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An Effective Exploration on Nature Inspired based Meta-Heuristic Algorithms and their Variants for Solving Decision Making Problems

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***Abstract*— In order to solve complex decision-making problems that were beyond the capability of traditional optimization methods, nature-inspired meta-heuristic algorithms were introduced and became widely used. The algorithms mimic the behavior of living beings, natural phenomena, and animal movements in the search of good solutions. The present paper is an in-depth exploration of these algorithms along with their various incarnations, with a particular focus on their application in decision-making. The paper discusses their mechanisms, advantages, and disadvantages, in both the traditional and modern forms. Besides, standard test problems are utilized in the study in order to evaluate these algorithms on the basis of the time taken to reach the solution, the level of accuracy, and the reliability of the solution. The objective is to highlight the areas for future research and to provide assistance to the experts in selecting the most appropriate algorithms for the resolution of the decision-making problems in the real world.**

***Keywords*— Optimization, Meta-heuristic, Classification of Meta-heuristics.**

I. INTRODUCTION

The optimization process has consistently been a crucial element in the decision-making process in various fields such as engineering, economics, healthcare, logistics, and intelligent systems. With the increasing complexity of real-world issues, the decision-makers are required to handle situations that involve non-linear relationships, multiple objectives, uncertain conditions, and large search areas. Although traditional optimization techniques are mathematically accurate, they frequently face difficulties in such cases due to their reliance on strict rules and particular problem setups. [4][5][41][27][28][33][37].

To solve these issues, a significant number of individuals have begun to apply heuristic and meta-heuristic methods. Meta-heuristics particularly, are versatile and can be applied to a variety of optimization problems. Such procedures are not dependent on gradient information and can traverse in an efficient manner through the realms of complex solutions. Nature-inspired meta-heuristics are now the most preferred methods among all due to their simplicity, adaptability and performance [4][5][41][27][28][33][37].

Algorithms based on nature have been created in various ways. Nature is the best teacher; by learning from the way creatures behave, we understand how they survive, reproduce, and thrive. We have developed a wide range of algorithms to help us improve efficiency in making best choices in our industry.

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For example, particle swarm optimization and genetic algorithms are great algorithms that use the concept of survival of the fittest to help us make the best decision. Today, with the growing knowledge of nature, we have created many new kinds of algorithms and improved our existing ones by looking at various aspects of nature and how they affect each other and their environment. [41][27][28][33][37].

Ongoing development of algorithms is an attempt to solve well-known problems such as when to stop improving a solution early, the balance between exploring new versus known options, and how results may depend on how settings have been chosen. To solve these issues, various techniques are being used by people that include combining approaches, automatically adjusting of settings, utilizing chaotic patterns, and learning from historical results. As a result of these developments, nature-inspired algorithms have improved to be able to handle increasingly complex decision-making problems. [4][5][41][27]

Studies that review existing research emphasize the need to perform testing in order to understand how well an algorithm performs. Standardized test problems (Sphere, Rastrigin, and Ackley) are used to determine the speed of the algorithm's ability to locate a solution, the accuracy of the solution it finds, and the stability of the solutions produced by the algorithm across different types of problem instances. By performing comparisons of the results of these tests, researchers can identify trends in algorithm performance and can determine which algorithms are optimal for specific problem types. [4][5][41][27]

There has been a proliferation of research on these types of algorithms, and since there are now many new algorithms and variations of old ones, it has become impossible for many researchers to determine when to use them, how to use them, and what makes one algorithm more efficient or useful than another. Most literature reviews concentrate on a subset of algorithms that are either specific types of algorithms or specific applications or users of algorithms. The author asserts that there is a need for a more comprehensive literature review to describe all the different nature-inspired types of algorithms and the various forms (improvements) they use to assist in making decisions. The objective of this literature review was to create a comprehensive account of nature-inspired algorithms that assist with the decision-making process, which includes aggregating and organizing previous research, identifying the inspirations behind the algorithms and their different forms (e.g., ant colony optimization), and summarizing how well each algorithm performs through experiment data, which will help with choosing the most appropriate algorithm, and suggesting ideas for future research into nature-inspired algorithms. [4][5][41][27][28][33][37].

A. Classification of Metaheuristic Algorithms: Metaheuristics can be broadly classified into:

Single-solution-based algorithms (e.g., simulated annealing, tabu search): These are single-solution-based algorithms that operate on a single solution and update it iteratively. They are intuitive and prove useful for problems where the exploration near a particular solution is adequate [4][5][41].

Example: In the traveling salesman problem (TSP), where the goal is to minimize total travel distance, Simulated Annealing starts with a random route and explores by swapping cities. It can occasionally accept less optimal routes to escape local optima, eventually approximating the shortest route.

Population-based algorithms: (e.g., Genetic Algorithms, Particle Swarm Optimization): These algorithms operate on a population of solutions and evolve them over time, enabling broader exploration of the solution space and reducing the chances of being stuck in local solutions [4][5][41].

Example: Genetic Algorithms are utilized in feature selection in machine learning. Chromosomes here represent various feature sets, seeking to determine the best set for the best model performance with fewer features.

B. Key Metaheuristic Algorithms: This section explains the most popular and influential metaheuristic algorithms in detail, including their working principles and algorithmic processes:

Genetic Algorithms (GA): The GA is inspired by the principles of Natural Selection and Genetic Evolution. A population of possible solutions is kept in addition to the treatment: Each individual will go through several generations through selection, crossover and mutation. Fitness is used to determine which individuals survive, allowing for improvement over time until a global optimum is attained. GA is useful for solving problems that involve combinations and multiple objectives; however, if diversity is not maintained, the algorithm may sometimes converge too early. Mimic the process of natural selection. Widely used for complex problem solving [4][5][41][27][28][33][37].

Particle Swarm Optimization (PSO): The PSO is driven by social actions that occur when birds flock together or when fish swim in schools. Each particle represents one possible solution and will adjust its velocity and location based on both its own personal best (as recorded) and the best solution found by the group of particles (the current global solution). The interaction among the particles allows for particularly fast convergence. The PSO performs well regarding CPU cycles spent per successful solution for optimization of continuous data; however, it may not do as well with very complicated or rugged landscapes that contain many local maxima. Inspired by social behavior of bird flocks and fish schools. Each particle represents a potential solution, and particles move through the solution space influenced by their own best experience and that of their neighbours [4][5][41][27][28][33][37].

