Research Paper

Survey on whale optimization algorithm: from fundamental principles to modern adaptations and applications

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ABSTRACT

The Whale Optimization Algorithm (WOA), inspired by the bubble-net hunting behavior of humpback whales, has emerged as one of the most influential swarm intelligence algorithms for solving complex optimization problems. Since its introduction, WOA has attracted substantial research attention due to its balance between exploration and exploitation, simplicity of implementation, and competitive performance across diverse problem domains. This survey provides a comprehensive analysis of WOA, encompassing its fundamental principles, mathematical formulation, variants, hybridizations, and extensive real-world applications. A systematic taxonomy is presented to classify WOA modifications into adaptive, chaotic, hybrid, discrete, multi-objective, and intelligent-learning-based frameworks. The review also highlights WOA's successful integration into fields such as structural engineering, energy systems, machine learning, bioinformatics, and emerging intelligent technologies including IoT and cloud computing. Comparative benchmarking and statistical analyses demonstrate the superiority of enhanced WOA variants over traditional metaheuristics in terms of convergence rate, stability, and accuracy. Finally, the paper identifies existing challenges and outlines promising research directions, including theoretical convergence proofs, parameter self-adaptation, large-scale optimization, and hybridization with deep learning and quantum paradigms. This work provides a consolidated and critical overview of WOA's evolution, serving as a valuable reference for researchers and practitioners in the field of metaheuristic optimization.

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1. INTRODUCTION

Metaheuristic algorithms have become a fundamental element in modern optimization methods because they provide strong adaptive solutions which researchers use to tackle complex high-dimensional nonlinear challenges that exist in engineering computer science energy systems and other domains [1]. The Whale Optimization Algorithm (WOA) exists as a simple method which anyone can easily implement yet it delivers competitive results across all test scenarios and actual applications [2]. The algorithm uses the humpback whale bubble-net foraging technique as its basis because this behavior provides a natural way to demonstrate how search activities should balance exploring new areas with executing their current goals.

Despite the fast rise in attention afforded to WOA research, many reviews are reducing it to basic mechanisms or compare it to the other few optimization algorithms. The essential survey needs to establish the basic principles along with the exhaustively complete modification taxonomy and hybridization methods and total WOA applications and their performance evaluation processes [3]. This paper aims to fill that gap by presenting an in-depth analysis of WOA from its theoretical foundations to its latest developments and future research directions. The researchers receive a unified summary of present advanced research together with identified potential research areas for future development [4].

The remainder of this paper is organized as follows: Section 2 explains the fundamentals of metaheuristic algorithms and the critical balance between exploration and exploitation. The Whale Optimization Algorithm establishes its core principles through Section 3 which explains its mathematical framework and operational framework and its source of inspiration. The first section provides a system to classify all the changes which have been suggested to improve WOA, while the following section shows all the different ways WOA can be used in various fields. Section 6 evaluates WOA performance through various tests which compare it to similar algorithms, while Section 7 presents newly developing research areas and existing difficulties and potential future research paths. The survey ends with Section 8 which presents important findings, and Section 9 lists the sources used in the research.

2. FUNDAMENTALS OF METAHEURISTIC ALGORITHMS

Metaheuristic algorithms stand as a wide-ranging category of stochastic optimization methods which operate at an advanced level to find nearly optimal solutions for intricate nonlinear problems that exist in high-dimensional space and exceed the capabilities of standard deterministic methods and gradient-based approaches which suffer from scalability and differentiability and convergence speed problems [5], [6]. Metaheuristics use probabilistic search methods which enable them to examine extensive and complex solution spaces while requiring only basic knowledge about the problem instead of needing specific problem details or gradient information which traditional mathematical programming methods demand.

These algorithms operate through iterative learning and adaptive processes to enhance multiple candidate solutions which use feedback from the fitness landscape for their development. Their operations use natural processes as the basis for their design because these processes provide effective methods to solve complex search problems through evolutionary and physical and animal group behavior patterns. The biologically and physically based framework enables metaheuristics to break free from deterministic methods while solving scientific and engineering problems that involve multiple solutions and sudden changes and extreme limitations [7].

Metaheuristic algorithms use their built-in capacity to balance between exploration and exploitation as their main fundamental feature. The exploration phase ensures sufficient diversity by encouraging the search to traverse broad regions of the solution space which prevents the search from stopping at local optimal solutions [8]. The exploitation phase deepens the search process by concentrating on areas which show potential to develop better solutions while the system moves closer to finding the global optimal solution. The successful operation of all metaheuristic algorithms depends on their ability to combine these two operational modes which work as their main functions [9], [10], [11].

Metaheuristics show exceptional strength and flexibility because they use adaptive control strategies and randomization operators and population-based evolution methods. The ability to adapt their methods to different situations makes these systems essential for solving optimization problems in engineering design machine learning energy systems and computational intelligence. Metaheuristic algorithms function as primary optimization methods because they develop new optimization methods which include hybrid and multi-objective and self-adaptive intelligent algorithms [12], [13].

