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Nature-inspired Metaheuristic Algorithms for Multi-modal Optimization Problems: A Comprehensive Review

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Abstract.

Recently, Nature-Inspired Algorithms (NIAs) have received significant attention in the literature reviews and applications. This algorithmic family mimics nature-based processes to tackle complex optimization problems. Many problems in the industry, science, medicine, and engineering are becoming optimization problem challenges. More than 500 algorithms have been proposed till today to tackle specific problems in the different articles. Many researchers call these algorithms novel; these algorithms will be explaining in this study. New taxonomy and classification would be described. It has been found that nature-based algorithms have some problems and time complexity limits that could lead to a new direction for them in the future. This research would be used to study and understand the time complexity and parameter affection the computation time of recently developed nature-based algorithms for multi-modal problems and applications.

Key words: Nature-based algorithms, meta-heuristic, optimization, multimodal , time complexity

1. Introduction

Optimization is now a big deal for every field from design to science to find optimal solution. It focuses on finding the optimal values of functions, or objective functions, in a relation to real-world issues while considering specific restrictions, and encompasses a diverse range of techniques derived from operation research, artificial intelligence, computer science, and machine learning [1]. Over the last four decades, the use of nature-inspired metaheuristic algorithms has become increasingly popular [1].

NIAs have complicated dynamic techniques with changing factors and characteristics, it's common for standard algorithms with only one search technique not to be able to solve optimization issues well or quickly as the problems get more complicated [2,3]. However, the cooperative actions of creatures become the foundation of inspiration for swarm intelligence algorithms (SIAs) which also known as Swarm-based algorithms. SIAs are one of the most popular paradigms in NIAs, have been extensively used in a variety of applications [3].

All NIAs have some limitations, or problems, over all algorithms do not guarantee global optimality when solving problems; they may identify the optimal solution during execution, but this does not ensure the selection of the best individual from the search space, some algorithms have many parameters to control the execution, when some of these parameters are changed, the result will be affected also, meaning they are sensitive to parameters.

Similarly, computational cost also affects algorithm performance, computational optimization is a subject of extensive research in a branch of artificial intelligence. Most of the time, solving optimization problems efficiently takes a lot of computing power and even though computers are getting faster and more powerful, brute-force methods are still not the best way to solve optimization issues [4]. When there is more than one possible answer to an optimization problem, it is called a multi-modal problem, and it will be difficult to solve and find optimal, both deterministic and stochastic methods to solve these problems, but stochastic approaches perform better with complicated, nonlinear, and high-dimensional problems [5] in many cases may . The No Free Lunch (NFL) principle asserts that a single metaheuristic algorithm cannot be considered the optimal solution to every optimization problem. This shows how unpredictable it can be whether an algorithm will work or not on different optimization problems [5,6]. Many recent algorithms are proposed to solve complex problems like; Child Drawing Development Optimization (CDDO) [7], Triple Distinct Search Dynamics (TDSD) [2], GOOSE algorithm [8], Botox Optimization Algorithm (BOA) [5], Shrike Optimization Algorithm (SHOA), [9], Lagrange Elementary Optimization (Leo) [10], The main contribution of this paper is

1. Most recent algorithms are studied from 2020 to 2024, and are in the current advanced metaheuristic algorithm.
2. Introduction of general steps of NIAs.
3. Algorithms classified based on life style and living nature, to the classification structure presented in the SHOA [9].
4. Computational complexity of algorithms affects search, and some other weaknesses.

The main objective of this study is summarizing the most recent algorithms and show differences and similarities between NIAs to understand some strategies that effect the search. The rest of this paper is organized as section 2 nature-inspired metaheuristic algorithms and some related literatures are reviewed, taxonomy of algorithms by inspiration of source are presented in the section 3, computational complexity and parameters of the reviewed algorithms are explained and summarized in the section 4, application of algorithm and conclusion explained in section 5, and 6 respectively.

2. Nature Inspired Metaheuristic Algorithms

A growing variety of optimization algorithms have been developed to handle complicated optimization issues, including nature inspired metaheuristic (NIMH) algorithms. These algorithms have complicated dynamical structures with changing parameters and properties such as rotation characteristics, large dimensions, and mathematical modeling complexity. As optimization problems get more complicated, classic algorithms with single searching mechanisms frequently exhibit poor search performance or sluggish convergence speed [2]. Four different NIMH algorithms in different fields are studied to show steps and structure of NIMH algorithms.

The CDDO algorithm is a method for estimating children's learning behaviors and intelligence in early infancy. It mimics cognitive learning and the phases of drawing in children by utilizing the golden ratio, a natural ratio. The algorithm transforms the child's drawing from scratch into an art work by adjusting factors such as hand tension, width, length, and golden ratio. The CDDO algorithm adds to the emerging field of social-inspired metaheuristics, a technique that draws inspiration from human behavior. The algorithm's simplicity, adaptability, and ability to avoid local optima make it a popular choice for problem resolution that does not require major modifications to its structure. Its simple architecture and ability to solve issues without relying on input derivation make it ideal for real-world situations, including impractical or unknown derivative information. One important shortcoming of the CDDO algorithm is its limited ability to solve specific, crucial, and difficult issues while doing badly on other tasks. The approach may improve computing complexity and convergence rate for particular issues; it may have limitations and weaknesses when addressing different problem sets successfully [7].

