan, equip prepare plan and welded bar plan). The results outlined that ABO is able to discover way better arrangements than other metaheuristic algorithms in these building issues as well.

A recent meta-heuristic algorithm named DHOA has been presented by Brammya *et al*. [26] and is motivated by how individuals chase deer. DHOA includes two seekers, a pioneer and a successor, who move toward the prey, overhauling their positions until they reach the target. DHOA's execution was compared to comparative optimization algorithms, and the result displayed that DHOA got the leading arrangements on 39 benchmark capacities and three designing applications. Moreover, DHOA was inspected in real-time building applications, and the comes about appeared that it beat existing optimization algorithms. By and large, the creators proposed a novel algorithm propelled by the chasing conduct of people and illustrated its adequacy in optimization and classification issues.

In Harifi *et al*. [37], the authors proposed a new metaheuristic algorithm namely Emperor Penguins Colony (EPC), which is inspired by the behavior of emperor penguins. The penguins' body heat radiation and their spiraling movements inside their colony serve as indicators for the algorithm. This research is significant because it demonstrates the potential of using nature-inspired algorithms to fix complex optimization problems. The EPC algorithm takes motivation from the behaviour of sovereign penguins, which is an inventive and curious approach to the algorithm plans. The conclusion outlined that the EPC algorithm demonstrated its proficiency in settling a different kind of optimization issues. As well because it compared with eight other metaheuristic algorithms utilizing ten benchmark capacities. The results show that the EPC algorithm got the leading comes about compared to the other metaheuristic algorithms in deciding the optimal solutions. In this way, the creators highlighted the significance of nature-inspired metaheuristics within the field of optimization and gave a novel approach to the algorithm plan which will lead to assist propels within the field.

The Sea Lion Optimization (SLnO) algorithm may be a later proposed nature-inspired metaheuristic optimization algorithm that mirrors the chasing conduct of sea lions in nature, particularly their utilize of hairs to distinguish prey [53]. SLnO depends on the chasing conduct of sea lions. Sea lions use their whiskers to detect the location of prey, and SLnO uses a similar approach to locate the best solution to an optimization issue. The two primary phases of the algorithm are exploitation and exploration. Sea lions look for viable answers in the search space during the exploration phase. In the exploitation phase, the sea lions concentrate on the search space's most promising areas. SLnO has been examined using benchmarks, and the optimization results demonstrated that SLnO achieved bast results in contrast to other well-known optimization methods as DA, PSO, WOA, GWO, and SCA.

Khishe and Mosavi [50] displayed the Chimp Optimization Algorithm (ChOA), a novel metaheuristic optimization algorithm modelled around chimpanzees' collective chasing strategies. ChOA is planned to illuminate high-dimensional issues by speeding up the joining and stuck-in neighborhood optima. The ChOA employments a scientific strategy of different insights and sexual boost, recreating four sorts of chimps: assailant, driver, chaser, and obstruction, to extend differences within the arrangement space. Within the ChOA, the parts are relegated to distinctive chimp sorts, and each chimp has its claim set of parameters to alter amid the optimization handle. The creators tried the ChOA algorithm on 30 benchmark capacities and utilized four comparable algorithms to assess the execution of ChOA. The assessment criteria contain the exactness, meeting speed, and probability of getting to be caught in neighborhood minima. The results showed that the ChOA beat the other algorithms in all assessment criteria. The algorithm accomplished a speedier merging speed, way better shirking of nearby optima, and higher exactness in getting the ideal arrangement.

Hayyolalam and Kazem [41] presented a new algorithm, called the Black Widow Optimization (BWO) Algorithm, for settling persistent nonlinear issues. The BWO is mimetic from the special mating behaviour of black widow creepy crawlies and contains an elite stage of cannibalism, which makes a difference in early merging by disposing of species with improper wellness. The execution of the BWO was assessed on 51 benchmark capacities, and the results illustrate that the BWO performed well in accomplishing the most excellent arrangements for the issues. The BWO is found to have highlights in different viewpoints, like speeding up meetings and getting ideal wellness values compared to other comparable algorithms. It moreover gives promising comes about and has the capability of settling issues within the genuine world with new and troublesome settings. The creators too connected the BWO to three distinctive challenging designing plan issues and appeared that it is viable in understanding these issues as well. The case about comes about appears how the recommended method can be utilized to illuminate down-to-earth issues.