2.1. Classification and Characteristics

- **Evolutionary Algorithms (EAs):** The algorithms operate on groups of potential solutions which they evolve through three processes: selection, crossover, and mutation. Genetic Algorithms (GA) serve as a standard method for solving both combinatorial and continuous optimization challenges according to reference [14].
- **Physics-Based Methods:** The method involves optimization techniques which operate through the simulation of natural physical processes according to the principles of simulated annealing (SA) [15] and gravitational search algorithms (GSA) which duplicate the functioning of gravitational forces [16].
- **Swarm-Based Techniques:** The methods use social animal group behavior patterns which researchers observe in bird flocks and fish schools as their foundation. Particle Swarm Optimization (PSO) [17], [18] and the Whale Optimization Algorithm (WOA) fall into this category. The system uses basic rules which enable agents to change their location based on their personal experiences and the experiences of nearby agents [19].

2.2. Balancing Exploration and Exploitation

The basic problem that all metaheuristic algorithms must solve requires them to find the right balance between two search methods which include global search and local search [20], [21]. The exploration phase enables the algorithm to traverse a wide area of the search space, while the exploitation phase focuses on refining existing promising solutions. The system will reach its first solution too early when investigators spend their time on other aspects instead of conducting experiments. WOA uses mechanisms which scientists based on humpback whales' bubble-net feeding behavior to create a system that directs its search between two types of search which include broad exploration and narrow exploitation.

3. WHALE OPTIMIZATION ALGORITHM: FUNDAMENTAL PRINCIPLES

The Whale Optimization Algorithm (WOA) is a swarm-based metaheuristic algorithm developed by Mirjalili [22] and Lewis in 2016, and it mimics the bubble-net hunting strategy of humpback whales, as shown in Figure 1. Humpback whales use a special hunting technique because they swim in spiral movements which produce specific bubble nets that they use to catch fish. WOA models these behaviors using mathematical equations and operators which enable it to simulate the process of encircling and updating through spirals and conducting random searches to find prey [23].

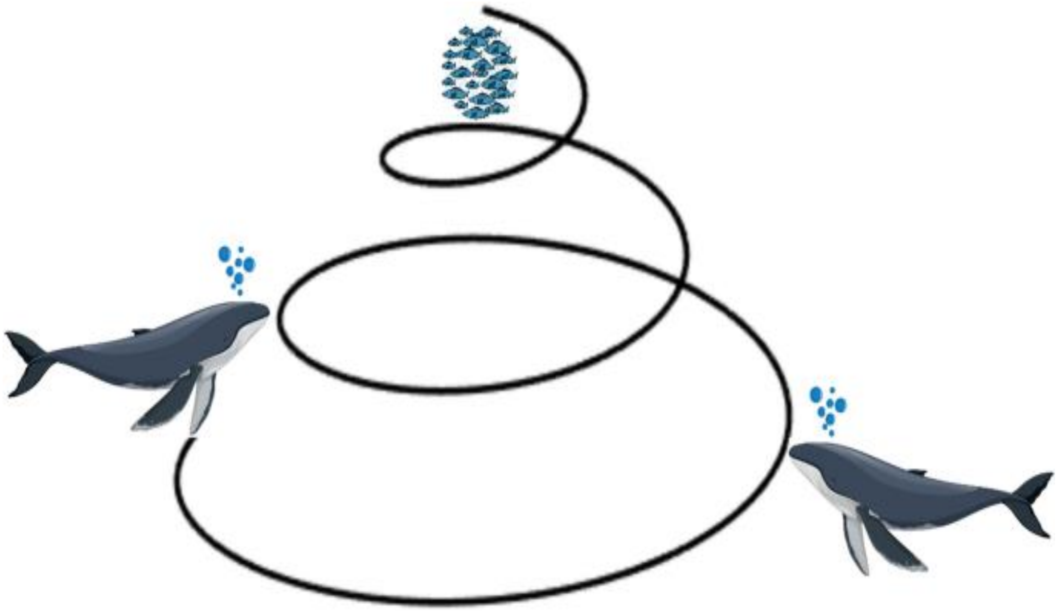

Figure 1. Whale Optimization Algorithm Hunting Strategy

3.1. Inspiration from Humpback Whales

Humpback whales demonstrate advanced skills in their hunting methods. The whale uses bubble-net feeding to create a circular barrier which traps fish within a spiral release of bubbles. The natural behavior breaks down into three separate stages according to WOA [2]:

- **Encircling Prey:** The algorithm assumes that the current population's best solution functions as the prey which all remaining candidate solutions must track to reach their most valuable candidate solution.
- **Bubble-Net Attacking (Spiral Updating):** Whales move through space by following a spiral pattern which leads them to their most optimal solution while imitating the bubble-net foraging method.
- **Search for Prey (Exploration):** Whales use random movement to search for prey because they need to stop their chances of reaching an early conclusion.

3.2. Mathematical Modeling of WOA

3.2.1. Encircling Prey

The encircling behavior is modeled mathematically by assuming that the best solution, X^*, is the target prey. The distance between a whale and the prey is defined as:

$$D = | C \cdot X^*(t) - X(t) |$$

Where

- $X(t)$ is the position vector of the current whale at iteration t,
- C is a coefficient vector defined as $C = 2 \cdot r$ (with r being a random vector in [0,1]).