Triple Distinct Search Dynamics (TDSD) comprise spherical search (SE), hypercube search (HS), and chaotic local search (CLS). The primary contributions include grouping SE, HS, and CLS, creating control algorithms for balancing these search processes, and performing sufficient trials to validate the performance of TDSD, which has a high computational complexity as a limitation [2].

The GOOSE algorithm was inspired by the behavior of geese. Geese are gregarious birds who spend almost all of their lives on the land with other animals and birds. People recognize them for their devoted attitude, which includes mate protection and protective behavior. The algorithm was based on the goose's defending behavior, which generates an appealing protective environment among itself. Performance differences among functions, dependency on parameter values, poor exploration, and complexity due to the large number of parameters are weaknesses of GOOSE [8].

The Botox Optimization Algorithm (BOA) is a technique for reducing face wrinkles involves injecting small amounts of botulinum toxin into certain hyperactive muscles. This injection causes regional muscular relaxation, which smooths the skin in overactive muscle areas. The BOA method is a population-based optimizer that solves optimization issues via an iterative procedure. The architecture is inspired by the injection of Botox and adjusts the position of population members inside the search space. Each individual who requests Botox injections is a member of the BOA population. The BOA technique improves candidate solutions by assigning a specific value, similar to Botox, to selected decision variables. The Body-Aware (BOA) design is a way for forecasting a patient's look following a Botox injection into the facial muscles; each time, modify the BOA member and maintain the best for the next generation, BOA performance variable with different problem functions [5].

In general, all NIMH start with an initial population; they can be generated randomly or based on some conditions and criteria for constraint problems. After determining the fitness of individuals in the initial population, all solutions enter a loop to search the space for better individuals until the stop condition is satisfied. While the algorithm operates, it selects individuals based on specific criteria, updates the individual's status, assesses the fitness of newly generated solutions, applies elitism, or adds new solutions to the population. These steps continue until the stop condition, which could be an objective function, maximum iteration, or specific problem criteria, the algorithms processing general techniques presented in Figure 1. The algorithm's steps must strike a balance between exploration and exploitation in order to search the overall space and exploit solutions to find the best individuals. Optimizing control settings for individual problems can enhance algorithm efficiency, but the process of finding unique parameter configurations for each issue can be laborious and expensive [11].

```
Initialize initial population
Find fitness of Initial population

While stop condition not met
        Select individual ( solution from population  ) using selection criteria
        Update individual
        Find fitness for  new  individual
        Apply elitism to keep best or update population
Return best individual as algorithm solution
```

Figure 1 General Pseudocode of Optimization Algorithms

3. Taxonomy by Source of Inspiration

Optimization algorithms have been developed based on the randomness of natural phenomena, including animal behavior, biological processes, physical processes, musical processes, population processes, and game-based processes, all related to nature-based metaheuristic algorithms [5,12]. The nature inspired algorithms depending on creatures' inspiration of algorithm technique classified to classes. In general, researchers create taxonomies on categories like evolutionary, swarm, human, etc., while in this study classes are used to specify algorithms, and the classes of nature inspired algorithm are presented in Figure 2; depending on the recently proposed algorithms' classes in [9]:

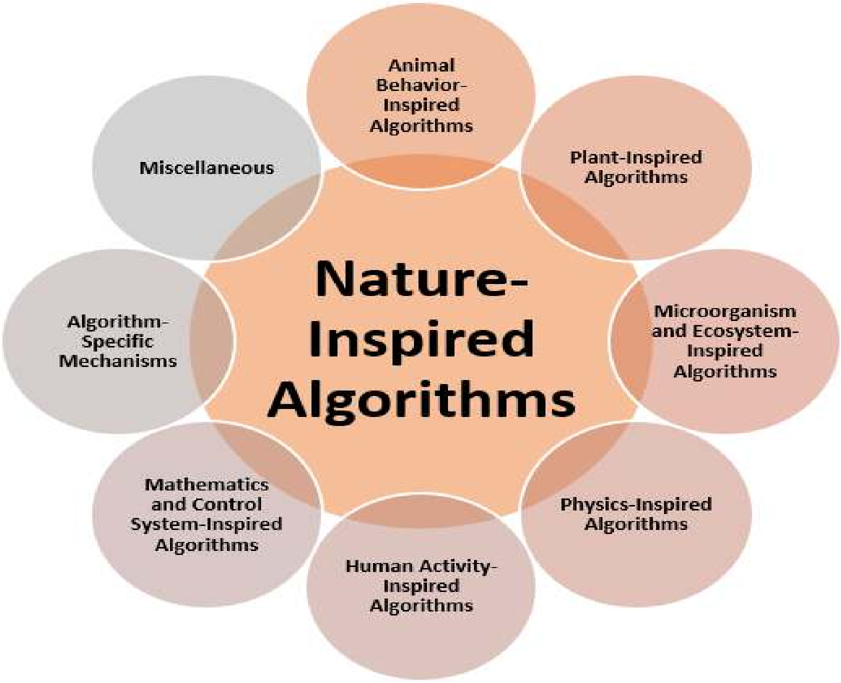

Figure 2 Nature Inspired Algorithm Classification

3.1 Animal Behavior-Inspired Algorithms

In this study some of the recently proposed algorithms from 2020 to 2024 with classes were studied, the list of animals is presented in Figure 3:

1. Bird-Inspired Algorithms
   Many optimization algorithms are modeling birds' inspiration in the nature some of them like; the African Vultures Optimization Algorithm (AVOA) is based on the way African vultures live. It involves making a new rotational search equation, modeling African vultures in two different ways, using two different mechanisms in the exploration phase to make the solutions more diverse, using four different mechanisms in the exploration phase to make the AVOA algorithm better at the exploitation phase, using LF-based patterns to improve local search with short, different jumps, and making a new coefficient vector F with different random r motions during the optimization operation [13].