Alsattar *et al*. [19] proposed the Bald Eagle Search (BES) algorithm, a novel optimization strategy modelled after bare eagles' fish-hunting strategies. Three steps make up the BES algorithm: swooping, selecting space, and looking in space. Beginning with choosing the space with the foremost prey. Within the moment arrange, it searches for prey inside that space, and within the third organize, it swoops down on the optimal point decided amid the look. The BES algorithm was assessed employing a three-part technique that includes benchmarking the optimization issue, comparing the algorithm's execution with other procedures, and assessing its execution based on standard deviation, normal, ideal point, and measurable tests. The results of the ponder showed that the BES algorithm performed well compared to other algorithms and conventional strategies.

The Rain Optimization Algorithm (ROA) could be a new metaheuristic algorithm that's propelled by the natural conduct of raindrops [54]. ROA is outlined to hunt for the worldwide least of a given work, whereas moreover being able to discover nearby minima. ROA could be a population-based algorithm which spoken to by a set of raindrops that move towards the least focus after coming to the soil. In various measurements and real-world optimization issues, the ROA strategy was compared to other algorithms counting PSO and BA on 26 benchmarks and three benchmarks. The results of these comparisons have appeared that ROA is competitive with other algorithms within the writing, and in a few cases beat them. ROA is able to decide the worldwide least of a work with tall exactness, whereas too being able to discover neighborhood minima.

The Shuffled Shepherd Optimization Algorithm (SSOA) may be a modern metaheuristic optimization algorithm that points to moving forward the optimization prepared by mimicking a shepherd's characteristic conduct [48]. The SSOA isolates the specialists into multi-communities and applies a rearranged shepherd administrator to move forward with the optimization preparation. The rearranged shepherd administrator is motivated by the behavior of a shepherd who moves the sheep from one area to another to rummage around for way better-brushing ranges. The administrator rearranges the specialists inside the communities and chooses the finest people as pioneers to direct the optimization prepare. A few well-known benchmark problems are given the SSOA algorithm treatment, and some visually appealing structures are optimized. The SSOA method performed better than different optimization techniques perform better in terms of solution quality and convergence speed.

Kaur *at al*. [46] proposed a recent optimization algorithm called Tunicate Swarm Algorithm (TSA) that is inspired by the navigation and foraging behaviours of tunicates. TSA uses of bio-inspired approaches, such as imitating the behaviours of tunicates, is a novel and interesting direction for optimization research. The performance of TSA is tested on various benchmark test problems, and its efficacy is compared with several other metaheuristic approaches. The TSA was also applied to several real problems to verify its robustness. The evaluation of TSA included sensitivity, convergence, and scalability analysis, as well as an ANOVA test. The outcomes illustrated that TSA outperformed other competitive algorithms in terms of generating better optimal solutions. Furthermore, TSA was shown to be efficient in fixing real case studies with various search spaces.

Kaveh and Eslamlou [47] presented a novel optimization paradigm called the Water Strider Algorithm (WSA) inspired by the behaviour and characteristics of water strider bugs. The method is population-based and consolidates regional conduct, mating fashion, swell communication, progression of water striders, and bolstering components in its scientific detailing. 44 numerical errands, 4 chronicled cases, 2 large-scale basic measure optimizations, and 1 auxiliary harm distinguishing proof were utilized to benchmark the WSA. The creators utilized two stages to guarantee the effectiveness of the WSA against potential inclinations. Different parametric and nonparametric tests were performed, and the algorithm is compared with trustworthy and cutting-edge algorithms to grandstand its usefulness. The results demonstrated that the WSA can effectively handle different challenging issues, counting conventional persistent and discrete basic plan issues, both constrained and intemperate.

In Abdollahzadeh *et al*. [3], the authors presented a modern metaheuristic algorithm named African Vultures Optimization Algorithm (AVOA) that's motivated by the scavenging and route practices of African vultures. In a comparison think about, the proficiency of the AVOA was surveyed on 36 common benchmark capacities and differentiated with several other algorithms. The discoveries illustrated that AVOA performed compared to the other algorithms on 30 of the 36 benchmark functions and on the most of designing plan issues. The Wilcoxon rank-sum test was utilized to factually assess the AVOA's execution, and it demonstrated that AVOA was altogether predominant to the other algorithms at a 95% certainty interim. The comes about illustrated the appropriateness and black-box nature of the AVOA algorithm, making it a promising approach for tackling optimization issues in different spaces.