The next position of a whale is updated using:

$$X(t+1) = X^*(t) - A \cdot D$$

Where $A = 2ar - a$ and a linearly decreases from 2 to 0 during the course of iterations 46.

3.2.2. Bubble-Net Attacking Method

WOA uses a spiral equation to simulate the bubble-net attack. After computing the distance between the whale and prey, the whale updates its position along a spiral-shaped path:

$$X(t+1) = D' \cdot e^{bl} \cdot \cos(2\pi l) + X^*(t)$$

Where

$$\text{-}D' = | X^*(t) - X(t) |$$

- b is a constant defining the spiral shape, and
- l is a uniformly distributed random number in $[-1,1]$ 6.

3.2.3. Random Search for Prey

When the algorithm decides to explore instead of exploit, the positions are updated through a random mechanism:

$$X(t+1) = X_{rand} - A \cdot | C \cdot X_{rand} - X(t) |$$

Here, X_{rand} is a random whale from the current population, encouraging the algorithm to diverge from the current best solution and maintain diversity in the population.

3.3. Algorithm Pseudocode and Flowchart

Below provides the pseudocode for the Whale Optimization Algorithm:

1. Initialize a simple but informative description of the WOA algorithm is provided here.
2. Evaluate the fitness of each whale.
3. While termination criteria are not met:
   i. Update the coefficient vectors A and C.
   ii. For each whale:
      - If a random probability p is less than 0.5, update position using the encircling prey model.
      - Otherwise, update position using the spiral updating model.
      - If exploration is chosen (based on parameter a), select a random whale X_{rand} and update the position accordingly.
   iii. Evaluate new opinion and renew the best solution X^*
4. Return the best solution found.

3.4. Strengths and Weaknesses

Strengths:

- Simplicity and no work.
- The system achieves fast convergence results with both unimodal and multimodal benchmark functions.
- The mechanism of adaptive control balances the tradeoff between exploration and exploitation very effectively.

Weaknesses:

- An overreliance on parameter settings, especially control parameters, is discouraged.
- Often, it is faced and stuck in local optima in the complex and high-dimensional problems.
- The search space is divided into binary securities or discrete securities and the individual can run that algorithm with aggressive results.