   The Eurasian oystercatcher optimizer (EOO) is inspired by the feeding behavior of Eurasian oystercatchers. In EOO, each bird in the population is used as a search agent and adjusts its candidate mussel based on the best solutions in order to reach the best outcome [14]. Golden Eagle Optimizer (GEO) is based on how smart golden eagles are at changing their speed at different points in their circle path to catch. In the beginning stages of their hunt, golden eagles are more likely to cruise around and look for food. In the final stages, they are more likely to attack. These parts are adjusted so that a golden eagle can catch the best food in the best places in the fastest amount of time [15].

The Osprey Optimization Algorithm (OOA) is a bird-inspired algorithm that models the ospreys' essential inspiration from hunting, which involves catching fish from the oceans [4], the Pelican Optimization Algorithm (POA) mimics pelicans' natural behaviors of hunting strategy, update position of bird depending on random factor [16]. The Sparrow Search Algorithm (SSA), inspired by the foraging and anti-predation behaviors of sparrows, it demonstrates superior performance in terms of searching precision, convergence rate, and stability [17].

The New Caledonian Crow Learning Algorithm (NCCLA) is a computational algorithm that draws inspiration from the social, and asocial mechanisms of learning seen in Caledonian crows to hunting [18]. The Fire Hawk Optimizer (FHO) is an algorithm that draws inspiration from the foraging behavior exhibited by whistling kites, black kites, and brown falcons [19].

The flexibility and intelligent behavior of black-winged kites help birds to adapt to environment and changes to target placements; this model is called the Black Winged Kite Algorithm (BKA). These birds are well-known for their skills in the fields of hunting and migrating. The BKA algorithm's goal is to find the optimum outcomes by making adjustments and repeating. Due to the algorithm's unique biological heuristic features, it is capable of adjusting to varying optimization settings and possesses robust dynamic search skills. Cauchy mutation: the method breaks out of local optimization and escapes the local optimum to the global range, where it finds better solutions in the global search space with the aid of a probability distribution. The leadership method in population helps the algorithm to effectively search for the current best solution and guide the search direction to better solutions. This method enhances the efficiency of the algorithm and also facilitates a balance between the best-known solutions and exploring new possibilities. It ensures that the algorithm does not stack in the local optimum, but it explores new regions to find the best possible responses [20].

2. Mammal-Inspired Algorithms: many recent algorithms are developed based on mammals' life style and foraging behavior, some of them; the Walrus Optimization Algorithm (WaOA) is inspired by the social interactions of walruses, it is a member with the longest tusk feeding others, migrating to rocky beaches, and defending or running from predators. Mimicking these techniques and avoiding early convergence and avoid trapping in local optima, the suggested WaOA architecture enhances global search and discovery capabilities. The algorithm's capacity to explore the space and exploit local solutions to converge to better answer, is enhanced by imitating the walrus's little displacements throughout the struggle by seeking better places. The mathematical modeling of characteristics served as the primary inspiration for the proposed WaOA technique [21]. The Fox optimizer (FOX) which mimics the hunting behavior of red foxes in snowy environments, the algorithm starts with random search, ultrasonic detection, and distance estimating techniques. The algorithm starts by doing a randomized search for prey, then detecting the animal's ultrasonic emissions. The gap between the fox and the prey is defined by the disparity in sound and time. The red fox proceeds to calculate the precise distance it must leap in order to capture its victim [22].

   The Capuchin Search Algorithm (CapSA) is a highly promising method for addressing optimization problems that solely on the input and output parameters and doesn't have any extra control parameters. By integrating the dynamic behavior of capuchin monkeys, it improves the solution[23]. The Squirrel Search Algorithm (SSA) is an optimizer that emulates the dynamic hunting behavior of southern flying squirrels [24] , and the Mountain Gazelle Optimizer (MGO) is an algorithm that takes inspiration from the social life of mountain gazelles [25]. The Cheetah (C) algorithm is inspired by the cheetah's foraging strategy [26].

Honey Badger Algorithm (HBA) [27], and Red Panda Optimization (RPO) [28], they imitate the natural behaviors of honey badger, red panda in nature. Red panda climbing trees to rest, foraging strategy while honey badger just foraging strategy will be algorithm inspiration strategy.

3. Insect-Inspired Algorithms include optimization algorithms that inspired by insects, recently the Aphids Optimization Algorithm (AOA) is a simulation of the foraging behavior of aphids with wings. It encompasses the creation of winged aphids, their flying behavior, and their attack behavior. It is evaluating the impact of natural environmental elements. The use of this approach improves the variety within the population and enhances its capacity to explore, while using the ideal solution as a guide insures precision [29].