Differential Evolution (DE): The DE is similar to the previous two algorithms regarding the population-based approach to finding new solutions, but instead of generating a new solution by combining selected individuals together using linear interpolation, the individuals generate their candidates by using their differences from randomly selected others. After generating the candidate(s) through linear mixing, they will undergo crossover and selection. The use of vectors for mutating individuals results in strong exploration of the candidate(s) and adaptability to solving the continuous optimization problem. The DE generally will find a solution faster than the GA, but in doing so the DE algorithm may require working out specific parameter settings to avoid becoming stuck at a local optimum. A simple yet powerful population-based algorithm designed for continuous optimization problems [4][5][41][27][28][33][37].

Ant Colony Optimization (ACO): Ant Colony Optimization mimics the actions of ants using pheromones to guide them on how to find food. Each artificial ant constructs a solution to the problem incrementally and once completed, each ant will deposit pheromone on the path taken if it was one of the successful paths to find the food source. Over the iterations, the more successful the ants were at finding food the stronger the pheromone trails become and subsequent ants will be guided by the pheromone trails to find food. Ant Colony Optimization has proven to be an effective solution approach for solving discrete combinatorial optimization problems (such as routing or scheduling a flight itinerary), but needs a large number of computational resources when the number of ants are large compared to the number of available resources (e.g., number of ant colonies). Based on the foraging behavior of ants. Ants lay down pheromones to mark good paths and follow paths with stronger pheromone intensity[4][5][41][27][28][33][37].

Simulated Annealing (SA): Simulated Annealing (SA) is based on an industrial process known as annealing (cooling something in a controlled manner) in order for a material to reach a low energy state. The algorithm proceeds by random deviations of a single solution and will probabilistically accept poorer solutions based upon the temperature used, allowing for escape from local optimal points. The implementation of a SA algorithm is relatively easy and can be performed on both continuous and discrete problems; however, the rate of convergence can be slow if a well-defined cooling schedule is not put into place. A probabilistic technique for approximating the global optimum. Accepts worse solutions with a certain probability to escape local minima[4][5][41][27][28][33][37].

Artificial Bee Colony (ABC): Artificial Bee Colony mimics the behavior of how bees search for food. The ABC Algorithm divides the bee populations into three groups (employed, onlooker and scout) and each group has different roles in searching and discovering food by exploring the search space and finding food. Using random scouting behaviour, ABC maintains diversity in solutions through empirically derived probability of selected solutions; thus, making it a robust solution approach for multimodal optimization problems. However, the rate of convergence of ABC can be quite low when compared to Particle Swarm Optimization (PSO) or Differential Evolution (DE) especially in high dimensional optimization problems. Emulates the behavior of honey bees in searching for food [35][41].

II. Literature Review

Cuckoo search [5] is an optimization technique based on the way cuckoos use other birds' nests for laying their eggs, allowing them to search for better solutions rather than remain stuck in poor-quality solutions. Therefore, CSA has been shown to be a powerful tool for solving complex problems with minimal tuning of parameters (Almufti et al., 2018) [5].

Ozkok (2020) [6] proposes a method of developing solutions that is iterative in nature and is based on sequential mathematical refinement (SMR). They state that this is an effective way to develop better, more accurate solutions without having to transform the solution into a more complex equation (Ozkok, 2020) [6].

Talatahari et al. (2021) describe the Material Generation Algorithm (MGA) [7] as an algorithm for the generation of new materials. It is based on how new materials are created and become stronger in nature and continually developing into better solutions for engineering challenges using fewer parameters and providing quicker, more accurate solutions than previous algorithms (Talatahari et al., 2021) [7].

The Capuchin Search Algorithm [8] was developed in 2021 based on the social behaviours and exploratory strategies used by capuchin monkeys. Like monkeys, it uses natural learning to explore new and improve upon

existing solutions and is mainly applied in engineering optimization, benchmark problems and real-world decision making [8].
The Blood Coagulation Algorithm [9] was developed in 2021 and is based on the biological processes that occur during blood coagulation. Much like the human body's response to trauma, when we cut ourselves, blood vessels close off and create a stable environment. As such, it also allows rapid convergence on the most promising areas of search while limiting unnecessary exploration. It is used for global optimization, engineering design and benchmark optimization [9].
The Binary Chimp Optimization Algorithm (BChOA) [10] was created in 2021 and is inspired by the intelligent hunting/social behaviours exhibited by chimpanzees. The algorithm has been extended to search the binary space in the same manner as the original chimp algorithm, i.e. identifying new candidates for solutions whilst improving the existing, and is applicable to combinatorial optimization, engineering design and decision making [10].
Parameter Setting of Meta-Heuristic Algorithms (2022) [11] in this paper the authors present a hybrid technique for optimally configuring meta-heuristic algorithm parameters. They also provide a method to create better solutions with faster convergence, etc., which is also useful in the following areas of application: engineering optimization; environmental modelling; complex real-world problems [11].
Emperor Penguin Optimizer - Review (2022) [12] In this review the author describes the Emperor Penguin Optimizer and illustrates how its behavior, which is inspired by the emperor penguin's huddling and movement, enhances the performance of the algorithm through benchmarking and comparison with current meta-heuristic algorithms [12].
Chaotically Enhanced Meta-Heuristic Algorithms (2022) [13] in this article the author talks about how chaotic maps are used to enhance meta-heuristic algorithms so they can explore the solution space and avoid becoming trapped in local optima. In addition, the author shows how the application of chaotic maps to the optimal truss structure design under frequency constraints leads to faster convergence and better quality of solutions [13].
CSBO stands for Circulatory System-Based Optimization (CSBO) [14] and is derived from human circulatory systems, where the circulatory system aids the human body in efficiently circulating blood and therefore delivering nutrients to all parts of the body. CSBO mimics this behavior, helping the CSBO algorithm to efficiently visit new solutions and improve existing ones. CSBO has been applied to many complex engineering and computational optimization scenarios [14].
The Eurasian Oystercatcher Optimizer (2022) [15] has modelled its behavior on the hunting and foraging behaviours exhibited by Eurasian oystercatchers. The EAOSA uses foraging techniques to visit new solutions and optimize existing ones. EAOSA has been employed to solve engineering design and optimization problems, as well as real-world benchmark problems [15].
The Wild Geese Migration Optimization Algorithm (2022) [16], like the Eurasian Oystercatcher Optimizer, was inspired by the cooperative migration and formation flying of wild geese, which is driven by leaders of the migration encouraging followers to stay close to them and to follow their path and therefore reach their goal more efficiently. The WGM-Optimization Algorithm mimics this behavior and therefore visits new solutions and enhances existing solutions efficiently, and it is being applied to solving robots' inverse kinematics problems, as well as engineering optimization challenges [16].
The Beautiful Mind Algorithm [17] takes its inspiration from humans' ability to think creatively and develop new ideas. Humans often improve existing concepts to develop better ways to solve a problem (i.e., the Beautiful Mind Algorithm). By mimicking the way people learn and make mistakes to come up with better decisions, the Beautiful Mind Algorithm can avoid generating bad solutions to problems and therefore has the potential to generate optimal algorithms for generating minimal covering arrays. The Beautiful Mind Algorithm can be used for software testing, combinatorial testing, fault detection and generating efficient test cases [17].
Fire Hawk Optimizer [18] is an optimization algorithm inspired by fire hawks, which use fire to drive out their prey. Fire Hawk Optimizer expands to cover a wide range of possibilities before concentrating on the most promising ones, making this algorithm easy to use and perform well, with no need to set or tune many parameters [18].
The dung beetle optimizer [19] uses the sun for direction and protection from obstacles as it rolls a dung ball to transport food to its nest. The dung beetle optimizer utilizes simple principles of nature regarding navigation and whereas it has been proved to be capable of performing well against benchmarks [19].
The mother optimization algorithm (MOA) [20] optimizes children's learning and development through improvement, guidance, and support that comes from mothers in a family setting. All optimization algorithms will produce effective and reliable results across multiple areas of engineering [20].