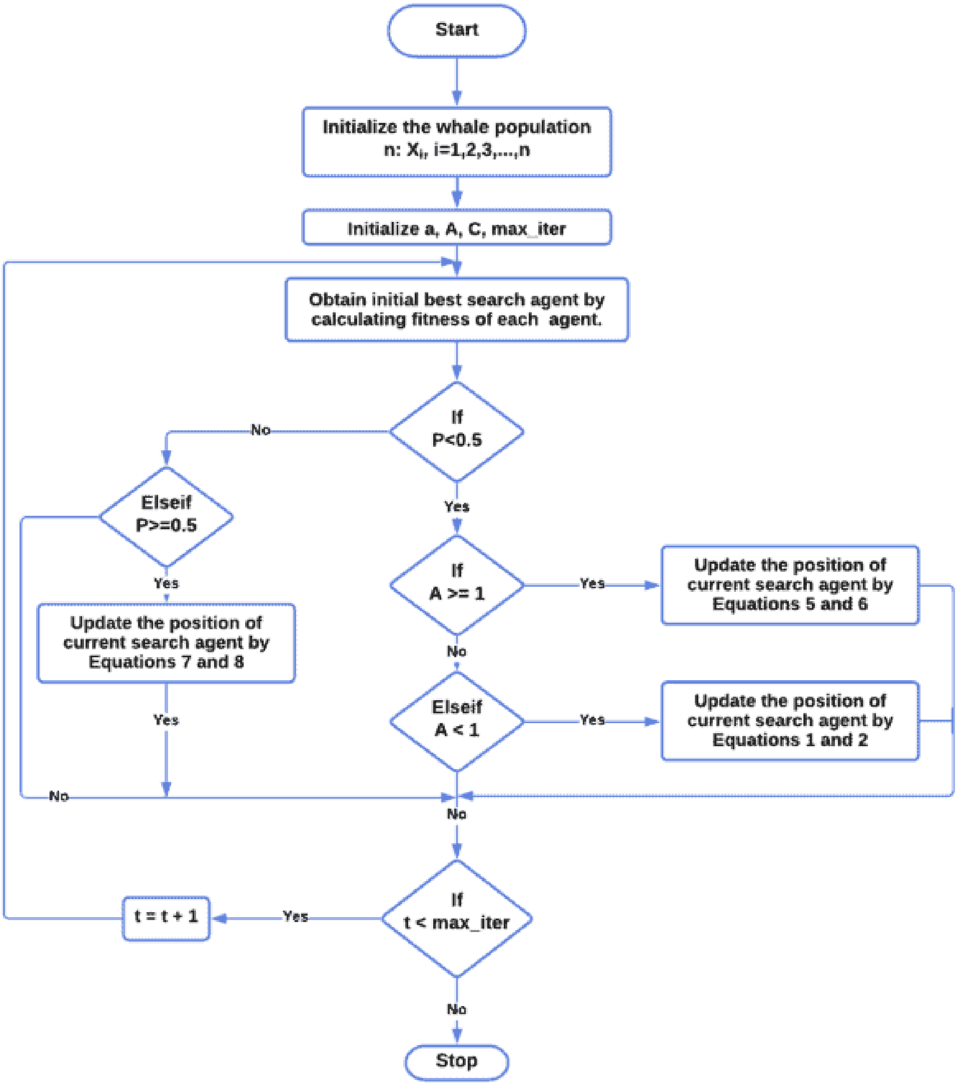

Figure 2. Whale Optimization Algorithm Flowchart

4. MODIFICATIONS AND HYBRIDIZATIONS OF THE WHALE OPTIMIZATION ALGORITHM

The Whale Optimization Algorithm (WOA) first became available to researchers in 2016 when Mirjalili and Lewis introduced it. Researchers have conducted extensive studies to find solutions for three main WOA weaknesses which include premature convergence and improper local search methods and issues with tuning control parameters. The development of multiple WOA variants enables better problem-solving performance through six main categories of modifications which include (i) parameter-adaptive modifications (ii) chaotic and randomness-enhanced variants (iii) hybrid metaheuristic combinations (iv) discrete and binary transformations (v) multi-objective extensions and (vi) intelligent and machine-learning-integrated frameworks.

Each modification aims to improve specific characteristics of the basic algorithm, which includes its exploration-exploitation balance and its convergence speed and its ability to produce accurate solutions. The following taxonomy summarizes the most prominent developments reported in recent literature.

4.1. Taxonomy of WOA Variants

1. **Parameter-Adaptive and Self-Tuning WOA:** The methods adjust the coefficients which include an A C l and p together with the population parameters according to the current iteration status and the entropy calculations and the range of fitness values. The three methods include Adaptive WOA which is known as AWOA and Self-Adaptive WOA which is referred to as SAWOA and Entropy-Controlled WOA which is used with the abbreviation EnWOA.
2. **Chaotic, Stochastic, and Randomized Variants:** The researchers used Chaotic WOA (CWOA) and Orthogonal Chaotic WOA (OCWOA) and Levy Flight WOA (LWOA) to show how they use chaotic sequences through logistic and tent and sine and Gauss maps.
3. **Hybrid Metaheuristic WOA Models:** Hybrid approaches combine WOA with various optimization methods which include PSO GA DE GWO ABC ACO FA TLBO and other techniques to achieve their optimal global and local performance. The methods use complementary mechanisms which result in greater system stability and better accuracy for reaching their objectives.
4. **Discrete, Binary, and Combinatorial Adaptations:** WOA has been modified to handle binary and integer problem domains in feature selection scheduling and routing problems through its implementation of transfer functions and encoding transformation methods which include Binary WOA and Improved Discrete WOA.
5. **Multi-Objective and Many-Objective WOA:** Multi-objective extensions (MOWOA, IMOWOA) use Pareto dominance combined with crowding distance and fuzzy logic to solve conflicting paradoxes which occur in engineering optimization together with machine learning tasks.
6. **Intelligent, Learning-Based, and Hybrid Control WOA:** Integration with neural networks, reinforcement learning, fuzzy control, and transfer learning enables WOA to autonomously tune its search dynamics, as seen in RL–WOA, Fuzzy WOA, and Deep Learning–WOA.
7. **Parallel, Distributed, and Multi-Population Approaches:** These methods distribute computation across multiple processors or sub-swarms, increasing scalability and computational efficiency (Parallel WOA, Multi-Swarm Cooperative WOA).

4.2. Comprehensive List of WOA Modifications and Hybrid Variants

Table 1, presents that the evolution of WOA has followed a clear trend toward hybridization and intelligent adaptation. The initial changes of the system targeted two main areas which included improving randomization and enhancing parameter management through AWOA and CWOA. The research conducted from 2021 until 2025 focuses on two main aspects which involve using multiple algorithms together with artificial intelligence to learn optimal operating parameters. The combination of WOA with PSO and WOA with DE and WOA with GWO and WOA with SMA has shown better results in engineering and medical and energy field applications. The current research field shows three main developments which include WOA enhancements through reinforcement learning and surrogate modeling techniques for better computational results and multi-population systems that enable better performance in solving complex high-dimensional challenges.

The algorithm shows three main abilities through its latest developments which show it can adapt to different situations while maintaining stable performance and working with new quantum optimization methods and deep neural network systems.

Table 1. WOA Modifications

Sr. No	Modification / Hybrid Type	Description
1.	Adaptive WOA (AWOA)	Dynamically adjusts control parameters to maintain balance between exploration and exploitation throughout iterations.