4. Fish and Marine Life-Inspired Algorithms creatures living in the water and their movement and foraging are modeled to algorithm like; the Orca Optimization Algorithm (OOA) is a meta-heuristic algorithm that can be classified for both fishing and mammals, but the fishing class is better because of life place and nature. The method is derived from the distinctive hunting strategy of wave-washing orcas, which involves many random candidates (orcas) employing the clever approach of hunting in groups and creating waves to dislodge seals from floating ice floes [30].

   An algorithm called the Pufferfish Optimization Algorithm (POA) has been presented to address optimization issues pertaining to the family of marine and estuarine fish. Because of their huge spines and sluggish mobility, pufferfish are often targeted by predators due to their comparable physical characteristics to porcupinefish. Their unique defensive technique is to create a big, spherical, spiky ball by sucking water into their mouth cavity. Predators are forced to retreat because pufferfish's sharp spines present a warning rather than an easy meal. The POA technique aims to replicate the actual steps a predator takes when attacking a pufferfish, as well as the pufferfish's defense mechanism against these attacks. This strategy seeks to decrease the number of fish that are injured by predators while simultaneously increasing fish efficiency [31].

   The Marine Predator Algorithm (MPA) is a metaheuristic algorithm designed to emulate the hunting behavior exhibited by marine predators [32]. The Tunicate Swarm Algorithm (TSA) it is mimics the swarm behaviors of tunicates during navigation and hunting. It aims to find the most optimal solution by searching for neighbors of the agent [33].

5. Reptile-Inspired Algorithms like; The Horned Lizard Optimization Algorithm (HLOA) is a metaheuristic optimization algorithm that emulates the mathematical principles behind freezing, darkness or lighting, blood-squirting, and move-to-escape defensive mechanisms. The horned lizard exhibits crypsis behavior, which entails the lizard undergoing a color change to achieve transparency, evading notice from its predators. The horned lizard has the ability to adjust the color of its skin, either becoming lighter or darker, in order to regulate its solar energy gain by reducing or increasing it accordingly [34], The Horned Lizard Optimization Algorithm (HLOA) and Artificial Lizard Search Optimization (ALSO) are two strategies used by lizards when looking for food. These strategies include jumping towards their prey while making adjustments to their angular position and velocity throughout the leap [35].

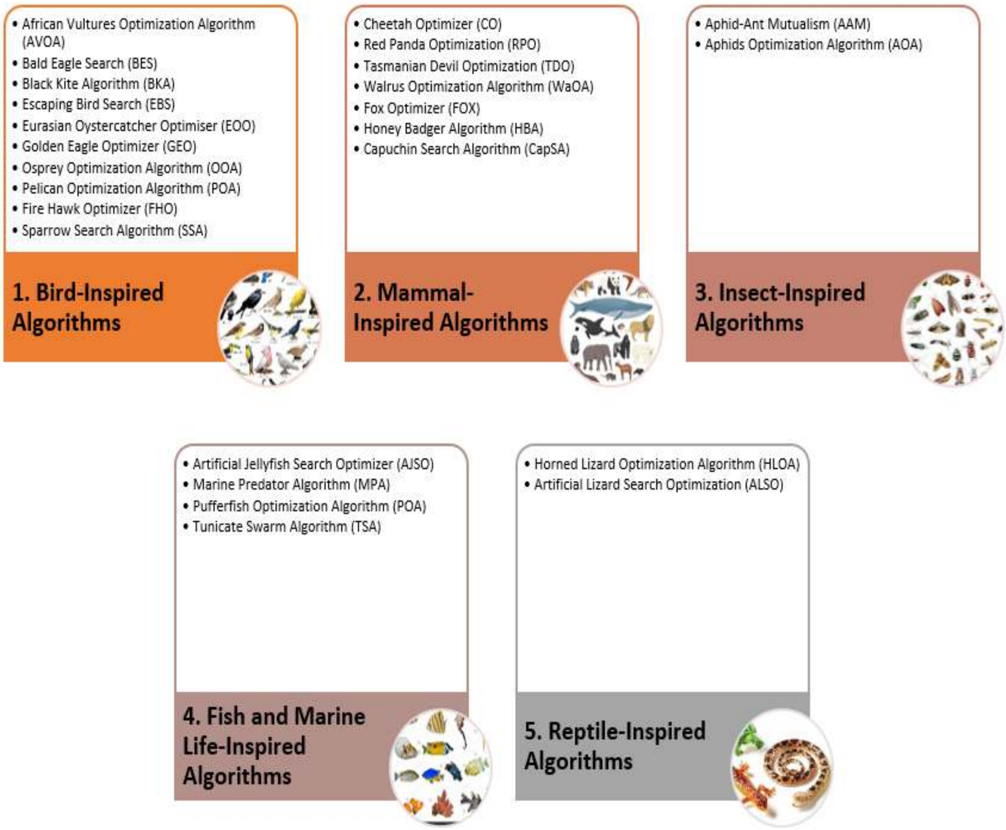

Figure 3 List of Animal-based Algorithms

3.2 Plant-Inspired Algorithms

The algorithms were created by studying plants like Water Wheel Plant Algorithm (WWPA) is a random optimization approach inspired from natural systems. The WWPA technique is derived by modeling the waterwheel plant's inherent behavior during a hunting journey, employing plants as search agents to locate prey [36].