The proposed Artificial Gorilla Troops Optimizer (GTO) may be a modern metaheuristic algorithm propelled by the social insights of gorilla troops in nature [4]. GTO algorithm employments scientific definitions of gorillas' collective life and joins modern investigation and exploitation instruments to settle optimization issues. To assess the effectiveness of the GTO, the algorithm was utilized to 52 standard benchmark capacities and seven building issues. The results were compared to a few existing metaheuristic algorithms utilizing factual tests. The results appeared that, for the lion's share of benchmark capacities, the GTO performed way better than the comparison algorithms, particularly for high-dimensional issues. This proposes that the GTO is a viable optimization algorithm that can surrender superior results than elective metaheuristics.

Arithmetic Optimization Method (AOM), presented by Abualigah *et al*. [9], is one of the recent optimization strategies that utilize the dissemination behavior of subtraction, expansion, division, and increase - the four essential number juggling operations in arithmetic. AOM is actualized and logically modelled to carry out the optimization over a wide range of look spaces. To show how pertinent AOM is, its execution was evaluated utilizing an assortment of real-world building plan challenges and 29 benchmark capacities. They think about inspecting AOM's computational complexity, merging behaviors, and execution in different settings. Agreeing with the testing outcomes, AOM fared way better at handling troublesome optimization issues than eleven other well-known optimization strategies. As a result, AOM offers a practical strategy for settling challenging optimization issues.

Propelled by the Ebola virus's mode of transmission, Oyelade *et al*. [60] presented the Ebola Optimization Search Algorithm (EOSA), a novel metaheuristic optimization algorithm. The altered SIR show, known as SEIR-HVQD, which consolidates additional sub-populations for immunized, hospitalized, isolated, and perished individuals, serves as the establishment for the algorithm. Two sets of benchmark functions - classical and constrained IEEE-CEC benchmark functions - were utilized to survey the execution of the EOSA. Based on versatility, merging, and affectability evaluations, the EOSA fared superior to other well-known metaheuristic algorithms, such as PSO, GA, and ABC. Moreover, the Convolutional Neural Network (CNN) hyperparameters were optimized utilizing the EOSA for advanced mammography picture categorization. The CNN engineering that was optimized was able to recognize breast cancer from computerized pictures with 96.0% exactness.

Motivated by the savvy chasing propensities of nectar badgers, Hashim *et al*. [39] formulated the Honey Badger Algorithm (HBA), a modern optimization method. The program breaks down the energetic look behavior of nectar badgers into stages of investigation and abuse in arrange to unravel optimization issues rapidly. Controlled randomization approaches are another tool that HBA uses to preserve population variety during the search. HBA's efficacy was evaluated by contrasting its results with those of ten popular metaheuristic algorithms: MFO, EHO, WOA, GOA, TEO, and HHO; SA, PSO; success-history based adaptive differential evolution variations with linear population size reduction; covariance matrix adaptation evolution strategy; and so on. the authors solved four engineering design challenges, the CEC'17 test-suite, and 24 common benchmark functions to assess performance. The outcomes of the experiment and the statistical analysis showed that HBA was better than the other study methods for resolving complicated search space optimization issues in terms of convergence speed and exploration-exploitation balance. Therefore, the proposed HBA algorithm might work well as an optimization method to solve real-world optimization problems.

Naruei and Keynia [59] presented a new optimization algorithm named the Wild Horse Optimizer (WHO) that takes inspiration from the group behaviour of wild horses, particularly their decency behaviour. The WHO algorithm mimics the behaviour of horses in a group, including mating, chasing, leading, dominating, and grazing. However, the crucial behaviour that determines horses is their decency behaviour, where foals leave the group before reaching puberty to prevent mating with their father or siblings. The WHO algorithm was examined with other similar algorithms using various sets functions like CEC2017 and CEC2019. The outcomes of the study showed that the WHO algorithm performed competitively and yielded promising results compared to other optimization algorithms.