2.	Improved WOA (IWOA)	The researchers established improved methods for local search through their development of refined solutions for encircling and spiral equations.
3.	Chaotic WOA (CWOA)	The system uses chaotic maps to conduct parameter updates which results in enhanced population diversity.
4.	Inertia-Based WOA (ILWOA/MWOA)	The system uses inertia-like terms which prevent stagnation while they help to speed up convergence.
5.	WOA–PSO Hybrid	The system achieves balanced performance through WOA exploration combined with PSO exploitation.
6.	WOA–DE Hybrid	In order to hasten the convergence process, DE operators, mutation, and crossover operators were integrated.
7.	WOA–GA Hybrid	Changes the binary transfer functions of WOA for the continuous problems.
8.	Binary WOA (BWOA)	Adjustments WOA to discrete issue by using binary transfer functions.
9.	Multi-Objective WOA (MOWOA)	It incorporates qubit representation and quantum superposition principles.
10.	Quantum WOA (QWOA)	The use of qubit representation and the quantum superposition principles is suggested.
11.	Levy Flight WOA (LWOA)	Lévy flights are best suited to global exploration.
12.	Opposition-Based WOA (OBWOA)	A lesser percentage of the current constituent assignment decreases perplexity.
13.	Hybrid WOA–GWO	The system executes WOA together with Grey Wolf Optimizer to achieve an equal distribution of their two fundamental tasks.
14.	Hybrid WOA–SCA	The system establishes global search capabilities by implementing Sine Cosine Algorithm dynamics into its framework.
15.	Chaos-Driven Adaptive WOA (CAWOA)	The system uses two techniques which include chaotic initialization and adaptive parameter control to execute its functions.
16.	Random Walk WOA (RWWOA)	The system establishes enhanced exploration capabilities through the implementation of stochastic random walks.
17.	Elite Opposition-Based WOA (EOBWOA)	The system achieves faster convergence through its use of elite opposition learning methods.
18.	Fuzzy WOA (FWOA)	The system employs fuzzy logic to perform automatic parameter adjustments which depend on the results of search activities.
19.	Mutation-Based WOA (MBWOA)	The system uses Gaussian or Cauchy mutations to create new population members through its mutation process.
20.	Ensemble WOA (EWOA)	The system operates multiple control strategies and sub-algorithms at the same time.
21.	Parallel WOA (PWOA)	The system partitions its computational tasks across various nodes to achieve faster completion times.
22.	Deep Learning–Integrated WOA (DL–WOA)	The system uses WOA to optimize neural networks while conducting neural network training and hyperparameter optimization processes.
23.	Hybrid WOA–SA	The system combines simulated annealing through its probabilistic acceptance feature while using WOA to perform its search process.

24.	Hybrid WOA–ACO	The system uses pheromone-based path development to handle routing and scheduling tasks.
25.	Dynamic WOA (DWOA)	The system uses time-dependent control coefficients which allow it to change its exploration speed dynamically based on current conditions.
26.	Orthogonal WOA (OWOA)	The system applies orthogonal experimental design methods to achieve effective process start-up.
27.	Enhanced WOA (EWOA)	The system presents a main category which shows both better resource use and better parameter adjustment methods.
28.	Self-Adaptive WOA (SAWOA)	The system maintains its control parameters through automatic feedback processes which monitor changes in fitness levels.
29.	Improved Convergence WOA (ICWOA)	The system uses nonlinear convergence control methods which help to speed up the optimization process.
30.	Gaussian WOA (GWOA)	The system applies Gaussian perturbation methods to create stronger local refinement processes.
31.	Cauchy WOA (CWOA2)	The system uses Cauchy distribution mutation methods as a way to research new paths.
32.	Exponential Decay WOA (EDWOA)	The system applies exponential decay control methods to its parameters so that it achieves more gradual progress toward its target.
33.	Differential WOA (DWOA2)	The system uses differential update methods to create better variants which increase system participation.
34.	Entropy-Controlled WOA (EnWOA)	The system uses information entropy measurements to adjust its search performance according to current conditions.
35.	Gradient-Guided WOA (GGWOA)	The system uses gradient information to achieve faster progress toward its goal.
36.	Momentum-Driven WOA (M-WOA)	The system uses information entropy measurements to adjust its search performance according to current conditions.
37.	K-Means Assisted WOA (KM–WOA)	The system uses clustering methods to create a balance between maintaining different options and focusing on areas with high potential.
38.	Hybrid WOA–BAT	The system combines an echolocation-based BAT algorithm with the operational methods found in WOA.
39.	Hybrid WOA–Firefly (WOA–FA)	The system uses light-intensity-based attraction methods to enhance its capacity for exploration.
40.	Hybrid WOA–ABC	Merges foraging-based search from ABC to refine local search.
41.	Hybrid WOA–HS	Incorporates harmony memory and pitch adjustment mechanisms.
42.	Hybrid WOA–TLBO	Leverages teaching–learning phases to strengthen WOA’s learning.
43.	Hybrid WOA–CSA	Combines crow memory strategy with WOA’s encircling behavior.
44.	Hybrid WOA–MFO	Integrates Moth Flame Optimization’s flight path search pattern.
45.	Hybrid WOA–SMA	Employs slime mould oscillatory behavior to enhance adaptability.
46.	Hybrid WOA–ALO	Uses trapping and random walk of ALO for exploratory improvement.
47.	Hybrid WOA–SOA	Combines seagull migration and attack phases with WOA’s model.
48.	Hybrid WOA–CS	Embeds Lévy-flight-based cuckoo dynamics for random search.