Givi and Hubalovska (2023) The Skill Optimization Algorithm (SOA) [21] is based upon human development of skills through practice and learning. Optimal Solutions become increasingly better as they learn from experience. It is a straightforward, adaptable, and efficient solution for assisting individuals in achieving solutions for complicated optimisation problems (Givi & Hubalovska, 2023) [21].

Kaveh & Khayatazad (2023) The One-at-a-Time and All-at-once (OOBO) [22] method allows for very gradual refining of the direction towards very productive outcomes, without requiring a lot of effort. The ease of use, rapidity of progression and simplicity is what makes this a useful tool for tackling day to day optimisation challenges (Kaveh & Khayatazad, 2023) [22].

Benmamoun et al (2024) - Bobcat Optimisation Algorithm (BOA) [23] is developed based upon bobcat hunting and team behaviour patterns. The way, bobcats adjust their behaviour in the hunt based upon the location and behaviour of their prey mirrors the behaviour of BOB cats (Bobcat Optimisation Algorithms) adjusting their search and way of exploring/adjusting the direction of new potential solutions. It is a simple solution and performs exceptionally well with engineering and supply chain related problems (Benmamoun et al, 2024) [23].

Ahmadianfar et al. (2024) The Arctic Puffin Optimisation Algorithm (APO) [24] is based upon how Arctic Puffins search for food when they forage flying and diving for fish. The combination of a large initial search region, with a focused region, leads to great success on both benchmark and real-world problems (Ahmadianfar et al, 2024) [24].

Sowmya et al. (2024) proposed an approach referred to as NRO [25], which takes the Newton-Raphson method and extends it from a single to multiple solutions. The NRO method increases accuracy while accelerating convergence and it generally converges relatively easily for continuous optimization problems [25].

Fang and Cao (2024) introduced an optimization technique called LIWO (Leaf in Wind Optimization) [26]. This technique mimics the random and erratic movement of leaves carried by a breeze, which is enhanced by the influence of a light breeze on the leaves' movements to guide them to areas of better solutions within a particular search space. This approach will yield accurate and efficient methods for complex optimization problems [26].

Rani et al. (2024) [27] reviewed and discussed various optimization algorithms that are based on biological systems and animals. They identified that these bio-based optimization algorithms exhibit solid performance through the use of benchmarking and hybridizing multiple bio-based algorithms [27].

Jomah and S (2024) [28] emphasized the benefits of swarm intelligence to task scheduling in the cloud through improved network resource utilization. Swarm intelligence methods can be applied in dynamic computing environments to improve job scheduling and task completion times [28].

CWO Carpet Weaver Optimization, an algorithm created by Alomari et al. in 2024 [29], is based on the teamwork that humans demonstrate when weaving carpets. The ideas created by solutions created in the algorithm will cooperate and collaborate to achieve an ideal resolution. This method is simplistic, cooperative and is effective for obtaining good results when solving engineering optimization problems [29].

AWKGWO is a new algorithm developed by Premkumar et al. in 2024 [30], based on the behaviours displayed by grey wolves hunting. The key aspect of the algorithm is that it uses K-means clusters, thereby increasing accuracy due to the grouping of individuals to obtain better clustering results. As a result, the accuracy and stability in complex data clustering tasks are greatly enhanced [30].

Flood Algorithm (FA) developed by Ozkan and Samli in 2024 [31] derives its inspiration from the way flood water naturally flows and pools into a single location. To find better solutions, the algorithm mimics water flowing toward that area and helps to prevent solutions from hitting a local optimum prematurely. The FA method effectively balances exploration of a wide area and focused improvement on a more limited area to arrive at a solution for diverse types of problems [31].

Secretary Bird Optimization, an algorithm developed by Fu et al. in 2024 [32], mimics the way in which secretary birds hunt efficiently. The algorithm mimics the secretary bird's hawk-like behaviour, which uses a wide area search to find the best locations for hunting. The technique allows for rapid convergence and has consistently demonstrated very strong accuracy and the ability to perform at a high level on benchmark tests [32].