The Mountain Gazelle Optimizer (MGO) could be a meta-heuristic optimization algorithm motivated by the social life and progression of wild mountain gazelles [5]. It employments a numerical detailing of gazelle conduct to create a look technique that can be utilized to fathom optimization issues. The MGO algorithm has been assessed and tried on both standard benchmark capacities and building issues, and it has been compared with nine other capable meta-heuristic algorithms to approve its about. The results of the tests illustrated that the MGO performed way better than the other algorithms on most benchmark capacities. Besides, the MGO keeps up its look capabilities and appears great execution indeed when expanding the measurements of the optimization issues. The performance of the MGO algorithm was demonstrated using Wilcoxon's rank-sum and Friedman's tests, which showed significant differences between the comparative algorithms.

2.4. Human Based Algorithms

Mousavirad and Ebrahimpour-Komleh [57] introduced a new metaheuristic optimization algorithm inspired by the hunting behavior of birds, called Human Mental Search (HMS). The algorithm mimics the strategies employed by birds in searching for prey, and it is effective in solving various optimization problems. The algorithm has three primary steps:

1. Mental search.
2. Grouping.
3. Moving solutions.

Mental search involves exploring the area of nearly every solution using Levy flight. Grouping locates a committed area, and going solutions include moving solutions to achieve the best strategy. The authors evaluated the performance of the HMS algorithm using several exam functions with various features and nine similar algorithms were used to conduct a comparison with HMS. Moreover, the discoveries were analyzed utilizing the Friedman test and the Wilcoxon marked rank test. Concurring with the testing discoveries, the HMS algorithm outflanked other algorithms in terms of yield. The commitment of the work is to supply a population-based metaheuristic algorithm that imitates the offered space investigation strategies in online barters while being clear and viable. The algorithm has applications in commerce, restorative, and agribusiness, among other divisions.

Inspired by the strategic movement of troops during conflicts, Ayyarao *et al.* [24] devised a new optimization technique dubbed War Strategy Optimization (WSO). Each soldier in the WSO algorithm moves dynamically in the direction of the optimal value, modeling two common combat strategies: attack and protection. The soldiers' positions on the battlefield are upgraded by the algorithm based on the strategy that is employed. The authors added a weak soldier's relocation technique and a novel weight-updating mechanism to increase the algorithm's robustness and convergence. The exploration and exploitation phases were well-balanced by the WSO algorithm. They also provided a thorough mathematical description of the algorithm and evaluated its performance on four engineering issues and 50 benchmark functions. The experimental findings for a variety of optimization issues demonstrated the superiority of the WSO method, whose performance was compared with ten well-known metaheuristic algorithms.

3. Analytical Analysis

This section shows a set of statistical analysis to compare the proposed MAs. The method is divided into two main groups; the first comparison is related to the journals used for publication and their characteristics as shown in Figures 2 and 3 while the second is related to the characteristics of each algorithm as shown in Tables 1 and 2.

Figure 2 illustrates the number of published articles (i.e., the proposed new algorithms) between 2017 and Feb-2024. The researchers relied on traditional algorithms for their research. Thus, it can be noticed that there are just two articles published in 2017. Research issuance continued until it reached its peak in 2020 when the number of proposed new algorithms was 16 algorithms. While in 2021 and 2022 the number of proposed new algorithms decreased to 8 and 7 algorithms, respectively. In 2023 the researchers introduced 15 new algorithms and they still working to introduce more novel nature-inspired algorithms where the number of published articles to 7 by Feb-2024.

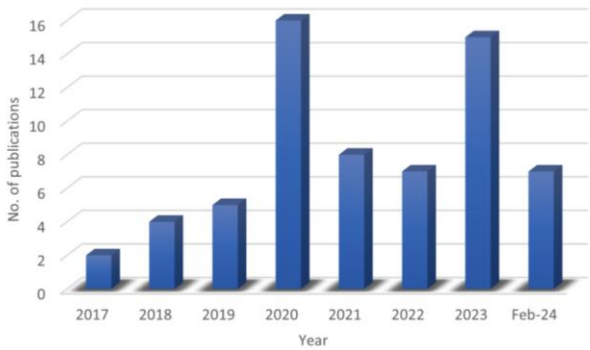

Figure 2. Number of articles between 2017- Feb-2024.

Figure 3 shows the number of articles that were accepted in different journals, as well as the impact factor of the journals. The aim of the figure is to show the strength of the proposed algorithm, which is directly related to the strength of the journal. Thus, it can be noticed that the highest impact factor to the artificial intelligence review journal. While the optimal journal is Expert System with Applications which achieved published the maximum number of articles with a high impact factor.