49.	Hybrid WOA–MPA	Fuses marine predator–prey dynamics with WOA's exploitation.
50.	Hybrid WOA–EPO	Incorporates penguin grouping and thermal dynamics principles.
51.	Hybrid WOA–GJO	Combines golden jackal chasing strategy with WOA's bubble-net phase.
52.	Multi-Population WOA (MPWOA)	Divides population into multiple sub-swarms for diversity maintenance.
53.	Multi-Swarm Cooperative WOA (MSWOA)	Enables information sharing among multiple WOA subgroups.
54.	Ensemble Learning–Driven WOA (EL–WOA)	Uses ensemble decision mechanisms among WOA variants.
55.	Surrogate-Assisted WOA (SA–WOA)	Employs surrogate modeling to handle computationally expensive evaluations.
56.	Transfer Learning–Based WOA (TL–WOA)	Transfers prior optimization knowledge to new problem instances.
57.	Reinforcement Learning–WOA (RL–WOA)	Utilizes RL agents to dynamically adjust parameters and strategies.
58.	Dynamic Population WOA (DPWOA)	Adjusts population size based on diversity and convergence indicators.
59.	Energy-Balanced WOA (EBWOA)	Applies bio-inspired energy consumption model to guide search.
60.	Thermal Exchange WOA (TEWOA)	Adapts heat transfer theory for dynamic search adaptation.
61.	Modified Spiral Search WOA (SSWOA)	Introduces variable-radius spiral equations for refined exploitation.
62.	Neighborhood Search WOA (NSWOA)	Incorporates local neighbor interactions for improved convergence.
63.	Orthogonal Chaotic WOA (OCWOA)	Combines orthogonal learning and chaos for initialization.
64.	Improved Discrete WOA (IDWOA)	Employs customized mapping for integer and permutation optimization.
65.	Hybrid WOA–EO	Integrates equilibrium optimizer's exploration rules.
66.	Hybrid WOA–SFO	Uses sailfish-inspired attacking–migrating strategies.
67.	Improved Multi-Objective WOA (IMOWOA)	Incorporates fuzzy dominance and crowding distance ranking.
68.	Hybrid WOA–Jellyfish Search (WOA–JS)	Combines time-controlled motion from JS for adaptive exploration.

5. APPLICATIONS OF THE WHALE OPTIMIZATION ALGORITHM (WOA)

The Whale Optimization Algorithm (WOA) has demonstrated its ability to adapt to various scientific fields and engineering disciplines and computational systems. The method uses simple mechanisms to achieve powerful results because it mimics humpback whales' bubble-net hunting technique. The upcoming section will present the primary application areas of WOA followed by an in-depth description of sample applications.

5.1. Engineering and Structural Optimization

The organization has reached multiple achievements in its structural and mechanical design work through its development of solutions for difficult nonlinear optimization problems which contain multiple constraints. The system has been tested successfully on traditional benchmark tests which include truss structure design and pressure vessel design and welded beam design and spring optimization tests, achieving results that match those of standard evolutionary algorithms. The system has enhanced design reliability through its combination of finite element modeling with multi-objective design frameworks which engineers use in both civil and mechanical engineering fields.

5.2. Energy and Power Systems

The Whale Optimization Algorithm has become the standard method for photovoltaic systems to achieve maximum power point tracking and for economic load dispatch and optimal power flow applications. The system achieves precise results through its ability to maintain performance during changing conditions which enhances its capacity to control renewable energy systems and microgrid operations and smart grid functions. The WOA–PSO and WOA–DE hybrid variants demonstrate strong performance for optimizing complex energy models which include both nonlinear and stochastic elements.

5.3. Computational Intelligence and Machine Learning

The WOA algorithm exists as a common method for three tasks which include selecting features and grouping data and tuning parameters within machine learning and deep learning systems. The system functions as an optimization tool which enhances the distinction accuracy and speed of convergence for neural networks and support vector machines and convolutional neural networks. The hybrid models WOA–GA and WOA–GWO and WOA–SCA have been created to solve premature convergence issues, which enables them to produce better outcomes on high-dimensional datasets.

5.4. Medical, Bioinformatics, and Image Processing

The World Ocean Assessment (WOA) maintains exceptional international search capabilities which enable it to provide precise results for biomedical research and medical imaging studies. Its applications include liver and brain tumor segmentation, disease classification, gene selection, and protein structure prediction. WOA has been used in image processing to perform multi-level thresholding and contrast enhancement and image segmentation which resulted in improved visual quality and enhanced diagnostic performance. The system provides support for DNA sequence alignment and drug–target interaction prediction tasks in bioinformatics.

5.5. Emerging Technologies and Smart Systems

The WOA system functions effectively with IoT networks and cloud and edge computing systems and cybersecurity protection systems. The system supports multiple functions which include task scheduling and resource provisioning and load balancing and intrusion detection. WOA has been used in robotics and path planning to create better travel routes and to manage multiple robots at once. The system has enhanced traffic signal timing and vehicle routing and supply chain management for smart transportation and logistics. The system uses real-time optimization to make WOA suitable for use in autonomous and intelligent systems.