3.3 Microorganism and Ecosystem-Inspired Algorithms

Microorganism are also very accurate organs, some of recently proposed algorithms like; new artificial protozoa optimizer (APO) called protozoa is based on biology and is meant to mimic how protozoa might act in stressed situations. The autotrophic foraging and hibernation help with discovery, while the heterotrophic foraging and reproduction help with exploitation. The APO copies these behaviors. Different mathematical models are used to show how euglena eats, sleeps, and reproduces [37].

The Corona-virus Search Optimizer (CVSO) was motivated by the mobility and spread of the coronavirus among various communities, as well as its high incidence and impact on mortality. It requires a control parameter [38]. The Coronavirus Herd Immunity Optimizer (CHIO) gets inspiration from the notion of herd immunity as a strategy to address the COVID-19 pandemic, the rate of transmission of the coronavirus is contingent upon the extent to which infected individuals come into close contact with other members of society [39,40].

3.4 Physics-Inspired Algorithms

Nowadays, researchers working on physics methods , and proposing new algorithms depending on physical disciplines, recently new algorithms proposed the Electron Radar Search Algorithm (ERSA) draws inspiration from the electron discharge process and utilizes three key features: local search atom enhancement and change, with a greater focus on superior solutions [41]. The Photon Search Algorithm (PSA) is a computational method that draws inspiration from photons' physics characteristics. Each photon acts as a search agent starts as best solution. Following each step, the photons transmit their solution values to the algorithm, which evaluates all the obtained solutions and retains the best one among them. The algorithm will produce the optimal solution value once it reaches the termination condition [42]. The Transient Search Optimization (TSO) method was created through looking at how switch electrical networks with storage elements like inductance and capacitance changes [43]. The Energy Valley Optimizer (EVO) is based on physics ideas about particle losses and stability, and it doesn't need any extra parameters [6].

The Momentum Search Algorithm (MSA) is based on two significant principles of physics: the law of conserving momentum and the law of conserving kinetic energy. MSA has three main steps creates an artificial time-discrete and closed system, applies momentum and conservation rules, and moves time in discrete steps until we meet a certain condition [12].

3.5 Human Activity-Inspired Algorithms

Recently, some algorithms are proposed depending on social and human activities like; an idea for the Hiking Optimization Algorithm (HOA) came from walkers who had to go through difficult terrain while trying to keep up their speed. Hikers go uphill, and HOA tries to figure out what the best tackle is for problems at the local or global level. The goal is to solve efficiency problems by making the experience like hiking. It is based on Tobler's Hiking Function, an exponential formula that works out how fast a hiker is going while taking into account how high the road is or where they are hiking. The HOA takes advantage of the unique ways walkers can think and the benefits of thinking with other people [44]. Recently, new developed the chef-based optimization algorithm (CBOA) as a metaheuristic algorithm to address optimization problems in various domains. CBOA draws inspiration from the pedagogy of acquiring culinary expertise through instructional programs. The CBOA method is founded on the notion that culinary learners and aspiring chefs engage in instructional programs to enhance their culinary abilities and ultimately attain the status of professional chefs. The algorithm employs mathematical modeling to create the CBOA, which is a population-based methodology [45]. Driving Instruction-Based Optimization (DTBO) emulates the process used by human driving instruction. The DTBO process is an intelligent method in which a novice acquires driving abilities through instruction from various instructors and personal practice. DTBO seeks to fill the research void in the field [46]. War Strategy Optimization (WSO) is a methodology that focuses on the strategic deployment of military forces during warfare, with each soldier intelligently maneuvering towards the most advantageous position. The algorithm being suggested encompasses two widely recognized battle methods, namely assault and defense strategies [47].

3.6 Mathematics and Control System-Inspired Algorithms

Many algorithms are generated based on some mathematical models like; The linear least square fitting model (LPE) is a mathematical framework that identifies approximate linear trends in sequential populations in order to accomplish iterative optimization. This phenomenon is rooted in the statistical principle that when a segment of a data sequence closely aligns with a linear trend, it is likely that the subsequent unknown data points in the sequence will likewise cluster around this trend. LPE algorithm assumes a fitting line that is not known and finds the best fitting line by reducing the sum of squared deviations between the input data and the unknown fitted line. The projected data is created using the computed regression line [48].

The gradient-based optimizer (GBO) is an approach that integrates gradient and population-based techniques to investigate the search domain. The search direction is determined by Newton's approach, which utilizes a collection of vectors and two primary operators: the gradient search rule and the local escape operator [49].

The Group Mean-Based Optimizer (GMBO) aims to generate quasi-optimal solutions by creating two compound members. The authors form these combination members by taking the mean of two selected groups from the population: one with good members and another with bad members. These composite members are then used by the GMBO to update the population matrix [50].

The Two-phase trigonometric Algorithm (TP-AB) is employed to solve optimization problems, both limited and unconstrained. If necessary, the algorithm may be employed with a tuning parameter and has been demonstrated to have superior capabilities in both exploration and exploitation when compared to other high-performing algorithms [51] .

The Advanced Arithmetic Optimization Algorithm (AOA) that utilizes the distribution characteristics of dominating mathematical operators to efficiently search for the optimal solution in a given search area. It achieves this by simulating the operations of addition, subtraction, multiplication, and division [52]. The Runge Kutta Optimizer (RUN) is a search engine that is built on the principles of the Runge Kutta method. RUN is comprised of two primary components: a search mechanism utilizing the Runge Kutta technique and an improved solution quality mechanism aimed at enhancing the quality of the results [53].