Table 1 shows a comparison between the features of the proposed algorithms. These features focus on the main mechanisms and the strengths of the MAs, such as the number of citations which refer to the efficiency of the algorithms (i.e., it proves its efficiency to deal with different problems in various fields), the exploration and exploitations search techniques indicates the ability of the algorithm to deal with global and local search, diversity convergence rate refer to the quality of the selected solutions and avoid stuck in the local optima. Finally, the dataset (i.e., benchmark functions and real problems) is used to evaluate the efficiency of the proposed algorithm.

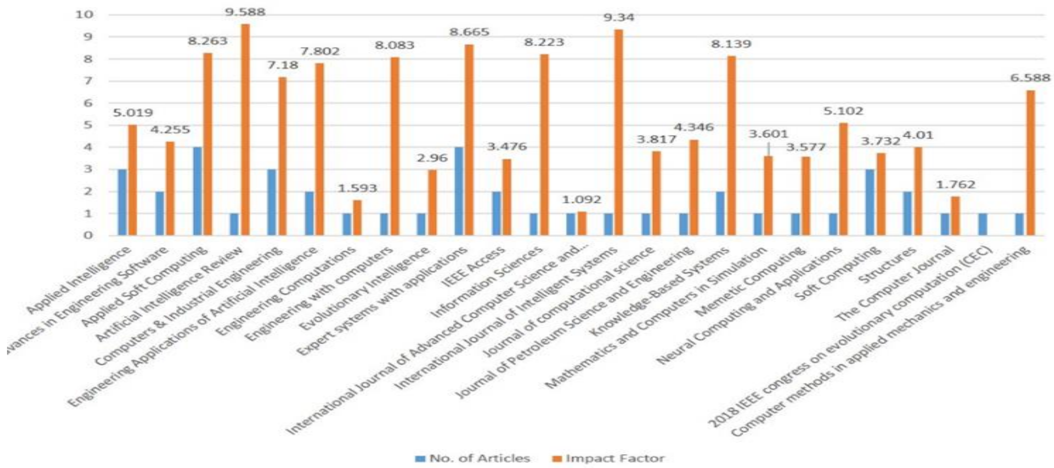

Figure 3. Number of published articles in different journals.

Table 1. The features of the recent metaheuristic algorithms.