Shaban and Ibrahim [2024][33], in their study of swarm algorithms, have highlighted the influence of the behavioural characteristics of animal and insect groups on the improvement of swarm algorithm performance through modifications and improvements. This paper provides an excellent reference for selecting and designing new and improved optimisation methodologies [33].

Abdel-Basset et al. [2025][34] proposed the Fungal Growth Optimiser (FGO), which takes inspiration from the growing and spreading of fungi in search of nutrients. Fungi grow and multiply until they locate their nutrients. Therefore, the FGO has been designed to adapt and evolve over time, ultimately leading to a better-formulated and more efficient method for finding solutions. The FGO is considered more robust than other classical algorithms [34].

Zhang and Zhang [2025][35] present the Aries Metaheuristic Algorithm (AMA), which is based upon human bold and adventurous behaviour. Like the famed Aries, the AMA goes boldly forth into the unknown worldwide while learning from previous experiences. Therefore, the AMA can be used effectively in performing global optimisation problems [35].

Zhang and Zhang [2025][36] propose the Classical Dance Metaheuristic (CDM) which is inspired by the smooth, graceful movements and co-ordination of dancers. Much like the way graceful dancers move, so do the solutions of the CDM Algorithm. The motion and elegance of the CDM Algorithm's solutions assist the solutions in reaching optimal results smoothly. As a result, the CDM Algorithm performs consistently well on standard benchmark tests [36].

Thengvall et al. (2025) [37], focus on a fair measure of performance for comparing two or more algorithms to determine the solution quality vs. time taken to compute and provides an evaluation framework suitable for real-life Optimization Problems [37].

Furio et al. (2025)[38], Hybrid Algorithm, use a "team effort" approach, leveraging the strengths of multiple methods, which produce a superior outcome than either method could provide individually. The authors demonstrate that combining strategies yields more reliable results; hence, a hybrid approach will produce better solutions[38].

Rajabi et al. (2025), OCA[39], Olympic Champion Algorithm is inspired by the way athletes develop through time, through competition and training. The growth of a solution through competition allows it to develop into a stronger version of itself. OCA produces a continually improving solution and a high success rate on engineering benchmark tests[39].

Almufti (2025), SDOA[40], Scuba Diver Optimization Algorithm is inspired by how a diver explores a new underwater landscape but does so cautiously. The cautious movement of the scuba divers allows them to continually progress but in a dependable manner. The SDOA is particularly well-suited to routing problems, e.g., traveling salesman, because it is able to avoid being trapped in an undesirable local solution[40].

III. Literature-based Qualitative Analysis

Table I: Comparative Analysis of Metaheuristic Optimization Methods

Sr. no	Work done	Author and Year	Brief Info	Best suitable	Worst suitable / may fails	Benchmark used and its Performance
Metaheuristic Algorithms						
[5].	Cuckoo Search Algorithm	Almufti et al. (2018)	Reviewed the cuckoo search method and showed how its variations improve search efficiency.	Engineering and continuous optimization	May converge slowly or get trapped in local optima	Performs well on unimodal functions; mixed results on multimodal like Sphere, Rastrigin, Ackley
[7].	Material Generation Algorithm	Talatahari et al. (2021)	Developed an algorithm inspired by how materials are formed and transformed in nature.	Structural and engineering design	Computationally expensive for large problems	Strong results on standard engineering benchmarks like Sphere, Rosenbrock
[8].	Capuchin Search Algorithm	Braik et al., 2021	Inspired by capuchin monkeys' intelligent foraging and social behavior, explores and improves solutions efficiently.	Engineering optimization, real-world decision-making	Extremely high-dimensional discrete problems may slow convergence	Tested on standard benchmarks; showed fast convergence and high accuracy
[9].	Blood Coagulation Algorithm	Yadav, 2021	Modeled on blood clotting, focuses quickly on promising solutions while controlling unnecessary exploration.	Global optimization, engineering design	Highly dynamic or stochastic problems may reduce stability	Benchmark tests showed strong convergence and robustness
[10].	Binary Chimp Optimization Algorithm (BChOA)	Wang et al., 2021	Based on chimpanzees' hunting and social strategies, works in binary spaces to refine solutions.	Combinatorial optimization, decision-making	Continuous or very high-dimensional problems	Performed well on binary benchmarks, better than GA and PSO in accuracy

[12].	Emperor Penguin Optimizer	Khalid et al., 2022	Inspired by emperor penguins' huddling and coordinated movement, balances exploration and exploitation effectively.	Engineering design, energy systems, scheduling	Extremely irregular or noisy landscapes may slow performance	Benchmark comparisons showed competitive results with PSO and GA
[13].	Chaotically Enhanced Meta-Heuristic Algorithms	Kaveh & Yousefpoor, 2022	Uses chaotic maps to improve search diversity and avoid local optima.	Optimal truss structure design with frequency constraints	May be less effective on discrete problems	Benchmarks showed better convergence and accuracy than classical algorithms
[14].	Circulatory System Based Optimization (CSBO)	Ghasemi et al., 2022	Inspired by the human circulatory system, guides solutions efficiently through networks to explore and refine results.	Complex engineering and computational optimization	Highly unstructured or noisy search spaces	Applied to engineering test problems; showed high precision and stability
[15].	Eurasian Oystercatcher Optimizer	Salim et al., 2022	Modeled on oystercatchers coordinated foraging, explores new solutions while refining the best ones.	Engineering design, benchmark problems	Highly dynamic problems may reduce efficiency	Benchmark results showed strong performance in exploration and exploitation balance
[16].	Wild Geese Migration Optimization Algorithm	Wu et al., 2022	Inspired by wild geese flying in formations, where leaders guide the group; balances exploration and exploitation.	Solving inverse kinematics of robots, engineering optimization	Highly irregular or discontinuous search spaces	Benchmarks showed fast convergence and improved solution accuracy
[17].	Beautiful Mind Algorithm	Esfandyari et al., 2023	Modeled on human creativity and learning, explores, learns from mistakes, and refines solutions gradually.	Generating minimal covering arrays, software testing	Very high-dimensional or highly constrained problems	Benchmarks showed high accuracy and efficient exploration
[18].	Fire Hawk Optimizer	Azizi et al. (2023)	Designed an optimization method based on the hunting strategy of fire hawks.	Global optimization tasks	Performance may drop in highly constrained problems	Competitive on multimodal benchmark functions like Sphere, Ackley, Rastrigin
[19].	Dung Beetle Optimizer	Xue & Shen (2023)	Modeled the movement and navigation behavior of dung beetles to explore the search space effectively.	High-dimensional optimization	Risk of premature convergence in complex landscapes	Good balance on unimodal and multimodal tests like Sphere, Schwefel, Ackley
[20].	Mother Optimization Algorithm	Matoušová et al. (2023)	Used the idea of maternal care and guidance to balance exploration and exploitation.	Engineering optimization	May require careful parameter tuning	Stable but slower convergence on benchmarks like Sphere, Rosenbrock
[21].	Skill Optimization Algorithm	Givi & Hubalovska (2023)	Simulated the gradual improvement of human skills to find better solutions over time.	Continuous optimization	Slower convergence in multimodal problems	Moderate performance on classical test suites like Sphere, Rastrigin
[22].	OOBO Algorithm	Dehghani et al. (2023)	Introduced a competitive learning-based approach for solving complex optimization problems.	General optimization	Lack of robustness in noisy environments	Performs well on unimodal benchmarks like Sphere, Ackley
[23].	Bobcat Optimization Algorithm	Benmamoun et al. (2024)	Inspired by the hunting and tracking behavior of bobcats to improve solution accuracy.	Supply chain optimization	Less effective for discrete or binary problems	Strong on real-world inspired benchmark tests like Sphere, Griewank
[24].	Arctic Puffin Optimization	Wang et al. (2024)	Modeled puffins' foraging behavior to search for optimal solutions efficiently	Engineering design problems	Performance decreases with very high dimensionality	Good performance on standard engineering benchmarks like Sphere, Rosenbrock