3.7 Algorithm-Specific Mechanisms

exploration and exploitation are balanced depending on some specific algorithms to create meta-heuristic technique optimizer like; The One-to-One-Based Optimizer (OOBO) is a metaheuristic that emphasizes the efficient utilization of various individuals in the population without depending on specific individuals throughout the process of updating the population [54].

The PID-based search algorithm (PSA) utilizes a discretized incremental PID algorithm to replicate the regulatory process of PID. This helps rectify the deviance of each individual relative to the best person, ultimately helping the entire population to achieve a more optimal state[55].

The primary functions of Spherical Search (SS) are computing the spherical boundaries and generating fresh trial solutions. Self-supervised learning (SS) has a smaller number of parameters, achieves a suitable equilibrium between exploration and exploitation, is invariant to rotations, maps the shape of the search space, and ensures a high level of variety throughout the optimization process [56]. The Crystal Structure Algorithm (CryStAl) algorithm is a parameter-free metaheuristic technique that is inspired by the concepts of crystal structure development, namely the addition of a basis to lattice points [57].

The Flow Direction Algorithm (FDA) imitates water movement in a drainage basin, directing the flow towards the neighboring position with the lowest elevation or most favorable objective function [58].

3.8 Miscellaneous

Many algorithms are developed depending on specific tactics and plans for example; The idea for the Giza Pyramids Construction (GPC) came from evolution and nature, with a focus on separating images [59]. Ali Baba and the Forty Thieves (AFT) uses the story of Ali Baba and the Forty Thieves as an example of how people should behave in groups. There are three main scenarios in which crooks search for Ali Baba. All of the thieves search quickly and thoroughly throughout the area, but Marjaneh's intelligence causes them to look in odd places [60].

The Material Generation Algorithm (MGA), emphasizes the advanced elements of material chemistry, particularly the arrangement of chemical substances and chemical processes in the creation of novel materials [61].

Soccer Game Optimization (SGO) is another program that depends on soccer ideas. It uses population-based methods that are based on how soccer players progress on the football field [4]. Golden Ball Metaheuristic (GB), splits its pool of possible answers into groups, with each group having its own training method. The GB has gotten a lot of attention from people in the connected field because it has been used to solve a lot of different problems and deal with real-life situations. For instance, it was thought about as a way to solve the problem of choosing automatically both the structure and parameters of a proportional-integral-derivative controller's control system [4]. In 2016, the World Cup Optimization (WCO) plan was made to use the FIFA event and battles between soccer teams to help them win the desired World Cup [4]. The Football Game Inspired Algorithm (FGIA) is one of the newest soccer-inspired methods. It was inspired by how footballers act during football games [4].

The Dark Forest Algorithm (DFA) creates a number of evenly distributed initial solutions in the search space. It then sorts civilizations into groups based on how adaptable they are, change’s locations based on the level of the civilization in query, and finally operates a more thorough search for the highest civilization in the last few iterations [62] .

The Squid Game Optimizer (SGO) is inspired by squid sports. The algorithm picks the best answer from a group of possible answers, with each answer acting like an attacking player trying to beat the defending players. The strategy of the squid game is shown mathematically using the optimization method. The initialization process begins in the first step, where the search area functions as a playroom and the solution possibilities (X_i) represent the players. In the second round, players are split into two groups of the same size: the offensive (off) and defensive (def) [3].

4. Computational Complexity and Parameters

The hunting and foraging behavior of creatures inspires many recently developed algorithms, which combine mathematical models with various strategies similar to natural behavior. Still, some algorithms outperform others in specific fields, and researchers will try to find new strategies and algorithms to cover many problems. The summary of statistics of contributions developed for the last four years from 2020 to 2024 which are studied in this paper is presented in Figure 4.

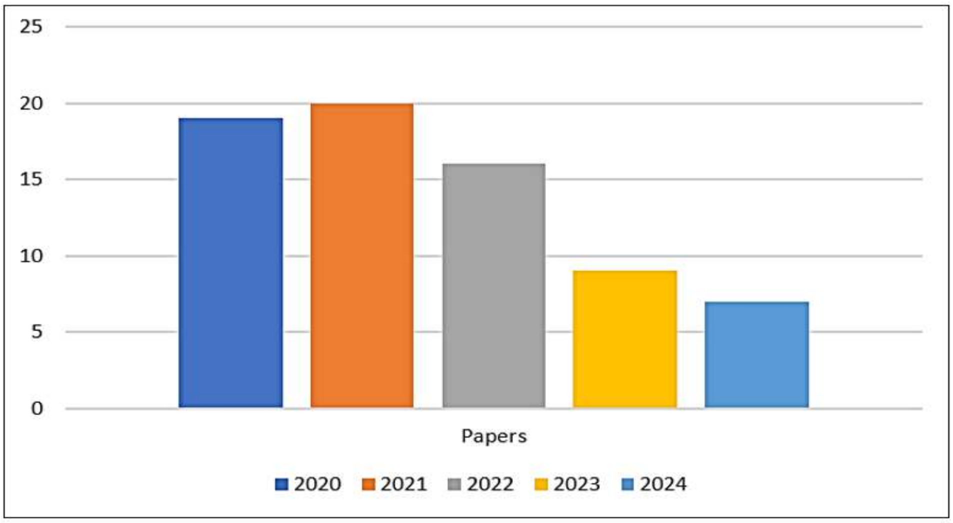

Figure 4 Number of Contributions Studied

Each algorithm's computational cost is determined by the techniques used to solve problems in an iterative way. Depending on the problem field, these algorithms may require tuning of certain parameters, which can affect the variation in complexity. Table 1 presents the computational complexity of original algorithms, where T represents the maximum iteration, M represents the problem size in the population, D represents a viable decision in the problem, and C represents the evaluation function.