Table 2. Applications of Whale Optimization Algorithm (WOA) Across Multiple Domains

Sr. No	Application Domain	Specific Application
1.	Structural Optimization	Truss structure design, welded beam design, pressure vessel optimization, and tension/compression spring design
2.	Energy Systems	Photovoltaic MPPT, renewable energy integration, economic load dispatch, and microgrid operation
3.	Power Systems	Optimal power flow, generator scheduling, capacitor placement, and load forecasting

4.	Image Processing	Image segmentation, contrast enhancement, thresholding, and image reconstruction
5.	Medical Diagnosis	Liver segmentation, brain tumor detection, toxicity classification, and COVID-19 diagnosis
6.	Data Clustering and Feature Selection	High-dimensional feature selection, clustering, and dimensionality reduction
7.	Control Systems	PID parameter tuning, adaptive control, and load frequency control
8.	Wireless Sensor Networks (WSNs)	Node deployment, energy-efficient clustering, and lifetime maximization
9.	Machine Learning and Deep Learning	Hyperparameter tuning for SVM, CNN, and hybrid WOA–DL frameworks
10.	Manufacturing and Scheduling	Job-shop scheduling, process planning, and production sequencing
11.	Communication Networks	Resource allocation, channel estimation, and QoS optimization in 5G
12.	Supply Chain and Logistics	Inventory optimization, routing, and transport cost minimization
13.	Robotics and Path Planning	Path optimization and swarm-based multi-robot coordination
14.	Financial Systems	Portfolio optimization, risk management, and stock trend prediction
15.	Water Resources Engineering	Reservoir operation and water distribution optimization
16.	Transportation Systems	Traffic control, route optimization, and intelligent scheduling
17.	Cybersecurity and Cryptography	Image encryption, key generation, and network intrusion detection
18.	Internet of Things (IoT)	Energy-efficient clustering, resource optimization, and device deployment
19.	Cloud and Edge Computing	Task allocation, VM scheduling, and resource provisioning
20.	Bioinformatics	Gene selection, protein folding, and DNA sequence alignment
21.	Renewable Energy Forecasting	Wind and solar power prediction using hybrid WOA–ML models
22.	Structural Health Monitoring	Damage detection and modal parameter estimation
23.	Environmental Systems	Pollution control, waste management, and ecosystem modeling
24.	Network Security	IDS optimization, DoS prevention, and secure communication
25.	Signal Processing	Filter design, spectral estimation, and biomedical signal analysis
26.	Software Engineering	Test case prioritization and software effort estimation
27.	Hydrology	Flood forecasting and watershed modeling
28.	Aerospace Engineering	UAV path planning and aerodynamic shape optimization
29.	Smart Grids	Load management, power prediction, and demand response
30.	Combinatorial Optimization	TSP, knapsack, and assignment problems

The algorithm demonstrates its ability to handle different types of problems through its ability to work with various applications. The current research trend shows a progressive transition from standalone implementations toward hybridized and domain-specific WOA variants, particularly in deep learning optimization, smart grid management, and IoT-driven automation. Recent studies demonstrate that multiple object and discrete system adaptations have extended the usability of WOA beyond its traditional continuous optimization applications.

6. PERFORMANCE EVALUATION AND BENCHMARKING

The essential element which determines the efficacy of any metaheuristic lies in its ability to solve benchmark functions and actual field applications. The performance of WOA has been assessed in multiple studies which compared it to three widely used optimization methods: Particle Swarm Optimization (PSO), Binary Ant Lion Optimizer (bALO), and Binary Dragonfly Algorithm (bDA).

6.1. Benchmark Function Evaluation

The original WOA paper validated the algorithm on benchmark functions which included both unimodal and multimodal functions and complex engineering design problems. The evaluation demonstrated that WOA achieved performance results which matched other methods but produced better solution outcomes. The results of the study reached statistical significance through the application of Wilcoxon rank-sum nonparametric test and other statistical tests.

6.2. Comparative Studies

Recent studies have compared various binary and hybrid versions of WOA on standard datasets:

- In feature selection tasks utilizing benchmark datasets from the UCI repository, the binary variants bWOA-S and bWOA-V outperformed other algorithms by achieving higher classification accuracy and better feature reduction.
- Hybrid algorithms combining WOA with PSO or DE have demonstrated superior performance on a number of constrained engineering design problems.

These results are typically summarized in comparative tables. An example table for Bechmarking has to be considered Table 3.

Table 3. Benchmarking and Comparative Performance of WOA Variants

Algorithm	Benchmark Test Functions	Performance Indicator
WOA (Original)	29 Unimodal & Multimodal Functions	Fast convergence, high accuracy
Binary WOA Variants (bWOA)	UCI Benchmark Datasets	Higher classification accuracy
WOA-PSO Hybrid	Constrained Engineering Problems	Improved global search and convergence
WOA-DE/WOA-GA Hybrid	Global Numerical Optimization Problems	Enhanced solution diversity

6.3. Statistical Analysis

The application of statistical tests, such as the Wilcoxon's rank-sum test at a 5% significance level, has been instrumental in establishing the superiority of enhanced WOA variants over traditional approaches. These tests confirm that modifications—ranging from chaotic adjustments to hybridization with other metaheuristics result in statistically significant improvements in convergence speed and solution quality.