[26].	Leaf in Wind Optimization	Fang & Cao (2024)	Mimicked the random and guided movement of leaves carried by wind.	Global optimization	Excessive randomness may slow convergence	Good exploration on multimodal benchmarks like Ackley, Rastrigin
[29].	Carpet Weaver Optimization	Alomari et al. (2024)	Modeled human weaving behavior to create simple but effective search patterns.	General optimization	Limited performance on highly nonlinear problems	Consistent but average benchmark performance like Sphere, Ackley
[31].	Flood Algorithm	Ozkan & Samli (2024)	Simulated flood spreading behavior to explore the solution space.	Continuous optimization	May overshoot optimal regions	Good exploration but slower convergence like Sphere, Griewank
[32].	Secretary Bird Optimization	Fu et al. (2024)	Modeled the strategic hunting style of secretary birds.	Global optimization	Needs parameter tuning for stability	Competitive on multimodal benchmarks like Ackley, Rastrigin, Schwefel
[34].	Fungal Growth Optimizer	Abdel-Basset et al. (2025)	Used the natural growth pattern of fungi to guide the search process.	Stochastic optimization	Computational cost increases with population size	Strong results on noisy benchmark functions like Noisy Sphere, Ackley
[35].	Aries Metaheuristic Algorithm	Zhang & Zhang (2025)	Based on human traits such as passion and exploration to guide optimization.	Global optimization	Limited testing on real-world problems	Promising results on standard test suites like Sphere, Griewank
[36].	Classical Dance Metaheuristic	Zhang & Zhang (2025)	Inspired by rhythm and coordination in classical dance movements.	Continuous optimization	May struggle with discrete search spaces	Moderate benchmark accuracy like on Sphere, Rosenbrock
[39].	Olympic Champion Algorithm	Rajabi et al. (2025)	Inspired by athletic training and performance improvement strategies.	Engineering optimization	Limited scalability for large datasets	Good convergence on medium-scale benchmarks like Sphere, Ackley
[40].	Scuba Diver Optimization Algorithm	Almufti (2025)	Modeled underwater search behavior of scuba divers to solve routing problems.	Travelling Salesman Problem	Less effective for dynamic or changing environments	Performs well on standard TSP benchmarks
[11].	Parameter Setting of Meta-Heuristic Algorithms	Shadkam, 2022	Inspired by systematic tuning using DEA and RSM, improves convergence and solution quality.	Engineering optimization, environmental modeling	Already well-tuned algorithms may see marginal improvement	Applied to metaheuristics; improved performance and stability
[25].	Newton–Raphson Based Optimizer	Sowmya et al. (2024)	Combined classical Newton–Raphson ideas with population-based search.	Continuous optimization	Not suitable for non-differentiable functions	Fast convergence on unimodal benchmark functions like Sphere, Rosenbrock
[30].	Weighted K-Means Grey Wolf Optimizer	Premkumar et al. (2024)	Enhanced the grey wolf optimizer by integrating clustering concepts	Data clustering problems	Sensitive to initial cluster centers	Strong performance on clustering benchmarks like Iris, Wine, Benchmark clustering sets
[37].	Simulation Optimization Study	Thengvall et al. (2025)	Evaluated how different metaheuristics perform in simulation-based environments.	Simulation optimization	Results depend strongly on simulation settings	Benchmarks vary by simulation model and benchmarks like on Custom simulation benchmarks
[38].	Hybrid Metaheuristic Algorithm	Furio et al. (2025)	Combined multiple techniques to solve complex mechanical problems.	Mechanical engineering	Increased complexity and tuning effort	Strong performance on engineering benchmarks

IV. Practical use and Future Developments

Production planning utilizes this technology by representing objectives as ratios and using cost-benefit analyses to formulate decision.