Table 1 Computational Complexity of Algorithms

Algorithm	Year	Time complexity	Parameters
Birds			
AVOA	2021	$O(T \times M) + O(T \times M \times D)$	
GEO	2021	$O(T \times M \times D)$	
POA	2022	$O(M + T(1 + D)(1 + 2M))$	
FHO	2022	$O(T \times M \times D \times 3) \times O(C)$	
BKA	2023	$O(M \times (T + T \times D + 1))$.	
OOA	2023	$O(D\times M(1+2T))$	
SHOA	2024	$O(N\times B(1 + M(1 + D))) + O(N \log N)$	B number of individual in populations
Mammals			
CapSA	2021	$O(V(T(MD+MC)))$	
C	2022	$O(V \times T\times D \times M \times C \times (mu + cr))$	(mu,cr) mutation , crossover) operation
FOX	2022	$O(M\times D \times T)$	
HBA	2022	$O(T\times M\times D)$	
MGO	2022	$O(T \times M\times 4)\times C)$	
WaOA	2023	$O(Nm(1 + 3T))$	
RPO	2023	$O(MD(1 + 2T)$.	
Plant-Inspired Algorithms			
WWPA	2023	$O(T \times M \times D)$	
Microorganism and Ecosystem-Inspired			
APO	2024	$O(T\times M\times (\log(M)+D+C)))$	
Physics-Inspired			
AOS	2021	$O(T \times M \times D \times C)$	
Human Activity-Inspired			

Algorithm	Year	Time complexity	Parameters
COA	2022	O(D(N+ 2KT + 3(N − K)T))	K extra problem dimension
WSO	2022	O((M+1)×D×T).	
DTBO	2022	O(MD(1 + 3T))	
HOA	2023	O(M×T)	
Mathematics and Control System			
AOA	2021	O(M × (T D+ 1))	
RUN	2021	$O(2M+(2M^2+T\times(3M+2M^2+3^2)))$	
Algorithm-Specific			
CryStAl	2021	O(T × MD × 4)× C)	
FDA	2021	O(M ×(D+1)T× C)	
OOBO	2023	O(M(2T(1 + D) + D))	
Miscellaneous			
GPC	2020	O(M×D×T)	
AFT	2022	O(1)+O(M×D)+O(T×M×D)+ O(T×M×C) +O(T×M×D)	