7. TRENDS, CHALLENGES, AND FUTURE DIRECTIONS

In monitoring the growth of WOA, one can remark in the process emerging trends and the outstanding issues and yet others already keen for future research.

7.1. Emerging Trends

Current trends indicate that the optimists have also started bridging the gap at World Optimism Association and are doing so much good work:

- **Hybridization:** The combination of WOA with PSO and DE and GA and local search methods has produced hybrid models that demonstrate superior performance compared to conventional algorithms in multiple application areas.
- **Adaptation in High-Dimensional Problems:** To remove the difficulties posed by the high-dimensional search space, efforts to nationwide-solve have been made to control the improved parameters, which include the adaptive mechanisms and the chaotic maps.
- **Application Expansion:** The application spectrum of WOA keeps expanding because recent studies investigate deep learning and feature selection methods for big data and real-time optimization of dynamic systems.

7.2. Challenges

While WOA has its positive points, it is facing several issues that need further research:

- **Parameter Sensitivity:** The performance of WOA depends on correct control parameter settings which include parameter a and the two vectors A and C. The search space will experience premature convergence or excessive wandering because of incorrect settings. The search space will experience premature convergence or excessive wandering because of incorrect settings.
- **Local Optima Trapping:** The surrounding mechanism can constrain algorithms from escaping from local optima, particularly in very complex multi-modal problems.
- **Scalability:** The extension of WOA to handle extreme high-dimensional challenges and discrete optimization situations which include binary feature selection and 0-1 knapsack problems needs further development work and it continues to be studied by researchers.

7.3. Future Research Directions

Various lines of future research are being studied further:

- **Theoretical Convergence Analysis:** Theoretical foundations for practical implementations will be established through more detailed mathematical analysis and convergence proof development of WOA and its various algorithms.
- **Parameter Self-Adaptation:** The algorithm will achieve better performance which shows increased strength because of its ability to automatically change control parameters through self-adaptive mechanisms.
- **Hybrid and Multi-Objective Optimization:** In the future, research is directed towards deep hybridization strategies as well as multi-objective versions of WOA, necessary for coping with the complex real-world scenarios.
- **Parallel and Distributed Implementations:** The implementation of modern parallel computing architectures together with distributed frameworks will enable WOA to perform large-scale optimization tasks because these technologies will decrease the required computational time.
- **Integration with Machine Learning:** The intersection of WOA with machine learning—especially in deep neural network feature selection and parameter tuning—promises fertile ground for future advancements.

8. CONCLUSION

An in-depth study of the Whale Optimization Algorithm (WOA) has taken into account the basic postulates of the algorithm, various modifications, a wide range of applications, and benchmarking the results. Insights I have gained from this study include:

- **Fundamental Innovation:** The WOA is based on the travelling structure of the bubble-net seen in gathering behavior of the humpback whale that in an elegant way blends the two strategies of exploration and exploitation guided by mathematically defined operators.
- **Algorithmic Enhancements:** The proposed solution uses several modifications and hybrid methods to improve system performance which currently suffers from parameter sensitivity and premature convergence issues.
- **Wide-Ranging Applications:** The WOA is based on the travelling structure of the bubble-net seen in gathering behavior of the humpback whale that in an elegant way blends the two strategies of exploration and exploitation guided by mathematically defined operators.
- **Performance and Benchmarking:** The improved versions of WOA show better performance in both speed and accuracy when compared with standard algorithms which include PSO and DE according to comparative research studies and statistical analysis.
- **Emerging Trends and Future Work:** Future research should focus on four main areas which include developing self-adaptive parameter systems and optimizing multi-objective and hybrid systems and applying contemporary machine learning methods.

The Whale Optimization Algorithm has become a major research topic because of its easy-to-use design and its effective real-world results. Researchers face three main challenges which include difficulty tuning parameters and solving scalability issues and developing theoretical frameworks. The development of hybrid systems together with innovative system changes will create advanced metaheuristic optimization methods.

Main Findings Summary:

- **WOA's Core Principle:** Adaptive parameterization and hybrids with other metaheuristics enable better global search.
- **Modifications & Hybridizations:** Adaptive parameterization and hybrids with other metaheuristics enable better global search.
- **Application Success:** This domain is referenced in engineering, energy, image processing, and clustering.
- **Future Directions:** Emphasis is placed on theoretical analysis in self-adaptive nature and integrated with distributed distributed computing and deep learning.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

Conflict of Interest Statement

The authors declare that there is no conflict of interest regarding the publication of this paper.

Informed Consent

This study is a survey and review paper based exclusively on previously published literature. It does not involve human participants, personal data, or identifiable information. Therefore, informed consent was not required.

Ethical Approval

Ethical approval was not required for this study, as it is a secondary research work that does not involve experiments on humans or animals, nor the collection of sensitive or private data.

Data Availability Statement

No new datasets were generated or analyzed during the current study. All data discussed in this survey are derived from publicly available and previously published sources cited in the reference list.
This study adopts the Contributor Roles Taxonomy (CRediT) to transparently describe the individual contributions of each author. All authors have made substantial contributions to the work and approved the final version of the manuscript. Saman M. Almufti is the corresponding author and was responsible for all correspondence related to the submission, revision, and publication processes.

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