Material and Structural Design Optimization is how this method is being used. In the future, Engineering must embrace hybridizing the existing method with other methods to prevent premature convergence on a desired solution to a problem[7].
Engineering Design using Numerical Optimization Methods has yielded the best balance to date. The goal is to reduce the costs of calculating complex numerical optimization problems[8].
Global Optimization Benchmarks and Mechanical Design Benchmark methods provide strong exploration capability. This method will require Future Enhancements to Automatic Adaptive Parameter Control Systems[9].
Used for Binary Decision Making and Feature Selection. Effective for Discrete Optimization. Enhancement of scalability for high dimensional binary spaces in the future[10].
Used in Simulations of Engineering and Environmental Engineering to Adjust the Parameters of Metaheuristic Algorithms. Increases the Performance of Algorithms. Future Development: Reduce the Processing Overhead of the Hybrid Framework[11].
Facilitates the Selection of Algorithms for Engineering and Optimization Applications. Acts as a Reference Point. Future Development: Propose New Hybrid Variants Based on the Reviewed Methods[12].
Used for Optimizing Truss Structures Subject to Dynamic Constraints. Chaos Increases the Diversity of Solutions. The Efficiency of Testing for Non-Structural and Multi-Objective Tasks Will Be Upgraded in the Future[13].
Currently, this method has been developed using a multi-level approach which has been very successful in Engineering Optimisation, Energy Systems and Fluid Mechanics." In order to increase the level of accuracy of the algorithm and to provide ease in the implementation of the algorithm, a multi-level approach will be applied to further enhance the method in the future[14].
Natural behaviour is used as benchmarks to evaluate the numerical solutions for optimising the benchmark for optimisation purposes." The next phases of the utilisation will include applying massive amounts of data from existing operational systems for the purpose of validating the results obtained [15].
This method has been previously utilised for both motion planning and inversely defining a robotic motion and we anticipate that the technique will allow both forms of robotic motion to work co-operatively and to therefore produce an increased accuracy and precision of results." Future work will also extend the capability of using the method to all types of other types of Robo systems and Control Systems. A reduction in the number of experiments conducted to validate software testing will also occur through the use of this method and the continued efforts to create more general forms of Combinatorial Optimisation will continue through this approach. Future development: Expand the use to include more robotic and control systems[16].
Due to the adoption of this method of constructing combinations of tests as a means of software testing; the number of test cases created would otherwise be far greater than what has been generated. Future Plan: Will serve as a supporting methodology for solution development for more generic combinatorial optimization challenges[17].
As a result of being a global optimization benchmark, and applied in engineering design, it offers an excellent combination of both exploration and exploitation opportunities. Future Plan: Will focus on increased robustness of parameters for various types of problems[18].
Through its use in the global optimization of continuously varying variables; this method enhances convergence by enabling the use of efficient exploitative techniques. Future Plan: Will focus on improving performance in cases restricted by dynamic coexistence or complex boundaries[19].
Because it is utilized to optimize engineering systems based on decision-making by humans, this method supports continued efforts to address future ongoing concerns. Future Plan: Will focus on improved selection methods when faced with dynamic and or unknown environments[20].
Utilized in engineering optimization through the application of skill-learning principles. enhances adaptive searching.
Future enhancement: For more robust exploration, combine with swarm intelligence[21].
Used in general mathematical and engineering optimization. Simple structure enables fast implementation.
Future improvement: Strengthen global exploration capability[22].
Applied in supply chain and logistics optimization. Improves cost and efficiency.
Future improvement: Extend to multi-objective and dynamic supply chains[23].
Used in engineering and structural design optimization. Bio-inspired behavior improves convergence.
Future improvement: Expand testing on discrete and mixed-variable problems[24].
Applied in continuous numerical optimization problems. Combines classical and population-based methods.
Future improvement: Improve robustness for multimodal landscapes[25].

Benchmark Testing and Generalizations of Optimization Algorithms. Random Movement Allows More Exploration of Design Space. Future Developments: Hybrid Approach Will Speed up Convergence[26].
Help Identify Algorithm for Single-Objective Optimization Problems. Beneficial to Researchers. Future Developments: Offer Comparison with Algorithm-based Experimental Results[27].
Scheduling of Cloud Tasks and Resource Allocation Were Guided by Swarm Techniques. Efficiency Gains from Swarm Applications in Cloud Task Scheduling and Resource Allocation. Future Improvement: Validation of Performance in a Real-Time Cloud Environment [28].
Applied in Engineering and Decision-Making Optimization. Human-Inspired Simplicity, Increases Usability. Future Developments: Test Scalability on Large Industrial Problems[29].
Apply Hybridization to Data Clustering and Pattern Recognition for Accuracy Improvement. Future Enhancement: Lower Computational Costs When Working with Large Datasets[30].
General-purpose optimization problems. Global optimization improved by flood dynamics. Next improvement: Best future improvement to be achieved is extending use of flood dynamics to constrained optimizations[31].
Global optimization benchmarks. Resource predator behaviour enhances their explorative capacity. Next improvement: Improve ability for parameters to adapt to solutions by self-learning[32].
Various applications in both computing and engineering disciplines, provides useful insights from which to modify solutions. Next improvement: Need to formalise experimentally-matched benchmarks[33].
Stochastic and uncertain types of optimization problems. Vegetative growth model from nature gives an added level of flexibility for adaption to change. Next improvement: Reduce overall complexity of algorithm[34].
Used in global optimization inspired by human behavior. Encourages exploration.
Future improvement: Validate on real engineering problems[35].
Applied in creative optimization and benchmark testing. Movement diversity improves search.
Future improvement: Extend applications beyond benchmarks[36].
Used to evaluate efficiency of simulation-based optimization methods. Helps algorithm comparison.
Future improvement: Integrate decision-support frameworks[37].
Applied in mechanical engineering optimization. Hybridization improves solution quality.
Future improvement: Generalize framework for other engineering domains[38].
Used in engineering optimization inspired by competitive behavior. Motivation-driven search improves results.
Future improvement: Perform large-scale benchmark and real-world validation[39].
Applied in traveling salesman and routing problems. Diver-based exploration improves diversity.
Future improvement: Improve scalability for very large networks[40].