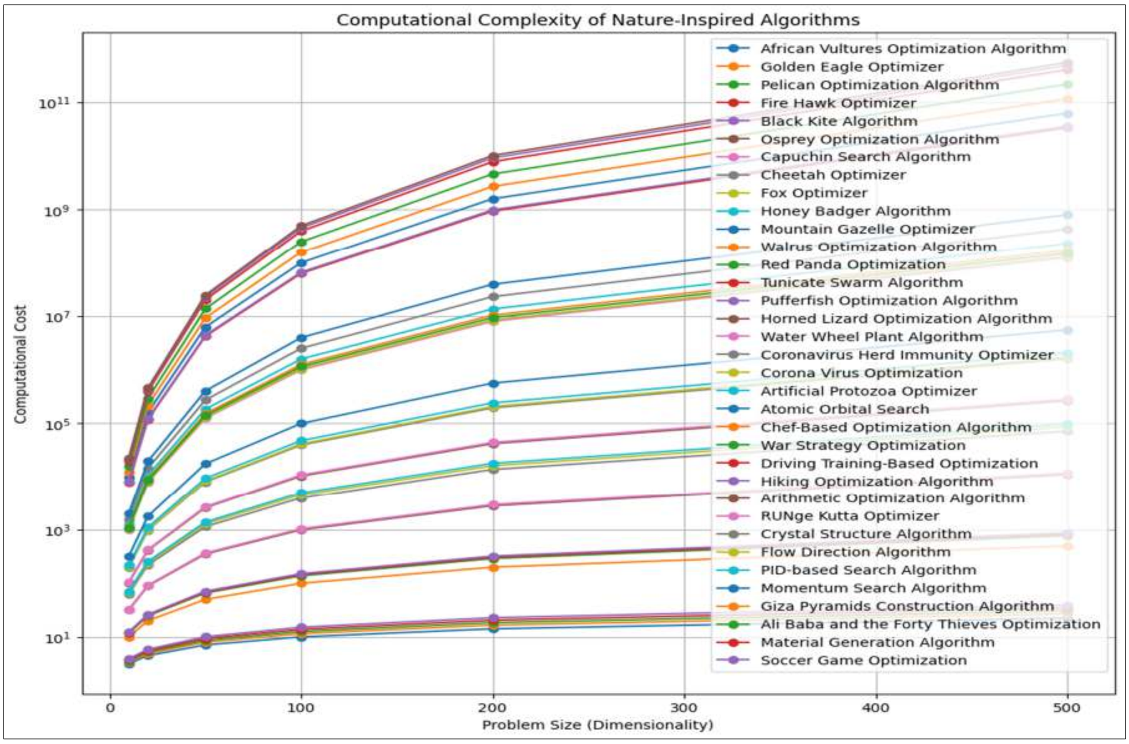

Figure 5 Computational Complexity Curve

The Figure 5 presents the computational cost curves for some NIAs, which demonstrate an increase in computational cost with increasing dimensions. The x-axis represents dimensions ranging from 0 to 500, whereas the y-axis represents computational time. For all dimensions, we assume the same maximum iteration and population size, specifying different start points to distinguish the curves. The sequence starts with the first group, the African Vultures Optimization Algorithm, until the Capuchin Search Algorithm, the second group starting from Cheetah Optimizer, until the Pufferfish Optimization Algorithm, and the last group at the bottom of the curves, starting with PID-based search. Overall, we display the logarithmic variation of complexity cost based on the changing dimensions.

5. Applications

Recently, metaheuristic algorithms have been effectively applied to decrease the computational expense involved in many fields.

The scheduling and transportation: Metaheuristics applied to solving TSP issues in less computational efforts, and have the capability to provide solutions that are very close to the ideal solution within a reasonable time frame [63]. In addition SSA is applied to solve scheduling and planning problems, and robotics to optimize the problems [64], POA and TSA are also solved scheduling and assignment problems and outperformed competitors [65,66], The GB has also been used to answer the open and capacitated vehicle routing problem, the multiple asymmetric traveling salesman problem, and other business and transportation-related problems that happen in the real world [4].

Industry: The industry uses many meta-heuristic algorithms because requires prediction and high profit margins. In most recent developments metaheuristics are applied to train neural networks for industrial applications [67]. However, AVOA successfully applied in robotic gripping mechanism [68].

The image processing: An improved Bald eagle search (BES) applied to feature selection from images; the performance is presented that BES performed better than compete algorithms [69], SSA also applied to image processing [64] , in addition WWPA and TSA applied in deep learning field for images [70–72], AOA and TSA are applied [73,74] for feature selection and classification processes.

Engineering design: A structural engineer responsible for designing a multi-story structure, must carefully choose materials and determine the appropriate proportions for various structural elements. The structural engineer does this to guarantee the safety and cost-effectiveness, SSA original or modified is used to solve many problems engineering design in mechanical, civil electrical and industry [64].

Healthcare problems : The problems in the healthcare need accuracy, however optimization algorithms used randomization, they used to tune parameters for learning strategy in healthcare systems, like; SSA applied to solve some health care problems to optimize the problems outcome [64], TSA with deep convolution applied to cancer image classification [74].

Power and Energy Systems: Energies are generally linked to many energy-generating locations in order to provide electricity to places. Power networks are linked, so disturbances in one place might impact others. Thus, the consistency of the system's frequency became one of the primary worries of the system's operators. The system's reliability is largely dependent on load frequency control to ensure power equilibrium between connecting regions under fluctuating load conditions, GEO applied in energy and power system to optimize power balance [75,76], improved MPA with PSO used to solve power dispatch problem [77], improved OOA used to solve power optimization problems [78], however for controlling heating and cooling systems perceptron models using WWPA proposed in [79], CapSA used in solar panels photovoltage models [80], WaOA for solving economic load dispatch problem [81], and SSA also applied to solve energy and control systems optimization problems [64].

Internet of Things (IOT): Unmanned Aerial Vehicles (UAVs) are highly used for both civil and military uses because of their ability to take off and land vertically, and operate in crowded areas. For the tasks to be successful, it is crucial that the UAVs adhere to a specific trajectory with

precision and speed. Particle swarm optimization (PSO) and Harris Hawks optimizer (HHO) used to optimize the parameters for UAVs. Both control methods have been assessed on paths with diverse geometries, such as rectangles, circles, and others. Researchers compared the results to the performance of a typical Proportional Integral-Derivative (PID) controller and found that the proposed controller outperforms both the traditional PID and PSO based controllers [82]. Moreover, TSA also applied to find routing in IOT with clustering [83].
Miscellaneous : SSA applied to solve networking optimization problems [64], although POA used in security [84].

6. Conclusion

This study aims to conduct a state-of-the-art survey of NIAs from 2020 to 2024. Algorithms can generate a variety of taxonomies, which can serve as potential research sources. This alignment with the natural world has provided academics with novel opportunities to explore the possible uses and impacts of algorithms influenced by nature in many situations to reduce complexity costs with increased dimensions.

There are several difficult and intricate challenges in various domains, such as industry, scientific research, engineering design, and the internet of things, where traditional approaches may face difficulties in effectively finding optimal or semi-optimal solutions within a reasonable timeframe and with high accuracy.

Our study over the last few years concludes that, despite the development of many algorithms for global optimization problems, there has been less application, particularly for recent algorithms. An increase in the problem dimension or parameter alters and increases the time complexity of every algorithm. It is worth to find a mechanism for applying the optimization mechanism to minimize time complexity while the problem dimension will increase. For future work, there are several ways to tune the parameters to minimize time complexity, such as hyper-optimization, which entails first optimizing the algorithm for the specific issue and then applying the optimal parameter setting (p). Another approach to parameter tuning is to use various loop structures to iteratively tune and solve the algorithm's parameter optimization.

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