Year	Author	Abbrev.	Citation	Exploitation technique	Exploration technique	Convergence rate	diversity	Benchmark functions	Real problem
2017	Mousavirad *et al.*[57]	HMS	171		√		√	√	
	Qi *et al.* [64]	ABO	85		√	√		√	
2018	Pierezan *et al.* [61]	COA	515	√	√		√	√	
	Shayanfar *et al.* [65]	FA	301		√	√		√	
	Wang *et al.* [72]	MS	748	√	√				
	Kallioras *et al.* [45]	PBA	105	√	√			√	
2019	Yapici *et al.* [74]	PFA	272	√	√			√	
	Arora *et al.* [23]	BOA	1238		√			√	√
	Brammya *et al.* [26]	DHOA	211	√	√	√		√	√
	Hariifi *et al.* [37]	EPC	152		√			√	
	Masadeh *et al.* [53]	SLnO	203	√	√	√		√	
2020	Zhao *et al.* [77]	AEO	308	√	√	√		√	√
	Kaveh *et al.* [49]	BOA	92	√	√			√	
	Hayyolalam *et al.* [41]	BWO	578	√	√	√		√	
	Khishe *et al.* [50]	ChOA	737	√	√	√			√
	Ghafil *et al.* [34]	DDAO	99		√	√		√	
	Faramarzi *et al.* [32]	EO	1525	√	√	√	√	√	√
	Ahmadianfar *et al.* [15]	GBO	505	√	√	√	√	√	√
	Faramarzi *et al.* [31]	MPA	1477	√	√	√	√	√	√
	Xu *et al.* [73]	MGPEA	52		√	√		√	√
	Alsattar *et al.* [19]	BES	433	√	√		√	√	
	Moazzeni *et al.* [54]	ROA	67	√	√	√		√	
	Fathollahi *et al.* [33]	RDA	352		√	√	√	√	√
	Kaveh *et al.* [48]	SSOA	127	√	√	√		√	√
	Qais *et al.* [63]	TSO	116	√	√	√		√	
	Kaur et al. [46]	TSA	875	√	√	√		√	√
	Kaveh *et al.* [47]	WSA	155	√	√	√	√	√	
2021	Abdollahzadeh *et al.* [3]	AVOA	684	√	√	√	√	√	√
	Abualigah *et al.* [12]	AO	1395	√	√	√		√	
	Hashim *et al.* [40]	AOA	679	√	√	√	√	√	√
	Abdollahzadeh *et al.* [4]	GTO	526	√	√	√		√	√
	Kumar *et al.* [51]	ALSO	28		√	√		√	√
	Mohammadi *et al.* [55]	GEO	261	√	√	√		√	√
	Ahmadianfar *et al.* [16]	RUN	616	√	√	√	√	√	√
	Abualigah *et al.* [9]	AOM	1748	√	√	√		√	√
2022	Oyelade *et al.* [60]	EOSA	282	√	√	√		√	√
	Hashim *et al.* [39]	HBA	588	√	√	√	√	√	√
	Ayyarao *et al.* [24]	WSO	147	√	√	√		√	√
	Naruei *et al.* [59]	WHO	236	√	√	√	√	√	√
	Hashim *et al.* [38]	SO	350	√	√	√		√	√
	Abualigah *et al.* [6]	RSA	795	√	√	√	√		√
	Abdollahzadeh *et al.* [3]	MGO	134	√	√	√		√	√
2023	Mohammed *et al.* [56]	FOX	40	√	√	√	√	√	
	Hu et al. [43]	CSA	34	√	√			√	√
	Tian *et al.* [71]	SGA	36	√	√	√		√	√
	Dehghani *et al.* [29]	KOA	5		√	√	√	√	
	Dehghani *et al.* [28]	LOA	2		√			√	
	Amiri *et al.* [21]	HO	-		√	√		√	
	Hu *et al.* [42]	GKS	21	√	√	√	√	√	√
	Agushaka *et al.* [14]	GOA	133	√	√	√		√	
	Dalirinia *et al.* [27]	LEA	3		√				√
	Majumder [52]	TAOA	4		√	√		√	
	Abdel-Basset *et al.* [2]	NOA	62	√	√	√	√	√	√
	Anaraki *et al.* [22]	HSOA	2		√		√	√	
	Zhao *et al.* [76]	SHO	63	√	√	√		√	
Feb, 2024	El-kenawy *et al.* [30]	GGO	39	√	√	√		√	√
	Han *et al.* [36]	WO	3		√		√	√	√
	Ahmed *et al.* [17]	GBO	1		√			√	
	Al-Betar *et al.* [18]	EHO	-	√	√	√		√	
	Abdel-Basset *et al.* [1]	CPO	-		√	√	√	√	
	Priyadarshini [62]	DGO	-	√	√	√	√	√	√

The results of the above table illustrate that the most effective algorithm such as AOA, EO, MPA, BOA, and MS algorithms achieved the highest citations 1039, 995, 909, 860, and 639, respectively (knowing that the number of citations was counted until February 29, 2024). It can be noticed that these algorithms included all features. It must be taken into account that the number of citations is related to the date of the algorithm's release. In other words, some new introduced algorithms may have high efficiency, but they didn't achieve high citations because of their short age.

In addition to the comparisons mentioned in Table 1. Table 2 shows more details of the recent proposed MAs, such as the number of parameters, time complexity, the non-parametric test used, and the availability of the source code.

Table 2. The details properties of the recent metaheuristic algorithms.