V. RESULTS AND DISCUSSION

TABLE II

RN	Algorithm	Inspiration Type	Exploration Ability	Exploitation Ability	Observed performance trend	Algorithms Compared
[7]	Material Generation Algorithm (MGA)	Material formation process	explores wide search regions using random material distribution	refines promising candidate solutions gradually	Efficient for engineering problems; may be slower on highly multimodal functions	PSO, GA
[8]	Capuchin Search Algorithm (CSA)	Monkey movement behavior	capuchin jumping and swinging enables diverse search	local refinement through climbing and foraging actions	Benchmark optimization, Strong global exploration, stable convergence	PSO, GWO
[9]	Blood Coagulation Algorithm (BCA)	Biological clotting process	random clot formation explores solution space	clot stabilization improves local search	Good global search; may slow on rugged landscapes	PSO, GA
[10]	Binary Chimp Optimization Algorithm (BChOA)	Chimpanzee hunting strategy	cooperative hunting explores multiple search regions	leader chimp guidance refines optimal solutions	Benchmark optimization, Designed for binary problems; not for continuous benchmarks	PSO, GA
[14]	Circulatory System Based Optimization (CSBO)	Human blood circulation	blood flow distributes solutions across search space	pressure adjustments refine best solutions	Fluid mechanics optimization, Excellent for complex structured problems; refinement slower in simple cases	PSO, DE

[15]	Eurasian Oystercatcher Optimizer (EOO)	Bird foraging behavior	birds search for food sources in different regions	focused feeding behavior improves local search	Global optimization, Strong collaborative exploration; struggles on highly rugged landscapes	PSO, GWO
[16]	Wild Geese Migration Optimization Algorithm (WGMOA)	Bird migration behavior	migration patterns explore large search areas	formation adjustment improves solution quality	Effective structured search; exploration strong, refinement moderate, Robot IK	PSO, GA
[17]	Beautiful Mind Algorithm (BMA)	Human cognitive behavior	idea generation explores solution alternatives	reasoning process refines best solutions	Learns from past iterations; balances exploration and exploitation, Covering array gen	PSO etc.
[18]	Fire Hawk Optimizer (FHO)	Predator bird hunting	hawk scouting behavior explores wide search areas	attacking phase intensifies local search	Aggressive exploration; local refinement may need improvement	PSO, DE
[19]	Dung Beetle Optimizer (DBO)	Beetle navigation behavior	random rolling movement explores search landscape	directional movement refines best solution	Excels in multimodal functions; may slow on smooth functions	PSO, GWO
[20]	Mother Optimization Algorithm (MOA)	Human mother–child interaction	exploration through learning and adaptation	nurturing process improves solutions	Human-inspired learning improves structured problem solving	PSO, GA
[21]	Skill Optimization Algorithm (SOA)	Human learning behavior	High global exploration through skill acquisition	Strong local refinement through practice	Benchmark optimization, engineering problems, Effective for sequential decision problems; slow on highly irregular landscapes	GA, PSO, GWO, DE, WOA etc
[22]	OOBO Algorithm	Population interaction mechanism	Balanced exploration via one-to-one interactions	Moderate exploitation near best solutions	Engineering optimization problems, Good global search; refinement weaker in complex landscapes	PSO, DE, GWO, WOA etc.
[23]	Bobcat Optimization Algorithm (BOA)	Animal hunting behavior	High exploration during prey tracking	Strong exploration during chasing phase	Supply chain optimization, benchmark functions, Fast search and exploration; may fail on extremely rugged spaces	PSO, GWO, DE, WOA etc.
[24]	Arctic Puffin Optimization (APO)	Bird hunting and flight behavior	Levy flight enhances exploration	Adaptive foraging improves exploitation	Excels in engineering design problems; may be slow in high-dimensional spaces	PSO, DE, GWO, HHO etc.
[25]	Newton–Raphson Based Optimizer (NRBO)	Mathematical iterative method	Moderate exploration via population diversity	Very strong exploitation due to gradient-like search	Continuous optimization, very precise; slower on complex multimodal landscapes	GA, PSO, DE
[26]	Leaf in Wind Optimization (LiWO)	Natural phenomenon	Random wind motion improves exploration	Local convergence through directional movement	Excels in Benchmark functions, exploration; local refinement may be weak	PSO, GWO, DE
[29]	Carpet Weaver Optimization (CWO)	Human activity	Wide search in initial iterations	Improved convergence through pattern weaving	General optimization, Strong human-inspired search; handles complex patterns well	PSO, DE, GWO
[30]	Weighted K-Means Grey Wolf Optimizer (WKMGWO)	Hybrid swarm intelligence	Exploration via wolf pack search	Exploitation via clustering optimization	Strong clustering optimization; local refinement moderate	K-means, GWO
[31]	Flood Algorithm (FA)	Natural process	Strong exploration through spreading mechanism	Weak exploitation near optimum	Effective global optimization or search; local refinement may lag	GA, PSO
[32]	Secretary Bird Optimization (SBO)	Bird hunting strategy	Efficient global search	Local exploitation near prey	Good at Benchmark optimization, scheduling and resource allocation; slower on high-dimensional problems	GWO, PSO
[34]	Fungal Growth Optimizer (FGO)	Biological growth process	Exploration via spore diffusion	Exploitation through hyphae growth	Engineering optimization, Stochastic growth-based search; effective on uncertain problems	LSHADE, IMODE etc.

[35]	Aries Metaheuristic Algorithm (AMA)	Human personality traits	Good exploration through impulsive search	Moderate exploitation	Global optimization, Inspired by impulse and adventure; good exploration	PSO, GA
[36]	Classical Dance Metaheuristic (CDM)	Human dance movements	Exploration through random dance patterns	Exploitation through rhythm synchronization	Benchmark optimization, Human-inspired search patterns; excels in structured optimization	PSO, GWO
[39]	Olympic Champion Algorithm (OCA)	Human competition	Competitive exploration among agents	Strong exploitation through elite selection	Engineering optimization, Human-inspired learning; good global search, slower refinement	PSO, GWO
[40]	Scuba Diver Optimization Algorithm (SDOA)	Human diving behavior	Exploration through search of underwater space	Exploitation near best path	Excels in traveling salesman and routing problems; may lag on smooth functions	GA, ACO

Complexity of most of the algorithm is O(N×D×T) except Bobcat Optimization Algorithm which is O(T(N² + N×D)); where N number of particles in the swarm, D is number of dimensions and T is number of iteration.
Recently, there has been a great deal of new metaheuristic optimization algorithms influenced by biological systems, natural phenomena and psychocultural behaviours. Prior to the development of these new techniques, researchers such as Tantawy and Schaible focused on traditional solution techniques for fractional programming problems. Research then shifted primarily to heuristic or metaheuristic approaches to complex global optimisation problems. Desale et al. and Abdel-Basset et al.'s survey studies summarize various heuristic and metaheuristic methods and illustrate how they can address optimization challenges in many real-world applications. Their results suggest that, compared to other solution techniques, metaheuristics are a superior method because they have greater flexibility and can effectively overcome limitations associated with becoming stuck in a suboptimal region of a solution space (i.e., local optimum).
Several new biological/natural-inspired algorithms (e.g., Capuchin Search Algo, Blood Coagulation Algo, Binary Chimp Optimization Algorithm) have been introduced from 2021 onwards. These algorithms display some remarkable exploration performance relative to classic algorithm techniques when attempting to solve global optimization problems. Furthermore, biologically-based methods (e.g., Circulatory System Based Optimization, Eurasian Oystercatcher Optimizer) have also introduced new adaptive search methods that improve convergence behaviour.