Abbrev.	Variables	Complexity	Non-parametric test	Code
HMS	9	$O((n+k)d)$	Wilcoxon rank sum and Friedman test	-
ABO	5	$O(n^2t)$	-	-
COA	4	$O(T2-T1)/T0$	Wilcoxon Mann Whitney and Friedman	-
FA	6	$O(N*D)+O(T*N*D)$	-	-
MS	4	$O(T*NP*D)$	-	-
PBA	5	$O(T*NP*n)$	-	Available in [72]
PFA	6	$O(N*D)*T_{Max}$	-	-
BOA	5	$O(N-N1)*D)$	Wilcoxon rank-sum test	-
DHOA	8	$O(H.k)$	-	Available in [70]
EPC	5	$O(k*n*Max_{iter}*N*d)$	Friedman's and Iman Davenport's	-
SLnO	6	$O(mn)$	-	-
AEO	5	$O((N*D+N*D+n)*T_{MAx})$	-	Available in [77]
BOA	5	$O(n^2+TD)*T$	-	-
BWO	6	$O(T(N^2+ND+N))$	-	-
ChOA	5	$O(T*3*D$	-	Available in [50]
DDAO	4	$O(T*N^2)-(T*D)$	-	Available in [34]
EO	6	$O(tnd-ten)$	Friedman's and Iman Davenport's	Available in [6]
GBO	7	$O(dE(P)r^2)$	-	Available in [15]
MPA	5	$O(t(nd+Cof*n))$	Friedman, Bonferroni Dunns and Holm	Available in [31]
MGPEA	4	$O(nNP)$	-	-
BES	6	$O(nd+n^2)$	Wilcoxon rank-sum test	Available in [69]
ROA	5	$O(N*(T+TD+1))$	-	-
RDA	4	$O(n*D*t_{max})$	-	Available in [67]
SSOA	6	$O(m^2)$	-	-
TSO	7	$O(N*(L_{max}D+L_{max}+1))$	Wilcoxon rank-sum test	-
TSA	4	$O(MAx_{iter}*n*d*N)$	Analysis of Variance	Available in [48]
WSA	4	$O(N+C*T)$	Kruskal Wallis	-
AVOA	6	$O(T*N*D)$	Wilcoxon rank-sum test	Available in [49]
AO	7	$O(N*(T*D+1))$	-	-
AOM	6	$O(T(1+2n+2nlogn))$	Wilcoxon rank-sum test	Available in [43]
GTO	5	$O(N*(1+T+TD)*2)$	Wilcoxon rank sum and Friedman test	-
ALSO	9	$O(nm^2)$	t test	Available in [75]
GEO	7	$O(n_{popul}*n_{dim})$	Kruskal Wallis	-
RUN	6	$O(2N+2N^2*(3N+N^2+3^2))$	-	Available in [55]
AOA	6	$O(N*(ML+1))$	Friedman test	Available in [63]
EOSA	8	$O(MS*M+MS+log(MS))$	Friedman test	Available in [9]
HBA	6	$O(t_{max}*N*D)$	Friedman test	Available in [60]
WSO	8	$O((N+1)*D*Max_{iter})$	Wilcoxon rank-sum test	-
WHO	6	$O(Nn+NTn+NTn+NTn)$	Friedman test	Available in [39]
SO	5	$O(m^3)$	-	Available in [40]
RSA	5	$O\left((N^2-N)*TD\right)*2$	Friedman test	-
MGO	7	$O(T(1+2nlogn))$	Wilcoxon rank sum and Friedman test	Available in [56]
FOX	4	$O(n^2)$	Wilcoxon rank-sum test	Available in [76]
CSA	5	$O(ln)$	Wilcoxon rank sum and Friedman test	Available in [66]
CMPA	3	$O(n)$	Wilcoxon rank-sum test	Available in [68]
KOA	4	$O(Nm(1+2T))$	Wilcoxon rank sum test	-
LOA	5	$O(Nm)$	Wilcoxon rank sum test	-
HO	3	$O(Nm\left(1+\frac{5*T}{2}\right))$	Wilcoxon rank sum and Friedman test	Available in [56]
SCSO	4	$O(N*m)$	Wilcoxon rank sum test	-
GKS	5	$O(Nm(1+T))$	Wilcoxon rank sum and Friedman test	-
GOA	3	$O(n)$	Wilcoxon rank sum and Friedman test	-
LEA	6	$O(n^2)$	Friedman test	Available in [10]
TAOA	4	$O(n^2*m)$	Wilcoxon rank sum test	-
NOA	5	$O(n^2)$	Friedman test	-
HSOA	5	$O(Max_{nfes}.D+f)$	Wilcoxon rank sum and Friedman test	Available in [22]
SHO	8	$O(ln)$	Friedman test	-
GGO	5	$O(Nm(1+T))$	Wilcoxon rank sum test	-
WO	4	$O(n^2)$	Wilcoxon rank sum and Friedman test	Available in [21]
GBO	5	$O(n^2*m)$	Wilcoxon rank sum test	-
EHO	6	-	Friedman test	-
CPO	4	-	Wilcoxon rank sum test	Available in [1]
DGO	6	-	Wilcoxon rank sum and Friedman test	-
SGA	4	$O(n^2)$	Wilcoxon rank sum and Friedman test	Available in [36]

The aim of Table 2 is to aid the researchers to select the optimal algorithm based on the complexity, the number of parameters and whether the code is available by the authors or not.

Moreover, the comparison is aimed at helping researchers distinguish the differences and similarities among the algorithms, providing insights into their strengths and weaknesses. So, the following points highlight the main terms of optimization algorithms.

- Exploration vs. Exploitation: each algorithm employs different strategies to balance exploration and exploitation. For instance, HMS uses Levy flight for mental search (exploration) and grouping for exploitation, while MS uses phototaxis behavior for both. The balance between these processes is crucial for achieving optimal solutions.
- Diversity and Convergence: algorithms like ABO and EPC maintain diversity through nature-inspired behaviors, preventing premature convergence. In contrast, algorithms like BWO and ChOA use unique mechanisms (cannibalism and role assignment, respectively) to enhance convergence speed while maintaining solution diversity.
- Performance Metrics: the algorithms were evaluated on various performance metrics, including accuracy, convergence speed, and robustness. Comparative studies on benchmark functions revealed that algorithms like HMS, COA, and DHOA consistently achieved high performance across different metrics.

4. Limitations and Potential Drawbacks

Despite the remarkable capabilities of the reviewed metaheuristic algorithms, it is crucial to acknowledge their limitations and potential drawbacks to provide a balanced and critical perspective. A common challenge across many of these algorithms is their dependency on specific problem structures. Algorithms like the HMS and COA often show diminished effectiveness when applied to problems with irregularities or non-uniform distributions of optimal solutions [44]. This can lead to premature convergence, where the algorithms get trapped in local optima, hindering their ability to explore the solution space thoroughly.

Parameter sensitivity is another significant limitation observed in several algorithms. The performance of COA, Farmland Fertility Algorithm, and others can be highly dependent on the careful tuning of parameters. This requirement for fine-tuning can be a barrier to their practical application, particularly in real-time scenarios or in cases where the problem characteristics are not well understood beforehand. Additionally, the computational complexity associated with some algorithms, such as the Farmland Fertility Algorithm and ChOA, can pose challenges when applied to large-scale or real-time optimization problems, as they require significant computational resources and time.

The reliance on specific natural or behavioral metaphors can also limit the adaptability of these algorithms. For instance, the MS Algorithm, ABO, and EPC Algorithm are based on the behaviors of certain animals or natural phenomena, which may not always translate effectively to diverse optimization problems. This reliance on specific behaviors can restrict the algorithms' applicability and robustness across various problem domains, particularly in highly complex or irregular search spaces.

Moreover, the balance between exploration and exploitation is a critical factor that can influence the effectiveness of these algorithms. Many of the reviewed algorithms, such as the DHOA and PFA, face challenges in maintaining this balance. Inadequate exploration can lead to early convergence, while insufficient exploitation may result in the algorithms failing to converge efficiently. This balance is particularly difficult to achieve in multimodal optimization landscapes, where the algorithms need to navigate through multiple local optima to find the global optimum.

Noisy environments and high-dimensional optimization problems also present significant challenges. Algorithms like the SLnO Algorithm and BWO Algorithm may struggle in noisy environments or when applied to high-dimensional problems, where the search space is vast and the signal-to-noise ratio is low. These conditions can impede the algorithms' ability to locate optimal solutions effectively.

5. Conclusions

This review collected 64 recent Metaheuristic Algorithms that were introduced during the period between 2017 and Feb-2024. Also, highlighted the mechanism of each algorithm. As well as, a set of comparisons have been made between the algorithms to enable researchers to distinguish between algorithms and choose the most appropriate algorithm to solve their problems. In addition, the review provides an indirect guide for researchers who plan to propose a new algorithm by taking advantage of the features of the previous methods, such as including both of search techniques (i.e., Exploration and Exploitation), increasing the diversity, keeping the convergence rate, applying benchmark functions and real word problems, providing the source code, and selecting the journal with high impact factors. These elements play an important role in classifying the algorithm and entering the field strength. In contrast, avoiding the obstacles of the previous methods.

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