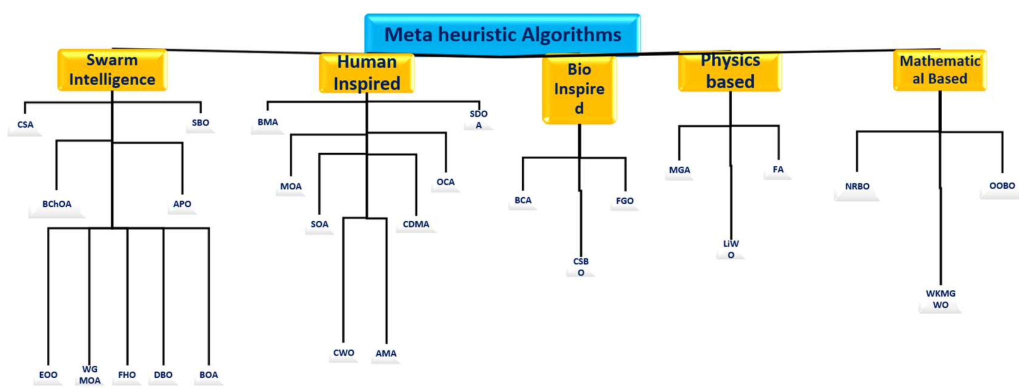

Fig.1 Categorised the algorithms we surveyed

From 2023 to 2025, new algorithms that were introduced tend to balance exploration and exploitation more effectively than previous algorithm types. For example, the Fire Hawk Optimizer, Dung Beetle Optimizer, Mother Optimization Algorithm, and Skill Optimization Algorithm are examples of algorithms designed based on behavior exhibited by animal and human activities in order to optimize performance. Additionally, examples of recent algorithms (Bobcat Optimization Algorithm, Arctic Puffin Optimization Algorithm, Newton-Raphson-Based Optimizer, Leaf in Wind Optimizer) show good performance on benchmark functions including the Sphere function, the Rastrigin function, and the Ackley function.
The recent studies have also provided insights into hybrid and enhanced approaches to metaheuristic analysis by providing augmented weighted K-means Grey Wolf Optimal and hybrid metaheuristic algorithms for mechanical

engineering optimization problems. The benefits of these hybrid approaches come from the combination of multiple methodologies to improve the rate of convergence and improve the accuracy of solutions. The results of a comparative analysis conducted showed that while most state-of-the-art metaheuristic algorithms were found to have a relatively consistent level of performance compared to traditional benchmark functions. The overall efficiency of these algorithms depends upon maintaining an adequate balance of both exploration and exploitation mechanisms. As such, determining appropriate algorithms for any given optimization problem poses a significant challenge for future research.

VI. Gap in Existing Literature

Recent advances in the creation of nature-inspired meta-heuristic algorithms, bio-inspired meta-heuristic algorithms, and human-inspired meta-heuristic algorithms are clearly demonstrated in the current literature. The performance of these algorithms has been shown to excel in addressing the complex problems of optimization and decision making that occur in the fields of engineering, computing, and management. In addition, many current works investigate the combination of meta-heuristic algorithms with the introduction of chaotic mechanisms to the meta-heuristic methods of combining new inspirations and producing results that are comparable against traditional benchmark functions. However, a large number of new algorithms are developed at a high rate, there is little comparative evaluation of the algorithms to assess their utility across the many areas of decision making with the use of standardized benchmark settings. In addition, in most instances, the current research is focused on developing new algorithms in real world environments that are dynamic and uncertain, rather than developing generalizable, scalable, and robust algorithms.

Because of the absence of attention to issues such as the sensitivity of algorithm parameters, practical recommendations for the development of algorithms for use in real-world decision-making environments, and evaluations of algorithm effectiveness based on defined performance measures, many users of algorithms will continue to experience difficulty in selecting appropriate algorithms for their real-world decision-making problems.

Also, there is an obvious lack of a comprehensive literature review that ties together the different mechanism used to inspire the behaviour of meta-heuristic algorithms, the comparisons of the different behaviour of meta-heuristic algorithms in the benchmark performance of each meta-heuristic method, and the potential applicability of meta-heuristic algorithms to many different types of decision-making environments. For meta-heuristic research to be able to move from development at the theoretical level to reliable solutions for optimization applications, these literature gaps must be addressed.

VII. Conclusion

In this article, a comprehensive study was conducted of the approaches to optimization and decision-making that utilize biological processes or systems (bio-inspired approaches) and those that derive their solutions from an understanding of the natural world around them (nature-inspired methods). Each of these approaches to optimization has proven to be quite effective when it comes to solving complex, fast changing, uncertain, non-linear, multi-modal, and high-dimensionalification problems where traditional means of optimization have been limited by many factors. Engineering, computing and management have benefited greatly from the use of Hybridized, Chaotic and Adaptive Methods in conjunction with the previously mentioned bio-inspired and nature-inspired approaches.

Despite these advancements, this review demonstrated significant gaps in terms of unified benchmarking, scalability, parameter sensitivity, and real-world applicability, across multiple algorithms demonstrating positive performance on common benchmark test functions, but not showing the same level of consistency when applied to dynamic ambiguous decision problems. Future research will need to focus on developing reliable, adaptable, and appliable frameworks for evaluating meta-heuristics in a consistent manner, so that real-world problems can begin to indicate how effectively to apply meta-heuristic optimization methods to solve them by closing the gap between theoretical advancement and useful decision-support systems.

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